DEVELOPMENT OF A COIN COUNTING SYSTEM BY USING MACHINE VISION

Submitted in accordance with the requirement of the Universiti Teknikal Malaysia Melaka (UTeM) for the Bachelor Degree of Manufacturing Engineering (Hons.)

by

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APPROVAL

This report is submitted to the Faculty of Industrial And Manufacturing Technology And Engineering of Universiti Teknikal Malaysia Melaka as a partial fulfillment of the requirements for the degree of Bachelor of Manufacturing Engineering (Hons.). The members of the supervisory committee are as follow:

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ABSTRAK

Kajian ini bertujuan untuk membangunkan penyelesaian pengiraan syiling automatik menggunakan teknologi penglihatan mesin bagi meningkatkan sistem pengiraan syiling sedia ada, terutamanya untuk perniagaan kecil yang menghadapi kaedah pengiraan syiling yang tidak efisien dan mahal. Objektif kajian ini adalah untuk mencipta sistem pengiraan syiling mudah alih serta untuk menganalisis kelajuan dan ketepatan sistem pengiraan syiling menggunakan teknik pemprosesan imej dengan Python OpenCV. Metodologi kajian ini melibatkan reka bentuk pemasangan mudah alih, pra pemprosesan syiling menggunakan konversi greyscale dan pelbagai teknik penambahbaikan imej, mengesan bentuk syiling, membezakan syiling berdasarkan saiz dan warna, dan memaparkan hasil akhir. Eksperimen dilakukan dengan lima set nilai syiling dan didapati bahawa sistem ini mencapai purata masa pengiraan kurang dari 0.013 saat dan ketepatan 100% di bawah keadaan optimal iaitu kecerahan sederhana, intensiti cahaya warna kuning hangat atau merah serta kawasan pengesanan imej selepas dipotong. Walau bagaimanapun, terdapat kekurangan seperti resolusi kamera yang rendah dan isu-isu pencahayaan yang kompleks. Cadangan untuk penambahbaikan termasuk menggunakan kamera resolusi tinggi, teknologi pemindahan data berkelajuan tinggi, rangkaian neural pancaran, dan sumber cahaya difus atau dome. Kajian akan datang boleh memberi tumpuan kepada penyertaan lebih banyak denominasi syiling dan pengesanan syiling palsu. Kesimpulannya, kajian ini telah mencapai semua objektifnya dan dapat menyumbang kepada pembangunan sistem pengenalan syiling yang lebih boleh dipercayai dan efisien.

ABSTRACT

This research focuses on developing an automated coin counting solution using machine vision technology to improve upon existing coin counting systems, particularly targeting small businesses facing inefficient and costly coin counting methods. The objectives of this study is to create a portable coin counting system. Also, by using image processing techniques with Python OpenCV, the research will also delve into the analysis of speed and accuracy of the coin counting system. The methodology involves designing a portable casing, preprocessing coins using greyscale conversion and various image enhancement techniques, detecting coin contours, differentiating coins based on sizes and colours and displaying the final results. Then, the experiment was done across 5 set of coin values and the average time taken to calculate the coins as well as average accuracy in terms of coin detection and calculation was obtained. Besides, the mean error as well as mean absolute error of the accuracy under different conditions were also explored. Tests conducted show promising results, with the system achieving an average calculation time of less than 0.013 s for different coin sets as well as 100% accuracy under optimal conditions in which medium brightness, light intensity of warm yellow or red tone as well as area of image detection after cropped should be used. However, the system has limitations, including low camera resolution and complex lighting issues. To address these, recommendations are made to improve the system, such as integrating a high-resolution camera, using high-speed data transfer technology, employing spiking neural networks, and utilizing a diffuse or dome light source. Future research could also focus on including more coin denominations and detecting counterfeit coins. Overall, this research had achieved all its objectives and is able to contribute to the development of more reliable and efficient coin recognition systems.

DEDICATION

I dedicate this project to my beloved parents which include my respected father, Liew Pai Lin and appreciated mother, Loh Joo See, whose unwavering love and support have been my constant inspiration throughout this journey. Their boundless strength and encouragement have been the driving force behind my perseverance, especially during moments when I felt on the verge of giving up. Beyond being my pillar of strength, they have also provided me with invaluable moral, emotional and monetary support, making it possible for me to pursue and complete this project successfully. This achievement is a testament to their enduring belief in my capabilities and their selfless dedication to my success. With heartfelt gratitude, I honour my parents for their immeasurable contributions to my academic and personal growth.

