Using Visual Technology to Increase the Productivity and Quality of Fruit Classification in Order to Make Retaining Labour Economically Viable

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Declaration

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Abstract

Advancements in Industry 4.0 technologies are leading to the digitalisation and automation of the agricultural sector. The risk of automation is that it could lead to the marginalisation of small and medium sized farms as well as an increase in unemployment. Therefore, Augmented Reality, with advanced visual capabilities, was studied as it has the potential to aid employees in the agricultural sector instead of displacing them. Within the fruit industry, avocado farms were selected as the focal point to test Augmented Reality. This was due to avocado farms providing significant improvement opportunities, with 50% of fruit being wasted, and the potential to increase the economic activity of very poor regions globally, as the climate to grow avocados are in these regions. The productivity and quality improvements were shown to be the most advantageous for farmers who still pack avocados on their farm, which is currently a manual process which could benefit from the collaboration between human and technology.

To test the possible productivity and quality improvements to avocado fruit classification process a prototype was developed. This prototype utilised Augmented Reality and Machine Learning technologies to assist a packer when classifying avocados according to size and grade, to improve the accuracy and speed of avocado classification. The practical implementation of Augmented Reality and Machine Learning technologies were done using the HoloLens 1 and Microsoft Azure respectively. Post development the prototype was tested, and the results showed a significant increase in packing quality as the accuracy increased from 73.3% when grading and 58.5% when sizing avocados to 83.0% and 73.3% respectively. To test the productivity improvement of the prototype both the packing speeds of a trained and untrained packer were evaluated with and without the prototype. The productivity improvement (measured in the packing speed increase) for the trained and untrained packers were 29.87% and 54.88% respectively when utilising the HoloLens 1. The results showed that both quality and productivity improvements can be made when Augmented Reality is implemented on avocado farms.

Having proven that both the quality and productivity of the avocado classification process have been improved it was then necessary to test the possible financial benefit that can be generated which would make retaining labour economically viable. The economic results show that for small and medium sized farmers who either pack their own fruit on the farm or utilise a packing facility there is a significant financial benefit when utilising the prototype. It is found that for small and medium sized farmers who currently pack their own fruit, who are also the mostly likely adopters of and would benefit the most from the prototype, the financial benefit is R438 426.99 and R2 192 134.96 respectively per annum. Therefore, the prototype, utilising Augmented Reality and Machine Learning technologies, was able to increase the quality and productivity of the fruit classification process, resulting in significant economic benefit, justifying the retention of labour on avocado farms, and potentially the entire agricultural sector.

Opsomming

Vooruitgang in Industry 4.0-tegnologieë lei tot die digitalisering en automatisering van die landbousektor. Die risiko van outomatisering is dat dit kan lei tot die marginalisering van klein en medium boere sowel as 'n toename in werkloosheid. Daarom was Verhoogde Werklikheid, met gevorderde visuele vermoëns, bestudeer aangesien dit die potensiaal het om werknemers in die landbousektor te help in plaas daarvan om hulle te verplaas. Binne die vrugtebedryf was avokadoplase gekies as die fokuspunt om Verhoogde Werklikheid te toets. Dit was te danke aan avokadoplase wat verbeteringsgeleenthede bied, met 50% van vrugte wat vermors word, en die potensiaal om die ekonomiese aktiwiteit van baie arm streke wêreldwyd te verhoog, aangesien die klimaat om avokadopere te kweek in hierdie streke is. Die produktiwiteit en gehalteverbeterings het getoon dat dit die voordeligste is vir boere wat nog avokadopere op hul plaas verpak, wat tans 'n handmatige proses is wat voordeel kan trek uit die samewerking tussen mens en tegnologie.

Om die moontlike produktiwiteit en gehalteverbeterings in die klassifikasieproses van avokadopere te toets, was 'n prototipe ontwikkel. Hierdie prototipe het Verhoogde Werklikheid en Masjienleer-tegnologie gebruik om 'n pakker te help om avokadopere volgens grootte en graad te klassifiseer, om die akkuraatheid en spoed van avokadopereklassifikasie te verbeter. Die praktiese implementering van Verhoogde Werklikheid en Masjienleer-tegnologie was met onderskeidelik die HoloLens 1 en Microsoft Azure geïmplementeer. Na ontwikkeling was die prototipe getoets, en die resultate het 'n beduidende toename in verpakkingsgehalte getoon, aangesien die akkuraatheid van 73.3% waneer graad gradering en 58.5% waneer grootte gradering van avokadopereklassifikasie tot 83.0% en 73.3% onderskeidelik gestyg het. Om die produktiwiteitsverbetering van die prototipe te toets, is beide die pakspoed van 'n opgeleide en onopgeleide pakker geëvalueer met en sonder die prototipe. Die produktiwiteitsverbetering (gemeet in die pakspoedverhoging) vir die opgeleide en onopgeleide pakkers was onderskeidelik 29.87% en 54.88% met die gebruik van die HoloLens 1. Die resultate het getoon dat beide 'n beduidende gehalte- en produktiwiteitsverbetering gemaak kan word wanneer Verhoogde Werklikheid geïmplementeer word op avokadoplase.

Nadat dit bewys was dat beide die gehalte en produktiwiteit van avokadopereklassifikasie verbeter kan word, was dit dan noodsaaklik om die moontlike finansiële voordeel te toets wat gegenereer kan word wat die behoud van arbeid ekonomies lewensvatbaar sou maak. Die ekonomiese resultate toon dat vir klein- en mediumgrootte boere wat óf hul eie vrugte op die plaas pak óf 'n verpakkingsfasiliteit gebruik maak, daar 'n aansienlike finansiële voordeel is wanneer die prototipe gebruik word. Daar was gevind dat vir klein- en mediumgrootte boere wat tans hul eie vrugte verpak, wat ook die mees waarskynlike aannemers van die prototipe is en die meeste daarby sal baat, die finansiële voordeel R438 426.99 en R2 192 134.96 onderskeidelik per jaar kan wees. Daarom was die prototipe wat gebruik gemaak het van Verhoogde Werklikheid en Masjienleer-tegnologie in staat om die gehalte en produktiwiteit van die vrugteklassifikasieproses te verhoog, wat beduidende ekonomiese voordeel tot gevolg gehad het wat die behoud van arbeid op avokadoplase, en moontlik die hele landbousektor, regverdig.

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List of Acronyms

AHP	Analytic Hierarchy Process
AI	Artificial Intelligence
API	Application Programming Interface
AR	Augmented Reality
cm	Centimetre
g	Gram
GAP	Good Agricultural Practices
IoT	Internet of Things
K	Kelvin
kg	Kilogram
KPI	Key Performance Indicator
LF	Lean Farming
m	Meter
ML	Machine Learning
MRL	Minimum Residue Level
MS	Microsoft
NDP	National Development Plan
PaaS	Platform as a Service
PC	Personal Computer
R^2	R-Squared
RGB	Red, Green, and Blue
RQ	Research Question
RTMF	Real Time Monitoring and Feedback
SaaS	Software as a Service
SCM	Supply Chain Management
SF	Smart Farming
SME	Small and Medium-Sized Enterprises
SQ	Sub-Research Question
ST	Systems Thinking
URL	Uniform Resource Locator

Glossary

Artificial Intelligence	Intelligence demonstrated by machines as opposed to natural intelligence displayed by animals and humans.
Computer Vision	Technology that allows image-based automatic inspection and analysis.
Cyber Physical System	A system in which a mechanism is controlled or monitored by a computer base algorithm.
Deep Learning	A subset of machine learning. A neural network with three or more layers.
Image Classification	A subset of computer vision in which an algorithm analyses an image and assigns a label to it from a subset of possible labels.
Image Segmentation	The process of partitioning an image into multiple segments.
Machine Learning	Type of artificial intelligence allowing software applications to become more accurate at predicting outcomes without being explicitly programmed to do so.
Object Detection	Subset of computer vision that detects instances of semantic objects of certain classes in digital images and videos.

Chapter 1 Introduction

The purpose of this chapter is to present the research that will be undertaken. The first part of this chapter focuses on the background. Thereafter the problem that this thesis aims to solve will be examined. The analysis will result in a problem statement which will introduce the research questions. The research question will be broken down into sub questions which will be answered throughout the rest of the thesis. The contribution that this thesis aims to provide is briefly discussed followed by the research methodology. Lastly, the chapter concludes with the limitations, delimitations, ethical considerations, and layout in the execution of this thesis.

1.1 Background

Agriculture started 8 to 10 thousand years ago from when it has grown significantly and is presently one of the most important industrial sectors [1]. This is because farming activities contribute 4% to the global GDP and employ 50% of the global work force [1], [2]. The relatively low GDP contribution compared to the employment contribution of the agricultural sector is a result of the economic situation of many of the individuals in this sector. The sector consists of 525 million farmers, many of whom are subsistence farmers who do not contribute significantly to the global GDP [3]. Many of the poorest people in the world are in the agricultural sector with over 65% of the poorest working individuals being employed in this sector [2]. In some of the countries where these individuals are located agriculture represents over 25% of the national GDP [2]. Due to the poverty of many communities who are involved in agriculture, its global GDP contribution does not reflect the size and importance of this sector.

1.1.1 Importance of Agriculture to South Africa

South Africa, which has seen little to no economic growth over the last few years, has been significantly impacted by the Covid-19 pandemic. During the first quarter of 2020, when South Africa only experienced the first part of the damaging effects of the virus, the economy contracted by 1.8% [4]. During the next quarter, quarter two, the South African economy suffered significantly more with the contraction increasing to 51% [4]. These contractions reduced the income and spending power of South Africans. This led to a reduction in the standard of living which has exacerbated the living conditions for many already struggling South Africans. Even before the pandemic it was estimated that 20-50% of South Africans were experiencing food insecurity [5].

To mitigate the effects brought about by the Covid-19 pandemic, which may last for another couple of years, it will be necessary for South Africa to focus on sectors which were less affected. The agricultural sector, which makes up 2.5% of the South African GDP and provides work for 5% of the South African population, can help the South African economy recover [5]–[7]. The overall contribution of the agricultural sector increases to 47% if the entire supply chain (SC) is considered and not just the direct GDP resulting from agriculture [5], [8]. The relative size of the agricultural sector is small compared to the other sectors of the South African economy [9]. The importance of the agricultural sector is not only the size of the GDP contribution but also the continuous growth of the sector and the economic role it plays in poor communities [5]. The agricultural sector was the fastest growing sector in South Africa in 2020 with a first and second quarter growth of 27.8% and 15.1% [4], [7] respectively. This growth has remained steady with the sector being one of the strongest sectors again in the second quarter of 2021 [10]. This continuous growth while the overall GDP contracted as severely as it did, shows a significant resilience to the effects of the global pandemic. It is this resilience and the ability of the agricultural sector to bring prosperity to South Africans who will likely be struggling because of Covid-19 that makes the agricultural sector so important.

1.1.2 The Agriculture Sector in South Africa

The agricultural sector in South Africa directly employs 885 000 people, but 8 500 000 people or 47% of the South African work force is employed in the greater agricultural SC [5], [8]. The reliance on the agricultural sector for labour employment is part of the reason why the agricultural sector is so important to South Africa. This sector is also the main employer and economic driver in rural South Africa and a large portion of the produce is exported which is important for bringing in foreign capital [5].

Agriculture in South Africa is dominated by 35 000 commercial farmers who produce 95% of the products on 87% of the available farm land [5]. There are also 4 000 000 smaller farmers, many of whom are subsistence farmers, who produce the remaining 5% of the produce on the other 13% of farmland [5]. The small farmers do not currently have access to the same opportunities as the larger commercial farmers [5]. This is because of both a lack of capital availability and economies of scale which make it hard to justify the purchase and utilisation of new and expensive equipment. Small-scale farmers are also struggling because of: poor farming practices, lack of resources, lack of farming skills, and soil depletion [5]. These smaller farmers, although they are struggling, play an important role in the future of South Africa. This is because they play an important role in creating employment opportunities as well as the distribution of wealth [11]. It is for this reason that the South African government is trying to focus on the sector, especially on the small farmers, as highlighted in the National Development Plan (NDP) [11]. This is an important document that was set up in 2012 to highlight the plans of the South African government to stimulate growth and reduce poverty as well as inequality in South Africa.

The NDP states that the government has the following goals pertaining to the agricultural sector: ensuring a food trade surplus, having 33% of all food being produced supplied by small farmers, significantly reduce unemployment, reduce poverty, and ensure food security for all South Africans [11]. To achieve these goals the government wants to make the agricultural sector more productive and increase its exports. This is because the South African government sees an increase in productivity as a way of increasing the wealth of the sector. If the agricultural sector is stimulated and more capital flows into it, it should bring increased prosperity to the rural community. This is especially true if it is done through the empowerment of small, up and coming farmers [11]. It should be noted, however, that there seems to be no clear guidelines of how the government plans to achieve its goals. The government does state that they plan to spend money on technology in the agricultural sector to make small-scale farming not only viable but profitable [11].

1.1.3 Automation and the Fruit Industry in South Africa

In the agricultural sector the fruit industry is of extreme economic importance since more than 50% of South African agricultural exports are fruit [12]. It is these exports which bring foreign capital into South Africa to stimulate the South African economy. It is not only the foreign capital that is important but also the fact that these industries employ a significant number of people. As stated, the agricultural sector employs 50% of the global work force. Most of these people are, however, extremely poor.

The envisaged growth of the agricultural sector will result in the uplifting of the world's poorest people. However, this vision is changing because of automation in the agricultural sector. With the adoption of automation in the agricultural sector, the sector is going to grow in terms of productivity but also reduce the number of people employed in the sector [2], [13], [14]. One of the areas that are going to be severely affected by this automation is the fruit industry since fruit classification can now be automated with the advancement in visual technologies [14]. Since improvements in visual technologies, which focus on automation in the agricultural industry, has now made it possible to increase the accuracy of fruit classification [14], [15]. These improvements are both necessary for increased food security and competitiveness of the agricultural sector [16]. The downside of automation in the agricultural sector, especially fruit classification which employs a lot of people, is that it will no longer be a vehicle for lifting the world's poor out of poverty, but instead lead to an increase in unemployment as people are displaced by technology [17].

1.1.4 Automation and the South African National Development Plan

The NPD plans to increase the participation of small farmers in the agricultural industry to reduce unemployment, reduce poverty, and ensure food security nationally [11]. Unfortunately, automation in the agricultural will not lead to employment, as discussed above, nor to the increase in emerging farmers. There are two reasons why automation will reduce the participation of emerging farmers [18]. Firstly, automation will make the large farmers even more competitive as it will enable them to scale more economically. Secondly, to automate is expensive, so the already high economic barriers to entry in the agricultural sector will be even higher. Therefore, automation will result in the large farmers maintaining 94% of the South African agricultural production, or even increasing their market share as they become more profitable utilising expensive equipment that small and emerging farmers simply cannot afford.

1.2 Research Problem Statement and Questions

1.2.1 Research Problem Statement

The above problem description leads to the following main problem statement:

PS: The problem is that the application of new visual technologies in agriculture has automation as a key component which is expensive and leads to the replacement of people by technology.

The problems with the current use of visual technologies leading to automation are:

- A rise in unemployment since the agricultural sector employs a significant number of people. A significant portion of the 50% of all employed people, 10% of South Africans working in the agricultural sector, and 63% of fruit packing jobs in Germany will be at risk of unemployment [2], [13].
- An increase in the market dominance of larger commercial farms, further excluding smaller farms from market participation [18].
- An increase in the barriers of entry into the farming sector, because expensive new technology requires more capital investment [18].
- All three above mentioned points are counterproductive to what we wish to achieve in the agricultural sector in South Africa, namely to increase employment by opening up the sector by having a dispersed market share supporting emerging farmers and encouraging them to enter the sector [11].

1.2.2 Research Questions

The above problem description leads to the following main research question:

RQ: Is there a visual technology available that will increase the productivity and quality of fruit classification making retaining labour economically viable?

To answer this main research question, the following sub-questions need to be answered:

SQ1. Does a visual technology exist that increases productivity and quality while retaining labour?

SQ2. Can KPIs be developed with which to measure the productivity and quality improvement of the fruit classification process when the visual technology is used?

SQ3. Does this visual technology significantly improve the productivity and quality of the fruit classification process?

SQ4. What are the economic benefits to the employer when implementing this visual technology?

1.3 Research Aim and Objectives

The objective of this study is to determine the feasibility of a visual technology that will increase productivity of the classification of fruit thus making retaining labour in the agricultural sector economically viable. In order to achieve this aim, the following objectives have been defined:

1. Research alternative visual technologies and select the most appropriate visual technology for increasing productivity while retaining labour.
2. Design a prototype to test the functionality of the selected visual technology.
3. Implement the prototype and collect quantitative and qualitative data regarding the productivity improvement when applying the prototype to a case study.
4. Analyse the quantitative and qualitative data to determine if statistically significant improvements were made.
5. Verify and validate measures to determine the accuracy and validity of results gathered in the study.
6. Do a cost-benefit analysis to determine the feasibility of implementing the visual technology for the use of fruit classification in the agricultural environment.

1.4 Research Contribution

Through research conducted in studying the use of Augmented Reality in agriculture it became clear that published results are limited [10]. Therefore, this thesis is applying Augmented Reality in the agricultural industry to determine if the technology can add value to the sector. Thus, it is the application of existing technologies in novel ways and to novel sectors that is the contribution of this thesis, as can be seen in Figure 1.1 below.

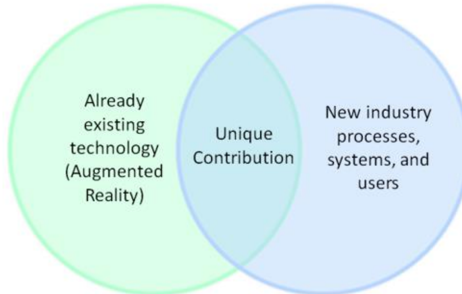

Figure 1.1 Figure of a Venn diagram showing that the unique contribution of this thesis is through the utilisation of existing technology in a novel sector

1.5 Research Design and Methodology

In order to conduct research systematically it was decided to utilise the research onion methodology [19]. It was decided to use the pragmatic approach when conducting research. This was done because in the study not only facts, such as the productivity and quality improvement data, will be collected and studied but also the opinions of farmers, related to their stance on technology utilisation. The reason why both facts and opinions will be studied is because the purpose of this thesis is to study the possible utilisation of visual technologies in the agricultural sector. If these technologies improve the productivity and quality of the classification process in the sector but do not appeal to farmers, it will not be adopted. Therefore, a pragmatic approach that is both focused on results but also the acceptance of the technology was adopted.

To support this research methodology a deductive research approach will be followed. This is because it is already known that visual technologies coupled with automation is leading to increased productivity and quality. Therefore, it is reasonable to assume that if a visual technology that can aid an employee instead of using automation should be able to also increase the productivity and quality of the employee. Thus, a deductive approach will be followed with the assumption that a visual technology that assists an employee could reduce the need for automation.

To test the research approach assumption a case study will be used as the research strategy for this thesis. This will be done by applying a visual technology to a specific fruit group to test the possible productivity and quality increase that can be achieved. In doing so hopefully the research conducted will be able to determine if there are areas where a visual technology can improve the classification processes without the need for automation.

The utilisation of a pragmatic approach will result in the research data that has been collected being both quantitative as well as qualitative. The focus will be on quantitative data testing the productivity and quality improvements achieved through the execution of a case study. However, qualitative data such as the farmers' opinions regarding the adoption and utilisation of new technologies will also be collected and utilised. Literature will also be consulted which is both qualitative and quantitative in nature since both facts and opinions are provided. Therefore, the data collection approach for this thesis will be mixed-methods approach.

The origin of the quantitative and qualitative data will be both primary and secondary. This is because originally literature will be consulted, which is secondary data, in order to have a deeper understanding of both the technologies and the case study of application. As the study progresses however, and the visual technology is applied to a case study, primary data will be collected.

By applying this structured approach when studying the implementation of a visual technology on the classification of fruit a thorough analysis can be done. The structure will allow for guidance during the execution of this thesis to ensure that the relevant research areas have been studied using the correct approach. In doing so both the researchers and readers of this thesis can have confidence in the results achieved and conclusions drawn.

1.6 Limitations and Delimitations

The focus of this project is the implementation of a system utilising visual technologies, that do not lead to automation, to improve the productivity and quality of fruit classification in order to make retaining labour economically viable for small and medium sized farms. The reason for not including large farmers is because as stated in section 1.1.4 they are already benefiting from automation implementation and benefiting considerably more than the small and medium sized farms. Therefore, the maximum benefit will be to the small and medium sized farms (who cannot afford expensive automation equipment), and they will also be the ones most likely to adopt an alternative. Thus, both large farmers and automation will be outside the scope of this project.

To test the effect of a visual technology the focus will not be on the development of new algorithms, rather it will be on implementing existing ones to classify fruit. Therefore, current visual technologies and supportive hardware and software will be implemented in a simple but effective manner, with the focus being on implementing a solution that is simple and effective for testing the application of visual technologies. If the visual technology selected is found to add value to the fruit classification process, then a more sophisticated solution can be implemented in the future.

1.7 Ethical Considerations

It is important that ethical consideration be made during the execution of this thesis. The first ethical consideration that must be adhered to is that of informed consent. The participants will be fully informed of the nature, procedures, and results of the study conducted so that they can make an informed decision when providing their voluntary consent to take part in the study. Secondly, all participants in the study are taking part of their own free will. They will also be free to leave the study at any time without any explanation required. Lastly, the identity of all participants will be protected. Therefore, no identifying information regarding any of the participants will be presented in this thesis in order to protect all the voluntary participants who have provided their informed consent in order to take part in this study.

1.8 Thesis Outline

The chapter outline of this thesis can be seen in Figure 1.2 below. The various chapters in the figure have the following purpose:

Chapter 1 introduces the study by discussing the background, problem statement, research questions, contribution, design, and framework of the research that will be conducted.

Chapter 2 introduces the literature surrounding the visual technology selected. It then continues by exploring various other Industry 4.0 technologies that support the selected visual technology and justifies the use of these other technologies. The chapter then concludes by exploring the impact that these technologies are having and will continue to have on the agricultural sector.

Chapter 3 justifies the selection of the avocado sector as the case study of this thesis. Thereafter, given that the avocado sector has been selected, it then expands upon the avocado industry in order to provide a broader understanding of the sector and avocado fruit classification parameters.

Chapter 4 is used to determine the required hardware and software that will be best suited for the design and development of this prototype. Therefore, within this chapter different hardware and software solutions will be evaluated and the best options will be selected.

Chapter 5's main purpose is to explain both the logic and the design methodology of the prototype system. The system logic will be discussed in detail, whereafter the development of the prototype will be described using a selected framework.

Chapter 6 examines the effects on both productivity and variation when the prototype is compared to the current classification method. Therefore, the prototype is implemented in this chapter and the data is captured. This data is then used to determine the effects that the visual technology has on fruit classification.

Chapter 7 is dedicated to determining the most likely adopters of a visual system, the effect on the farms who implement the system, and the potential size of the market that will be interested in the system. This data is then used in conjunction with the benefit provided by the visual technology to determine the profitability of implementing the visual technology when classifying fruit.

Chapter 8 is focused on whether the right system was designed and developed to test the research questions in Chapter 1.

Chapter 9 concludes the thesis by providing an overall summary; answering the research questions; discussing the study's limitations; providing recommendation; and examining the contributions of the thesis; and future studies that can be conducted.

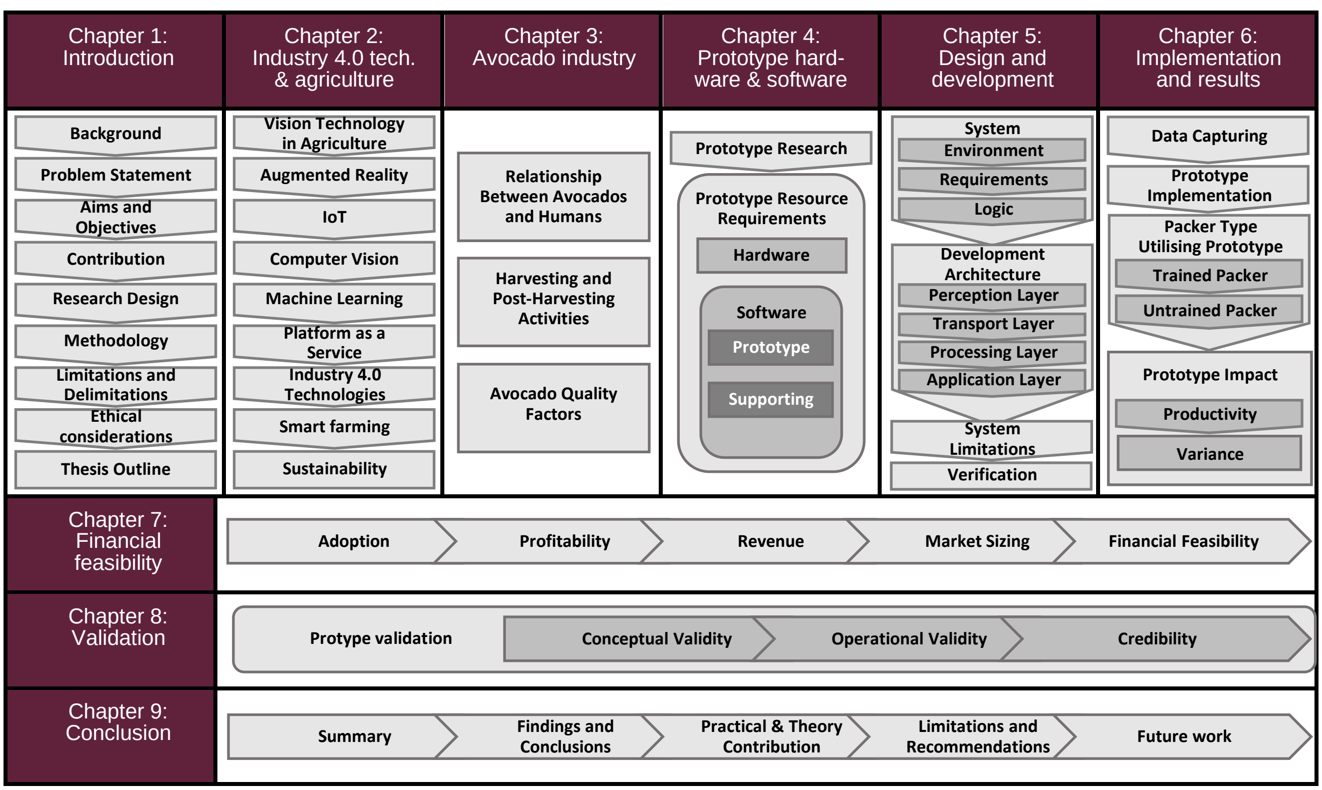

Figure 1.2: Figure of the thesis outline.

1.9 Conclusion

A brief overview of both the importance and the threat of automation, as a key component of visual technologies, to the agricultural industry is discussed to provide a background to the thesis. It is then discussed that the problem of automation is that it can lead to large scale unemployment and the marginalisation of small and medium farmers as it is expensive for them to procure automation equipment. Therefore, the main research question was formulated which asks, “Is there a visual technology available that will increase the productivity and quality of fruit classification making retaining labour economically viable?”. To ensure that this thesis is executed in a methodical manner the research onion was utilised to guide this project. The chapter then considers the limitations and delimitations of this project to ensure that the researchers’ focus is on the most critical aspects of the research question. The ethical considerations and the thesis outline which will be followed through the execution of this study are then addressed.

Chapter 2 Literature Review Related Industry 4.0 Technologies and the Digitalisation in Agriculture

This chapter is devoted to reviewing the literature relevant to understanding the most appropriate vision technology, coupled with other Industry 4.0 technologies, that can add the most value to the agricultural sector. These technologies, as well as the drive towards utilising relevant data, are changing how farmers are conducting day-to-day farming operations. Therefore, digitalisation in the agricultural industry is examined. Through studying both digitalisation and the technologies driving this change, the future of farming as well as the gaps and shortcomings of the technologies implemented can be assessed.

2.1 Vision Technology in Agriculture

Emergence of more advanced visual technologies can play a crucial role in agriculture. This is because these technologies can work with colour, which is an important parameter in this industry. When the colour of fruit is analysed, it contributes to the grading of fruit quality, which aids the farmer in determining the fruit grade. The fruit grade then determines the end destination of the final product [20]–[22]. The visual attractiveness of the fruit significantly impacts sales as consumers select fruit based on visual qualities, with the better-looking fruit being chosen over fruit with bruises or other blemishes [20].

When considering visual technologies the available options are photography, video, videography, Augmented Reality (AR), and Virtual Reality [23]. During the study photography was excluded as it is a static visual medium. The static medium does not support a dynamic production environment for the purpose of providing feedback to the user [24]. Virtual Reality was also excluded, as it works with a non-real environment. AR was compared to video and videography to identify which one would provide the greatest benefit to the user [23].

To investigate the potential that AR can provide to a user, compared to other channels, it was compared to (1) video and (2) video with static markers in a working environment [24]. Compared to (1) AR had a shorter processing time during assembly tasks but was not statistically better than (2). The AR prototype created was simple and had many complex features which would have increased the user's performance but were omitted. The researchers also tested the user's experience when using AR, (1), and (2). The researchers found that although the AR prototype was relatively simple - the users had a positive experience, with 80% of users preferring AR over (1) and (2). This demonstrated that the use of AR as a visual technology is promising and can provide the user with a tool for increased productivity and work satisfaction. Therefore, AR was selected as the visual medium of choice to be utilized throughout this project.

2.2 Augmented Reality

AR is a technology used to alter the user's perspective of the real world by layering atop it images, sounds, or vibrations [25]. The addition of extra information atop the user's reality is meant to aid the user by providing them with key data points which can aid them in their respective tasks. To ensure that AR is not limited to specific technologies it should conform to the following criteria: combining real and virtual experiences, no delay in interaction, and must be able to process and project 3D imagery [26].

When AR is used to display quantitative data, the representation of the data is more intuitive, since it can be interpreted by other senses as well as enabling data visualisation within context, thus allowing for data and information to be integrated into practice in an more intuitive manner [27]. The use of AR is not only to alter reality but also to capture vital data points present in the user's environment, and to store it for analysis or record- keeping [27]. The ability of AR technology to both collect and project information means it can be seen as both a sensor and projector of information that aids the user by simplifying complex tasks or capturing data that would otherwise be time consuming**.**

The ability of AR to capture data enables it to be a valuable tool in the agricultural industry where valuable data can be collected to aid in decision-making [27]. AR is also useful in agriculture because it can assist operators in tasks which are ambiguous in nature such as identifying vegetable ripeness based on fruit colour, or sizes based on shape [27], [28]. Due to these uses the literature available on AR makes it clear that it has many useful applications in the agricultural industry. There is also a lack of literature regarding the use of AR in an agricultural environment [29]. This could be a result of the agricultural sector being a slow adaptor of new technology [30]. This has led to fewer publications of Industry 4.0 technologies applied in agriculture as it is less financially attractive than applying this research in other industries. Therefore, data regarding the results which have been achieved using AR was gathered not only from agricultural studies, but also from publications that tested AR in other sectors.

2.2.1 Current State of AR

The agricultural sector is a slow adopter of technology compared to other industries, and with AR being a relatively new technology, the sector has not yet produced substantial literature regarding the application of AR in agriculture [29], [30]. With only a small selection of academic literature regarding the use of AR in an agricultural setting it is necessary to investigate other sectors for relevant information regarding the status of AR and how it can be applied to the agricultural sector. Thus, it was necessary to investigate AR in a broad context and draw comparisons with agriculture to understand what is currently possible in agriculture using AR technologies.

The four areas where AR literature is most prevalent are in collaboration, education, entertainment, and industrial purposes [31]. Of the four most prevalent uses of AR, industrial applications has the closest resemblance to farming since both focus on the use of AR as a tool in the work place to increase productivity and quality of activities [31]. Within industrial applications the most academic articles are based on maintenance and manufacturing. To investigate the current abilities of AR that could be applied to an agricultural environment the use of AR in maintenance and manufacturing environment was conducted.

In the research reviewed, AR was applied in a maintenance environment. When AR was applied to a complex maintenance task the results showed that the task was completed faster and that the quality of the task was higher, since there was a reduction in the error rate [32]. Improved quality and a reduction in task time is a trend that has been observed when studying the effects of applying AR in an agricultural environment [27]. The improvements in productivity and quality in the maintenance sector are a consequence of AR's usefulness when the user is involved in the manipulation of physical objects. Therefore, it can also be seen as an ideal tool when object manipulation is required in the agricultural sector [32]. The above research confirms the assumption that studying the use of AR in maintenance can be extrapolated to an agricultural setting.

In maintenance the use of AR is more ergonomic as it reduces the number of head and eye movements during task execution [31], [32]. It can be theorised that less movements during task execution should lead to a reduction in user fatigue allowing users to be productive for longer. The reduction in the number of head and eye movements also leads to quicker task execution as well as faster task finding, both of which lead to higher levels of productivity. During maintenance, physical objects are constantly interacted with, which is similar to an agricultural operational environment.

Research conducted into the application of AR in maintenance found that AR technology is not yet a mature technology [32]. The factors that hinder AR adoption and cause its lack of maturity is AR's robustness and reliability [32]. The required levels of robustness and reliability have not yet been reached; therefore, issues still arise when using the technology. There is also no consensus yet on a universal framework or method of application for AR technology [32]. Research also shows that AR is a rapidly developing technology with its user base and rate of application growing exponentially [32]. The shortfalls that AR has and the lack of clarity regarding its potential, adoption, and implementation roadmap has not stunted its growth. Thus, current research is important to help unlock the technology's full potential so that the agricultural as well as other sectors may benefit.

2.2.2 Value Offering of AR in Agriculture

Research conducted into the application of AR in an agricultural environment resulted in the confirmation of the lack of academic research; also that the research available is solely focused on the technical implementation of AR and not the larger implications of this new technology [21], [27], [29], [33]–[35]. Therefore, this sub-section will provide a case as to why AR as a tool, when applied correctly, will add substantial value to the agricultural sector.

Colour Processing:

Colour is a very important attribute of fruits and vegetables since it is an important indicator of product quality which influences product sales [20], [21], [36]. The utilisation of colour to assess fruits and vegetables is fast and also does not harm produce, both of which are positives when having to constantly assess fruit and vegetable quality [20], [21]. Colour influences customer perception and customer perception determines whether produce is bought or not [20]. Therefore, the agricultural sector can utilise colour parameters to enhance produce management leading to improved customer perception which should result in increased sales revenue.

Given that colour is a key indicator of fruit quality, it influences the customer's opinion of good quality fruit [20]. Good quality food is defined as food which has good taste, nutritional value, is not over-ripe, and lacks defects [20]. Defects could be poor fruit or vegetable development or damage, which could have been inflicted during produce harvesting, post harvesting activities, or ripening. Colour is indicative of produce quality because there is a strong correlation between the two [20]. Proper fruit or vegetable development can be seen by the colour that the fruits or vegetables display. Any incidents in the development, or damage post development, can thus be seen on the produce. All fruits and vegetables have a colour band which determines the product's optimal quality [20]. This band can be utilised for a fruit or vegetable to evaluate harvested produce.

Through research into colour as a method of determining fruit and vegetable quality, it became clear that there is a need for technologies to utilise colour to detect the quality of fruit [20]. AR can be used to grade fruits and vegetables based on colour because it is a visual technology [36]. Utilising AR's visual capabilities can enable the cultivation and harvesting of higher quality produce, which could lead to increased customer satisfaction, increased nutrition, and a decrease in food waste. In doing so the revenue for the farmer can be increased and other parties such as the wholesaler and final customer will also benefit, thus the overall value of the entire SC can be enhanced.

Contextualisation:

AR enables the projection of data in a way that makes the data easily understandable and available in the appropriate context [35]. The context referred to is the environment in which the data provided is to be used. The aim is to provide the user with relevant data only when it is required [35]. By doing so the user can make sense of complex data since the information that the data is trying to portray can be better understood in the correct context. Also, only relevant information is provided, so confusion is less likely to occur. When AR is used to display quantitative data the representation of the data is more intuitive since it can be interpreted by other senses like hearing and touch, thus allowing for data and information to be integrated into practice in an intuitive manner [27]. In doing so AR empowers the user to make the best decisions with the data available since the data will be accessible and not be confined to large clumps of data that is inaccessible during task execution. The information that data can provide the user through AR technologies is useful in a variety of contexts. Contextualisation also makes manual tasks easier as data and information can be provided regarding the manipulation of physical objects [35]. The data and information in relation to physical objects is important for the agricultural industry as it is very manual in nature.

Real- Time Monitoring and Feedback:

Real-time monitoring and feedback (RTMF) has both a monitoring and a feedback component. RTMF is enabled by AR being a two-way communication device. AR can both extract data from the user's surroundings and use; or store the data captured; and also project information onto the user's environment [25]. The duality of purpose makes an AR device a tool that can enhance the user's experience because all the projected information is in real-time, which makes the data relevant to the user's immediate situation [27]. The use of AR to provide the user with information is very important. A key activity that will drastically enhance productivity in the agricultural sector is the ability to provide people with key information about tasks at critical times [33]. This use of AR to track tasks and give feedback based on best practices will be a major improvement to the agricultural sector. The use of AR as a tool to provide the user RTMF is not yet widely adopted, however there is evidence that when it is used as such, productivity and quality of tasks will significantly improve [30], [32], [35], [37].

RTMF does not just affect primary production but the entire agricultural process. Monitoring and feedback allows for a more transparent and information-centred farming environment [38]. This allows for more information availability regarding the status of different areas of interest. The availability of this information empowers users by enabling better decision- making, resulting in more impactful actions as decisions are based on relevant and timely information [30], [38]. RTMF also has other advantages such as enabling more efficient use of resources. This was tested in Chile where soil moisture sensors allowed for more effective irrigation practices which resulted in a 70% decrease in water usage [38].

