Industrial augmented reality as an approach for device identification within a manufacturing plant for property alteration purposes

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Declaration

I, **TSHEPO GODFREY KUKUNI**, student number , do hereby declare that this research project, which has been submitted to the Central University of Technology, Free State, for the degree DOCTOR OF ENGINEERING IN ELECTRICAL ENGINEERING, is my independent work and complies with the code of Academic Integrity, as well as the other relevant policies, procedures, rules and regulations of the Central University of Technology, Free State, and has not yet been submitted before by any other person in fulfilment of the requirement of any qualification.

T.G KUKUNI Date: June 2021

Signature:

Dedication

Tshimologo ya botlhale kego tshaba morena; go itse moitshepi ke yona tlhaloganyo (Diane 9:10)

The fear of the Lord is the beginning of wisdom, and knowledge of the holy one is understanding (Proverbs 9:10).

I dedicate this thesis to the following late personnel who meant a lot to me: Pule John Kukuni, Jackson Kgowe, Kereng Kukuni, France Kukuni, Tebogo Kukuni, Gomolemo Kukuni, Eva Kgowe, and Beauty Malebo, who believed and invested in my education.

I further dedicate this thesis to my beloved grandmother, Mamoitatli Dorcas Kukuni, and my parents, Monnapule Elby Modise and Pulane Lorraine Modise. Additionally, to both the Kukuni and Modise families, as well as my siblings, Matshidiso Evelyn Modise, Madintletse Modise, Rearabetswe Portia Modise and Kgosietsile Modise and my cousin, Itumeleng Goodenough Ditlhage, and the family at large, as well as Mr Edwin Malebo, who gave me the chance in life when I started with my career and for all the support they have shown to me throughout this study.

Ke rata go leboga Thaba-Nchu Circuit YMG Vice President Tshediso Moilwa le President Max Mokhotswa le Calvary Methodist YMG President Akhona Gxamza le Vice President Yandi Galade mmogo le phuthego yotlhe ya Selosesha le Calvary Methodist Church YMG ka dithapelo le di kgothatso tseo bang mphileng tsone gore kebe ke falole dithuto tsaka.

Owing to the Covid-19 pandemic that the world has experienced in late 2019 towards the beginning of 2020, we would like to pass our sincere condolences to all the families around the world that have lost their beloved ones.

Go home, my people, and lock your doors! Hide yourselves for a little while until the LORD's anger has passed. (Isaiah 26:20)

Modimo wa Kgotso le poloko abe le rona…ka lebitso la Ntate, lela Morwa lela Moya o Boitshepo ….Amen.

Acknowledgments

I thank All Mighty God, the Holy Spirit, and Lord Jesus Christ for affording me the opportunity to study and the strength to complete this research, as well as to provide funding for my studies, even though it wasn’t an easy journey.

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Thanks to Thaba-Nchu (Selosesha) community for continuous efforts to support and rebuild our town.

Knowledge is in the past and not the future, while ignorance is in the future because it hasn’t experimented.

Abstract

The introduction of 3D computer graphics has led to an increase in the processing capacity of the computational units monumentally, along with speed, memory and transmission bandwidth. Augmented Reality (AR) has modelled remarkable progress towards real-world consumer applications. Considering the fact that mass production occurs daily in the manufacturing plants with large sums of wastage, caused either by human error, load-shedding (power outage), machine malfunction, or the time it takes the engineers to identify and fix the problem, are observed in high volumes.

Therefore, the need to identify strategies and solutions to reduce such problems on-site with accurate data, rather than outsourcing or depending solely on the Supervisory Control and Data Acquisition (SCADA) system data, which might damage the integrity and economy of the manufacturing plant, needs to be developed and implemented.

In a controlled network, identification and detection of a component in the process are difficult without prior knowledge and background in the design and implementation process.

Thus, the concept of device identification with the aid of augmented reality, utilising markerless identifiers, such as machine vision, other than Quick Response Codes (QR codes) or Radio Frequency Identification (RFID), needs to be investigated.

It is because of such reasons that the deployment of new types of technologies, such as “augmented reality” and “machine vision” need to further be investigated to obtain the device details, based on their positions and features within the indoor manufacturing plant to procure and commercialise this solution technology.

This study proposes an optimal and efficient model, utilising machine vision application to detect and identify devices, based on their positions and features within the manufacturing plant with the aid of an augmented reality application for extending the device details.

The study has outlined a machine vision application developed for object detection, based on colour and shape. Additionally, another method based on the augmented reality application was developed for the identification and augmentation of device details, based on the feature and position of the device within the indoor manufacturing plant. The study proved to be very successful in the identification and detection of objects, making use of machine vision algorithms, namely colour, shape and Canny Edge detection and the identification of devices (robotic arm and motors), based on their features and position within an indoor manufacturing environment set-up.

For the optimal efficiency of this model, the Simultaneous Localisation and Mapping (SLAM) algorithm (ORB-SLAM) was used, in conjunction with the bundle adjustment algorithm as an alternative solution in the absence of the user built-in maps for the calculation of the device positions, based on the uncertainties of the exact locations within the indoor manufacturing environment set-up.

However, some of the shortcomings were identified and addressed, such as the communication speed and the room's light conditions, which impacted the sensing of the camera to detect the correct objects. These shortcomings were, however, addressed by conducting two studies, namely the day and night study to compare the best light settings and also to reduce the distance between the devices and the AR application to compensate for the communication speed issues.

The scientific contribution of this study is the recognition of components by means of vision identification within such a process within an indoor manufacturing set-up. By means of identification, the user will have the capability to view and adjust the parameters of the process in a scaled plant. This contribution makes use of a modelled JPEG image. An AR image that the user can identify the devices apart from, relying on the SCADA system alone, was physically modelled on Blender3D for utilisation in Unity3D, as opposed to utilisation of any image and referencing it which would make the process tedious and reduce the processing speed. Subsequently, it has been depicted as part of a new knowledge contribution, that the identification of the devices can be achieved by placing the smartphone at any angle of the device (robotic arm or motor), and the detection and augmentation will be achieved without any change in the settings.

As part of result validation, a video was taken and uploaded on YouTube to receive a user perspective on the developed AR application. After the video upload, a survey was shared with 20 individuals, together with the YouTube link to indicate a broader base evaluation. However, the results came back positive with the majority of the sample individuals recommending the adoption of the application and its utilisation in the scaled manufacturing plant.

In addition to the results verification, a SCADA model was developed in National Instruments^{TM} Labview^{TM} and was integrated with the AR application for evaluation purposes. The results showed that the AR application doesn't require any alteration, despite utilising a different SCADA model in different software applications, provided that the array index is the same. Only when the array index differs, is it that alterations are necessary utilising the AR application in order to have

the same array elements and avoid having a null index that might cause the application to crash or not to debug. It is therefore noted that the AR application is compatible and reliable for integration with other SCADA models without alteration requirements.

The entire work outlined in this thesis was validated by two sets of physical experiments, namely GPS-based detection, and the ORB-SLAM, integrated with the Bundle Adjustment algorithm for feature and position detection. However, despite the prior knowledge of the GPS's inconsistent operation within a scaled indoor environment, it was necessary to perform the test to obtain more insight into this inconsistency and inaccurate data results.

Acronyms, Abbreviations

IAR	Industrial Augmented Reality
AR	Augmented Reality
VR	Virtual Reality
MR	Mixed Reality
SCADA	Supervisory Control and Data Acquisition
MV	Machine Vision
CV	Computer Vision
APP	Application
MD	Mobile Device
MC	Mobile Camera
RA	Robotic Arm
OpenCV	Open Source Computer Vision Library

Keywords:

Augmented Reality

Mixed Reality

Virtual Reality

SCADA

Manufacturing Plant

Computer Vision

Machine Vision

OpenCV

Camera

Robotic Arm

Motor

Markerless Marker

Emgu CV

N.B. The following words are used interchangeably in this thesis

i. Position and Location

ii. Manufacturing environment and Manufacturing factory or Manufacturing plant

iii. Components and Apparatus

Table of Contents

List of Figures

List of Tables

Chapter 1: Introduction to the study

This chapter outlines the study overview, research problem, aim & objectives, contribution to knowledge, proposed exploration process, hypothesis, and the achieved study with the chapter layout necessary for developing the progress report and easy tracking of each chapter`s aim.

1.1. Introduction

In recent years, the introduction of 3 Dimensional (3D) computer graphics has led to an increase in the processing capacity of the computational units monumentally, along with transmission bandwidth, memory, and speed. This has spurred enthusiasm for further research in the field of Mixed Reality (MR). The research in Augmented Reality (AR) has modelled remarkable progress towards real-world consumer applications, such as health and manufacturing.

It is with such reasons that AR technologies have naturally attracted the attention of many researchers and lately are attracting the subject of extensive research within the field. In 2014, Google turned the Virtual Reality (VR) world upside down when it released Google Cardboard. Google Cardboard (GC) is regarded as an extremely low-cost head-mounted virtual reality system that can be purchased for as little as $15, which amounts to R216.62 in South African Rand [1, p. 1].

Furthermore, many approaches make use of Image Processing (IP) in either a 2 Dimensional (2D) or 3D platform to detect obstacles, based on a variety of components, such as colour, size, and shape. However, the use of 2D technology alone is not enough to overcome the performance shortcoming of the IP. It has been observed that visual inspection and the quality in the manufacturing environment are performed by human experts, however, it is not an easy task to find people with such skills [2]. The inclusion of both histogram and 3D features are based on unique techniques, which together with the 2D feature are used to overcome the performance of other techniques relying only on the topological features [3, pp. 137-143]. The reason for citing this reference is due to its historical contribution towards the growth in mixed reality technology.

VR is defined as a completely computer-generated, engrossed, and three-dimensional environment that is displayed either on a computer screen or through a special stereoscopic display, such as

Oculus Rift [4, pp. 344-349]. In addition to the VR concept, sophisticated VR platforms can also be implemented. However, the term “sophisticated” in this context is aligned with the wrap-around display screens, such as actual VR rooms and wearable computers.

VR application can be transmuted into an AR application by adding real elements, such as the live video feeds to the virtual world. Acquiring information about the surrounding objects effectively is a crucial factor for many people, including people with disabilities, such as the blind.

The introduction of AR, which is denoted as a powerful user interface technology that augments the user`s environment with computer-generated entities [5, p. 1], is very crucial in this study.

In an AR technology setup, the information about reality becomes more interactive between the user`s perceptions of the real and virtual world. The perception happens through the application of real-time object detection and recognition algorithms that enable recognition of the surrounding objects in the real environment to align the computer-generated images with the objects in the AR view [6, p. 1]. In invariance with VR, users can see virtual objects and the real world concurrently in an AR system.

Since both VR and AR are virtual objects related phenomenon, the concept of enhancing the illusions that the virtual objects are present in a real scene, has led to more research with attention focusing on the occlusion problem.

Occlusion refers to the occurrence of the real-world objects being in front of the virtual objects in a scene [7, p. 2886]. However, the information can be inserted in a contextual-dependant way, which therefore allows AR to act as a substitute for the traditional assembly.

The concepts of utilising AR technology as a possible Quick Response (QR) improved system through the use of Machine Learning (ML) by integrating, a well-known AR toolkit can be utilised. The integration is proposed as a good way to obtain good reputation data, because of the easy-to-use automated and robust toolkit [8].

Furthermore, the basic concepts in AR applications are dependent on the identification of real-world objects on the screen by tracking them, then augmenting the scene with an artificial object. Tracking is often combined with some estimation of the correct 2D or 3D world coordinates, for proper placement of augmentations in the scene. In addition, the applications can further be discriminated into building artificial markers for object detection and those with the ability to use “natural” image features [9], [10], [11].

However, for this study, markerless identifiers are denoted for the use of the feature and location device identification, as opposed to the use of QR codes.

1.2. Problem statement

Despite the perceived advantages that augmented reality brings in the Fourth Industrial Revolution (4IR) concept, there have been constraints associated with the AR technology. The predominant constraints are categorised into two, namely technology and environment.

Technological constraint on Mobile Augmented Reality (MAR) is aligned with the resources on most smart devices. These constraints are substantiated predominantly with limited memory, limited computational capability, as well as limited graphics capability. It is for such reasons that AR capabilities need to be further investigated, concerning object detection, recognition, and identification within a manufacturing environment set-up.

The use of Supervisory Control and Data Acquisition (SCADA), as a centralised platform in large manufacturing environments, has led to several questions emerging, since it is used both as a control system and as a feedback communication platform between the systems and the users. Due to this factor, companies lose vast amounts of money, due to the late detection of faults within the devices, such as motors and robotic arms.

In a control network, the identification of a component in the process is difficult without the knowledge and background in the design and implementation process. Therefore, the concept of device identification, with the aid of augmented reality utilising identifiers, such as machine vision other than QR code and RFID needs to be investigated.

The challenge currently experienced by the industry is to develop, implement and integrate MR systems, such as VR and AR systems by ensuring that both technologies can augment manufacturing operations, as well as deliverables of cost-effectiveness and time-efficiency and ameliorate the quality of service and products (QoS).

1.3. The objective of the study

i. To prove that vision identification (id) could be used for device identification, rather than tags or QR codes;
ii. To use AR technology for identification of the robotic arm angles in the manufacturing plant;
iii. To develop a testbench that operates as a manufacturing plant;
iv. To determine the device details by means of their position in the process within the manufacturing environment.

1.4. Proposed exploration process

A key upcoming type of technology called Mixed Reality (MR) will be used in the same principle in which the QR technology has upgraded the barcode technology. The device tracking will be utilising the Mobile Device (MD) camera, machine vision, augmented reality, and SCADA technology.

Augmented reality is regarded as the computer technology that enhances real environments through visual represented information which has the following features:

i. Object tracking;
ii. Ability to superimpose virtual objects onto a user`s view of a real-world scene;
iii. The positioning of virtual objects in a real-world scene;
iv. To combine real-world images with virtual images in real-time.

Machine Vision (MV) is defined as a piece of knowledge and approach cast-off to provide an image-based automatic examination for quality control, process control, and robot guidance [12, p. 1].

The sensory part of the system will have the input functionalities from the sensors for reading in the device`s temperature, light conditions from light, device number, and humidity and write out the outputs for a pneumatic on the SCADA`s Graphical User Interface (GUI).

The application design for this study will be used for detecting the factory phenomena, such as temperature and device position, which are obtained from the SCADA. Then, the SCADA will also act as the control system to control the movement of the motors, robotic arms and also to direct the conveyer belt within the manufacturing environment.

1.5. Limitations of the study

To achieve the objectives of the study, it is limited to:

i. The design and development of a small-scale manufacturing plant;
ii. SCADA and AR application to provide a more significant and increased productivity time during the motor operational inspection in the manufacturing plants;
iii. The system implementation will be based on three phenomena, namely automation, sensing, and vision, using the SCADA system augmented reality and machine vision.

1.6. Achieved study outcomes

To successfully measure the study outcomes, a physical testbench was developed to test the prototype in a physical environment; additionally, the augmented reality application is the focus or main technological area of focus in this thesis.

Therefore, as the AR application is the focus area of this research study, it is important to physically develop this technological application and test its feasibility for detection, recognition, and alteration of properties in the manufacturing plant.

In addition, the data augmentation of the devices (robotic arms and motors) is important, based on the identification of devices utilising their positions in the process.

i. A physical testbench operation, based on SCADA's functionality in a manufacturing environment.
ii. Development of an AR application used to detect and recognise the devices within a manufacturing environment with the ability to determine their position by means of vision.
iii. Obtaining the device information by means of augmented data, based on the device position and feature in the process.

1.7. Hypothesis

Several hypotheses are derived for this research study:

i. By developing a built prototype of an AR model, the detection and identification of motor information will be obtained;

ii. By integrating multiple libraries containing algorithms relating to image processing, a corresponded computation of the object signature will be developed in 3D technology;

iii. By developing a testbench for a manufacturing plant, the SCADA control system will be developed for controlling the devices and the conveyor belt.

1.8. Contribution to knowledge

i. Recognition of automation components by means of vision identification within such a process.

ii. By means of identification, the user will have the capability to view and adjust the parameters of the process in a scaled plant.

iii. Identification of devices from any angle utilising AR application.

iv. Transmission of sensory and angular data from the SCADA system to the AR application to prove the concept of data matching and data identification between the SCADA system and the AR application without human intervention.

v. Improving data transfer between the sensory data stored in the SCADA database and by demonstrating how it can be improved through the AR application.

1.9. Publications and presentations during the study

During the journey of this study, the following articles and journal papers were presented and published:

i. T.G Kukuni, Dr B. Kotze. "Industrial Augmented Reality (IAR) As an Approach for Device Identification within a Manufacturing Plant for Property Alteration Purpose", The

Fourth International Conference on Applications and Systems of Visual Paradigms, 30 June 2019 – 04 July 2019, Rome, Italy.

1.10. Thesis structure

This thesis has been structured into five chapters as follows:

Chapter 1 is an introductory chapter to the thesis study, outlining the background, problem statement, objectives, contribution to knowledge, proposed exploration process, and hypothesis for the research conducted.

Chapter 2 provides an overview of augmented reality and computer vision components, then advances to the review of related work in the field of industrial augmented reality and outlines the shortcomings relating to them focusing on markerless tracking identifiers.

Chapter 3 describes the development of the physical model comprising of augmented reality applications, built on Unity3D and simulated on an Android platform. Furthermore, the development of machine vision based on object detection and recognition, utilising OpenCV and Emgu CV and their integration with SCADA development GUI on Microsoft® Visual Studio® 2012 are discussed.

Chapter 4 focuses on the analyses of results obtained from the developed prototype in chapter 3. The results are evaluated, analysed, and discussed to assess the feasibility of commercialising the product and the merits of the study in achieving the study`s objectives and hypothesis**.**

Chapter 5 refers to the study conclusion, as well as the suggested future work in augmented reality and machine vision platforms, focusing on the improvements of computer applications, based on augmented reality in the manufacturing industry. The future works are also outlined with the essential work that can still be improved from this study.

Chapter 2: The review of AR applications

This chapter appraises the theoretical overview of the existing AR systems for both mobile and industrial use.

2.1. Introduction

Augmented Reality (AR) is outlined as an enabling technology for the user to experience a virtual world with the perception of the real world. AR technology has the advantage of many possible applications in a vast range of fields, such as laboratories, education, military, health, and manufacturing. However, despite AR technology recently surfacing, it has been observed that this technology has been around for approximately 60 years with the first prototype being developed by Sutherland in the late 1960s [13, pp. 757-764], and this citation is used due to its historical contribution to the subject.

Industrial Augmented Reality (IAR) is defined as a disregarded photo-based augmentation that has proved to be effective in an industrial process [14, pp. 355-385]. However, the reference citing the IAR is derived from the old definition of the word. It is, however, believed that the definition changed as a result of the emerging technology when the word "IAR" was merged with "application" to be Industrial Augmented Reality Applications (IARA). IARA is defined as systems used in a product lifecycle process, utilising the concept of the spatially aligned and interactive overlay of computer-generated information in a working context [15, p. 287]. The existing systems and approaches on machine vision and data control, utilising SCADA are reviewed together with their shortcomings.

2.2. Review on approaches of the existing systems in the field of AR

In recent years, computers have gained a great deal of popularity due to their capability to make human life much easier. As the growth and improvement in technology inflated, mobile devices also gained widespread recognition and are considered a technological game-changer due to their powerful processors. According to Milgram *et al.* [16], "Augmented Reality: A class of displays on the reality-virtuality continuum, Telemanipular and Telepresence Technologies" present the AR definition as a continuum figure where he outlines the closeness of the AR system to the real environment and Augmented Virtual (AV - closer to the virtual environment), which both lie between the real environment and virtual as indicated in Figure 2.1.

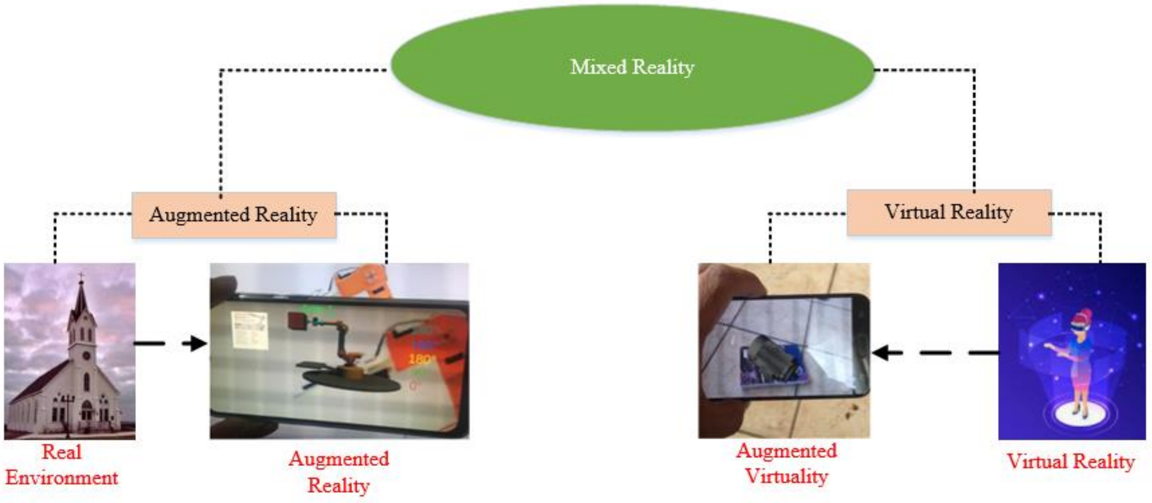


Figure 2.1: Reality-Virtuality Continuum *[16]*.

Milgram`s definition of AR is supported by Azuma and Stapleton, however, Milgram did not include the 3D aspect of the AR technology. Moreover, Gausemeier *et al.* [17, p. 2003], in, "Development of a real-time image-based object recognition method for mobile ar-devices ", developed an application of interest in the information display. Gausemeier`s study focused on image-based object recognition and tracking for AR applications, for inserting information into the user's field of view through the mobile device system. Gausemeier's model's fundamental basis development is aligned with the 3D-CAD file to the 3D model of the derived object. From the video point of view, Gausemeier used the streams, edges, colour, and textile information. However, Gausemeier`s method is based on extracted pictures for filtering and comparison, as compared to utilisation of a live video in real-time for object detection and identification.

Silva *et al.* [18, p. 5] in their paper, "Applying Object Recognition and Tracking to Augmented Reality for Information Visualization" outlined the method of utilising the Bayesian Network Model, by calculating the probability of an event. Silva`s model is a simplified model based on the Jensen Bayesian network model [19]. However, Silva classifies this model as a simplified model by discarding the third element, which in this case, is the texture, and focuses his study only on the colour and shape.

With this said approach, a new approach of augmented reality, based on "Server-side object recognition and client-side object tracking for mobile augmented reality" by Gammeter *et al.* [20] emphasises the capability of a hybrid client-server approach on an android platform.

However, Gammeter supports the idea that the introduction of smartphones has significantly assisted the AR technology, due to their increased processing capabilities. In addition, Gammeter further highlights the client-server approach as the first system that demonstrates a complete pipeline for augmented reality on smartphones due to the following reasons:

i. The ability to recognise objects built on a multi-modal combination of visual features and sensor measurements.
ii. Retrieval of the database, using vocabularies of local visual features.

However, through the evidence provided by Gammeter, there is a window for debate. The integration of multiple systems onto a single platform does not automatically grant the completeness of any kind of technology or system.

Furthermore, the evidence concerning this discipline is supplied by Hoffmann *et al.* [21], in, "Commissioning of manufacturing systems, a review and new approaches for simplification" who highlight that by interfacing the virtual model with a Programmable Logic Controller (PLC), then possibly testing the control software through simulation before the real system can be realised. However, for the current study, only the physical models with augmented reality simulations will be accounted for.

Antonijevic *et al.* [22, p. 1] in, "Augmented Reality for Substation Automation by Utilising IEC 61850 Communication" highlight the combination of IEC 61850 features with augmented reality technologies for providing added value visualisation capabilities in the substation automation domain. However, Antonijevic's study is not making use of WiFi connectivity as the mode of data transfer communication tool, and also the augmented reality is still based on device identification utilising QR codes rather than machine vision.

Dos Reis *et al.* [23, p. 1] in, "Visualisation of Power Systems Based on Paranomic Augmented Environments" present an application that uses Paranomic Augmented Environments to extend the information shown to power systems operators by supporting data interpretation, monitoring, and manipulation. Dos Reis's study is based on a live environment and has proved the feasibility of Industrial Augmented Reality.

In addition to Industrial Augmented Reality, Marcincin *et al.* [24], present a new attitude in imaging of a combined working environment and its practicality realisation, based on the principle of the utilisation of a half-silvered surface, which provides the advantages for displaying AR objects directly in the working view of the user and free motion without hardware device connectivity.

The industrial revolution has been realised, due to the management of large amounts of data, connected to the whole value chain of the digital technologies and the adoption of digitalisation for strategic manufacturing and logistic, as well as putting Machine to Machine (M2M) communication between each other through the use of the Internet of Things (IoT).

Furthermore, Baldassarre`s view of Industrial 4.0 is further highlighted by Cappellin *et al.* [25], where they outline the network as a means by which communication occurs between the physical and virtual reality.

Amaral *et al.* [26, p. 7], highlight the fault diagnosis procedure by identifying the index compactness and the distance between the xc coordinates of the gravity center of the region and the x coordinates of the mean upper point of the region as the key features in fault diagnosis.

2.3. Technology trends

Due to the rise and endless possibilities that the Industrial 4.0 revolution brings to the world, several technologies are emerging, and most of the technologies have not even reached their peak potential, due to the daily improvements in technology. This is a result of high-speed internet technologies, improved chip designs, and fast processors, both in computers and mobile device technologies. Industrial 4.0 components, such as AI, automation, MR, and cybersecurity are currently operational.

However, there is still more room for research and improvements to be conducted, to further understand and explore more possibilities for these technologies.

With this said, the Gartner-Hype cycle outlines the emerging technologies for 2018, as indicated in Figure 2.2. The main aim of this study is based on device identification and alteration, based on markerless technology utilising augmented reality. It is therefore important to focus the study on the AR component from the Gartner-Hype cycle, seeing its advantage over other technologies.

Thanks to Gartner-Hype for emerging technologies 2018 and by outlining the technological future trends as indicated in Figure 2.2 [27].

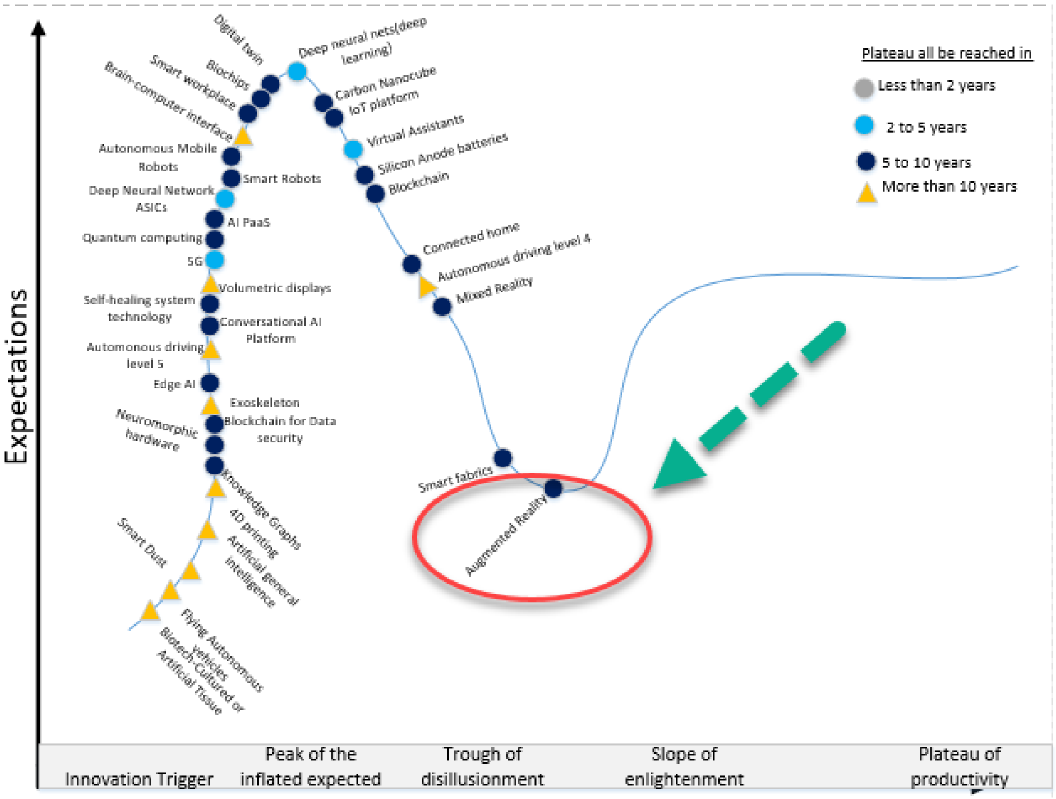


Figure 2.2: Hype Cycle for Emerging Technology Trends 2018 *[27]*.

Due to the fast-growing pace in AR technology applications, Gartner-Hype predicts that AR has high potential growth in the next five to ten years, which provides good motivation to further the study of this technology and to enhance its benefits in the future. However, accordingly to Gartner, augmented reality in the year 2020 has reached maturity and is no longer considered as a maturing technology, hence it is removed post-2018 when this research study was in an advanced stage.

Subsequently, AR markets have shown a vast growth into one of the highest competitive markets aimed at reaching approximately $90 billion by the year 2020, as indicated in Figure 2. 3 [28].

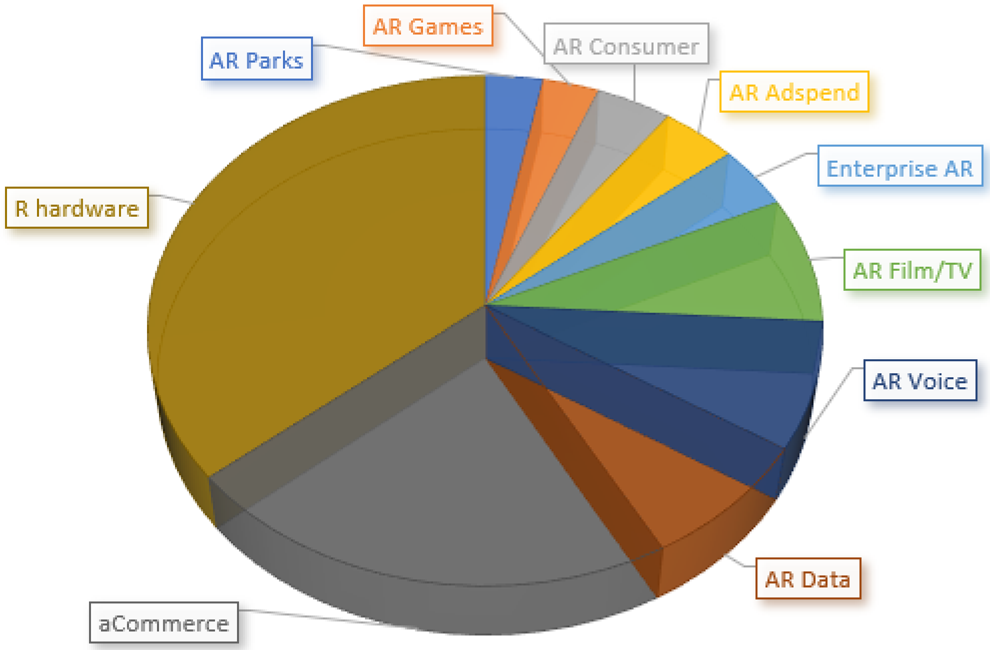


Figure 2.3:Estimated AR markets in 2020 *[28]*.

Figure 2.3 gives a high-level overview of the estimation markets for the emerging augmented reality markets. Augmented reality is divided into several sectors with AR hardware leading the market, followed by aCommerce. As noted in Figure 2.3, AR filming/TV is also getting attention and is growing steadily with a promising forecast for cracking the markets.

2.4. Tracking and identification techniques in augmented reality systems

This section outlines the current methods or techniques used in augmented reality applications for device tracking and their applications in the manufacturing environment. However, these systems are referenced or compared to the study at hand in terms of software development and the applications of this technology.

2.4.1. Image recognition and identification

Image identification and recognition systems are based on finding objects in the real world from real-world objects that are stored in a database prior to recognition. Through the use of the Unity3D platform, which is a platform that is full of integrated development engines and is capable of delivering a wide range of functionality for the creation of 3D content, AR application development can be achieved.

Unity3D, through its various engines, has a vision detection tracking functionality that can be achieved, using the Vuforia AR extension. Silva further outlines the use of Bayesian Network for image recognition, based on colour and shape by performing feature detection and extraction from a video sequence [29]. Subsequently, Unity3D can recognise both marker-based objects using techniques such as edges and feature-based detection. However, for the study at hand, only markerless detection, recognition, and feature-based detection will be investigated.

Table 2.1 outlines the different tracking techniques charted by Papagiannakis and Di Verdi, respectively. The table further outlines the advantages of each technology over the other. However, for this study, only markers-based and markerless technology are accounted for, based on the selection of the best choice from the analysis concluded from Table 2.1 [30], [31].

Other technologies, such as WiFi and sensors are randomly chosen without comparison, as is the author's discretion.

Table 2.1: Comparison table for common tracking technologies *[30]*- *[31]*.

Technology	**Range (m)**	**Setup Time (hr)**	**Precision (mm)**	**Time (s)**	**Environment**
Optical: (marker-based)	10	0	10	infinite	in/out
Optical: (markerless)	50	0-1	10	infinite	in/out
optical: (outside-in)	10	10	10	infinite	in
Optical: (In-outside)	50	0-1	10	infinite	in/out
GPS	infinite	0	5000	infinite	out
WIFI	100	10	1000	infinite	in/out
Accelerometer	1000	0	100	1000	in/out
Magnetic	1	1	1	infinite	in/out
Ultrasound	10	1	10	infinite	in
Inertia	1	0	1	10	in/out
Hybrid	30	10	1	infinite	in/out
RFID (active)	20-100	When is required	500	infinite	in
UWB	10-300	10	500	infinite	in/out
RFID (passive)	0.05-5	When is required	500	infinite	in/out

2.4.2. Vuforia development tool

In the precursory, Vuforia was known as “QCAR”. Vuforia is regarded as a Software Development Kit (SDK) for the development of augmented reality applications on mobile devices and is compatible with both the Android and IOS platforms. However, for this study, the development is based on an Android platform.