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Also, I want to express special thanks to my closest friends who provided me with motivation and mental support in crafting this report. Their words of encouragement have always supported me throughout the duration of this whole project.

Lastly, I would like to bid thank you to my family members who have always provided me with an excellent education and fought tirelessly for my success up to this stage of life. I am really grateful for their love, prayers, concern and support as I work to complete this project. In conclusion, I extend my thanks to everyone who played a crucial role in the completion of this FYP report. I apologize for not being able to personally mention each one of you. Your contributions are sincerely appreciated.

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LIST OF ABBREVIATIONS

OpenCV	-	Open Source Computer Vision Library
USB	-	Universal Serial Bus
DC	-	Direct Current
LCD	-	Liquid Crystal Display
IDE	-	Integrated Development Environment
EMAT	-	Electromagnetic Acoustic Trandsucer
FPGA	-	Field Programmable Gate Array
ID3	-	Iterative Dichotomiser 3
SIFT	-	Scale-Invariant Feature Transform
DDR	-	Double Data Rate
DTC	-	Distributed Trigger Counting
CNN	-	Convulation Neural Network
ReLU	-	Rectified Linear Unit
ANN	-	Artificial Neural Network
MLP	-	Multi-Layer Perceptron
GA	-	Genetic Algorithm
BP	-	Back Propagation
RGB	-	Red, Green and Blue
MSE	-	Mean Square Errors
PSNR	-	Peak Signal to Noise Ratio

PHT	-	Polar Harmonic Transform
LSTM	-	Long Short Term Memory
MLBPN	-	Multi-Layered Back Propagation Neural Network
BBSC	-	Binned Borders in Spherical Coordinates
SVM	-	Support Vector Machine
KNN	-	K-Nearest Neighbour
Rs	-	Indian Rupees
HOG	-	Histogram of Oriented Gradients
RFR	-	Region Binary Pattern
LDMT	-	Local Difference Magnitude Transform
MLCPN	-	Multi-Level Counter Propagation Neural Network
FV	-	Fisher Vector
BoVW	-	Bag of Visual Words
RANSAC	-	Random Sample Consensus
HD	-	High Definition
Hz	-	Hertz
RAM	-	Random Access Memory
CAD	-	Computer Aided Design
LED	-	Light-Emitting Diode

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND OF STUDY

Money, which exists in the form of coins and currency notes inside our financial ecosystem is a fundamental prerequisite for society. However, even slight mistakes in counting coins can cause major consequences. With that being said, separating and managing coins is a more difficult operation than for monetary notes (Naveen Kumar et al., 2018). Back then in the old days, individuals had to rely on manual counting in the absence of coin counting machines, which was a time-consuming and tiresome process for those assigned to the job (Syafarudy et al., 2009). This situation is also supported by (Naveen Kumar et al., 2018) as the application of an automated coin handling system will definitely be beneficial in our daily lives. In addition, the traditional manual method of coin counting lacks recording mechanism regarding results for future reference. Hence, an automated solution is necessary to cope these challenges. There is no doubt that implementing automation in conjunction with flexibility ensures efficient outcomes and provides a feasible alternative to streamline the coin counting process (Rangan, 2018).

There are numerous approaches across several stages in the field of coin handling systems, including recognition, discrimination, sorting and counting. According to Huber-Mrk et al., (2012), the three main techniques that dominate the coin handling system landscape: (i) mechanical methods, (ii) electromagnetic systems, and (iii) image processing methods, with the latter becoming increasingly popular in recent years. This is because image processing techniques are able to utilize powerful algorithms to recognize visual attributes of coins and value them. In addition, there are various more categories that are included, such as sensor-based, microcontroller-based and electromagnetic-based approaches. Furthermore, the integration of deep learning as well as digital technology methods is augmenting the advancements in coin handling systems.

This project aims to develop a coin counting system by using machine vision. The system will visually recognize and analyse coins using algorithms and cameras. By capturing images of coins and performing necessary processing steps to identify distinctive characteristics and ascertaining their values, it generates an automated process of calculating the coins. According to Rangan, (2018), it makes use of digital image processing technology to assist in the detection and differentiation of coins, thereby improving the accuracy of the process. As a result, the system can count the coins quickly and accurately.