The advantages offered by AR in terms of colour processing, contextualisation, and RTMF can be summarised in Figure 2.1 below. The figure shows how each of the three components contributes to positive aspects of AR, which enables better decision-making. Better decision-making leads to increased food quality, organisation productivity and resource management. These factors make businesses more profitable, increase the overall value in the SC, and promote sustainability which is important for the agricultural sector to expand and prosper.

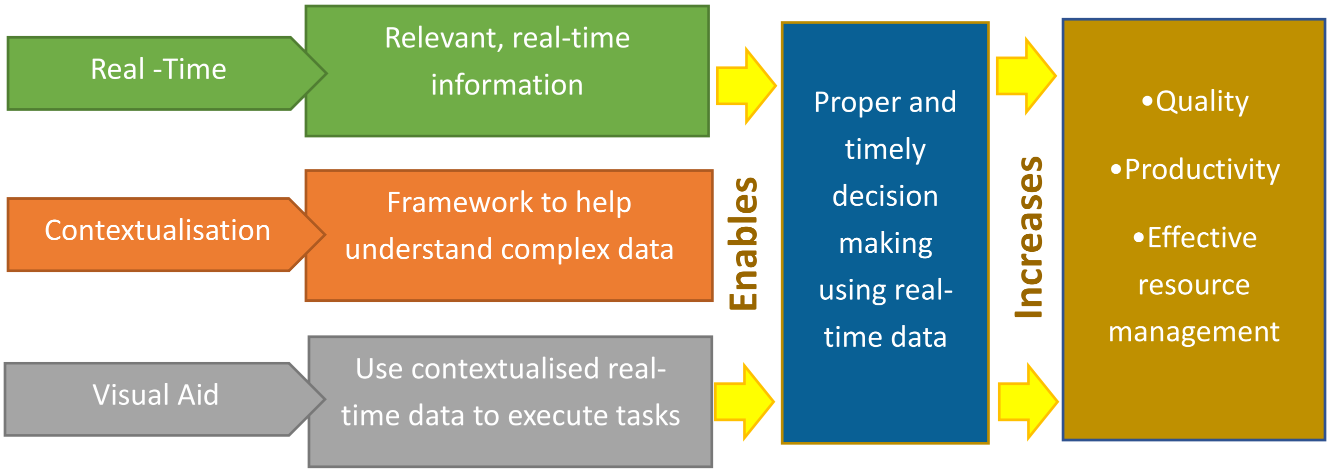

Figure 2.1: Figure of the value offering of AR in terms of colour processing, contextualisation, and RTMF

2.2.3 AR's Part in a Larger System

In the previous section the value of AR in agriculture was discussed. From this it is logical to view AR as an input/output device used to capture data from the user's environment and present information back to the user. It is important to note that the captured data itself is meaningless if not managed, transformed, and stored correctly. AR on its own will not be optimally utilised and therefore needs to be enabled by a supporting system. This supporting system will process the data it receives and present contextualised information to the user by superimposing this information onto the user's environment [26]. Therefore, AR needs to be supported by other technologies in order for it to be an effective tool.

The system that supports AR will not be a separate entity to AR but rather a system that utilises the capabilities of AR to provide maximum value and functionality to the user [35]. Thus, the system is not a part of AR, but rather AR is a part of a larger system. The use of the larger system will enable effortless data capturing and meaningful information presentation [35]. The larger system, which AR is a part of, will enable AR to be a more impactful tool [35].

The larger system needs to consist of technologies which support the unique value offering of AR technology. To support AR the following technologies were utilised in the larger system: Internet of Things (IoT), computer vision, and Machine Learning (ML). IoT needs to be part of the larger system since this technology enables the transfer of data to and from an AR device [35], [39]. Computer vision and ML technologies are also necessary to analyse the environment in which AR is used [40], [41].

2.3 IoT

IoT is a collection of objects with the necessary hardware and software for processing, collecting, sending, receiving and/or acting upon received data for the purpose of communicating and using data sent over a network [39]. The definition of IoT is comprised of different components. The different components in an IoT system can be categorized into three sectors: the different objects which use and communicate data over a network; the network infrastructure which allow for different objects to send and receive data; and the data processing and storage unit which transforms the data sent over the network [39]. It should be noted that the data processing component of IoT overlaps considerably with computer vision and ML. In the definition of IoT and AR it is clear that AR can be a key component in an IoT system.

2.3.1 IoT Challenges

The challenges surrounding IoT need~~s~~ to be examined in order to determine the impact of the risks on AR as part of a wider IoT system in the agricultural sector. The main focus of this thesis is AR but the wider system containing IoT needs to be examined as it will directly impact the feasibility of the AR solution. Six different challenges that were investigated are presented. Of the six, three are minor, with solutions likely to manifest as more research is done in renewable energy, better materials, and Industry 4.0 technologies. The other three challenges are more serious and will require an active solution.

Minor:

- Energy: Industry 4.0 technologies have a significant electrical component. This will cause a significant increase in demand for energy as this will be a necessary input for new technologies [42]. It is therefore important that energy sources, preferable renewable, be created in tandem with the acceptance of new technologies.
- Lack of maturity: IoT is a new technology resulting in some aspects of IoT technologies not being mature [42]. This may lead to some inefficiency and other issues which may inconvenience the users of IoT technology. This challenge should hopefully be resolved in the near future as significant research and development is currently underway in IoT [30].
- Materials: The materials used to manufacture IoT, and other Industry 4.0 technologies, are not environmentally friendly [42]. The type of materials used have few alternatives which result in a dependency on certain materials [42]. The issue should not persist in the long term as there is already a global move away from plastic to alternatives, such as silicon, which is being investigated with some degree of success [43], [44].

Serious:

- Security: IoT offers a potential unsecured portal through which the organisation's networks can be hacked. If not addressed then the large scale adoption of IoT might be hindered since IoT can pose a risk to the whole organisation [45].
- Scalability: As the number of devices in a network grows, more devices must connect through the same node for security purposes. This node may become a bottle-neck and slow down the company’s networks or at least some IoT devices [45].
- Data Ownership: With the collection of data the ownership of this data becomes an important question. It becomes uncertain whether the data belongs to the party that owns the devices, the party that uses the data for daily operations, or the beneficiary of the service [45].

For the serious challenges mitigating actions will have to be implemented since these challenges could pose a serious risk to the future of IoT, as well as affecting AR as a viable solution if not addressed. An effective solution to mitigate risks posed by these challenges is a blockchain component in an IoT system [45]. The inclusion of a blockchain component is not to provide an in-depth study into the technology; rather it is to show that blockchain will be able to mitigate some of the current issues of IoT. In doing so it is clear that IoT is a suitable solution in the agricultural sector.

2.3.2 Blockchain Component

Blockchain technology is an encrypted digital technology comprised of a database that is broken down into individual records [45], [46]. These records are then stored amongst the different users of the blockchain which creates a public ledger. The nature of the public ledger makes it such that each transaction/change to the ledger must be verified by a majority of users of the blockchain. The ledger is a digital way of keeping track of proceedings between the different users. Due to the nature of the technology records cannot be erased, allowing for a trustworthy transaction history to be available [45], [46]. The behaviour of blockchain makes it ideal to address the serious challenges mentioned above since:

- The blockchain ledger is set up in such a way that the different parties cannot alter it, and therefore the different parties involved do not need to trust each other since they can trust the ledger.
- Blockchain has built-in encryption and thus it enhances the security level of the IoT network.
- The ledger is transparent and independent. It can be accessed by all parties involved and data ownership is clear. Thus, all parties can access and use the data as needed depending on the agreement.
- Blockchain technology can process large amounts of transactions in a short period of time. This should decelerate the slowing down of the IoT network as more devices are added, enabling many devices to be added without significant drawbacks.

Blockchain not only helps to mitigate some of the challenges currently being faced by users of IoT, it also has added benefits to help enhance IoT's functionality. Advantages of incorporating blockchain in an IoT system are improved food traceability, improved food safety, and a method of fair payment [47].

Having a tamperproof, permanent record of every activity that takes place makes it possible to reliably trace produce all the way up the food chain to its origin. This food traceability is important because it makes it possible to reward farmers and distributors for good quality, and hold them accountable for poor quality or even dangerous produce [47]. With food traceability the condition of produce can be derived at its current location and therefore produce which may be detrimental to consumers can be traced and removed from the SC [47]. An important aspect of blockchain technology is a secure and traceable method of payment that can be used with food traceability to reward good quality and address poor quality [47].

The uniqueness of blockchain technology and the advantages it provides makes it an ideal contribution to the IoT system. It helps address some of IoT's most important challenges, and it helps make IoT more effective. Therefore, blockchain will be an important part of the IoT system, and for this project will be seen as part of an IoT system.

2.4 Computer Vision

Computer vision is defined as, "the host of techniques to acquire, process, analyse, and understand complex higher-dimensional data from our environment for scientific and technical exploration" [48]. When examining the definition of AR, in section 2.2, AR and computer vision both have image capture as a key function. AR, however, does not in itself process, analyse, or extract information from an image. Rather it relies on computer vision with the aid of IoT technologies to do this. The boundaries of what can be considered AR and computer vision can be seen in the Venn diagram below.

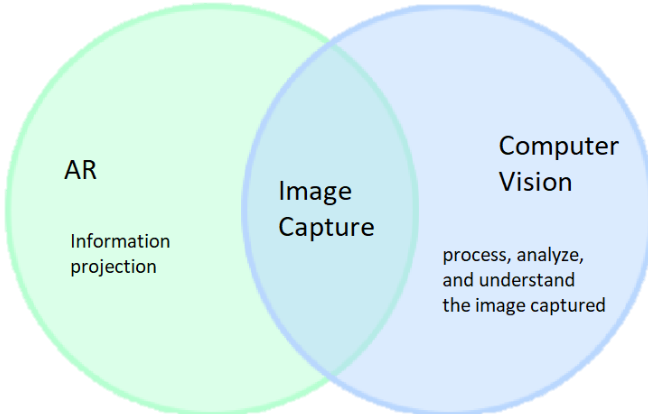

Figure 2.2: Figure of a Venn diagram showing the boundaries of what can be considered AR and what can be considered computer vision[48], [26].

Computer vision is not part of AR. It is becoming more important in a system that contains AR technology in order to have a larger system that can extract useful information from the environment [40].

2.5 Machine Learning

The AR device captures the image whereafter the image needs to be processed, analysed, and sent back to the AR device to aid the user. The analysis of the image data is an important part of a computer vision system. It is important because the value of the insights and conclusions drawn are directly correlated to the degree that the image data is analysed and key insights are extracted [49]. ML takes place in computer vision to find patterns or key insights regarding the data captured [49]. It is for the purpose of analysis that ML forms an integral part of most current computer vision systems that are being deployed in the real world [50].

ML is a subsection of AI [41]. AI is when a computer system is trained using various approaches, so that it can execute functions similar to that which would be performed by humans [41], [51]. AI is a very broad term and encompasses almost everything that has to do with machines simulating human intelligence [51]. Within the broader scope of AI there is ML which is when computer systems are used specifically to perform tasks traditionally done by humans[41]. ML is focused on creating computer systems that can improve on their own using historical data without changing core processes, as well as the focus on the body of knowledge surrounding the laws that govern learning systems [50], [52]. A critical aspect of ML and why it is so valuable is the ability of ML algorithms to uncover hidden or unconventional relationships [53]. It can do this because the algorithms will use all the variables available to determine relationships without being told what those relationships are. It is also this ability of ML to find relationships by itself that has made it easier to implement ML than to manually code algorithms [50]. It is now easier to develop a system where algorithms are developed based on training from inputs received rather than to manually develop software based on anticipated expectations. Thus, these algorithms are capable of identifying patterns without preconceived biases as to which patterns exist and how these patterns relate to each other. These patterns can then act as a blueprint for future actions.

During computer vision model development using ML there are three main steps which are universal [49]. Firstly, data is gathered to train the model. Secondly, the model is trained using the data gathered. Lastly, the trained model is used to make predictions for the computer vision model. During the second step, the model training can either be supervised learning, unsupervised learning, or reinforcement learning [41],[52].

2.5.1 Supervised:

Supervised learning is typically used when the key objects/elements that we wish to determine are known. These objects/elements are identified using labels. Therefore, supervised learning works with labels: a data set that has been cleaned and organised, so that the right answers have already been provided to the question "what objects/elements are in the data set?". It independently learns the relationships between the different labelled objects/elements based on the labels provided so that the algorithm can determine the best way to get to the right answer. The logic behind supervised learning can be seen in Figure 2.3 below. Within supervised learning the programmer must choose between classification and regression. For this thesis classification is used because it tries to place an object in a class where regression tries to predict a single end value, such as a numeric value.

2.5.2 Unsupervised:

The difference between supervised and unsupervised learning is that human input is required with supervised learning whereas no input other than the historical data is required for unsupervised learning. Unsupervised learning is normally done in the absence of a specifically desired attribute. It is normally done with large amounts of data where all the variables are used as input and the algorithms attempt to determine the relationships between the different variables in order to derive key insights regarding the data. Therefore, unsupervised learning uses a data set containing unlabelled data. The algorithm developed sorts the unlabelled data into clusters. The clusters are based on relationships in the data set that are more than just noise. The way the unsupervised algorithm partitions the dataset into subsets, or clusters, depends on predetermined parameters that were chosen. The reason why unsupervised learning is used is either because labelling is difficult, or the relationship between the sub data sets are unknown.

2.5.3 Reinforcement Learning:

An algorithm is independently trained such that it maximises the probability of achieving a reward. The algorithm makes decisions based on the current state and environment so that it has the highest probability of achieving a predetermined optimal state. Decisions that the algorithm makes are either rewarded or punished based on whether the current situation is closer or further away from the desired state. The downside is that a lengthy training period is required for the algorithm to yield meaningful results.

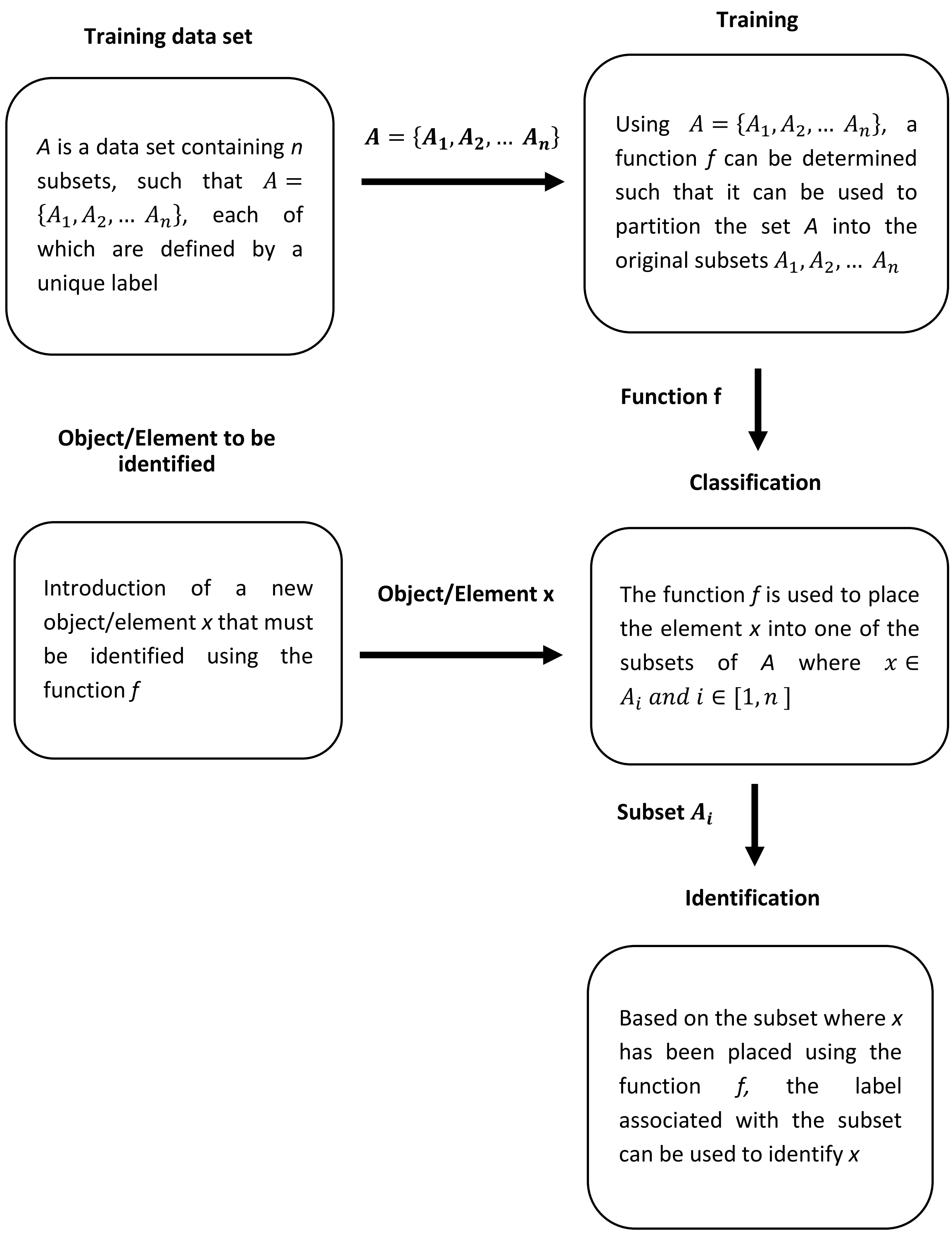

Figure 2.3: Figure showing the logic of a supervised algorithm [41]

2.5.4 Training:

When training an algorithm, it is important to consider how accurate the trained algorithm will be when applied to a real-world problem. A simpler model cannot account for all the relational factors that distinguish one label from another. Therefore, simpler models have an error referred to as model bias, as the model is only distinguishing between factors that have been identified [54]. This type of error occurs when the model has not been trained enough. When this happens the trained algorithms is described as one that has been underfitted [54]. This underfitting can be seen in Figure 2.4 and Figure 2.5. If the model is too complex, then some intra-dataset variance may be classified as distinguishing factors between datasets. Due to the complexity of the model too many factors are considered, and the model is sensitive to small variations between the training and test data sets, resulting in an error referred to as variance. When this happens it is called overfitting, as can be seen in Figure 2.4 and Figure 2.5 below.

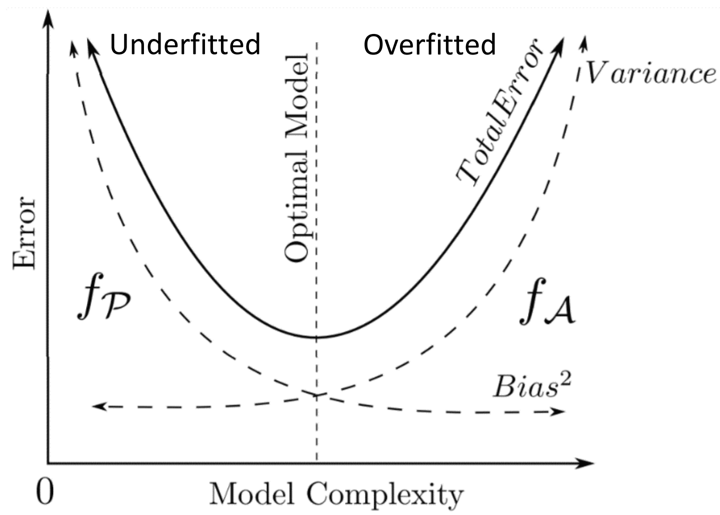

Figure 2.4: A figure showing the behaviour of a model, in terms of underfitting and overfitting, during model training [55]

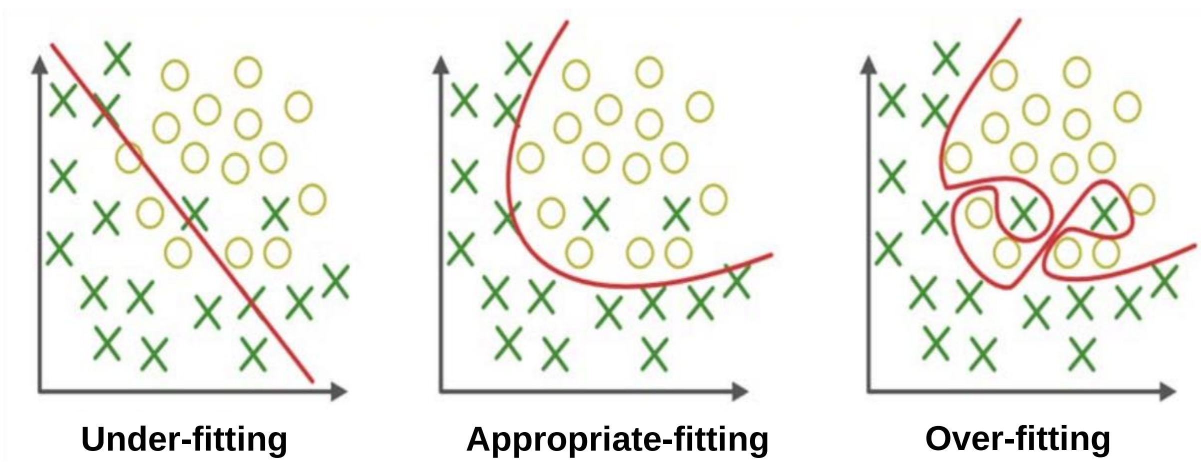

Figure 2.5: Figure showing how two different samples in the same sample space is separated using underfitting, appropriate-fitting, and overfitting [54]

Overfitting occurs when the algorithm tries to be too accurate because it has over analysed a limited data set [54]. This is a typical problem during ML algorithm training because of the desire to have highly accurate results [55]. It is important to note that a trained algorithm may not be 100% accurate and trying to achieve this during training may decrease the accuracy of the algorithm during implementation. In order to achieve the best results when training an algorithm, it is necessary to train the algorithm sufficiently so that the most distinguishing features can be identified, but not so much that overfitting occurs.

2.6 The Utilisation of a Platform as a Service Model

Computer vision and ML algorithms are increasing in complexity [56]. It is for this reason that private companies provide software platforms to give developers easy access to sophisticated computer vision and ML services [56], [57]. The software platforms provide computer vision and ML software solutions to developers who do not have the knowledge, skills, or time to program the required algorithms. The platforms provided are more than just software as a service (SaaS) because hardware is also offered to run and manage some ML computations. Therefore, the services provided are referred to as platform as a service (PaaS).

PaaS can be defined as the provision of technology, hardware and software, as a service for the purpose of enabling developers and independent software vendors to host software or SaaS solutions [58]. PaaS is an expansion of SaaS which provides the technology to host and develop systems, e.g. software development platforms [58]. In doing so PaaS simplifies and eases the processes of acquiring the technology (hardware, software, and skills) to create and run complex software applications.

Private companies, by providing computer visions and ML as a PaaS, are lowering the barriers to entry for these technologies [57]. Due to the increase of accessibility and increased usability, computer vision and ML are becoming more popular [57]. Of the private companies that provide computer vision and ML PaaS, the three industry leaders are Amazon, Google, and Microsoft (MS) [57].

The three above-mentioned services, although very similar in what they provide as an end product, have different underlying software which produces the end result [57]. The underlying software is not accessible to the user; i.e., when the user of the PaaS technology trains the ML model they wish to use, the results of the model will be accessible but the specific algorithms used to derive the solution will remain unknown to the user[57]. The ML algorithms are probabilistic in nature which results in the model output varying significantly depending on the input. Due to the variability of results the ML models still have a high degree of uncertainty during execution. It is for this reason that ML coupled with computer vision is still considered to be in the premature phase and not yet classified as technologically ready [57]. This does not mean that the technology is not being adopted, but that it is not yet ready for applications in which mistakes cannot be tolerated.

2.7 Industry 4.0 Technologies That Will Be Utilised

In summary of the technologies discussed, AR and computer vision collects data from the environment and projects information back onto that environment to aid the user of the technology. The data that is captured is transferred via the use of IoT. The data is transferred from AR to where it is stored. The stored data is then processed using ML and computer vision technologies into something that is useful. The integration of these four technologies, as seen in Figure 2.6 below, is important for this project and changing the agricultural industry.

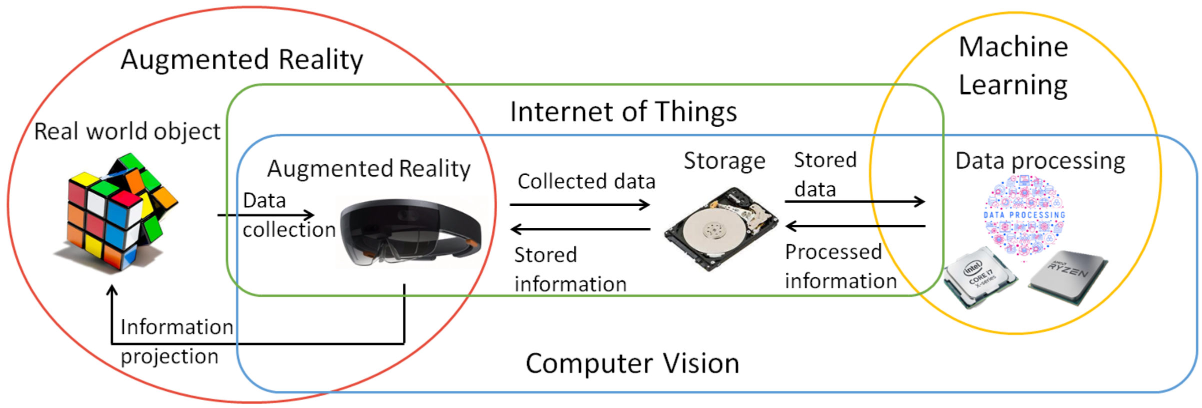

Figure 2.6: Figure of the four key Industry 4.0 technologies utilised in this study

2.7.1 Impact of Industry 4.0 Technologies on Farming

The use of IoT systems is resulting in the increase in accumulation of large quantities of data [34], [39]. The data captured is from farming operations. The effective utilisation of this data will result in greater insight regarding the internal processes and performance of various farming activities [33], [34], [59], [60]. Industry 4.0 technologies support the retrieval, processing, and projecting of data and information in real time which directly supports RTMF.

With more data available, companies in the food SC will be able to solve many current challenges caused by lack of data. These challenges relate to mistakes made within the food distribution channel, record- keeping and food traceability, as well as workforce management [47]. These need to be dealt with since they directly impact on the competitiveness and profitability of the business. If these challenges are not dealt with, companies will not be able to expand effectively since these issues will only be exacerbated with expansion. As an answer to these, and other challenges, organizations are digitalising [47]. This is taking place since Industry 4.0 technologies enables critical data capturing and processing. With data capturing the state of food in the SC can be better monitored and controlled which should enable a reduction of food waste. Industry 4.0 technologies also provide the user with more up-to-date information, and allows for more effective control which will enable companies to scale more effectively [61]. With scalability companies that adopt Industry 4.0 technologies can, with fewer obstructions, become major players in their sector.

With more data available, processes will become more data oriented, which will result in changes in the way farming and the agricultural sector operate [39]. This change will result in more informed actions and a reduction in uncertainties, which will affect activities such as decision-making, and resource management due to the availability of more data [33], [59]. These changes in farming activities will lead to a new operating model in the agricultural sector [39]. Thus, with the introduction of Industry 4.0 technologies in the agricultural sector the sector will radically change to a new way of farming called smart farming.

2.8 Smart Farming

The introduction of Industry 4.0 technologies is changing how businesses operate in every sector to which it is applied [39]. In agriculture, farming is changing with a new way of farming emerging called smart farming (SF). SF is data focused and concentrates on using technology that can be integrated into farming operations through the provision of information and Industry 4.0 technologies to increase productivity, produce quality, sustainability, and profit for farmers [34], [36], [62]. SF is expected to result in a disruptive shift away from the current ways of farming to ones which are more data and Industry 4.0 focused [30], [34], [38]. Within the literature surrounding SF, the most common recurring technology that supports SF is IoT [30]. This is due to the benefits IoT provides. However, as previously stated, it is the combination of the various Industry 4.0 technologies which will yield the greatest benefit as they complement each other. The benefits of Industry 4.0 technologies for SF are scalability; reduction of unnecessary wastes; identification of crop locations to increase efficiency and quality of activities executed; solving of not yet discovered problems via analytical endeavours; and assistance both in coping with, and benefit from, changes brought about by SF [27], [62].

The agricultural sector is a slow adopter of new technology and thus the transformation to SF will be a gradual process [30]. Slow adoption by the agricultural sector may be explained by the demographics in the agricultural environment and lack of investment in Industry 4.0 technologies in agriculture [33]. The average age of a farmer globally is 49 years, while that of the average African farmer is 60 years [63]. This age is increasing as young educated people move to the cities in the hope of finding more lucrative occupations [33]. Losing educated people, and an aging population, are problematic as both less-educated and older people are less likely to adopt new technologies [33], [64]. Therefore, there needs to be initiatives to encourage young, educated people to remain or move to agricultural industries since they will adapt better and help promote the use of Industry 4.0 technologies which in turn will speed up the transformation to SF.

Lack of investment also leads to slow adoption since new technologies first need to be tailored to the agricultural sector before they can be adopted [65]. Most investments in Industry 4.0 technologies are occurring in IT and communication, electronics, process industry, automotive industry, as well as manufacturing and engineering [66]. Agriculture is not one of these main investment areas. The reason for this could be due to the size of the agricultural sector in developed countries. In Germany, the country doing most of the Industry 4.0 research, the agricultural sector is only 0.7 % of the total economy [67]. Due to agriculture only being a small part of the German economy, and Germany contributing the most research to Industry 4.0, it is only logical that little attention will be given to SF since Germany and other developed countries would rather invest in their more prominent sectors.

Research that is being conducted is predominately done by China, 31.84%, and the USA, 8.84%, who together have contributed more than 40% of the global research [30]. The USA and China are in the top three highest producers of food and most advanced countries in terms of agriculture globally [68]. It can thus be seen that there is a correlation between SF research, being advanced in agriculture, and producing the most food. Therefore, it can be concluded that SF research is beneficial to the agricultural performance of a country, and that countries with large agricultural industries would be more willing to invest in agricultural research.

2.8.1 Shifting Paradigm

Even though research and adoption may be slow the industry is changing with both an increase in the number of farmers who are adopting technology and the complexity of technology being adopted [69]–[73]. These technologies do not only include Industry 4.0 technologies, but new technologies in general. For example, avocado farmers in the Tzaneen region of South Africa have planted trees created by cloning other avocado trees with superior genetics [72].

That being said a significant amount of new technology implantation has centred on data collection [69], [72], [73]. This was observed in two separate interviews where avocado farmers in the Tzaneen region of South Africa were consulted. In the first interview a local farmer has implemented smart water-level monitoring devices [72]. This was done because the farm is in a more mountainous part of the region resulting in some orchards having a 50-75m elevation above other orchards on the same farm. This results in a significant moisture content difference between various regions of the farm and thus smart water-level monitoring devices were installed to keep track of the moisture content of the different orchards. This is especially relevant during irrigation, as it was discovered (using these smart devices), that the top orchards did not receive enough water while the bottom orchards were being overwatered due to the water running down. In the second interview, the farmer had spent a significant amount of capital investing in a smart irrigation system, for delivering both water and nutrition to the trees, as well as other smart sensors throughout the farm [69]. This was done so that current farming practices, especially with regards to irrigation and nutrition, could be more in line with the current best practices of the industry.

Both examples show how the use of Industry 4.0 technologies, via the use of IoT and probably some form of ML, can improve current farming practices. These two interviews and others conducted also lead to the conclusion that the responsibilities of farmers are going to change. The level of change, however, was not agreed upon. The one farmer stated that, "Some responsibilities of a farmer are going to become more similar to those of a computer scientist than those of a traditional farmer" [69]. Another was more conservative in their estimate, believing that companies will likely implement new technologies [70]. The second farmer, however, believes that one should have the knowledge and skills to have a basic understanding of the technologies implemented and the data generated. What was agreed upon by all the farmers is that farming is changing, from an occupation requiring instinct, to one where farmers, or outside organisations, must be able to interpret data and information to make decisions [69]–[73]. Therefore, conventional farming will transform into SF which will be data and information driven similar to manufacturing today.

2.8.2 Data Focus and the Incorporation of Industry 4.0 Technologies

SF is enabled by Industry 4.0 technologies [38]. The adoption of Industry 4.0 technologies facilitates new and improved operational capabilities since the functionality of farming equipment and farming practices are improved [30], [33]. These improvements in the capabilities of farming equipment includes IT technologies integrated into farming equipment for the purpose of increasing the tool functionality and effectiveness, as well as enabling tools to be automated [38]. The other improvement is in the execution of farming activities which will be improved due to the availability of data and information to guide the farmer [33], [34]. This improvement will be brought about due to the data capturing capabilities of Industry 4.0 technologies [34]. Data capturing is as important as, or potentially even more important than, adopting large new equipment to improve farming operations [38].

With data on the different processes and operations of a farm, and other parts of the agricultural sector, the farmer has greater insight into what is going on around them through RTMF. This allows for more information availability regarding the status of different areas of interest. The availability of this information allows for more informed decisions which empowers farmers by enabling their actions to be more effective and thus make more of an impact [38].

Data focus will also improve supply chain management (SCM). The condition of fresh fruits and vegetables are often unknown and have to be anticipated [59]. But with the data capturing and analytical capabilities of Industry 4.0 technologies in a SF environment, predictive analysis can be used to track the condition of fresh fruits and vegetables in the SC [34], [59]. With this information SCM can be improved. The information allows for the current state of products to be determined, within a certain margin of error, and these products can then be optimally managed within the SC. Perishable products with significant lead times have less time available to be idle on shelves in warehouses and retail outlets since they will expire. Industry 4.0 technologies can be used to manage these perishable products by providing data that can reduce the percentage of products reaching their expiration date before being sold. Food traceability will also enforce greater accountability for bad produce from producers, logistic companies, and retailers since fruits and vegetables will be traceable to specific individuals or corporations [47].

Agriculture is not only impacted by self-captured data but also by information from external sources. Often farming practices have a hereditary aspect to them in the sense that farming practices are passed on from one generation to the next [33]. This has led to the prevalence of outdated farming practices still being prevalent in less-developed areas of the world. For these farmers getting information from the internet such as best practices will lead to better farming methods and this will have the greatest impact for these farmers. It is also in areas of information delivery that AR has a crucial role, since it can present farmers with key knowledge at crucial times [33].

2.8.3 Smart Farming Trends

SF will become the dominant way of farming in the future, and it is therefore important to do research now, so that the progression can be steered towards the best possible version of SF. The drivers of SF, both direct and indirect, will determine the future of farming. The main drivers behind Industry 4.0 technologies are: increased production, increased control, resource efficiency, and RTMF [74]. These drivers encourage businesses to adopt Industry 4.0 technologies. Adoption of these technologies has been proven to make companies in the manufacturing sector more profitable, increasing market share, and improving their overall competitiveness [75].

The competitive advantage provided by the adoption of these technologies has forced others to adopt these technologies as well [75]. This is because failure to adopt these technologies has caused companies to lag behind their competitors. Thus, there is a chain reaction with more and more companies adopting Industry 4.0 technologies, further driving Industry 4.0 adoption. For this reason, it can be concluded that the complete transformation of industries is inevitable. The manufacturing sector was selected to research the effect of Industry 4.0 technology adoption because this sector has seen adoption on a large scale and thus the effects of adoption can be measured.

Within the array of Industry 4.0 technologies which provide a competitive advantage IoT has been singled out as one of the most important technologies [75]. This is because IoT is data-centric and data has been responsible for the greatest change in the manufacturing industry [75]. With IoT real-time data about business processes is available at any time. This, coupled with other Industry 4.0 technologies with analytical capabilities, provides quick and effective responses to unexpected events, which results in quicker and better decision-making and a reduction in forced downtime [75].

The agricultural sector, just like the manufacturing sector, will be profoundly changed due to Industry 4.0 technologies and data-based farming. The new farming paradigm will be SF. Within this paradigm lies a fundamental new farming philosophy which is lean farming. This way of farming will revolutionise the industry and bring it on par with other changing industries.

2.8.3.1 Lean Farming

Lean farming (LF) is using lean principles and methods, by applying them to farming, in order to acquire the benefits that this philosophy has granted to other industries that it has been applied to, such as manufacturing [76], [77]. Industry 4.0 technologies discussed previously are key components of SF and are uniquely poised to make farming leaner. AR and other IoT sensors are useful since they can be used to observe tasks and collect data regarding different activities. This data can be fed to the ML and computer vision system, which can then provide information regarding the efficiency of task execution and possible areas of waste. Measuring allows for the control of process. This process control allows for LF resulting in farming activities being more value adding while simultaneously reducing inputs such as resources, time, and cost.

In theory LF will have the following benefits: doubling of productivity; reduce inventory by 90%, saving space and cost; reduce throughput time by 90%, thus having a faster reaction time to customer demand; reduce errors and injuries which will decrease unnecessary expenses since this will result in higher quality and less downtime [77]. Case studies support these benefits, though the benefits are not as extreme. This was tested in a case study where IoT was used to support lean practices in a plant with dynamic demand. When the IoT system was used for dynamic control and to apply lean practices, it was observed that process efficiency was 30% better and storage time was 20% less [60], thus proving that an IoT supports lean farming, since efficiency was increased and costs were decreased.

LF and the benefits it provides will occur slowly since the agricultural sector is a slow adopter of technology, as previously stated. The adoption of Industry 4.0 technologies can encourage the agricultural sector to become leaner. LF can be very important to SF since it can increase the efficiency and effectiveness of farming and the agricultural sector. Also, food waste can potentially be reduced as the time produce spends in the SC can be shortened. This will not only affect farms but also the whole industry as this will affect multiple industry stakeholders from fertilizer manufacturers to fruit and vegetable packing facilities [33].

2.9 Sustainability

When considering economic endeavours, a very important consideration out of both a moral and financial standpoint, is sustainability [78]. Sustainability is a balance between human aspiration towards prosperity and the finite capacity of resources provided by nature [79]. According to the World Commission on Environment and Development, sustainability is defined as: Actions, “that meet the needs of the present without compromising the ability of future generations to meet their own needs” [80].