Vuforia gives developers the possibility to use 2D and 3D markers, which serve as a reference point in the real physical world.

The fiducial markers are then pursued by the built-in tracking method within the device, which makes it easy to apply animations or other computer-generated graphics, responding to the markers. The coordinate system will be centered at the marker and rotated according to the marker's orientation in the 3D environment. After this process, the resources are then used by the Unity3D library for functionality, which again is called upon by the developers.

Figure 2.4 depicts the Vuforia system, however, this is based on the QCAR library rather than the Unity3D platform [32].

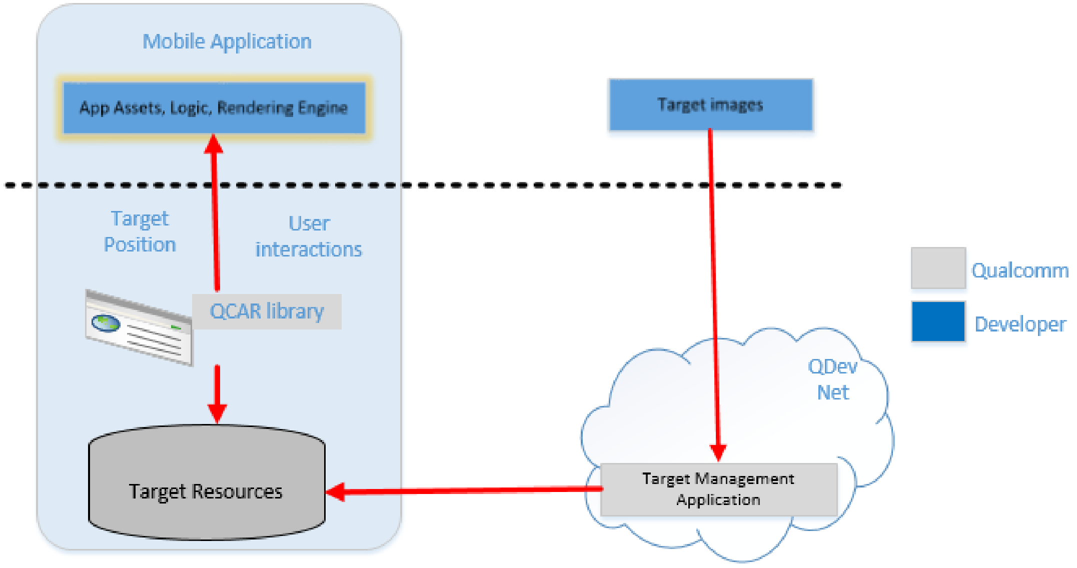


Figure 2.4: Vuforia - System Overview based on QCAR library *[32]*.

2.4.3. Application of computer vision tracking techniques in an AR environment

Augmented reality enlists computer vision potential to properly integrate the real-world and virtual world, despite the integration of the user location, object-based interaction, 2D or 3D comments, or error-free alignment of image overlays [33]. Computer vision, however, assures that the alignment between the real and the virtual world is accurate, based on the pixels in an orderly manner, and this is due to visual features that are present in the camera.

The are several methods that use computer vision for tracking and recognition of objects, which are outlined, such as tracking by detection approach, which is regarded as a less accurate approach, because of the recursive approach that usually has a narrow peak basin of convergence, hence it is not considered for this study [34, pp. 1-2].

Computer vision renders 3D virtual objects from the same standpoint of which the image of the real scene is taken by the tracking camera. The reconstruction stage uses data obtained from the first stage to reconstruct real-world images. Furthermore, the 2D feature, relating to the constraint camera pose estimation, is outlined in Figure 2.5 where the pose estimation algorithm is explained graphically [35, pp. 774-779].

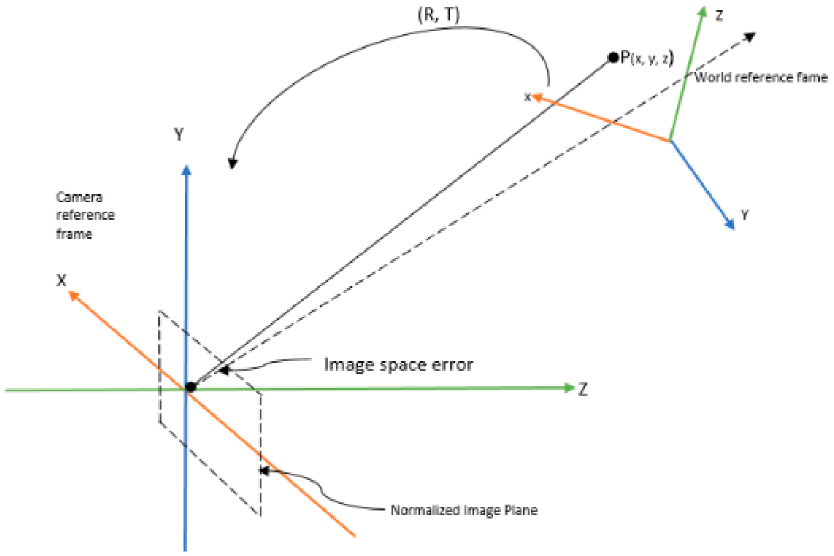


Figure 2.5: Constraint point for camera pose problem *[35].*

The computer vision algorithm is deemed as a difficult approach in terms of real-time tracking. However, computer vision has methods, relating to vision recognition, such as Model-Based-Vision (MBV), which is outlined as a method where prior knowledge about the object geometry is required. Furthermore, this method is assumed to require multiplexed algorithms, which makes it one of the complex computer vision algorithms [36]. Through various studies, relating to vision tracking, it is seen that all vision-based tracking algorithms heavily rely on Lepetit`s fundamentals, as indicated in Figure 2.6.

Lepetit indicates that for the vision-based tracking to be optimally effective, the camera has to obtain the image, then process the image by making use of the algorithms (based on the application), then apply the feature detection and lastly estimate the pose of the image [37]. However, in most cases, the reference image is always stored and referenced before this task can take place.

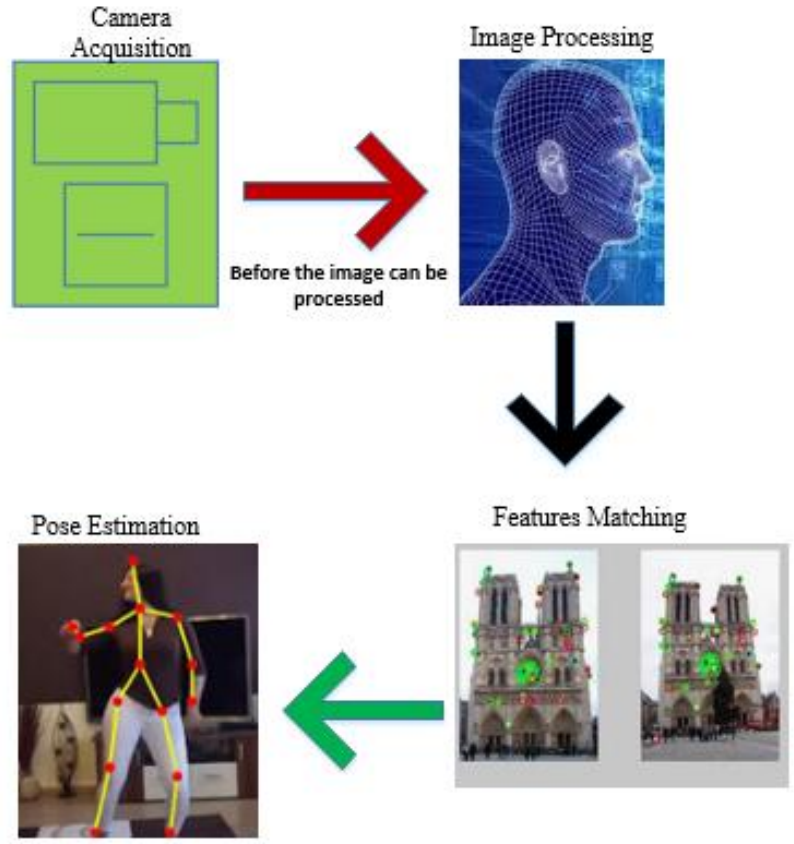


Figure 2.6: Main Steps in the vision tracking system *[37]*.

Figure 2.6 further highlights vision tracking steps, citing Lepitit, however, due to advancements in software and resources, many vision models are available, but the principle operation behind it is still the same.

2.4.4. Computer vision techniques in AR technology

Computer vision has greatly shown the probable for augmented reality applications. Computer vision can rely on visual features that are present to register the camera (camera frame). Moreover, computer vision has the capability of aligning between the real world and the virtual world with an accuracy of the order of the pixel. However, this has been notably seen in the use of the AR system, integrated with computer vision applications.

The development of machine vision is based on OpenCV and Emgu CV algorithms. OpenCV is open-source software that is associated with the development of vision applications and is a C++-based software and can process low-level image functions and high-level algorithms [38]. The low-level image processing relates to the extraction of descriptors from the images, i.e. colour, edges, and lines, while the high level refers to semantic image features, which are images commonly used by humans. Emgu CV is a cross-platform image-processing that is regarded as a .NET wrapper [39].

Furthermore, the advancement of technology in terms of resources and processing power has shown a record by relying only on computer vision with the ability to register the camera, without any prior knowledge on the pose estimation being introduced as indicated in Figure 2.7.

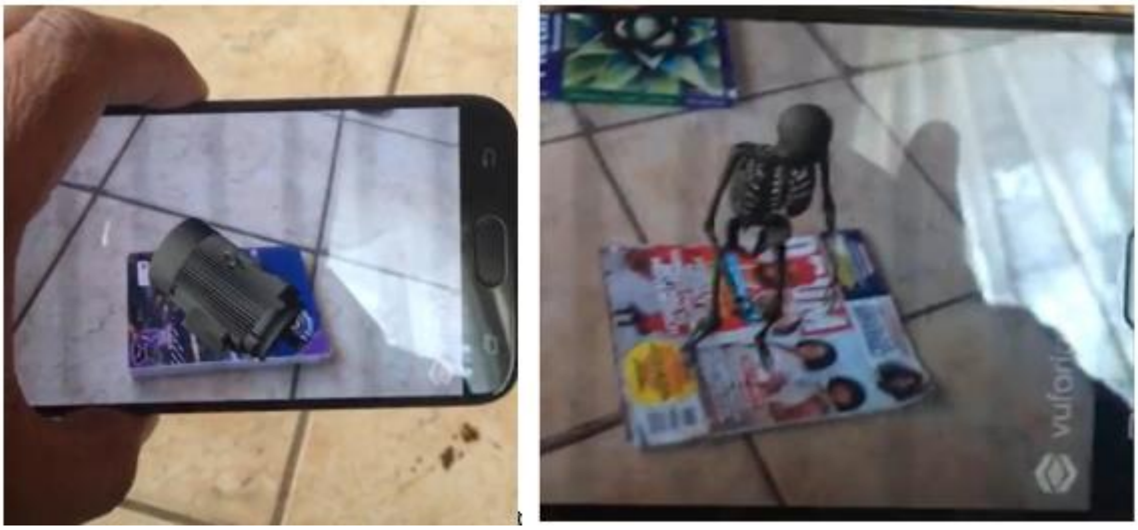


Figure 2.7: 3D Pose estimation example derived from a book.

Figure 2.7 further outlines the feature recognition conducted between two different books with different sizes and features. This exercise was initiated as a sampling test for using AR applications in Unity3D.

2.4.5. Android device selection

Vuforia has been outlined as an AR-based SDK platform and is an Android and IOS compatible platform. However, for this study, only the Android version of the application is developed. The prototype application development was conducted using Samsung Galaxy A50 with particular specifications [40]. The reason for the selection of this device was due to its ability to support

ARCore SDK/ emulator and also the support for WiFi competence, as outlined in the specifications.

The following specifications are for Samsung Galaxy A50, which is a device/smartphone that was utilised for AR application design and simulation on Unity3D

- OS Android 7.0 (Nougat)
- Resolution (Main display) – 2340 X 1080 (FHD+)
- Rear camera resolutions – 25.0 MP + 5 MP + 8 MP
- Video recording resolution – FHD (1920 X 1080)@30fps
- 2G GSM
- 4G FDD LTE
- 3G UMTS
- 4G TDD LTE
- WiFi – 802.11 a/b/g/n/ac 2.4G+5GHz, VHT80
- Location technology – GPS, Glonass, Beidou, Galileo
- Sensors – Accelerometer, fingerprint, geomagnetic, hall, light, and proximity sensor

2.4.6. The AR-based markerless tracking system

The markerless tracking in this study is based on the device's features and location. However, in this study, an algorithm called Simultaneous Localisation and Mapping (SLAM) is utilised to achieve the objectives. SLAM algorithm is a process by which the AR application device calculates the spatial relationship between itself and multiple key points [41]. SLAM algorithm is used in conjunction with augmented reality, due to its ability to solve the following challenges:

i. Unknown environments
ii. Real-time tracking
iii. Drift-free
iv. Use of monocular camera

The selection of markerless tracking was one of the studies' objectives. Augmented reality has three (3) components of visual tracking, namely marker-based tracking system, model-based tracking system, and markerless-based tracking system; all of which rely on the camera for the actual virtual view.

i. Marker-based tracking system – refers to markers that are placed in an environment and are detected by an AR system to aid registration.
ii. Model-based tracking system – refers to the 3D objects that have a known shape and can be detected by an AR system.
iii. A markerless-based tracking system – refers to an approach for tracking natural features in a completely unknown environment [42].

It is outlined that marker-based applications have an operational shortcoming of operating only on related designs, hence the attraction of markerless-based models is the key factor in this study. Authors of ref [43], use tracking techniques for texture planar targets, based on 6 Degrees of Freedom (6DOF), at real-time with frame rates of 20Hz using a mobile device built-in camera.

Markerless tracking is an important phenomenon in this study because the study is conducted in a factory environment set-up, therefore, the feature and location knowledge are important.

The use of other tracking methods such as marker-based will result in a tedious exercise to mark all the devices within a manufacturing environment set-up. Markerless tracking, unlike marker-based tracking, is mapped for unknown environments.

Markerless tracking comprises of the following structures, namely: pose estimation, matching, and feature detection. Furthermore, Ufkes *et al.* [44], proposed the recursive tracking method that is found in the markerless trackers and pose estimation, as an alternative tracking solution that can be applied to markerless tracking.

2.5.Manufacturing factory design and modelling

The operational efficiency in factory environments requires clear solutions in using technology to minimise deaths and increase productivity with less human intervention. Additionally, industrial vision systems have gained a lot of attention mainly in the manufacturing sector, due to the following reasons:

i. Control of quality manufacturing goods;

ii. Providing robotic assembly with the necessary information, relating to the assembly of complex products.

Additionally, these relate to Malama et al.'s [45] study, where they focus on industrial vision, by outlining the graphical representation of an industrial vision system. Figure 2.8 outlines the high-level process used in industrial vision systems, such as the facilitation of image acquisition, a centralised processing unit, as well as the manufacturing procedures and position placement of the tracking camera.

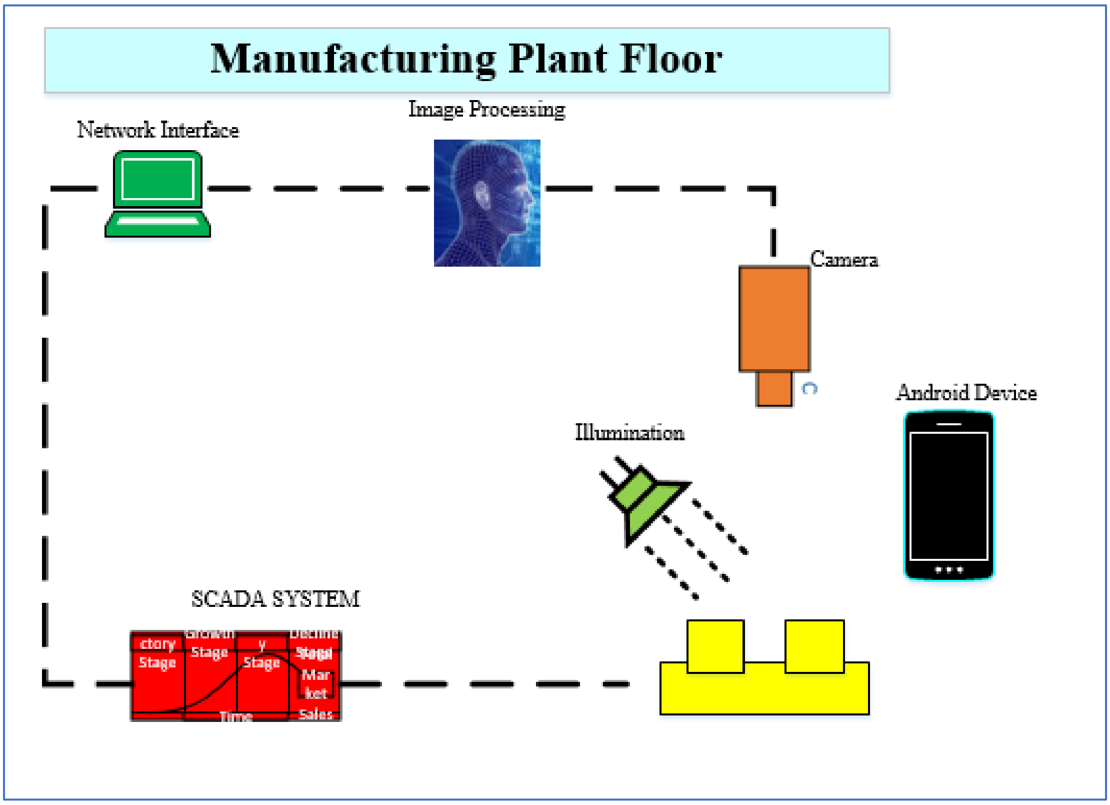


Figure 2.8: Industrial vision system *[45]*.

Is also important to note that the process in Figure 2.8 is a one-directional process, due to the importance of a computer scan for any unwanted defects on the produced objects. Furthermore, the process is advanced, due to the interaction between the SCADA interface and machine vision application.

2.5.1. SCADA history

The SCADA system is a system used for data acquisition, monitoring, and procedure control for spot devices and is a computer-based production procedure control and also a dispatching automation system [46]. The SCADA's inception in the manufacturing environment remains unknown with many authors assuming or citing the precise first use of the term “SCADA” to the year 1960 [47, p. 11]. However, due to the evolution and improvements in technology, the SCADA system is subjected to two unmistakable approaches, namely technology and market.

SCADA communications protocols were developed by different Remote Terminal Units (RTU) vendors. Due to the technological capabilities during that time, the protocols were able to only permit scanning and control between the master computer and slave, which are remotely connected [48].

Figure 2.9 presents the graphical representation of the first-generation SCADA system architecture, highlighting the communication between the server and the client [49].

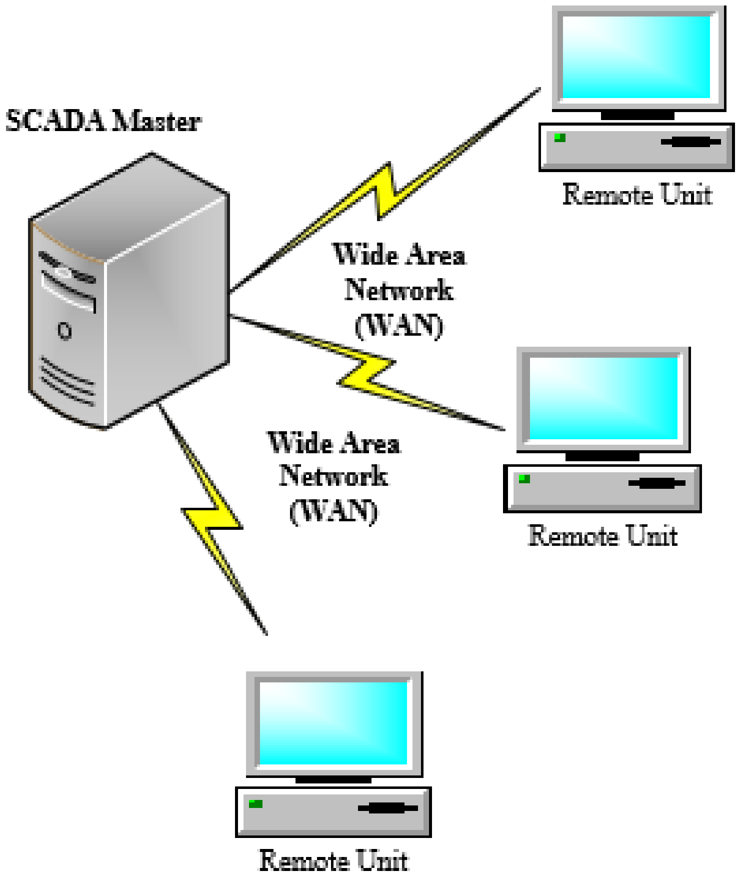


Figure 2.9: First-generation SCADA architecture *[49]*.

The SCADA system is regarded as the legacy communication system, due to technological inconsistencies and the lack of a high-quality processor, and slow internet connectivity. As a result, the entire manufacturing plant had to be connected to one master SCADA. However, the connection was mainly a physical Local Area Network (LAN) connection and just a few slaves were on the Wide Area Network (WAN).

2.5.2. Applications of SCADA in a factory setup

A SCADA is a system that comprises of both the software and hardware elements that permit the industrial organisations to do the following, but are not limited to:

i. Analyse and control complex control signals;
ii. Trigger the alarm for any anomalies;
iii. Data acquisition;
iv. Industrial processes, including those of manufacturing, production, power generation, fabrication, and refining, and may run continuously and these are connected to LAN with no other device used to display the information;
v. Infrastructure processes may be public or private and include water treatment and distribution, as well as wastewater collection and treatment.

Furthermore, a SCADA system consists of several Remote Terminal Units (or RTUs), which collect the field data that are connected back to a master station via a communications system. On a more complex SCADA system, there are essentially five levels or hierarchies, as outlined in ref [50]:

i. Field level instrumentation and control devices;
ii. Marshalling terminals and RTUs;
iii. Communications system;
iv. The master station(s);
v. The commercial data processing department computer system.

The SCADA is regarded as a supervisory system, rather than a full control system. It is a software package that is positioned on top of the hardware to which it is interfaced. The interface, in general, manufacturing practices, is achieved via Programmable Logic Controllers (PLCs), while in this study the SCADA system was developed, utilising C-sharp (C#) programming language.

The data transfer from sensors to the SCADA system was often achieved via a Local Area Network (LAN) as indicated and as a result, the system would be reliable and have a high speed. However, due to improvements and advances in technology over the years, the SCADA systems can function efficiently in a wireless network setup. However, due to the complexity of the current study and the introduction of the AR application, a broader wireless network had to be used and, in this case, WiFi connectivity is utilised.

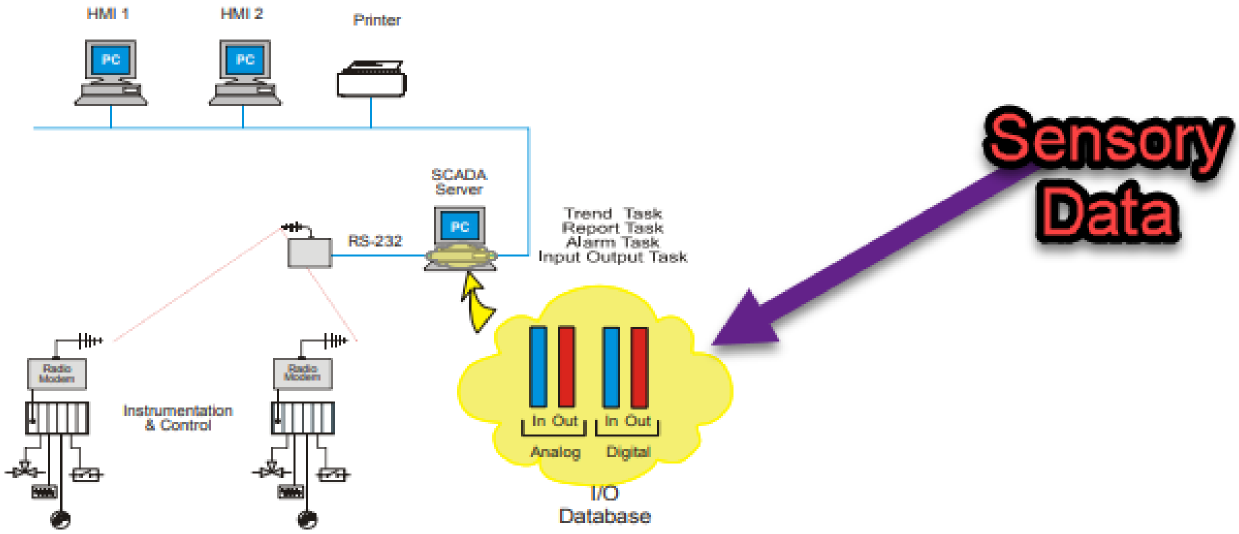


Figure 2.10: Typical SCADA system with data acquisition *[49]*.

In reference to the study conducted, the Input/Output (I/O) database ports outlined in Figure 2.10, comprise of the sensory data from physical sensors. However, the placements or methodology of how the sensors are attached will be outlined in the design chapter. Furthermore, the sensory data are stored in the database and this database is embedded onto the SCADA and only the data file is called for transmission to the AR application.

2.5.3. AR applications in manufacturing plant

The rise in technological advancements, such as high powerful processors that can be used in most devices, has also opened an opportunity for advancement in an AR applications across different fields. As a result, AR applications have grown vast in different fields, such as military (enhancement of the pilot view of the real world), as well as medical (aid during surgery by augmenting patients' organs before drilling or conduction of surgery).

Furthermore, the AR system provides a complex view of the handled areas and relevant processes. These methods are used for the enhancement of user environment utilisation in many industrial domains.

Table 2.2 outlines some of the AR applications and their use on each application. However, AR is not limited to the below application fields, as outlined in Table 2.2.

Table 2.2: AR applications and usage *[51]*- *[52]*.

Application Fields	**Field usage**
Wayfinding application	Wikitude Navigation is an AR navigation system that presents the user with a turn-by-turn Global Positioning System (GPS)-based guidance with convenience and safety benefits [51].
Entertainment	AR Karaoke is a concept where users perform their favorite dramatic scenes with virtual actors [52].
Construction	AR can be used for visualisation of infrastructure, e.g. (roads, buildings).

2.6. Summary

This chapter has provided an overview of the research conducted in the field of augmented reality and computer vision. The current developments making use of the 3D modelling tools, such as Vuforia and SCADA set-up were also outlined.

However, it has been noted from the literature that there are still expiation probabilities within these two fields and a lot of research still needs to be conducted as such. The improvement of existing SCADA and QR codes are deemed as the main area of focus, due to the improvements that Industrial 4.0 is bringing, such as high-speed internet and powerful processors.

This chapter has also identified research work that can make a significant contribution to the computer vision and augmented reality research area, by highlighting these within the researched articles and journals in the literature review section.

Chapter 3: Design and development of machine vision, SCADA, and augmented reality application for device identification

This chapter outlines the process development model of the physical and simulation model; the simulation model comprising of the augmented reality application, built on Unity3D and simulated on an Android platform. The development of machine vision is based on object detection and recognition, utilising OpenCV and Emgu CV, and their integration with SCADA development GUI are developed on Microsoft® Visual Studio® 2012. Furthermore, this chapter discusses the development process and integration of these components, as well as the sensory data flow model from the SCADA system to the AR application.

3.1. Introduction

AR applications depend on the identification of the real-world objects on the screen by tracking them and then augmenting the scene with an artificial object [53]. Several examples linking to AR applications, such as inspection and the assembly process are outlined, i.e. System Failure Mode and Effect Analysis (SFMEA), Total Production Maintenance (TPM), to name a few [54]- [55]. However, the use of the augmented reality application in this study is aimed at improving the efficiency of the quality of systems or products through device identification and property alterations within the manufacturing environment.

In an AR environment, the augmentation of the user`s perception and interaction of the real world can be achieved by making use of AR headsets, such as smart glasses or smartphones. It is for such reasons that in the modern era, the demand for software resources has increased drastically, due to the rise in smartphone hardware, which allows for better development of AR applications making use of AR frameworks and resources.

Considering that the mass production needs to happen daily in the manufacturing plants, there is a need to reduce the malfunctions on-site with accurate data, rather than outsourcing or depending on the SCADA data, which might damage the integrity and economy of the manufacturing plant, due to a lack of skills in operating the SCADA application.

This chapter further presents the method for developing and utilising machine vision, the SCADA system, and augmented reality in a manufacturing environment set-up, by identifying the devices based on their positions and features within the manufacturing plan to effectively solve such problems.

As an addition to the proposed model, the development of machine vision based on the OpenCV and Emgu CV libraries is utilised, while SCADA is developed in C-sharp (C#) and accommodating the output results of the machine vision application.

Subsequently, an augmented reality application is developed in the Unity3D platform and augments the same data on an Android device as the data that reflect on the SCADA application for both the robotic arms and the motors, since the data is transferred from the SCADA system to the AR application.

3.2. Proposed theoretical approach

In recent years, QR codes have been identified as an improvement technology to Bar Code (BC) technology. The introduction of QR technology came about, because of the limitations that are experienced in BC technology, such as storage capacity and the character type. However, the QR code introduction came about, because of the capabilities of encoding and decoding the different types of data such as binary, numeric, alphanumeric, as indicated in Figure 3.1 [56]. The QR codes are pinpointed to have a significant problem associated with slow QR detection. Hence the need to investigate the use of machine vision, as opposed to this technology.

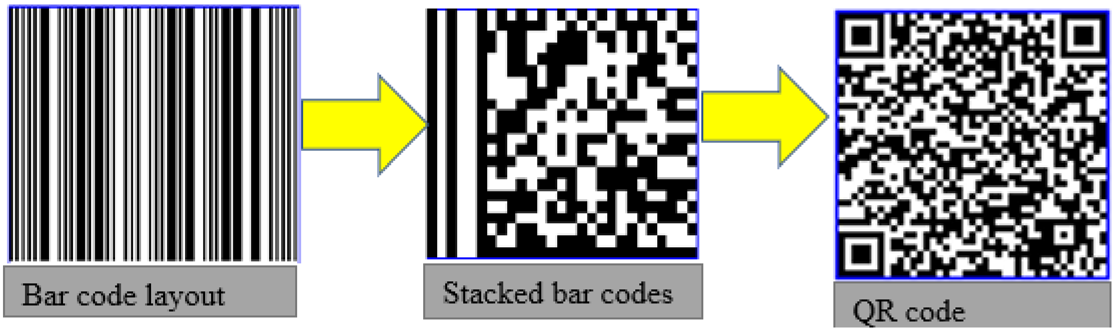


Figure 3.1: Multiple bar code to 2D code *[56]*.

In the context of machine vision, there are several shortcomings, such as light intensity for the camera to sense. However, such shortcomings are depicted by the sensors and transferred to the SCADA system, as is the acting control system used to monitor and alert for any anomalies within the factory set-up by displaying the light intensity on both the AR application and the SCADA system.

This process is accomplished by the developing vision applications, based on open-source software, called OpenCV and Emgu CV, and these libraries were used, due to the cost affiliated with them. C++-based software, called OpenCV, provides the tools needed to solve computer vision problems and can process both low-level image functions and high-level algorithms. Subsequently, OpenCV has provided a common infrastructure for computer vision applications and also accelerate the use of machine perception in the manufacturing environment [57], [58] as indicated in Figure 3.2.

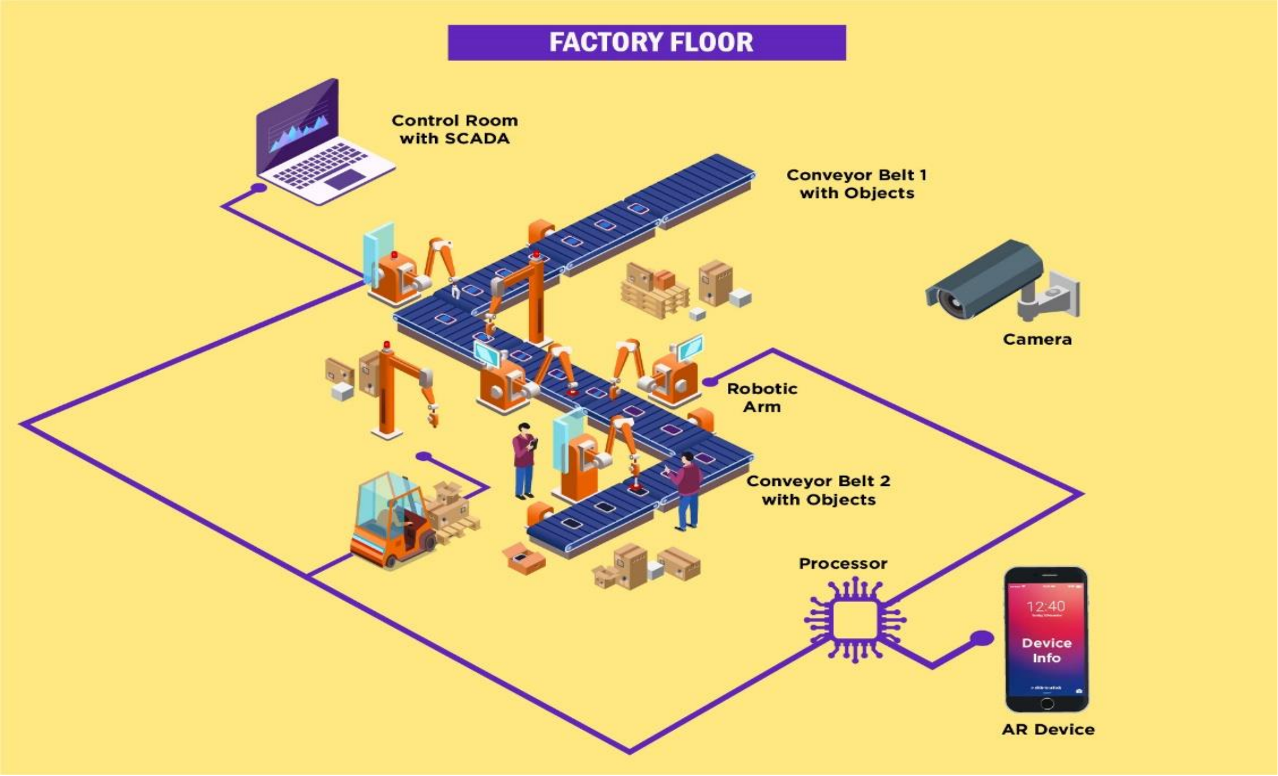


Figure 3.2: Proposed architectural solution for AR identification system within a manufacturing environment.