1.2 PROBLEM STATEMENT

Counting money, particularly coins, is a simple operation that causes many organisations to lose several minutes each day and may be efficiently performed by an application. Although many physical machines can fulfil this task, they possess some drawbacks. They can be expensive, particularly when great precision is required. Additionally, they are bulky, not easily portable, and are deemed an unnecessary expense, especially for small enterprises. Counting devices can be readily replaced by an application capable of discerning the denominations of coins and precisely calculating their cumulative value. An application for coin counting can be beneficial for accurately estimating the precise number of coins in a remote deposit account or for tallying coins at the end of a business shift (Fanca et al., 2022). The heterogeneous attributes of coins, which comprise dimensions, denominations, shapes, engravings, colours, patterns and materials which can lead to different weights (Putra, 2023). Therefore, standardizing coin counting devices based on mechanical properties presents significant challenges for engineers. The absence of uniformity presents a significant obstacle to the smooth worldwide incorporation of automated coin counting systems. Apart from that, contrary to mechanical sorters, image processing systems primarily rely on software and do not require frequent maintenance to address mechanical damage. Software upgrades often facilitate the incorporation of updates and improvements without necessitating any physical modifications to the equipment (Valente et al., 2023).

The application of machine vision technology offers a potentially efficient answer to this problem. The use of machine vision allows for the creation of algorithms that can standardise coin counting systems for different sets of coins, resulting in enhanced speed and accuracy. By employing image processing techniques, it is possible to quickly and accurately identify and classify coins based on their visual characteristics. This improves the efficiency of coin recognition procedures, which are essential for coin counting system (Valente et al., 2023). The aim of this project is to address the limitations of current coin counting techniques by creating an automated alternative that utilises machine vision technology. The transformative capacity of a powerful algorithm in the process of counting coins resides in its capability to diminish errors, hence obviating the necessity for manual intervention (Rangan, 2018).

1.3 OBJECTIVES

1. To develop a portable coin counting system.
2. To utilize image processing techniques for the coin counting system by using machine vision through Python OpenCV.
3. To evaluate the speed and accuracy of the system with a diverse set of coin values.

1.4 SCOPE OF PROJECT

First of all, for the portable coin counting system, the prototype will include a box casing that features Sony PS3 Eye webcam as the main camera to detect the coins, laptop with AMD Radeon Graphics as the medium processor, together with a commercial ring light. In addition, the amount of the coins that could be processed in this project will solely depend on the size of the coin tray designed as well as the quality of the image depending on various factors such as camera resolution and field of vision as well as lighting that are affecting it. Also, the camera will be designed to be mounted on the top of the casing.

Next, the coin counting system will be designed using Python OpenCV. Hence, the performance of the system will be optimized based on the quality of the webcam. Apart from that, the three types of chosen coins for the project are the third series of Malaysian coins introduced in the early 2012, including the gold-coloured 50 sen and 20 sen, as well as the silver-coloured 10 sen, each with defined dimensions shown in Figure 1.1 and Table 1.1 respectively. All the coins should be in perfect condition. Next, for pre-processing, algorithms such as Gaussian blur and Canny edge detection will be utilized. After that, the system will perform contour analysis. Then, it will differentiate coins based on their sizes and colours. Hence, sufficient distance between coins must be maintained to prevent misinterpretation as a single coin or coin stacking issue. Furthermore, this project will only be tested at one location. Lastly, this project will compare the performance of the current coin counting system that will be developed with other coin counting technologies available.

Figure 1.1: The Third Series of Malaysian Coins (Only 10 sen, 20 sen and 50 sen will be used) (Rahim, 2022).

Table 1.1 : Technical Specifications of Third Series of Malaysian Coins (Rahim, 2022).

Face Value	50 sen	20 sen	10 sen
Alloy	Nickel Brass Clad Copper	Nickel Brass	Stainless Steel
Diameter (mm)	22.65	20.60	18.80
Weight (gram)	5.66	4.18	2.98

1.5 SUMMARY

Chapter 1 discusses the importance of accurate and automated coin counting systems, especially for small businesses and medium enterprises (SMEs) as well as individuals by looking at the challenges of existing methods. The problem statement identifies the limitations of existing methods and the potential benefits of machine vision technology to alleviate all the constraints. A low-cost portable coin counting system, using image processing techniques and evaluating system speed and accuracy will be done. The project scope includes the prototype components and specific coins used for testing.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

In this chapter, various machines or automatic system with applications in coin handling systems will be discussed that involves multiple steps such as recognition or identification, coin discrimination, coin sorting as well as coin counting. The approaches were separated according to the techniques, theories, methods as well as principles related to the coin system. Examining and comprehending the literature review is crucial as it serves as a guideline and roadmap for the project.