Contemporary perspectives on sustainability were very environmentally focused [78]. Through this view of sustainability, the definition above can also lead one to see sustainability as a concept which is focused on preserving the environment. Sustainability is more than just the environment. It also incorporates other aspects such as people, businesses, and societies as a whole [79]. To ensure that sustainability is holistic, the UN in its general assembly of 1997, defined sustainable development as follows: "Development is a multidimensional undertaking to achieve a higher quality of life for all people. Economic development, social development and environmental protection are interdependent and mutually reinforcing components of sustainable development" [81]. These two definitions of sustainability can be combined into one definition which will be the definition of sustainability in this thesis which is: Actions today which protect the environment, strengthen communities, and promote business while simultaneously enabling future generations to do the same.

Sustainability is not just important from a moral perspective, since it is important to grant others the opportunities which we take for granted at present, but it can also grant businesses a competitive advantage [78]. The competitive advantage is enabled due to two factors. Firstly, through the efforts of organisations to be sustainable, the public should become more supportive of the organisation, thus allowing for the organisation's brand name and company awareness to grow. Through a better company image and customer awareness, employee retention and investments will grow since the company will be more attractive as a business[82]. Secondly, the company will have some operational advantages since some risks, mostly environmental in nature, will be reduced; enabling the company to cope in a future with fewer resources available; to reduce waste, thus reduce operational costs [78], [82].

Industry 4.0 technologies, especially IoT, enable better and more effective resource management. This reduces waste which leads to a lean way of farming. The reduction of waste also leads to sustainability since there are more resources available for future generations. It can thus be seen that there is a connection between a lean operational philosophy and sustainability. It should be stated that Industry 4.0 technologies also have a connection with sustainability. This relationship, however, is already contained within the connection between lean and sustainability, because lean is enabled through Industry 4.0 technologies. Therefore, the relationship between Industry 4.0 and sustainability is contained in the relationship between lean and sustainability in this context.

2.9.1 Sustainable Farming

System thinking (ST) is used to examine the relationship between lean and sustainability. This is due to the system having to be considered for the two entities to be seen as related despite being separate. The bigger picture needs to be examined, because when looking too narrowly, one might simply see resource conservation and not the effect that this would have on reaching sustainable production [78]. When considering ST it becomes clear that SF and sustainability are linked. It is important to note, however, that this link can be positive or negative depending on how SF is implemented in relation to sustainability [78]. It is important that SF be implemented within a framework where a holistic sustainability approach is not compromised. This will enable SF endeavours, which should also be sustainable in nature, to be executed. When considering the entire system it is important for all three pillars of sustainability (people, profit, and environment) to be satisfied for it to be considered sustainable [76], [78].

2.9.1.1 Environment

In land-based farming everything is soil related. Thus, if the soil is not in good condition, the yields will be lower and of poorer quality. Therefore, the first step in sustainable farming is replacing the nutrients and minerals absorbed by the animals, fruits, or vegetables. By putting nutrients and minerals back into the ground, the soil will be able to deliver high- and better-quality produce annually. This can be accomplished, for example, by planting complementary plants such as beans or other crops when farming with vegetables. These plants will also provide soil covering to reduce erosion and produce a cheap crop to feed poorer communities [76]. This type of farming will be more complex, requiring an increase in management responsibility and new knowledge, all of which can be facilitated via the use of Industry 4.0 technologies when practicing SF. Industry 4.0 technologies can also be used to protect the environment since they can be used to facilitate the use of renewable resources, for example; when solar and battery technology combined with electric vehicles are used, renewable infrastructure is created [76].

The elimination of waste is fundamental in enabling a more sustainable future. The use of new technologies to manage resources will enable better and more efficient use and management of resources, which should result in the reduction of waste [62]. IoT can lead to a reduction in the amount of fertiliser and pesticide required, thereby reducing the amount of harmful chemicals which contaminate the water and soil [33]. In the agricultural sector SF also enables the conservation of water and energy sources, as well as increasing food security [62]. Thus, SF will lead to a reduction in waste which will decrease the strain on the environment, especially in terms of food, water, soil, and energy.

2.9.1.2 Society

Sustainable farming does not only ensure food production in the short term but focuses on ensuring food security for future generations [76]. This will enable more stable and prosperous societies in the future. SF could also help connect people in urban and rural areas [76]. This can be achieved by creating platforms where people in urban areas can invest, communicate, and/or build relationships with people in rural areas. It does not have to be for investment purposes only; it can also be for commerce. If someone in an urban area is satisfied with a certain farmer's produce they can build a relationship with that farmer, thus leading to the creation of mutually beneficial relationships [38]. This type of behaviour can help bring societies closer and bridge the societal gap between people living in rural and urban areas [76].

SF also focuses on improving processes by empowering and improving the skills of employees [78]. This is particularly important in the agricultural sector because the skilled people migrate to the cities to find work, leaving behind older and unskilled individuals [33]. Thus, SF that enables sustainability will lead to a more skilled and empowered work force. SF should drive sustainability by bringing societies closer together and improving employees' skills, both of which create positive societal change.

2.9.1.3 Economic

Currently the agricultural sector is heavily reliant on energy. Most of this energy consumption is in the form of fossil fuels [76]. Fossil fuels are also non-renewable; thus, they will eventually be depleted. Farmers need to take this into consideration and plan accordingly. This energy consumption is expected to become more expensive, both in terms of carbon tax and fuel cost [83]. Thus, current energy consumption is unsuitable. These issues can be addressed if farmers become more sustainable, as explained under 2.9.1.1. New technology can lead to resource efficiency and more renewable resources being utilised

Another impact of reducing waste is that input volumes will be reduced. This could potentially have knock on effects as it could lead to the reduction of other inputs. For example, by implementing SF, storage may be reduced by more than 90% [77]. A reduction in inventory will reduce other costs such as electricity. Sustainable farming can be an effective way to cut costs and increase profitability which will help ensure long term success.

2.9.2 Sustainable Farming is the Future of Farming

Sustainability, just like SF, will most likely be inevitable. Sustainability will be driven by customer perspective, comparative advantage, and new technologies. Being sustainable provides many benefits. These benefits are not only economic but also societal and environmental. Thus, it is holistic in nature and benefits everyone. With sustainability providing a competitive advantage it will form a chain reaction of adoption. If others wish to survive, they will be forced to also become more sustainable. Thus, as some become more sustainable there will be a positive chain reaction throughout the whole sector. This is important as the current way of farming, in terms of resource consumption for example, is not sustainable and changes will have to be made for the agriculture sector to thrive in the future.

2.10 Conclusion

The purpose of this chapter was to examine which visual technology, coupled with Industry 4.0 technologies, can add the most value to the agricultural sector. It was found that AR is the vision technology that, when used by agricultural workers, has the greatest potential to add value to the agricultural sector, without leading to automation. Through the study of AR, it was found that when it is coupled with other Industry 4.0 technologies such as ML, IoT, and computer vision it can add more value than if it were to be utilised on its own. The use of the above-mentioned technologies in the agricultural sector, coupled with the increased reliance on data, is digitalising conventional farming. By digitalising farming, the industry is changing to a new way of farming referred to as SF. Research related to SF shows that it has the potential to be leaner and more sustainable compared to conventional farming.

Chapter 3 Literature Review Related to the Avocado Industry

This chapter is related to the justification for using avocados as the case study for this thesis, and the examination of this industry in order to draw vital conclusions during the case study implementation. Therefore, this chapter will examine the relationship between avocados and communities they benefit. Next, the value that avocados have, coupled with other factors are examined to justify the selection of this industry as the basis for the case study. The inner working of this industry as well as the area of implementation, i.e., fruit classification, will be studied.

3.1 The Relationship Between Avocados and Humans

It is unknown when the relationship between humans and avocados began, but through anthropology and other research it is clear that avocados were known to humans 11 000 years ago [17]. Avocados are estimated to have their origin in the region of southern Mexico and form part of the Laurel family [17], [84]. Its region of origin is mountainous with a high summer rainfall and dry winters. Avocados are adaptable to most soil types and climates with the exception of cold weather since frost can damage the tree and its fruit [17].

Avocados, through evolution and the extinction of mega-fauna around 11 000 years ago, have become solely dependent on humans for their propagation. In return humans became semi-dependent on the avocado fruit due to its high energy and nutrient content [17]. Since 9 000 years ago avocados have been utilised as a valuable crop and important food source to people living in southern Mexico due to the fruit's edible value [17]. Since then, the relationship between humans and avocados has continued. The relationship between humans and avocados, and the value that the avocado industry provides, is one of three reasons why this fruit was selected as the case study for this project. The other two reasons were data availability, as well as an industry that provides significant opportunity for productivity and quality improvements.

3.1.1 Socio-Economic Impact of Avocados

Currently avocados are valued for their nutritional, cultural, and economic significance. Avocados are one of the most nutrient and mineral dense foods with high amounts of: fat; protein (especially for a fruit); potassium; antioxidants; vitamin A; vitamin E; and vitamin B [17]. The high-fat content of avocados makes it an excellent source of energy. It is also significant that the fats are mostly mono-unsaturated with a low level of saturated fats [17]. This makes avocados especially healthy as an energy source.

The health benefits of avocados can be beneficial for both developed and developing countries as a dietary aid. The relatively high fat and nutritional levels may assist in reducing cancer, diabetes, and heart attacks - which have become significant health issues in developed countries [17]. In developing countries the proteins, minerals, and monounsaturated fats can help to alleviate food and nutritional issues. This is important since many of the countries struggling with food security are located in the tropics [85]. Avocados can also be easily cultivated in the tropical regions, since this is similar to the fruit's region of origin [17]. Thus, through the cultivation of avocados in less developed tropical areas, there may be a reduction in food insecurity and malnutrition.

Avocados are also culturally important, particularly in southern Mexico where they originate. In southern American countries avocados form part of cultural cuisines such as guacamole and other traditional dishes [17]. Avocado leaves and fruit are also used in folk remedies and natural medicines where they are used to heal bruises, cure coughs, help with stomach diseases, and promote hair growth [17].

Avocados are economically important with them being a vital commodity, since they are the most important commodity of the Laurel family [17]. The avocado, when compared to other food products, has an average annual production volume [17]. The reason for it not having a high production volume is that it is not a staple food such as corn or wheat, which have been cultivated widely for a long period of time. Even with avocados having only an average annual production volume, with approximately 3,5 million metric tons produced per year, it is still a large industry [17]. Of the fruit produced 80% is consumed in the country of origin and 20% is exported of which the majority, 90%, is of the Hass variety [17]. Avocados are also linked to other industries, other than the fruit and its derivatives, such as the making of dye and honey [17]. These industries form a small fragment of the economy surrounding avocados, but they need to be acknowledged to show the importance of the economic web surrounding the avocado industry.

Unfortunately, the high degree of cultivation also has negative attributes. As with corn and other crops some varieties are favoured above others. These varieties are more financially rewarding and thus become the dominant variety. In the process the other varieties become marginalized, with some being excluded completely as an economic crop. The danger in this is that biodiversity is being diminished and an increased risk of crop failure occurs. This is because if a pathogen emerges that affects the most popular cultivars, the avocado industry may suffer [17].

3.1.2 Data Availability

Strategic connections and relationships between the researcher(s) and key individuals in the avocado industry in South Africa, particularly in the Tzaneen area, were established. Both the number of relationships, and the fact that the relationships were with key members of the industry, allowed for deep insights into the industry to be garnered. These connections are: one of the most respected botanists in the region; the leader of the main research groups in the region; a benchmarking company in the region; two different sorting and packing facilities, a farmer who was willing to share with us both his production data and financial statements; a contractor who constructs avocado packing facilities for several African companies; as well as three individual farmers. This array of connections allowed for quality data collection and feedback during the execution of this study.

3.1.3 Opportunity for Improvement

Avocados are at the point of maximum quality right before harvest [17]. Quality cannot be added to the fruit during or post-harvest as these activities can only reduce the quality of avocados. Therefore, the point where avocados are at their highest quality is as soon as the fruit reach maturity and are ready to be harvested. Quality in the context of an avocado can be defined as a product that looks appealing and flavourful so that it has value, from the perspective of the customer [17]. Quality is important for the avocado industry because a lack of quality will result in poor reputation and a reduction in sales. Higher quality products result in a higher selling price which leads to greater profits for the avocado industry. That being said, the way that avocados are handled in packing facilities directly impacts the shelf-life and consumer satisfaction [86].

Currently quality is an issue in the avocado industry with 50% of fruit harvested not being consumed [17]. Another study in Australia showed that 40% of Hass avocados sampled in Australian retail stores had at least 10% of their flesh defected by either bruising or decay [17]. The study also showed that the longer the SC, and the more time in the SC - the greater the risk for poor quality avocados with damaged flesh or fruit that become overripe. The poor quality is concerning, but it shows that there are opportunities for new technologies to be utilised to improve the quality of avocados and improve both the reputation of the participants in the avocado SC and the confidence of customers.

It is not only quality that can be improved. As stated in section 1.1.3 productivity is also significantly improved with the introduction of new technologies. This is because Industry 4.0 technologies, by providing data during sorting and packing processes, are being introduced to the agricultural sector, which is drastically increasing productivity [86]. Unfortunately, new studies have found that current mechanisation is also causing significant quality issues in the packing of avocados [17]. This is especially true with mechanical rollers which are resulting in permanent negative quality impacts. Therefore, AR, which enables collaboration between humans and robots has a unique opportunity to provide significant quality and productivity improvements [86]. Research has shown that AR could provide an average of 21% productivity increase with an improvement of up to 35% being possible [115], [116].

3.2 Harvesting and Post-Harvesting Activities

The point of this study is to assess the productivity and quality improvements that visual technologies can have in the agricultural sector, with the main area of application being fruit sorting and packing. To better understand sorting and packing a small farm was studied, for more information about the farm, refer to Appendix A. This farm both packs their own boxes of avocados and sends a significant portion to a sorting and packing facility, which will simply be referred to as a packing facility in the future. By studying a farm who packs their own boxes, as well as sending avocados to a packing facility - the sorting and packing of most processes of most farms could be examined. During the investigation it was found that sorting and packing happens in parallel with the picking of fruit. However, when avocados are sent to a packing facility the fruit are sorted and packed a few hours after being picked.

3.2.1 Picking Timing

The timing of picking is important since it contributes significantly to the sales of avocados, which are the farmer's main source of income. To determine when to pick four main factors need to be considered: climatic conditions, fruit maturity levels, supply and demand (due to higher prices being more rewarding), and the availability of a distribution network [17]. Besides the maturity levels, temperature and rainfall also affect avocados that are being harvested. Problems occur with avocados harvested during atmospheric temperatures of 30 degrees Celsius and above because this causes flesh discolouration and fruit decay which are significant quality factors [17]. Harvesting during rain also makes avocados more susceptible to mechanical damage [17].

These four factors need to be balanced against the time available to harvest. Avocado farmers have the advantage of being able to leave the fruit on the tree for up to six months once the minimum maturity levels have been reached. Thus, fruits do not have to be picked immediately, but farms can wait for better environmental and financial conditions before harvesting. This delayed harvest should also be balanced against the time availability to harvest all of the fruit as late-harvested fruit are more prone to pests, disease, and faster ripening [17].

3.2.2 Picking Process

Once the avocados, which are still on the trees, have been determined to be at the right maturity levels for harvest, and the environmental and market conditions are favourable, the farmer indicates that it is time to harvest the fruit. This can be seen as the start of the harvesting process. The avocados are picked from the tree with 2cm or more of the fruit stem still attached. To carry the avocados, labourers will use crates, with a capacity of 16kg. These crates are then transported to a central location where the stems are cut so that only 1 cm of stem remains. The trimmed stems are then dipped in an anti-fungal and anti-bacterial solution and placed back into crates. These crates are either stored for collection, or to be taken to a packing facility on the farm for sorting and packing on the farm.

3.2.3 Sorting Guidelines

The South African government published a regulatory document in 1990 to establish quality measures considered to be a requirement for the sale of avocados within South Africa [87]. The document states that the minimum requirement for an avocado is that it needs to be absent of any sign of decay or quality defect that may cause the fruit to be inedible. It also stipulates that the fruit needs to be correctly graded and sized. When packing a box of avocados, only fruit of the same size and grade are packed into a box.

The sorting requirements for each avocado can be seen in Table 3.1 below as well as in Table A.1 and Table A.2 in Appendix A. An extract of Table A.2 in Appendix A can be seen below in Table 3.2 to illustrate the grading guidelines. Avocado weights determine the size categories which are represented by even numbers from 4 to 32. These numbers are size codes displaying the number of avocados packed into a standard avocado box as shown in Table 3.1. The second table shows some of the quality factors which determine if the fruit is graded as a class 1, class 2, or unclassified (usually referred to as a class 3).

Originally when the South African government document was set up in 1990, mechanisation was not yet widely prevalent. Thus, weighing avocados when packing was not practical as it would have been a very slow process. This resulted in a box of avocados being graded as good quality if the avocados in the box are uniformly packed; visually similar in size; all of the same grade; and no significant gaps between avocados. To show what quality is using the above-mentioned method Figure 3.1 and Figure 3.2 show an avocado box with good and bad quality respectively. In Figure 3.2 there are three clear quality issues which are shown by: the green oval which shows a class 3 avocado while the other avocados are class 2; the orange arrows showing significant gaps between the avocados packed; and the blue arrows showing avocados which are clearly of different size categories.

Table 3.1: Table extract quantifying the different size codes or size classifications as provided by the South African government [87]

Mass range in grammes	Size code
> 781	4
576 - 780	6
461 - 575	8
366 - 460	10
306 - 365	12
266 - 305	14
236 - 265	16
211 - 235	18
191 - 210	20
171 - 190	22
156 - 170	24
146 - 155	26
136 - 145	28
125 - 135	30
100 - 124	32

Table 3.2: Table showing an extract of the guiding document used to classify avocados according to class [87]

Quality Factor	Class 1	Class 2	Unclassified
(a) Decay (e.g. stem end decay, vascular browning, internal spot, anthracnose, dothiorella rot)	1%	5%	*
(b) Injuries	4%	6%	*
(c) Bruises	4%	6%	*
(d) Malformation			
(aa) Epidermal notches	10%	15%	*
(bb) Epidermal bumps	10%	15%	*
(cc) Bent necks	8%	15%	*
(e) Over maturity	6%	10%	*
(f) Visible chemical residues	5%	5%	*

Figure 3.1: Figure of a box of avocados packed correctly using subjective measurements

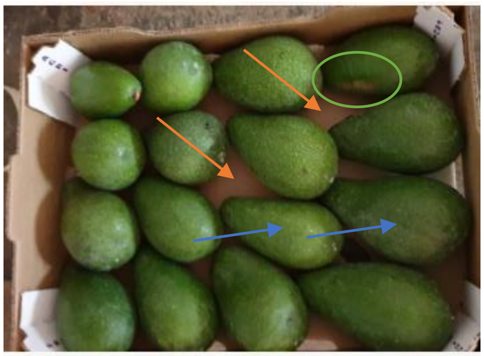

Figure 3.2: Figure of a box of avocados packed incorrectly using subjective measurements

It should be noted that grading boxes of avocados using subjective measures, such as looking for uniformity and lack of gaps, does not conform to any quality standards. Therefore, these methods of sorting avocados can only be used when selling avocados locally in South Africa and cannot be used when exporting fruit. To ensure proper quality - packing facilities have cameras which are used to visually grade avocados, as well as conveyor belts with scales to weigh the avocados. Therefore, avocados need to be sent to packing facilities for the fruit to be exported or be sent to high-end retailers such as Woolworths. The use of packing facilities is unfortunately also expensive, especially for farmers sending small batch sizes of avocados. Therefore, avocados are either packed on the farm or in a packing facility, depending on the farm size and/or the farm's SCM strategy.

3.2.4 Sorting and Packing on the Farm

When sorting on the farm, the crate of avocados is emptied onto a large sorting table, as can be seen by the area in white in Figure 3.3 below. A packer will place a box on the sorting table, in the orange marked areas in Figure 3.3. From the avocados on the sorting table, a packer will select avocados which are of the same grade and size category, using their intuition and training, and will place these avocados into a box. Once the box is packed, the packer will inspect the box to ensure that it contains avocados which: are of an even number, are of the same grade, are uniformly packed, have no significant size differences between the smallest and largest fruit, and have no significant gaps present. These boxes are then packed onto a pallet and either sold directly to consumers, at the fresh fruit market, or to retailers for further distribution.

Figure 3.3: Figure showing the position of avocados as well as avocado box on a packing table when a packer is packing and sorting fruit

3.2.5 Sorting and Packing at a Packing Facility

Before avocados can be sorted and packed at a packing facility the previous batch of avocados must be completely processed. This is done so that it is clear which avocados are the property of which farmer. Once the previous batch is finished the crates of avocados are emptied onto a conveyor belt. These avocados are then submerged in an anti-bacterial and anti-fungal wax to clean and protect the fruit. Next, the class 3 avocados are removed from the conveyor belt and placed into 16 kg bags in which they will be sold. After removing the class 3 avocados, the remaining avocados on the current conveyor belt are automatically transferred to another conveyor system. This conveyor system is comprised of individual buckets, each being large enough for a single avocado. The avocados in these buckets also turn, vertically along the avocado's axis, so that the avocados can be observed from all angles. These turning avocados on the conveyor system pass under a section with cameras. These cameras take pictures of the avocados which are then sent to a system which grades the avocados as either class 1 or class 2. Next, the bucket in which the avocado was placed weighs the avocado. The sized and graded avocado in the bucket then travels along the conveyor system until its respective packing station is reached whereafter it is released from its bucket. The avocados at each packing station are then packed manually into boxes by packers.

Packing facilities mark the bags and boxes of avocados for quality assurance and produce traceability [17]. It is important for fruit that are going to be exported or stored for a considerable amount of time to be cooled as soon as possible. This is to ensure that the avocados will ripen slower; allowing for adequate time to be transported and have a longer shelf-life upon arriving at the required destination [17]. Therefore, avocado boxes and bags are immediately placed into large refrigerators at packing facilities. Some sorting at packing facilities is still done manually, but in general automated systems are used, as they reduce labour costs and increase efficiency and quality of the sorting process [17].

3.3 Avocado Quality

To address quality, it is necessary to understand what the different quality perspectives are. Directly and indirectly all stakeholders desire avocados which are, or will be, flavourful and appear appealing to the final customer. The parameters that translate to good quality, however, are different depending on the stakeholder. The different perspectives are shown using Table 3.3 below.

Table 3.3: Table showing the different perspectives of quality from the different stakeholders[17], [87]–[89]

Perspective	Grower	Packer	Retailer	Consumer	Government
Quality Parameter	Size	Gradable defects	Size	Size	Edibility
	Shape	Absence from defects from pests	Shape	Shape	Uniformly packed box
	Skin defects	Size	Ripeness stage	Skin defects	Sized correctly
	Maturity	Uniformly packed	Maturity	Ripeness stage	Graded correctly
			Absence from defects from pests	Free from harmful chemicals	MRL
			Minimum residue level (MRL)	Flavour	Produce traceability
				Texture	

Farmers and packers want avocados to be of a quality to satisfy retailers while conforming to government regulations. Retailers want to source and sell fruit that are of a quality sufficient to satisfy and instil confidence from the consumer’s perspective. The government needs to protect the consumer through legislation since it needs to preserve the right of the citizens of the country not to be harmed. Thus, all perspectives want to satisfy, directly or indirectly, the needs of the consumer. It is therefore necessarily to understand the needs of the consumer to understand the quality perspectives of the other stakeholders.

3.3.1 The Consumer

The consumer’s main objective is to buy an avocado that is flavourful, texturally pleasing, and free from harmful chemicals at a reasonable price. Texture is determined by the stage and quality of the ripening process [17]. This process affects the firmness of the fruit and the amount of oil present which gives it the buttery texture. Poor quality ripening may result in uneven ripening, decaying of vascular fibres, or hard lumps in the flesh of the fruit. Flavour is influenced by texture, fruit ripeness, and cultivar of avocado. Overripe fruit greatly reduces the flavour and is a quality concern. To achieve good texture and flavour it is necessary that avocados ripen properly to the right ripeness stage, and not become overripe, with little to no damage to the flesh of the fruit. The consumer trusts that the fruit being consumed will not adversely affect their health. Thus, avocados free from harmful chemicals are an important consideration for the consumer.

Mechanical damage to avocados is one of the most significant quality factors avocado farmers and packing facilities have control over. Mechanical damage affects the avocado's skin resulting in bruising on the inside of the fruit causing browning and decay of fruit's flesh. The damage on the skin causes the skin to make black marks which are not visually appealing, causing the avocado to be less attractive to buy. These black areas may also ripen faster than the rest of the avocado which will result in browning of the flesh in these areas due to decay [17]. Browning flesh has an inferior taste which also reduces the quality of the avocado. This damage can be caused by rough fruit handling, extreme temperatures, or diseases [17].

Rough fruit handling damage can be caused by conveyor systems as previously stated [86]. It is for this reason that there is significant room for the reintroduction of people into the packing processes if it can be done cheaply and have the same efficiency as well as quality as a conveyor system. The potential is for either AR or other forms of human-robot collaboration. This is because the accuracy and efficiency of Industry 4.0 technologies can be used in conjunction with human employee for better quality, whilst maintaining high productivity levels. In doing so hopefully a significant portion of the 40% of bruised avocados sold to consumers can be reduced [17].

3.3.2 Government and Retail Regulatory Bodies

Decaying avocados not only affect the consumers' perception but may also be a hazard to their health. Avocados with excessive levels of certain chemicals or compounds can also be a danger to the consumer. To ensure avocados are safe to consume both private companies and government departments have been established to ensure that avocados meet the minimum quality requirements [87], [89]. Government departments ensure that avocados are edible while private entities try to ensure both food safety and an ethical production environment. Governments cannot always ensure ethical behaviour in the production environment because food may be sourced outside of the government's jurisdiction. Companies can act across borders because they can utilise supply and demand to ensure that quality avocados are sourced from ethical producers, which will force producers to adopt acceptable standards of quality and ethics [89].

To ensure proper food quality and an ethical production environment good agricultural practices (GAP) standards were developed [88]. GAP standards are quality standards which state that a farm's practices result in quality produce which is safe for consumption and are sustainable from an environmental, economic, and social perspective [88]. GAP ensures best practices since quality is based on scientific knowledge to ensure good quality products [89]. GAP standards arose due to concerns regarding the safety of food being produced. This became a larger concern with globalization as food was, and still is, being sourced from around the world. Global trade results in a disconnection between producer and consumer. The consequences of poor-quality produce are no longer as significant of an economic concern for many producers as there are limited repercussions resulting from poor quality, harmful chemical usage, or inhumane working conditions due to the disconnect. Europe is strict with their import laws, but they cannot determine the working conditions and chemicals used during the faming process. To address the disconnection, GAP standards were formed to ensure quality produce that is ethically produced is being sourced.

In Europe GLOBALGAP was formed by a group of supermarket chains to ensure quality products in order to satisfy and instil confidence in their consumers [88]. From a South African perspective it is important for avocado farmers to comply with this quality standard as 96% of South African avocados are exported to Europe [90]. The requirements of GLOBALGAP entail that a farm's activities be monitored, and that food traceability is possible to hold producers accountable for poor or dangerous produce. GLOBALGAP is strict about residue and compound limits commonly referred to as minimum residue levels (MRLs) in products as these may be harmful [88]. Thus, strict records are kept ensuring that all the requirements of GLOBALGAP standards are met. GLOBALGAP is a voluntary quality standard that is increasingly being required by retailers as a quality measure of agricultural products [88]. GAP is becoming a requirement for quality which will lead to it becoming a minimum industry standard although it is currently voluntary. This is because more companies and even countries are starting to demand GAP certificates to ensure quality products [89].

3.3.3 Impact of Quality

Quality has a significant financial impact on the avocado farm. This quality impact is both on fruits sold locally and those exported. Fruits sold locally are evaluated according to the subjective method as stated in section 3.2.3. Unfortunately, farmers who pack on the farm have poorer packing quality compared to avocados packed at a packing facility. The result is that farmers who send their produce, which will be sold locally, to a packing facility will get 10-15% higher prices [69]. This was stated both during the interview with a packing facility consultant, who advises in the construction of packing facilities in Africa, as well as the company that benchmarks avocado data for farmers. These farmers can unfortunately not export either due to the poor quality and lack of regulation adherence, as stated by South African legislation.

The quality perspective from the customer is not always addressed by the farmer or packing facility because there is often no direct link between the consumer and the producer/packing-facility. But this is expected to change in the future as food traceability is adopted. As mentioned before, in section 2.3.2, IoT coupled with blockchain technology could be revolutionary for food traceability. Once this is achieved good quality from the customer perspective will play a vital role in the financial situation of both the farmer and the packing facility, as consumers will have the ability to procure from specific producers or packing facilities. It is this quality perspective from the customer that could also drive future demand for AR as it can help reduce poor quality during sorting and packing, for example the bruising of fruit.

3.4 Conclusion

The purpose of this chapter was to both justify the selection of avocados as the case study for this thesis, as well as to consult literature related to the avocado industry so that the inner working of the relevant aspects of the industry can be understood. Therefore, the avocado industry's value to humans, the ability of the researchers to gather good quality data, and the opportunity for significant productivity and quality improvements was used as justification for selecting the avocado industry as the case study for this thesis. To better understand the fruit classification aspect of the avocado industry, avocado fruit sorting and packing guidelines were studied. It was found that avocados of the same size and grade should be packed together into the same box. It was also found that farmers do not always conform to this standard, especially when selling fruit nationally. However, if farmers wish to export, they must conform to the required quality standards. The other effects of quality were also investigated, and it was found that farmers who have better quality sorting and packing systems generate 10-15% higher revenues per box of avocados sold. This quality can also be achieved with a 21% productivity improvement. Therefore, there is an economic incentive for the use of visual technologies to increase the quality and productivity of the avocado sorting and packing process.

Chapter 4 Prototype Hardware and Software Selection

To test the effect of AR when it is applied to the sorting and packing process, within the avocado industry, a prototype will be used. Various considerations need to be made before design and development of the prototype can be undertaken. The purpose of this chapter is to determine what hardware and software will be best suited for the design and development of this prototype. Therefore, within this chapter different hardware and software solutions will be evaluated and the best options will be selected. The different options need to be evaluated carefully because once an option is selected, it will be utilised throughout the rest of the project.

4.1 Prototype

Advancement in Industry 4.0 technologies are leading to the digitalisation of the agriculture sector. Of these technologies, one that is well suited to the fruit industry is AR because it is a visual technology. AR will also require other Industry 4.0 technologies such as IoT, ML, and computer vision for it to provide ideal value. Within the fruit industry avocado sorting and packing provides an area of opportunity. The reasons are: improving this sector could have socio-economic benefits; data is available which is essential for a proper study; and there is room for significant productivity and quality improvements. The productivity improvement will materialise from farmers who still pack avocados on the farm without the assistance of any technologies. The avocado packers only have access to their intuition and training when packing. This is also leading to quality issues as the packers are struggling to sort and pack fruit to an objective standard, efficiently.

To test the possible productivity and quality improvements to the avocado sorting and packing process a prototype will be developed. This prototype will utilise AR and other Industry 4.0 technologies to assist a packer when sorting and packing avocados. The AR prototype will do this by classifying avocados according to size and grade for the packer who then only needs to pack the fruit, thus providing technological intervention to enable packers to sort and pack fruit to an objective standard. Before undertaking the prototype design and development it is first necessary to determine the hardware and software available to develop the prototype. The reason for this is because AR is a new technology, so it is important to first identify the resources available.

4.2 Hardware

Dedicated AR and other mobile devices are used to facilitate the uses of AR technology [91], [92]. Therefore, there is an array of different devices which can be used to operate AR software as can be seen in Figure 4.1. Of these devices it was decided that the head-mounted AR devices would be the best suited for avocado sorting and packing. This is because packers need both hands during sorting and packing operations. Research showed that head-mounted devices should also work better because tasks completed with both hands are more efficient, effective, intuitive, and ergonomic for the user [92]. Two different head-mounted devices are available: smart glasses and AR headsets. Smart glasses are not as encompassing as a full AR headset with only a portion of the user's vision being available for projecting information [92]. This is not optimal as a wide field of vision will be required for the user to sort and pack avocados. Therefore, only head-mounted AR devices were considered as the AR device of choice for the prototype.

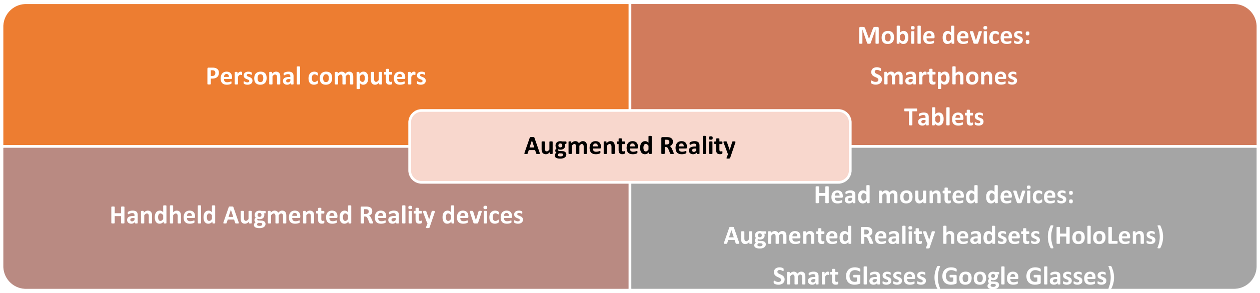

Figure 4.1: Figure showing the different AR hardware categories with a focus on the head mounted device options [91]

To select an appropriate pilot device the three most popular and sophisticated head-mounted AR devices available were compared [93]. The three devices, namely HoloLens 1, HoloLens 2, and Magic Leap 1 were compared using different factors which were used as selection criteria. The factors were chosen based on the capabilities of each device as well as the support provided. The following factors were selected: development support, cost, ergonomics, display area, and resolution.

The three were compared using the Analytic Hierarchy Process (AHP) method, which assigns relative weights to the different factors used as selection criteria [94]. Of the five factors selected the factor that was considered the most important was development support. This factor was considered most important because the success of the project is directly related to the support and documentation available during project development. If there is a lack of support, then development may be delayed. Development support can be in the form of tutorials, documentation, or community development available on the internet. Given that development support was identified as the most important factor, the other factors were compared to it using the AHP method. The AHP method was used with a consistency index of 0% meaning there is no deviation in the relative scores for the different factors. Therefore, only development support needed to be tabulated with the other factors compared to it. Table 4.1 below shows the relative scores of the factors, out of 1, compared to development support.

Table 4.1: Table showing the relative importance score of cost, ergonomics, display area, and resolution compared to development support

	Factors compared to development support					
	Development support	Cost	Ergonomics	Display area (degrees)	Resolution	Total
Ddevelopment support	1.00	0.75	0.40	0.33	0.25	2.73
AHP weight (portion our of total)	**0.37**	**0.27**	**0.15**	**0.12**	**0.09**	**1.00**

The AHP weighting was used with a score given to each factor for each device to determine which device would be best suited for this project. The total score for the HoloLens 1 is calculated using Equation 4.1 below. The reason for each score is given in Table 2 below. The cost of the HoloLens 1 is given as $0. This is because this device was readily available at the institution where the study took place. The HoloLens 1 would not be considered free if it had to be bought, but considering the project is a prototype, cost is an important consideration. Therefore, an available device with zero added cost should also be considered. The cost score was calculated using Equation 4.2 below. It was considered out of $5 000 as this was considered too expensive. This is because $5 000 is double the average annual disposable income of citizens from South Africa, the country where the study took place [95]. The display area is out of 60, because this is the peripheral field of vision of humans [96]. The resolution score is simply compared to that of the HoloLens 2 as it is the best of the three [97]. The product of the AHP weights, the scores given, and the reasoning behind the scores can be seen in Table 4.2. It was determined that the HoloLens 1 would the best device for the prototype. It should, however, be noted that were cost not a factor or the HoloLens 1 not already available, the HoloLens 2 would have been considered the best device.

$$Total\ weight = \sum_{i\,=Development\ Support}^{Resolution} \text{i AHP weight} * \text{HoloLens 1 i score};\ i \in \begin{cases} Development\ support \\ Cost \\ Ergonomics \\ Display\ area \\ Resolution \end{cases} \tag{4.1}$$

$$Total\ weight = 0.37 \times 0.7 + 0.27 \times 1 + 0.15 \times 0.5 + 0.12 \times 0.57 + 0.09 \times 0.42 = 0.71$$

$$Cost = 1 - \frac{HoloLens\ 1\ Cost}{\$\ 5000} = 1 - \frac{0}{5000} = 1 \tag{4.2}$$

Table 4.2: Table showing the AHP weighting per factor, score per factor for each device, and the total scores for the three different devices [93]–[97]

Factor	**AHP Weight**	**HoloLens 1**		**HoloLens 2**		**Magic Leap One**	
		Reason	Score	Reason	Score	Reason	Score
Develop-ment Support	0.37	Microsoft realised very well-designed tutorials, but community documentation is not as abundant as that for the HoloLens 2	0.7	Microsoft realised very well-designed tutorials and made development easier, with a fair amount of community documentation	0.8	Tutorials available but not as well designed as those by Microsoft and community documentation is scarce	0.5
Cost	0.27	HoloLens 1 would cost $0 as it is currently available.	1	HoloLens 2 currently costs $3500 new	0.3	Magic Leap One currently costs $2295 new	0.54
Ergono-mics	0.15	Heavy device that can cause discomfort. Semi fragile frame that requires careful handling	0.5	Compared to HoloLens 1: Slightly lighter, better balanced, special knobs added for user comfort	0.7	Well balanced with pads to ensure user comfort. Does connect with a cable that might disturb the user	0.8
Display Area (degrees)	0.12	34 of 60 field of vision	0.57	52 of 60 field of vision	0.87	50 of 60 field of vision	0.83
Resolution	0.09	1280x720	0.42	2048x1080	1	1300x1300	0.76
Total	1	Best for prototype	**0.71**	Second	**0.68**	Third	**0.62**

4.3 Software

In the literature study, in section 2.6, it was discussed that a PaaS would be the best option for this prototype. This is because as ML algorithms are becoming more complex, they require higher computer programming skills and time to program the ML component effectively [56], [57]. Also, since this project is only a prototype the focus should not be only any one component but rather the complete AR system. Therefore, if the ML component requires too many resources, then the entire prototype may not be completed in time. It was thus decided that it would be better to use a PaaS. If the prototype shows promising results, then a fully operational system may utilise an in-house developed ML algorithm.