Figure 3.2 highlights the proposed system for the AR application solution, interfaced with a SCADA system for device detection and identification, based on the AR application developed in Unity3D on an Android platform. A SCADA application is developed in open-source, based platforms, and MVis realised using two open-source libraries, called OpenCV and Emgu CV, by importing them and manipulating them for shape and colour detection through which they were used in conjunction with an Arduino microcontroller and high-quality resolution camera.

Furthermore, object recognition, identification, and detection was used based on the motors, as indicated in Figure 3.2 for detection and identification of motor information, such as motor speed, motor direction, and motor number. However, the model did not use any images for referencing purposes, as the markerless trackers are used.

The information obtained from the SCADA application matches the information provided by the AR application and vice versa to improve productivity and to have an earlier notification of the device malfunction within the manufacturing plant, as indicated in Figure 3.3.

The light sensor is a critical sensory part of the study, since the study is based on machine vision, due to the reasons that MV depends on image acquisition, utilising appropriate cameras and light, depending on the application.

The light sensorcontrolled the light intensity of the factory to accommodate the camera that was used and to carry the vision, for the camera to capture accurate data. With this said, the study is divided into three sections, namely sensing, automation, and vision.

The SCADA system implementation requires the use of the Emgu CV library, which is a library that can allow for C++ libraries from OpenCV to be used in a C# (C-sharp) environment. After this process, the SCADA application was linked to all the system components of the manufacturing plant, such as the conveyer belt, motors driving the conveyer belt, the robotic arms, as well as the sensors that provides the manufacturing environment`s speed, direction, light intensity, and the temperature.

These sensors therefore indicated when to activate the cooling system/fan, and/or how negatively does the light intensity affects the vision camera and adjustments that needed to be done. In addition to the sensor’s responsiveness, MV was accomplished using a high-resolution camera that wasplaced in a fixed position to monitor, detect and identify (inspect) objects within the manufacturing plant.

Several OpenCV algorithms, such as image recognition, colour detection, and shape detection were utilised, based on the kind of obstacles that wereunearthed, while utilising machine vision application.

Due to the progress in AR technology, related researches, along with advanced computer hardware and software, has led to AR technologies getting more attention. An AR application was built with several functionalities, such as identification, detection, and recognition of devices.

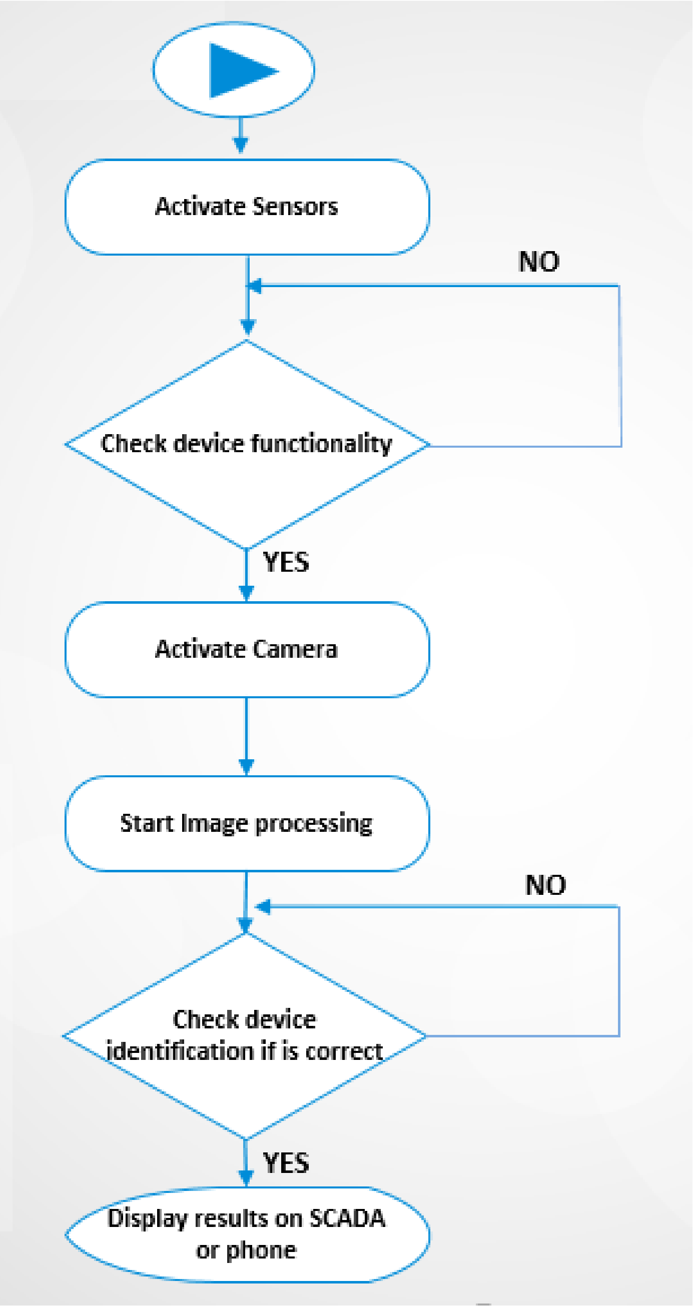

Activate Sensors
NO
Check device functionality
YES
Activate Camera
Start Image processing
NO
Check device identification if is correct
YES
Display results on SCADA or phone

Figure 3.3: Flowchart indicating the test methodology.

Figure 3.3 outlines the step-by-step approach of the system functionality, based on the proposed model. For the system to allow the functionality of the AR application to be active, the state of the machine is required to always be true. If not, the state has to be re-tested until it is true for the function to be active. Figure 3.3 is primarily based on the application of the sensor integration to the SCADA system. The sensory data provided data that was compared against the datasheet specification to identify if the devices are functional or not. For example, for a motor, the input power is 5W (depending on the gearbox) for it to operate and the supply power from the Arduino microcontroller to the L298 bridge might be insufficient, and this has to flag that there is a problem with the motor or the motor driver.

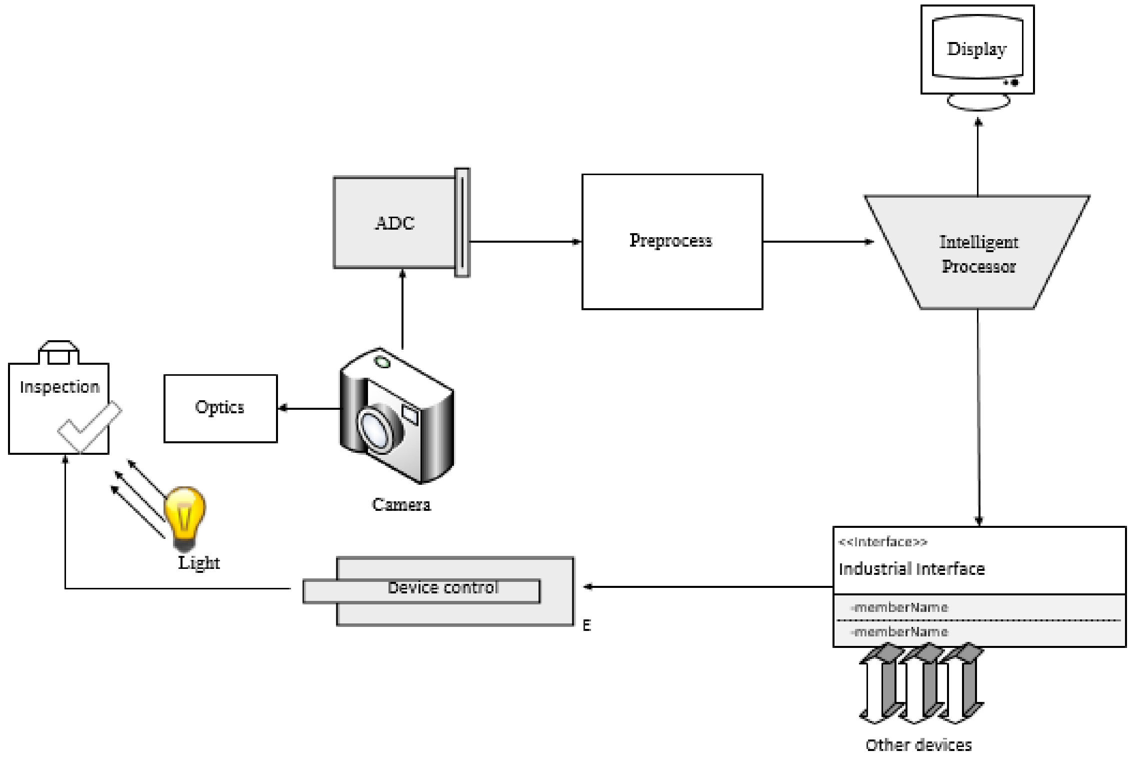


Figure 3.4: Industrial machine vision system for inspection.

One of the most important applications of machine vision is the use of this technology for the inspection of dents. Figure 3.4 depicts the integration of multiple technologies, utilising machine vision technology for object inspection. In the case of the inspection or application of machine vision for this study, the objects were inspected, based on colour and shape. As a result, this inspection application resonates with the application of this study.

In conducting the device inspection in a manufacturing plant, the process outlined in Figure 3.4 of the Industrial Machine Vision (IMV) operation wasfollowed, comprising of the following types of equipment:

i. Lighting;

ii. Optics;

iii. Image-sensing;

iv. Image-processing.

The application of the sensory part of this study was to store the sensory data in the SQL database and display the updates in the SCADA system. However, post-data storage of the sensory data was transferred to the AR application via the WiFi connectivity, where the data can be augmented, using the AR application.

3.3. Augmented reality marker comparison

The introduction of the augmented reality marker comparison section is to give context on the selection of software and other apparatus, which are used in the development of the prototype in its entirety for this study.

In the Mixed Reality (MR) environment, identification and detection are important, as the algorithm must recognise the object by its uniqueness, which can be of a different model, colour, shape, feature, or position, depending on the application. However, for AR application in this research study, the uniqueness is defined, based on both the feature and position of the device in the manufacturing plant, while for machine vision the uniqueness is defined, based on the colour and shape.

The fiducial markers are deemed as essential elements of the camera tracking systems, which are used in robotics and AR applications to stabilise a field of view [59, p. 2]. This explanation gives more context in understanding the reason for further research in this field, using machine vision, as opposed to the use of Quick Response (QR) codes as identifiers, due to the reasons outlined in Table 3.1.

Table 3.1 depicts the difference between the QR codes and image recognition technology. The analysis of information provided in Table 3.1 shows the effectiveness and reasons why the research in the use of machine vision, as opposed to QR codes or any other identifiers, is important in the 4th Industrial Revolution era [60].

Table 3.1: Comparison between computer vision and QR [60].

Computer vision	QR Code
USABILITY	
i. Ability to scan the entire image from difficult angles and low light conditions.	i. Capture the specific section of the QR code. Each QR code is unique and has a different distance specification.
PLACEMENT	
ii. The entire image can be recognised and no extra graphic needs to be added.	ii. The specific graphic marker must be visibly placed, and this can obtrusive to the end piece.
FLEXIBILITY	
iii. The content is completely flexible. The content can be updated anytime.	iii. The user must decide which items to include in the mobile experience before adding the codes.
FEATURES	
iv. Ability to have multiple features at the same time: video playing, interactive augmented reality.	iv. You are restricted to one feature per scan, usually an URL.

The replacement of QR codes is linked to the results presented by Kumar *et al.* ref [61] where he outlines the advantages and disadvantages of QR marker error and features comparisons as indicated in Table 3.2 and Table 3.3.

Below are some of the reasons outlined for the advantages and disadvantages of QR marker errors. Apart from the already identified tracking techniques, there are a few common fields, namely the sensor-based and vision-based approaches, which are used in this study.

i. The sensor-based tracker consists of the use of sensors, such as an accelerometer, mechanical, gyroscope. However, the sensor-based trackers are good at motion prediction;
ii. The vision-based approach uses image processing methods, making use of computer vision algorithms to calculate the camera pose. However, vision-based approaches often make use of model and feature-based tracking techniques.

Table 3.2: QR marker error correction *[61]- [62]*.

Level	**Approximation % codes (Restored)**
L	7%
M	15%
H	25%
Q	30%

Table 3.2 outlines the possibilities of error correction that are feasible in a QR environment.

The levels section presented in Table 3.2, outlines the level possibilities for decoding and restoring the QR code data in an AR environment. The levels outlined in Table 3.2 depict the percentages of QR restoration possibility, e.g. L-Low level represents that if the QR code is damaged, there is a 7% chance that data from the QR code can be restored. However, for this research study, Table 3.2 was not utilised, as the construction of QR codes and data restoration was not part of the study. However, Table 3.2 is added to highlight the possibility of data restoration from the previous studies [61]- [62].

Furthermore, Table 3.2 links directly with Table 3.3 in terms of outlining the ability of code reconstruction for camera scanning, as the lens cannot always be positioned perfectly. Therefore, the angular recognition of markers is important and it has also been outlined in the discussion section.

Table 3.3 further presents the superiority of the QR code over other fiducial markers, but this does not include machine vision. Table 3.3 outlines the difference between QR codes and fiducial markers. From the data analysis point of view in Table 3.3, fiducial markers are deemed the best marker selection, which supports the motivation for using them in this research study.

Table 3.3: Feature comparison of QR markers with the fiducial marker *[63]*.

Feature	**QR Code**	**Fiducial Marker**
Need to pre-register	No	Yes
Model-storing	Internet	Local
A limited number of markers	Larger	Smaller
Universality	Universal barcode	Standalone

Table 3.3. outlines the difference between QR codes, Webtag, and other fiducial markers. However, from the data analysis, based on Table 3.3, the systems utilising decoder-maker techniques have limitations, such as a limited number of markers, and as a result of that limitation, a new approach must be developed. Due to the limitations found in fiducial markers, an alternative technique called Webtag is used. However, despite this approach having 4X1012 characters, it still cannot handle more characters, as compared to the QR code [63]. However, this research study is focused on the comparison between the QR code and machine vision, as outlined in Table 3.1.

3.4. Development of the test set-up

This section outlines the method used in designing and modelling the prototype for two technologies, namely AR and machine vision technologies. Before outlining the process used to develop these prototypes, the apparatus/components are firstly outlined to provide more context in the development phase of the section. The components outlined in this section are assembled in a manner that satisfies the proposed methodology, as well as the hypothesis of the study.

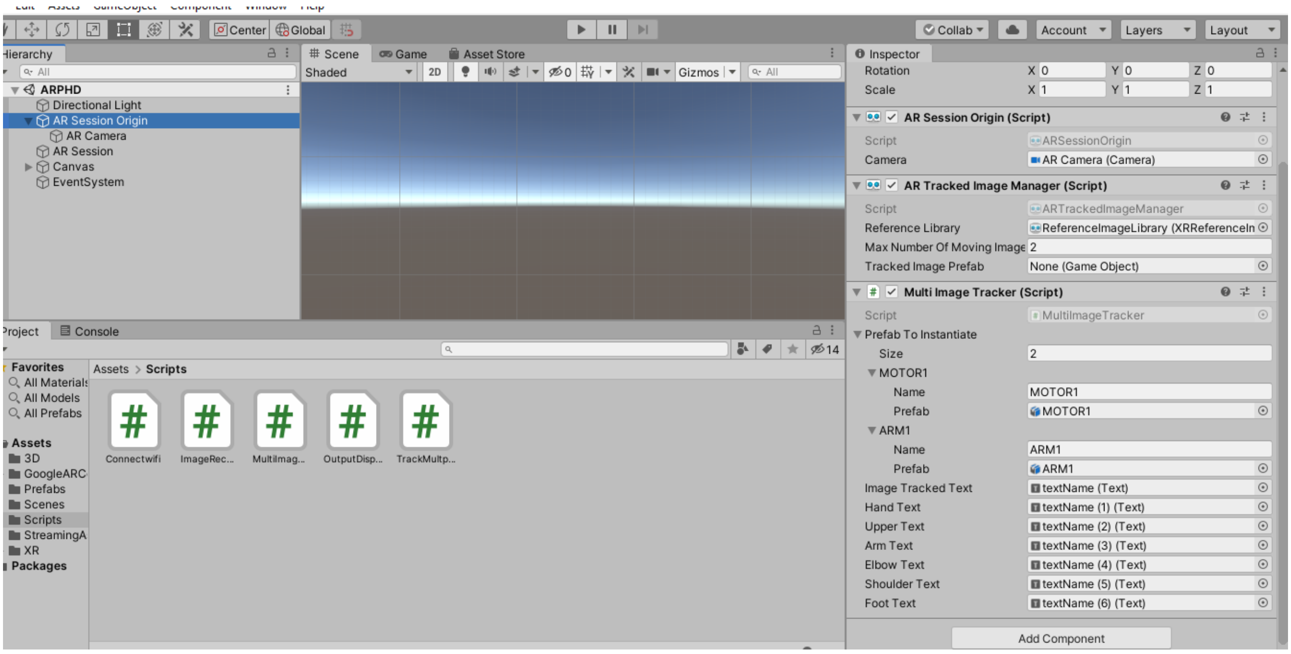
The study is made up of three (3) sections, namely:

i. SCADA,

ii. AR application;

iii. Machine vision.

The physical conveyer belt is utilised, while the SCADA, AR application, and machine vision are based on the software and electronic components.



Rotation X 0 Y 0 Z 0
Scale X 1 Y 1 Z 1

AR Session Origin (Script)
Script: ARSessionOrigin
Camera: AR Camera (Camera)

AR Tracked Image Manager (Script)
Script: ARTrackedImageManager
Reference Library: ReferenceImageLibrary (XRReferenceIn
Max Number Of Moving Image: 2
Tracked Image Prefab: None (Game Object)

Multi Image Tracker (Script)
Script: MultiImageTracker
Prefab To Instantiate
Size: 2
MOTOR1
Name: MOTOR1
Prefab: MOTOR1
ARM1
Name: ARM1
Prefab: ARM1
Image Tracked Text: textName (Text)
Hand Text: textName (1) (Text)
Upper Text: textName (2) (Text)
Arm Text: textName (3) (Text)
Elbow Text: textName (4) (Text)
Shoulder Text: textName (5) (Text)
Foot Text: textName (6) (Text)

Figure 3.5: importing of assets into Unity3D.

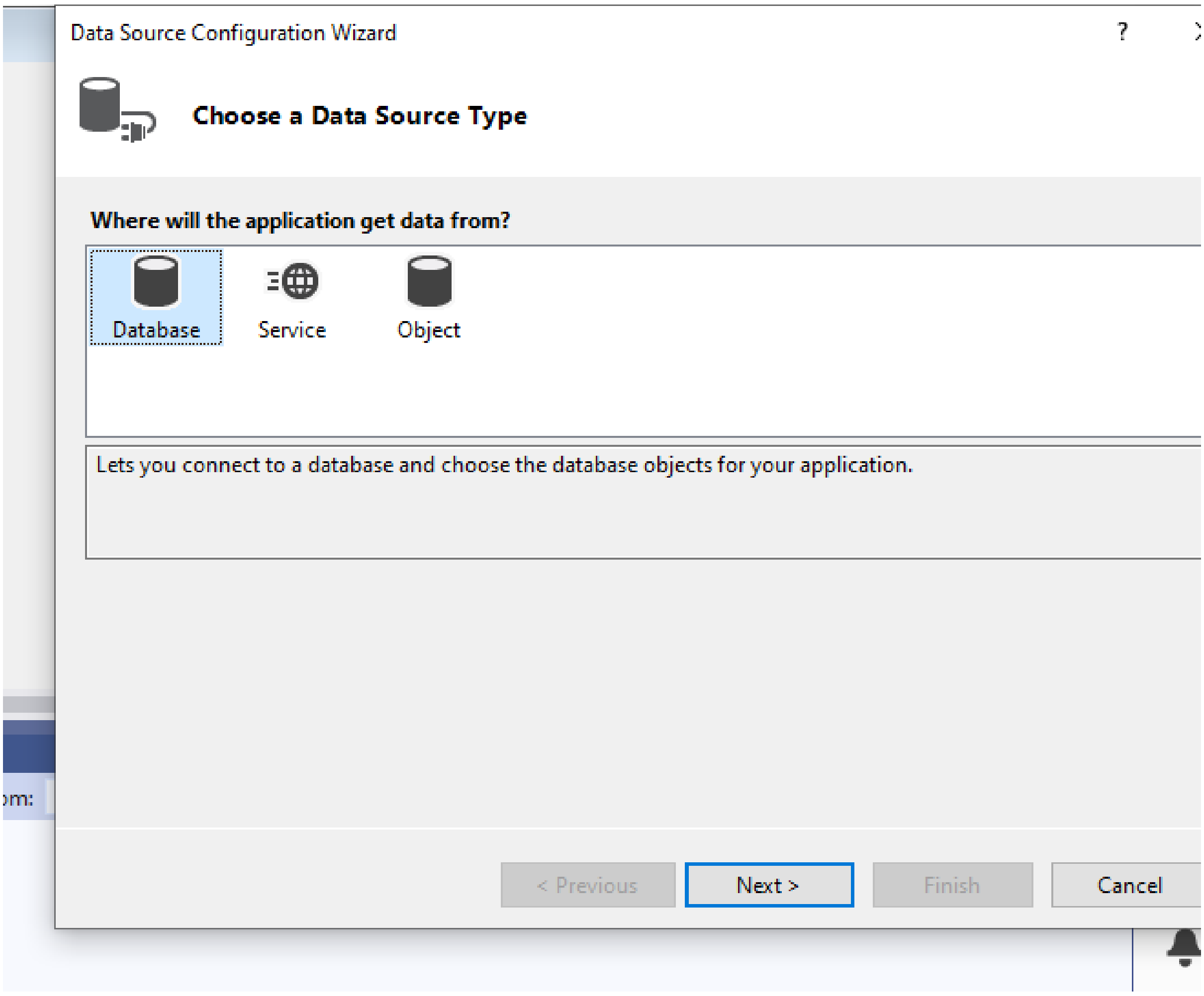
In the development of the test set-up, as outlined in Figure 3.5, the scripts are imported into Unity3D for simulation purposes. In this research study, the following scripts are used, namely connect WiFi, image recognition, and output display. The connect WiFi script is used to enable WiFi connectivity; image recognition for the recognition of the modelled AR-based images (robotic arm and motor); and output display for augmentation of the output data. Furthermore, these application settings are modified for the study at hand.

3.4.1. Apparatus used for designing SCADA system

The components outlined in this section were used in the design of the CorelDraw designed objects and the conveyer belt. The conveyer belt is built both for augmented reality application simulation and machine vision, as a scaled model. The reason for scaling the conveyer belt is to allow for precision positioning of the mounted camera and robotic arm, in parallel with the conveyer belt, bearing in mind the size of the objects and the speed at which the motors driving the conveyer belt are moving.

The graphical representation and the usage of the apparatus are outlined in-depth in section 3.6. Subsequently, the blueprint of the manufacturing plant was developed making use of the scaled apparatus. In addition, the selection of the WiFi protocol for data transfer was investigated. However, due to the compatibility of the test phone device in this study, the 802.11b WiFi protocol was used and it was important to observe the amount of data packets that might get lost on the way from the SCADA via the Wemo module to the Samsung device.

The SCADA system was designed, using the drag and drop feature of Microsoft® Visual Studio® 2012 to design the graphical user interface by dragging the Combobox, text boxes, and DataGridView. Since this toolbox creates methods automatically in a C# windows application by drag and drop feature, the C# code was then embedded into each created method. Following the completion of this process, the Relational Database Management System (RDMS) database was designed on Microsoft ® SQL Server ® Management 2008 to store the sensory data and this database was then configured in Microsoft® Visual Studio® 2012 by choosing the dataset as outlined in Figure 3.6.



Data Source Configuration Wizard

Choose a Data Source Type

Where will the application get data from?

Lets you connect to a database and choose the database objects for your application.

Figure 3.6: Data source selection for adding database into a C# application.

Figure 3.6 depicts how the database configuration in Microsoft ® Visual Studio® 2012 with the SQL database was integrated or connected to the C# application. The raw data obtained from the sensors were manipulated by writing SQL scripts and integrating the scripts into Micorsoft® Visual Studio® 2012, since the two platforms have already been connected. After this, the data was then projected to the SCADA system.

3.4.1.1. Components used for collecting sensory data

The SCADA apparatus outlined, are used for the transmission of data from the sensors to the SCADA system. Upon retrieval of the sensory data, the SCADA can transmit the data to the AR applications.

The apparatus are outlined as follows:

i. Infrared sensors
ii. Wemos 8266 WiFi Module
iii. Arduino Uno microcontroller
iv. Light Dependent Resistor (LDR)
v. Microsoft Visual Studio (C# Language)
vi. Red Perspex
vii. Blue Perspex
viii. LM35 temperature sensor

Figure 3.7 outlines the object design in CorelDraw software. CorelDraw is a graphics design software that has the capabilities for photo-editing and design tools. The designed objects work in parallel with machine vision. This is as a basis that the machine vision application model has to account for a specific colour and shape. The SCADA system, using the Arduino microcontroller, extracts the sensory data from the sensors, then stores it in the embedded SQL database. The SCADA system is developed to act as the Graphical User Interface (GUI), therefore, upon every change in the sensory data, the SCADA system projects updated data.

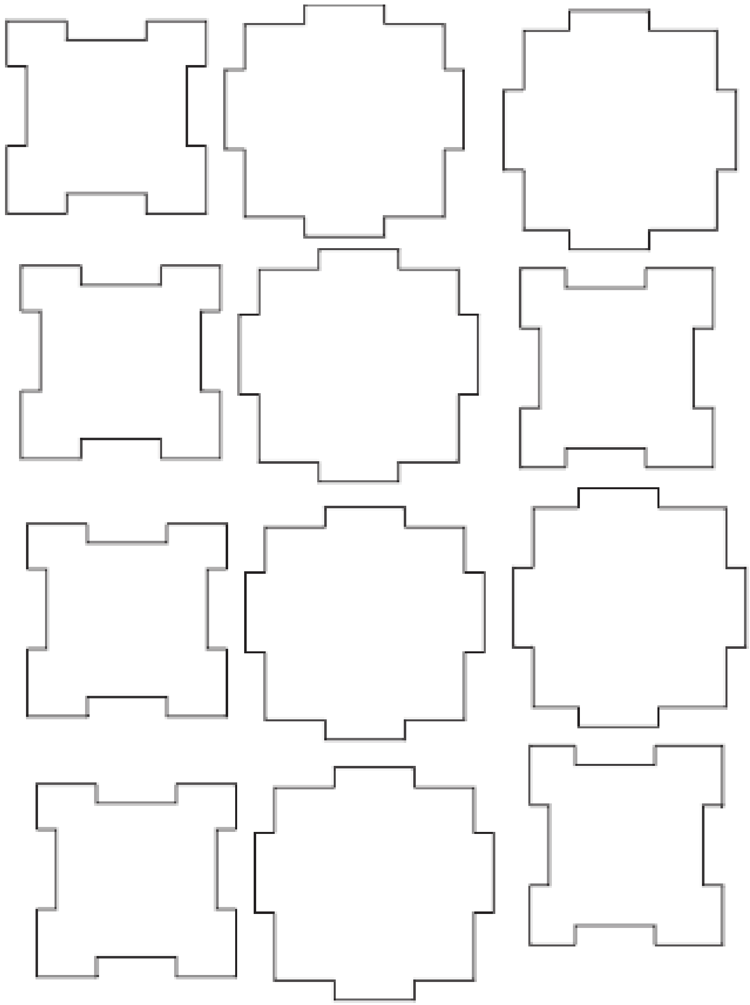


Figure 3.7: Objects designs on CorelDraw.

Upon the satisfactory component designs with accurate measurements of 50mm X 50mm, the designs are printed on wood, and then the wood is inserted into the laser cut machine. Once the machine has completed fabricating the designs, the components are mounted together, using the glue gun. After the objects are merged, they are covered with both blue and red covers to have two different colours so that the concept can be tested and proven.

Subsequently, the objects are tested individually for object detection for a red squared object, using a machine vision application. Once this test is completed, the vision application is then integrated with the robotic arm for the pick and place application as outlined in Table 3.4.

Table 3.4: Object modelling steps.

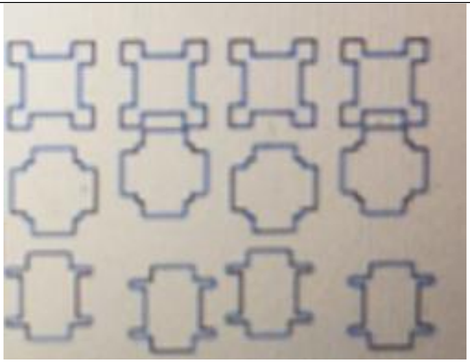
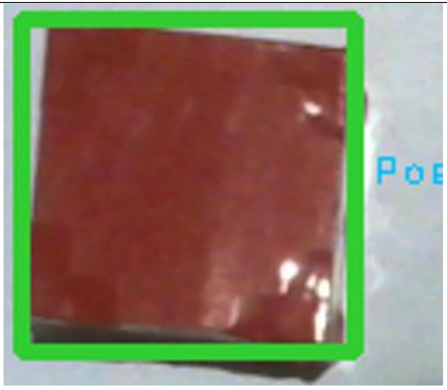
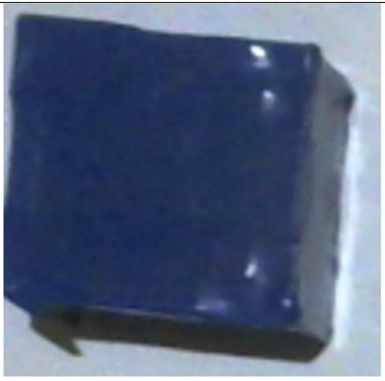
Initial Corel Draw Design	Red Output object	Blue Output object
Step 1	Step 2	Step 3
		

Table 3.4 outlines the object creation process from CorelDraw software to the finished product. Furthermore, Table 3.4 depicts the individual test where the vision application can identify the red squared objects by highlighting the object with a green square to show the detected object. The camera was then switched to the blue object and the vision application could not identify or detect this object, hence no sign of detection appears.

3.4.2. The design and development of the robotic arm

The smartphone selection was based on the ability to process and simulate Mixed Reality (MR) applications. Upon completion of the robotic arm models, a set of robotic image models were loaded onto Vuforia in Unity 3D for further modelling and fine-tuning, as the study is not utilising known elements, such as barcodes or QR codes.

The robotic arm modelling was based on angular parameters, which are developed on the probability 1:2 ratio. The ratio was based on the likeliness of the input parameters in the SCADA system for the arm to move between 0° and 180°.

The complexity of the robotic arm design was based on the accommodation of the angular motion inside Vuforia, as a result of joints. Therefore, modelling software had to be identified and learned. The two modelling software were identified, namely Cinema 4D and Blender3D. Blender3D was therefore compared against Cinema 4D and from the summary comparison in Table 3.5, it was concluded that Blender3D was the best software solution for this research study. Table 3.5 depicts

Blender3D's advantages over Cinema 4D, such as free and open-source software, as compared to Cinema 4D with a monthly cost [64].

Table 3.5: Authors comparison of Cinema 4D vs Blender3D *[64]*.

	Cinema 4D	**Blender3D**
Availability	Paid, R700 – 1200 per month	Free
Source	Closed	Open
Applications	Animation Rendering Texturing	Animation Rendering Texturing Game Asset Production 3D printing
Learning curve	Easy to learn	A hard learning curve at the beginning
User interface	User-friendly	Not such intuitive

Blender3D software was used as a modelling tool, due to the reasons outlined in Table 3.5. After this task was completed, Blender3D ".bli file" was then converted to the ".fbx" so that the file can be imported into Unity3D for simulation. The reason for importing the model file is to allow Unity3D as the game engine software to fully animate, build and simulate the modelled arm inside the AR application.

However, this process was done on a laptop, but it was seen that the laptop had low processing power and poor graphics. As a result, the Lenovo ThinkPad laptop was upgraded by adding the following system apparatus to compensate for the low processing power and poor graphics.

Modification apparatus for Lenovo ThinkPad Laptop:

i. Operating system – Windows 10 pro;
ii. Processor – Intel ® Core ™ i7-7500U;
iii. CPU @ 2.70GHz – 2.90GHz;
iv. RAM – 8.00 GB;
v. System type – 64-bit operating system;
vi. Graphics card – Intel HD 620 graphics card;

The internal graphics card was replaced by the OpenGL graphics card to boost the graphic's quality of the model. The arm design was constructed, using 3D blocks on Blender3D. Figure 3.8 outlines the modelled robotic arm image in the system.

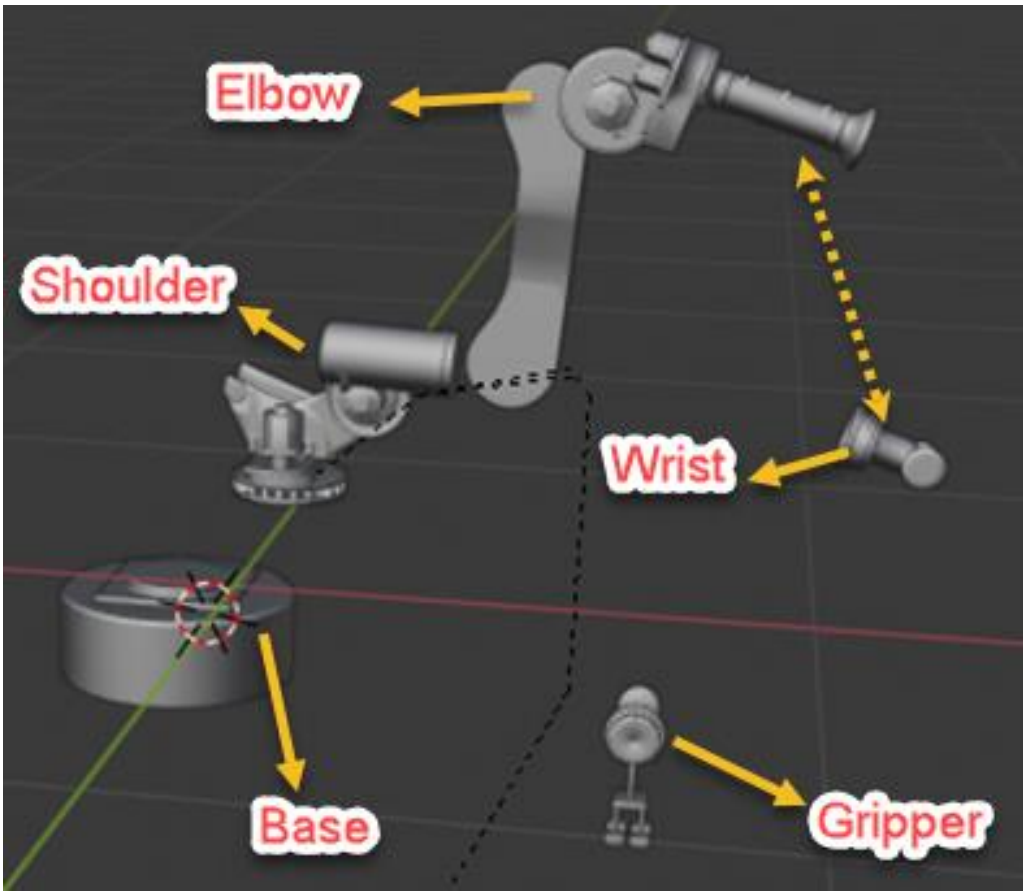


Figure 3.8: Output design model from Blender3D.