An examination of existing technologies reveals the presence of three distinct techniques related to coin handling system: (i) mechanical methods; (ii) electromagnetic system and (iii) image processing methods which are notably prominent in recent times. Numerous image recognition techniques which are usually have been developed to identify the unique characteristics of each coin, enabling the determination of its corresponding value (Huber-Mrk et al., 2012). Other than that, there are also other methods involved such as sensor based, microcontroller base, electromechanical based, electromagnetic based, combination of electrical, mechanical and electromagnetic based, deep learning based, digital based and algorithm based. Each of them will be further discussed in the following section. Since this project is about developing a coin counting system by using machine vision, hence it will be further explored under the category of image processing-based techniques.

2.2 MECHANICAL BASED COIN HANDLING SYSTEM

2.2.1 Coin Radius or Diameter Based Coin Handling Technologies

Zhao et al., (2017) developed the sieve-plate coin counting machine to improve coin sorting and counting efficiency. The system integrated an inclined vibrating sieve plate, which was driven by a 12V FB775 DC gear motor. It also contained various components for coin separation, screening, identification of counterfeit one-yuan coins, counting, and a rack. The operational principle of the device was based on the use of sieve plates with varying aperture sizes and controlled vibration to separate coins. A coin counting system that utilised an infrared light tube and presented the findings on a screen. Although it improved the speed of sorting and decreased the need for manual input, this system had several limitations. The drawbacks included were its specialised design for specific currency denominations and its sensitivity to the quality of coins, which necessitated regular maintenance.

Next, Dabhade et al., (2020) introduced a coin sorting device with a simple design consisting of a main frame, vertically aligned coin collection containers, a sorting mechanism, and a motor. Arranged in a vertical manner, each coin tray is designated to a specific denomination based on its measurements. The sorting mechanism positioned above the tray categorised coins based on their diameters as they moved through the motorised system utilising rollers of varying sizes. Alternatively, the sifting machine could employ sensors to determine the weight and thickness. The economic benefit of the mechanical sorting process, in comparison to other technologies like image processing was due to its simplicity that was based on easily observable physical qualities.

Han & Liu, (2021) devised a coin sorter that comprised a coin storage box, a rocker driving mechanism, a coin sorting box, a helical delivery mechanism, a coin counting and packaging mechanism as well as a bracket. The storage container was a triangular box that included nine sieve plates, each with different hole diameters used to classify coins based on their diameter. Firstly, coins will be passed over these plates and fell to the bottom of the container. Subsequently, the rocker driving mechanism regulated the motion of the sorting container while the helical delivery mechanism conveyed coins to the counting and packing machinery. The machine was simple and economical. This was due to the fact that the rocker mechanism which eliminated the need for an electric motor and gearbox, resulting in reduced noise and resource use.

2.2.2 Coin Handling Technologies Based On Magnetic Properties

Tsuchida et al., (2013) devised a coin sorter that use a mobile magnet to tackle the problem of differentiating low magnetic coins, hence decreasing expenses and facilitating simple modifications. Nevertheless, the sorting efficiency received criticism because the precision was affected by the velocity of the coins, which might potentially result in misclassification. Therefore, proposed future proposals aimed to resolve speed-related concerns and guarantee precise coin identification in different situations. Furthermore, the patent did not provide details regarding the particular categories of ferromagnetic and non-magnetic coins that were examined, emphasising the necessity for additional research involving diverse coin compositions and materials.

2.3 SENSOR BASED COIN HANDLING SYSTEM

2.3.1 Optical Sensor Coin Discrimination System

The optical coin discrimination system, patented by Borg et al., (2017), employed an optical sensor to take an image of a coin. Subsequently, an algorithm was utilised to analyse the image and ascertain the shape of the coins. The technique employed the identified contour to calculate the diameter of coins and generated a rectangle image using a log-polar transform, which is beneficial for assessing circular objects. Afterwards, the rectangular image was subjected to a sequence of Fourier transformations which separated the signal into its individual frequencies. Then, the Fourier transform analysed the locations and intensities of the spectral peaks of the coins. Also, the system utilised known data for various coins to assess parameters such as diameter, spectral peak location and intensity to determine the coin's class and value. However, the practical limits involved the need for high-quality images and precise determination of spectral peak positions and intensities.