The three industry PaaS leaders as mentioned before, in the literature study in section 2.6 are - Amazon, Google, and MS who provide the following three services respectively: Amazon Web Service Recognition (AWS Recognition), Google Cloud Vision (GCV), and MS Azure Computer Vision (Azure) [57]. Due to the owners of these services being private companies, the algorithms behind these services are currently unknown and inaccessible [57]. It is for this reason that although the services provided may be similar in how they function, the behaviour of the systems may be very different. It should also be noted that using a PaaS in the long term may have an added advantage, as the newest ML algorithms would be available [57]. The unique nature of each service also makes it such that the services are not interchangeable or easily integrable, but rather that one service must be selected and used for the duration of a project [57]. The three services: AWS, GCV, and Azure each have their own distinct advantages and disadvantages which need to be evaluated to determine which one will be the best for this project. It should also be noted that the HoloLens 1, a MS device, has already been selected as the hardware of choice.

AWS Recognition is currently the most popular computer vision and ML PaaS and is mainly designed to be used on a personal computer (PC) [56], [98]. The platform is easy to use and cost effective for the services provided which makes it a popular choice [56]. A disadvantage of AWS Recognition is that it restricts the quality of images by placing a restriction on the maximum size of an image [56]. Images are important, both to train a computer vision model, as well as to act as input for a fully functioning model. Therefore, restrictions on image sizes may lead to images with poor resolution which may result in poor object recognition. When looking specifically at the integration between AWS Recognition and the HoloLens 1, the integration between the two is complex and arduous, with the tutorials available not providing in-depth assistance [99], [100]. Therefore, when considering all the information, AWS Recognition is a possible candidate to use as a PaaS, but it is better suited for computer vision development on a PC compared with the HoloLens 1.

GCV is similar to AWS Recognition in that it is also simple and logical to use given the complexity of the underlying algorithms [56]. The cost structure is pay-as-you-go so only that which is used is paid for, resulting in GCV being cost effective as long as the model being created is not too large and complex [56]. GCV, being a Google product, has the highest security, privacy, and compliance control because it uses the same underlying security, privacy, and compliance control as Google's browsing software [56]. A disadvantage of GCV is that it has a significant error rate if the "noise" in the image is above a certain threshold [57]. This results in an image that is easily identifiable by humans but indecipherable to GCV. GCV can connect to the HoloLens 1 with resources available on how this is done, with one freely available tutorial online which was developed by the SAP community [101]. Therefore, GCV seems to be a better alternative than AWS Recognition, but the significant error rate may be problematic.

The last computer vision PaaS worth considering is Azure. Azure has a complex and extensive AI, computer vision, and ML PaaS available that is difficult to navigate [102]. The usage of Azure may be expensive as the cost structure is vague resulting in it being difficult to predict what the final cost will be [56], [102]. This could be problematic when implementing a commercial solution, however it was only seen as concerning since the aim was to implement a prototype and not a commercially ready solution. It should, however, be noted that a 30-day free trial is available with a $100 balance available to be spent during that period [102]. There are, however, a significant amount of resources available to help the user navigate the PaaS infrastructure, which helps to facilitate learning and a user-friendly experience [56], [103]. The availability of resources reduces the complexity and time required to use or develop software using a PaaS. The reduction in complexity and time would allow a project to work as intended and be completed within the time allowed for the project.

Azure also allows for the URL of an image to be passed to the computer vision service which enables remote access and allows the AR devices to use the Azure services remotely [56], [103]. The response time of Azure is also better than GCV and AWS Recognition which makes it a more attractive alternative for remote usage [56]. MS provides the tools for HoloLens 1 to be able to integrate with Azure and other MS products [104]. MS is focused on increasing the integration capabilities between all of their products [104]. The focus on integration can be seen with the HoloLens 2 having built-in integration tools with Azure. This integration can be expected to increase in the future. This should result in an increase in the ease with which Azure will integrate with future generations of the HoloLens. When considering the advantages and disadvantages Azure would be the best PaaS to use in conjunction with the HoloLens. For the three PaaS options, the advantages and disadvantages have been summarised in the Table 4.3 below.

Table 4.3: Table comparing the three most popular PaaS solutions [56]–[58], [102], [104]

Characteristics	PaaS contenders		
	Amazon Web Service Recognition	Google Cloud Vision	Microsoft Azure
User Interface	User friendly	User friendly	Complex (resources available)
Cost	Cost effective	Pay-as-you-go (only pay for what is used)	Vague with a free trial and $100 available
Online resources	Little (existing are complex with little useful information)	Available (but limited)	Significant amounts available
HoloLens 1 Integration	Complex (almost no resources to assist development)	Possible	Facilitated (Azure + HoloLens Microsoft products so built-in compatibility)
Response Time	Medium	Medium	Fast (comparatively)
Other significant disadvantages	Limited image size (may result in poor computer vision capabilities)	Low "noise" tolerance (may result in poor computer vision capabilities)	None

4.4 Supporting Software

The HoloLens is a revolutionary device, with development having been rapidly executed. A consequence of the speed of development and the novelty of the device was that software has not yet been developed specifically for the HoloLens, or other AR and holographic devices [105]. It was discovered, however, that holographic software behaviour is similar to that found in 3D game development software [105]. This resulted in 3D game development software being tailored and used to develop applications on holographic devices. One of the key adjustments that had to be made was 3D object placements. In 3D games even though objects give the appearance of being 3D, these objects must be designed to be displayed on a screen, which is a 2D environment. On the other hand, 3D objects when being projected from an AR device, have to interact with an environment which is actually 3D [105].

A 3D game development software package that offers this tailoring capability is Unity. It is for this reason that Unity has become a popular 3D game engine for developing software that can be executed on the HoloLens [105]. Unity is a software program that is used to create complex 3D gaming environments in which 3D objects can be created for interaction with an actual 3D environment [105]. Another advantage of Unity, making it a good choice for development, is that scripts can be coded in C# which is MS's preferred programming language [105].

The software used to create the environment in which the code itself is created and tested is Visual Studio. Visual Studio is a programming environment created by MS to enable coding in C#, as well as other programming languages [105]. Unity and Visual Studio also have a significant level of integration with newer versions of the two software programs being developed with the purpose of being used together [105]. Therefore, Unity and Visual Studio can be integrated in a way that is both intuitive and easy to implement. Unity is used to create 3D objects and place them(using x, y, and z co-ordinates) in the location where they should be observed in the real world when wearing the HoloLens. Visual Studio is then used to write the script which dictates the behaviour of the 3D objects which will determine how they will interact with the surrounding environment [105]. Thus, with the combination of Unity and Visual studio a virtual, holographic, 3D environment can be created that can be superimposed onto the physical reality observed by the wearer of a HoloLens.

4.5 Conclusion

To design and develop the prototype effectively, the right hardware and software needed to be selected. In order to do this, various hardware and software solutions were evaluated. To determine the right hardware device, the AHP method was used to compare the different options against each other, and as a result the HoloLens 1 was selected. Besides hardware, software options were also considered, and it was decided to use a PaaS. This was because PaaS would make the prototype design and development easier, allowing the prototype to be completed within the time and resource constraints. The three most popular PaaS options were evaluated by considering the advantages and the disadvantages of each. By evaluating the three different options, the best option for this prototype could be selected, which was Azure. Besides Azure, other software platforms such as Unity and Visual Studio were also studies since they will also be utilised during the prototype design and development.

Chapter 5 Design and Development

The main purpose of this chapter is to explain both the logic and the design methodology of the prototype system. To do so a short summary of the current system environment will be provided, this will be followed by a description of the requirements for the prototype system. The system logic will be discussed in detail, whereafter the development of the prototype will be described using an IoT architecture, as a framework. The developed systems accuracy for avocado classification according to grade and size is compared to the current system to determine if there is a statistically significant increase in the packing quality. Lastly, system limitations and verification will be done to ensure that the system is built correctly.

5.1 System Environment

The current sorting and packing system is explained in depth in section 3.2.4, but a brief and supplemental informational overview will be provided here to provide context. Currently a packing table having a height of 0.9 m and cross-sectional dimensions of 0.813 x 2.032 m is being used. This packing table was not changed, but different background colours were added so as to improve the detection capability. Two background colours, white and black, were tested. White was too light as it resulted in the avocados appearing dark, causing the blemishes on the avocado to be undetectable. The black performed better, but the dark colour did not contrast the avocado adequately. As a result, the avocados appeared darker than they really are, and some blemishes remained undetectable. Further research suggested a contrasting colour would perform better, which was why maroon, which on the colour wheel is the opposite of green, was selected, providing the best results [106].

Lighting is also important when designing a visual system because the lighting will directly influence how the objects presented will be captured. In an experiment testing different light sources, three different kinds of light bulbs were compared. The light bulbs were of different warmths measured in Kelvin and were 2000K, 2700K, and 6000K respectively. It was found that the 6000K light was the best and coupled with a dark background, such as maroon, created a good environment for object detection of avocados. The lighting environment in which the present sorting and packing operations were performed had a rating of 6500K, meaning additional lighting was not required and that the current lighting environment was adequate for the experiment.

To sort and pack avocados a packer, the person who both sorts and packs avocados, packs a box of avocados using their experience or intuition. To do so they place a box on the sorting table and select avocados, from the table in front of them, which are similar, in quality and size, and pack them into the box. There is little guidance when sorting and packing the avocados, resulting in inefficiencies. There are strict sorting requirements, such as the weight of the avocado determining the size category of the fruit, as explained in section 3.2.3. However, without utilising time-consuming or expensive equipment the packer has little guidance when sorting except for their intuition and experience. This results in the possibility of serious quality and productivity issues. The productivity is affected because the packer requires time to determine the classification of the fruit to ensure decent quality. It is for this reason, to aid a packer during sorting and packing, that a prototype AR system was designed and developed.

5.2 System Requirements

For a packer to be assisted when sorting and packing similar avocados into a box, the criteria by which the fruit are sorted needed to be determined. The sorting criteria has been explained in section 3.2.3, however a short summary will be provided to give context in this section. The avocados are classified according to a quality grade and size category. The avocado grade and size are determined based on guidelines provided by the South African government. Quality factors determine if the fruit is graded as a class 1, class 2, or unclassified (usually referred to as a class 3). Avocado weights determine the size category which are even numbers from 4 to 32. These numbers represent the number of avocados packed into a standard avocado box, weighing 4kg.

5.3 System Logic

To develop the prototype, the right hardware and software needed to be selected. The HoloLens 1, which will henceforth simply be referred to as HoloLens, and MS Azure were selected, as justified in section 4.2 and section 4.3 respectively. The system logic was developed using the architecture that will be discussed in the next sub-section. However, with a comprehensive overview of the system logic, the architecture used to develop the prototype can be better understood.

On the sorting table used in the prototype, with the avocados present, there is a marker. The marker is a blue disk-shaped object with a diameter of 30mm. Blue was selected as it contrasts both green (the avocado) and maroon (the background colour) [106]. The reason for the marker was because the distance measured by the HoloLens was not always accurate. Therefore, introducing a marker, an object of known size, the prototype would be more accurate, as some of the complex distance calculations could be simplified. The inaccuracy of the HoloLens distance sensor can be described as “noise” [107]. The noise meant that a distance of 1m was measured to be anywhere between 1.2m or 0.8m. This variability was tested by taking 30 sample measurements, and the results were as follows: 10 measurements had more than a 5% deviation; 4 had more than 10%; and 1 had over 20%. These results indicated that there is significant noise in the prototype system as a result of the inaccuracy of the distance sensor.

By introducing the marker, the size of the avocado could be determined relative to the size of the marker. The size calculation now being a relative measure, and not an absolute measure, made the calculation more accurate. This was confirmed when a linear regression was used to test the accuracy of predicting the weight of avocados with and without a marker present. With a marker the R-squared (R^2) value improved from 55.22% to 65.27%. The R^2 was determined by comparing the actual weight of the avocados to the estimated weights. The estimated weights were derived using the avocado’s distance and the number of pixels that make up the avocado, as well as the marker’s distance and pixel number, if it was present. More information regarding regression and R^2 can be found in section 5.7.2.

Having examined the justification for the presence of a marker in the prototype system, the system development and logic can now commence. The system logic can be seen in Figure 5.1 below. The figure is a flow diagram showing the steps taken, from when an image is taken until all the avocados of a specific size and class have been identified and marked. The process starts when the HoloLens captures an image of the avocados on the sorting table. The centre point of the image (in terms of x, y, and z co-ordinates) is stored so that after the image has been processed, it can project back to the centre of where the image was taken. These co-ordinates are an anchor point from which all the projections onto the user’s environment will be projected. Next the image is loaded onto MS Azure using a unique URL and prediction-key to direct the image to the correct storage location, from where it will be loaded and processed. The practical implementation of the code for both the URL and prediction key can be seen in Figure B.1 in Appendix B. Next the marker in the image is identified, using ML. If the marker is not present, then the program simply stops, and no valuable output is provided. It should be noted that, at the start, just before an image is taken, a green cursor is present in the middle of the image. When the image is taken the cursor becomes red so that the user knows the image is being processed. If the program yields no useful information and the image is fully processed, then the cursor will become green again to let the operator know that nothing significant has happened.

If the marker is identified, then the number of pixels in the marker and the x and y co-ordinates of the marker are stored. These parameters are used to scale a label on the marker labelled "marker" which is transparent during implementation but is still present for the purposes of debugging. The scaling of the label for both the marker and that of the avocados is necessary as there is a scaling difference between the size of the original image taken and the image analysed by Azure. Next a loop is initiated which first determines if there is an avocado present.

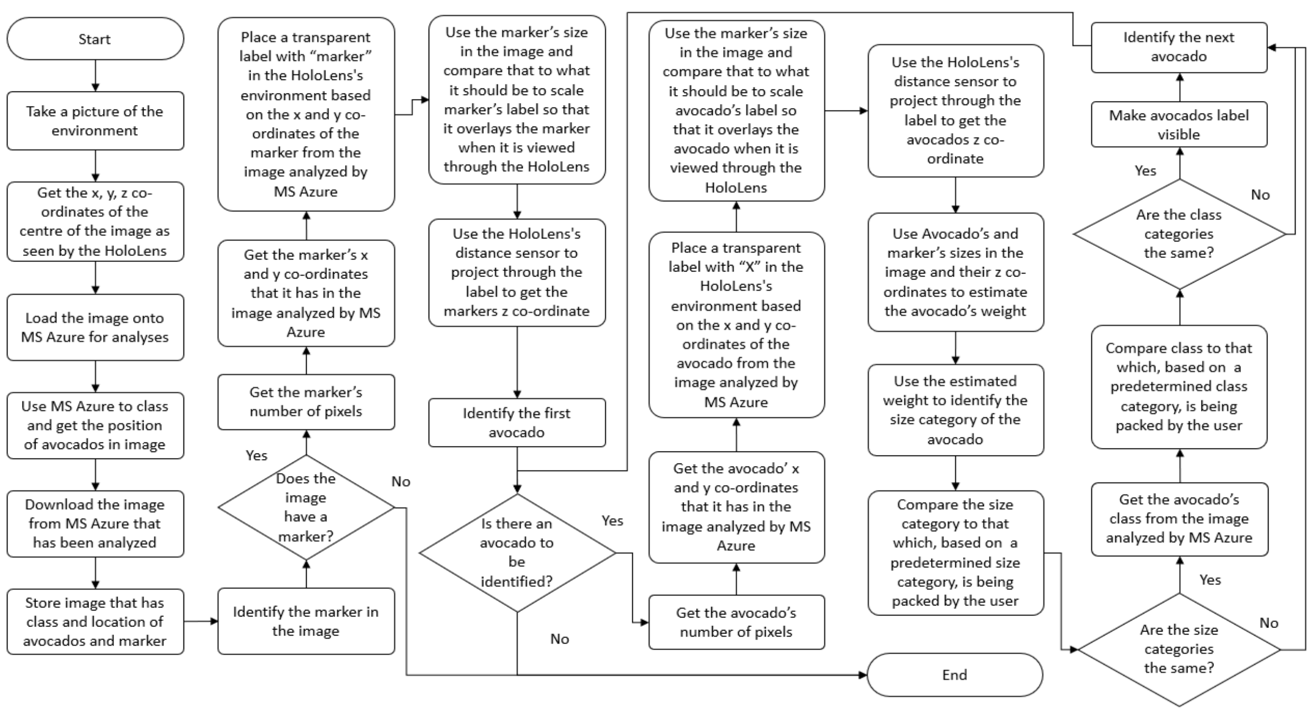

Figure 5.1: Figure of a flow diagram showing the logic of the prototype from when an image is taken to when all the avocado within the image have been sized and graded

The ML algorithm, training, and implementation will be explained in the next sub-section. Using the data from the ML algorithm, the number of pixels in the avocado can be determined as well as the x and y co-ordinates. A transparent label labelled "x" is then placed on the avocado based on its location, provided by the image analysed by Azure. The marker's number of pixels, as well as the x and y co-ordinates, are used to scale the location of the label so that it perfectly overlays the actual avocado being analysed. Next the avocado's size and grade are determined and if both parameters are equal to that which is being packed, then the transparent label becomes visible.

Once all the avocados have been classified according to size and class, and the required avocados have been identified, the loop stops and the cursor turns green. This indicates to the packer that those avocados with an "x"-label can now be packed. The planned user interface can be seen in Figure 5.2 below. The logic for this design was to have a simple, effective, and clear way for the packer to identify the avocados that should be packed. Once all the avocados have been packed, the next batch can be classified by taking another photo. When the photo is taken all the old labels are removed, whereafter another photo is taken and processed.

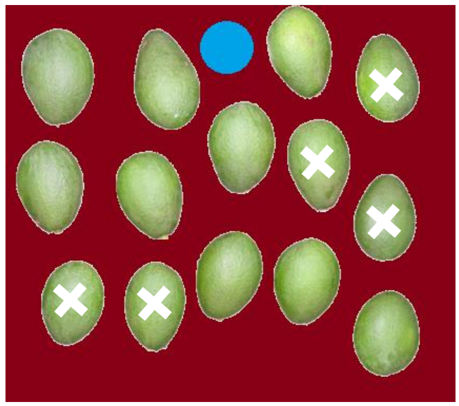

Figure 5.2: Figure showing what the desired user interface will look like through the HoloLens when classifying avocados

5.4 Development Architecture

Given the significant role that IoT plays as an Industry 4.0 technology in the prototype system, and the fact that the HoloLens can be considered an IoT device as discussed in section 2.3, an IoT architecture was selected [108]. The IoT architecture that was selected for the development of this prototype needed to be simple to use, provide the correct level of detail, and have practical steps that can be implemented during development [108]. It is because of these requirements that the five-layer architecture was selected. There are other alternatives, such as the three-layer, but it does not provide enough detail for research purposes [108] The layers in the 5-layer architecture in order of development are [108]:

Perception layer, which is the physical layer comprising sensors which gather data from the surrounding environment. The purpose of this layer is to identify key data points in the surrounding environment or identify other smart objects in the immediate vicinity.

Transport layer, which utilises networks to transfer data and information between the perception layer and the processing layer.

Processing layer, which stores, analyses, and processes large amounts of data which are delivered to it via the transport layer. It supports the lower levels by managing and providing them with a wide-ranging set of services. The technologies typically associated with this layer are databases, cloud computing, AI, ML, and other big data processing software.

Application layer, which is tailored to provide the user with a desired service, via the use of IoT technologies such as smart homes.

Business layer, which controls the entire IoT system for the purpose of making profit for business and providing privacy to the users of the system.

This project is a prototype so it will not utilise the business layer, as this will only be incorporated if the prototype is deemed financially feasible. Therefore, the business layer will not be discussed further. The rest of the architecture components and the relevant system logic will be explained in more detail below.

5.5 Perception Layer

The HoloLens, when collecting visual data from the environment, acts as an IoT device. What makes the HoloLens particularly useful, as explained in section 2.2, is that it collects data from the user's current field of vision. In doing so visual data around the user can be extracted and analysed allowing for useful information to be augmented back to the user. To be able to analyse the data around the user, that data must first be captured. Ideally, the data captured would be video data because then there would be a continuous stream of data between the various layers. However, given the constraints of the technology, as will be explained in section 5.9, and to simplify the prototype being developed, photographic data was used instead. The image captured by the HoloLens image sensor, or simply the HoloLens camera, is the data that the prototype collects to extract information to help the user. To capture an image, it was decided that the user should initiate the command. The reasoning behind this was that the prototype would be tested, by initiating it, when it was required by the user.

The data capturing part of the system was programmed to let the user know when the system is ready, and an image can be captured. This was done by having a coloured cursor in the middle of the user's vision that is green when an image can be taken and red when the system is currently busy. If the cursor is green, the user uses the tap gesture which would then take an image of the user's environment, store that image on the HoloLens, and send a copy of the image, over the internet, to MS Azure's prediction API.

5.6 Transport Layer

To send the image to MS Azure, the end point of the prediction API, in the form of a URL, is coded into the prototype system logic [109]. In order to send the image to the end point using the URL the HoloLens requires internet connection capabilities. Luckily, the HoloLens 1 has a fully functional Windows 10 operating system and functions like a normal laptop with full internet capabilities via WIFI connection. Therefore, the ability of the HoloLens to connect to the internet can be utilised to send the image taken to MS Azure as directed by the URL.

5.7 Processing Layer

The processing of the image data is done both with the use of MS Azure and on the HoloLens. The avocados in the image are graded, using MS Azure, whereafter the avocados are classified into different size categories, using logic programmed on the HoloLens. The processing of the image data to grade and size the avocados is explained below.

5.7.1 Avocado Grade Classification

Once an image has been sent to MS Azure, that image is stored in the project where the ML algorithms have been trained, and the image will be analysed. To determine which ML trained algorithm will be used to analyse the image, a prediction-key is required [109]. This prediction key is also coded into the prototype system logic. Therefore, once an image is captured, the URL and prediction-key will direct the image to the location to be stored, and also identify the trained prediction algorithm which will be used to analyse the image. The prediction algorithm used is unknown to the user, as this is knowledge only known to the PaaS provider, as explained in section 2.6. Fortunately, the algorithm does not have to be known for it to be used, if the platform providing the service is reputable and reliable, such as MS Azure [57].

The prediction-key, as stated previously, is used to identify the trained prediction algorithm to be used to grade the avocado. Therefore, the algorithm, that is not known to the user, must be trained. To do this, 1053 images of avocados were used to train the algorithm. After training, the trained algorithm was used to grade avocados. The image containing the avocados that have been graded is referred to as an information-rich image. The reason being that the image contains useful information, not only for grading, but also sizing the avocados.

The 1053 images used to train the prediction algorithm were from avocados that were stringently pre-sorted. Using the guidelines as found in section 3.2.3 the avocados were sorted into either class 1, class 2, or class 3. A farmer was also consulted to ensure that the avocados were sorted correctly [72]. Once the 1053 avocados were sorted, they were photographed. It should be noted that only one side of the fruit can be captured by the HoloLens. So, the part of the avocado, usually the side with the most skin damage on the fruit skin, was captured as this determines the class of the avocado. A class 1 avocado does not have any significant skin damage so any side would have been photographed. Once the avocado is photographed it is tagged with the relevant grade. These tagged images were then the input data for training the algorithm.

The accuracy of class classification is determined from precision and recall. Precision is the percentage of predicted positives which are true positive [110]. Recall is the percentage of true positives that are predicted as positive [110]. Using the 1053 images of avocados, the precision and recall scores were determined. The precision score was 85% and the recall score was 81%. These values were provided by MS Azure once training was complete, as can be seen in the Figure 5.3 below. The f1 score, the accuracy using both precision and recall, seen in Equation 5.1 below is calculated to be 83%. An f1 score of 83% was deemed sufficient for this prototype as will be explained in more depth in section 5.10 below.

$$f1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{5.1}$$

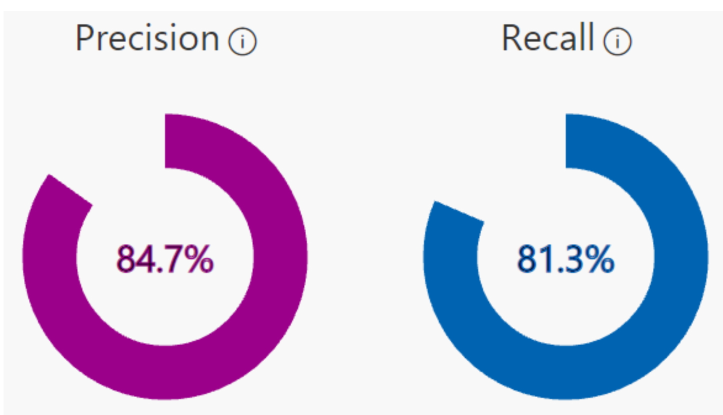

Figure 5.3: Figure showing the precision and recall values of the grade classification system as provided by MS Azure

Once the trained algorithm was deemed accurate enough, it was then used to grade avocados. After grading the avocado, MS Azure sends a JSON string to the HoloLens. The JSON string contains a list of predictions. It is this JSON string combined with the original image that is referred to as the information-rich image. Each prediction has a probability, tag ID, tag name, and bounding box properties associated with it. The tag name is the grade of the avocado, and the probability is a value from 0% to 100% based on the likelihood that it is the right tag name. The bounding box properties are explained below in section 5.7.2 because these properties were used to get the size of the avocado. The probability is used as a restricting criterion so that only graded avocados with a high likelihood of being classed correctly are shown. The probability threshold was found to be effective at 70%. This was determined when testing various probability values. It was found that if the probability value was set too high, then not all avocados were graded, and if it was set too low then some avocados would be graded into two different grade classes. At a probability value of 70% all the avocados that were graded using the prototype were classed and none were classed twice.

5.7.2 Avocado Size Classification

The information-rich image also contains information about the bounding boxes, as previously stated in section 5.7.1. The bounding box information comes in the form of four variables, as can be seen in Figure 5.4 below, namely: top, left, height, and width. The value of each of the variables is in the form of a value between 0 and 1. The reason why it is a value from 0 to 1, is because the variables are in the form of a proportion. Therefore, the top value is what proportion of the total y portion of the image has passed before the top part of the boundary box begins. Then height will dictate what proportion of the y axis of the image the bounding box, around the avocado, occupies. The same is true for the left and width variable in respect to the x axis of the image. Using all four of these values the location and size of the bounding box can be calculated.

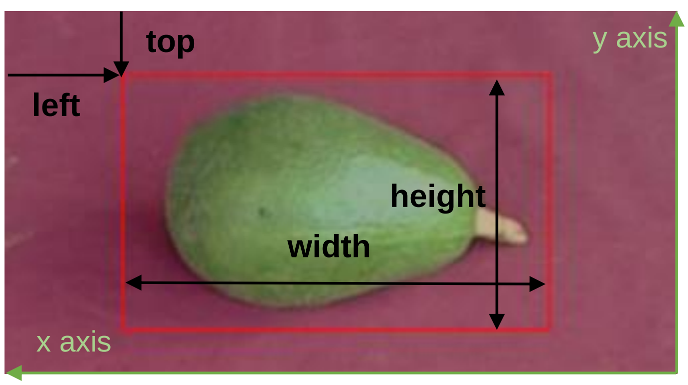

Figure 5.4: Figure showing the four variables contained within the bounding box array and how these variables relate to the x and y-axis

Using only the pixels in the bounding box, the green pixels were grouped together to determine the number of pixels in the avocado. The way a computer interprets colour is in terms of a RGB scale in the form of a 3-dimensional vector (r, g, b). Each of the variables can have a variable value from 0 to 255 as can be seen in Figure 5.5 below. Each unique configuration of the RGB vector indicates a new colour representation, with white being (255, 255, 255) and black being (0, 0, 0). It was calculated that in the RGB vector that, if the g component is bigger than the r component, it would be a pixel in the avocado. Four samples were taken, as seen in Figure 5.5, to show that g needed to be greater than r to be considered a pixel on the avocado. The first sample is off of the avocado, so the r component was larger than the g component. The other three samples were taken from pixels on the avocado and each time the g component was found to be larger than the r component. Therefore, all the pixels with a g variable larger than the r variable were counted in the bounding box to get the number of pixels in the avocado. The actual implementation of the code to determine the number of pixels in each avocado can be seen in Figure B.2 in Appendix B. The same was done with the marker except the b variable had to be larger than the r variable. The code for the marker is not shown as it is much like the code seen in Figure B.2.

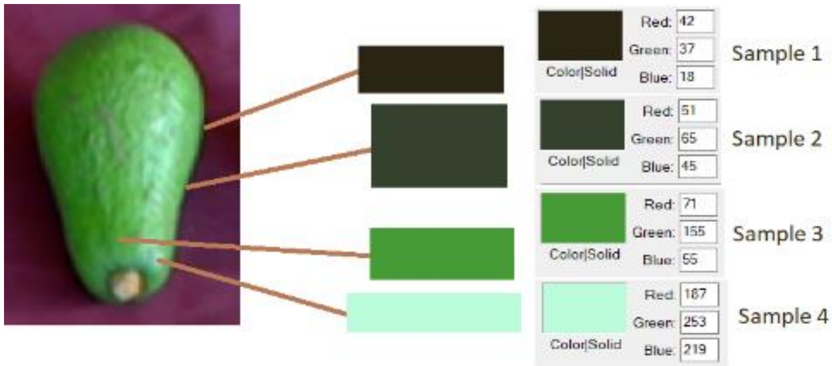

Figure 5.5: Figure showing four, pixel, samples taken and the RGB value of each pixel

Having both a marker and avocados present and having to use the number of pixels and the distance of each, four variables were used to calculate the avocado's weight. These four variables can be seen in Figure 5.6 below. In the figure there is a string value on every avocado and on the blue marker in the middle of the image. The string value on every avocado is comprised of two number components separated by an underscore. The first number is the distance to the HoloLens and the second number is the number of pixels in the avocado. The marker is the same except the two numbers are separated by a hyphen instead of an underscore. To determine the size of the avocado, the two numbers in the string component for both that avocado and the marker are used.

The co-efficient of the four variables and a constant needed to be determined to predict the weight of the avocado. To determine the value of the five unknowns, a linear regression was performed with the y-variable being the known avocado weight, which was weighed using a scale, and the x-variables being the avocado's and marker's distance and number of pixels. With the co-efficients and the constant variable being calculated, an equation could be determined with which to predict the weight of the avocado. The equation for determining the weight of the avocado can be seen in Equation 5.2 below.

$$y = c + x_0 \times a_0 + x_1 \times a_1 + x_2 \times a_2 + x_3 \times a_3; where \begin{cases} y = Avocado\ Weight \\ c\ is\ a\ constant \\ a_0 = \ number\ of\ pixels\ in\ the\ avocado \\ a_1 = \ distance\ of\ the\ avocado \\ a_2 = \ number\ of\ pixels\ in\ the\ marker \\ a_3 = \ distance\ of\ the\ marker \\ x_0, x_1, x_2, x_3\ are\ the\ constants\ to\ a_0, a_1, a_2, a_3 \end{cases} \tag{5.2}$$

Figure 5.6: Figure of a photo taken from the HoloLens during development which shows the distance to the HoloLens and the number of pixels contained within each avocado in the HoloLens' field of vision

To test the relationship between the avocado's weight and the avocado's and marker's distance and number of pixels the R^2 value was calculated. The R^2 value shows the effectiveness in using the avocado's and marker's distance and number of pixels, to predict the actual weight of the avocado The regression executed yielded an R^2 of 65.27% for a sample size of 60 avocados. By only using the avocado's and marker's distance and number of pixels, it was assumed that the relationship between these four variables and the predicted weigh of the avocado is linear. To test if it's not linear the avocado's and marker's distance and number of pixels were all squared and added to the equation. The regression was analysed and the R^2 improved to 73.38%. Two more regressions were executed where the avocado's and marker's distance and number of pixels were cubed and then taken to the power four. These regressions were also tested and yielded R^2 values of 77.91% and 78.74% respectively. It was noticed that the R-squared improvements became smaller as the power increased till the difference between 77.91% and 78.74% was approximately 1%. With the improvement being so small it was assumed that after cubing the avocado's and marker's distance and number of pixels the regression is no longer going to improve significantly and that it is close to a local optimum. The equation for the avocado's and marker's distance and number of pixels cubed can be seen in Equation 5.3 below. MS Excel was utilised to execute the linear regression model.

$$
\begin{gathered}
y = c + x_0 \times a_0 + x_1 \times a_1 + x_2 \times a_2 + x_3 \times a_3 + x_4 \times a_4 + x_5 \times a_5 + x_6 \times a_6 + x_7 \times a_7 + x_8 \times a_8 \\
+ x_9 \times a_9 + x_{10} \times a_{10} + x_{11} \times a_{11};
\end{gathered}
$$

$$
where \begin{cases}
y = Avocado\ Weight \\
c\ is\ a\ constant \\
a_0 = number\ of\ pixels\ in\ the\ avocado;\ \ a_4 = a_0^2;\ \ and\ a_8 = a_0^3 \\
a_1 = distance\ of\ the\ avocado;\ \ a_5 = a_1^2;\ \ and\ a_9 = a_1^3 \\
a_2 = number\ of\ pixels\ in\ the\ marker;\ \ a_6 = a_2^2;\ \ and\ a_{10} = a_2^3 \\
a_3 = distance\ of\ the\ marker;\ \ a_7 = a_3^2;\ \ and\ a_{11} = a_3^3 \\
x_0, x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}\ are\ the\ constants\ to\ a_0, a_1, a_2, a_3, a_4, a_5, a_6, a_7, a_8, a_9, a_{10}, a_{11}
\end{cases} \tag{5.3}
$$

Using MS Excel, the variable values for the model were calculated and tabulated in Table B.1 in Appendix B. The tabulated variables were then utilised when code was developed to predict the weight of the avocado. The code developed can also be seen in Figure B.3. Once the weight was predicted the size category could then be predicted using Table 5.1 below. The weight calculated can be used in Table 5.1 to determine what size category the predicted avocado weight will have. It should be noted that the upper band of size category n does not perfectly overlap with the next lower size category, which is size category n-2. Therefore, it is possible for an avocado to be in two size categories when being classified. To compare the actual size category to the predicted size category Table 5.2 was constructed. In the table the actual and predicted weights and the size categories, as determined by the lower and upper bounds derived from Table 5.1 are shown. For the actual weight of the avocado, it can be in two size categories, however for the predicted size category there can only be one category as only one prediction can be made.

The weight category selected is the second last column in Table 5.2 and the logic used to select the category can be seen in Figure 5.7. If the predicted weight is 264g, for example, then it can be classified as a size category 14 or 16. The reason for this is because 264g is more than 258g so it is category 14, but it is also less than 274g so it also category 16, as can be seen in Table 5.1. The predicted weight of 264g is further away from the 274g bound than the 258g bound. Therefore, the predicted weight is more centred in the 16-size category. Therefore, it is more likely to be in category 16 and the error caused by the "noise", which is depicted by the red areas in Figure 5.7, is smaller. This error will be a type 1 error as it is the probability that an avocado is falsely rejected from the right size category. It should be noted for a type I error to occur, the data must be normally distributed, which it will be according to the central limit theorem for a sufficiently large sample, which will occur during implementation. The last column of Table 5.2 evaluates whether the avocado was placed in the correct size category. Using Table 5.2, 73.33% of avocados were predicted to be in the correct weight category. The 73.33% accuracy was deemed sufficient for this prototype as will be explained in more depth in section 5.10 below.

Table 5.1: Table which shows the values from Table 3.1, but are transposed

Weight (g)	Lower Bound	144	151	165	155	203	227	258	300	364	456
	Upper Bound	157	175	196	217	243	274	313	371	462	576
Size Category		26	24	22	20	18	16	14	12	10	8

Table 5.2: Table showing how size classification was executed

# Data Points	Actual Size	Distance of Avocado (m)	Calculated Weight	% Error	Actual Classification		Calculated Classification			Correct Classification
					Upper Bound	Lower Bound	Upper Bound	Lower Bound	Selected Size Category	
1	195	0.69	209.91	0.08	20	22	18	20	20	True
2	255	0.64	243.00	-0.05	16	16	16	18	16	True
3	218	0.64	220.14	0.01	18	18	18	18	18	True
4	202	0.61	205.05	0.02	20	20	18	20	20	True
56	245	0.77	233.53	-0.05	16	16	16	18	18	False
57	205	0.99	199.31	-0.03	18	20	20	20	20	True
58	209	0.91	203.35	-0.03	18	20	18	20	20	True
59	194	0.93	188.10	-0.03	20	22	20	22	20	True
60	210	0.91	221.81	0.06	18	20	18	18	18	True
					Percentage of avocados classified correctly					73.33%

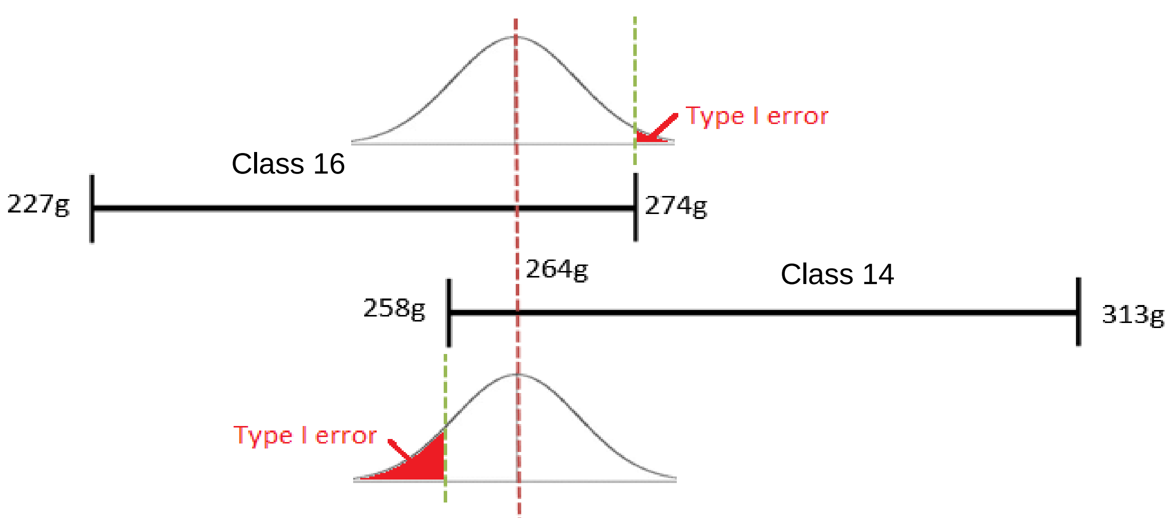

Figure 5.7: Figure of an image showing why an avocado with a weight of 264g should be graded as a class 14 avocado to minimise the probability of a type I error occurring

5.7.3 Current System Parameters

To determine the significance of the quality and productivity improvements made, these results need to be evaluated against the current system output. The current sorting and packing process is explained in depth in section 3.2.4. To determine the current quality and productivity parameter's samples of avocados at the end of each process were taken. These sample values were then evaluated against the correct size and grade of each avocado as stipulated in section 3.2.3.