The AR augmentation is based on the angular joints of the robotic arm, and this is achieved by displaying the following parameters or variables of the robotic arm:

i. Robotic arm number -> determined by the robotic arm position in the manufacturing environment;

ii. 5 degree of freedom.

The basic operation of the robotic arm is dependent on the SCADA system input data because these data enable the robotic arm to change the angles for the pick and place. Additionally, computer vision application, during an inspection, allows for the robotic arm to change the state from sleep mode to active mode upon detecting or identifying the correct object. Furthermore, the robotic arm can be identified, using the AR application.

As a result, this approach determines the correctness of the object status in three sections as outlined:

i. The shoulder moves perpendicular to the conveyer belt;
ii. Elbow was developed to move vertically ;
iii. The wrist moves between 0^o, which is the inertia position, and 90^0. The wrist's fundamental function is to pick up the correct objects upon inspection from the conveyer belt and place them into the box. Other joints are working as supporting structures to the robotic arm application.

The SCADA parameters relating to the robotic arm functionality, are transmitted as a data packet via the Wemo WiFi module into the AR application, using WiFi connectivity. The conveyer belt pauses once the object reaches the inspection camera position/station. Upon the object inspection, for example, the red squared object, the conveyer belt moves at the controlled speed rate, which is determined by the Arduino microcontroller, which is pre-programmed in Arduino IDE software and integrated with the vision application.

Once the required object is detected, the conveyer belt carrying the object will move to the robotic arm station or position. At this point, the robotic arm parts move from their current state to the inertia state, since it is out of sleep. The robotic arm design is constructed in a logical form that, before the string of data packets from the SCADA system can be activated in the arm, the arm has to be in its inertia state. The reason for this is that the previous circle might have moved the arm at different angles and the new data might result in the arm not even facing the conveyer belt, which results in the objective of the pick and place not taking place.

Once the arm is in an inertia state, the parameters sent from the SCADA system are received and the robotic arm moves in reference to those parameters and the AR application can be refreshed to update the new data for the arm. After this process, the pick and place occur as outlined in Figure 3.9.

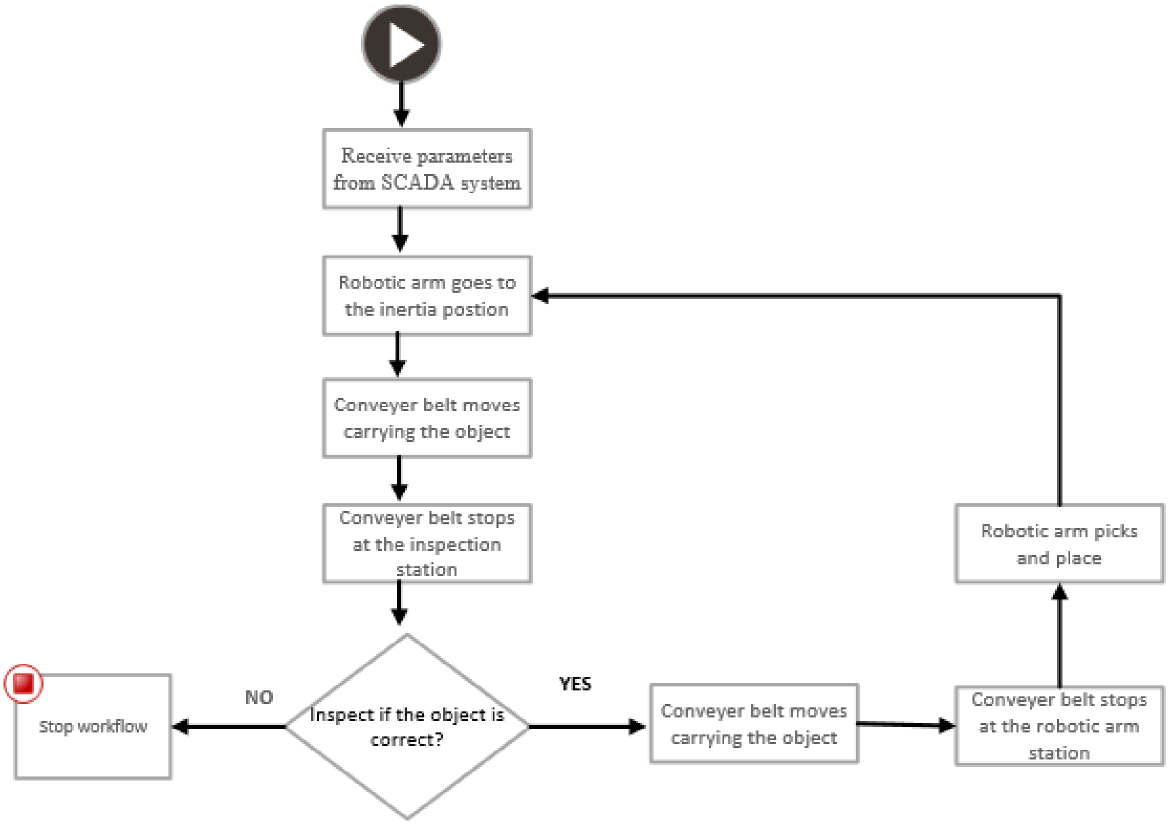

Receive parameters from SCADA system
Robotic arm goes to the inertia postion
Conveyer belt moves carrying the object
Conveyer belt stops at the inspection station
Inspect if the object is correct?
NO
Stop workflow
YES
Conveyer belt moves carrying the object
Conveyer belt stops at the robotic arm station
Robotic arm picks and place

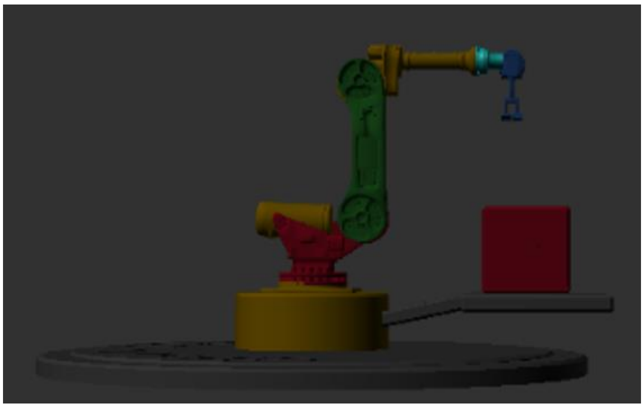
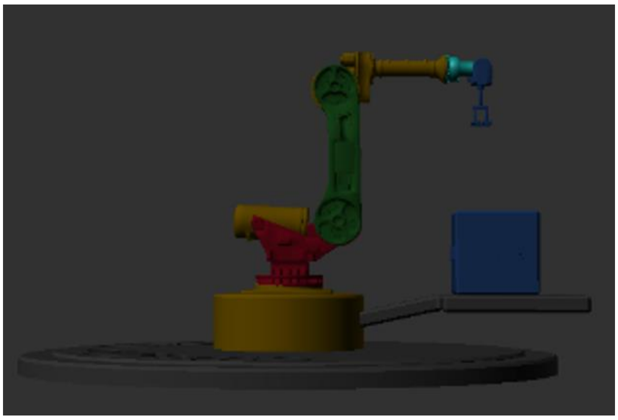
Figure 3.9: Robotic arm interface to the process workflow.

Figure 3.9 outlines the object detection process and the picking method by the robotic arm/device. In Figure 3.9, the user inputs the data into the SCADA system, which is directly connected to the robotic arm and the conveyer belt. In this process, the control system is the Arduino microcontroller that controls the operations.

At the inspection station, the vision application is activated and checks if the objects carried by the conveyer belt are the correct objects, in terms of shape and colour. If the objects are not correct, the vision application sends a signal to the microcontroller to stop the operation. However, if the status is true and the objects are correct, the signal is sent to the Arduino microcontroller to move the conveyer belt. The conveyer belt is then stopped at the pick and place station (robotic arm station) and the object is picked and placed into a box.

Table 3.6 depicts the modelled robotic arm with different test objects for the vision application. The robotic arm with a blue squared object depicts the inability of the vision application to identify and recognise the blue object, while the robotic arm with red squared object depicts the ability of the vision application to identify and recognise the red object.

Table 3.6: Comparison between red and blue objects.

Robotic arm with a red squared object	Robotic arm with a blue squared object
	

The robotic arm with the blue squared objects depicts the vision-based application for locating the blue objects within the conveyer belt. However, due to the shape and colour detection algorithm utilised in this application, the RGB colour conversion of (255, 0, 0) was utilised for the application to recognise the colour red, and this algorithm was integrated with the shape detection algorithm. However, the RGB blue conversion of (0, 0, 255) was not utilised in this research study.

The selection of the device (robotic arm) choice is done from the SCADA system through the use of the drop-down function that is built-in C#. The data transfer algorithm is used throughout the system. For the robotic arm, both computer vision and AR application work concurrently with the SCADA system.

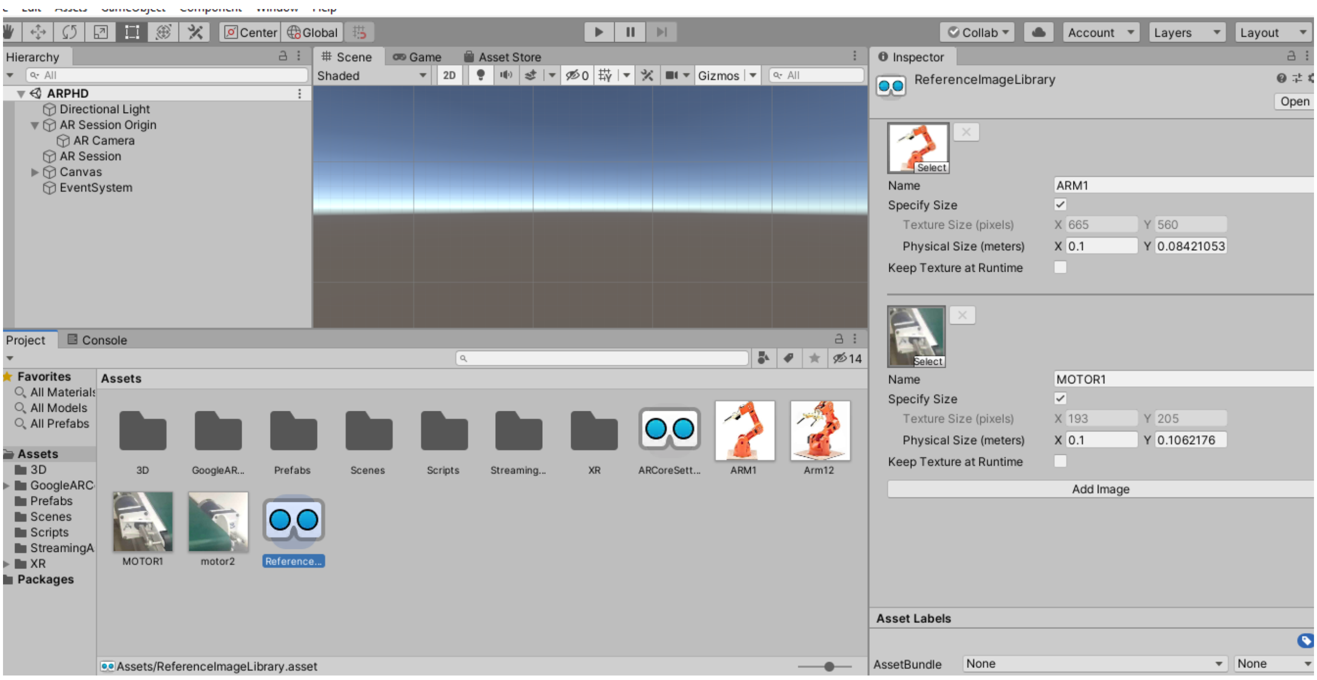
The device selection on the SCADA system is obtained, using the dropdown or a Combobox in Microsoft® Visual Studio ® 2012 to select the device, namely either the robotic arm or the motors. The robotic arm`s functionality depends on the input of the SCADA data before it can be transferred to the AR application via WiFi connectivity

3.5. System integration development process

The design of industrial MR applications can lead to saving lives, especially in high-risk industries, such as mining if implemented correctly, as the users can virtually test processes and have virtual tours before physically executing them. The methodology used for this study is focusing on the use of Vuforia (AR Development tool), EmguCV, and OpenCV libraries (Machine Vision) for the design and modelling of the prototypes. The sensory output data gets projected on the SCADA system and the augmented reality device output data gets projected on the AR application.

3.5.1. AR application development setup

The development of the AR application was based on scenario-testing to accomplish the best results that can identify the devices, based on their position and features in the manufacturing plant. Firstly, the robotic arm was modelled in Blender3D, as outlined in sub-section 3.4.2 and the .bli.file was imported into Unity3D. In Unity3D, the converted .fbx file was assigned attributes or features that are unique from other .fbx files, using the integration of Unity3D and SLAM algorithm. However, the motor image was taken from the laboratory set-up and it was modified so that two motors have two different features. They then were added to the AR development database where it was also assigned the features as outlined in Figure 3.10.



Assets/ReferenceImageLibrary.asset

ReferenceImageLibrary

Name: ARM1
Specify Size: ✓
Texture Size (pixels): X 665 Y 560
Physical Size (meters): X 0.1 Y 0.08421053
Keep Texture at Runtime: □

Name: MOTOR1
Specify Size: ✓
Texture Size (pixels): X 193 Y 205
Physical Size (meters): X 0.1 Y 0.1062176
Keep Texture at Runtime: □

AssetBundle: None None

Figure 3.10: Modelled device imported into the Unity3D assets directory.

Figure 3.10 depicts the AR application of modelled images. The device images were modelled in Blender3D and features were added for the application to distinguish between the two devices. Additionally, each reference image parameter is represented differently, as outlined in Figure 3.10.

Figure 3.11 presents the method for the AR Application development program flow diagram.

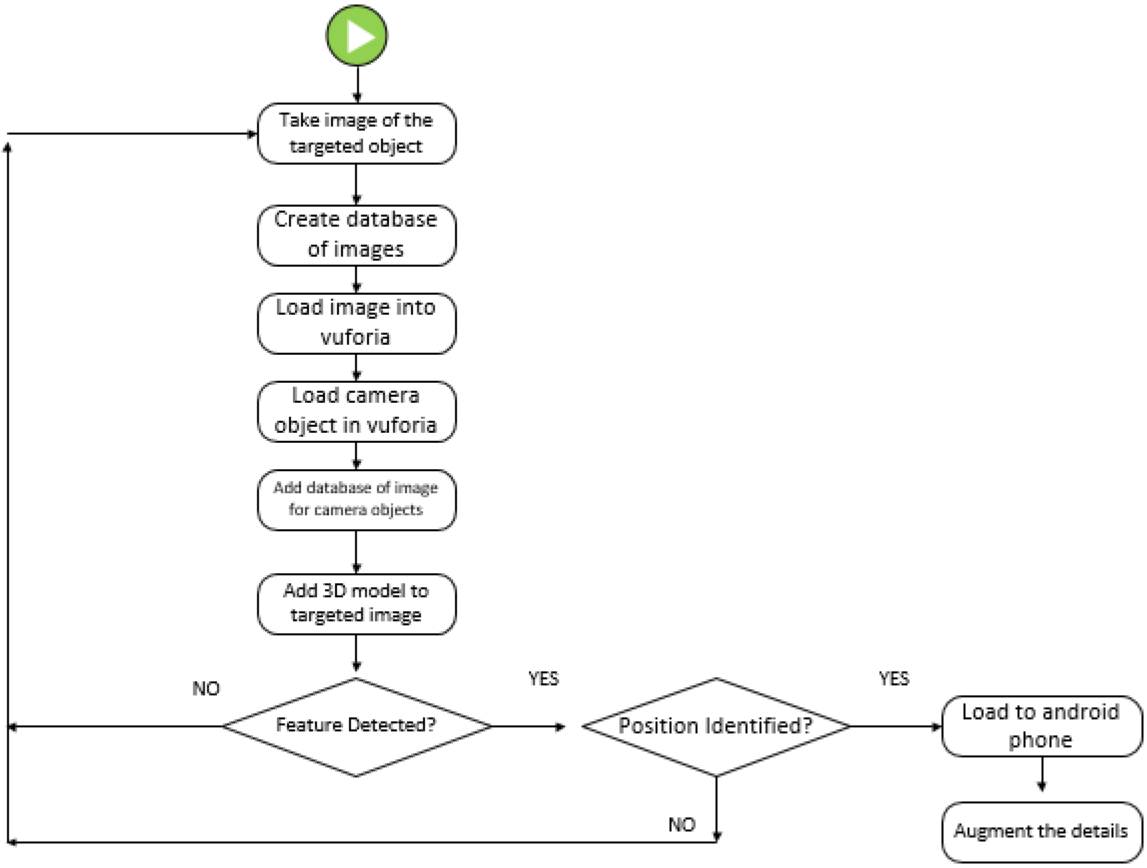

Take image of the targeted object
Create database of images
Load image into vuforia
Load camera object in vuforia
Add database of image for camera objects
Add 3D model to targeted image
NO
Feature Detected?
YES
Position Identified?
YES
Load to android phone
NO
Augment the details

Figure 3.11: Flow diagram of the AR development method.

Figure 3.11 depicts the AR application development flow diagram. In the initial AR application development process, a .JPEG image of the first sample test of the conveyer belt was added to the AR database and loaded onto Vuforia. After the assets and Vuforia libraries are correctly imported, the AR camera becomes active on the GameObject menu. After this, the AR camera was opened inside Unity3D and the features were assigned to the image, and detection was tested. Once the web-camera can detect the image features, the application can be loaded on the smartphone and the actual application can be tested, using the smartphone.

However, after the feature test was conducted, the GPS module was used and placed on each motor at a 2-meter distance apart. The second motor with the same gearbox, but with a different feature (colour), was used, following the same testing process as outlined in Figure 3.11. However, it was noted that the GPS modules are not accurate in an indoor environment, even after adding external antennas.

As a result of the inaccurate data recognition, it was noted that GPS coordinates in the first approach were not accurate, thus beacons and satellite dependency were a big disadvantage and as a result, this model cannot be efficiently applied on a large scale. Large scale in this context relates to manufacturing plants like Coca-Cola, Eskom, where many robotic arms and conveyor belts are placed close to each other. Hence, the utilisation of the second approach, which therefore resulted in an alternative model of utilising the SLAM algorithm.

Subsequent to the observations relating to Figure 3.11, the SLAM algorithm was used in conjunction with AR application, due to its ability to solve the challenges of unknown environments and real-time tracking.

The alternative model of utilising the modelling algorithm was used in conjunction with augmented reality, due to its ability to solve the following challenges that were tricky to be solved, using a GPS module, as the feature detection was not a problem.

The identified challenges that the SLAM algorithm can solve are as follows:

i. Unknown environments;
ii. Real-time tracking.

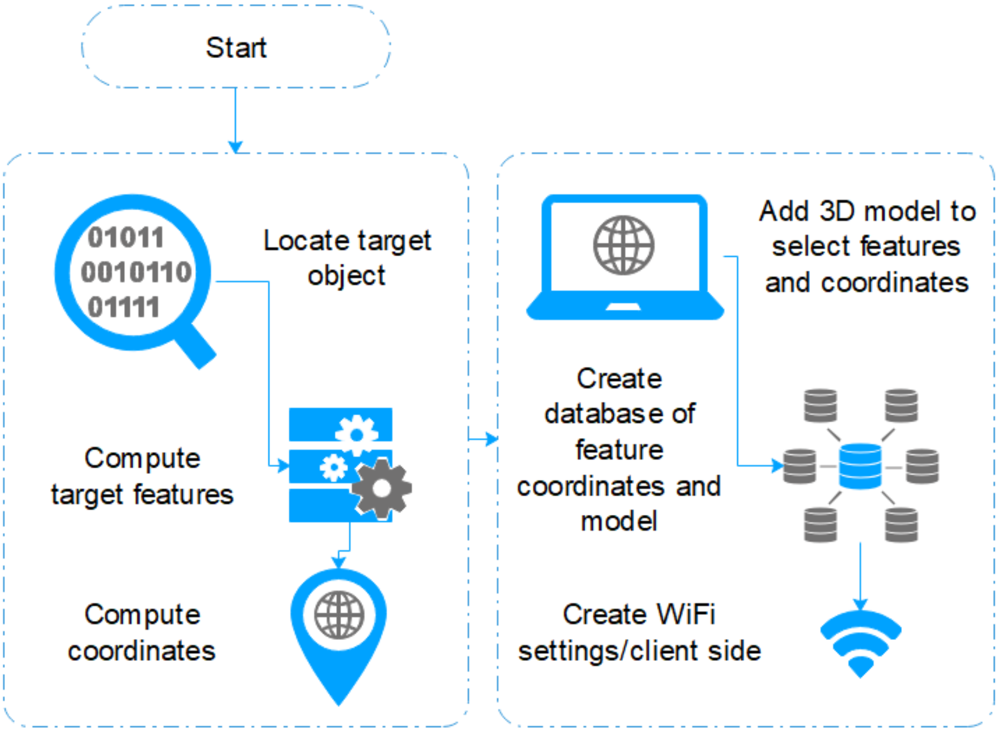

Start
01011
0010110
01111
Locate target object
Compute target features
Compute coordinates
Add 3D model to select features and coordinates
Create database of feature coordinates and model
Create WiFi settings/client side

Figure 3.12: System process flow for the AR application.

Figure 3.12 highlights the steps for setting up the SLAM algorithm:

i. Inspection for features by applying the SLAM feature algorithm on the devices that are in the manufacturing plant;

ii. Upon finding the device unique features, the data is then saved onto the AR database for reference, and then adds the appropriate model;

iii. Then compute the coordinates of those features and store them in the same AR database, but with a different name for reference purposes;

iv. Create a WiFi connection between the AR application and the SCADA system;

v. Integrate the Bundle Adjustment algorithm to calculate the device positions, based on uncertainties.

Once the Bundel Adjustment and the ORB-SLAM algorithm are successfully integrated and implemented for simultaneous computation, a test is ran, using the web camera to note if the application can detect the devices. Upon the web camera's successful trial test, the application is loaded on the smartphone for simulation of the AR application.

The device images are loaded into the AR database as stated, for computation by an image matching or reference imaging principle, for example, the ability to detect and augment data, based on the features of the reference image or object. The image reference means that the features of the image in the AR database are compared against the detected image in the real scene. Due to numerous AR systems using various approaches, such as markerless and maker-based for visual augmentation of the scenes, the selection of the best features (which is the comparison of multiple images and select the one with more unique features) are conducted.

The natural feature and location-based features were deemed the most relevant, as the study focuses on device identification, based on the location and the unique feature. In the motor application context, the natural feature was added with regards to identifying the correct motor, based on its uniqueness despite the location change.

The use of natural features, integrated with feature detection in augmented reality, is currently noted as the future for industrial applications. However, these two detection approaches are not well adapted in the augmented reality field, due to the bandwidth limitations and the power consumption of data communication [65]. Hence, this research study approach is conducted on a small scale (using two devices as compared to 10 devices, however, the principle operation can be scaled up), due to improvement in technological resources by utilising scaled components as outlined in the apparatus section.

3.5.2. Development of machine vision for object detection and recognition in a .NET framework

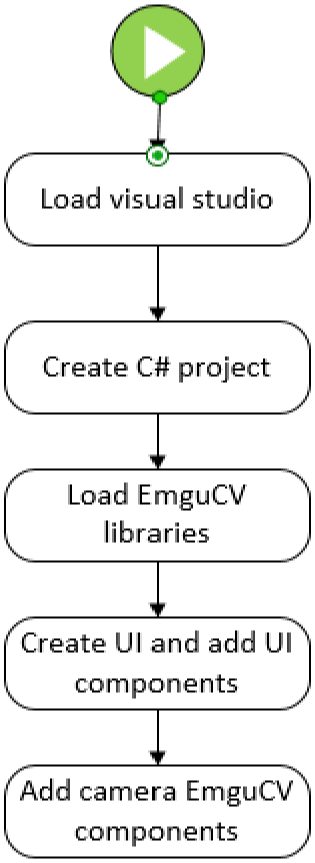


Figure 3.13: Flow diagram for the development of machine vision application.

Figure 3.13 outlines the flow diagram for the development of the machine vision application. Microsoft® Visual Studio ® 2012 is opened and the C# windows application is created. The object's images are taken and stored in the working directory of the application. Once this is done, Emgu CV libraries are also loaded onto the application by importing them and also copying them into the debug folder of the C# application. After this, the SCADA system is then modified to add components of Emgu CV, such as camera window onto the SCADA User Interface (UI).

Figure 3.14 outlines the initial SCADA concept of the UI design. The design incorporates EmguCV libraries with the same process method as outlined in Figure 3.13.

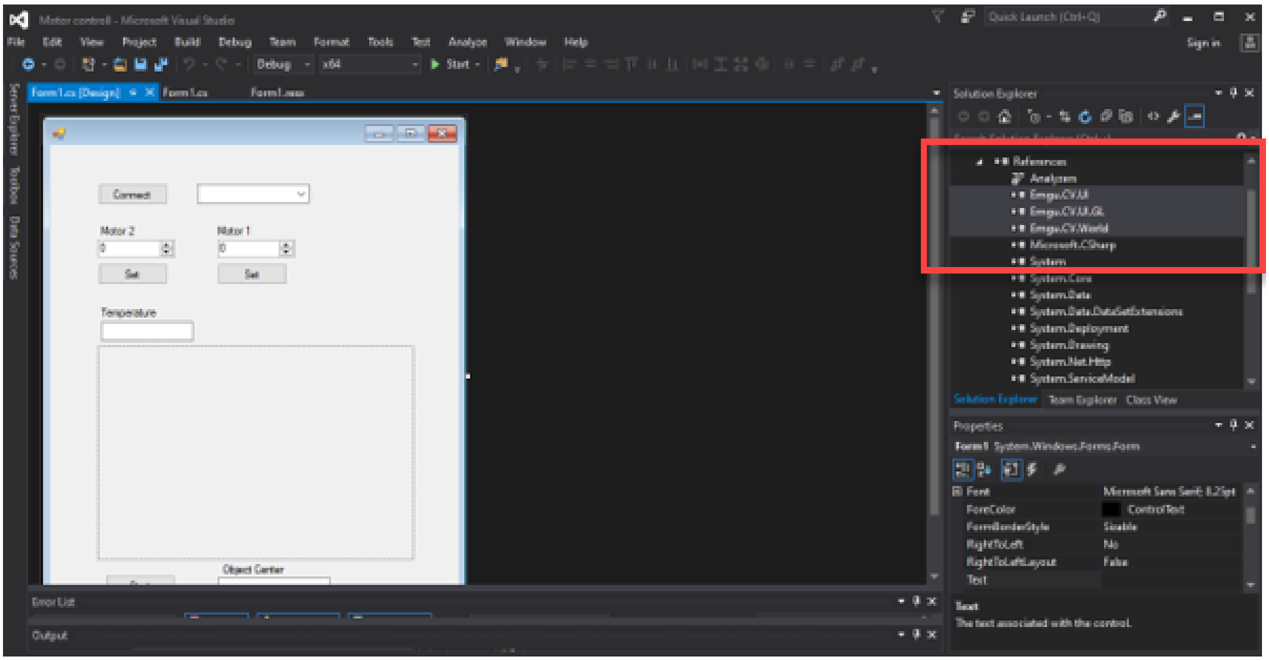


Figure 3.14: SCADA C# interface with machine vision on visual studio.

Table 3.7 highlights the C# code for calling the VideoCapture algorithm. VideoCapture`s function is to open the video from the GUI. Furthermore, the Emgu CV libraries highlighted in Table 3.7 are used to wrap the OpenCV libraries and grant OpenCV to function in a C# environment.

Table 3.7: High-level pseudocode for opening the camera capture.

```
Algorithm: VideoCapture()
Function: Begin()
    Private Capture capture = NULL
    Private bool captureInProgress = FALSE
    Int cameraDevice = 0
    Video_Device[] webcams
        IF capture == NULL
        THEN
            Capture = new VideoCapture(1)
        ELSE
            Capture.ImageGrabber += capture.ImageGrabber
            Capture.Start()
END
```

The external High Definition (HD) camera cable is connected to the laptop`s communication port to establish a connection to the machine vision application. After the connection is successful, the live video starts, the image processing algorithms are activated, and the inspection of the object can commence by identifying red squared objects.

3.6 SLAM development application operational process

The ORB-SLAM algorithm is regarded as a feature-based monocular SLAM system that operates in real-time, in small and large indoor and outdoor environments [66]. This algorithm is considered as a visual algorithm that does not use or require the odometry from the accelerometer. However, for this application, the ORB-SLAM algorithm was used in conjunction with the Bundle Adjustment algorithm. The ORB was then based on the underlying keypoints for the generation of descriptors, as indicated in Figure 3.15.

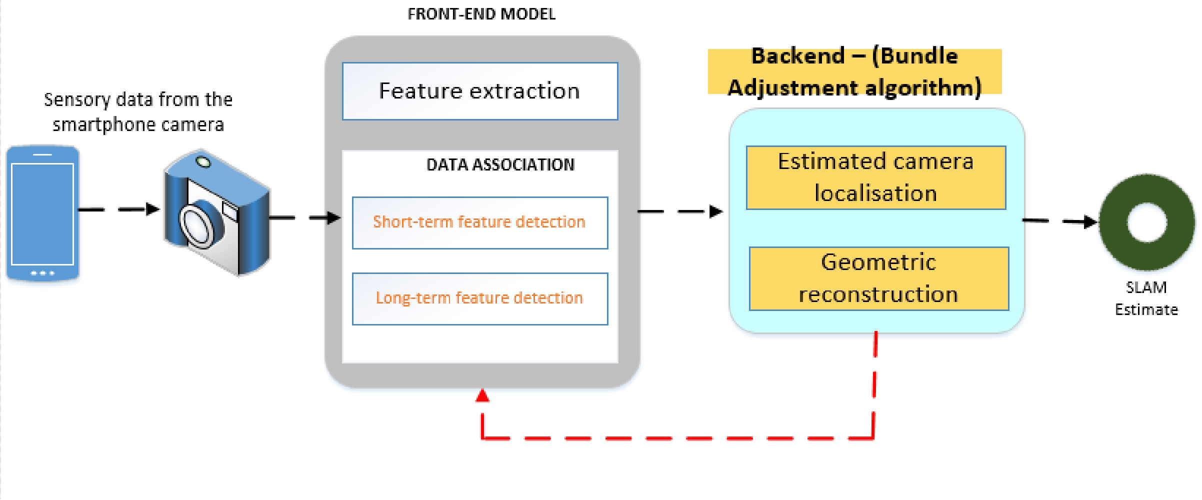

FRONT-END MODEL
Sensory data from the smartphone camera
Feature extraction
DATA ASSOCIATION
Short-term feature detection
Long-term feature detection
Backend – (Bundle Adjustment algorithm)
Estimated camera localisation
Geometric reconstruction
SLAM Estimate

Figure 3.15: SLAM algorithm integrated with Bundle Adjustment algorithm model *[66]*.

The system model is designed as follows:

i. The smartphone uses its built-in camera to act as a sensor to capture the data to be utilised by the AR application;

ii. In the front-end, the device features are detected and extracted from the in-data received from the camera sensor, and these features are then associated with landmarks/keypoints with a 3D position. However, this process is achieved through video camera live tracking;

iii. The Bundle Adjustment algorithm then establishes the relationship between different frames as the in-data keeps being received by localising the camera pose model and overall geometry reconstruction;

iv. Upon successful establishment of frame relationship, the SLAM estimate then captures the results, carrying the tracked features, their relations, and locations, also including the camera position within the environment.

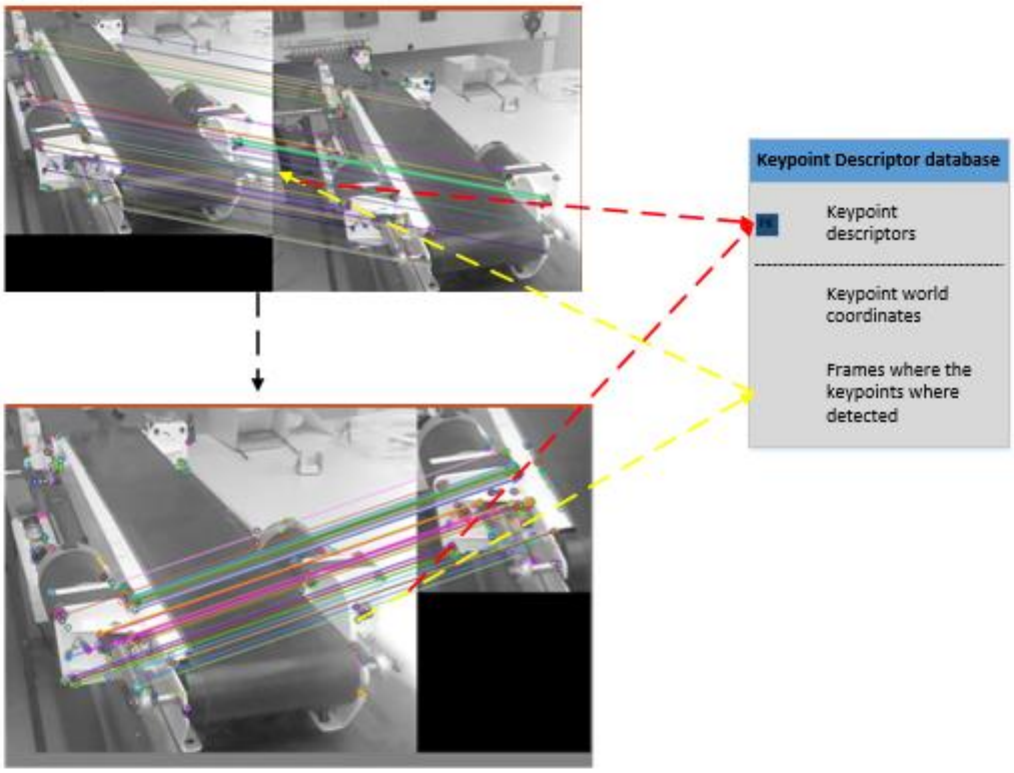

Keypoint Descriptor database
Keypoint descriptors
Keypoint world coordinates
Frames where the keypoints where detected

Figure 3.16: Keypoints detected in frames.