2.3.2 Auto-Positioning Sensor Coin Counting Device

The auto-positioning coin sensor, invented by D. A. Martin, (2013) was a device integrated into coin counting machines to precisely determine the values of deposited coins. The device was fitted with a coin sensor to precisely ascertain a physical attribute of an object, such as its diameter. Furthermore, a mobile device was operationally linked to the coin sensor. The moving device can automatically adjust the location of the coin sensor to align with the centre of a coin that is moving along the coin route and has passed by the sensor. The coin sensor in most devices was often placed in the approximate centre of the coins that travelled down the coin route.

2.4 MICROCONTROLLER COIN HANDLING SYSTEM

2.4.1 Coin Sorting and Counting System by Using Arduino

Goh, (2016) introduced an automatic coin sorting and counting system using an Arduino microcontroller to record coin quantities and values and manage automatic coin allocation. The system included a security door requiring a password for coin retrieval and sorted six types of Malaysian coins, rejecting foreign or fraudulent ones. It communicated counting results to a computer, stored data, printed copies, and maintained a comprehensive counting history. Key components included a power supply, sensing unit, control panel (Arduino Mega), sorting unit, and display unit. A coin acceptor verified coin authenticity, while the microcontroller managed sorting, quantity, value determination, and security. Real-time information was displayed on an LCD, with transaction history viewable on a computer monitor. Functions related to coin identification, counting, classification and security control were implemented using the Arduino IDE. Although the paper did not discuss coin counting machine accuracy controversies, it highlighted features enhancing reliability. The absence of data on user group preferences indicated potential for further research.

The coin sorting machine, which was developed by A.Paramasivam et al., (2021), employed a lining mechanism to accurately measure the diameter, thickness and weight of coins to ascertain their value. The purpose of its development was to optimise the efficiency of coin sorting and counting by minimising human tiredness and improving accuracy. The mechanism had the ability to accept coins of different sizes and shapes. The mingling of the coins was averted by employing an Arduino-controlled servo actuator and an image sensor. In addition, the coins were directed to move in a precise direction by manually rotating a table, resulting in consistent alignment. Apart from that, the device consisted of a fixed arranging head, a spinning plate with a pliable upper surface and coin escape doors for the purpose of sorting. The structure consisted of a single base component and many coin chutes, each of which funnelled coins into separate components. Lastly, it was also outfitted with a feed mechanism, a coin container with a receptacle and a coin discriminator sensor.

2.4.2 Coin Sorting and Counting System by Using Maker NANO

Jayanthi et al., (2021) introduced a coin sorting and counting system that employed a sloped surface with specifically designed gaps to differentiate between coins of various denominations. The box was fabricated with precisely dimensioned slots tailored to the size of the coins and each coin was individually placed in a distinct box positioned beneath its corresponding slot. In accordance to that, four infrared sensor modules were placed in the slots to detect the coins. Upon inserting a penny into a container, upon detection by the corresponding infrared sensor, the count on the Maker NANO board was triggered to increment proportionately. The approach systematically arranged and calculated the Indian currency denominations, which included 1, 2, and 5 rupees. The authors suggested implementing the technique at banks, currency counters and similar establishments to decrease the need for manual sorting and counting of money. The technology demonstrated high efficacy in accurately classifying coins.

2.4.3 Comparison Between Arduino UNO, Maker NANO and Raspberry PI Microcontroller Coin Handling Systems

The research by Dr S.M. Shamsheer Daula et al., (2022) conducted a survey to assess the performance of three embedded processors, including Arduino UNO, Maker NANO, and Raspberry Pi, in automated coin sorting and counting systems. The study examined variables such as cost, design intricacy, efficiency, and accuracy. Although the Arduino UNO was more affordable, it had drawbacks in terms of speed and accuracy, which made it less suitable for modern requirements. However, Maker NANO provided greater speed and accuracy with a reduced number of parts, despite its higher cost. The Raspberry Pi distinguished itself with its remarkable speed, accuracy, and a cutting-edge design that minimised complexity. Although it was priced higher than the UNO, it was significantly more affordable than the Maker NANO. In the end, the Arduino NANO proved to be the most suitable controller, striking a balance between performance and affordability. The research recognised the possibility of integrating coins using advanced programming methods.