30 samples of avocados were chosen to determine what percentage of avocados are currently being graded accurately, based on the quality class of the fruit. These 30 samples and the associated accuracy of the grading processes can be seen in Table 5.3 below. From the 30 samples 22 (or 73.33%) were graded correctly and 8 were graded incorrectly. The 73.33% denotes the accuracy of the current grading processes. The HoloLens system, which is a prototype, had an accuracy of 83% or a 10% better result compared with the current system.

Table 5.3: Table showing 30 samples of avocados which have been evaluated to determine how many have been graded accurately during the sorting and packing process

Sample number	Grading accuracy	Sample number	Grading accuracy	Sample number	Grading accuracy
1	Correct class	11	Correct class	21	Correct class
2	Incorrect class	12	Correct class	22	Incorrect class
3	Correct class	13	Correct class	23	Correct class
4	Correct class	14	Correct class	24	Correct class
5	Correct class	15	Incorrect class	25	Correct class
6	Correct class	16	Correct class	26	Incorrect class
7	Correct class	17	Correct class	27	Incorrect class
8	Correct class	18	Correct class	28	Correct class
9	Correct class	19	Correct class	29	Correct class
10	Incorrect class	20	Incorrect class	30	Correct class

Like Table 5.3 above, samples of avocados were taken and evaluated to determine the accuracy of the size classification processes. During the sampling processes 200 samples were taken and summarised into Table 5.4 below. More samples were taken in order to have a sufficient number of samples for each size category. When examining the results from Table 5.4, a trend can be observed, whereby the larger avocados, size categories 12 and 14 - have a lower accuracy when compared to the smaller avocados. The table also shows that only 58.50% of avocados are sized correctly. This is compared to the 73.33% when utilising the HoloLens prototype, as seen from Table 5.2. Therefore, in terms of classifying the avocado into the correct size category the HoloLens, even though it is not perfectly accurate, is significantly better than the current system.

Table 5.4: Table showing 200 samples of avocados that have been weighed to determine what percentage of avocados have been placed into the correct size category during the sorting and packing process

Size category	Number of samples	Percentage correct
20	60	65.00%
16	48	60.42%
14	56	51.79%
12	36	55.56%
Total	200	58.50%

The implications of the increased accuracy of both the size and grade classification processes are as follows: not only has a key goal of the project been achieved, namely increased quality during packing and sorting, but the prototype system can become an implementable system. This is because a box of avocados incorrectly packed would lead to both decreased remuneration per box and penalties from regulatory bodies, as explained in section 3.2.3 and section 3.3.2. Thus, a system that can increase the accuracy of the processes used to size and grade avocados will lead to increased remuneration and compliance with regulatory requirements. Therefore, for the prototype to prove useful it was required that improvements in the packing and sorting processes were made. It should be noted that even if productivity were to increase with the implementation of the HoloLens system, but the accuracy of the classification processes was to reduce, the project would not be financially feasible. The impact on productivity is studied later, in order to examine if productivity is adversely impacted by greater accuracy. To conclude, even though the classification processes when utilising the HoloLens is not perfect, it is better than the current system which is sufficient motivation for utilising the HoloLens system for sorting and packing avocados.

5.8 Application Layer

The HoloLens was programmed in such a way that it would identify all the avocados in its field of vision that were of a predetermined size and class. By packing for a set size and class, boxes of avocados (with uniform characteristics) could be packed. To achieve this, the operational faculties of the HoloLens needed to be understood. The way the HoloLens perceives a point in its environment can be seen in Figure 5.8 below. In the figure a point can be represented by point P, as seen from the HoloLens, which is located at point Oc, which has an x, y, and z co-ordinate, representing height, width, and depth parameter as seen from the HoloLens.

The HoloLens simply sees a rough 3D canvas with protrusion, such as point P, in Figure 5.8, at various depths. The HoloLens cannot know what those protrusions are as it can only know 3D holograms that have been placed by the HoloLens.

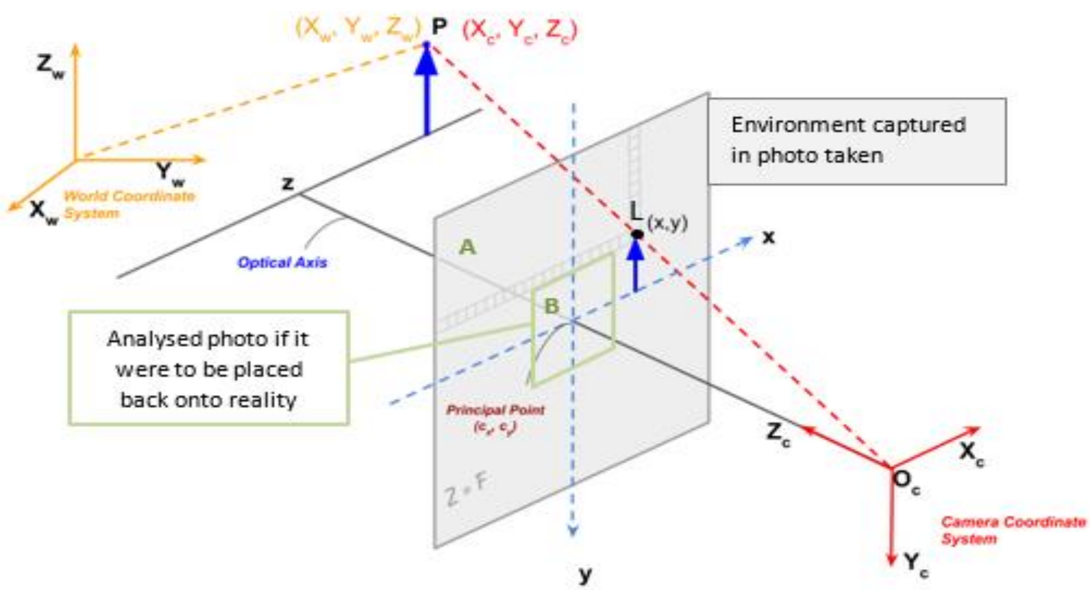

Figure 5.8: Figure showing how x, y, and z co-ordinates are utilised using the HoloLens 1 [111]

Some parts of the rough canvas can be labelled, however, so that when a human operator views their environment through the HoloLens, they will have more detail about their surroundings. This will occur when an image of the environment is taken by the HoloLens, analysed, and information is projected onto the environment. That image will be analysed using ML software. The ML software identifies the avocados, classes them, and provides x and y co-ordinates of the avocados in the image. The x and y co-ordinates of the avocado in the image were used to get the x and y co-ordinates of the placement of the label of the avocado.

To translate the x and y co-ordinates of the avocado in the image to x and y co-ordinates from the HoloLens perspective, it is first necessary to "remember" which area of the environment was photographed. To "remember", a cursor was always present when viewing the environment through the HoloLens. This cursor was the middle point of that which was currently being viewed through the HoloLens. The cursor was important because its co-ordinates were stored when an image was taken, as can be seen by the principle point in Figure 5.8. The image that was taken is represented by the plane A in Figure 5.8 above and the image A in Figure 5.9 below. After the image is taken, it is analysed using ML, and in doing so becomes an information-rich image.

The information-rich image contains the placement of the relevant objects in that image and information about each object. When the information-rich image is projected back onto the original image it is scaled differently. Therefore, the information-rich image is represented by the plane B in Figure 5.8 and the image B in Figure 5.9. It was found through experimentation that the information-rich image tended to be smaller than the original image. So, although the middle point of the image matches the middle point of the environment where the image was taken, the rest of the image is scaled differently.

To counter this, the information-rich image needed to be scaled so that it overlaid the original image perfectly. This was another reason why the marker of a known size was introduced. If the marker's size is known, the information-rich image of the environment can be scaled so that the image of the marker is the same size as the actual marker. Once this is done both images observed through the HoloLens should also be the same size. In practice the whole image was not scaled, but the co-ordinates of labels that needed to be placed on real world objects were, to get the correct x and y co-ordinates. Once this was done the labels were then pushed back until they collided with the canvas seen by the HoloLens. This canvas had protrusions which indicated objects, such as avocados, seen by the HoloLens. The location of the z-coordinate of the label, after being pushed back until it collided with the avocado, was used to get the z- value of the avocado.

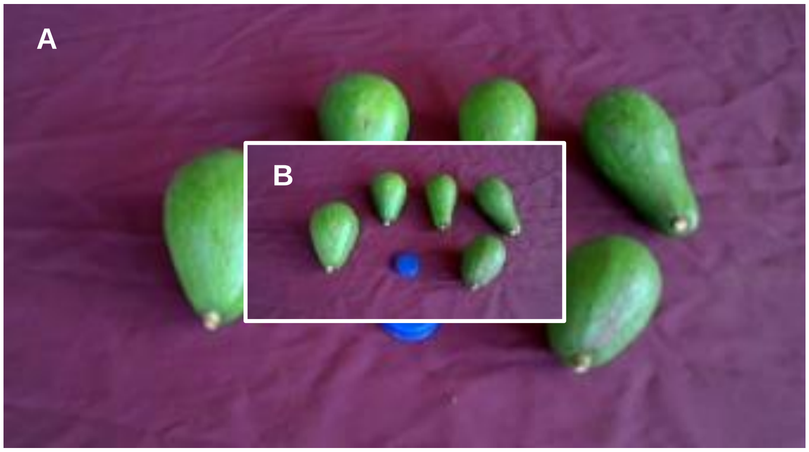

Figure 5.9: Figure showing of the original image A and data rich image B are scaled

Given that the way the HoloLens perceives a point and the correct placement of labels have been explained, the actual implementation of the prototype could now be developed. Once both the class and size of the avocado is identifiable, as can be seen in Figure 5.10, the packer can pack avocados of the same size and class. In Figure 5.10 there is a string value on every avocado once again. This string value has two sting components separated by a forward slash. The code used to develop the string to classify each avocado can be seen in Figure B.4 in Appendix B. The first string component starting with a “C-“ is followed by a number which indicates the class of the avocado. The second string component starting with a “S-“ is followed by a number which indicates the size of the avocado. By being able to visualise the class and size of the avocado, quality checks could be done to ensure that the prototype classes and sizes the avocados correctly. This will be explained in greater depth when validation and verification will be explained in section 5.10 and section 8.1 respectively.

After having visually confirmed that the avocados are sized and graded correctly the prototype was programmed to identify only avocados of the same size and class at any time. The implementation of this prototype can be seen in Figure 5.11 below where only avocados of size 14 and class 2 were identified to be packed. The code used to show only the avocados to be packed can be seen in Figure B.5. These avocados are indicated by white crosses being visible on the avocados. The distance and the number of pixels of the marker remained as a quality control measure.

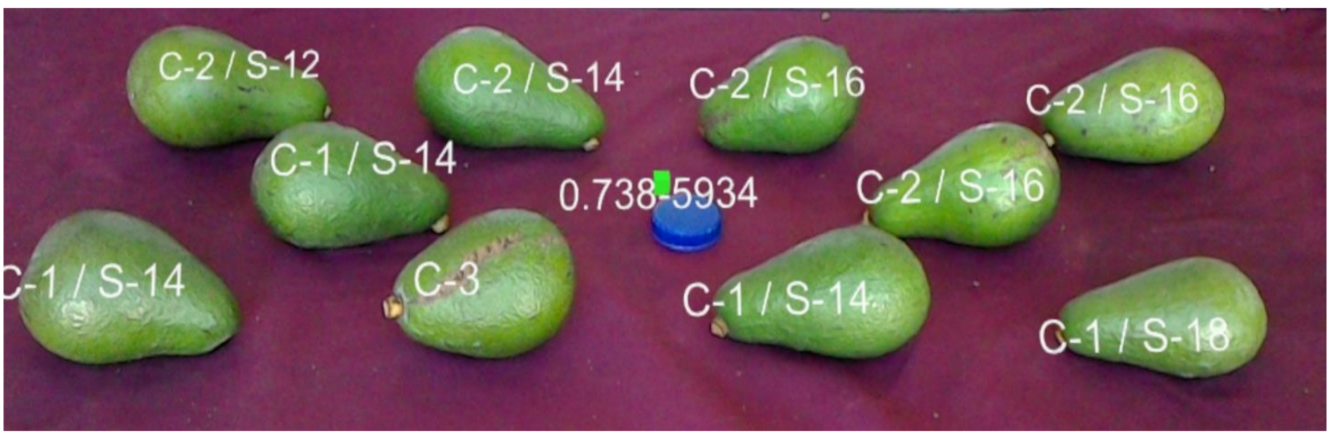

Figure 5.10: Figure of a photo taken from the HoloLens during development which shows the class and size of the various avocados, except for class 3 avocados because the size for these avocados does not matter

Figure 5.11: Figure of a photo taken from the HoloLens at the end of development showing class 2 size 14 avocados with an “x”-label that have been identified using the prototype system

When currently implementing the prototype, it takes 13 seconds from when an image is taken till the avocado is identified with an x. The 13-second delay by the MS Azure PaaS means the prototype does not classify avocados on a continual basis, but that there is a discontinuity during each classification event. This is different to how the avocados are currently being packed. Currently the employees pack an avocado box till it is fully packed with an even number of the same class. However, the current HoloLens prototype takes 13 seconds to classify the avocados and only the avocados in the field of vision, when the photo is taken, are classified. Therefore, less avocados will be classified then necessary to fill a box, and there will be a 13 second delay between iterations. To solve this problem and test the functionality of the prototype, the times when the avocado box was being packed were isolated. This was done so that only packing times were examined. In this way the current system and the HoloLens system behave similarly, and a comparison can be made. The logic for this system can be seen in Figure 5.12 below. By stitching the packing times for different iterations together till a box is packed, the time taken using the HoloLens could be determined.

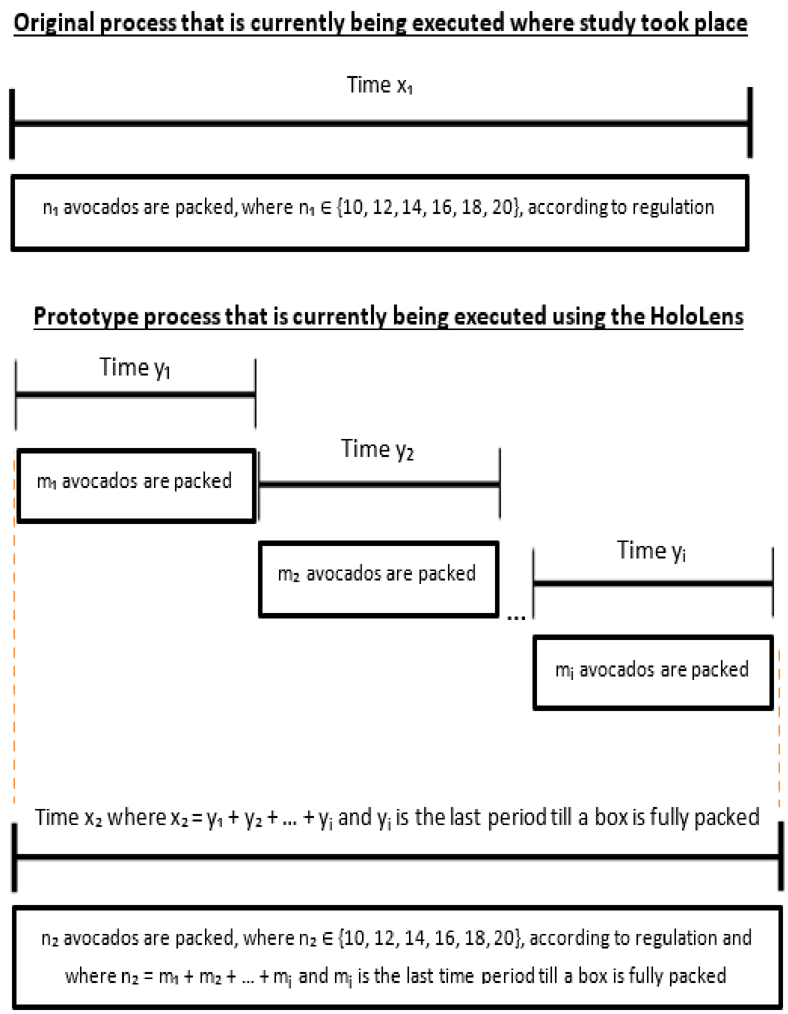

Figure 5.12: Figure showing how the avocados packing times were measured both with and without the HoloLens

5.9 Limitations of the Prototype System

The prototype developed has some limitations which results from two sources. Firstly, AR technology is new and developing rapidly. Therefore, some software has not yet been developed to be fully integrated with AR. Secondly, to develop an AR prototype using ML is a complex and time-consuming task. Therefore, to ensure that the prototype was developed given the time constraints of the project, some simplifications and assumptions were made. Due to these two reasons the prototype does have some limitations.

The first limitation is due to technological constraints. These constraints result in two fundamental differences between the prototype and how an ideal system would work. If these constraints were resolved, it would allow the system to work seamlessly and continuously with the environment. The ideal system would work with a continuous feed from the HoloLens to maximize data points and to provide continuous feedback. Firstly, the software would be programmed on the device, or in such a way that most of the work would be on the device to ensure minimal interaction with the internet or in such a way as to reduce the time which the HoloLens user needs to wait for an internet function to complete. Secondly, the ideal system would work with ML which is programmed to work with video or at least a 3D environment. Currently the ML software that is available works with a 2D image. This is because 3D is new, so the ML infrastructure has not yet been developed to meet this need. This can be seen by the fact that the software used on the HoloLens has been adapted from 3D gaming engines and not dedicated 3D software for AR [105]. The lack of a continuous data feed resulted in only one side of the avocado being captured. In the future when it is possible to have a continuous monitoring of the environment through the HoloLens then a conveyor belt can be utilised. This conveyor belt can replace the simple sorting table which will then turn the avocados so that it can be visualised from all sides.

The simplification of the prototype resulted in avocados having to be separated from one another. This was implemented because the prototype only tested whether an improvement in productivity and quality could be achieved. Once it can be confirmed that productivity and quality could be increased then the prototype can be improved. It is simpler when testing the prototype to count the number of pixels in an avocado than to implement prediction software that will forecast the size of the avocado given the portion of the avocado that is visible. Therefore, to simplify the prototype, development predicting the size of the avocado was forgone to ensure project completion.

5.10 Verification

Verification is an important metric when evaluating a developed system to assess whether the system was built correctly. This is done to ensure that the system can be implemented without any unexpected errors which could affect the prototype results.

The process of verification used to test if the prototype was built correctly is stipulated in Law [112]. During model development, four of the verification techniques were utilised. The first technique employed was developing the software in modular segments instead of large segments of code. Each of the segments developed was then individually tested, allowing for easier debugging. An example of this can be seen in Figure 5.10 and Figure 5.11 in section 5.8. In this example the size and grade of the avocado was first built and tested before the logic of the “x”-label was programmed. The reasoning for first writing code to visualise the grade and size of the avocado before proceeding, was so that the coder could verify that the code was behaving as expected. This technique had the added benefit of allowing for the re-use of code making the programming simpler. This re-use of code was utilised when similar code could be used for identifying the number of pixels in the marker and the avocados. Once each segment was thoroughly evaluated and found to be correct, it was then incorporated into the rest of the model.

Secondly, several "traces" were used to determine the model's ability to accurately size and grade avocados. This was done by selecting avocados of known but random size and grade and using the model to classify these avocados. The grade that the prototype predicts the avocados to be, was then compared to the actual grade of the fruit. After this the model then sizes the avocados and the calculated size is then compared to the actual size of the avocado. If errors occurred in either step, the model was debugged or recalibrated to ensure accurate results. This procedure was repeated several times to establish that the grade and sizes calculations could be considered as accurate.

Thirdly, visual feedback was produced after each step to easily gauge the results. This technique is an alteration of the animation technique as explained in Law [112]. Instead of animation showing how entities flow throughout a system, the model displays each avocado step by step with its grade and size. This is done by immediately displaying the results after each step and comparing the results to what they are expected to be. This allows for the visualisation of the processes whereby avocados are classified. This technique makes use of the previous two techniques in order to have a bird's eye view of the processes that are taking place.

Having this bird's eye view of the classification processes used to size and class the avocados, it was observed that these processes are not perfect, as can be seen in section 5.7.1 and section 5.7.2. However, a significant improvement in the accuracy of the grade and size classification processes was achieved. This is important for two reasons. Firstly, a significant improvement was expected when looking at the literature in section 3.1.3. Therefore, the improvement itself is a form of validation because the improvement that was expected was realised. Secondly, the improvement was a project goal, so having achieved this improvement further analysis can be executed.

5.11 Conclusion

In this chapter a brief overview and supplementary information regarding the system environment was provided. This was followed by a discussion with regard to the system requirements, which are that avocados need to be classified according to size and grade as stipulated in guidelines provided by the South African government. An in-depth examination of the system logic was then conducted in order to understand and plan the system development. The system was then developed using the 5-layer IoT development architecture, consisting of the perception, transport, processing, application, and business layers. Using this layered architecture, the development of the classification processes was done in the processing layer. The classification requirements were determined by the system requirements, where avocados need to be classified according to size and grade. Once development was completed the HoloLens system was tested and it had an accuracy, when grading and sizing the avocados, of 83% and 73.33% respectively. This is a significant improvement when compared to the current processes, which yielded accuracy scores of 73.33% and 58.50%, when grading and sizing avocados.

The HoloLens system is not a continuous monitoring system since the ML component only uses 2D imagery and because each image takes 13 sec to be analysed. Therefore, packing a box of avocados using the HoloLens system will take several iterations, where classified avocados will be packed into a box till there either are no more avocados to be packed or the box is packed to completion. Once a box is fully packed all the times taken from the different iterations will be averaged to get a packing time per box. In stitching and adding the times of various iterations, the behaviour of the HoloLens system can be compared to the current sorting and packing process. To ensure that the HoloLens system could be compared with the current system, the system limitations, validation, and verification were also discussed. There were no obvious or serious limitations, but future improvements due to better software and more development time were examined. Verification was done to provide confirmation and to instil faith that the system was designed and developed correctly.

Chapter 6 Implementation and Results

The designed and developed prototype was implemented on an avocado farm. To test the prototype, it was compared against a baseline, i.e., packers utilising their intuition, as well as an ideal case, represented by stickers placed on the avocado to be packed. The study included both a trained and an untrained packer to evaluate what effect training has on the productivity increase of the packer when utilising the HoloLens as well as stickers. During the study, not only was a productivity increase evaluated but also the effect that the prototype and stickers had on the packing speed variance. The results of the prototype implementation are discussed below.

6.1 Data Capturing

The development undergone in the previous chapter was done to test the performance of the HoloLens compared to the current sorting and packing processes on the farm. To test the current performance ability of the prototype, it will also be compared to an ideal state. This ideal state will consist of a packer packing pre-sorted avocados with stickers on them. The stickers will be used to identify the avocados to be packed similarly to the "x"-label identifying the avocados to be packed when the HoloLens is used. An example of the experiment containing the stickers can be seen in Figure 6.1 below. In the figure the yellow stickers indicated, to the packer, which avocados need to be packed.

Figure 6.1: Figure of a photo captured showing how the experiment with stickers will be visualised by the packer, with the yellow stickers indicating which avocados should be packed

The reason why stickers can be considered an ideal state is because there is no mechanical interference by the HoloLens, and avocados can be packed continually without the need for stitching packing times together. The mechanical interference by the HoloLens is a result of the weight of the device, restricting or slowing head movement, and due to the limited display area of the HoloLens. The HoloLens cannot project information of the entire visual periphery of the packer so head movement is required to determine if some of the avocados to be packed have been identified. Through testing it was also determined that the area that is captured by the camera of the HoloLens is significantly wider than the display area. Therefore, all the avocados can be captured and analysed, but not all the avocados that are marked can be seen by the packer at the same time. Head movement, which is slowed due to the weight of the device, is therefore required to identify all the avocados that should be packed.

Placing stickers on the avocados also does not require avocado packing times to be stitched together. Therefore, boxes can be packed to completion without the need to stop the sorting and packing process. By packing continuously, delays that might occur from having to stop and start the sorting and packing avocados will not be present. Additional benefits of comparing the HoloLens system to an ideal state are that the HoloLens system can be validated, and potential future benefits can be determined. If the HoloLens system preforms better or significantly worse than the ideal state, then the HoloLens system needs to be re-evaluated because the results deviate from what can be expected. The HoloLens system is still just a prototype so as the system is refined, and technology improves, the benefits of the HoloLens system should more closely resemble the ideal state compared with the current HoloLens system.

With the introduction of an ideal state, utilising stickers, there will be three different packing scenarios that will be tested. These three scenarios will be: the current packing state which utilises intuition to pack avocados, the use of the HoloLens prototype, and the use of stickers. These three packing scenarios will be tested by two packers with different skill levels to test the impact of the technology on skill level. The first packer is one that has been trained and has been packing avocados for over 5 years. The second packer is an untrained packer who typically does not pack avocados when working. Therefore, six data sets had to be collected depending on the packing scenario and skill level of packer.

6.2 Prototype Implementation

The prototype sorting and packing process is explained in depth in section 3.2.4 and section 5.7. It should be noted, however, that there were slight differences in the experimental set-up for each of the three packing scenarios. The deviation of the HoloLens system from when stickers are used is explained below, however these differences did not result in significantly different outcomes.

6.2.1 HoloLens Utilisation

When the HoloLens was used, the avocados had to be separated as can be seen in Figure 6.2 below. This resulted in avocados having to be pre-packed onto the table before a photo could be taken. Once the avocados have been pre-packed, a photo can be taken. This photo is then analysed, and “x”-labels are placed on the avocados to be packed. Thereafter, the avocados are packed as explained in section 5.8 and as can be seen in Figure 5.12. The times for the different iterations were captured with a stopwatch and were then added together. As soon as the “x”-labels appeared on the avocados, the packer would announce “start” and once there were no more labelled avocados or the box was fully packed, the packer would announce “stop”. The times between “start” and “stop” were captured with the stopwatch.

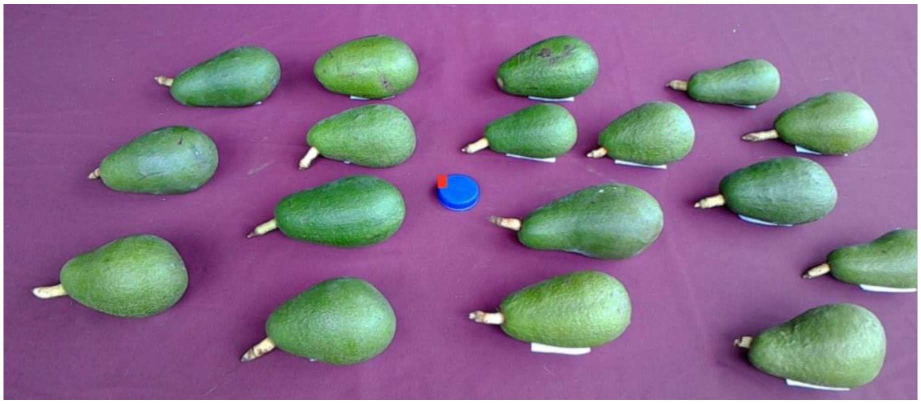

Figure 6.2: Figure of a photo captured showing how the experiment is visualised by a packer using the HoloLens before the image of the avocados has been analysed using ML

6.2.2 Sticker Utilisation

When stickers were placed on the avocados the set-up closely resembled the current state, except that some avocados had stickers placed on them identifying them as the avocados to be packed. To determine which avocados should get stickers a large section of avocados was weighed and classed before the packing process. The fruit were weighed using a scale and classed with the help of the farmer in accordance with the South African government's guidelines, as explained in section 3.2.3. Once an avocado was weighed and classed, these parameters were denoted on a small piece of paper and the avocado was placed on the packing table on top of the paper. This was done until the table was full. If it was then decided that class 2 size 16 avocados were to be packed, then all the avocados on the table which were of the desired class and size were marked. Once marking was completed, the time taken to pack the box of avocados with stickers on, would be measured with a stopwatch and recorded.

6.3 Training

Two types of trainings were required for successful and accurate data collection. Firstly, the packers were shown how to use the HoloLens and get comfortable with using the technology. This was done because AR is a relatively new concept and the packers had to familiarise themselves with how the HoloLens functioned. Secondly, the untrained packer was provided basic training in how to pack a box of avocados. This was done to minimise the effect that the learning curve would have on the data collected [113]. The point of the basic training was not to train the packer but to reach a point where the untrained packer would pack with a higher degree of consistency. This was achieved when the untrained packer would consistently pack a box of avocados under 120 seconds. It was noted that when an untrained packed in under 120 sec they did not make significant packing errors that lead to lengthy packing times. Prior to training the variability was significantly higher, with some boxes taking over 200 seconds to be packed because of confusion when packing a box. It was also required to train the untrained packer how to grade and size avocados. If this was not done then the trained packer would pack the correct size and class and the untrained packer would not, thus making the data sets different which would call into question the validity of the productivity increase. Therefore, training was done to teach the packers how to use the HoloLens; to ensure that packing was done as close as reasonably possible to the packing guidelines; and to prevent very long packing speed outliers which would make the HoloLens system appear to show an even greater improvement.

6.4 Trained Packer

Using the experimental set-ups as explained above, data was collected for a trained packer when packing boxes of avocados. The packing times can be seen in Table 6.1 below. The results can be visualised in Figure 6.3 which shows the times per sample, as well as the average (in seconds) taken by a trained packer to pack 30 boxes of avocados for each scenario. The top yellow line in Figure 6.3 shows the time (in seconds) of each of the 30 samples taken when a packer packed a box of avocados using their intuition. The grey line shows the times of the samples taken when the HoloLens was used. Finally, the bottom orange line shows the individual sample times when stickers were used to pack the boxes of avocados. The dark blue, green, and light blue lines show the average times taken to pack a box of avocados for the 3 scenarios.

Table 6.1: Table showings the times, in seconds, taken by a trained packer to pack 30 boxes of avocados, as fast and as close to the regulatory requirements as reasonably possible, using: stickers, a HoloLens with the help of Microsoft Azure, or their intuition

Sample	Stickers	HoloLens	Intuition	Sample	Stickers	HoloLens	Intuition	Sample	Stickers	HoloLens	Intuition
1	25.56	31.57	37.17	11	23.16	27.11	42.81	21	24.07	30.09	28.6
2	24.05	27.31	47.15	12	22.76	28.38	35.04	22	25.02	28.43	57.68
3	23.52	26.4	38.84	13	26.41	27	47.79	23	24.85	26.77	34.66
4	24.09	23.94	29.8	14	22.94	28.41	30.05	24	23.59	27.18	32.04
5	22.32	25.1	61.45	15	24.05	26.93	34.7	25	22.15	25.53	25.28
6	22.4	26.32	34.48	16	22.54	30.62	38.65	26	23.81	26.93	34.67
7	24.03	29.58	33.25	17	21.18	25.84	35.96	27	22.66	24.64	36.34
8	23.73	27.13	29.73	18	23.08	30.95	37.84	28	22.92	29.12	31.02
9	23.93	27.41	49.77	19	25.49	25.91	62.11	29	24.46	27.58	37.25
10	25.25	25.33	32.87	20	22.25	25.56	37.55	30	24.33	26.2	53.69

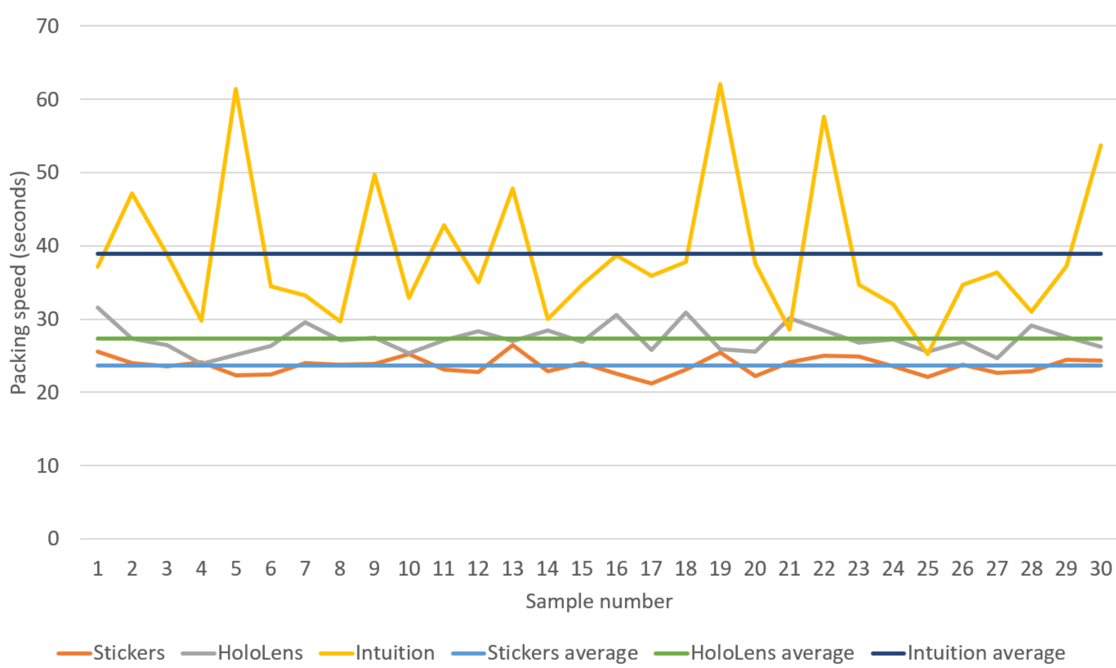

Figure 6.3: Figure of a graph showings the times per sample as well as the average, in seconds, taken by a trained packer to pack 30 boxes of avocados, as fast and as close to the regulatory requirements as reasonably possible, using: stickers, a HoloLens with the help of Microsoft Azure, or their intuition

When the avocados were packed with intuition, the times taken to pack a box fluctuated significantly. This can be seen by the fact that 2 data points captured took longer than 60 sec while 4 others were below 30 sec. The variance was calculated as 93.97 sec. The reason for the large deviation was observed to be due to uncertainties while packing. It was observed while packing occurred that these long packing times were caused when a box needed to be repacked or avocados had to be searched for, when packing. The repacking of boxes occurred when a full box was packed but there were either significant gaps between some of the avocados or a box contained an odd number of avocados. During repacking some avocados needed to be taken out of the packed box and replaced with other avocados till both the gaps had been reduced significantly and the box contained an even number of avocados. Long packing times are also occurred when the right avocados needed to be searched for. The problem, as mentioned in the introduction, is that avocados appear very similar, so it is often difficult to judge which avocados should be packed. Thus, when most of the avocados of a similar size that were close to the packer have been packed, other avocados further away had to be looked for. But, with avocados looking so similar, it is often difficult to find an avocado of the right size.

To make comparisons between the three different data sets collected, it is necessary to determine if the data sets are statistically significantly different from one another [114]. Bekker states that sets may vary numerically but for comparison purposes these states need to be statistically significantly different [114] . If two states are statistically significantly different, then there is cross-sample variation between them, otherwise there is only in-sample variation [114]. When there is cross-sample variation then the two data sets can be classified as data sets that are not related to each other. This is necessary because if the data sets only have in-sample variation, then the two data sets are seen as being from the same data set and comparisons cannot be made. To determine if data sets are statistically significantly different t-tests were conducted. For the data collected from the trained packer, three t-tests were done, each time comparing two specific data sets. For two data sets to have cross-sample variation, the p-value must be less than 5%, or 0.05 [114] .

The three different data sets were:

1) Trained packer packing avocados using stickers
2) Trained packer packing avocados using the HoloLens
3) Trained packer packing avocados using experience or intuition only

The statistical process is as follows [114] :

i. Set H_0 to be the hypothesis that two states have cross-sample variation
ii. Calculate t and v using formulas 6.1 and 6.2 respectively

$$t_{\frac{p}{2};v-1} = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}; where \left\{ \begin{array}{c} t\ is\ a\ critical\ value\ calculated\ for\ a\ hypothesis\ test\ used\ to\ evaluate\ H_0 \\ p\ is\ the\ proability\ that\ H_0 it\ true\ for\ a\ calculated\ t\ value \\ v\ is\ a\ parameter\ that\ is\ calculated\ in\ order\ to\ determine\ p \\ \bar{x}_i\ is\ the\ average\ of\ sample\ i \\ s_i^2\ is\ the\ varience\ of\ sample\ i \\ n_i is\ the\ number\ of\ samples\ in\ sample\ i \end{array} \right\} \quad (6.1)$$

$$v = \frac{\left(\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}\right)^2}{\frac{\left(\frac{s_1^2}{n_1}\right)^2}{n_1} + \frac{\left(\frac{s_2^2}{n_2}\right)^2}{n_2}} \tag{6.2}$$

iii. Calculate the p-value using a t-table, where v is rounded because it is defined to be $v \in \mathbb{N}$

iv. If the p-value < 0.5, then there is not enough evidence to reject H_0 and the two data sets can be considered statistically significantly different.