Figure 3.16 outlines the ORB-SLAM algorithm that analyses the keypoint frames. Upon the map storage of the device keyframes, the detected keypoints are referenced and stored in the AR database. In addition, to the keypoints detection, the features are also aligned with Figure 3.17 for video-tracking for feature detection.

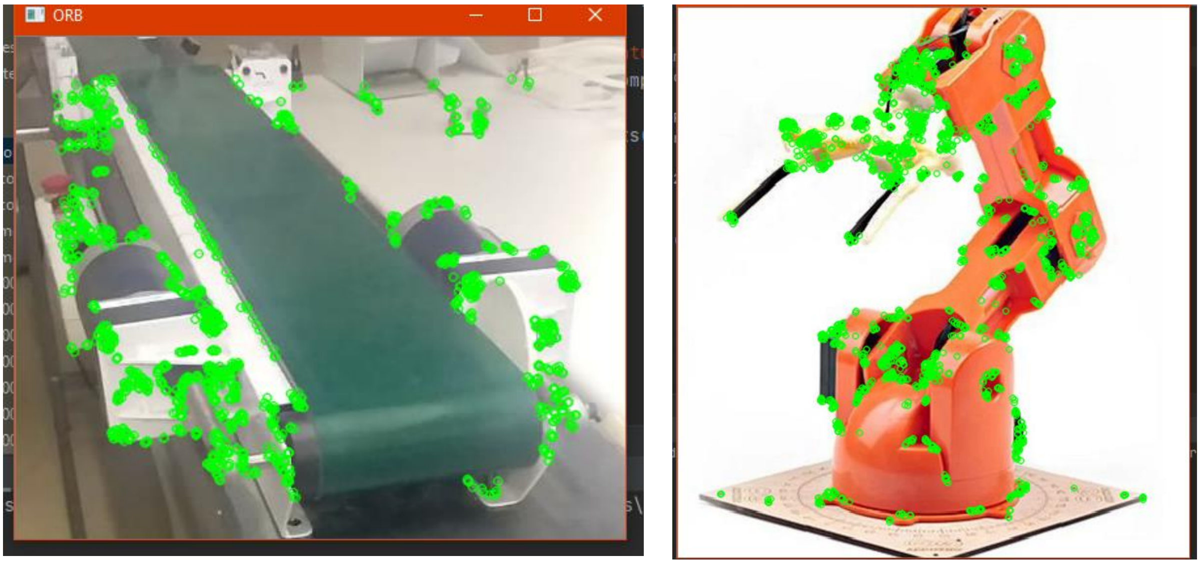


Figure 3.17: Feature detection on devices.

Figure 3.17 outlines the feature detection where the feature points are detected by the algorithm, during the video-tracking and saving the data into the database.

3.7. Data transfer WiFi-based protocols

The data transfer section outlines the process in which the data is transferred from the SCADA system to the AR application. Furthermore, the input data in the SCADA system controls the movement of the robotic arm. However, the data first have to be transferred to the AR application via WiFi connectivity, which is the principle that is discussed in this section.

The robotic arm utilised in this study comprises of 5-degree joints/angles. However, due to the complexity of integrating the physical sensors on the robotic arm joints, an alternative method of using manual user input is utilised. As indicated in Figure 3.18, the user inputs data into the SCADA system, and then the data becomes accessible for viewing and altering in the SCADA system. However, for security reasons, the user has to login into the system for any alteration of data and non-logged-in users can only view the output data.

The SCADA data is then sent every one second to the Wemo WiFi module, which is a WiFi module that transfers data packets over the network to the destination IP address. The data are then transferred to the AR application where is stored and can be viewed at anytime, provided that the robotic arm is available and for the data to be updated, the user is required to update the application.

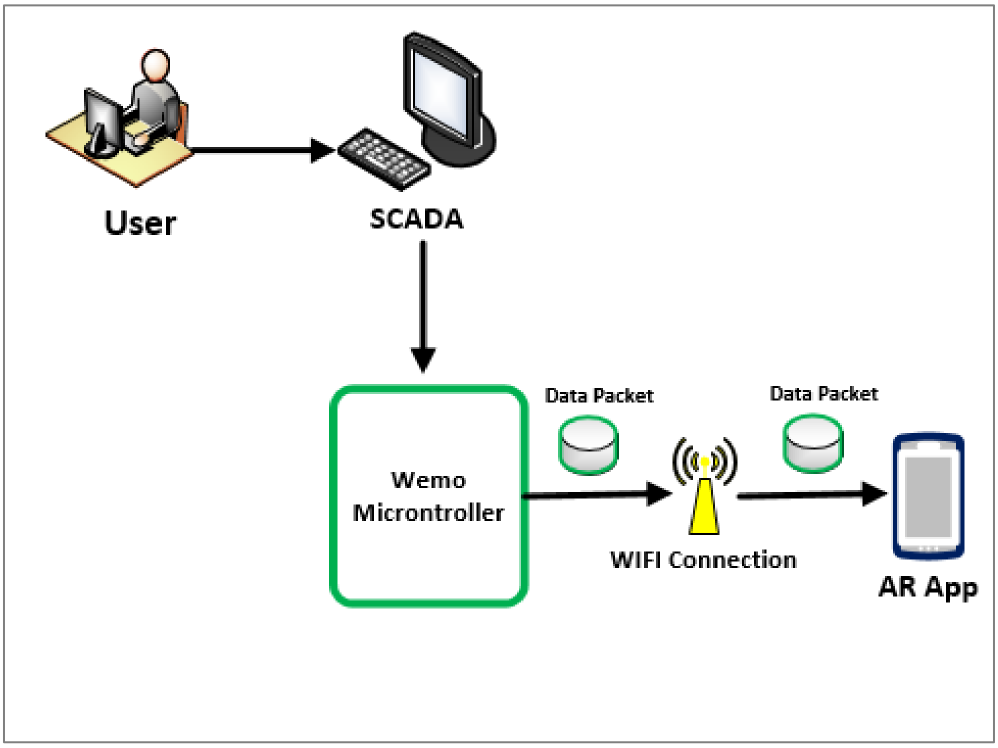


Figure 3.18: User data input and data transfer.

Due to the size and non-complexity of the transferable data packets from the SCADA system, only one data packet with a string of values is transmitted to the smartphone device, utilising the 802.11b WiFi protocol. The selection of the protocol is based on test device/smartphone compatibility. This protocol is used with reference to the availability of the Wemo WiFi module, which reads the output data from the Arduino microcontroller and transfers that data to the Smartphone device via the 802.11b WiFi protocol.

The test was based on the WiFi connectivity inside the manufacturing plant. However, the WiFi connectivity in the context of this research study gave reference to data transfer protocol by making use of Transmission Control Protocol (TCP)/IP protocol), which is a connection-oriented communication protocol. TCP/IP protocol is arranged to send data packets over the network and ensure that they are delivered to the static destination IP address.

In this section, a method in which the sensors are placed and how the data are transferred from the SCADA system to the AR application via WiFi connectivity is discussed. The sensory part comprises of the following sensors:

i. Light Dependent Resistor (LDR) – Room light;

ii. LM35 – Motor temperature;

iii. Proximity sensor – Direction and speed.

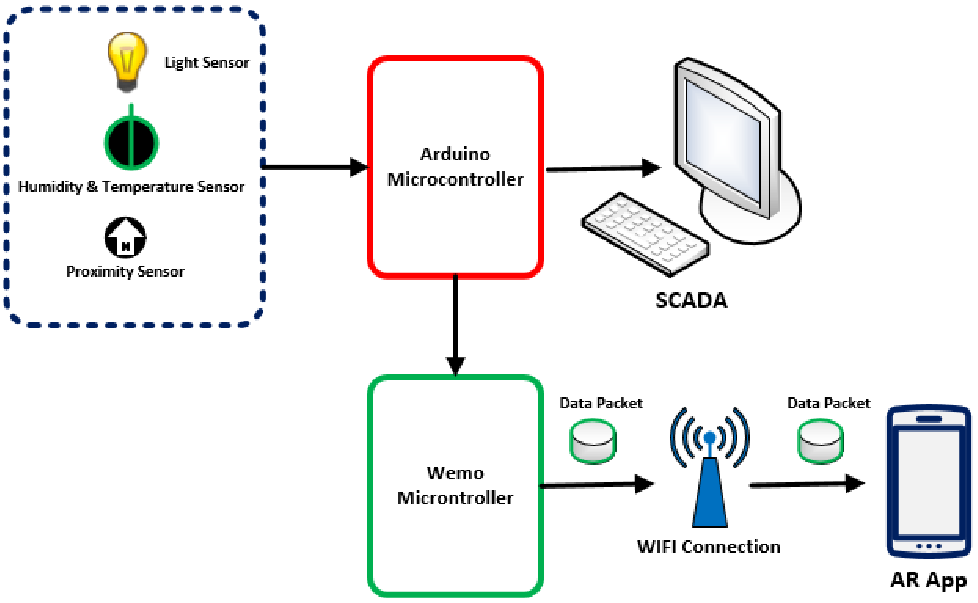


Figure 3.19: System data transfer process.

Figure 3.19 highlights the system data transfer process from the sensors to the data transfer protocols. The sensors are connected to the Arduino microcontroller at the fixed points to determine the room light, direction and device’s temperature. However, due to the complexity of mounting the proximity sensor on the motors, the basic guidance was depicted from the ref [67] method of mounting sensors on the motors, despite the approaching model being an old technique.

The method utilised by ref [67] calculates the device speed and direction by attaching the timing disc to the rotational shaft, opposite the timing shaft, and mounting the two spaced -together with the proximity sensor at a given distance apart.

Figure 3.19 further depicts the data acquisition process from the SCADA to the application. Data acquisition is regarded as the process of retrieving control information from the equipment, which is out of order or may lead to some problem or when decisions need to be taken, according to the situation in the equipment [68]. The data acquisition is then based on the continuous monitoring of the equipment data that are gathered by sensors, relays, valves, and motors.

Machine vision is denoted as the use of a camera or multiple cameras to inspect and analyse objects automatically and this process can be in an industrial or production environment [69]. Machine vision makes use of arrays of pixels. MV has as an element of the 4th Industrial Revolution (4IR), which has advanced from a typical analog system to a digital system with multiple uses, such as tracking, data collection, and machine monitoring.

The data transfer in this study refers to the hardware data (SCADA system) being shared with the AR application, via WiFi connectivity.

The transfer is accomplished using a WiFi-based module, called the Wemo module. The Wemo module is connected to the Arduino microcontroller. After the Arduino reads the sensory data and displays it on the SCADA system, and the module immediately sends the string of data packets to the AR application, via the WiFi through the Wemo module. This process is defined as Machine to Machine (M2M) interface, which is a protocol, within the Internet of Things (IoT) system where data are transferred from one machine to the other without any human intervention.

Table 3.8 outlines the different WiFi protocols and data rates derived from ref [70]. However, due to the size and non-complexity of the data packets transfer protocol, the 802.11b protocol was used, due to its compatibility with the test phone specifications.

The test was based on WiFi connectivity inside the manufacturing plan prototype. Through the WiFi connectivity, the data transfer was accomplished using Transmission Control Protocol (TCP)/IP protocol), which is a connection-oriented communication protocol. TCP is arranged to send data packets over the network and ensure that it is delivered to the destination IP address, which is configured to be a static IP address for all devices (Smartphones) in the context of this study.

The sensory data is read from the Arduino microcontroller as a packet of 32 bits string and transferred via the Wemo module through the WiFi, using protocols and logic.

Table 3.8: Summary TCP/IP data transfer protocol *[70]*.

<table>
<tr><td colspan="3">Source Port</td><td>Destination Port</td></tr>
<tr><td colspan="4">Sequence Number</td></tr>
<tr><td colspan="4">Acknowledgment Number</td></tr>
<tr><td>Data offset</td><td>Reserved</td><td>Flags</td><td>Window (Sliding window)</td></tr>
<tr><td colspan="3">Checksum</td><td>Urgent pointer</td></tr>
<tr><td colspan="3">Options</td><td>Padding</td></tr>
<tr><td colspan="4">Data</td></tr>
</table>

The test set-up model has a new feature of identifying objects, based on their colour and shape within the manufacturing environment, where utilisation of the machine vision is outlined. Machine Vision (MV) is denoted as the use of a camera or multiple cameras to inspect and analyse objects automatically and this process can be in an industrial or production environment [71]. Machine vision makes use of arrays of pixels. MV has as an element of the 4th Industrial Revolution (4IR), which has advanced from a typical analog system to a digital system with multiple uses, such as tracking, data collection, and machine monitoring.

MV output was incorporated into the SCADA system to display the overall research study data in one window. The sensory data are displayed on the SCADA and use the Wemo microcontroller and WiFi connectivity for the shared data to the AR application.

The physical configuration based on the Wemo microcontroller is the connection to the Arduino Microcontroller. Upon the sensory data retrieval from the database, the Wemo microcontroller immediately sends the packet of strings to the AR application via the WiFi connectivity.

The sensory data are read from the Arduino microcontroller as a packet of 32 bits string and transferred via the Wemo microcontroller through the WiFi connectivity. Figure 3.20 depicts the machine vision set-up method. The initial testing of the machine vision integrated system was based on red squared objects, then blue squared objects as outlined in Figure 3.20. However, despite the evolution of protocols, the test was based on the availability of WiFi connectivity in the manufacturing plant.

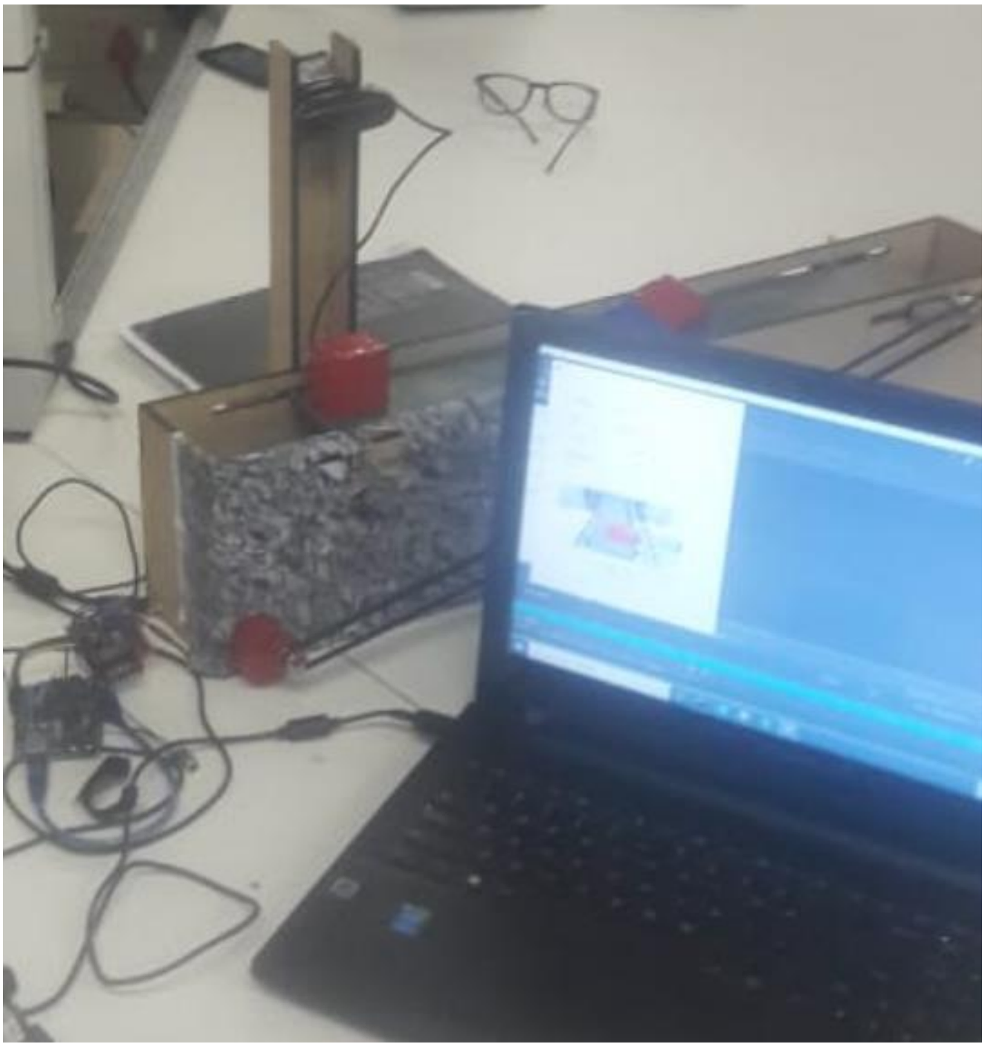
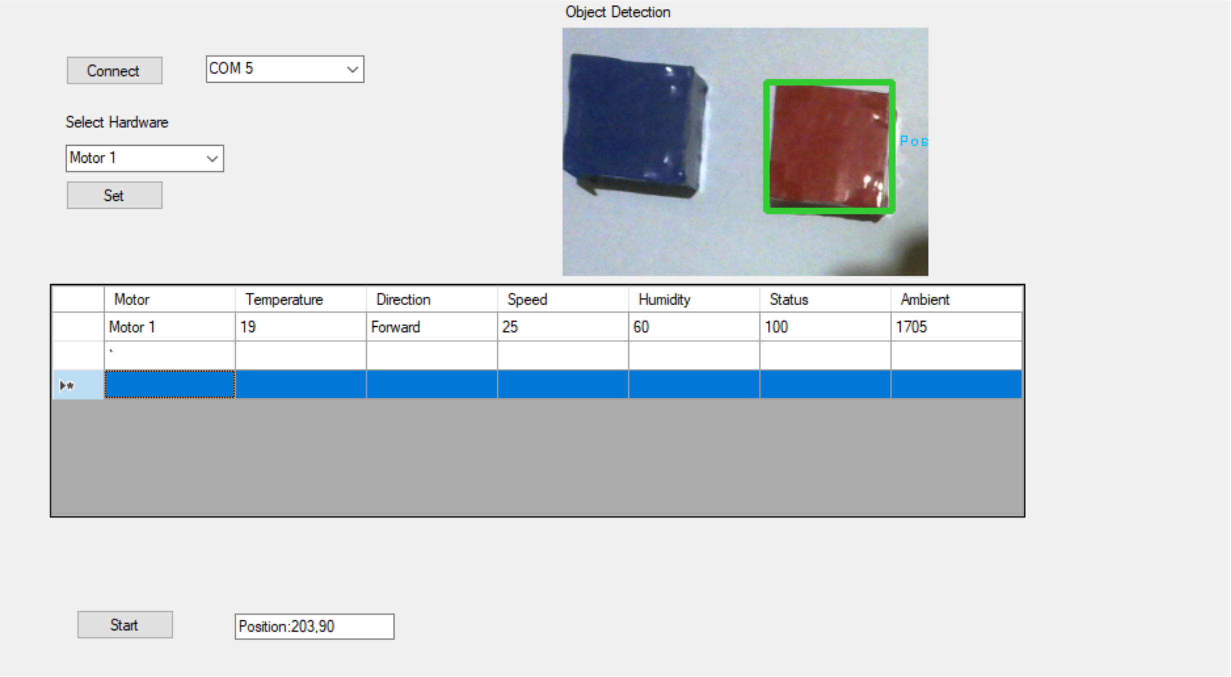


Figure 3.20: Machine vision application on a small scale for tracking red objects.

Figure 3.20 depicts the obstacle tracking, based on shape and colour, utilising image processing and machine vision techniques. The object recognition in the context of this study is based on the contour approximation technique, while the colour detection is based on defining images' lower-pixel and upper-pixel values.

Once the pixel value definition is achieved, the cv.inRange method is used to return the mask of pixel values. Upon having the correct mask, the cv2.bitwise function can be applied to the target image.

Furthermore, Figure 3.21 outlines the use of machine vision as an interim test together with the SCADA system.



COM 5

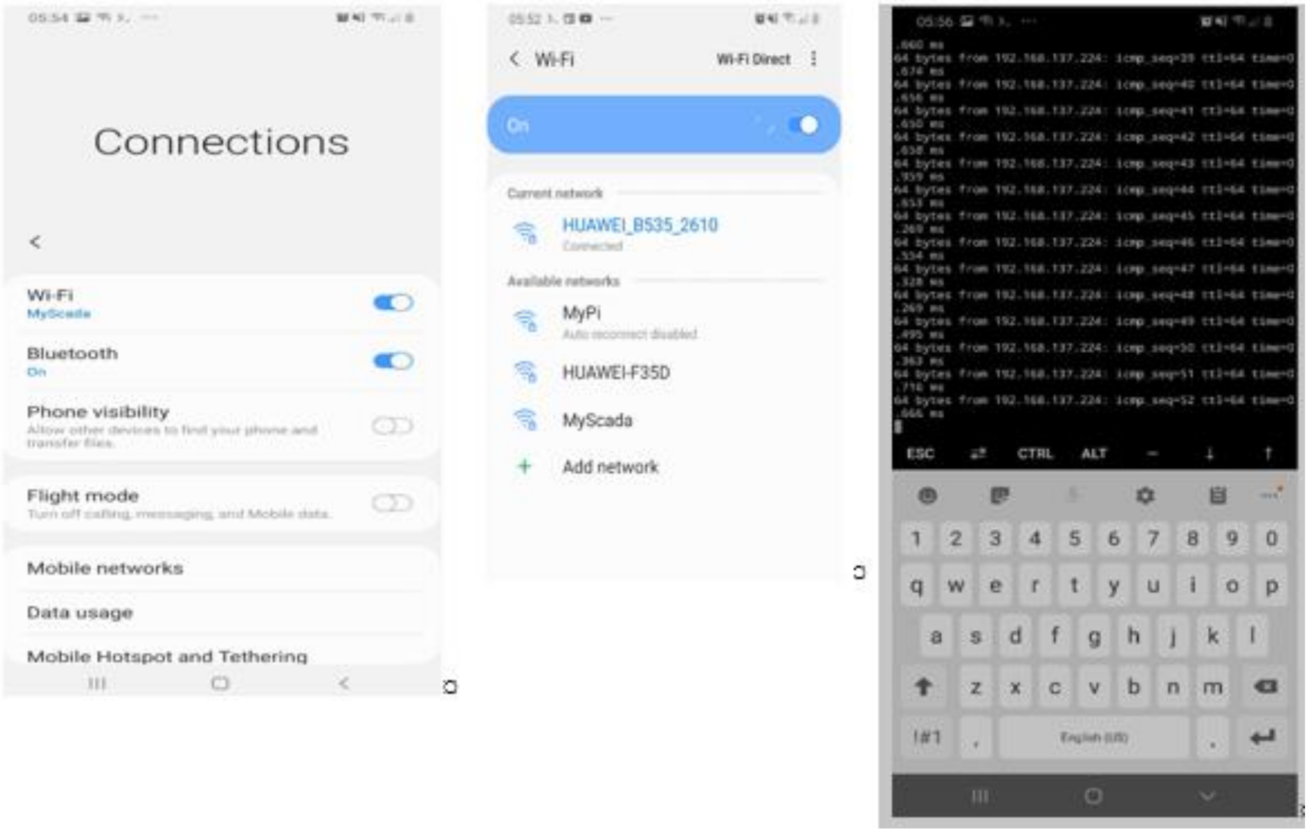
Motor 1

Motor	Temperature	Direction	Speed	Humidity	Status	Ambient
Motor 1	19	Forward	25	60	100	1705

Position:203,90

Figure 3.21: SCADA results output for object detection and device identification.

Figure 3.21 outlines the detected objects, utilising machine vision and the output is displayed on the SCADA system. In order to know which object is detected, a green square is drawn upon the detected object as per the study requirements for the differentiation between the detected and non-detect objects. Furthermore, the DataGridView displays the selected output for motor 1, which will be sent to the AR application.



Connections

Wi-Fi
MyScada

Bluetooth
On

Phone visibility
Allow other devices to find your phone and transfer files.

Flight mode
Turn off calling, messaging, and Mobile data.

Mobile networks

Data usage

Mobile Hotspot and Tethering

Wi-Fi

Wi-Fi Direct

On

Current network

HUAWEI_B535_2610
Connected

Available networks

MyPi
Auto reconnect disabled

HUAWEI-F35D

MyScada

Add network

```
.660 ms
64 bytes from 192.168.137.224: icmp_seq=39 ttl=64 time=0
.674 ms
64 bytes from 192.168.137.224: icmp_seq=40 ttl=64 time=0
.656 ms
64 bytes from 192.168.137.224: icmp_seq=41 ttl=64 time=0
.650 ms
64 bytes from 192.168.137.224: icmp_seq=42 ttl=64 time=0
.638 ms
64 bytes from 192.168.137.224: icmp_seq=43 ttl=64 time=0
.959 ms
64 bytes from 192.168.137.224: icmp_seq=44 ttl=64 time=0
.653 ms
64 bytes from 192.168.137.224: icmp_seq=45 ttl=64 time=0
.269 ms
64 bytes from 192.168.137.224: icmp_seq=46 ttl=64 time=0
.554 ms
64 bytes from 192.168.137.224: icmp_seq=47 ttl=64 time=0
.328 ms
64 bytes from 192.168.137.224: icmp_seq=48 ttl=64 time=0
.269 ms
64 bytes from 192.168.137.224: icmp_seq=49 ttl=64 time=0
.495 ms
64 bytes from 192.168.137.224: icmp_seq=50 ttl=64 time=0
.363 ms
64 bytes from 192.168.137.224: icmp_seq=51 ttl=64 time=0
.716 ms
64 bytes from 192.168.137.224: icmp_seq=52 ttl=64 time=0
.666 ms
```

Figure 3.22: Data testing screen.

The test screen depicts the pinging of data. Firstly, the connection is established, and once the connection is successful, the device is pinged, using the IP address. The reason for conducting this test is to observe the latency of the data transferred from the SCADA system to the AR application. The initial step in the functioning of the SCADA system is to connect the SCADA to the machine vision application. Once the connection is successful, the hardware (motor one and motor two) is selected and set and the process or application can commence by pressing the start button. After setting this, the sensory data will be retrieved and outputted on the SCADA system. Subsequently, the camera will be used to detect the objects and the red squared object will be highlighted or marked with a green square over the detected object.

Furthermore, the methods, such as filtering can be conducted by formalising the distance transform technique [72]. Equation 1 highlights the mathematical approach in obtaining the distance for each control point.

$$d_{ij} = DT(F)\left[m_{ij}\right] = \frac{min}{f}\ dist(m_{ij}, f), \tag{1}$$

Where:

d_{ij} denotes the distance measured for each m_{ij}(control point)

$m_{ij} - f_e$ denotes the Euclidean distance

Figures 3.23 depicts the conveyer belt that was already constructed. However, this conveyer belt was optimised in Blender3D for location and feature detection, using augmented reality in Unity3D. The movement or direction of the motor is shown on both the SCADA system and the AR application, because the SCADA system shares data with the AR application, using the data transfer protocols outlined earlier.

Furthermore, the feature detection used to detect the motor outlined in Figure 3.23, is only focusing on a few numbers of motors, which is an approach that would yield positive scientific practices if the study is conducted on a broader scale. However, in the AR application, the motors can be differentiated by their uniqueness, which in this case is the feature and their position within the manufacturing plant.

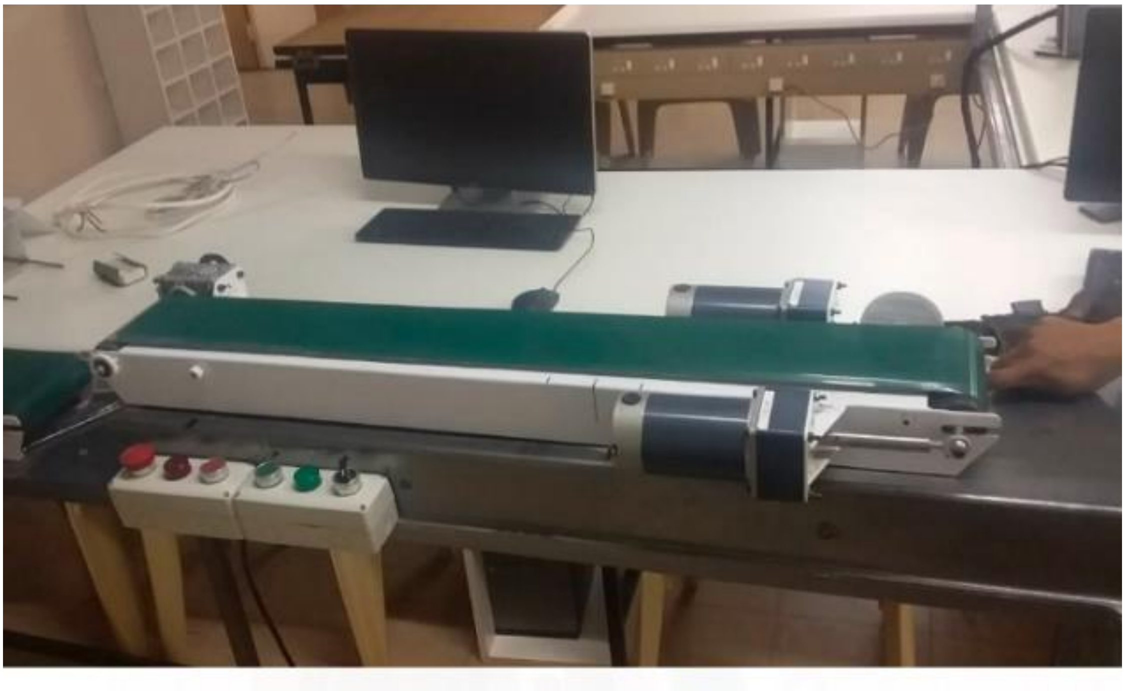


Figure 3.23: Conveyer belt construction.

Furthermore, this conveyer belt was used as part of the test set-up for the physical model testing. The AR application was able to detect and augment the motor details, based on their unique feature and the location within the manufacturing environment.

The constructed conveyor belt's (outlined in Figure 3.23) motion, speed and direction are controlled by the input data that are being fed by the SCADA system. Post this, the objects are placed onto the belt and their motion is controlled based on the inspection results.

3.8. Summary

This chapter describes the development of the following physical models:

i. conveyer belt, sensory application;
ii. the AR application built on an Android platform;
iii. machine vision for object detection and recognition, as well as the development of the SCADA system.

The development of a computer vision application was presented. In the development of this application, the RGB conversion of (255, 0, 0) was integrated with colour and shape detection algorithms from OpenCV. As a result, the camera could only identify the objects with the defined elements in the algorithm and nothing else. In addition, the AR application development, detailing the algorithms and how these algorithms were manipulated to achieve the objectives of this study, are outlined as follows:

There were two AR development models presented namely:

i. the standard reference imaging;
ii. the ORB-SLAM-Bundle Adjustment integration approach.

Due to the study objectives, it was observed that the standard image referencing model was not adequate for this study, due to limitations and the unreliability of utilising the GPS module for pinpointing the correct device. The inaccuracy was observed to be as a result that the GPS depends on the satellite data and position. Furthermore, during the test and development phase, the two devices were placed at a 2-meter distance apart from each other and it was noted that the GPS in an indoor environment is inaccurate. After noting this development shortcoming, extra antennas were added to the GPS module, however, it did not change the results or have a positive impact on improving the accuracy of the GPS. Subsequent to this test, the devices were carried and tested outside and it was then that the GPS operated optimally with correct position identification, however, the results were not consistent.

After the observations were noted in the first approach, alternative algorithms had to be investigated and applied to the research study. It was noted that the ORB-SLAM algorithm integration with the Bundle Adjustment algorithm would provide more consistent results to identify the device by its position and features in an indoor environment. This integration is due to the fact that the Bundle Adjustment algorithm is used to minimise the errors in each feature placement. The Bundle Adjustment algorithm was imported into the working directory of the project and the localisation method was reconstructed to be active only when the features and position status are true, hence the selection of the Bundle Adjustment algorithm.

Furthermore, the prototype testing methodology was outlined, citing the individual modelling and testing, as well as the integrated system testing. In addition, the method for transferring the sensory data flow from the SCADA system to the AR application, utilising WiFi connectivity was outlined. However, there was no optimisation or development of WiFi connectivity. Subsequently, the design process and operations of the robotic arm and its application and integration to the complete system, including but not limited to input data flow from the SCADA system to the AR application and the control of the robotic arm by the Arduino microcontroller.

Chapter 4: Results and discussions

This chapter covers the system results obtained from the development chapter. The system results are evaluated, analysed and discussed to assess the feasibility of commercialising the product and the merits of the study in achieving the study`s objectives and hypothesis.

4.1. Introduction

This chapter appraises the results of the tests conducted for this research study. The results are based on three research study components, namely:

i. AR application development;
ii. machine vision application in the manufacturing plant;
iii. SCADA system development and data transfer.

The AR application is established and developed on the Android smartphone to identify the devices in a manufacturing environment by augmenting their details, based on their location and feature within the manufacturing plant. The machine vision application's primary function was to identify objects on the conveyer belt at the object inspection station where the object`s colour and shape are inspected before the robotic arm can be activated. The reason for the introduction of the introspection station is to proportionally save electricity by allowing the robotic arm to be on sleep mode and only operate upon a trigger signal, waking the arm.

Furthermore, it was of great importance that the SCADA system can retrieve the device's sensory data, namely position, number, speed, direction, temperature, and room light, and can transfer this data packet via WiFi connectivity to the AR application where it is replicated. The reason for that is to ensure that the SCADA data and AR application data do not overlap and as a result, the user can alter the device details. However, to obtain the sensory data, a detailed motor configuration method was outlined in chapter 3.