2.5 ELECTROMAGNETIC COIN HANDLING SYSTEM

2.5.1 Electromagnetic Transducer (EMAT) Coin Handling System

Dao et al., (2022) introduced a new method for identifying counterfeit coins using an EMAT system. This method utilised ultrasonic pulses to assess the inherent acoustic frequency response of coins, providing on-site analysis without the need for sample preparation. The EMAT system which included components such as a microphone receiver and a pulse-driven EMAT obtained a classification accuracy of 98.5% for coins. Although recognising the potential enhancements that could be achieved by modern signal processing, there were limitations to consider including the expense and complexity of the system, the influence on wear and tear and the requirement for accurate equipment to evaluate the weight, density, and thickness of the coins. Furthermore, the efficacy of the system was called into question due to issues such as low excitation efficiency and a subpar signal-to-noise (SNR) ratio. Overall, additional investigation is required to comprehend the level of accuracy of EMAT in the categorization of coins.

2.6 DIGITAL BASED COIN HANDLING SYSTEM

2.6.1 FPGA Based Coin Recognition and Counting System

Krishna et al., (2019) highlighted the significance of efficient hardware design in coin handling systems, with a specific focus on performance, development time, reconfigurability and flexibility. A novel approach utilising FPGA technology was suggested to tackle the difficulties associated with detecting Indian coins that exhibited various changes in size, shape, colour, dirt and scratches. The method entailed storing pixel values of an image in the memory of an FPGA and executing image enhancement procedures using Verilog. The system might achieve efficient coin recognition by combining a Basys 3 FPGA with an OV7670 camera. The authors asserted that their system possessed the capability to accurately detect and count coins, however they did not furnish any explicit measurements of precision. The superiority of FPGA-based processing was claimed compared to other coin recognition systems, highlighting the system's efficiency in identifying and tallying coins.

2.7 DEEP LEARNING BASED COIN HANDLING SYSTEM

2.7.1 ANN Technique Coin Recognition System

Bawa & Modi, (2011) created an automated system for identifying Indian coins, utilising an Artificial Neural Network (ANN) to handle rotation invariance. The system employed techniques such as Pattern Averaging and Hough Transformation to extract features from RGB coin pictures. The trained ANN demonstrated superior performance compared to electromagnetic approaches in accurately differentiating between different coin denominations. The experimental findings demonstrated a high identification rate of 97.74%

with a low false positive rate of 2.26%. However, the study recognised the possible challenges in adapting coins from various regions. Thus, potential enhancements could involve training the system with datasets that are invariant to rotation, so improving its capacity to identify coins regardless of their location or orientation.

Malik et al., (2014) developed a coin recognition system that uses an Artificial Neural Network (ANN) based on a multi-step strategy. The system performed pre-processing on coin pictures using edge detection, noise reduction and normalisation techniques. The second stage utilised a non-uniformly spaced frequency Fourier transform for extracting distinctive characteristics. These characteristics were then utilised to train a neural network that could identify coins in any position, regardless of their rotation. The system accuracy and output quality were assessed using evaluation measures such as mean square error (MSE) and peak signal-to-noise ratio (PSNR). However, there was a research gap in the absence of empirical testing conducted on coin identification algorithms, mostly depending on datasets consisting of static images. Hence, additional research might be conducted to investigate the practical applications of this technology, namely examining its accuracy, speed, and dependability in real-world scenarios such as cash registers or vending machines.

Kaur & Kaur, (2015) developed a coin recognition system that employed Artificial Neural Networks (ANN) and the Phase Harmonic Transform (PHT) approach so that it could provide consistent recognition of coins regardless of rotation. The system conducted an analysis on RGB coin images by converting them to grayscale, cropping them to reduce noise and extracting shape and texture attributes using a histogram. As a result, the system demonstrated an exceptional level of precision, properly identifying various currency denominations with a remarkable accuracy of 98%. However, the limited dataset, comprising only 100 pieces raised concerns about the capacity of the system to generalise to coins from various countries. In addition, it was essential to conduct empirical assessments and comparative analyses against established coin identification systems.

2.7.2 CNN Technique Coin Recognition System

Qiu et al., (2017) employed Hough detection, radius ratio, colour features, and relative position constraints to remove unwanted circles and identify coins in real-world environments. Their study specifically targeted Chinese and Hong Kong coins from six different categories. The CNN was utilised for the ultimate recognition and classification. The report recognised the difficulties associated with identifying coins in real-life pictures, but the main point of debate was the effectiveness of the system in handling challenging lighting situations. Additional research could investigate the suitability of the proposed method in more complex scenarios.