Using the statistical processes stated above, the value for t was calculated as can be seen in Table 6.2, Table 6.3, and Table 6.4. In each table p is significantly smaller than 0.05 and therefore there is not enough evidence, when executing the t-test, to reject H_0. Therefore, the three data sets are statistically significantly different and comparisons between the data sets can be made.

Table 6.2: Table showing the results from Equation 6.1 and 6.2 used to determine the p-value and t critical when comparing the data generated when packing using stickers and using the HoloLens for a trained packer

	Stickers	*HoloLens*
Mean	23.6866667	27.309
Variance	1.4075954	3.57417483
Observations	30	30
Hypothesized Mean Difference	0	
v (df)	49	
t Stat	-8.8890877	
P(T<=t) two-tail	8.6319E-12	
t Critical two-tail	2.00957524	

Table 6.3: Table showing the results from Equation 6.1 and 6.2 used to determine the p-value and t critical when comparing the data generated when packing using stickers and the packer's intuition for a trained packer

	Stickers	*Intuition*
Mean	23.68666667	38.94133333
Variance	1.407595402	93.97420506
Observations	30	30
Hypothesized Mean Difference	0	
v (df)	30	
t Stat	-8.55520837	
P(T<=t) two-tail	1.5174E-09	
t Critical two-tail	2.042272456	

Table 6.4: Table showing the results from Equation 6.1 and 6.2 used to determine the p-value and t critical when comparing the data generated when packing using the HoloLens and a packer's intuition for a trained packer

	HoloLens	*Intuition*
Mean	27.309	38.94133333
Variance	3.574174828	93.97420506
Observations	30	30
Hypothesized Mean Difference	0	
v (df)	31	
t Stat	-6.45085731	
P(T<=t) two-tail	3.42489E-07	
t Critical two-tail	2.039513446	

Comparing the average times of the three different data sets, as can be seen in Figure 6.3, the HoloLens is 29.87% faster than when the packer uses their intuition to pack a box of avocados. Comparing the average packing times also showed that when using stickers, the average packing time is 13.26% faster than when using the HoloLens. The most significant difference was between the use of stickers, which was 39.17% faster, compared with packers using only their intuition.

6.5 Untrained Packer

As with the trained packer, there are three data sets which have been collected for an untrained packer depending on the packing scenarios. The packing times of 30 samples, in seconds, of each packing scenario were captured and can be seen in Table 6.5 below. To visualise this data a graph was constructed, seen in Figure 6.4 below, which shows the times per sample as well as the average time, in seconds, taken by an untrained packer to pack 30 boxes of avocados for each scenario. The grey, orange, and dark blue lines represent the 30 individual samples taken when avocados were packed by the packer using their intuition, the HoloLens, and stickers respectively. The average packing times when avocados were packed using intuition, the HoloLens, and stickers can be seen by the green, light blue, and yellow lines respectively.

Table 6.5: Table showings the times taken by an untrained packer to pack 30 boxes of avocados, as fast and as close to the regulatory requirements as reasonably possible, using: stickers, a HoloLens with the help of Microsoft Azure, or their intuition

Sample	Stickers	HoloLens	Intuition	Sample	Stickers	HoloLens	Intuition	Sample	Stickers	HoloLens	Intuition
1	23.36	31.31	88.98	11	27.01	31.04	55.65	21	24.19	30.69	81.6
2	26.89	28.01	41.26	12	21.77	32.92	43.66	22	25.17	31.32	79.18
3	24.27	32.64	59.96	13	24.51	30.47	80.23	23	25.53	30.93	50.39
4	27.02	30.43	55.02	14	26.91	34	57.5	24	26.26	31.06	76.06
5	24.36	26.99	72.69	15	25.64	31.36	65.01	25	26.93	32.44	77.01
6	26.3	30.97	80.68	16	24.27	27.39	57.59	26	22.92	29.96	97.03
7	27.14	28.27	99.17	17	26	33.1	75.35	27	23.3	30.37	48.8
8	23.73	32.82	51.38	18	27.13	28.89	44.41	28	25.89	31.8	65.43
9	26.13	29.83	61.25	19	25	26.64	98.36	29	22.68	28.98	57.36
10	26.52	32.42	74.24	20	28.6	32.57	69.34	30	24.88	34.42	83.28

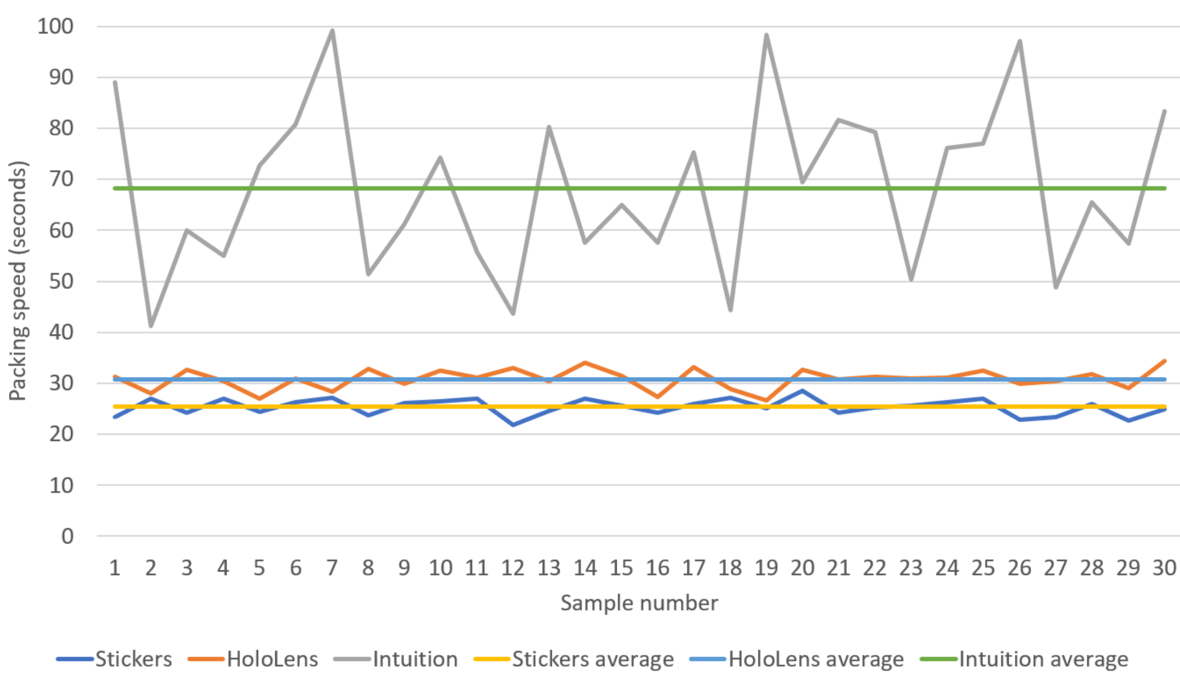

Figure 6.4: Figure of a graph showings the times per sample as well as the average, in seconds, taken by an untrained packer to pack 30 boxes of avocados, as fast and as close to the regulatory requirements as reasonably possible, using: stickers, a HoloLens with the help of Microsoft Azure, or their intuition

When an untrained packer packed avocados, it was once again observed that when packers pack using their intuition, there was significant variance in the packing speeds, with the slowest packing times being double the fastest packing times. It was also observed that the packing speed from the perspective of the observer was that the untrained packer packed slower than a trained packer. This was caused by more repacking than was done by a trained packer, and general indecision, due to not yet being able to determine the size of the avocados quickly. Therefore, before comparing the recorded packing speeds of a trained and untrained packer, using only the packer's intuition, it can be expected that the packing times for an untrained packer will be significantly longer.

The three data sets also had to be tested to determine if they are statistically significantly different. Using the procedure as outlined in the previous sub section, tables Table 6.6, Table 6.7, and Table 6.8 could be constructed. In each table p is significantly smaller than 0.05, and therefore there is not enough evidence, when executing the t-test, to reject H_0. Therefore, the three data sets are statistically significantly different and comparisons between the data sets can be made.

Table 6.6: Table showing the results from Equation 6.1 and 6.2 used to determine the p-value and t critical when comparing the data generated when packing using stickers and using the HoloLens for an untrained packer

	Stickers	*HoloLens*
Mean	25.34366667	30.8013333
Variance	2.644672299	4.06004644
Observations	30	30
Hypothesized Mean Difference	0	
df	56	
t Stat	-11.54455913	
P(T<=t) two-tail	1.94769E-16	
t Critical two-tail	2.003240719	

Table 6.7: Table showing the results from Equation 6.1 and 6.2 used to determine the p-value and t critical when comparing the data generated when packing using stickers and the packer's intuition for an untrained packer

	Stickers	*Intuition*
Mean	25.34366667	68.26233333
Variance	2.644672299	272.011184
Observations	30	30
Hypothesized Mean Difference	0	
df	30	
t Stat	-14.18444727	
P(T<=t) two-tail	7.67329E-15	
t Critical two-tail	2.042272456	

Table 6.8: Table showing the results from Equation 6.1 and 6.2 used to determine the p-value and t critical when comparing the data generated when packing using the HoloLens and a packer's intuition for an untrained packer

	HoloLens	*Intuition*
Mean	30.80133333	68.26233333
Variance	4.060046437	272.011184
Observations	30	30
Hypothesized Mean Difference	0	
df	30	
t Stat	-12.34893254	
P(T<=t) two-tail	2.71731E-13	
t Critical two-tail	2.042272456	

Comparing the average times of the three different data sets, as can be seen in Figure 6.4, the HoloLens is 54.88% faster than when the packer uses their intuition to pack a box of avocados. Comparing the average packing times also shows that when using stickers, the average packing time is 17,72% faster than when using the HoloLens. The most significant difference is between the use of stickers, which is 62.87% faster, compared to packers using only their intuition.

6.6 Productivity Increase

One of the main goals of the project is to determine the productivity increase for a small or medium sized farm when implementing AR technologies. The results from the data collected in the previous two sub sections look promising. To compare the different average packing times the data has been summarised in Table 6.9 below. These values were used to construct Table 6.10 using Equation 6.4. Equation 6.4 is the same as Equation 6.3, but it has been rewritten so that the reduced packing time is the object of the formula. When Table 6.10 was constructed using Equation 6.4, each of the percentage values were calculated from the left column value and the top row value associated with it. For example, when the time taken by a trained packer utilising the HoloLens is compared to a trained packer using stickers, the HoloLens is 13.26% slower. It is slower because Equation 6.4 states that the packing time reduction is the object of the formula. Thus, if the formula yields a negative value, then a packing time increase is experienced. Therefore, the HoloLens is 13.26% slower compared to when stickers are used.

Table 6.9: Table showing the average packing time for the six different data sets based on the packing scenario and skill level of the packer

Packing scenario	Average packing time
Stickers (trained)	23.69
HoloLens (trained)	27.31
Intuition (trained)	38.94
Stickers (untrained)	25.34
HoloLens (untrained)	30.80
Intuition (untrained)	68.26

$$left\ column\ value * (1 + reduced\ packing\ time) = top\ row\ value \tag{6.3}$$

$$reduced\ packing\ time = \frac{top\ row\ value}{left\ column\ value} - 1 \tag{6.4}$$

When the different packing speeds are compared to each other in Table 6.10 below the data can be separated into two categories. The first category consists of the cells highlighted in yellow which are when the packing times were compared with each other for both the trained and untrained packer. These data points are useful because for both trained and untrained packer, the productivity improvement can be observed if employees are equipped with AR technology. The second category is the cells highlighted in blue, irrespective of the shade used, which show when the trained packer values are compared with the untrained packer values. Both are discussed further below.

Table 6.10: Table showing the reduction in packing times when the average of the packing speed associated with the left column value is compared to the average packing speed associated with the top row value

Packing scenario	Stickers (trained)	HoloLens (trained)	Intuition (trained)	Stickers (untrained)	HoloLens (untrained)	Intuition (untrained)
Stickers (trained)	0.00%					
HoloLens (trained)	-13.26%	0.00%				
Intuition (trained)	-39.17%	-29.87%	0.00%			
Stickers (untrained)	-6.54%	7.75%	53.65%	0.00%		
HoloLens (untrained)	-23.10%	-11.34%	26.43%	-17.72%	0.00%	
Intuition (untrained)	-65.30%	-59.99%	-42.95%	-62.87%	-54.88%	0.00%

6.6.1 Intra Packing Skill Packing Speed Comparison

When comparing the orange values top left corner in Table 6.10 to the bottom right values then the first noticeable difference in these two sets of results is that the bottom right values are more negative. This means that the improvements resulting from when stickers and the HoloLens are used, are larger for an untrained packer compared to a trained packer. Therefore, some skills learned when training a packer can be performed by the HoloLens and stickers. Another observation is that the improvement when stickers are used instead of the HoloLens is smaller, for both a trained and untrained packer, than between the HoloLens and stickers compared with when only intuition is used. This means that the HoloLens system is closer to an ideal state than it is to the current packing and sorting process.

The results from the HoloLens prototype were compared to the benefits expected according to literature. Literature states that an average of 21%, with up to a 35%, improvement can be expected with the use of AR [115], [116]. The prototype had a 29.87% productivity improvement for a trained packer, therefore with refinement the results may be even better than 35%. It is not currently reasonable to expect the HoloLens system to perform as well as when stickers were used. This is because with stickers the situations were close to perfect whereas with the HoloLens interference may still arise from technological or mechanical interference. With further refinements, a further improvement can be obtained bringing it closer to "ideal". Also, when comparing the prototype's performance with that experienced in industry, the prototype performs above average. Therefore, even though the project is only a prototype, a significant and above average productivity increase is experienced which shows that there is potential for the use of AR in the agricultural sector.

6.6.2 Inter Packing Skill Packing Speed Comparison

The values in Table 6.10 highlighted in blue show the packing speed increase of a trained packer compared with an untrained packer. In order to compare these three data sets it first needs to be determined if they are statistically significantly different. Using the procedure as outlined in the previous sub section, Table 6.11, Table 6.12, and Table 6.13 could be constructed. In each table p is significantly smaller than 0.05 and therefore there is not enough evidence, when executing the t-test, to reject H_0. Therefore, the three data sets are statistically significantly different and comparisons between the data sets can be made.

Table 6.11: Table showing the results from Equation 6.1 and 6.2 used to determine the p-value and t critical when comparing the data generated when packing using stickers for a trained and an untrained packer

	Trained	*Untrained*
Mean	23.6867	25.3437
Variance	1.4076	2.64467
Observations	30	30
Hypothesized Mean Difference	0	
df	53	
t Stat	-4.50852	
P(T<=t) two-tail	3.6E-05	
t Critical two-tail	2.00575	

Table 6.12: Table showing the results from Equation 6.1 and 6.2 used to determine the p-value and t critical when comparing the data generated when packing using the HoloLens for a trained and an untrained packer

	Trained	*Untrained*
Mean	27.309	30.8013
Variance	3.57417	4.06005
Observations	30	30
Hypothesized Mean Difference	0	
df	58	
t Stat	-6.92299	
P(T<=t) two-tail	3.9E-09	
t Critical two-tail	2.00172	

Table 6.13: Table showing the results from Equation 6.1 and 6.2 used to determine the p-value and t critical when comparing the data generated when packing using the packer's intuition for a trained and an untrained packer

	Trained	*Untrained*
Mean	38.9413	68.2623
Variance	93.9742	272.011
Observations	30	30
Hypothesized Mean Difference	0	
df	47	
t Stat	-8.39475	
P(T<=t) two-tail	6.6E-11	
t Critical two-tail	2.01174	

Comparing the packing speeds when a trained and an untrained packer pack a box of avocados using stickers, the trained packer is statistically significantly faster. What this shows is that not all the skills that years of training provides can be replaced by a technology that augments information onto the user's field of vision. However, the difference can be reduced from 42.95% to 11.34% for the HoloLens and further to 6.54% difference for an optimal state. This is a significant reduction, as can be seen from the cells highlighted in dark blue.

Another value of critical importance is the cell comparing an untrained packer using the HoloLens with a trained packer using their intuition, which is highlighted with white and blue stripes. What is significant about this value is that an untrained packer using the HoloLens will perform 26.43% faster than a packer with years of experience. Meaning that new farms that do implement an AR system who pack fruit on the farm will pack faster than farms who have spent years training their staff to sort and pack. Meaning that technology can aid an employee and provided significant benefits when compared with traditional packing and sorting methods. Also, with the reduction in the packing speed difference between a trained and untrained packer when using the HoloLens, training will be less important. If staff cannot be trained then the packing speed will not be as high, but the difference in packing speed is significantly reduced, resulting in less productivity loss through having to replace, or being unable to train, staff.

6.7 Reduction in Variance

During packing speed data capturing, it was noticed that there is a significant amount of variation when a trained and untrained packer are packing avocados without the aid of the HoloLens or stickers. This can be seen in Figure 6.3 and Figure 6.4 where the packing times when a packer is using their intuition are considerably more scattered compared with when the HoloLens or stickers are used to aid the packer. This observation leads to variance being measured to determine what the reduction in variance is when packers are assisted.

The variance values for each data set can be seen in Table 6.11, Table 6.12, and Table 6.13. These values were used to construct Table 6.14 below. When observing the variance values, there is significantly more variation for both a trained and an untrained packer when they are only using their intuition. This variation decrease is so dramatic that a trained packer had a 98.50% and a 96.20% reduction in variation when using stickers and the HoloLens compared with using their intuition. The variation decrease is similar for an untrained packer with a reduction of 99.03% and 98.51% respectively.

To understand why this variation is so high when packers use their intuition, the packers were observed during sorting and packing. It was observed that packers would sometimes hesitate when they were about to select a fruit. This is most likely due to packers' re-evaluation as to whether they were selecting the right fruit. This hesitation was longer for the untrained packer. This packer was also affected by repacking. It was observed that the untrained packer who did not have the required training would sometimes pack a box in such a way that it had big gaps or did not have an even number of fruit when packed. This packer was then forced to repack their box of avocados to rectify these mistakes. This resulted in longer packing times and greater variation in packing times for an untrained packer.

Table 6.14: Table showing the reduction in packing speed variation when the average of the packing speed associated with the left column value is compared to the average packing speed associated with the top row value

Packing scenario	Stickers (trained)	HoloLens (trained)	Intuition (trained)	Stickers (untrained)	HoloLens (untrained)	Intuition (untrained)
Stickers (trained)	0.00%					
HoloLens (trained)	-60.62%	0.00%				
Intuition (trained)	-98.50%	-96.20%	0.00%			
Stickers (untrained)	-46.78%	35.15%	3453.34%	0.00%		
HoloLens (untrained)	-65.33%	-11.97%	2214.61%	-34.86%	0.00%	
Intuition (untrained)	-99.48%	-98.69%	-65.45%	-99.03%	-98.51%	0.00%

When comparing the variation of a trained packer using their intuition with an untrained packer using the HoloLens there was a 2214.61% increase in the variation. Meaning that when a trained packer uses their intuition the variation is 22 times more than when an untrained packer uses the HoloLens. This significant reduction in variation once again shows the advantage of humans and technology collaborating to find solutions to current problems.

Reduced variation has a variety of benefits such as better sorting and packing time requirement predictability, enabling a more predictable process. This could reduce time fruit spends in the SC as there will be better SC predictability which in turn could reduce food waste. The reduction in variation is linked to productivity increase. This is because the hesitation as well as repacking is reduced or eliminated with the introduction of the HoloLens or stickers. The elimination of the poorer performing packing times reduces variation and increases productivity.

6.8 Conclusion

In this chapter the effects on both productivity and variation were evaluated when the HoloLens and stickers were compared with the current sorting and packing method, which relies on the packer's intuition. In this chapter we saw that the results from stickers were better than those of the HoloLens for every measurement taken, thus showing that although the HoloLens is already a significant improvement, even greater improvements can be expected as the technology improves.

With regards to productivity three key observations were made. Firstly, the HoloLens and stickers resulted in a 29.87% and 39.17% increase for a trained packer compared with only utilising their intuition. The productivity improvements for an untrained packer were even greater with a 54.88% and 62.87% respectively. Secondly, when observing the introduction of the HoloLens for both the trained and untrained packers the trained packer was still 11.34% faster indicating that not all sorting and packing skills can be transferred with the introduction of technology. Thirdly, a trained packer using their intuition packs 26.43% slower than an untrained packer utilising the HoloLens. This shows that technology provides such a large productivity increase that it even exceeds the effect of training on productivity. It also shows that an untrained workforce with technology will perform better than a trained workforce without technology, thus providing the case for human robot collaboration in order to increase the competitiveness of new or emerging farmers.

Similarly, to the productivity increase, variance was decreased with the introduction of the HoloLens and stickers. Both for a trained and an untrained packer variance decreased dramatically with the smallest variation decrease being 96.20%. It was also found that a trained packer using their intuition had a variance 22 times larger than an untrained packer using the HoloLens.

Thus, the result from this chapter shows that the HoloLens improves the packing speed and reduces variability for both trained and untrained packers. The HoloLens also reduces the difference in productivity, and significantly reduces the difference in variability between a trained and an untrained packer. Meaning if staff cannot be trained, in the case of a farmer trying to break into the industry, then the significance of training becomes less consequential if the farmer has access to an AR system. However, a farm with untrained staff implementing the HoloLens system will have higher quality and productivity, and reduced packing speed variance compared with a farm that has been packing the same way for years. This shows the influential role that technology can have in agricultural industry.

Chapter 7 The Financial Feasibility of an AR system

This chapter is dedicated to determining who will be most likely to implement an AR system, and what the financial benefits will be for those who do implement this technology. This includes both the farmers who pack their own fruit as well as those who are sending their produce to a packing facility. This chapter also looks at the potential market size of an AR solution in the area where the study took place. Using this market size, the costs of an AR solution for both small and medium farmers could be determined. All this information was then used to determine the financial feasibility of an AR solution in the Tzaneen region where this study took place.

7.1 Adoption

Some farmers will adopt the AR system but will not be the primary or initial source of adoption within industry [70], [72]. Farmers will not be the primary or initial source of adoption because farmers, who have done things the same way for a long time, find it both difficult and an unnecessary risk to change [70]. Also there will be a significant investment and technical skills requirement, which farmers and most small companies struggle with [117]. However, they will be willing to test the technology once ready, if there is an economic incentive to do so. Farming will become more computer science oriented, as stated in section 2.8.1. That, however, does not mean that farmers themselves want to become computer scientists. Rather they will outsource the responsibility to others while they perform the day-to-day operations of a farm.

The entity that applies this prototype will be one of two types of organisations. The first is a start-up. Their disadvantage will be that they will not have the relationship with customers and suppliers yet. The advantage is that they, with the right team members, can be technologically advanced in an industry lagging in technology adoption. The second is a current packing facility, who can leverage both their current customers and suppliers. In doing so the relationship structures will already be in place and an AR system simply has to be implemented, as many do not have automated packing equipment as seen when visiting various facilities. The justification for both a start-up and packing facility adopting an AR system is for profitability, innovation, and market-share/market growth driven by an increase in quality, productivity, and the adoption of new technologies.

The implementation of new technologies could disrupt the industry and increase the farmer’s competitiveness. It could also result in an increase in market share or market growth. This is because currently 10% of small and medium farmers pack avocados on the farm, and thus do not use packing facilities [73]. Also, some areas are very remote and thus do not have access to packing facilities. These farmers can be assisted without having to pack their avocados at the packing facility. This is especially true in some regions in Africa where avocados are grown on a small scale. Farmers typically have 10 to 50 trees, and the avocados are grown for a small but significant additional source of revenue. For these farmers there is no incentive to send such small batches to a packing facility. Also, there are no large and technologically advanced packing facilities as the volume to justify such a packing facility is not present. With the AR system, however, smaller volumes can be packed in these regions. This can either be achieved by a third party providing the AR system or farmers from the community coming together to purchase such a system. In doing so these farmers can have higher quality produce and productivity, which will increase the sales value of their fruit. It is difficult for farmers to achieve the sales price without some form of intervention. This is because they do not have access to objective grading systems, nor will they garner the reputation required without one.

7.2 Profitability

To determine the economic feasibility of the developed technology in this thesis, the additional revenue and costs need to be calculated. The magnitude of the additional revenue will depend on whether the farmer currently packs avocados on the farm, or if they make use of packing facilities. The cost portion of the calculation will have two major components. The first component will be the cost of the physical HoloLens and the second will be the cost of the software. There are also other costs, such as labour costs, but these are relatively small compared to the software and hardware costs.

7.3 Revenue

A small portion, 10% of small and medium sized farms, currently pack avocados on the farm [73]. These farms have a different customer profile; thus, the source and magnitude of the additional revenue will be different. This is why the additional revenue section will be broken into two parts, namely the benefit for farms that self-pack and for those that use packing facilities.

7.3.1 Self-Pack

In order to calculate the impact of an AR system the revenue and cost data first need to be collected. Most of the data for this section was collected through interviews and data provided by the farm where the case study took place. Through the data collection processes Table 7.1, Table 7.2, and additional non-tabulated data were collected. Table 7.1 shows the size of a small, medium, and large farm based on the farm size in hectares. The average size of a farm in each size category was also determined. For small farms a detailed breakdown of the different farms and the sizes was received so the average size of a small farm could be calculated. For the medium and large farms this was not the case. Therefore, the average size of a medium sized farm was simply taken as the midpoint of the category which is 150 hectares. Large farms are outside the scope of this project.

The data in Table 7.2 shows the percentage of boxes sold locally as well as exported, and the revenue and cost of these boxes depending on the destination. It should be noted that the sum of the percentage of harvest for local and export does not add up to 1. This is because 23% of the harvest is class 3 avocados which are sorted but are not packed, as they are typically sold in 18kg bags. These avocados still require some processing. However, the processing is minimal and through time studies it was found that only about a third of the time is required compared with avocados that need to be sorted and packed. This is because these fruits do not need to be sized but only graded. Therefore, a significant portion of the benefits provided by the prototype is not applicable to this grade of fruit. It is for these reasons that class 3 avocados were not considered during the economic calculation in this chapter.

Table 7.1: Table showing what constitutes a small, medium, and large farm, in hectares, as well as the average farm size in each category and the number of farmers in each category in the Tzaneen area [71]–[73].

Property	Farm classification according to size		
	Small	Medium	Large
Size range (ha)	Less than 100	100 - 200	Greater than 200
Average size per farm (ha)	30	150	Unknown
Number of farmers	197	25	10

Table 7.2: Table showing the percentage, revenue, and cost of avocado boxes sold locally and exported when utilising a packing facility[72], [73].

Property	Destination	
	Local	Export
Percentage of harvest	20%	57%
Revenue per carton	R 95.00	R 153.61
Cost of packing	R 16.50	R 18.50

The tables are only a portion of the data collected. It was also stated that a 10-15% increase in revenue can be expected when farmers utilise packing facilities to pack their fruit compared with packing on the farm [69], [73]. This difference is due to the higher quality of packing experienced when utilising packing facilities. Besides the revenue increase, two other parameters which are average yield and labour cost, also need to be considered to determine the total impact of the prototype on revenue. The average yield and labour cost are 2160/hectare and R21.69/hour which were utilised in Table 7.3 below [73].

Table 7.3: Table showing the financial benefit due to labour cost saving for a small and medium size farm

Financial benefit from labour cost saved		
Farm classification	Small	Medium
Average size per farm (ha)	30	150
Number of boxes per hectare	2160	2160
Total number of boxes per year	**64800**	**324000**
Time saved per box packed (sec)	11.63	11.63
Total time saved (hours)	209.382	1046.91
Labour cost per hour	R 21.69	R 21.69
Labour cost savings	**R 4 541.50**	**R 22 707.48**

As previously stated, the additional revenue is dependent on whether avocados are packed on the farm or at a packing facility. It is known that 10% of small and medium sized farms do not use a packing facility. This is an important segment as these farmers will be the most receptive to the AR system [69], [71]–[73]. The reason for this is that there would be no drastic changes in operations on the farm. The AR system would integrate into the current sorting and packing operation, with few alterations having to be made. Therefore, if this segment can be persuaded through financial means, they will most likely be the first segment to adopt the AR system. It should also be noted that the 10% of farmers who self-pack will most likely not export. The reasons are that cost of poor quality is higher when exporting, and packing facilities typically control the relationships with exporters [69], [70], [72]. Also, the GLOBALGAP certification, as discussed in section 3.3.2, is expensive to obtain and retain. Therefore, farmers that self-pack will typically sell all their fruit on the local market until they reach economies of scale to justify exporting.

The financial benefit of the AR system will be a 29.87% reduction in labour cost when packing and sorting, as well as the 10% increase in revenue. The calculation for the financial benefits can be seen in Table 7.3, Table 7.4, and Table 7.5. Table 7.3 shows the financial benefits due to labour cost saving through the productivity increase of the HoloLens. In the table the average size of the small and medium sized farms are multiplied by the yield per hectare to get the total number of boxes packed per year. The number of boxes packed is multiplied by the time saved per box. This yields a time saving of 209.38 and 1046.91 hours for small and medium sized farmers, resulting in a labour cost saving of R4 541.50 and R22 707.48 respectively. This is a small labour cost saving. It should also be noted that in the case of the farm where the study took place, the labour time saved could be repurposed. On other farms this may not be the case and thus the productivity increase would not be beneficial to them. Therefore, the productivity increase alone would not justify the implementation of an AR system.

Labour cost saving was not the only financial benefit. The AR system yielded a significant increase in quality during the sorting and packing process. This improvement is not significant enough to make the AR system's quality comparable with the quality at a packing facility. However, it should be noted that the AR system developed during this project is only a prototype. Technology is also improving at a rapid rate. Therefore, if a significant improvement is achieved using the prototype, then a system yielding even higher quality that is comparable with a packing facility can most likely be developed. This improved AR system with higher quality will enable farmers who do not send their avocados to a packing facility to experience a 10% increase in revenue due to the improved quality. Table 7.4 shows the financial benefit of the additional 10% in revenue. To determine this, the revenue was first calculated, with the number of boxes packed per year multiplied by the revenue per box. After the revenue was calculated, 10% of the total revenue was then used to determine the additional revenue which amounts to R474 012.00 and R2 370 060.00 for small and medium farmers. It is worth noting that the extra revenue can have a profound impact of the profit margin of the farm. Due to both the labour cost saving and the additional revenue, the total financial benefit of the HoloLens for farmers that self-pack are R478 553.50 and R2 392 767.48 for small and medium farmers per annum, as seen in Table 7.5.

Table 7.4: Table showing the additional revenue because of the increase in the quality of the sorting and packing process

Financial benefit from increased revenue as a result of increased packing quality		
	Small	Medium
Average size per farm (ha)	30	150
Number of boxes per hectares	2160	2160
Total number of boxes per year	**64800**	**324000**
Percentage of harvest sold locally	77%	77%
Revenue per carton	R 95.00	R 95.00
Total yearly revenue	**R 4 740 210.00**	**R 23 700 600.00**
Percentage revenue increase	10%	10%
Additional revenue (10%)	**R 474 012.00**	**R 2 370 060.00**

Table 7.5: Table showing the total financial benefit for the 10% of farmers that self-pack

Total financial benefit for 10% of farmers who currently self-pack		
Labour cost savings	R 4 541.50	R 22 707.48
Additional revenue (10%)	R 474 012.00	R 2 370 060.00
Total financial benefit	R 478 553.50	R 2 392 767.48

The financial benefits originating from the labour cost saving is two orders of magnitude less than the benefits resulting from the 10% additional revenue. This is due to two reasons. Firstly, the farm's main income is from selling avocados. So, by increasing the revenue by 10%, the entire farm is affected therefore the scale of improvement should be significantly greater. Secondly, sorting and packing is only one activity of many that are essential in avocado farming. This can be seen in Table 7.6 where picking, sorting, and packing range from 11% to 29% of work done on the farm. Of the total spent on all three activities, approximately one third is only spent on sorting and packing. Therefore, sorting and packing, as seen in Table 7.6 is only a small percentage of the total labour time utilised.

Table 7.6: Table showing the percentage of time labour spends on picking, sorting and packing as well as only sorting and packing in 2017, 2018, 2019, and 2020 [72]

Year	2017	2018	2019	2020
Total productive time (hours)	18762.2	20881	28439	28220
Time spent picking/sorting/packing (hours)	2512.15	6091	3245	4839
Picking/sorting/packing as a percentage of the total work time	13.39%	29.17%	11.41%	17.15%
Only sorting and packing	4.46%	9.72%	3.80%	5.72%

The benefit of the quality is not unexpected as a key factor for selecting avocados as the fruit industry on which to test the prototype, is that there is significant potential for improvement, as explained in section 3.1.3. The benefit of the productivity increase in conjunction with the quality increase is that the significant financial benefit of the quality improvement can be realised without putting strain on or changing current processes.

7.3.2 Packing Facilities

The 10% of farmers who currently self-pack will not be the only possible beneficiaries of the AR system. The other 90% of farmers could potentially insource their sorting and packing operations to reduce costs while maintaining a high packing quality. There are two assumptions that are being made. Firstly, it is assumed that the packing quality provided by the AR system will be equivalent to the packing quality that is present within packing facilities. This is not currently the case but given the quality increase already achieved and taking into account that the project is a prototype, this assumption seems reasonable. Secondly, the adoption of the AR system does not negatively affect current relationships and channels pertaining to the distribution of avocados.

After accepting the above-mentioned assumptions, the benchmark cost of packing, in Table 7.2, can be converted to a cost savings amount if packing is insourced. The benchmark packing cost includes the price of the avocado box, which must be subtracted as it will not result in a cost saving and does not include the packing facility's levies. The cost of an avocado box is R6.80 and the levies amount to R1 per box, as calculated from Table 7.7. Table 7.7 shows the income and cost breakdown for 11 shipments of avocados sold locally by the farm where the case study took place. Using the data provided by the farm where the case study took place, the levy cost, which can be saved when insourcing, can be added to the benchmark cost of packing a box of avocados by a packing facility. In doing so the total cost saving that can be realised when insourcing, can be calculated. The 11 shipments, in Table 7.7, amounted to 446 boxes, so given total levies of R446, resulted in the R1 levy per box. The other costs in Table 7.7, other than the levy cost and packing cost, are not related to the packing facility so the AR system will not result in those costs being reduced.

Table 7.7: Table showing the cost breakdown of 11 shipments, containing 446 boxes, of avocados sold locally in 2020 by the farm where the case study took place [72]

Gross	Cost breakdown	VAT	Income and deductions
Price Paid	R -	R -	R 74 408.02
Less: Overseas Costs	R -	R -	R -
Nett Payment FOB	R -	R -	R 74 408.02
Less: Local Costs	R -	R -	-R 8 261.39
Local cost	-R 2 495.91	R -	R -
Transport	-R 317.90	R -	R -
Margin	-R 5 447.59	R -	R -
Nett Payment DIP	R -	R -	R 66 146.63
Less: Other	R -	R -	-R 12 173.76
Board levies	-R 446.00	R -	R -
Packing	-R 9755.90	R -	R -
Transport	-R 1971.86	R -	R -
Total Payments	R -	R -	R 53 972.87
Less: Advances	R -	R -	R -
Nett Payment	R -	R -	R 53 972.87

It is assumed that the levy cost per box to export avocados is the same as for avocados sold locally. This may not be true as the levies may be more but, considering that a detailed cost breakdown for export avocados is not available, the levy costs were assumed to be the same. Therefore, using the benchmark data, cost per box, and levy cost per box, the cost saving per box for both avocados that will be sold locally and exported can be seen in Table 7.8 and Table 7.9 respectively.

Table 7.8: Table showing the activity cost of packing and sorting a box of avocados as well as the levies charged by a packing facility for a box that will be sold locally [72]

Benchmark cost to pack a box to be sold locally	R 16.50
Box cost	-R 6.80
Packing facility levies	R 1.00
Total cost saving per box when insourcing	R 10.70

Table 7.9: Table showing the activity cost of packing and sorting a box of avocados as well as the levies charged by a packing facility for a box that will be exported [72]

Benchmark cost to pack a box to be exported	R 18.50
Box cost	-R 6.80
Packing facility levies	R 1.00
Total cost saving per box when insourcing	R 12.70

The data from Table 7.8 and Table 7.9 can be used in conjunction with the size per farm in Table 7.1, percentage of harvest data from Table 7.2, and the harvest per hectare which is 2160 boxes, as previously stated, to determine the cost saving for small and medium farmers. The cost saving was calculated, in Table 7.10, to be R597 096.83 and R2 985 484.15 for small and medium farms respectively using Equation 7.1. It should be noted, however, that Table 7.10 was constructed using benchmark data which may not necessarily be the costs experienced by small farmers. Therefore, the actual cost saving for the farm where the case study took place was calculated to compare the actual cost experienced by a small farm to the benchmark data.

$$Costs\ saved = Costs\ saved\ from\ avocados\ sold\ localy\ and\ internationaly - additional\ labour\ costs \quad (7.1)$$

Table 7.10: Table showing the financial benefit, using benchmark data, for both small and medium sized farms if they chose to insource the sorting and packing of fruit using the AR system[72], [73]

	Farms Size			
	Small		Medium	
Packing costs saved on avocados sold locally	**R**	**138 672.00**	**R**	**693 360.00**
Cost of packing a box sold locally	R	10.70	R	10.70
Number of boxes packed (20% of avocados for local)		12960		64800
Packing costs saved on avocados sold internationally	**R**	**469 087.20**	**R**	**2 345 436.00**
Cost of packing a box sold internationally	R	12.70	R	12.70
Number of boxes packed (57% of avocados for export)		36936		184680
Additional labour cost incurred	**R**	**10 662.37**	**R**	**53 311.85**
Labour cost per hour	R	21.69	R	21.69
Time taken to pack a box using the HoloLens (sec)		27.31		27.31
Number of boxes packed (local and export)		64 800		324 000
Total costs saved	**R**	**597 096.83**	**R**	**2 985 484.15**

The actual cost was calculated in Appendix C and the results were that it costs small farmers R21.25 and R23.25 to pack avocados for local and export markets respectively. This data can be expected to be more accurate as benchmark data simply takes the aggregate over all the clients. This average cost data is not the true cost for smaller farmers who do not have economies of scale to achieve benchmark costs. The reason for significant higher cost saving is because small farms typically pay more for small packing quantities. This can be seen in Table C.2 in Appendix C, where the three largest packing costs per box came from small batches while the lowest cost came from the second-largest batch. Therefore, they pay more for their smaller batch sizes as calculated in Appendix C. Using the actual cost for small farmers and the benchmark costs for medium farmers the cost saving when using the AR system to insource packing was calculated in Table 7.11. It was calculated that the cost saving will be R1 123 298.28 and R2 985 484.15 for small and medium sized farms respectively. These costs savings cannot be realised without an AR system or other expensive equipment as it is difficult to retain good quality through other measures. The farm where this study was done has tried to implement quality improvement measures, but these have proven to be unsuccessful. The farm stated this is because it is difficult to improve the quality without a solution which can measure the avocados size and grade accurately.