In this research study, two experiments were conducted, namely:

i. Experiment 1 - focused on the use of GPS modules for position identification in an indoor manufacturing plant;

ii. Experiment 2 – focused on the integration of the ORB-SLAM and Bundle Adjustment algorithm to identify different devices, based on their features and positions within the indoor manufacturing environment without the built-in map.

Furthermore, it was noted that both the sensory and the input SCADA data, transferred to the AR application, was achievable. However, for the AR application to update the data it needs to be refreshed before it can augment updated SCADA-related data.

4.2. SCADA data transfer and AR motor application outcome

This section outlines the tests conducted and the results thereof. The results for both machine vision and the AR application detection, showed detection effectiveness, as a result of strong WiFi connectivity. Furthermore, since most manufacturing plants operate 24 hours a day, a night test and day test were deemed important to examine the applications for both night and day operation. However, it observed that accurate device detection was realised more during the day (natural light), as compared to the night (artificial light). During the night test, the device would still be detected, but it required the user to move the smartphone and camera around to find the best light condition.

In addition to the day and night device detection tests, another two sets of tests were conducted for the AR application, namely:

i. use of pre-defined images, using GPS module;
ii. use of ORB-SLAM algorithm, integrated with Bundle Adjustment algorithm.

The test set-up was further formulated into two scenario experiments where the two scenarios were analysed, based on the case study, relating to the test set-up outlined earlier.

<u>Scenario 1: device testing for correct features and inconsistent device position.</u>

In this scenario, the device reference image from the AR database was utilised. A sample of two motors with the same features was placed close to each other at a 600 cm distance apart. During this scenario test, it was the author`s prerogative to determine at what distance the motors can be placed apart, bearing in mind that in the final test, the devices are placed two meters apart. However, it was observed that the AR application could recognise both motors, due to the identicality of the features. Furthermore, the motor that had one correct identifier was able to be augmented, but without augmenting the device details. This is a result of one identifier being correct or either the feature or the position.

Figure 4.1 depicts the results for the AR application experiment for scenario 1, where the motor test was evaluated for one correct identifier. This scenario experiment was conducted against the study objectives of augmenting the device, based on its features and location within the manufacturing plant.

Scenario 2: device testing for correct device position and incorrect device features.

The same requirement outlined in Scenario 1 was applied in scenario 2. However, in scenario 2 the variables were swapped around, but with the distance between the devices still at 600 cm. Utilising the GPS module, the motor coordinates were not stable as outlined in chapter 3. Despite those shortcomings, the experiment was still carried out to understand the behaviour of the system for future applications. Scenario 2 still augmented the results of the motor, however, due to the inconsistency of its position the application cannot track the correct position variable, hence the results depicted in Figure 4.1.

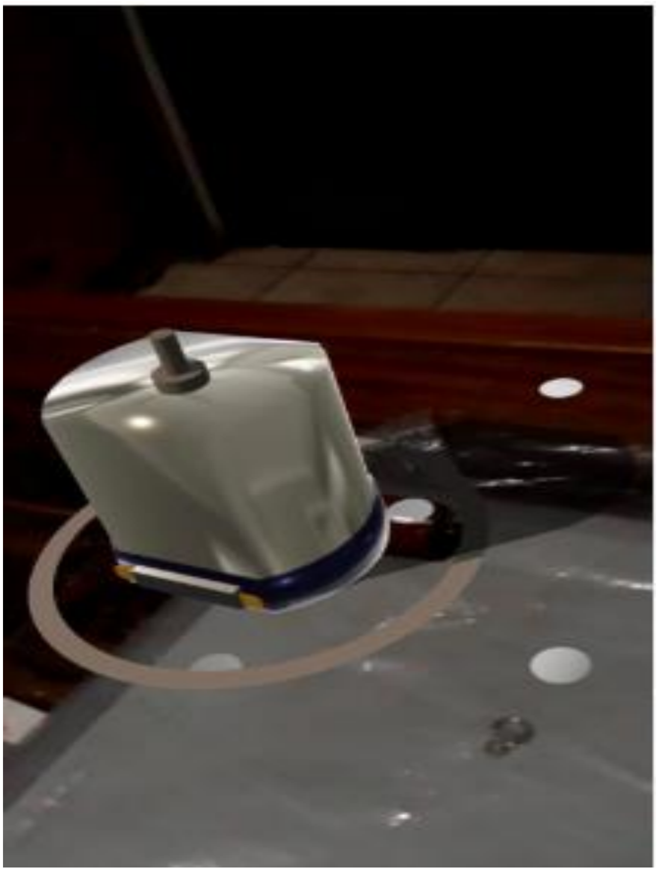


Figure 4.1: Augmented results of a variable with one correct identifier.

Figure 4.2 and Figure 4.3 outlines the output results of the AR application, based on the motor recognition algorithms containing the same data as the data appearing on the SCADA system. However, the results in these figures are based on the feature detection and GPS coordinates from experiment 1 which was outlined earlier. Furthermore, in the AR development application, a view datasheet button was developed to allow the users to view the motor datasheet for technical, non-technical, as well as new employees to understand the motor functionality and to allow them to see if the motors are not behaving as they are supposed to.

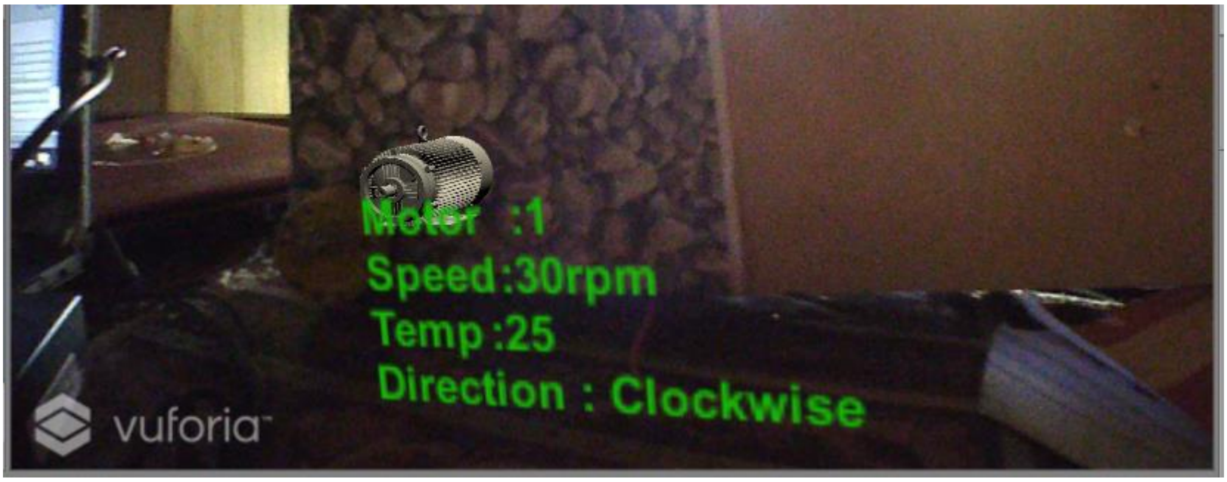


Figure 4.2: Motor 1 recognition based on GPS module configuration.

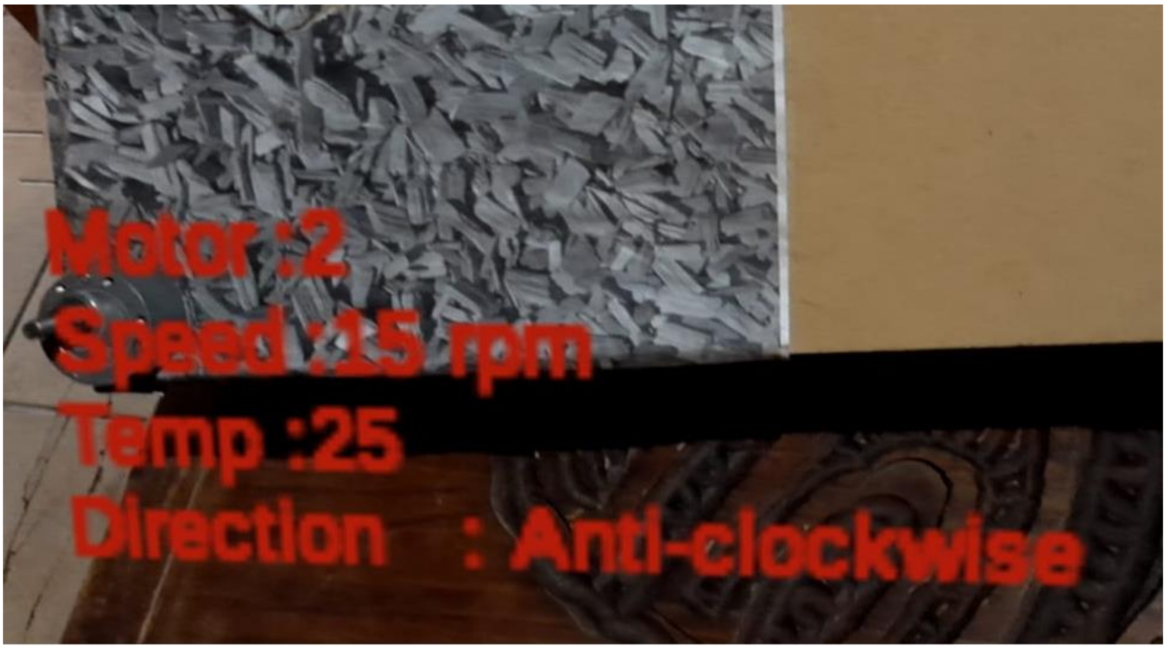


Figure 4.3: Motor 2 recognition based on GPS module configuration.

Additionally, the observations were made on the first model (GPS-based model), and it was found that experiment 1's results are not sustainable and cannot be deemed reliable, since it depends on the GPS module for position detection. However, since the GPS depends on the satellite position, the coordinates were not fixed and as a result, the detection could not happen at the first glance of opening the application. Moreover, the approach of moving the AR application around the conveyer belt was deemed unreliable and inefficient. Therefore, experiment 1's results can still be augmented with correct device details, as outlined in Figure 4.2 and Figure 4.3. Moreover, to obtain the correct details the user is supposed to manoeuvre the motor around and with high chances of augmentation happening, as depicted in Figure 4.1 due to the device features.

After conducting several tests with the experiment 1 model, alternative models had to be developed that could be more stable, reliable, and efficient for experiments to be conducted. In experiment 2 outlined earlier, the same model was used, however, due to the reasons outlined based on the results obtained from experiment 1, two algorithms were manipulated by adjusting the position and features of the device and importing the modified libraries into the working directory. The sample code is outlined in Annexure A.

This section further outlines the relationship between augmented reality application and the output augmentation of the robotic arm operation, utilising augmented reality and machine vision in an integrated system. The augmented output data in this section relies on the input data on the SCADA system. Figure 4.6 outlines the input data on the SCADA system and Figures 4 4 and 4 5 outlines the augmented output data on the motor recognition on the AR application. The transfer of data was based on the data transfer protocol where the data from the SCADA system was transferred via the Wemo WiFi module through WiFi connectivity to the AR application.

The testing phase was based on the accuracy of the transferred data with reference to the following:

i. device identification, making use of the AR application;
ii. augmentation of correct device details, based on their features and location within the manufacturing plant;
iii. complimentary data between the SCADA system and the AR application.

As a result of the use of the second approach, the detection and identification of devices, based on their location by localising the environment and examining the device features, were achieved.

Figure 4.4 to Figure 4.5 depict the output results for two different motors, namely motor 1 and motor 2. The AR application can change the device details of one motor, i.e. motor 1 to motor 2, by just pointing at the different motor and this is achieved through the position and feature detection model. Furthermore, this model or process does not require any change in parameters from the SCADA or any human intervention, in terms of motor selection, unless the device locations are changed within the manufacturing plant.

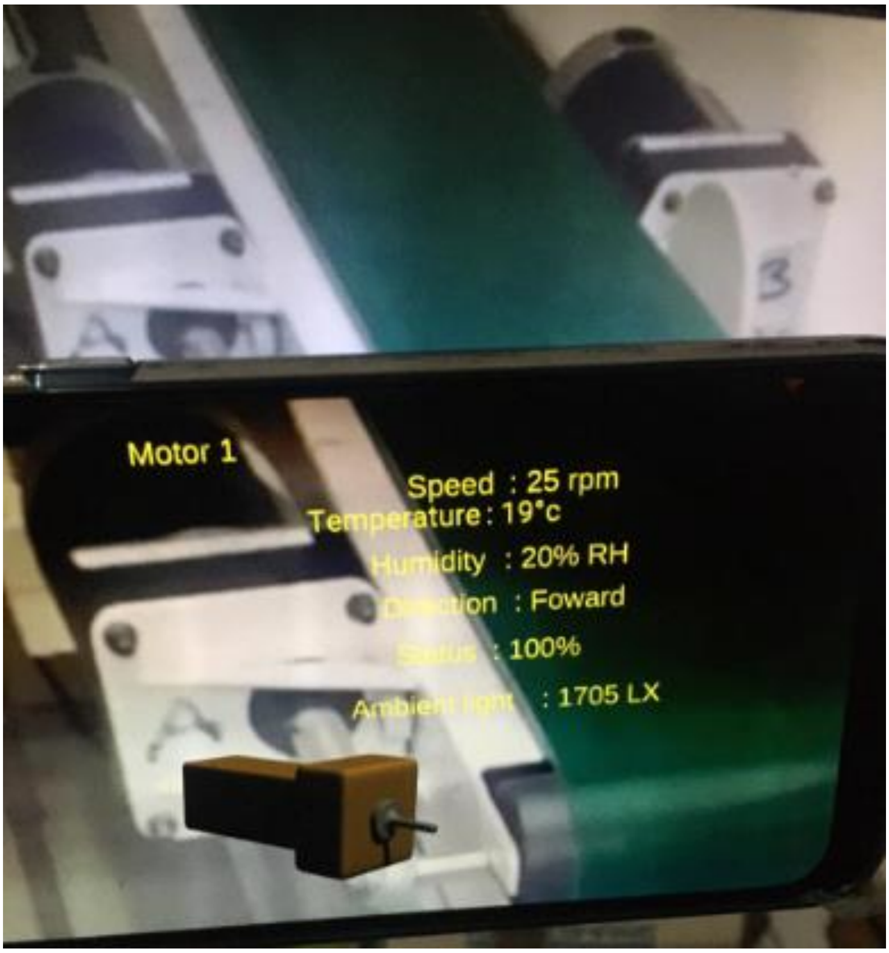
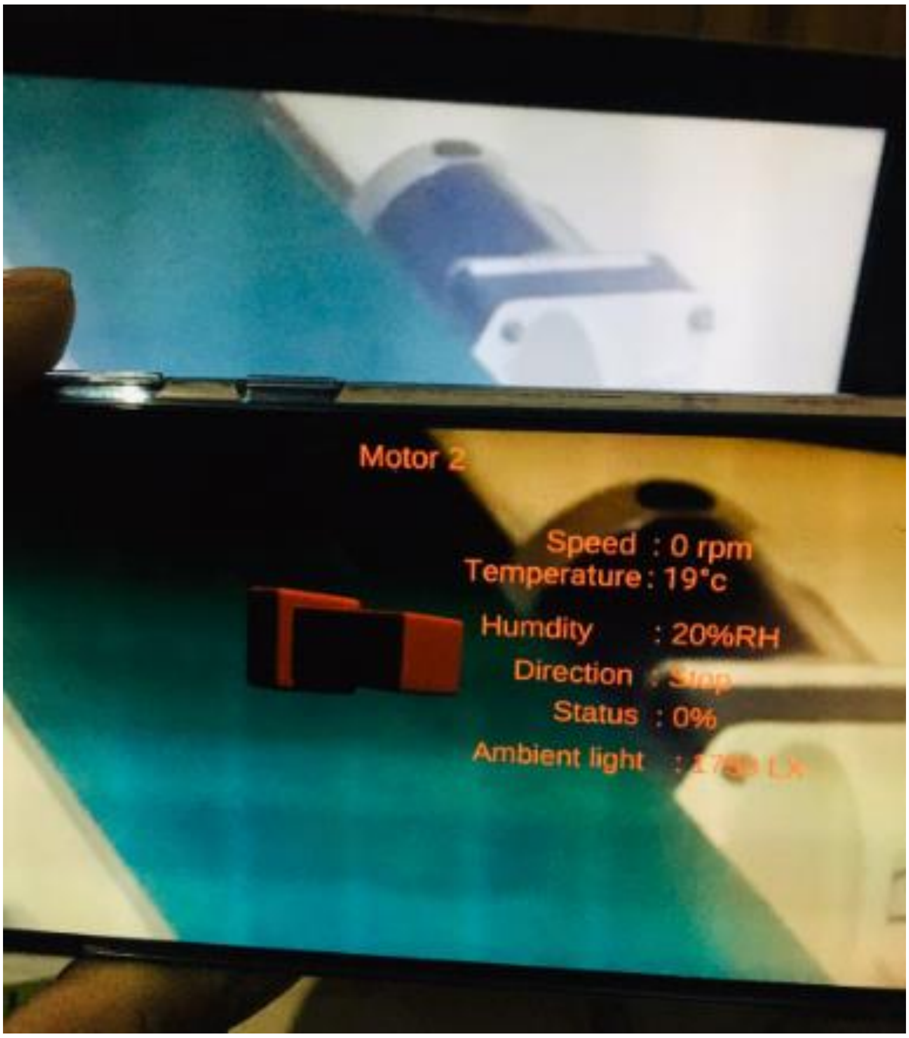


Figure 4.4: Output results for motor 1 obtained using the second model.

Figure 4.4 depicts motor 1’s results for the re-examined conveyer belt. The results are obtained from pointing to the AR application to the motor, and due to the intelligence provided by the algorithm, the motor details will be augmented, provided that the features and position are correct as outlined in Figure 4.4. Additionally, an add-on button to augment the motor`s datasheet is included for a technical understanding of the device's operation.



Motor 2

Speed : 0 rpm
Temperature : 19°c
Humdity : 20%RH
Direction : Stop
Status : 0%
Ambient light : 1780 Lx

Figure 4.5: Output results for motor 2 obtained, using the second model.

Figure 4.5 depicts the same results as the results obtained in Figure 4.4. However, Figure 4.5 depicts motor 2's results by augmenting the results with different colour and motor numbers to distinguish that these are two different motors with the motor feature and location being the differentiator.

In addition, it is important to take note that the sensory data parameters are obtained from the SCADA system. However, the AR application, through the integrated use of manipulation of multiple algorithms, was feasible for the application to differentiate between the two motors, bearing in mind that the SCADA sends two data packets together to the application via the Wemo WiFi module. These data packets are saved on the application itself, hence the automatic change in parameters is feasible without sending another string of data packets to the application.

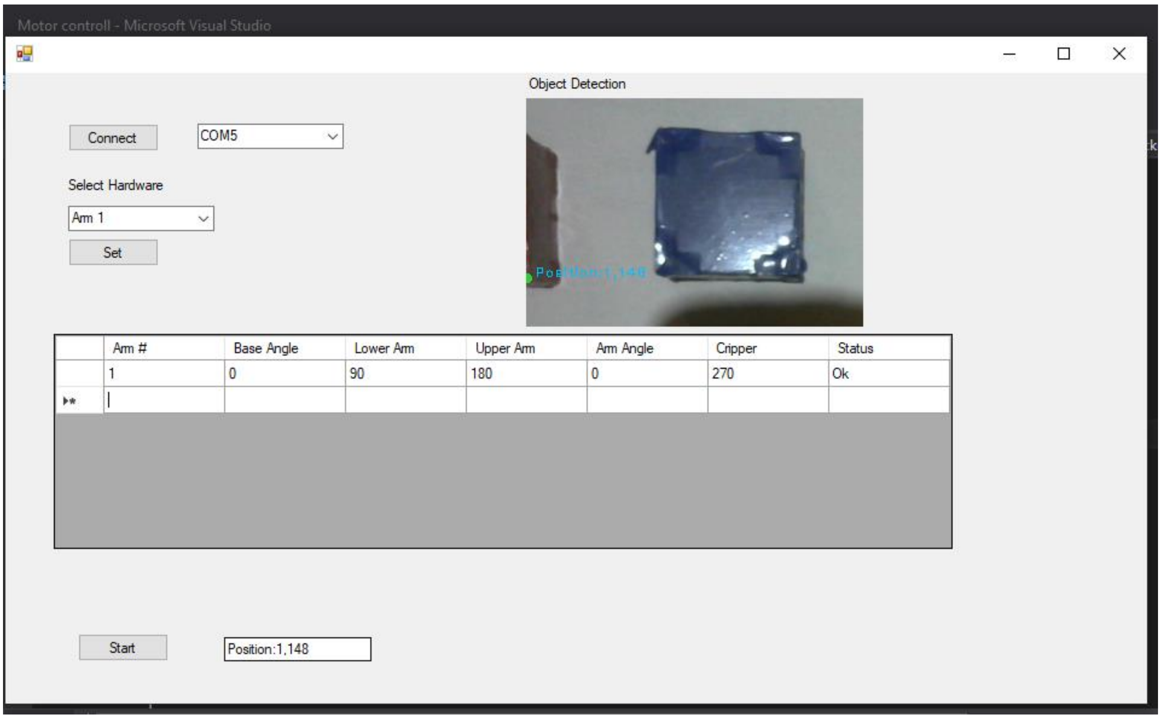
Additionally, a button that acts as an option for viewing the datasheets of each motor is added to the application as a reference parameter for an additional understanding of the functional operations of each device. This development is done to simplify the application for users so that even non-technical people can understand how the motor works and be able to note if is not functioning properly.

In these figures, the parameters of the motor are speed, temperature, humidity, direction status, and ambient light. These parameters selection was based on the daily operations of the motor and the direct influence of the functionality of the device. However, the ambient light was selected as a means to improve the camera identification and detection of the motors and produce the required accurate data as it reflects on the SCADA system for motor identification, utilising augmented reality.

4.3. SCADA data transfer and robotic arm position outcome

This section outlines the relationship between augmented reality and the output augmentation of the robotic arm operation, utilising this technology. The augmented output data in this section relies on the input data on the SCADA system. Figure 4.6 outlines the input data on the SCADA system, while Figure 4.7 and Figure 4.8 outline the augmented output data on the AR application. The transfer of data was based on the data transfer protocol where the data from the SCADA system was transferred via the Wemo module through WiFi connectivity to the AR application.

To achieve this, an alternative approach, as outlined earlier, was utilised, due to the lessons learned from the first experiment conducted for the motor identification application and it was deemed irrelevant to even pursue that approach.



COM5

Arm 1

	Arm #	Base Angle	Lower Arm	Upper Arm	Arm Angle	Cripper	Status
	1	0	90	180	0	270	Ok
▸*							

Position:1,148

Figure 4.6: Output data on the SCADA system.

Figure 4.6 depicts the SCADA output results for the robotic arm. In Figure 4.6, the user selects the hardware (motor or robotic arm) and set the DatagridView to be optimised for the selected hardware. Once this process is concluded, the data is manually inputted and the system is started, whereafter data can be transferred to the AR application. However, the SCADA system outlined in Figure 4.6, also acts as the output system for machine vision application. As outlined earlier, the machine vision application was developed to detect only the red square objects, hence there is no green square highlighting that the object has been detected. Figure 4.6's source code is depicted in Annexure C.

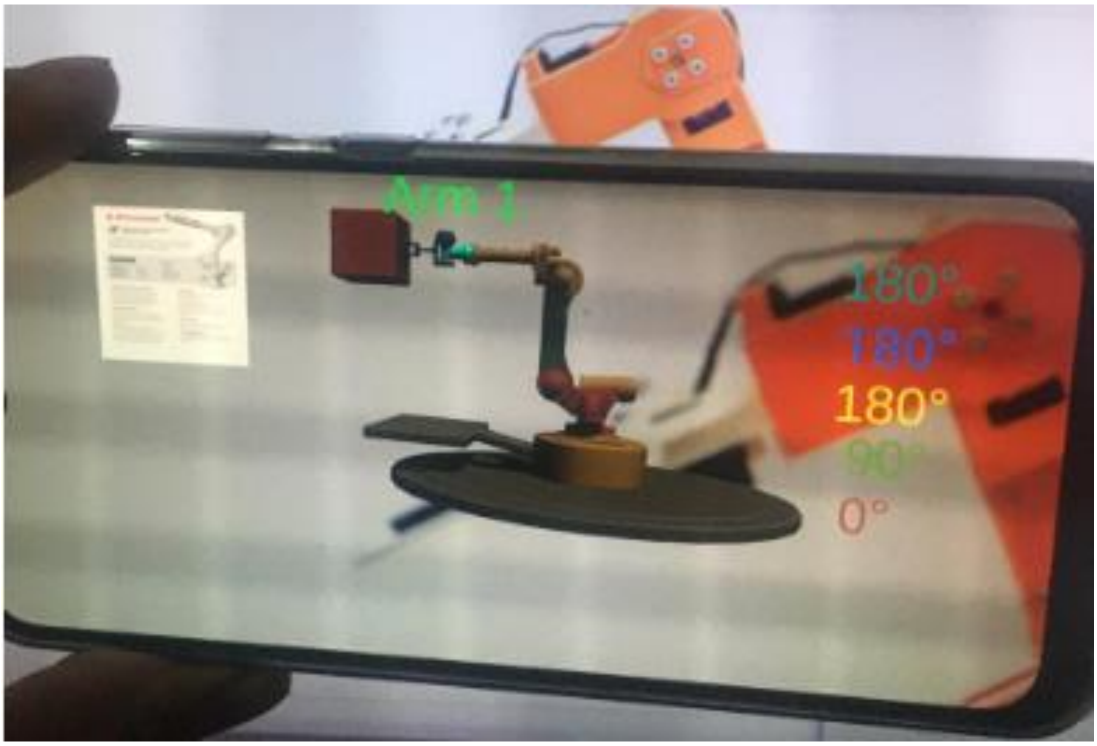


Figure 4.7: Augmented output data based on the identified object.

Figure 4.7 depicts the augmented output data for the robotic arm, including the datasheet for the arm. For further understanding of the robotic arm operation, the robotic arm datasheet is embedded and can also be augmented, as opposed to using a different tool to check the device operation. Furthermore, the parameters outlined in Figure 4.7 are obtained from the SCADA system and transmitted to the AR application via the Wemo module, using WiFi connectivity. However, to be able to distinguish between the robotic arms, the robotic arm number is used as an identifier, i.e. Arm 1 or Arm 2 and this is accomplished through position and feature detection.

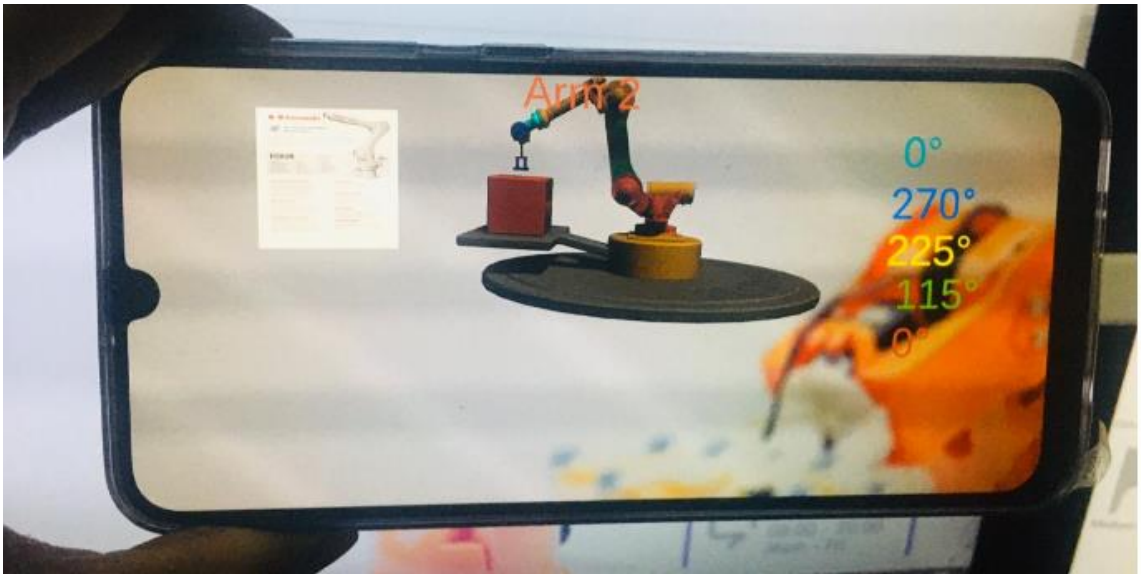


Figure 4.8: Augmented output data, based on the identified object.

Figure 4.8 outlines the augmentation of the output data, based on the parameter input from the SCADA system. This operation is further determined by the object inspection before the robotic arm function can be activated. The movement of the robotic arm parts is determined by the results of the inspection station. If the identified object is correct, the robotic arm joints will change the positions, as they prepare to pick and place the object.

However, if the object is not recognisable from the inspection station, then the robotic arm joints stay at the inertia position of 0^0. For further understanding of the robotic arm operation, the robotic arm datasheet is embedded and can also be augmented, as opposed to using a different tool to check the device operation. The degree turn for every joint is augmented on the side and the joint degree is highlighted by their colour to resemble which joint it is.

Figure 4.7 and Figure 4.8 further outline the augmentation of the output data, based on the parameter input from the SCADA system. This operation is again further determined by the object inspection before the robotic arm function can be activated.

4.4. User experience feedback results

Upon the completion of the AR application, it was important to obtain user feedback by either sharing the application Android Application Package (APK) in a .apk format or sharing a video link. However, despite drafting high-level documentation and briefing the volunteers on the APK installation, the volunteers did not understand. As a result, a decision was taken to take a video, upload it on YouTube, and share the link for both the survey (Google Forms) and the YouTube link.

In three weeks from the date of the video upload, there were 59 views and 10 “thumbs up” for the video, with zero “thumbs down”.

Apart from being able to augment and detect the devices, based on their features and position, the user experience also had to be tested in a survey format. A video was uploaded on YouTube and a survey was drafted and shared amongst 20 volunteers. Figure 4.9 outlines the survey response from the sample that took part in the survey. Figure 4.9 depicts the results with the majority of the sample rating the application good, with the initial data being positive from rating six to rating 10.

However, a balanced sample number was satisfied with the detection, reliability, and datasheet integration, and as a result of the data obtained in Figure 4.9, the UI feedback was positive with more than 70% of the sample opting to use the application. In addition, the UI results are outlined in Figure 4.9 with both YouTube and survey links outlined below Figure 4.9.

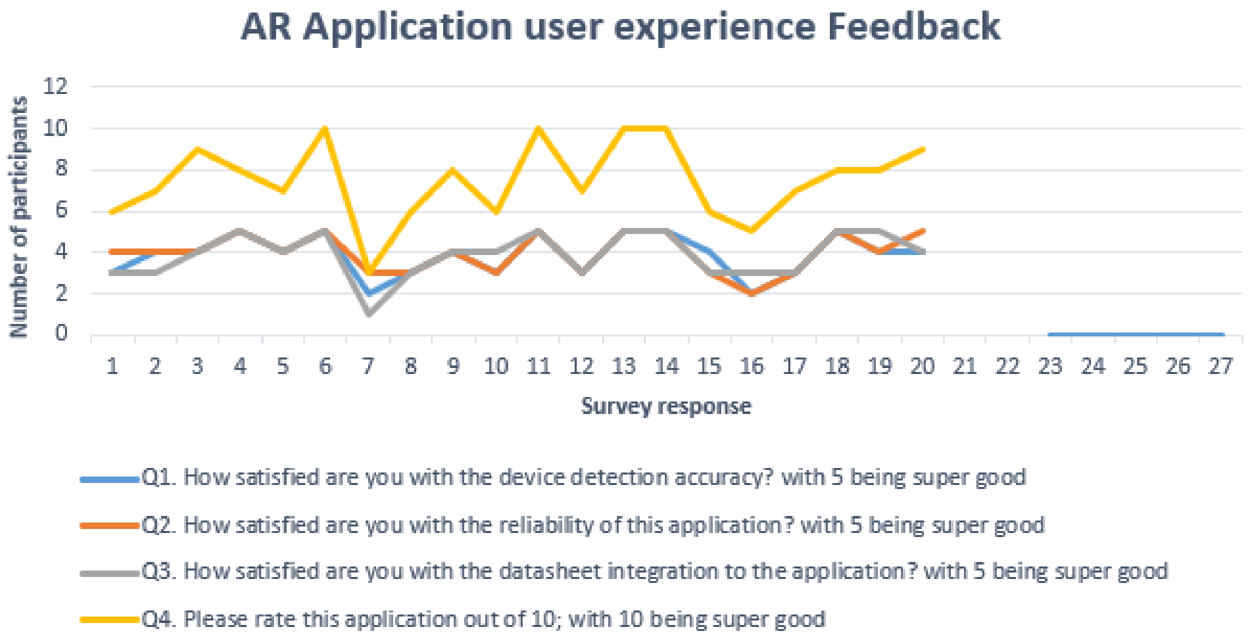


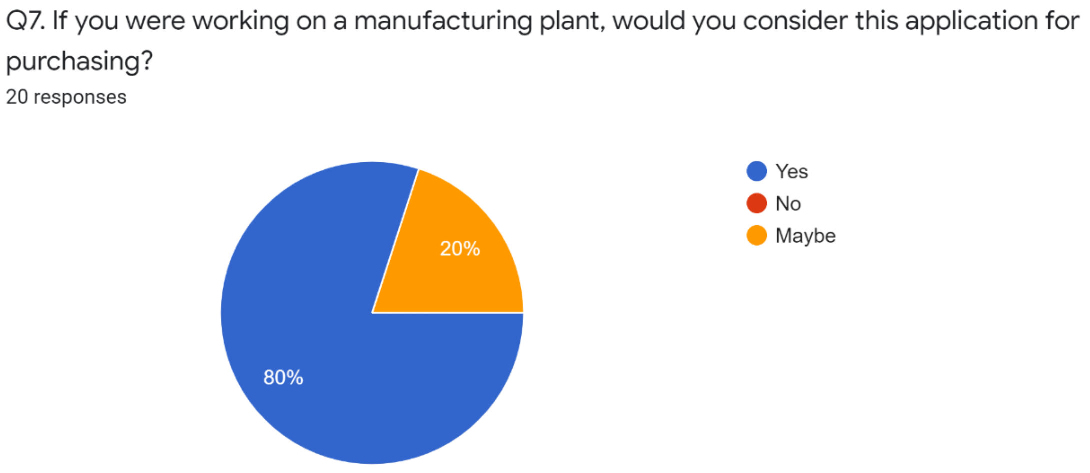
Figure 4.9: AR Application user experience survey feedback.

i. https://www.youtube.com/watch?v=Eh5wyuosP5U&t=19s

ii. https://docs.google.com/forms/d/e/1FAIpQLSdWanqngQzEkxGMADa470weZQyIs0dyeYlE0JTLvzkDpC7mdg/closedform

The survey conducted in Google Forms is outlined in Annexure B.