Rosidi et al., (2022) sought to develop an automated system for identifying Malaysian coins by employing advanced pre-trained convolutional neural network (CNN) models, including AlexNet, GoogLeNet, and MobileNetV2. The study utilised a dataset consisting of 2,400 coin images that were tagged and classified into four distinct categories: 5 sen, 10 sen, 20 sen, and 50 sen. The dataset included photos of both the front (obverse) and back (reverse) sides of the coins. After that, the training procedure utilised transfer learning by employing pretrained convolutional neural network (CNN) models. Lastly, the final layers of the models were replaced specifically for the purpose of categorization. As a result, GoogLeNet outperformed the other models with an impressive testing accuracy of 99.2%. The study proved the efficacy of the deep learning methodology in accurately identifying and classifying coins. Hence, potential future studies could involve integrating with embedded devices to conduct clinical testing on visually impaired individuals.

Katariya et al., (2022) had integrated long short-term memory (LSTM) cells and CNN to recognize Indian coins. The method addressed challenges of conventional systems related to illumination, scale and orientation variations by autonomously extracting features from input images using CNN. The features were then processed through fully linked layers with LSTM capturing temporal relationships in the feature vectors. The proposed method outperformed traditional systems, achieving 98.5% accuracy on the test set swiftly. Despite its success, the study also highlighted the drawbacks of the system, particularly the fixed receptive field which could potentially limit the global feature identification.

Putra, (2023) introduced a CNN algorithm for coin classification. The architecture included two convolution layers, one subsampling layer, and two fully connected layers with

ReLU activation. The input was a 250 x 250 image processed through a 3 x 3 convolution layer with 32 filters and ReLU activation. A 2 x 2 subsampling layer reduced overfitting by decreasing feature map dimensions. An additional 3 × 3 convolution layer was used, consisting of 64 filters, to extract further characteristics. The classification output was processed using a fully connected layer of 128 neurons, and the efficacy of the model was assessed using cross-entropy loss.

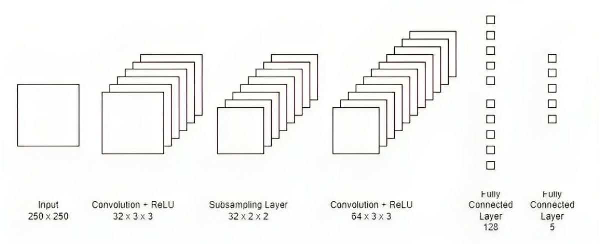


Figure 2.1: CNN Architecture (Putra, 2023).

The study had shown efficacy in differentiating between similar coins and enhancing coin sorting systems. The algorithm successfully made precise predictions for all categories of coins in the validation set. Nevertheless, doubts had been expressed over the generalizability of the findings to other currencies due to restrictions such as the small dataset size and the limited focus on Indonesian Rupiah coins. Besides, the research was limited by the small scope of the categorization job, which only included five specific coin classifications. Although there were limits, the research emphasised the need for additional exploration to improve performance with different coin values and to explore different structures for classifying coins. Moreover, the approach showed promise for expanding to other tasks involving the classification of objects and various types of images.

2.7.3 MLBPN Technique Coin Recognition System

The study by Roomi & Rajee, (2015) aimed to develop a robust and rotationally invariant approach for identifying coins using a multilayer backpropagation neural network (MLBPNN). The method employed Fourier approximation of coin images to extract characteristics, guaranteeing rotational invariance by encoding them using Fourier coefficients on polar images. The MLBPNN was subsequently taught to classify coins based on their unique characteristics, resulting in a remarkable accuracy of 98.5% in recognising different denominations of Indian coins. However, there were concerns about the applicability to coins from different currencies as the study exclusively focused on Indian coinage. Furthermore, it was seen that there was no comparative analysis conducted with established coin identification algorithms, and the research did not acknowledge any shortcomings that may be addressed for improvement. These areas have been identified as potential subjects for additional investigation.

2.7.4 DDR-Coin Algorithm Coin Handling System

In their study, S. Kim & Park, (2020) introduced the DDR-Coin algorithm, which employed a hierarchical structure consisting of nodes connected at various levels. Some of these nodes had the additional function of serving as internal vertices to oversee the behaviour of coins. The programme utilised a probabilistic approach to identify triggers, with the goal of reducing the likelihood of a failure on one side, increasing the likelihood of detecting true triggers and avoiding false positives. The experimental results unequivocally shown that DDR-Coin surpassed other DTC algorithms in terms of both maxima received message load and complexity. Furthermore, the implementation of DDR-Coin was carried out using NetLogo 6.1.1 and validated through the use of measured data, showcasing a notable degree of precision. Further investigation involved analysing overflow-coin messages and developing library packages to handle node failures, message delays, and network topology limitations.