Table 7.11: Table showing the financial benefit, using both benchmark data and packing cost data provided by the farm where the case study took place, for both small and medium sized farms if they chose to insource the sorting and packing of fruit using the AR system [72], [73]

	Farms Size			
	Small		Medium	
Packing costs saved on avocados sold locally	**R**	**275 347.70**	**R**	**693 360.00**
Cost of packing a box sold locally	R	21.25	R	10.70
Number of boxes packed (20% of avocados for local)		12960		64800
Packing costs saved on avocados sold internationally	**R**	**858 612.95**	**R**	**2 345 436.00**
Cost of packing a box sold internationally	R	23.25	R	12.70
Number of boxes packed (57% of avocados for export)		36936		184680
Additional labour cost incurred	**R**	**10 662.37**	**R**	**53 311.85**
Labour cost per hour	R	21.69	R	21.69
Time taken to pack a box using the HoloLens (sec)		27.31		27.31
Number of boxes packed (local and export)		64 800		324 000
Total costs saved	**R**	**1 123 298.28**	**R**	**2 985 484.15**

The cost saving when insourcing sorting and packing calculated in Table 7.11 is substantial. This was confirmed when consulting the farmer where the study took place, with him stating that the costs in the table are equivalent to approximately 20% of the total revenue generated by the farmer. He also stated that there has been a significant trend towards utilising packing facilities instead of self-packing on the farm. He said this was due to three factors. Firstly, farmers are increasing their exports because it is more financially rewarding. Secondly, there is not sufficient internal demand for farmers to sell most of their produce locally anymore. If a significant portion of farmers decided to sell a greater portion of their produce locally the local price per box of avocados would decrease dramatically resulting a significant loss in revenue. The focus on the export market requires farmers to have accurate sorting and packing processes which they can only, currently, be guaranteed when utilising a packing facility. Thirdly, farms are expanding rapidly so they do not have the time nor the labour capacity to train the required number of packers. The above three reasons justify why farmers are willing to spend significant amounts of capital to ensure that they have good quality sorting and packing processes that classify avocados accurately.

7.4 Market Sizing

The market size needs to be determined before the system cost can be calculated. This is because the size of the system will directly impact the cost of the system. To determine the possible market size, farmers from the area were consulted. One medium and three small farmers were interviewed. All were shown the functionality of the AR system. The feedback was that everyone interviewed was at least partially interested in the adoption of the AR system, as will be further explored in section 8.1.3. All four farmers said that there was a need for the system during early season harvesting. Some avocado varieties are more valuable than others and when there are no avocados available on the market, any avocado available will generate a higher-than-average income. To capture both the early to market, late season, and also the higher value avocados, the AR system has a significant value offering. The reason is that during these packing times, volumes are lower. The lower volumes of fruit, as previously discussed, leads to significantly higher sorting and packing costs. Thus, even though avocados are available they are not worth picking or sending to packing facilities, because the lower volumes generate significantly higher costs. The AR system could be a critical component when lower volumes are being harvested. It was also stated by all the farmers interviewed that the AR system could become a requirement when technology progresses to where it can determine the ripeness of the fruit. There is current research being done that finds non-destructive and visual infrared technologies can be used to test the water content of leaves [118]. If this same technology can be implemented in the avocado industry via the AR system, then early and late picking may be possible as the water content is related to the ripeness of the fruit [17].

The medium sized and one of the small farmers are not currently interested in using the prototype system to augment their sorting and packing activities. This because they are both currently making use of packing facilities to sort and pack the majority of their avocados. When asked about using the AR system, the medium farmer responded that the farm is currently optimised for picking the fruit and delivering it to a packing facility to sort, pack, and sell the avocados. Also, the medium size farmer has shares in the packing facility he uses to sort and pack his produce which results in him having a vested interest in the utilisation of the packing facility.

The remaining two small farmers, of which the farm where the case study took place is one, were interested in the AR system provided it is economically viable and yields measurable improvements. The farm where the case study took place, who currently self-pack 50-60% of their produce, believe that such a system would enable them to be more competitive if it is cost effective. The productivity and quality improvement are positive for the farm where the case study took place. The only concern that they had was cost. The other small farm, who currently self-pack a significant portion of their produce, are looking to mechanise within the next 2 to 4 years as they want to reduce costs and improve quality. Therefore, they would also consider using the AR system if a substantial enough improvement can be realised without it being too expensive.

The positive feedback from the farmers who predominantly self-pack confirms the hypothesis that it would be preferable to first target this section of avocado farmers. The feedback was also that the farms are comfortable with new technology provided it’s cost effective, has measurable positive results, and does not change the current farming processes significantly. Given the positive reception of the farmers to the AR system, it is necessary to look at overall technology adoption of SMEs in South Africa, to determine the possible adoption rate of small and medium sized farmers. The reason why further research is done is because the four farmers consulted are not deemed a large enough sample size from which to draw market sizing conclusions. The interviews show that farmers are open to the adoption of the AR system; however, the extent of the adoption is determined by looking at overall SMEs adoption of technology.

SMEs in South Africa have been embracing new technology. The movement of small SMEs towards technology adoption in South Africa can be seen in the adoption of cloud technologies. In 2017, 13% of companies surveyed utilized the cloud. This number increased to 22% in 2018 and then to 61% in 2020 [117]. Also a recent report by S. Weber, who surveyed 200 accountants and the owners of 400 small businesses, found that 41% of SMEs surveyed are eager to adopt even more technology [117]. The report also found that companies who adopted new technology have found that it has become a core part of how their company operates [117]. The trend of adoption, according to the survey, has increased in recent years because new technology has driven costs down making the companies more competitive.

It is known that the adoption of technology in the agriculture sector is most likely slower than in the SMEs surveyed [30]. Therefore, the adoption rate will not be the same. However, the survey does show that there is a trend towards greater technology adoption. Thus, even though the level of adoption in the agricultural sector is lower than in other sectors it will most likely be significantly higher in the future if this trend continues. It also shows that there is a relatively high level of technological acceptance by SMEs. The survey also indicates that financial benefit is a significant reason for technological adoption. Therefore, if the prototype can provide financial benefit, it is likely that there will be a motivation for adoption. This financial benefit is quite significant, as discussed in the previous section, so there is clear financial impact but the incentive to implement such a system still needs to be evaluated.

The level of adoption for small and medium farmers who self-pack is assumed to be around 30%. The reason for the 30% is firstly, because it is assumed that the AR system will be profitable, as previously stated, and secondly, we know that 41% of SMEs are eager for further technology adoption in SA. We know that technology adoption of farmers is lower than other sectors therefore it is not assumed that technology adoption by farmers will be 41% [30]. Rather it is estimated that technology adoption would be about 30% of farmers who self-pack. Using the estimated number of self-packing farmers who would be interested in the AR system, Table 7.12 could be constructed showing the number of HoloLenses required to satisfy this demand. From the table we can see that 5 HoloLenses will be required which will be distributed amongst the various farmers as needed, assuming they will share the technology to reduce the overall cost.

Table 7.12: Table showing the total number of HoloLenses required in order to the estimated market size

Factors	Farm classification according to size	
Farm size	Small	Medium
Size range per farm (ha)	Less than 100	100 – 200
Average size per farm (ha)	30	150
Number of farmers per size range	**197**	**25**
The number of farmers who self-pack (10%)	19.7	2.5
The number of farmers who self-pack and adopt (3% = 10% × 30%)	5.91	0.75
The number of farmers who self-pack and adopt (3% rounded up)	6	1
Total hectares per farm size range	**180**	**150**
Boxes per Hectare	2160	2160
Total number of boxes	**388800**	**324000**
Time required (hr)	2949.37	3504.72
Employee workload per hour (hr)	2259.00	2259.00
Number of HoloLens required (100% utilization)	**1.31**	**1.55**
Utilization rate	69%	69%
Number of HoloLens required (69% utilization)	**1.89**	**2.25**
Total (sum of small and medium farms rounded up)	**5.00**	

7.5 Cost

The average lifespan of software is 9 years with a minimum of 2 and a maximum of 20 [119]. The three main reasons why software becomes decommissioned are: Significant changes in hardware or system architecture, software irrelevance due to changing business practices, and increasing cost of maintaining legacy systems [119].

Smartphones typically last between 2 to 3 years after which they are disposed of, and a newer model is purchased. However, with good care and repair they can last up to 5 years [120]. This seems to be the industry trend as laptops only last 3 to 5 years [121]. Also, there was a 4-year difference between the release date of the HoloLens 1 and 2 [122], [123]. Therefore, it was determined that the system HoloLens hardware will be replaced every 4 years. This is due to the fact that electronic hardware tends to last 3 to 5 years, and for newer, more updated, hardware to also be released in that time frame.

That being said, the agricultural industry in South Africa is notorious for the short lifespan of hardware. Therefore, it is estimated that 2 devices will be replaced every year. It is also estimated that newer devices will be bought when available. Therefore, there will not be a batch replacement of old hardware with new hardware but rather a gradual replacement of old devices with newer models.

Given that software on average remains relevant for 8 years and hardware for 4 years, it was assumed that hardware will be able to integrate with the software for two generations. Therefore, the system is estimated to have a life span of 8 years and the cost calculations are done for the next 8 years.

The cost calculation will have two components: namely the hardware and the software components. The number of HoloLenses that are estimated to be required over the next 8 years is calculated to be 22 as seen in Table 7.13. The current cost of the 22 HoloLens is R1 148 840.00.

Table 7.13: Table showing the number of HoloLenses required over the system life span of 8 years

Justification for HoloLens acquisition	Number of devices	Justification for number purchased
Starting number of devices	5	Refer to Table 7.12
Device replacement rate per year	2	Assume 40% replacement per year
Back-up device	1	Assume 1 back-up device
Total number of devices required over 8 years	22	Number of devices over 8 years which is estimated useful life of the system

In Table 7.13 it 5 HoloLenses are required as calculated in Table 7.12. It was estimated that 2 HoloLenses would be replaced each year. This was determined after having consulted the farmer where the study took place and discussing with him how long he would expect the HoloLenses would last given how often other farming equipment of a similar nature needs to be replaced. It was also estimated that one back-up device will be required in case one HoloLenses breaks or is malfunctioning. Therefore, 22 devices will be required using Equation 7.2 below.

$$Total\ HoloLenses = starting\ number\ of\ devices + backup\ device + 8 \times devices\ replaced\ each\ year \tag{7.2}$$

Table 7.14 shows the 8-year cost of the software design and development to be R848 413.31. This was calculated averaging the costs of three different sources namely: using 3 internet sources, cost estimate of prototype developed in this study, and consulting an engineer who works at a computer vision company. Thus, the total cost of the AR system over 8 years in present value terms will be R1 997 253.31, if the costs of the 22 HoloLenses are added to the 8-year software cost. Therefore, the yearly cost in present value terms will be R249 656.66 as it is simply the 8-year cost divided by 8.

Table 7.14: Table showing the average cost of the HoloLens software as determined by using three online sources, a local engineer, and the prototype developed [124]–[126]

Source for estimating the software cost of the HoloLens system	**Once-off**	**Yearly cost**	**8 Yearly cost**
Average cost from online sources	R 451 386.42	R 90 520.62	R1 175 551.39
Raul Incza and AI and machine learning entrepreneur	R 540 203.70	R 52 560.36	R 960 686.58
phData an online AI machine learning service provider	R 229 951.58	R 131 400.90	R1 281 158.78
Computer vision system used to count apples	R 584 004.00	R 87 600.60	R2 284 808.80
Cost estimate based on prototype developed	R 219 001.50	R 43 435.88	R 566 488.55
An engineer working for a computer vision company	R -	R 100 400.00	R 803 200.00
Average	**R 223 462.64**	**R 78 118.83**	**R 848 413.31**

7.6 Financial Feasibility for Self-Packing Farmers

The gross profit margin in the technology sector over the last 5 quarters averages 54.67% [127]. This means that the revenue that will be generated through the prototype implementation per year will be R550 729.43 as calculated using Equation 7.3. This cost will be distributed over the 6 small farms and 1 medium farm determined from the market sizing section, as seen by Equation 7.4 for a small farm. The total additional revenue calculated for these 7 farms, if they self-pack (as it will be potentially more for those who are currently using a packing facility), can be seen in Table 7.4. Therefore, the additional revenue for small farmers, who already packs their own fruit, can be calculated using the additional revenue and cost. Individually the small farms will make an additional R423 945.69profit and for the medium farm it will be R2 119 728.44 as can be seen in Table 7.15.

$$R550\ 729.43 = \frac{R249\ 656.66}{(1 - 54.67\%)} \tag{7.3}$$

$$R50\ 066.31 = \frac{R550\ 729.43}{6 \times hectares\ of\ small\ farm + hectares\ of\ medium\ farmer} \times hectares\ of\ a\ small\ farm \tag{7.4}$$

Table 7.15: Table estimating total additional profit for the farms that implement the AR system as determined from the market size

Farm classification	Small		Medium	
Financial benefit per farm	R	474 012.00	R	2 370 060.00
Cost per farm	R	50 066.31	R	250 331.56
Total additional profit	R	423 945.69	R	2 119 728.44

More importantly, there is a profitable alterative to making use of packing facilities. Some farmers in the region have also taken note of this (independently of this study). One small farmer interviewed said that he was looking to purchase a small sorting system from an overseas supplier for between R 1 000 000 and R 2 000 000. The farmer said that if there are cheaper alternatives they would also be strongly considered.

The farmer's willingness to spend this capital shows three things. Firstly, it shows that farmers are already looking for quality improvement solutions, supporting the argument that there is a market for an AR solution. Secondly, the farmers are willing to spend a significant amount in order to improve the quality of their sorting and packing process. Thirdly, the AR system solution seems to be considerably cheaper than the alternative, as well as being a very cheap solution when compared with the capital the farmer is willing to spend. This last point is extremely important. With a solution this cost-effective for the potential benefit which the farmer could achieve, the solution could be a very attractive option for the sorting and packing processes in the avocado industry.

7.7 Conclusion

The AR system enables small and medium size farmers to have technology available that supports smaller scale operations in a cost-effective manner. Thus, the HoloLens supports both small and medium sized farmers, which is more labour-intensive per hectare and provides an alternative to automation. AR systems also have other potential applications which can provide significant value to other areas of the farming environment. The AR system is also significantly cheaper than the alternatives available, making an AR system an appealing solution as a productivity and quality enhancing tool in the sorting and packing process in the avocado industry. By implementing the AR system, a farmer that currently sorts and packs their own produce on the farm can increase their revenue substantially at a reasonable cost. These farmers could also potentially gain access to the export markets which could increase the revenue benefit of the AR system even more.

The financial impact on small and medium sized farmers that utilise packing facilities is even greater. These farmers are reliant on packing facilities. This is due to the financial benefit of exporting fruit, the local market not having the capacity to absorb all the fruit produced internally, as well as the lack of skilled labour required to sort and pack fruit accurately. For these farmers the AR system can potentially provide a more cost-effective way to still have good quality sorting and packing processes. In doing so the sorting and packing processes could potentially be relocated back to the farm which can create new employment opportunities.

The financial impact that the AR system could have on both farms that currently self-pack and those who utilise packing facilities is significant. By having this impact, the AR system justifies the retention of labour on farms that current pack their own fruit. However, it also provides a potential justification for farmers that currently utilise packing facilities to relocate their sorting and packing process back to the farms. In doing so the AR system will not only conserve labour but also potentially create new employment opportunities within the avocado industry.

Chapter 8 Validation

Validation is a metric used to test whether the prototype built is the correct prototype to test the value of AR, and other Industry 4.0 technologies, in an avocado sorting and packing process. To test validity three parameters: namely conceptually valid, operationally valid, and credible are evaluated. Once these three parameters have been evaluated, it can be determined if the prototype is valid.

8.1 Prototype Validation

To ensure that the right prototype was developed Bekker [114] states that three types of validities should be considered. Each validity is summarised in Table 8.1 which demonstrates both the validity and the question which should be answered to ensure that it is satisfied. To test for conceptual and operational validity the prototype is analysed, and literature is consulted. To determine credibility, various experts are consulted through unstructured interviews.

Table 8.1: Table representing the three types of validity according to Bekker [114]

Type of validity	Question
Conceptual Validity	Whether the prototype adequately represents the real world
Operational Validity	Whether prototype data can be associated with real world data
Credibility	Does the end-user have confidence in the prototype results

8.1.1 Conceptual Validity

To ensure that concept validity is satisfied the model is built using mathematical models, reputable software services, which is tested regularly to determine if it resembles reality adequately. The tests are conducted on the prototype developed. The tests used to determine the accuracy of the grading and sizing processes are also used to conceptually validate these sections. As previously stated at the end of the verification section 5.10, the grading and sizing accuracy results make sense. The accuracy is not perfect; however, this is a prototype and significant improvements are made, when compared to the current operations, as was expected according to literature in section 6.6.1. Therefore, given that mathematical models and reputable software providers are used, and that the grading and sizing results make sense, conceptual validity is achieved with respect to the prototype developed.

8.1.2 Operational Validity

According to Bekker [114] operational validity involves the evaluation of technical data and information to ensure that the model behaves similarly to the real-world system. Evaluation is done on two sets of data. The first set consists of the avocado sizes before and after the model is used. The second consists of the packing speed both with and without the assistance of the model. For the evaluation, both sets involve a comparison between the expected result and the actual result that is observed when the model is implemented.

When inspecting the size classification of the avocados before and after the implementation of the prototype, the change in accuracy can be used to determine the validity of the prototype. The change in accuracy can be observed in Figure 8.1 below. In the figure the blue line shows the probability distribution of various weights of avocados, rounded to the nearest gram, being classed as a size 14 avocado. The orange line is similar to the blue line except that it is the probability distribution when using no assistance. The two vertical yellow lines are the bounds, in grams, which define what a size 14 avocado is when using weight as a classification measurement, as explained in section 3.2.3. From the figure two important observations can be made which strengthen the operational validity of the prototype. Firstly, the prototype has a smaller standard deviation compared with when no assistance is used. This can be seen by the fact that the blue line in Figure 8.1 has a higher and narrower peak. This is expected since the use of the prototype should reduce the variability of avocados packed, as explained in section 6.7. Secondly, the probability distribution peak when the prototype is used lies just off-centre between the two yellow lines. Meaning, when the prototype is used the accuracy is significantly improved, which is what is expected, according to section 6.6.1. Therefore, processes used to determine the size of the avocado exhibit operational validity, as the prototype data can be associated with real-world data.

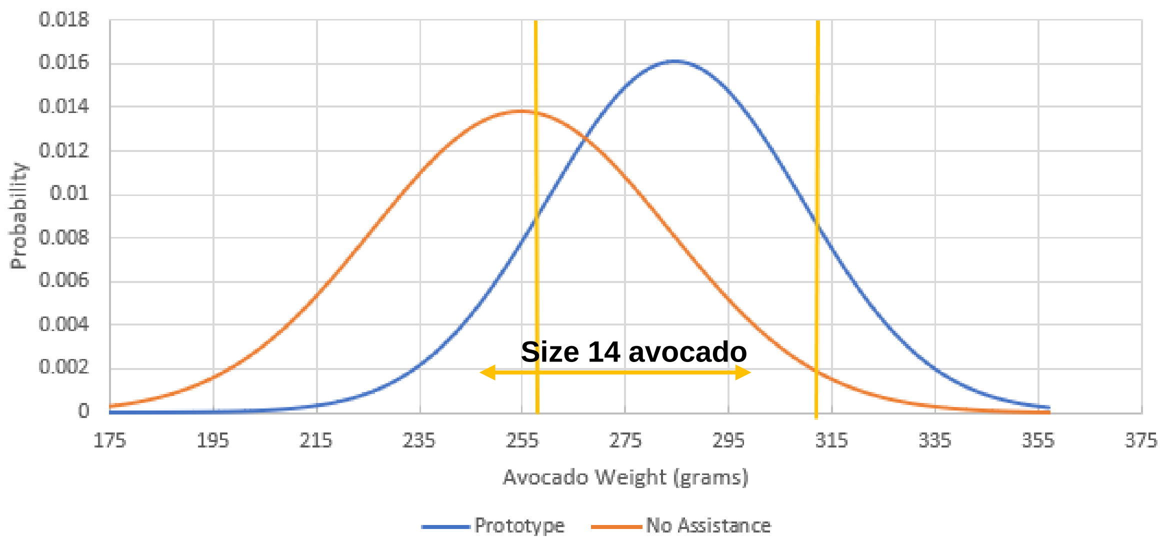

Figure 8.1: A probability distribution showing the probability that an avocado with a given weight will be packed into a size 14 box when using the prototype and when using no assistance

Next the packing data is collected and analysed. Literature is consulted both as a benchmark and as a form of validation. From literature it is clear that an average of 21% productivity improvement can be expected with a productivity improvement of up to 35% being possible when augmented reality is utilised [115], [116]. The prototype developed yields a productivity increase of 29.87%. The prototype is, however, a rough prototype thus with improvements made the results may improve to 35% or higher. Lastly the standard deviation is measured. It is found that there is a 96.20% reduction in the standard deviation when the HoloLens is used. Thus, the results of the prototype can be associated with real-world results that would occur for both data sets.

8.1.3 Credibility

For the prototype to be credible the following has to be proven and demonstrated so that the end user will trust the end product:

1) There is an increase in the quality of the output of the packing process through an increase in the accuracy of the size classification of the avocados.
2) The quality output can be achieved faster, through an increase in productivity.
3) The prototype provides a viable improvement to the sorting and packing process for small and medium sized farms.

The results delivered by the solution include:

1) An increase in the quality of the grade and size classification is achieved, as explained in detail in section 5.7.1 and section 5.7.2.
2) An increase in productivity is achieved, as is explained in detail in section 6.6.1.
3) The prototype yields results that are an improvement on the current system, as is expected based on the literature consulted leading to the credibility of the prototype. Therefore, the prototype seems credible, however, the final verdict on credibility can only be determined once the prototype system is adopted. To evaluate the likelihood of adoption, different stakeholders in the community like farmers, local research organisations, a packing facility consultant, and experts from technology companies were consulted.

   Feedback from farmers:
   The overall feedback was overwhelmingly positive. All four farmers saw potential in the technology albeit to various degrees. The first farmer interviewed was the one where the study took place. This farm was very positive about the prototype and would strongly consider implementation once the technology is mature and a fully functional product is developed. The prototype has the advantage that it decreases the risk of labour dependency where the farmer becomes reliant on trained labour in various areas of the farming environment. The farmer specifically stated that an increase in quality and productivity, as well as a decrease in training is sorely needed, especially if it can be offered at a competitive price.

   The second farmer interviewed is a farmer who has invested significantly in automation equipment to reduce his dependence on labour. The farmer also no longer packs his own fruit as he sends it to a packing facility. He stated, however, that he sees a lot of value in AR in agriculture, yet he would not currently implement the AR system for sorting and packing on his farm. The reasons for not implementing the AR system are that (through all the automation efforts) he no longer has the labour capacity to pack and sort his own fruit. Were he still doing it himself, or had he the capacity to do so, it is something he would strongly consider. The additional value that the farmer sees in the AR system is in data gathering, communication, quality control, and training. The farmer stated that with his efforts to automate his farm, he can extract considerable value from an AR system if it has wider capabilities. The risks of the AR system according to this farmer are that the equipment is expensive and fragile. The equipment needs to be tailored to the rough agricultural environment before he will consider implementing such a system.

   The third farmer interviewed is currently a medium sized farmer with the aspirations of becoming a large farmer. The farmer also no longer packs his own fruit as he sends it to a packing facility. He used to pack his own fruit about a decade ago. Upon showing the farmer the AR system, the farmer was sceptical. After further explanations and showing the farmer the results, he became positive towards the AR system. He stated that his farms are now too large and complex. So, he does not want to increase the complexity further by once again sorting and packing his own fruit. He would rather focus on his core business and outsource the sorting and packing to a packing facility. However, he states that if his business were smaller or if he was still sorting and packing his own fruit, he would strongly consider such an AR system. He also states that he is broadly very positive about AR technologies and sees potential in communication, quality control, training, as well as early harvesting. Early harvesting is when AR can be used, with infrared capabilities, to detect avocados that can be harvested earlier than normal, allowing famers to sell fruit out of season at a higher price. The farmer also stated that there has been considerable increase in labour prices over the last 5 years. This could, however, lead to fewer farmers wanting to adopt AR, but rather opting for a system that leads to automation. That being said, he stated that under the current labour conditions an AR system could be very beneficial.

The fourth farmer is a small farmer who sorts and packs all his own fruit. He is also looking for a one-to-two-million-rand investment to optimise his sorting and packing system. Like farmer 3, upon being shown the AR system, the farmer was sceptical. After further explanations and showing the farmer the results, he also became positive towards the AR system. He stated that if the AR system was ready, he would consider it as an option for his sorting and packing system upgrade. He also stated that the current increases in labour cost are concerning. However, if the AR system can be coupled with an organisation that could market fruit for export, he would be very interested. He stated that packing facilities currently also provide channels for fruit export. So, if the AR system could also provide an export channel, it would enable him to export, which would make the technology very attractive.

Local research organisations:

Two local research organisations were consulted. The one is the primary avocado research organisation which focuses on introducing new technology to the avocado farmers in the region. The other is focused on avocados and other fruit, but they have their own experts doing wider research. Both research groups were very positive about the AR system, stating that many of the farmers in the region would be interested. Both stated that particularly small farmers and those who currently still pack their own fruit will be interested as this could increase productivity and quality, as well as enable these farms to scale as sorting and packing training would be reduced. Both also invited the researcher to present the results at local conferences, however this is still being discussed. The only concern from the research organisations is the robustness of the HoloLens and they would really like to see it being adapted for application in the agricultural sector.

Packing facility consultant:

A packing facility consultant was also asked to provide his input with regards to his overall impression of the AR system. His response was positive, but in his opinion in South Africa the scope might be limited to farms who still pack their own avocados, as well as a limited number of farmers who send their produce to packing facilities. He stated that in less-developed or more sparsely-populated regions the AR system could have a considerable amount of value. This is because there is either a lack of capital or economies of scale required to erect packing facilities. These regions also have serious quality issues. Thus, for these regions the AR system could be very important to enable small or medium sized farms to be globally competitive.

Experts from technology companies:

The first expert was a senior member of a strategy department for a large technology company, while the second is currently a senior member of a technology company and has been involved in the deployment of several Industry 4.0 solutions. The first expert stated that from a technology perspective the prototype shows that AR works and has useful applications in the agricultural sector. The impact of the AR prototype is important, both from the perspective of studying a new and innovative technology, as well as applying technology in the agricultural sector. The AR system also has larger consequences in that it can promote smart farming systems in which this AR system will form part of a larger IoT system. The expert also stated that the prototype is an excellent solution to the current socio-economic changes in South Africa with regard to unemployment and profitability of farms. The expert also stated that there is a risk that the cost of labour could continue to increase drastically, which could make the case for automating fully greater than the case for using AR.

The second expert stated, firstly, that the AR could lower the barrier to entry of new or emerging farmers into the avocado industry. This is because a trained packer without the HoloLens packed a box slower and in poorer quality than an untrained packer with the HoloLens. Secondly, the expert stated that the AR system makes smaller farms more competitive due to the increase in quality and productivity. This could allow for smaller farms to be economically viable and enable new entrants who do not have significant capital into the avocado farming sector. Thirdly, the expert stated that there is also less dependency on skilled labour. Therefore, storing and packing will have less labour risks and can be more scalable as new packers do not have to be trained extensively. Finally, the expert stated that, "The prototype is immensely important in that it is a model that has been created which showcases how technology and humans can collaborate to solve socio-economic challenges such as keeping labour relevant in a digital age. The value of this prototype is not only in this specific-use case of avocado sorting and packing but in the fact that it is a model that can be used in the future to solve other socio-economic problems through the collaboration between humans and new technologies."

8.1.3.1 Credibility Conclusion

The feedback from the various stakeholders is extremely positive, leading to the conclusion that there is a high likelihood of a working system being implemented if it is introduced to the farming community in this region. This shows that, from the perspective of the community that will benefit from the AR system, there is trust in the AR prototype developed.

8.2 Conclusion

To test the validity of this prototype three parameters namely conceptual validity, operational validity, and credibility were evaluated. All three paraments yield a result that shows the prototype is valid from that perspective. Being valid from all three perspectives means that the right system has been built to test the value of an AR system in the avocado packing and sorting process.

Chapter 9 Summary, Conclusions and Recommendations

This chapter concludes the project by answering the research questions, discussing the contribution of this study, addressing the limitations of the study, and suggesting potential future work. The first part of this chapter focuses on the research questions stated in section 1.2.2. Thereafter, both the theoretical and practical contributions of this study will be examined. Finally, the chapter will conclude with the limitations of this study and future work sparked by the research done.

9.1 Research Summary

The focus of this project is the implementation of a system utilising visual technologies that do not lead to automation, to improve the productivity and quality of fruit classification, in order to make retaining labour economically viable for small and medium size farms. The reason why this topic is being explored is because in section 1.1 it was shown that the agriculture sector is being affected by the implementation of visual technologies supported by automation. The impact of automation in the sector can be severe as 50% of all working individuals are employed in this sector. Preliminary research also shows that automation technologies will marginalise small and medium farms as they will become less competitive, since they will not be able to afford the new and expensive equipment. To test the impact of a visual technology that does not have automation as a key component, it was decided, in section 1.5, that the research strategy to be implemented would be a case study.

To implement a case study effectively, it was important to first identify which visual technology has the greatest potential to improve fruit classification. Through studying the various visual technologies available it was decided that AR has the greatest value-adding potential. It was also identified that AR would have the greatest potential benefit if it is used in conjunction with other Industry 4.0 technologies such as ML, IoT, and computer vision. These technologies, as well as the increased utilisation of data, is digitalising the farming industry. Through digitalisation the industry may become leaner and more sustainable.

After having identified that the most appropriate visual technology for the case study was AR it was then required to identify which fruit sector would be selected. It was decided to focus on the avocado sector as the fruit sector on which the case study would be implemented. The avocado sector was selected because it is an important socio-economic crop, key relationships within the avocado industry had already been established, and there was significant potential for productivity and quality improvements. A productivity improvement of 21% can be expected and the quality improvement can lead to a 10-15% increase in the sales price of a box of avocados. To understand how the productivity and quality improvements would be realised, the avocado classification processes had to be understood. It was found that avocados of the same size and grade had to be packed into the same box, but that this has been a challenge for farmers. Therefore, if AR could be used to assist farmers to pack avocados better and at a faster rate there could be a considerable opportunity for the technology.

To test the utilisation of this technology in the avocado industry, a prototype needed to be designed and developed. However, before the designing and developing of the prototype, it was first necessary to determine the hardware and software which would be utilised. There were three different AR device options. Using the

AHP method it was determined that the HoloLens 1 would be the best hardware device for testing the prototype. Next it was decided to utilise a PaaS to provide the ML capabilities of the system. Here there were once again three options available. Azure was selected after the pros and cons of each option were considered. Other than Azure, Unity and Visual Studio which are complementary software deployment platforms were also utilised.

To design and develop the prototype a framework was required. It was decided, both due to the intimate relationship between AR and IoT and the importance of IoT in the fourth industrial revolution, that an IoT framework would be utilised, as discussed in section 5.5. Therefore, the 5-layer IoT development architecture, consisting of the perception, transport, processing, application, and business layer was used. Within the processing layer of the development architecture, the development of the classification processes was done. The classification requirements were determined by the system requirements, which were that avocados need to be classified according to size and grade. Post-design and development of the HoloLens system was tested, and the results showed that the prototype accuracy when grading and sizing the avocados are 83% and 73.33% respectively. This is a significant quality improvement over the current system which has an accuracy score of 73.33% and 58.50% when grading and sizing avocados.

The AR system does, unfortunately, have some limitations. One of them being that during the classification, the system cannot monitor the avocados continuously. This is unfortunately due to Azure only utilising 2D imagery and not 3D video. This limitation was overcome by packing a box of avocados using the HoloLens over several iterations. This limitation is expected to be resolved in the future as the software supporting AR becomes more advanced and sophisticated. After development was completed, the system was validated to ensure that the system built was built correctly. The system validity was confirmed, meaning that the system could be utilised to test the potential productivity improvement of the AR prototype.

To test the productivity improvement six different scenarios were tested. Firstly, the current classification system was tested using a trained packer. Secondly, the AR prototype was tested using a trained packer. Thirdly, a scenario where stickers were placed on the avocados that needed to be packed by a trained packer was tested. The third scenario with stickers was tested because it represented a scenario that closely resembled the optimal state of an AR system. The fourth, fifth, and sixth scenarios were the same as the first three scenarios except that an untrained packer packed the boxes of avocados, instead of a trained packer.

When the productivity of each of the scenarios was tested, three key observations were made. Firstly, it was observed that the utilisation of the HoloLens and stickers resulted in a significant productivity improvement over the current system. This improvement was even larger for an untrained packer compared to a trained packer. This improvement was noticed when the HoloLens and stickers resulted in a 29.87% and 39.17% increase for a trained packer compared with when the packer are only utilising their intuition. These productivity improvements increased to 54.88% and 62.87% when an untrained packer utilised the HoloLens and stickers respectively. Secondly, when both a trained and an untrained packer utilised the HoloLens, the trained packer was 11.34% faster than the untrained one indicating that not all sorting and packing skills can be transferred with the introduction of technology. Thirdly, a trained packer, relying only on their intuition to pack a box of avocados, packed a box 26.43% slower than an untrained packer utilising the HoloLens. This shows that technology can provide a larger productivity increase compared to training and conventional sorting and packing methods.

While studying the productivity increase provided by the HoloLens and stickers it was observed that when packers relied on their intuition to pack a box of avocados the results had significantly more variation. Therefore, the impact that the HoloLens and stickers had on variation was also studied. It was observed that the variation during the packing processes was significantly reduced with the introduction of the HoloLens and stickers. This was seen by the fact that the smallest variation decrease observed was 96.20%. It was also observed that when a trained packer used their intuition compared with an untrained packer utilising the HoloLens, the trained packer had a variation 22 times larger than that of the untrained packer.

The incorporation of the HoloLens and stickers resulted in two key findings. Firstly, the HoloLens and stickers provided a significant increase in productivity and a significant decrease in variation. Secondly, the results showed that an untrained packer utilising the HoloLens packs a box of avocados significantly faster and with greater constancy compared with a trained packer only utilising their intuition. This shows that the introduction of technology into the classification process will have significant productivity and quality improvements as discussed earlier, as well as reducing variation. It also shows that a new or emerging farmer utilising technology could potentially perform better when classifying fruit compared with a farmer who has trained packers but does not utilise technology.

Having proven that both the quality and productivity of the avocado classification process has been improved it then had to be determined if sufficient financial benefit could be generated in order to make retaining labour economically viable. The economic results showed that for a small and medium sized farmer who either packs their own fruit on the farm or utilises a packing facility there is a significant financial benefit when utilising an AR system. The AR system is also cheaper than the alternatives that farmers are looking to implement in order to improve the productivity and quality of the avocado classification process. Therefore, the AR system justifies the retention of labour on farms that currently pack their own fruit, as well as potential hiring of new packers as farms insource their fruit classification process.

The AR system is also significantly cheaper than the alternatives available, such as large packing machines, making an AR system an appealing solution as a productivity and quality enhancing tool in the sorting and packing process in the avocado industry. By implementing the AR system, a famer that currently sorts and packs their own produce on the farm can increase their revenue substantially at a reasonable cost. These farmers could also potentially gain access to the export markets which could increase the revenue benefit of the AR system even further.

Once the prototype was developed and tested it could be evaluated to ensure that the right system was built in order to test a visual technology to improve fruit classification whilst making retaining labour economically viable. To test validity three parameters namely conceptually validity, operationally validity, and credibility were tested. After testing all three parameters it was found that the prototype is valid meaning that the correct system was designed, developed, and implemented.

9.2 Findings and Conclusions.

To establish whether this thesis achieved what it set out to do, it is necessary to address the main research question (RQ) in section 1.2.2. This will be done by answering the research sub-questions (SQ) first. In doing so a holistic view of the answer to the RQ can be attained.

SQ1. Does a visual technology exist that increases productivity and quality while retaining labour?

The various visual technologies were evaluated in section 2.1 where photography, video, videography, AR, and Virtual Reality were considered. Of these visual technologies, Virtual Reality and photography were excluded as viable options. Thereafter, AR, video, and videography were compared to identify which option would be the most appropriate. In a study done it was found that AR had a better user experience, compared to video and videography, as well as showing promise in improving the productivity when utilised [23]. AR also does not result in automation since it is a tool dedicated to assisting a human worker during task execution [25].