As depicted from Figure 4.9 outlining the survey, the majority of the sample, rated this application well, with the minimal number not having great confidence in the application detection accuracy. Also, the majority think that the system is reliable and can be used in a factory setup. The individual breakdown of the survey response is also outlined in Figure 4.10 to Figure 4.13. It is noted, that the survey shows a positive response, with the majority of the sample opting for the adoption of the application and utilising it in a manufacturing environment.

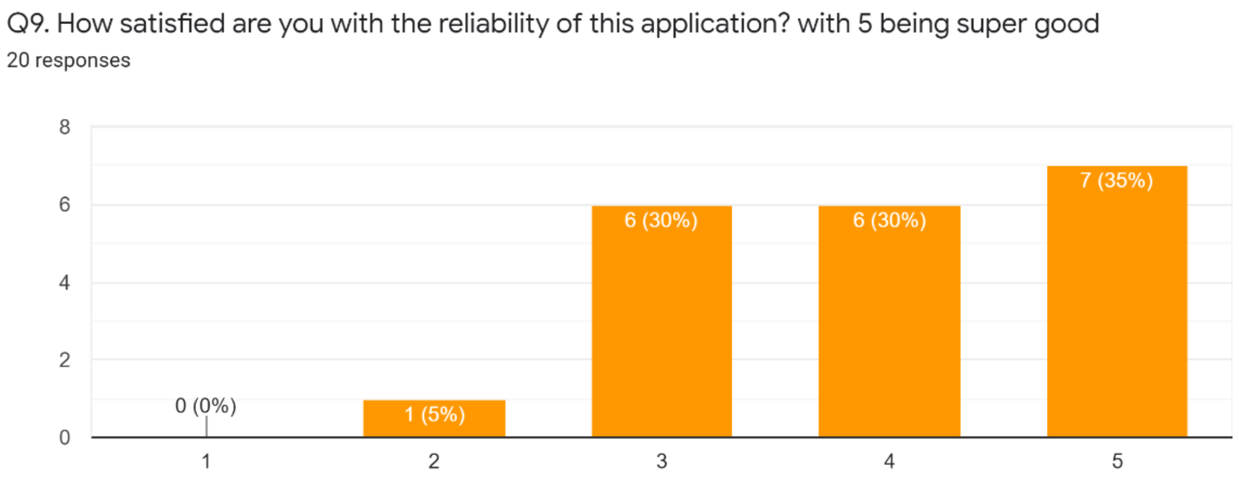


Q7. If you were working on a manufacturing plant, would you consider this application for purchasing?

20 responses

Figure 4.10: Application purchasing for utilisation in a manufacturing plant.

Figure 4.10 outlines the survey results, looking at the user feedback regarding the AR application. 80% of the users who watched the YouTube video of the operation of the AR application recommended that if they were working at the manufacturing plants they would purchase the application for use.

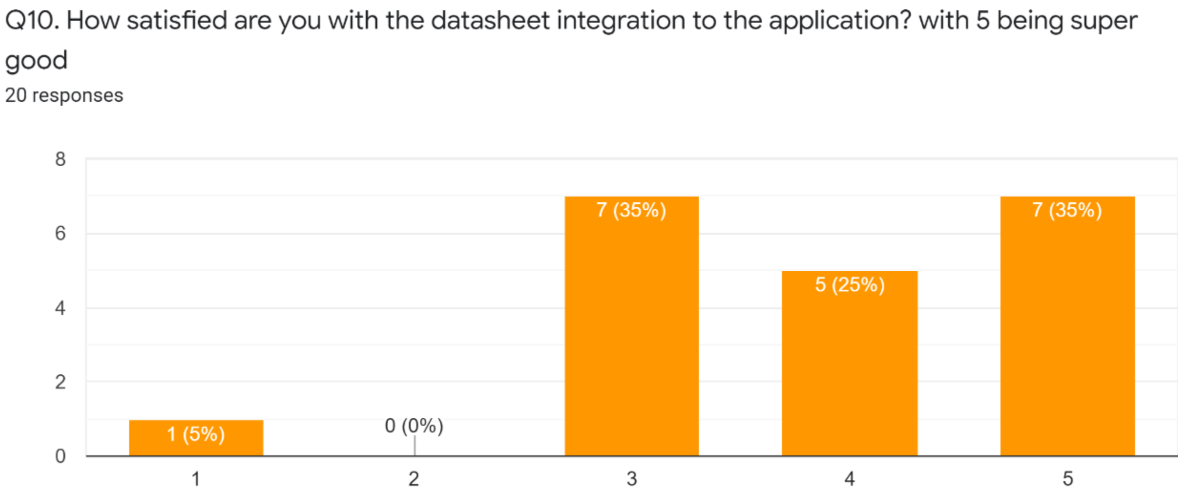


Q9. How satisfied are you with the reliability of this application? with 5 being super good

20 responses

Figure 4.11: Reliability of the application.

Figure 4.11 looks at the AR application reliability. The reliability was tested with reference to the two scenarios outlined in Chapter 3. Out of the 20 sampled people who took part in the survey, 65% of the sample said that the AR application is stable, and this is seen when the detection is accomplished by testing different angles. 30% of the sample were comfortable with the reliability and 5% were not satisfied with the reliability.



Q10. How satisfied are you with the datasheet integration to the application? with 5 being super good

20 responses

Figure 4.12: Datasheet integration on the AR application.

In Figure 4.12, 35% of the samples felt average with the datasheet integration, while 35% felt happy with integration. However, 35% might be deemed engineers who know systems and models, and the other 35% being new users of such applications. Therefore, Figure 4.12 was not deemed very convincing, due to the outlined reasons, and it was noted that it would have been ideal to merge Question 1 and Question 10, to understand the reasons behind the response.

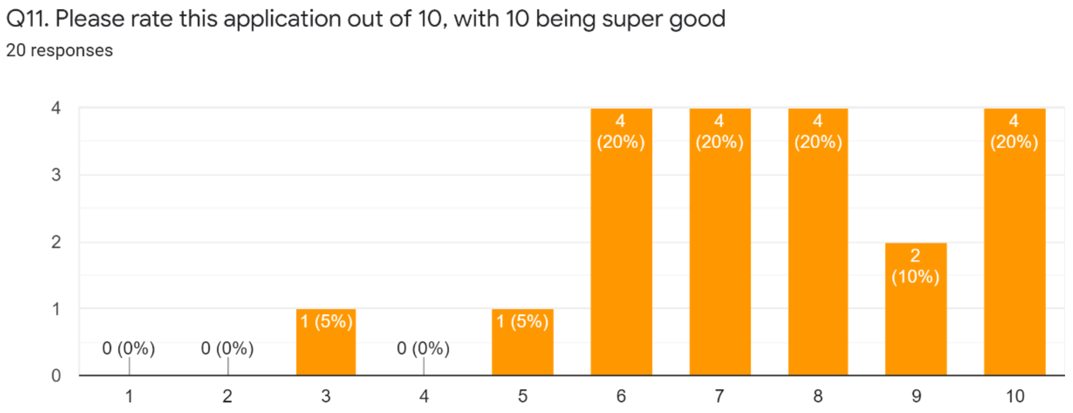


Figure 4.13: Application rating.

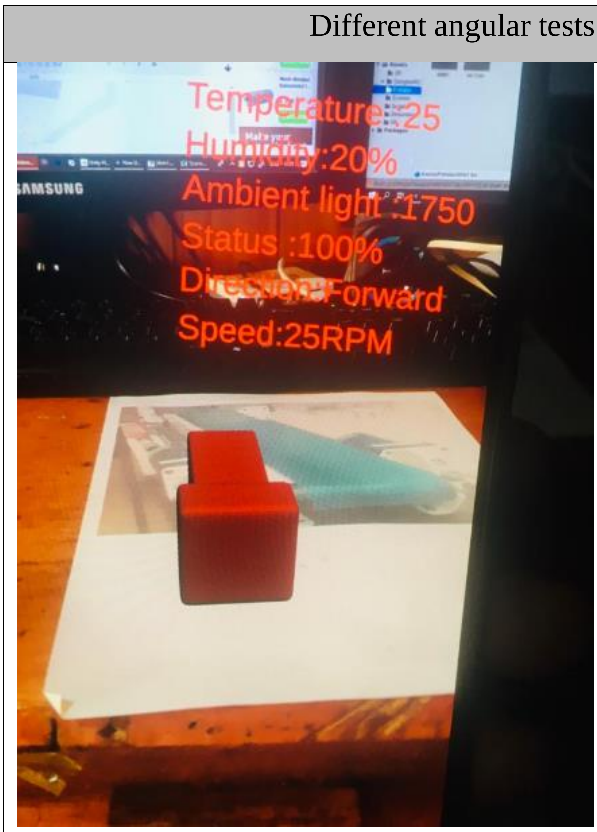
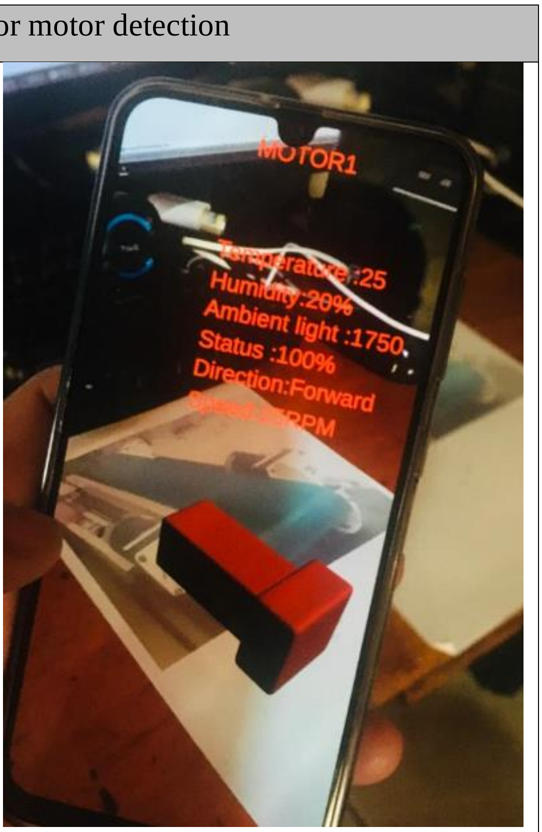
Figure 4.13 outlines the user rating for the application. 18/20 personnel rated the application well, with 1 person (5%) rating the application average and another 5% rating the application poor. It is, therefore, seen that the majority (90%) of the people who participated in this survey deemed the application useful and needed by the industry to enhance the manufacturing operations.

4.5. Robotic arm angular test results

The robotic arm angular test was conducted to determine the data accuracy. In this test, the devices were tested to determine if they can detect the robotic arm from different angles, and whether they change the sizes or not. Also, the change in size during testing was of importance, to see if the detection is affected or not.

Table 4.1 outlines the motor results taken during the testing phase, however, it is noted that the application did not lose any data nor did the angular detection affect the accuracy of the system in any way. The results outlined in Table 4.1 depict the simulation results in motor 1. However, these results also apply to motor 2, since the study was conducted using two devices.

Table 4.1: Motor identification in different angles.

<table>
<tr><th colspan="2">Different angular tests for motor detection</th></tr>
<tr><td>
</td><td>
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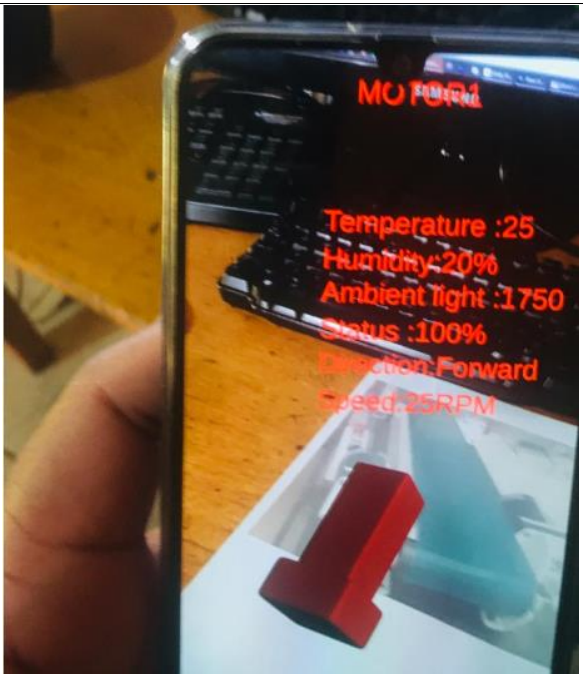
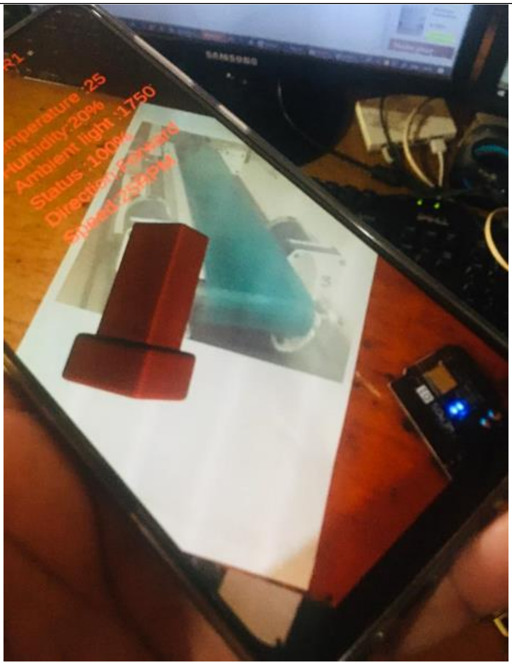
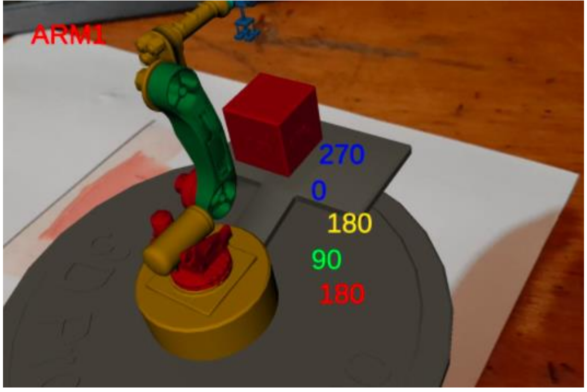
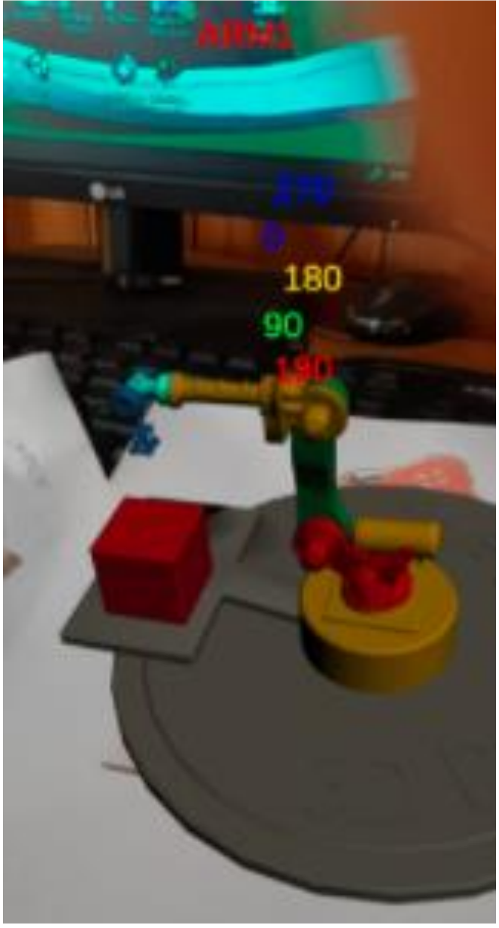
<tr><td>
</td><td>
</td></tr>
</table>

Table 4.2 outlines the simulation results for the robotic arm taken during the testing phase. Through the evidence seen in Table 4.2, the application did not lose any data nor did the angular detection affect the accuracy of the system in any way. The results outlined in Table 4.2 also apply to robotic

arm 2. It is, therefore, noted that the application is stable and this resonates with the survey results outlined in section 4.4.

Table 4.2: Comparison results based on angular device detection.

<table>
<tr><th colspan="2">Different angular tests for robotic arm detection</th></tr>
<tr>
<td>
</td>
<td>
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</tr>
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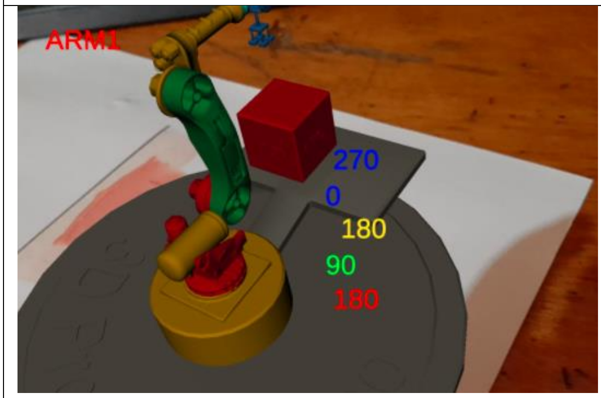
<td>
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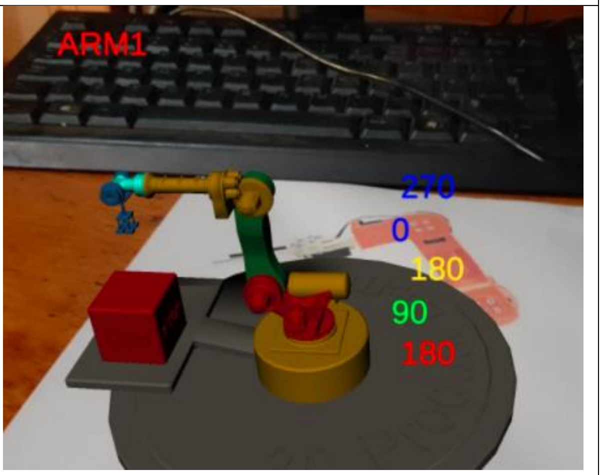
<td>
</td>
</tr>
</table>

4.6. Machine vision identification and recognition

The results projected in the results chapter (Figure 4.1 to 4.8) depict the results obtained, based on the object accuracy in terms of the distance and the camera frame from the device camera to the targeted object. These results analysis is based on the recognition of the feature and location-based identifiers for augmented reality applications, utilising the Unity3D platform.

Secondly, this thesis based the direct recognition and identification of objects on utilising machine vision technology by applying multiple OpenCV libraries in conjunction with Emgu CV libraries for object detection. However, the colour selection section was based on the processing and computing of colour and a green squared identifier was placed on top of the detected object and projected the results on the SCADA system.

Moreover, it has been noted through evidence provided in Figures 4.1 to 4.8, that the study did achieve its objectives and the detection of the devices and objects was achieved.

4.7. Time-based data acquisition and rendering over the WiFi

To model the application to function as intended, it was necessary to have the input JPEG image sample from the Android camera transferred to the object tracker Unity3D AR database and escort the tracked bounding box onto the preview screen. The sensory data results were taken and stored into the SQL database and after their storage, they were transferred via the Wemo WiFi module, through the WiFi connectivity, as a string of data packets to the AR application. Furthermore, another system analysis were conducted, based on the following scenarios:

<u>The analysis of the two systems’ run time were as follows:</u>

The implementation of the system runtime was based on the size of the data packet transferred from the SCADA system to the AR application. In this context, the SCADA system was acting as the server and the cell phone as the client. Therefore, the client-server connection was based on the basic three-way handshake protocol, synchronisation, and acknowledgment.

Based on the computational time frame interval, the SCADA can detect when a packet has been converted into the binary state (0 or 1) and if it is not transmitted, by not receiving the acknowledgment from the cell-phone or AR application, and as a result, the SCADA system will continue to transmit data until the connection is disconnected.

In addition to determining the time intervals for the period it takes the data packets from the SCADA system to the AR application, an OpenCV function was used to calculate the time it took the data to be transferred from the SCADA system to the client, as outlined in the below sample code
“std::cout << float(clock () - begin_time) / CLOCKS_PER_SEC”.

Subsequently, the data packet transfer rate was measured with four samples distance as indicated in Table 4.3. The latency test was conducted for the input data, which are transferrable from the SCADA system to the AR application. As indicated in Table 4.3, the latency increases as the distance increases, however, this does not affect the success rate.

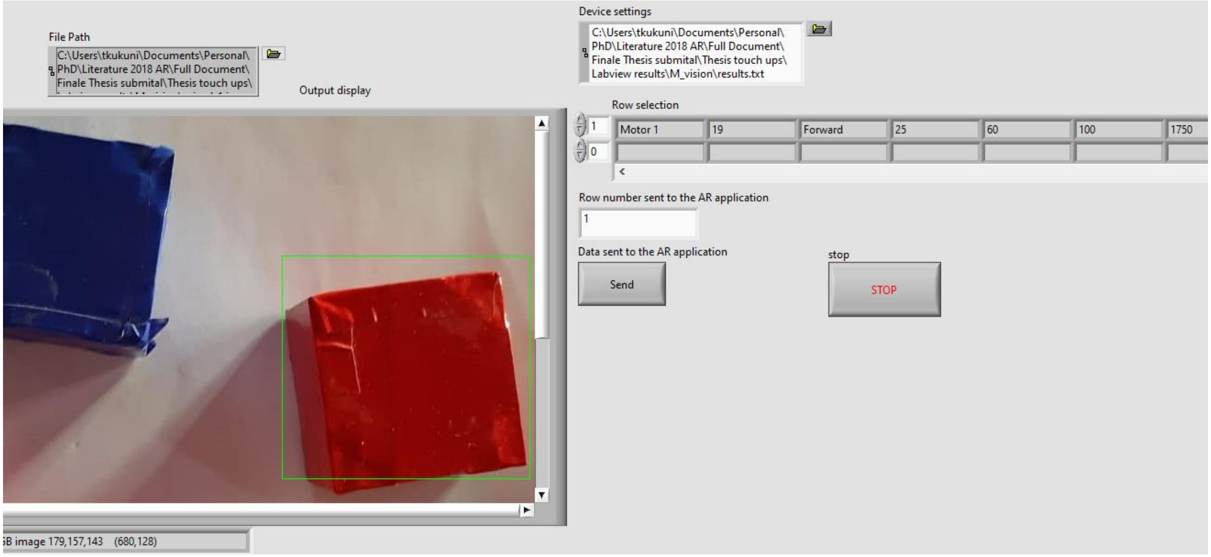
Table 4.3: Latency and packet rate success rate.

Distance between STA and API (meters)	**Ping Latency (ms)**	**Packet transfer rate (%)**
2	150	100%
4	238	100%
8	330	100%
10	420	100%

Table 4.3 was not developed by the researcher, however, the test was conducted using the SPEED CHECK application in Android. The application was used to examine if there was a delay in the WiFi reception and how this would influence the data or transmission speed of the data sent. However, it has been noted that the transmission speed does get affected as a result of the distance, but this does not affect the success rate, provided that the WiFi connectivity is still within range.

4.8. Labview based results verification

This section outlines the results verification for this research study. A subsequent industry-rated software (SCADA), namely National Instruments^{TM} Labview^{TM} was utilised to examine the possibility and reliability of the integration of the AR application to an industry-rated SCADA, as opposed to a newly modelled SCADA. It was, however, discovered that the AR application is still compatible with National Instruments^{TM} Labview^{TM} SCADA. Furthermore, for further reference, Figure 4.14's source code can be found in Annexure D.



File Path
C:\Users\tkukuni\Documents\Personal\ PhD\Literature 2018 AR\Full Document\ Finale Thesis submital\Thesis touch ups\

Device settings
C:\Users\tkukuni\Documents\Personal\ PhD\Literature 2018 AR\Full Document\ Finale Thesis submital\Thesis touch ups\ Labview results\M_vision\results.txt

Row selection

1	Motor 1	19	Forward	25	60	100	1750
0							

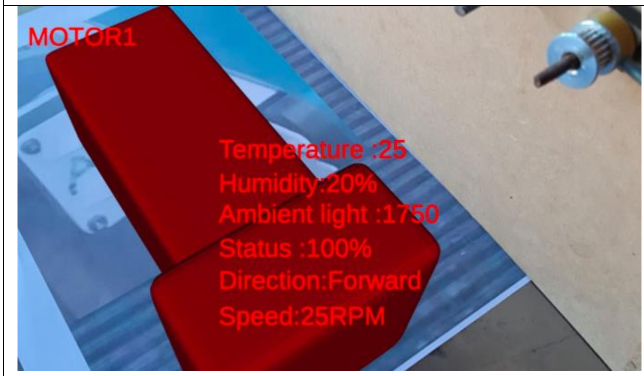
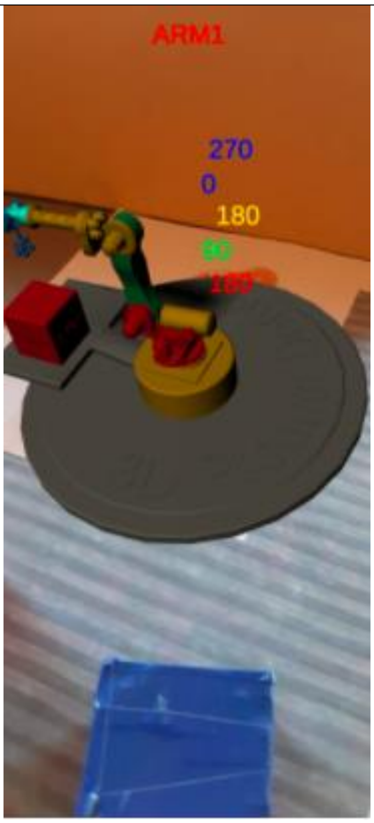
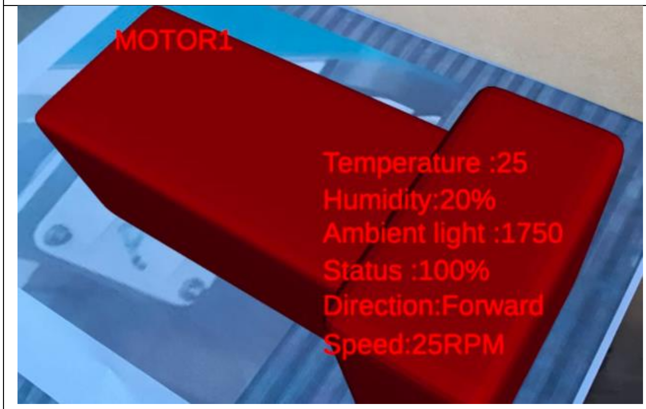
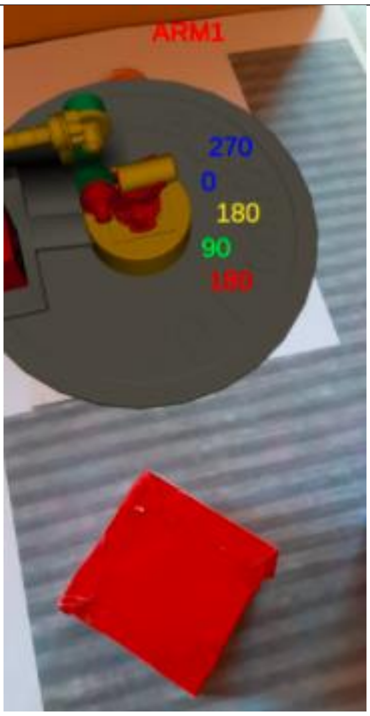
Row number sent to the AR application
1

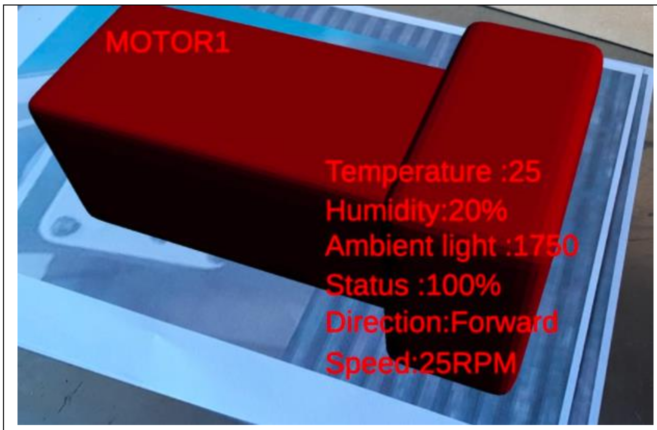
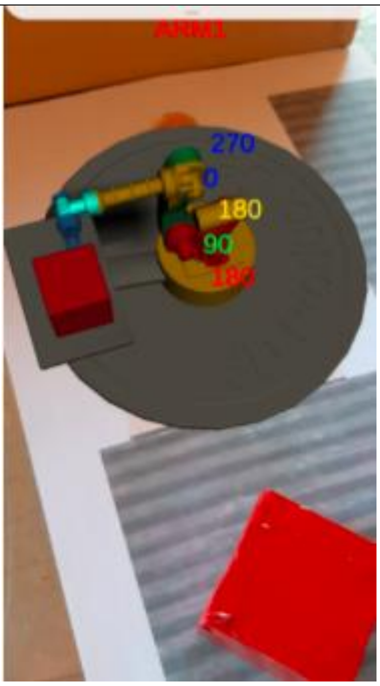
3B image 179,157,143 (680,128)

Figure 4.14: Labview based SCADA with AR application integration.

Figure 4.14 depicts the National Instruments^{TM} Labview^{TM} SCADA. This SCADA was tested on National Instruments^{TM} Labview^{TM} and it was able to be controlled and integrated into the AR application without the need to modify the AR application. Furthermore, Table 4.4 depicts the output results based on National Instruments^{TM} Labview^{TM} SCADA integrated into the AR application, utilising WiFi connectivity.

Table 4.4: Labview based AR application output.

Motor 1	Robotic Arm 1
 MOTOR1 Temperature :25 Humidity:20% Ambient light :1750 Status :100% Direction:Forward Speed:25RPM	
 MOTOR1 Temperature :25 Humidity:20% Ambient light :1750 Status :100% Direction:Forward Speed:25RPM	

 MOTOR1 Temperature :25 Humidity:20% Ambient light :1750 Status :100% Direction:Forward Speed:25RPM	

4.9. Summary

In this chapter, the analyses and evaluation of results obtained from the augmented reality application and machine vision were discussed. The development of the prototypes were deemed successful, and they were analysed in conjunction with the study objectives and hypothesis. The analysed results were based on two tests, namely functionality of augmented reality application and object detection, conducted by utilising machine vision application.

The results presentation on both models were observed as follows:

i. <u>Augmented reality application:</u>

The outlining of the augmented reality model is based on both the robotic arm application and the motor application.

It has been observed that the AR application is efficient when compared to the isolation use of the SCADA system. The use of the SCADA system alone poses a high risk for late detection, as the technician must always visit the SCADA room to check the updates on the factory details and this is deemed as a difficult and tedious exercise without prior knowledge of the manufacturing plant. As a result of the observations, the AR application has proven its efficiency and effectiveness in shortening the time it takes to identify the device and its details, such as the motors and robotic arms, even with no prior knowledge of the manufacturing plant, by identifying the devices, based on their features and location.

ii. Machine vision application

Due to the rise in technological intelligence, the improvement for digitalising the use of manual sorting of materials in the factories was developed, implemented, and tested, utilising machine vision technology. The technology was used to inspect the object's shape and colour, using the camera device (machine vision algorithms). After this process, the conveyer belt moves to the robotic arm station where the robotic arm can be activated to pick and place the specific objects or not depending on the inspection results.

It is, therefore, based on the study objectives, concluded that the study outcomes do correlate with the study objectives and hypothesis. The system integration was obtained and even the automation for data updated was noted, apart from data update in the AR application. The automation on the AR application was not deemed necessary, as the study focused on the login and off on the application, as compared to the open application throughout the testing phase.

In addition, a subsequent test was conducted where the application`s reliability and compatibility were examined against the industry-rated SCADA. It was, however, noted that the AR application is compatible with multiple SCADAs, provided that there is WiFi connectivity. It was further noted that the AR application can only be modified if the SCADA parameters are not consistent with the database parameters, i.e. the robotic arm has five parameters that are part of the modelled schema. If the SCADA parameters are greater than the array length, then the modelling has to be altered.

Chapter 5: Conclusion & Future Work

This chapter summarizes the research conclusion, original thesis contribution and suggests the possible future directions in this field of study.

5.1. Conclusions to the research conducted

In this study, an overview of the technology trends and their applications in the manufacturing plants making use of AR technology and machine vision were outlined in Chapters 1 and 2. In addition, three experiments were conducted, namely machine vision application, augmented reality application, and the integration of the two applications to function as a single unit in Chapter 3.

The first test, namely machine vision was tested for object detection and identification of specific objects type (colour and shape detection), utilising the camera device to sense, detect and display the output results on the SCADA system, either on National Instruments™ Labview™ SCADA or Microsoft ® Visual Studio® 2012 (C#) based SCADA.

Secondly, an augmented reality application was also was developed and tested for augmentation of the device details based on their positions and features within the manufacturing environment, with the data obtained from the SCADA system.

Lastly, the applications were integrated and tested as a single unit with tested results displayed on both the SCADA systems and the AR application for both devices.

This research study has produced positive results with reference to the aims, objectives, and hypotheses. Additionally, the recommendations with reference to the room light of the laboratory also are noted, especially when image processing-related studies are conducted. Furthermore, the correlation between sensory data sent from the SCADA system to the AR application, via the Wemo module in a WiFi-connected environment, was discussed. The data were deemed accurate as indicated in Chapter 4.

To further validate the results, the user's experience survey was conducted, and the results from this questionnaire indicated that the majority of the sample individuals would use or recommend the adoption of such a technology in a manufacturing plant setup.