Further study into the value offering provided by AR to an agricultural environment found that it provides colour processing, contextualisation, and RTMF as summarised in Figure 2.1 in section 2.2.2. The value offering enables the user to have better decision-making capabilities. The improved decision-making capabilities results in increased productivity, improved quality, and better resource management. The productivity improvement was corroborated through further research which showed that an average of 21% productivity improvement can be expected with the improvement possibly even being as high as 35% [115], [116]. With regard to quality it was found, as stated in section 5.7.3, that with more data-focused farming practices/activities, which are enabled by AR, quality is significantly increased. Therefore, SQ1 can be answered with a yes, there is a visual technology, AR, that can increase productivity and quality while retaining labour.

SQ2. Can KPIs be developed with which to measure the productivity and quality improvement of the fruit classification process when the visual technology is used?

To develop KPIs to measure the productivity and quality improvements it was first required to understand how productivity and quality are measured. Therefore, after the selection of avocados as the case study on which AR was to be implemented, the avocado fruit classification parameters were studied. These parameters were studied in section 3.2.3. It was found that avocados are classified according to grade and size, and that when a box of avocados are packed, the avocados in the box all have the same size and grade classification. To achieve good quality, it is therefore necessary that the avocados are classified correctly and that a box only contains avocados from the same size and class classification. Therefore, the quality KPI was established, which measures whether an avocado is the right size and class compared with the intended size and class of avocados packed. As for productivity, the KPI was simply the speed with which a box of avocados is packed with the avocados packed conforming (as closely as reasonably possible) to the regulatory requirements. Therefore, SQ2 can be answered with a yes, KPIs can be developed with which to measure the productivity and quality improvement of the fruit classification process when the visual technology is used.

SQ3. Does this visual technology significantly improve the productivity and quality of the fruit classification process?

Research indicated that AR should provide productivity and quality improvements to the fruit classification process. This was tested by designing and developing a prototype that was implemented to classify avocados. The quality improvements were achieved when the prototype graded and sized the avocados with greater accuracy compared with the current avocado classification process. Avocados were graded using Azure, a ML PaaS, which resulted in the grading accuracy increasing from 73.33% to 83%. To determine the avocado's size an algorithm was programmed onto the HoloLens. This algorithm increased the accuracy of the sizing of the avocados from 58.50% to 73.33%.

The prototype developed was then implemented by both a trained and an untrained packer as depicted in Figure 5.12 in section 5.8. The trained and untrained packer, when utilising the HoloLens had a 29.87% and a 54.88% productivity increase respectively. It was also observed that the trained packer using their intuition compared with the untrained packer using the HoloLens was 26.43% less productive. To ensure that the productivity improvement is meaningful a t-test was conducted on the different samples collected. The results from the t-test showed that the different productivity samples are all statistically significantly different from one another. This means that the productivity differences are significant enough that conclusions can be drawn between the difference in the productivity measurements of various samples taken. This shows that the HoloLens provides a significant productivity improvement, with it being even more effective than training for increasing productivity. Therefore, SQ3 can be answered with a yes, this visual technology does significantly improve the productivity and quality of the fruit classification process.

SQ4. What are the economic benefits to the employer when implementing this visual technology?

The economic benefit, for a farmer who packs his own fruit, of an AR system is from both the increased productivity and quality that the system provides. This is because the productivity will result in the labour cost per box of avocados packed being reduced, while the quality increase will result in a 10-15% increase in sales revenue. For a farmer who packs his own fruit, such as the farm where the case study was done, the results are summarised in Table 7.5 in section 7.3.1 and Table 7.15 in section 7.6. In Table 7.5 the benefit from the productivity increase is two orders of magnitude smaller than the benefit resulting from the increase in quality. However, the productivity increase was only for one farming activity, avocado classification. If the AR system is used throughout the farm the benefits will be significantly higher. The results from Table 7.15 showed that the total additional profit of the increased productivity and quality is R 438 426.99 and R 2 192 134.96 for a small and medium sized farm respectively. Table 7.15 also shows that this profit can be achieved at a cost one order of magnitude smaller. Showing that the benefit significantly outweighs the cost, and that the solution is affordable for farmers. Therefore, SQ4 can be answered yes, since it is shown that the visual technology solution is affordable and that it can provide significant financial benefit to farmers.

RQ: Is there a visual technology available that will increase the productivity and quality of fruit classification making retaining labour economically viable?

Having answered all the research SQs, which provide a holistic answer to the final RQ, the final RQ can be answered. Therefore, RQ can be answered with a yes, there is a visual technology available that will increase the productivity and quality of fruit classification making retaining labour economically viable.

9.3 Practical and Theoretical Contributions of the Research

The practical contribution of this research is that AR can be used to increase the productivity and quality of the fruit classification process. The study also showed that in doing so farms could possibly both retain labour and become more profitable. There is also the practical benefit that it has been proven that there are alternatives to automation which can be studied further by other researchers. This research also provides a technological alternative to expensive automation equipment when classifying fruit, thus enabling new or emerging farmers to enter the avocado farming sector whilst being competitive with regard to fruit classification. Thus, the practical benefit of this study is that it added to the body of knowledge with regard to the application of AR to improve the productivity and quality of manual tasks as an alternative to automation.

The theoretical contribution is that it proved that a visual technology exists that can improve the productivity and quality of tasks currently done by humans. In doing so there is an opportunity for providing people with technology instead of replacing them with technology. By providing people with technology, they can be provided with the most relevant information required to make important decisions. Thus, reducing time required to make decisions and leading to a reduction in the number of errors. Therefore, the theoretical benefit of this study is to show that people can be empowered with technology. This can hopefully both reduce the need for automation as well as increase the overall productivity and quality of tasks. This thesis also adds to the body of knowledge with regards to possible areas of application of AR and other visual technologies.

9.4 Limitations and Recommendations

Having completed this study it is necessary to address the main limitations encountered and the recommendations that can be made to solve these limitations in the future. The limitations encountered can be broken down into two main categories: namely technological readiness and technology adoption.

Through the development of the prototype, it is clear that most of the technology available in the AR system can already benefit the fruit industry when classifying fruit. However, it was also clear that in some areas the technology is not yet mature enough for an AR system to be implemented upon the delivering of this thesis. With AR being such a novel technology, the software needed still needs to be improved. This is because AR works in a 3D environment, while supporting software was designed and developed for a 2D environment. This has resulted in the supporting software not being able to fully integrate with the HoloLens. Examples of this are Azure, which was only able to use 2D pictures, and unity, which had to be modified as it was originally created to develop 3D environments to be displayed on 2D displays and not 3D environments.

Another technological readiness aspect of Industry 4.0 technologies that is not often discussed but was encountered through the development of the prototype is the disconnect between various Industry 4.0 technologies. Most Industry 4.0 technologies are novel and seen as standalone solutions when implemented. These technologies are often difficult to integrate with other novel technologies. This was experienced with Azure, which is a ML PaaS. When utilising Azure, the solution has to be built around the functionality of Azure. Therefore, to utilise Azure the input from the HoloLens had to be photos. This was a drawback as the HoloLens would ideally have provided Azure with video input so that the avocados could continually be monitored. Therefore, currently a 13 second delay will exist if the prototype system will be implemented. This is a significant drawback and is considered a serious limitation. It was also discussed in section 2.7 that when various Industry 4.0 technologies are utilised together, they can potentially add more value than if only one is utilised in isolation. Therefore, as Industry 4.0 technologies advance and become more interoperable their usefulness will be compounded.

The second limitation is adoption. This was experienced when presenting the HoloLens initially to farmers. The farmers were sceptical even though they already had a trusting relationship with the researchers. These farmers were eventually convinced and were extremely positive with regards to the benefit that AR could provide to the farming industry. However, this shows that even if the technology was ready for implementation, there would most likely still be hesitancy and resistance from farmers to implement the technology. Faith in an AR system would most likely only be achieved after the technology has proven itself which would require time and capital from those who are introducing the technology to the agricultural sector.

The above limitations will most likely be solved through further technological advancement and the implementation of technological solutions by parties who already have close ties with the various stakeholders in the agricultural sector. Therefore, as AR becomes more widely adopted and is improved, the software supporting it will improve. This will be true for Industry 4.0 technologies in general. These technologies will advance and be utilised with other Industry 4.0 technologies. Therefore, it is very likely that the Industry 4.0 technologies will evolve to be utilised together because in doing so they will add the most value.

The limitation of adoption will most likely be addressed by parties, other than farmers, that implement and manage the technology for the benefit of farmers. In doing so, the farmer will be more likely to implement the technology as there will be a reduced risk and the potential for greater overall benefit. Also, the farmer does not require the necessary skill to operate and manage an AR system as this can be outsourced to an expert instead.

9.5 Future Work

The completion of this thesis has also acted as a steppingstone from which further research can be conducted. The first area of future research proposed is with regards to the development of a more sophisticated solution once the technology has matured sufficiently to make such a development possible. Secondly, further research can be conducted in the utilisation of AR both within and outside of the agricultural sector. It was brought to the attention of the researchers that there are other possible applications of AR in the avocado sector such as early harvesting and harvest predictions. The use of AR to classify fruit outside of the avocado sector should also be studied to determine if the value provided to the avocado industry is transferable to other fruit sectors. The transfer of value of AR should also be investigated outside of the agricultural sectors. Tasks or areas similar to fruit classification can be studied, such as part identification. Thirdly, the financial benefit provided by AR could be further studied as the technology advances and the costs of implementing new technology changes. In doing so the adopters of new technologies will be able to determine if the cost benefit analysis of implementing new technologies is favourable. Finally, integration of Industry 4.0 technologies should be studied. As stated in the previous section there is still a disconnect between the various Industry 4.0 technologies. Through further research, a system composed of the various Industry 4.0 technologies could be developed which will not only classify fruit but have a significantly wider area of application.

9.6 Conclusion

In this chapter as short summary of the entire project was provided. The main research question was answered, showing that there is a visual technology available that will increase the productivity and quality of fruit classification making retaining labour economically viable. Thereafter, the practical and theoretical contributions of this project were discussed, showing that both practical and theoretical knowledge was contributed through the execution of this study. The limitations encountered were stated and recommendations to resolve these limitations were made. This chapter was then concluded by providing possible areas of future research so that more knowledge can be gathered when applying visual and other Industry 4.0 technologies. Thus, through the completion of this chapter this thesis is also concluded.

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Appendix A Farm Where Study Took Place

This appendix contains the information about the farm where the study took place as well as grading guidelines followed by the farm during the sorting and packing process.

A.1 The Farm

The farm where the study took place is in the Tzaneen area of South Africa. The farm has 30 to 40 ha of avocados trees currently producing fruit. Of the trees currently producing avocados, there is not one single dominant variety; rather the farm's trees are from 7 different varieties. However, when the study was done the fruit that were being harvested were Feurte. Therefore, the fruit predominantly studied and used to train the ML algorithm were Feurte. The farm was selected for two reasons. Firstly, a relationship had already been established between the farmer and the researchers, enabling the researchers to have access to the farm to test the prototype and data needed to do further analysis. Secondly, the farm is already starting to implement newer technologies such as a smart water-level monitoring system in their orchards. Therefore, it is more likely that the farm will be open to other new technologies.

A.2 Sorting Process Grading Guidelines

The two tables below are the avocado grading guidelines as provided by the South African Government [87].

Table A.1: Table describing the different characteristics of Class 1, Class 2, and Unclassified avocados as provided by the South African government [87]

Quality factor	Class 1	Class 2	Unclassified
(a). General appearance	Sound, attractive, clean, fresh, intact and true to cultivar	Sound, attractive, clean, fresh, intact and true to cultivar	*
(b). Shape	Well-formed and typical of the cultivar concerned	Well-formed and typical of the cultivar concerned	*
(c) $Maturity	Mature, firm, shall not show any signs of softening and with a maximum moisture content of: (i) Fuerte, Pinkerton, Reed, Rinton and Ryan: 80% (ii) Hass: 77% (iii) Any other cultivars: 75%	Mature, firm, shall not show any signs of softening and with a maximum moisture content of: (i) Fuerte, Pinkerton, Reed, Rinton and Ryan: 80% (ii) Hass: 77% (iii) Any other cultivars: 75%	Mature, firm, shall not show any signs of softening and with a maximum moisture content of: (i) Fuerte, Pinkerton, Reed, Rinton and Ryan: 80% (ii) Hass: 77% (iii) Any other cultivars: 75%
(d) Minimum fruit mass	100 g	100 g	*
(e) Cold damage			
(aa) Internal cold and frost damage	Total surface area, collectively or individually: May not exceed 100 mm^2	Total surface area, collectively or individually: May not exceed 100 mm^2	*
(bb) Damage due to low storage temperatures	Shall not occur	Shall not occur	*
(f) Foreign matter			
(aa) Visible chemical residues	No conspicuous drop marks or other continuous or localized deposits shall be allowed	No conspicuous drop marks or other continuous or localized deposits shall be allowed	
(bb) Other	Shall not occur	Shall not occur	*
(g) Pedicels	(i) If pedicels are present these may not be longer than 10 mm	(i) If pedicals are present these may not be longer than 12 mm	*

	(ii) The absence thereof is not considered a defect on condition that the place of stalk attachment is dry and intact	(ii) The absence thereof is not considered a defect on condition that the place of stalk attachment is dry and intact	*
(h) Malformation			
(aa) Epidermal notches	Not more than three notches, each with a maximum depth of 3 mm and which individually or collectively constitutes not more than 50% of the length of the fruit is permissible	Not more than five notches, each with a maximum depth of 3 mm and which individually or collectively constitutes not more than 60% of the length of the fruit is permissible	*
(bb) Epidermal bumps	Not more than three prominent bumps, each with a maximum height of 2 mm and a maximum of 3 mm in diameter, which occur on the skin and do not detrimentally affect the appearance of the avocado, is permissible: Provided that no injuries occur on the bumps and that small bumps caused by wind damage, insect damage or physiological disorders, have been disregarded	Not more than five prominent bumps, each with a maximum height of 6 mm and a maximum of 5 mm in diameter, which occur on the skin and do not detrimentally affect the appearance of the avocado, is permissible: Provided that no injuries occur on the bumps and that small bumps caused by wind damage, insect damage or physiological disorders, have been disregarded	
(cc) Bent necks	Maximum permissible as depicted in photo 2 of Set 14 of the Colour Charts	Maximum permissible as depicted in photo 3 of Set 14 of the Colour Charts	*
(i) Bruises			
(aa) Single bruise	Maximum total area shall not exceed 20 mm²	Maximum total area shall not exceed 20 mm²	*
(bb) Multiple bruises	Bruises with a combined surface area larger than 25 mm²: Provided that no bruise shall be more than 2 mm in depth	Bruises with a combined surface area larger than 25 mm²: Provided that no bruise shall be more than 2 mm in depth	*
(j) Cercospora spot	Maximum permissible as depicted in photo 1 of Set 9 of the Colour Charts: Provided that the blemish is dry and not cracked	/Maximum permissible as depicted in photo 3 of Set 9 of the Colour Charts: Provided that the blemish is dry and not cracked	

(k) (aa) Sunburn - yellow	Maximum permissible with regard to damage and intensity as depicted in photo 2 of Set 2 of the Colour Charts	Maximum permissible with regard to damage and intensity as depicted in photo 4 of Set 2 of the Colour Charts	*
(bb) Sunburn - brown	Maximum permissible with regard to damage and intensity as depicted in photo 2 of Set 3 of the Colour Charts	Maximum permissible with regard to damage and intensity as depicted in photo 3 of Set 3 of the Colour Charts	*
(cc) Sunburn - dark	Maximum permissible as depicted in photo 1 of Set 8 of the Colour Charts: Provided that if yellow and brown sun-burn is combined, it shall be individually within the specified limits: Provided further that dark sunburn is permissible if no cracks are present	Maximum permissible as depicted in photo 1 of Set 8 of the Colour Charts: Provided that if yellow and brown sunburn is combined, it shall be individually within the specified limits: Provided further that dark sunburn is permissible if no cracks are present	
(l) Carapace skin	Maximum area permis-sible as depicted in photo 4 of Set 4 of the Colour Charts	Maximum total area shall not exceed 80 mm²	*
(m) Hail damage	Maximum permissible as depicted in photo 3 of Set 5 of the Colour Charts: Provided that no hail mark shall be deeper than 2 mm	Maximum permissible as depicted in photo 4 of Set 5 of the Colour Charts: Provided that no hail mark shall be deeper than 2 mm	*
(n) Sooty mould	Maximum area permis-sible as depicted in photo 2 of Set 6 of the Colour Charts	Maximum area permis-sible as depicted in photo 2 of Set 6 of the Colour Charts	*
(o) Insect damage	Maximum permissible as depicted in photo 3 of Set 7 of the Colour Charts	Maximum permissible as depicted in photo 4 of Set 7 of the Colour Charts	*
(p) Other defects - internal			
(aa) Stem end decay	Shall not occur	Shall not occur	*
(bb) Vascular browning	Shall not occur	Shall not occur	*
(cc) Internal spot	Shall not occur	Shall not occur	*
(dd) Antracnose	Shall not occur	Shall not occur	*
(q) Other defects -			

xternal (aa) Cold damage on skin	Maximum total area shall not exceed 225 mm²	Maximum total area shall not exceed 400 mm²	*
(bb) Dothiorella rot	Shall not occur	Shall not occur	*
(cc) Anthracnose	Shall not occur	Shall not occur	*
(dd) Fruit fly damage	Shall not occur	Shall not occur	*
(r) Lenticel damage (aa) Hass	Maximum permissible on the worst side of the fruit as depicted in photo 4 of Set 10b of the Colour Charts: Provided that no diffusion of lenticels are allowed	Maximum permissible on the worst side of the fruit as depicted in photo 3 of Set 10b of the Colour Charts: Provided that no diffusion of lenticels are allowed	*
(bb) All other cultivars	Maximum permissible on the worst side of the fruit as depicted in photo 3 of Set 10 of the Colour Charts: Provided that no diffusion of lenticels are allowed	Maximum permissible on the worst side of the fruit as depicted in photo 4 of Set 10 of the Colour Charts: Provided that no diffusion of lenticels are allowed	*
(s) Netting - all cultivars	Maximum permissible on the worst side of the fruit as depicted in photo 4 of Set 11 of the Colour Charts	*	*
(t) Wind damage - Dark	Maximum permissible as depicted in photo 4 of Set 12 of the Colour Charts	Maximum total area shall not exceed 100 mm²	*
(u) Scale infestation	A maximum of 6 scale per fruit is permissible	A maximum of 6 scale per fruit is permissible	*
(v) Collectively for skin defects (corkiness, healed lenticels and sunburn)	Maximum area shall not exceed 6 cm²	Maximum area shall not exceed 100 mm²	*
(w). Unspecified internal or external quality defects not mentioned above	May deviate to the extent set out in Table 2	May deviate to the extent set out in Table 2	*

* Denotes no specification

$ Any consignment of fruit which does not comply with the maturity requirements shall be downgraded to Lowest Class and stamped/marked "Immature" --

Table A.2: Table Qualifying the different characteristics of Class 1, Class 2, and Unclassified avocados as provided by the South African government [87]

Quality Factor	Class 1	Class 2	Unclassified
(a) Decay (e.g. stem end decay, vascular browning, internal spot, anthracnose, dothiorella rot)	1%	5%	*
(b) Injuries	4%	6%	*
(c) Bruises	4%	6%	*
(d) Malformation			
(aa) Epidermal notches	10%	15%	*
(bb) Epidermal bumps	10%	15%	*
(cc) Bent necks	8%	15%	*
(e) Over maturity	6%	10%	*
(f) Visible chemical residues	5%	5%	*
(g) Cold damage			
(aa) Internal cold and frost damage	5%	10%	*
(bb) Damage due to low storage temperatures	Not allowed	Not allowed	*
(h) Blemishes:			
(aa) Skin damage, cercospora, sunburn (all types, exclucluding dark sunburn), carapace skin, hail damage, sooty mould, insect damage, lenticel damage, netting, dark wind damage	10%	15%	*
(bb) Dark sunburn	5%	10%	*
(i) Occurrence of scale: No fruit shall contain more than twice the number of scale per fruit with the exception of a tolerance of two fruits per consignment or 0,4% of the fruit examined, whichever is the greater: Provided the percentage of fruit with scale in excess of the number permitted per fruit, for the count in question, does not exceed 2%	10%	10%	*

exceed 2%			
(j) Mass range	10%: Provided that no avocados may be smaller or larger types, excluding range immediately below or above the declared minimum or maximum mass: Provided further that avocados which deviate 2% or less from the declared minimum mass or 10% or less from the declared maximum mass of the range shall not be taken into account	10%: Provided that no avocados may be smaller or larger than the mass range immediately below or above the declared minimum or maximum mass: Provided further that avocados which deviate 2% or less from the declared minimum mass or 10% or less from the declared maximum mass of the range shall not be taken into account	*
(k) Long pedicels	10%	10%	*
(l) Deviations from packing requirements as prescribed in regulation 5	One container per pallet	One container per pallet	*
(m) Deviations from marking requirements as prescribed in regulation 10	One container per pallet	One container per pallet	*
(n) All deviations including unspecified defects, combined: Provied that such deviations are individually within the limits as specified in regulations (a)< (b), (c), (d), (e), (f), (g), (h), (i), (j), and (k) of this table	15%	20%	*

Appendix B Image Segmentation

This appendix contains screenshots and a table which shows the implementation of the design steps contained in Chapter 5.

B.1 The URL and Prediction Key for the Code on the HoloLens

In section 5.3 it is stated that for Azure to connect to the HoloLens both the URL and the prediction key of the trained algorithm must be present. To show the implementation of both these variables a blue box has been drawn around each in Figure B.1 below. The data assigned to these two variables was done previously in the code.

```
using (UnityWebRequest unityWebRequest = UnityWebRequest.Post(predictionEndpoint, webForm))
{
    // Gets a byte array out of the saved image
    imageBytes = GetImageAsByteArray(imagePath);

    unityWebRequest.SetRequestHeader("Content-Type", "application/octet-stream");
    unityWebRequest.SetRequestHeader("Prediction-Key", predictionKey);
```

Figure B.1: Figure of a screenshot of the code containing the URL, ladled as the prediction endpoint, and prediction key

B.2 The Code Used to Get the Number of Pixels in an Avocado

In section 5.7.2 it was stated that the number of pixels contained in an avocado is counted as the number of pixels that have a larger green variable than red variable. The code used to determine the number of pixels can be seen in Figure B.2 below. An array img_Avo_Pixels was also created which is an image of the avocado with the counted pixels being black and the pixels not counted being white. This image was compared with the images of the avocados during development to ensure that the correct pixels were counted.

```
for (int i = 0; i < img_Avo_Pixels_1.Length; i++) //x-value
{
    if (img_Avo_Pixels_1[i].r*1 <= img_Avo_Pixels_1[i].g)
    {
        Pixels = Pixels + 1;
        img_Avo_Pixels_1[i] = new Color(1, 1, 1, 1);
    }
    else
    {
        //Pixels = Pixels + 1;
        img_Avo_Pixels_1[i] = new Color(0, 0, 0, 1);
    }

}
```

Figure B.2: Figure of a screenshot of the code used to count the number of pixels in an avocado using the r and g variable in the RGB colour vector

B.3 The Variables and Code Used in the Linear Regression Model

In section 5.7.2 the linear regression model is discussed. However, it is discussed in principle only and the actual values are not presented in that sub-section. Rather the linear regression model values and code used to implement it, are discussed below. MS Excel was used to determine the linear regression model values as can be seen in Table B.1 below. These values were then implemented when developing the code used to determine the size of the avocado as can be seen in Figure B.3 below. The predicted value of the avocado is labelled in Figure B.3 as variable "ADA".

Table B.1: Table showing the values of the different variables in the linear regression model used to determine the weight of the avocado

Variables	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Constant	-305011.7723	167224.0314	-1.823970932	0.074385277	-641238.2221	31214.67747	-641238.2221	31214.67747
Avocado_Distance	-10267.84903	4240.040706	-2.421639258	0.019278586	-18793.02225	-1742.675811	-18793.02225	-1742.675811
Avocado_Distance²	14342.85368	5554.339926	2.5822787	0.01292117	3175.104771	25510.60259	3175.104771	25510.60259
Avocado_Distance³	-6343.470896	2397.8833	-2.645446046	0.010995696	-11164.7384	-1522.203388	-11164.7384	-1522.203388
Avocado_Pixels	4128.989908	3019.876693	1.367271027	0.17790931	-1942.879136	10200.85895	-1942.879136	10200.85895
Avocado_Pixels²	-11219.77066	12263.95911	-0.914857148	0.364839748	-35878.11312	13438.5718	-35878.11312	13438.5718
Avocado_Pixels³	13000.80519	16091.09923	0.807950097	0.42310544	-19352.51821	45354.12859	-19352.51821	45354.12859
Marker_Distance	1302934.279	680627.6721	1.914312821	0.061551642	-65559.3757	2671427.933	-65559.3757	2671427.933
Marker_Distance²	-1658216.058	874142.8813	-1.896962263	0.063858462	-3415798.119	99366.00194	-3415798.119	99366.00194
Marker_Distance³	703165.694	374014.513	1.880049222	0.06617759	-48840.88565	1455172.274	-48840.88565	1455172.274
Marker_Pixels	-128283.5633	44410.57439	-2.888581493	0.005790209	-217577.0077	-38990.1188	-217577.0077	-38990.1188
Marker_Pixels²	120712.5144	41918.99873	2.879661205	0.00593133	36428.71855	204996.3102	36428.71855	204996.3102
Marker_Pixels³	0	0	65535	#NUM!	0	0	0	0

```
float Constant = (float)-305011.7723;
float Avocado_Distance = (float)-10267.84903;
float Avocado_Distance2 = (float)14342.85368;
float Avocado_Distance3 = (float)-6343.470896;
float Avocado_Pixels = (float)4128.989908;
float Avocado_Pixels2 = (float)-11219.77066;
float Avocado_Pixels3 = (float)13000.80519;
float Marker_Distance = (float)1302934.279;
float Marker_Distance2 = (float)-1658216.058;
float Marker_Distance3 = (float)703165.694;
float Marker_Pixels = (float)-128283.5633;
float Marker_Pixels2 = (float)120712.5144;
float Marker_Pixels3 = (float)0;


float ADA1 = Constant;
float ADA2 = (float)lastLabelPlaced.position.z * Avocado_Distance;
float ADA3 = (float)lastLabelPlaced.position.z * (float)lastLabelPlaced.position.z * Avocado_Distance2;
float ADA4 = (float)lastLabelPlaced.position.z * (float)lastLabelPlaced.position.z * (float)lastLabelPlaced.position.z * Avocado_Distance3;
float ADA5 = (float)n_Pixels * Avocado_Pixels;
float ADA6 = (float)n_Pixels * (float)n_Pixels * Avocado_Pixels2;
float ADA7 = (float)n_Pixels * (float)n_Pixels * (float)n_Pixels * Avocado_Pixels3;
float ADA8 = (float)f_Marker_z * Marker_Distance;
float ADA9 = (float)f_Marker_z * (float)f_Marker_z * Marker_Distance2;
float ADA10 = (float)f_Marker_z * (float)f_Marker_z * (float)f_Marker_z * Marker_Distance3;
float ADA11 = (float)f_Marker_Pixels * Marker_Pixels;
float ADA12 = (float)f_Marker_Pixels * (float)f_Marker_Pixels * Marker_Pixels2;
float ADA13 = (float)f_Marker_Pixels * (float)f_Marker_Pixels * (float)f_Marker_Pixels * Marker_Pixels3;

float ADA = ADA1 + ADA2 + ADA3 + ADA4 + ADA5 + ADA6 + ADA7 + ADA8 + ADA9 + ADA10 + ADA11 + ADA12 + ADA13;
```

Figure B.3: Figure of a screenshot of the code where the various variable in the linear regression model was utilised to determine the weight of the avocado, ladled ADA

B.4 The Code Used to Identify the Size and Class of Each Avocado

In section 5.8 Figure 5.10 the output of the code developed in Figure B.4 can be seen. The logic of the code written in Figure B.4 is as follows: the class 3 avocados are identified using the class predicted by Azure; the avocado size is predicted using the code in Figure B.3 ; the class of the avocado is then also identified using the class predicted by Azure; if the weight of the avocado is such that it is neither size 12, 14, 16, 18, nor 20 then the avocado is also classified as a class 3 avocado.

```
if (bestPrediction.tagName == "Class 3")
{
    lastLabelPlacedText.text = "C-3";

}

else

{
    if ((ADA > 300) && (ADA <= 371))
    {
        if (bestPrediction.tagName == "Class 1")
        {
            lastLabelPlacedText.text = "C-1 / S-12";
        }
        else
        {
            lastLabelPlacedText.text = "C-2 / S-12";
        }
    }
```

Figure B.4: Figure of a partial screenshot of the code used to determine the size and class of each avocado

In section 5.8 Figure 5.11 the output of the code developed in Figure B.4 and Figure B.5 can be seen. The code in Figure B.5 simply identifies the avocado of a desired class and size and labels these avocados with an “x”. These avocados will then be packed. In the code for this prototype, the size and class of the avocados to be packed were assigned randomly. In a more sophisticated system complicated software can be developed to determine which avocados should be packed.

```
if (lastLabelPlacedText.text == "C-2 / S-14")
{
    lastLabelPlacedText.text = "x";
}
else
{
    lastLabelPlacedText.text = "";
}
```

Figure B.5: Figure of a screenshot of the code where the label given to each avocado, as developed in Figure B.4, is used to display only an “x” on the avocados of the desired size and class to be packed

Appendix C Packing Facility Cost for a Small Farm

The farm where this study took place provided the costing data with which to calculate how much they are paying to pack at packing facilities. This data will enable a more accurate calculation of the price for small farmers when they utilise a packing facility.

C.1 Packing Facility Cost Using the Data Provided

The costing data made available can be seen for export avocados in Table C.1 and avocados sold locally in Table C.2. The results indicate that a cost of R82.47 and R45.82, the difference between the "Price p/ctn" and "Final Price p/ctn rounded, per box was charged to pack for export and locally sold avocados respectively. A detailed breakdown of the costs for export avocados is not provided to the farm where the case study took place, but it is for avocados that are packed which are sold locally. This breakdown can be seen in Table 7.7 and Table C.3 and is summarised in Table C.4. Table 7.7 shows the cost breakdown of 11 shipments, which amounted to 446 boxes of avocados sold locally in 2020. From this table the transport costs can be seen. These costs are not related to sorting and packing, and these will still need to be undergone. The transport cost per box on average in Table 7.7 is R5.13 per box.

Table C.1: Table showing the invoice of 10 shipments of avocados which were exported in 2020 [72]

Inv No	Type	Cultivar	Cartons	Price per c	Overseas cost	FOB	Local Cost	DIP	Cost per carton	Ave per Kg DIP	Ave cost per kg	Kg	Gross	Cost	DIP total
FP2002964	Export	Hass	42	R274.43	-R 84.80	R190.03	-R 173.31	R 16.72	R 257.71	R 1.67	R 64.43	168	R 11 526.06	R 10 823.82	R 702.24
FP2003063	Export	Rintin	264	R 90.75	R -	R 90.75	-R 44.15	R 46.60	R 44.15	R 11.65	R 11.04	1056	R 23 958.00	R 11 655.60	R 12 302.40
FP2003074	Export	Hass	104	R125.80	-R 23.10	R102.79	-R 79.59	R 23.20	R 102.60	R 4.50	R 25.65	416	R 13 083.20	R 10 670.40	R 2 412.80
FP2003111	Export	Hass	34	R303.73	-R 59.62	R244.11	-R 174.84	R 69.27	R 234.46	R 6.93	R 23.45	340	R 10 326.82	R 7 971.64	R 2 355.18
FP2003271	Export	Ryan	1 021	R 92.60	R -	R 92.60	-R 40.35	R 52.25	R 40.35	R 13.06	R 10.09	4084	R 94 544.60	R 41 197.35	R 53 347.25
FP2003282	Export	Ryan	11	R180.43	-R 19.92	R160.50	-R 74.05	R 86.45	R 93.98	R 21.61	R 23.50	44	R 1 984.73	R 1 033.78	R 950.95
FP2003283	Export	Ryan	1050	R185.58	-R 20.81	R164.77	-R 75.81	R 88.96	R 96.62	R 22.24	R 24.16	4200	R194 859.00	R101 451.00	R 93 408.00
FP2001959	Export	MHH	94	R267.13	-R 34.54	R232.59	-R 151.41	R 81.18	R 185.95	R 8.12	R 18.60	940	R 25 110.22	R 17 479.30	R 7 630.92
FP2002178	Export	MHH	286	R240.72	-R 26.58	R213.87	-R 84.61	R129.26	R 111.46	R 32.32	R 27.87	1144	R 68 845.92	R 31 877.56	R 36 968.36
FP2002385	Export	Pinkerton	232	R162.88	-R 25.98	R136.90	-R 80.13	R 56.77	R 106.11	R 14.19	R 26.53	928	R 37 788.16	R 24 617.52	R 13 170.64
Total	**Export**	**All**	**3138**	**R153.61**	**-R 14.96**	**R138.64**	**-R 67.49**	**R 71.14**	**R 82.47**	**R 136.29**	**R 255.29**	**13 320**	**R482 026.71**	**R258 777.97**	**R223 248.74**

Table C.2: Table showing the invoice of 11 shipments of avocados which were sold locally in 2020 [72]

Comm	Variety	Grade	Pack	Size	Ctns Paid	Price p/ctn	Overseas Cost p/ctn	FOB	Local Cost p/ctn	DIP	Producer Cost p/ctn	Final Price p/ctn
AV	FUE	1	A04L	12	15	137.63	0	137.63	-14.93	122.71	-23.58	99.13
AV	FUE	LC1	A04L	12	6	113.06	0	113.06	-12.89	100.17	-23.58	76.59
AV	FUE	LC1	A04L	14	85	147.37	0	147.37	-16.15	131.22	-23.58	107.65
AV	FUE	LC1	A04L	16	108	152.48	0	152.48	-16.63	135.85	-23.58	112.28
AV	FUE	LC1	A04L	18	92	142.98	0	142.98	-15.73	127.25	-23.58	103.67
AV	FUE	LC1	A04L	20	107	144.29	0	144.29	-15.85	128.43	-23.58	104.86
AV	FUE	LC1	F20S	POLY	11	606.4	0	606.4	-69.19	537.2	-78.58	458.62
AV	FUE	LC1	A04L	12	2	81.9	0	81.9	-9.32	72.57	-23.77	48.8
AV	FUE	LC1	A10L	30	3	195.2	0	195.2	-23.54	171.66	-59.16	112.5
AV	FUE	LC1	A10L	32	2	195.2	0	195.2	-23.54	171.66	-59.16	112.5
AV	FUE	LC1	F20S	POLY	15	417.86	0	417.86	-50.05	367.8	-81.97	285.84
Total	**Export**	**All**	**All**	**All**	**446**	**R 166.83**	**R -**	**R 166.83**	**-R 18.52**	**R 148.31**	**-R 27.30**	**R 121.02**

After taking the transport costs into consideration the market costs need to be considered. This is normally covered by the packing facility so it will need to be subtracted to determine the cost saving. The market costs can be seen in Table C.3. This table shows the total average market cost per box of avocados to be R12.64.

Table C.3: Table showing the total average market cost per box sold as determined from 8 statements showing the market cost breakdown provided by the farm where the case study took place [72]

Statement number	1	2	3	4	5	6	7	8	Total
Number of boxes	288	272	36	15	82	28	3	9	733
Total costs	-R 3 588.06	-R 3 927.33	-R 346.44	-R 149.74	-R 750.05	-R 274.11	-R 60.38	-R 171.07	-R 9 267.18
Market fees	-R 1 324.80	-R 1 450.44	-R124.20	-R48.88	-R271.41	-R 96.84	-R24.15	-R 68.43	-R 3 409.15
Avocado levy	-R 264.96	-R 290.09	-R 24.84	-R 9.78	-R 54.29	-R 14.77	R -	R -	-R 658.73
Agent commission	-R 1 987.20	-R 2 175.70	-R186.30	-R73.31	-R407.10	-R145.25	-R36.23	-R102.64	-R 5 113.73
Bank costs	-R 11.10	-R 11.10	-R 11.10	-R17.77	-R 17.25	-R 17.25	R -	R -	-R 85.57
Market cost per box sold	-R 12.46	-R 14.44	-R 9.62	-R 9.98	-R 9.15	-R 9.79	-R 20.13	-R 19.01	-R 12.64

Finally, the total packing, sorting, and packing facility costs can be calculated. The final cost per box as experienced by the farm where the case study took place can be seen in Table C.4. In this table the transport cost, market cost, and cost of the actual box is deducted from the cost charged by the packing facility for a box of avocados sold locally. Therefore, the R21.25 is the cost that the farm where the case study took place will save if they decide to insource their packing and sorting operations. The difference between the cost determined using benchmark data and the actual cost experienced by the farm where the case study took place is R10.55. This is approximately double the cost calculated using the benchmark data.

The R21.25 is the cost for the packing and sorting of locally sold avocados. The same detailed calculation with which the R21.25 was calculated can unfortunately not be done for export avocados as the same detailed cost breakdown is not available. If it is assumed that the same difference exists for export boxes, then it will cost R23.25 per box to pack boxes of avocados for export.

Table C.4: Table showing the actual activity cost of packing and sorting a box of avocados as well as the levies charged by a packing facility for a box that will be sold locally experienced by the farm where the case study took place, as small farm [72]

Cost of packing a box as invoiced by packing facility	**R 45.82**
Additional costs when insourcing	**-R 24.58**
Transport	-R 5.13
Market fees	-R 12.64
Box costs	-R 6.80
Packing, sorting, and packing facility attributed costs	**R 21.25**