The conclusion from this questionnaire is that the AR application developed in this research study would yield positive results in enhancing the operations in the manufacturing plants for augmenting and altering the device details utilising the AR application as opposed to only the reliance on the SCADA system. Furthermore, these results depicts the possibility of improving the application for better commercialisation and adoption purposes.

Additionally, the user experience questionnaire was used to test the usability and feasibility of its adoption in an industrial setup.

5.2. Original contributions of this study

The research study presented in this thesis has led to the recognition for the importance of acquiring and supplementing SCADA systems with industrial augmented reality for ease of device detection within a manufacturing environment setup.

Furthermore, this research study has introduced an alternative AR application model that is compatible with integration of multiple SCADA systems without any alterations required. This research study has further contributed to human knowledge by altering and modifying the Bundle Adjustment algorithm functions to work in par with the ORB-SLAM algorithm for utilisation in position and feature detection of multiple devices within an unknown indoor environmental setup. This modification was necessary as to allow the application to differentiate between multiple devices even though there are in a close proximity.

Furthermore, a function was remodelled on the AR application to reduce any customisation for industry-rated SCADA systems such as National Instruments^{TM} Labview^{TM} SCADA to prove that this AR application is not only compatible with C# based SCADA systems.

Moreover, this concept proved to be efficient and effective, as it reduces the time spent on the redevelopment or alteration of new AR applications to allow for compatibility with other industry and non-rated industry-related SCADA models. It is, therefore, concluded that this model has yielded positive results and brought about a new dynamic (contribution) in the use of industrial augmented reality applications in the manufacturing setup.

This research study has produced peer-reviewed publications.

5.3. Suggestions for future research

The primary study objective was to identify devices, based on their positions in the manufacturing plant. As a result of the outlined evidence in this study, the aims and objectives were successfully achieved. However, the optimisation of the algorithm enabled the positioning of two identical devices near each other to be achieved by making use of the ORB-SLAM and the Bundle Adjustment algorithm to counter the challenge.

The successful transmission of sensory data depends on network bandwidth as to be expected. However, as a result of the scope of the research, the network bandwidth was not calculated or accounted for.

Upon the completion of the successful data transfer from the SCADA system to the AR application, the user was required to refresh the AR application to update the new data. For the verification of the projected data, it was expected from the user to write down the values and compare them to the actual process flow of the actual SCADA data.

Therefore, the development of a new model that can notify the user/technician on both the successful or unsuccessful data transfer and automatic data update on the AR application, needs to be further investigated and developed.

In addition, the advancements such as the data packet breakdown can be investigated and their integration into the model further studies. Subsequently, a method of enforcing direct multiple conditions need to be implemented to avoid ambiguous data or identification.

<u>Robotic arm application future work:</u>

The physical mounting of the sensors on the robotic arm for obtaining live sensory data, as opposed to manual SCADA input data, needs to be investigated and developed. The development of a mathematical model for calculating the distance between an angular position and object circumference for a more accurate object pick and place process, as opposed to just measuring the robotic arm joint degree, needs to be investigated.

Therefore, this study has opened a window for further research in the field of machine vision and augmented reality and the application of these technologies in the manufacturing industries.

References

[1] B. Boyles, "Virtual Reality and Augmented Reality in Education," Center for Teaching Excellence, United States Military, 2017. [Online]. Available: https://www.westpoint.edu/sites/default/files/inline-images/centers_research/center_for_teching_excellence/PDFs/mtp_project_papers/Boyles_17.pdf. [Accessed 15 April 2019].

[2] A. Mital, M. Govindaraju and B. Subramani, "A Comparison between manual and hybrid methods in parts inspection," *Integrated Manufacturing Systems,* vol. 9, no. 6, pp. 344-349, 1 December 1998.

[3] S. Jagannathan, D. Seebaluck and J. D. Jenness, "Intelligent Inspection of Wave Soldered Joints," *Journal of Manufacturing Systems,* vol. 11, pp. 137-143, 1992.

[4] H. Glockner, K. Jannek, J. Mahn and B. Theis, "Augmented Reality in Logistics," DHL Customer solutions and Innovations, 2014. [Online]. Available: https://www.dhl.com/content/dam/downloads/g0/about_us/logistics_insights/csi_augmented_reality_report_290414.pdf. [Accessed 10 April 2020].

[5] G. Reitmayr and D. Schmalstieg, "Location based Applications for Mobile Augmented Reality," vol. 18, p. 1, January 2003.

[6] V. Beglov, M. Hauta-Kasari and V. Bochko, "Object information based on marker recognition," p. 1, 11 12 2013.

[7] Y. Tian, T. Guan and C. Wang, "Real-Time occlusion handling in Augmented Reality Based on Object Tracking," *Sensors,* vol. 10, no. 4, p. 2886, 29 March 2010.

[8] H. Kato and M. Billinghurst, "Marker Tracking and HMD Calibration for a Video-Based Augmented Reality Conference System," *Proceedings of the 2nd IEEE and ACM International Workshop on Augmented Reality 99,* pp. 85-94, 20-21 October 1999.

[9] D. Wagner and D. Schmalstieg, “First steps towards handheld augmented reality,” in *Conference: Wearable Computers, 2003. Proceedings. Seventh IEEE International Symposium on*, Vienna, Austria, 2005.

[10] V. Ferrari, T. Tuytelaars and L. V. Gool, “Markerless augmented reality with a real-time affine region tracker,” in *4th International Symposium on Augmented Reality (ISAR 2001)*, New York. NY, USA, 2001.

[11] G. Klein and D. Murry, “Improving the agility of keyframe-based SLAM,” *European Conference in Computer Vision-ECCV 2008*, vol. 5303, pp. 802-815, 2008.

[12] S. Sathiyamoorthy, “Industrial Application of Machine Vision,” *IJRET: International Journal of Research in Engineering and Technology*, vol. 03, no. 01, p. 1, May 2014.

[13] I. E. Sutherland, “A head-mounted three-dimensional display,” in *Fall joint computer conference part 1*, Slat Lake City, Utah, 1968.

[14] R. T. Azuma, “A survey of Augmented Reality,” *Presence: Teleoperators and virtual environments*, vol. 6, no. 4, pp. 355-385, 1997.

[15] H. Regenbrecht, “Industrial Augmented Reality Applications,” in *In book: Emerging Technologies of Augmented Reality: Interface and design*, New Zealand, IGI Global, 2006, p. 287.

[16] P. Milgramn, H. Takemura, A. Utsumi and F. Kishino, “Augmented Reality: A class of displays on the reality reality-virtuality continuum,” *Telemanipular and Telepresence Technologies*, pp. 282-292, January 1994.

[17] J. Gausemeier, J. Fruend, C. Matysczok, B. Bruederlin and D. Beier, “Development of a real time image based object recognition method for mobile ar-devices,” *In AFRIGRAPH 03: Proceedings of the 2nd international conference on Computer graphics, virtual Reality, visualisation and interaction in Africa*, pp. 133-139, 2003.

[18] R. L. Silva, P. S. Rodrigues, D. Mazala and G. Giraldi, “Applying Object Recognition and Tracking to Augmented Reality for Information Visualization,” *Information Visualization, Augmented Reality, Object Tracking, Object Recognition. Pose Estimation, Bayesian Network*, p. 5, 3 June 2014.

[19] F. V. Jensen and T. D. Nielsen, “Bayesian Networks and Decision Graphs,” in *Information Science and Statistics*, Second ed., New York, USA, Springer, 2007, pp. 1-427.

[20] S. Gammeter, A. Gassmann, L. Bossard, T. Quack, L. Van Gool, E. Zurich, K. AG and K. Leuven, “Server-side object recognition and client-side object tracking form mobile augmented reality,” in *Conference: Computer Vision and Pattern Recognition Workshops (CVPRW), 2010 IEEE Computer Society Conference on*, 2010.

[21] P. Hoffmann, R. Schumann, M. T. Maksoud and C. G. Premier, “Virtual commissioning of manufacturing systems a review and new approaches for simplification,” *In proceedings of the 24th European Conference on Modelling and Simulation ECM*, pp. 1-2, 2010.

[22] A. Antonijevi, S. Sucic and H. Keserica, “Augmented Reality for Substation Automation by Utilizing IEC 61850 Communication,” in *39th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO)*, Opatijia, Croatia, 2016.

[23] P. R. dos Reis, D. L. G. Junior, A. S. de Araujo, G. B. Junior, A. C. Silva and A. C. de Paiva, “Visualization of Power Systems Based on Panoramic Augmented Environments,” in *Salento AVR 2014*, Leece, Italy, 2014.

[24] J. N. Marcincin, J. Barna, M. Janak and L. N. Marcincinova, “Augmented Reality Aided Manufacturing,” *Science Direct*, vol. 25, pp. 23-31, 2013.

[25] R. Cappllin, M. Baravelli, M. Bellandi, R. Camagni, S. Capasso, E. Ciciotti and E. Marelli, “Investmenti, Innovazione e nuove strategie d`impresa.,” *Quale ruolo per la nuova politica industriale e regionale?* , 2017.

[26] T. G. Amaral, V. F. Pires, J. F. Martins, A. J. Pires and M. M. Crisostomo, “Image Processing based classifier for detection and diagnosis of induction motor stator fault,” in *image Processing*, IntechOpen`s Journal, 2009, p. 7.

[27] K. Panetta, “Gartner,” 16 August 2018. [Online]. Available: https://www.gartner.com/smarterwithgartner/5-trends-emerge-in-gartner-hype-cycle-for-emerging-technologies-2018/. [Accessed 13 February 2019].

[28] J. Peddie, “Augmented Reality,” *Trends and Opportunities*, p. 16, January 2017.

[29] R. Silva, P. S. Rodriques, D. Mazala and G. Giraldi, “Object recognition using Bayesian networks for augmented reality applications,” in *SVR VII Symposium on Virtual Reality* , Sao Paulo, 2004.

[30] G. Papagiannakis, G. Singh and N. Magnenat-Thalmann, “A survey of mobile and wireless technologies for augmented reality systems,” *Computer Animation and Virtual worlds,* vol. 19, no. 1, pp. 3-22, February 2008.

[31] S. Di Verdi and T. Hollerer, “GroundCam: A Tracking modality for mixed reality,” *Virtual reality conference,* pp. 75-82, 10-14 March 2007.

[32] E. Gravdal, “Augmented Reality and Object Tracking for Mobile Devices,” Institutt for teknisk kybernetikk, Trondheim, 2012.

[33] M. Turk and V. Fragoso, “Computer Vision for Mobile Augmented Reality,” USA, Springer International Publishing, 2015, p. 3.

[34] V. Lepetit, “On Computer Vision for Augmented Reality,” in *2008 International Symposium on Ubiquitous Virtual Reality*, Gwangji, South Korea, 2008.

[35] F. Ababsa and M. Mallem, “Robust camera pose estimation combining 2D/3D points and line tracking,” in *2008. IEEE International Symposium on Industrial Electronics,*, Cambridge, UK, 2008.

[36] C. H. Chen and A. C. Kak, “A robot vision system for recognizing 3d objects in low order polynomial time,” *IEEE Trans. On System. Man and Cybernetics,* pp. 1535-1563, 1989.

[37] V. Lepetit and P. Fua, “Monocular Model-based 3D Tracking of rigid objects,” *Fundamentals and trends in computer graphics and vision,* pp. 1-89, 2005.

[38] B. G. Batchelor and D. W. Braggins, “Commercial Vision System,” *In Commercial Vision: Theory and Industrial Application,* p. 406, 1992.

[39] Shin Shi, Emgu CV Essentials, Birmingham: PACKT Publishing, 2013, p. 5.

[40] Samsung. [Online]. Available: https://www.samsung.com/za/smartphones/galaxy-a50-a505/SM-A505FZBCXFA/. [Accessed 5 08 2020].

[41] ANDREASJAKL, "https://www.andreasjakl.com/basics-of-ar-slam-simultaneous-localization-and-mapping/," [Online]. Available: https://www.andreasjakl.com/basics-of-ar-slam-simultaneous-localization-and-mapping/. [Accessed 10 05 2020].

[42] C. Van Wyk, "Markerless Augmented Reality on Ubiquitous Mobile Devices with Integrated Sensors," Cape Town, 2011.

[43] D. Wagner, G. Reitmayr, A. Mulloni, T. Drummond and D. Schmalstieg, "Pose Tracking from Natural features on mobile phones," *Internation symposium of mixed and augmented reality*, pp. 125-134, 2008.

[44] A. Ufkes and M. Fiala, "A markerless augmented reality system for mobile devices," *2013 International Conference on computer and robot vision*, pp. 226-233, 2013.

[45] E. N. Malamas, "A survey on industrial vision systems, applications and tools, Image and Vision Computing," *Image and Vision Computing*, vol. 21, no. 2, pp. 171-188, 10 February 2003.

[46] Pampashree and M. Ansari, "Design and implementation of SCADA based induction motor control," *Int.J.Eng.Res.Appl*, pp. 5-18, 2014.

[47] A. Ujvarosi, "Evolution of SCADA systems," vol. 9, no. 1, p. 63, 2016.

[48] T. Adams, "SCADA Systems intermediate Overview," *Supervisory Control and Data Acquisition (SCADA) Systems*, p. 11, 2004.

[49] R. H. McClanahan, "The benefits of networked SCADA Systems utilising IP enabled networks, rural electric power conference," in *2002 Rural Electric Power Conference - 46th Annual Conference*, Colorado Springs, USA, 2002.

[50] I. Technologies, "Practical scada systems for industry," [Online]. Available: https://www.elsevier.com/books/practical-scada-for-industry/bailey/978-0-7506-5805-8. [Accessed 26 03 2020].

[51] A. Gstoll, Wikitude, [Online]. Available: http://www.wikitude.com/showcase/wikitude-navigation/. [Accessed 15 March 2019].

[52] M. Gandy, B. MacIntyre, P. Presti, S. Dow, J. Bolter, B. Yarbrough and N. O`Rear, “AR Karaoke: Acting in your favourite scenes,” in *Fourth IEEE and ACM international Symposium on Mixed Augmented Reality (ISMAR`05)*, Atlanta, GA 30332, USA, 2005.

[53] T. G. Kukuni and B. Kotze, “Industrial Augmented Reality (IAR) as an Approach for Device Identification within a Manufacturing Plant for Property Alteration Purpose,” in *Visual 2019: The Fourth international Conference on Applications and Systems of Visual Paradigms*, Rome, Italy, 2019.

[54] J. Defeo and J. Juran, “Juran`s Quality Handbook: The Complete Guide to Performance Excellence 9/e.Mcgraw-hill,” 2010.

[55] J. P. Russell, “The ASQ Auditing Handbook. ASQ Quality Press,” fourth ed., 2012.

[56] D. Wave, “To two-dimensional code from the bar code [Available],” [Online]. Available: http://www.qrcode.com/aboutqr.html.

[57] K. Pulli, A. Baksheev, K. Kornyakov and V. Eruhimov, “Real-time computer vision with OPENCV,” *Communications of the ACM*, vol. 55, pp. 61-69.

[58] OpenCV, 10 September 2018. [Online]. Available: http://opencv.org/.. [Accessed 10 November 2018].

[59] A. Sagitov, K. Shabalina, R. Lavrenov and E. Magid, “Comparing Fiducial Marker Systems in the Presence of Occlusion,” in *2017 International Conference on Mechanical, System and Control Engineering*, St. Petersburg, Russia, 2017.

[60] Catchroom, “Why Is Image Recognition Better Than QR Codes?,” catchroom, 7 December 2017. [Online]. Available: https://catchoom.com/blog/why-is-image-recognition-better-than-qr-codes/. [Accessed 25 03 2020].

[61] S. Kumar, N. Das and S. Islam, “Performance analysis of substation automation systems architecture based on IEC 61850,” *In proceedings of the 2014 Australasian University Power Engineering Conference (AUPEC)*, pp. 1-6, 28-1 September-October 2014.

[62] G. Muhammed, R. B. Bahaweres and K. Hulliyah, “Applying merging conventional marker and backpropagation neural network in QR code augmented reality tracking,” *International journal on smart sensing and intelligent systems*, vol. 6, no. 5, p. 4, 16 December 2013.

[63] M. Fiala, “ARTag, fiducial marker system using digital techniques,” in *2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05)*, 2005.

[64] K. Plewa, “Sculpteo,” 28 August 2019. [Online]. Available: https://www.sculpteo.com/blog/2019/08/28/battle-of-software-cinema-4d-vs-blender/. [Accessed 16 04 2020].

[65] R. Paucher and M. Turk, “Location-based augmented reality on mobile phones,” in *2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops*, San Francisco, CA, USA, 2010.

[66] R. Mur-Artal and J. J. Montiel, “ORB-SLAM: A Versatile and Accurate Monocular SLAM system,” *IEEE Transactions on Robotics,* vol. 31, no. 5, pp. 1147-1163, October 2015.

[67] R. D. Porter, Greene, M. W. Pankow and Buffalo, “Sensing motor speed and rotation”. United States Patent Patent 5446376, 29 August 1995.

[68] W. Sailawi, “SCADA System and Industrial Network for Petroleum Industry,” p. 4, 1 1 2017.

[69] C. engineering, “Control Engineering,” [Online]. Available: https://www.controleng.com/articles/what-is-machine-vision-and-how-can-it-help/. [Accessed 12 01 2020].

[70] Intel, “https://www.intel.com/content/www/us/en/support/articles/000005725/network-and-i-o/wireless-networking.html.,” 31 01 2020. [Online]. Available: https://www.intel.com/content/www/us/en/support/articles/000005725/network-and-i-o/wireless-networking.html.. [Accessed 11 03 2020].

[71] C. Engineering, “Control Engineering,” [Online]. Available: https://www.controleng.com/articles/what-is-machine-vision-and-how-can-it-help/. [Accessed 12 01 2020].

[72] M. Loizou and P. Kaimakis, “Model-based 3D Visual Tracking of Rigid bodies using distance transform,” in *VISUAL 2019: The Fourth International Conference on Applications and Systems of Visual Paradigms*, Rome, Italy, 2019.

Appendix

Annexure A: User experience survey template

10/27/2020 Machine Vision Device Tracking Application in a Manufacturing Environment based on Augmented Reality

https://docs.google.com/forms/d/1wL743qU7L8Gd3dTmBzthxkjEeV5MbQXDRkb4qw3WPYs/viewform?gxids=7757&edit_requested=true 1/4

<u>Central University of Technology Augmented Reality Application UX Testing</u>

Yes - I am working or studying in these fields

Yes - I am a technology hobbyist

No - I have no idea

Machine Vision Device Tracking Application in a Manufacturing Environment based on Augmented Reality

We would like to invite you to our user feedback survey interview. This interview is about the user experience of our Augmented Reality Application. This application was developed as part of the Ph.D. study. My paper title is Utilisation of Machine Vision for Device Tracking in a Manufacturing Environment based on Augmented Reality.

(For the APK to function, the user is required to have an AR core supporting device preferably an Android device)

* Required

Q1. Are you relative to engineering or information technology? *

Yes - I am working or studying in these fields

Yes - I am a technology hobbyist

No - I have no idea

Q2. Are you familiar with augmented reality technology? *

Yes - I develop augmented reality applications

Yes - I have played or used AR applications

No - I am only familiar with the media hype of AR

Q3. Have you downloaded and tested the application? *

Yes - I have downloaded and tested the application

Yes - but my phone is not supported

No - I do not know where to download the application

No - I am not interested

Q4. Do you think that this application needs improvement? *

Yes

No

Maybe

Q5. If your answer is yes to the previous questions, please explain what kind of improvements would you recommend (please see and choose from the predictive answers provided)

Improve UI/UX

Increase data latency and the application range

Provide access to low entry smartphones

Q6. How satisfied are you with the device detection accuracy? with 5 being super good *

1 2 3 4 5

Q7. If you were working on a manufacturing plant, would you consider this application for purchasing? *

Yes

No

Maybe

Q8. Would you recommend this application to colleagues or industry experts? *

Yes

No

Maybe

Q9. How satisfied are you with the reliability of this application? with 5 being super good *

1 2 3 4 5

Q10. How satisfied are you with the datasheet integration to the application? with 5 being super good *

1 2 3 4 5

Q11. Please rate this application out of 10, with 10 being super good *

1 2 3 4 5 6 7 8 9 10

Annexure B: AR application source code

```
using System.Collections;
using System.Collections.Generic;
using UnityEngine;
using UnityEngine.XR.ARFoundation;
using UnityEngine.UI;
public class MultiImageTracker : MonoBehaviour
{
private ARTrackedImageManager m_trackedImageManager;
[SerializeField]
private TrackedPrefab[] prefabToInstantiate;
[SerializeField]
private Text ImageTrackedText;
[SerializeField]
private Text handText;
[SerializeField]
private Text upperText;
[SerializeField]
private Text armText;
[SerializeField]
private Text elbowText;
[SerializeField]
private Text shoulderText;
[SerializeField]
private Text FootText;
private Dictionary<string, GameObject> instanciatePrefab;
private void Awake()
{
m_trackedImageManager = GetComponent<ARTrackedImageManager>();
instanciatePrefab = new Dictionary<string, GameObject>();
}
private void OnEnable()
```

```
{
m_trackedImageManager.trackedImagesChanged += OnTrackedImageChanged;
}
private void OnDisable()
{
m_trackedImageManager.trackedImagesChanged -= OnTrackedImageChanged;
}
private void OnTrackedImageChanged(ARTrackedImagesChangedEventArgs eventArgs)
{
foreach (ARTrackedImage addedImage in eventArgs.added)
{
InstantiateGameObject(addedImage);
}
foreach (ARTrackedImage updatedImage in eventArgs.updated)
{
if (updatedImage.trackingState == UnityEngine.XR.ARSubsystems.TrackingState.Tracking)
{
UpdateTrackingGameObject(updatedImage);
}
else if (updatedImage.trackingState == UnityEngine.XR.ARSubsystems.TrackingState.Limited)
{
UpdateLimitedGameObject(updatedImage);
}
else
{
UpdateNoneGameObject(updatedImage);
}
}
foreach (ARTrackedImage removedImage in
eventArgs.removed)
{
DestroyGameObject(removedImage);
}
}
```

```
private void InstantiateGameObject(ARTrackedImage addedImage)
{
for (int i = 0; i < prefabToInstantiate.Length; i++)
{
if (addedImage.referenceImage.name == prefabToInstantiate[i].name)
{
GameObject prefab = Instantiate<GameObject>(prefabToInstantiate[i].prefab,
transform.parent);
prefab.transform.position = addedImage.transform.position;
prefab.transform.rotation = addedImage.transform.rotation;
instanciatePrefab.Add(addedImage.referenceImage.name, prefab);
}
}
}
private void UpdateTrackingGameObject(ARTrackedImage updatedImage)
{
for (int i = 0; i < instanciatePrefab.Count; i++)
{
if (instanciatePrefab.TryGetValue(updatedImage.referenceImage.name, out GameObject
prefab))
{
prefab.transform.position = updatedImage.transform.position;
prefab.transform.rotation = updatedImage.transform.rotation;
prefab.SetActive(true);
switch (updatedImage.referenceImage.name)
{
```

```
case "ARM1":
ImageTrackedText.text = updatedImage.referenceImage.name;
ImageTrackedText.color = Color.red;
handText.text = " 270";
handText.color = Color.blue;
upperText.text = " 0";
upperText.color = Color.blue;
armText.text = " 180";
armText.color = Color.yellow;
elbowText.text = " 90";
elbowText.color = Color.green;
shoulderText.text = " 180";
shoulderText.color = Color.red;
FootText.text = "";
break;
case "MOTOR1":
ImageTrackedText.text = updatedImage.referenceImage.name;
ImageTrackedText.color = Color.red;
handText.text = "Temperature :25";
handText.color = Color.red;
upperText.text = "Humidity:20%";
upperText.color = Color.red;
armText.text = "Ambient light :1750 LUX";
armText.color = Color.red;
elbowText.text = "Status :100%";
elbowText.color = Color.red;
shoulderText.text = "Direction:Forward";
shoulderText.color = Color.red;
FootText.text = "Speed:25RPM";
FootText.color = Color.red;



break;
```

```
default:
break;
}
}
}

}

private void UpdateLimitedGameObject(ARTrackedImage updatedImage)
{
for (int i = 0; i < instanciatePrefab.Count; i++)
{
if (instanciatePrefab.TryGetValue(updatedImage.referenceImage.name, out GameObject prefab))
{
if (!prefab.GetComponent<ARTrackedImage>().destroyOnRemoval)
{
prefab.transform.position = updatedImage.transform.position;
prefab.transform.rotation = updatedImage.transform.rotation;
prefab.SetActive(true);
}
else
{
prefab.SetActive(false);
}
}
}
}
private void UpdateNoneGameObject(ARTrackedImage updateImage)
{
for (int i = 0; i < instanciatePrefab.Count; i++)
{
if (instanciatePrefab.TryGetValue(updateImage.referenceImage.name, out GameObject prefab))
{
prefab.SetActive(false);
}
}
}
private void DestroyGameObject(ARTrackedImage removedImage)
{
for (int i = 0; i < instanciatePrefab.Count; i++)
{
if (instanciatePrefab.TryGetValue(removedImage.referenceImage.name, out GameObject prefab))
{
instanciatePrefab.Remove(removedImage.referenceImage.name);
Destroy(prefab);
}
}
}
}
```

```
[System.Serializable]
public struct TrackedPrefab
{
public string name;
public GameObject prefab;
}
```

Annexure C: SCADA and OpenCV source code

```
using System;
using System.Collections.Generic;
using System.ComponentModel;
using System.Data;
using System.Drawing;
using System.Linq;
using System.Text;
using System.Threading.Tasks;
using System.Windows.Forms;
using System.IO;
using System.IO.Ports;
using Emgu.CV;
using Emgu.CV.CvEnum;
using Emgu.CV.Util;
using Emgu.CV.Structure;
using Emgu.Util.TypeEnum;
namespace Motor_controll
{
public partial class Form1: Form
{
VideoCapture capture;
SerialPort myPort;
Random rand = new Random();
public Form1()
{
InitializeComponent();
}
private void Form1_Load(object sender, EventArgs e)
{
// textBox2.Text = "" + rand.Next(0, 50);
updatePorts();
```

```
if (capture == null)
{
capture = new VideoCapture(1);
}
capture.ImageGrabbed += Capture_ImageGrabbed;
capture.Start();
}
private void updatePorts()
{
string[] ports = SerialPort.GetPortNames();
foreach(string port in ports)
{
comboBox1.Items.Add(port);
```

```
}
}
private void button4_Click(object sender, EventArgs e)
{
if (capture == null)
{
capture = new VideoCapture(1);
}
capture.ImageGrabbed += Capture_ImageGrabbed;
capture.Start();
}
private void Capture_ImageGrabbed(object sender, EventArgs e)
{
try
{
Mat m = new Mat();
capture.Retrieve(m);
Mat imgHSV = new Mat(m.Size, DepthType.Cv8U, 3);
Mat Treshlow = new Mat(m.Size, DepthType.Cv8U, 1);
Mat TreshHigh = new Mat(m.Size, DepthType.Cv8U, 1);
Mat Tresh = new Mat(m.Size, DepthType.Cv8U, 1);
Mat Tresh1 = new Mat(m.Size, DepthType.Cv8U, 1);
CvInvoke.CvtColor(m, imgHSV, ColorConversion.Bgr2Hsv);
CvInvoke.InRange(imgHSV, new ScalarArray(new MCvScalar(0, 100, 100)), new
ScalarArray(new MCvScalar(10, 255, 255)), Treshlow);
CvInvoke.InRange(imgHSV, new ScalarArray(new MCvScalar(160, 100, 100)), new
ScalarArray(new MCvScalar(179, 255, 255)), TreshHigh);
CvInvoke.Add(Treshlow, TreshHigh, Tresh);
CvInvoke.GaussianBlur(Tresh, Tresh, new Size(3, 3), 0);
Mat structureE = CvInvoke.GetStructuringElement(ElementShape.Rectangle, new Size(3, 3),
new Point(-1, -1));
CvInvoke.Dilate(Tresh, Tresh, structureE, new Point(-1, -1), 1, BorderType.Default, new
MCvScalar(0, 0, 0));
```

```
CvInvoke.Erode(Tresh, Tresh, structureE, new Point(-1, -1), 1, BorderType.Default, new
MCvScalar(0, 0, 0));
CvInvoke.Canny(Tresh, Tresh, 120, 180, 3,true);
VectorOfVectorOfPoint contours = new Emgu.CV.Util.VectorOfVectorOfPoint();
Image <Gray, Byte> canny = Tresh.ToImage<Gray, Byte>();
CvInvoke.FindContours(canny,contours, null, RetrType.Tree,
ChainApproxMethod.ChainApproxNone);
```

```
if(contours.Size>0)
{
double maxArea = 0;
int chosen = 0;
for(int i =0;i<contours.Size;i++)
{
VectorOfPoint contour = contours[i];
double area = CvInvoke.ContourArea(contour);
if(area>maxArea)
{
maxArea = area;
chosen = i;
}
}
Rectangle box = CvInvoke.BoundingRectangle(contours[chosen]);
CvInvoke.Rectangle(m, box,new Bgr(Color.LimeGreen).MCvScalar,3);
Point center = new Point(box.X + box.Width / 2, box.Y + box.Height / 2);
var info = new string[] { $"Position:{center.X},{center.Y}" };
for (int i = 0; i < info.Length; i++)
{
int y = i * 10 + center.Y;
CvInvoke.PutText(m, info[i], new Point(box.Right + 5, center.Y),FontFace.HersheyPlain,0.8,
new Bgr(Color.DeepSkyBlue).MCvScalar);
textBox1.Text = info[i];
pictureBox1.Image = m.ToImage<Bgr, byte>().Bitmap;
}
}
}
catch (Exception)
{
}
}
private void button1_Click(object sender, EventArgs e)
{
```

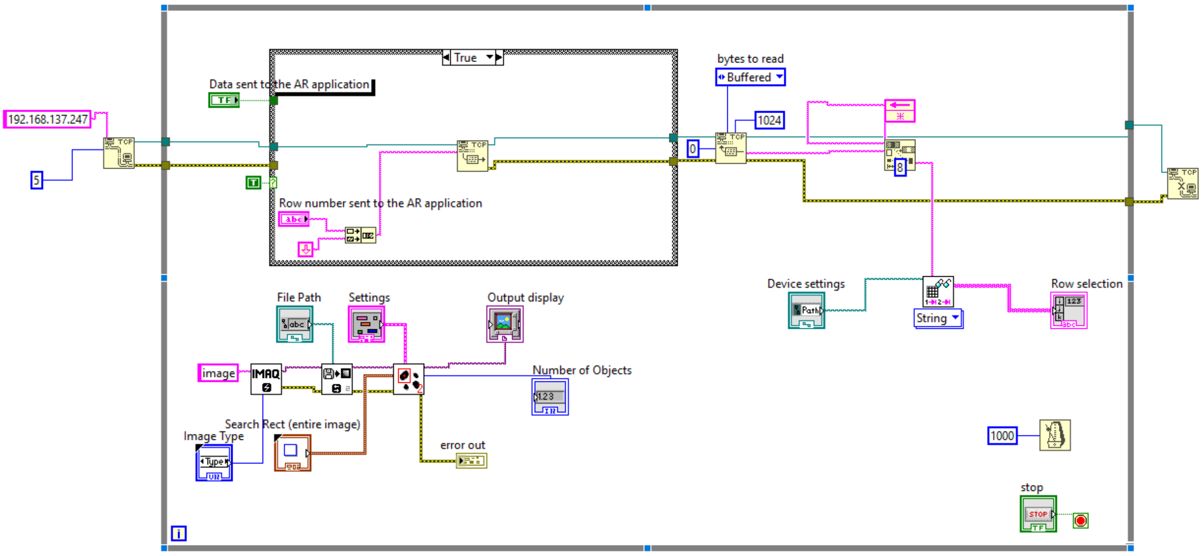
```
if (capture == null)
{
capture = new VideoCapture(1);
}
capture.ImageGrabbed += Capture_ImageGrabbed;
capture.Start();
```

```
/* textBox2.Text = "" + rand.Next(0, 50);
if(myPort.IsOpen)
{
switch (domainUpDown1.Text)
{
case "0":
myPort.WriteLine("Speed:0 RPM\nTemperature:"+textBox2.Text+"\nClockwise");
break;
case "75":
myPort.WriteLine("Speed:75 RPM\nTemperature:" + textBox2.Text+ "\nClockwise");
break;
case "100":
myPort.WriteLine("Speed:100 RPM\nTemperature:" + textBox2.Text+ "\nClockwise");
break;
case "125":
myPort.WriteLine("Speed:125 RPM\nTemperature:" + textBox2.Text);
break;
case "150":
myPort.WriteLine("Speed:150 RPM\nTemperature:" + textBox2.Text);
break;
case "175":
myPort.WriteLine("Speed:175 RPM\nTemperature:" + textBox2.Text);
break;
case "200":
myPort.WriteLine("Speed:200 RPM\nTemperature:" + textBox2.Text);
break;
case "225":
myPort.WriteLine("Speed:225 RPM\nTemperature:" + textBox2.Text);
break;
case "255":
myPort.WriteLine("Speed:255 RPM\nTemperature:" + textBox2.Text);
break;
}
}*/
```

```
}
private void button2_Click(object sender, EventArgs e)
{
if (comboBox1.SelectedItem.ToString() != null)
{
myPort = new SerialPort(comboBox1.SelectedItem.ToString(), 115200, Parity.None, 8,
StopBits.One);
myPort.Open();
MessageBox.Show("Connected to port :" + comboBox1.SelectedItem.ToString());
}
else
{
```

```
MessageBox.Show("Select Comport");
}
}
private void textBox2_TextChanged(object sender, EventArgs e)
{
}
private void pictureBox1_Click(object sender, EventArgs e)
{
}
private void label4_Click(object sender, EventArgs e)
{
}
private void label1_Click(object sender, EventArgs e)
{
}
private void dataGridView1_CellContentClick(object sender, DataGridViewCellEventArgs e)
{
}
private void dataGridView1_CellContentClick_1(object sender, DataGridViewCellEventArgs e)
{
}
}
}
```

Annexure D: Labview based source code


True
Data sent to the AR application
192.168.137.247
5
TCP
Row number sent to the AR application
bytes to read
Buffered
1024
0
8
Device settings
String
Row selection
File Path
Settings
Output display
image
IMAQ
Number of Objects
Search Rect (entire image)
Image Type
error out
1000
stop
STOP
i