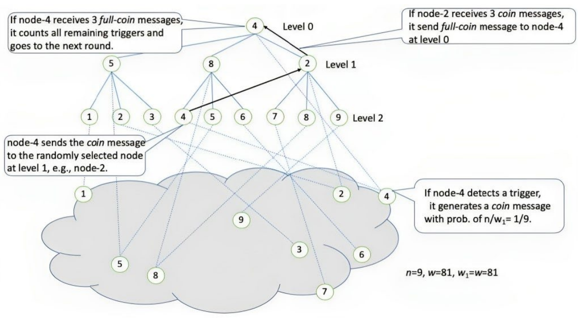


Figure 2.2: An example of DDR-coin in round 1 when n = 9 and w = 81 (Kim & Park, 2020).

2.7.5 Deep Convolutional Network for Face Profiles Recognition in Coins

Schlag & Arandjelovi´c, (2017) made a significant contribution to the analysis of ancient Roman Imperial coins using computer vision techniques. A profile face recognition deep convolutional network was created to identify the issuing authority by analysing the relief on the obverse. The effectiveness was demonstrated by three annotated datasets. Despite being trained on a little dataset, the network demonstrated an impressive accuracy of 97.5% when tested on a much larger dataset and a separate diversified dataset. The approach demonstrated its ability to withstand changes in lighting conditions and the quality of the surface, therefore emphasising its practical use in verifying the authenticity of ancient coins. However, the necessity for additional investigation into alternate forms of currency was identified. Also, the limitation of the research was its exclusive concentration on analysing the relief representation on the reverse side of Roman Imperial coins in order to determine the authority that issued them. In addition, further characteristics such as inverted patterns or engravings could be incorporated to improve the thoroughness of the existing method for identification or categorization.

2.7.6 Coin Detection and Counting System with TensorFlow and Keras

The work conducted Fanca et al., (2022) demonstrated successful coin edge recognition, image cropping for categorization, and precise calculation of the overall value of the coins. However, the precision of the results was compromised due to constraints in handling environmental factors such reflecting backdrops and overlapping coins. The system achieved an accuracy of more than 85% in coin identification tasks, with the size of the training dataset and the filters in the convolutional layer being crucial factors in deciding the performance. Future enhancements should give priority to addressing these limitations by improving edge detection techniques, mitigating overfitting issues, and expanding the database to enhance the system's robustness and practicality in real-world scenarios involving coin counting.

2.8 IMAGE PROCESSING COIN HANDLING SYSTEM

2.8.1 3D Height Map Image Analysis Method Coin Identification System

In the paper by Khazaee et al., (2021), a new method called 3D height-map image analysis was presented to address limitations associated with 2D analysis. Initially, the system employed a 3D scanner to capture the surface of coins, resulting in height-map pictures that were subsequently converted into triangulated representations. Subsequently, a clustering strategy utilising the Fuzzy C-Means algorithm was employed to cluster the triangles and identify the boundaries of the coin surface that indicate a steep drop-off. The precipice borders refer to the areas on the edges of the coin surface where the height fluctuates fast. These borders are crucial for identifying counterfeit coins.

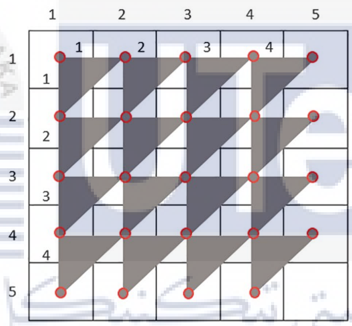


Figure 2.3: Triangulation of height-map image (Khazaee et al., 2021).

In the next phases, the algorithm employed the BBSC technique to accurately extract features from the edges of precipices, hence improving the capabilities of feature extraction. The collected characteristics were utilised to train an ensemble classifier that relied on matrices rather than vectors. Each row was treated as an independent entity. This strategy tackled obstacles like as deterioration, corrosion, or wear that could impede the identification of counterfeit coins using conventional 2D techniques. The comparative analysis of stack classification using support vector machine (SVM), k-nearest neighbour (KNN), and Random Forest classifiers revealed that the ensemble classifier exhibited higher accuracy and processing efficiency. The algorithm's adaptability enabled it to analyse the boundaries of steep cliffs from different polar and azimuthal angles, facilitating accurate categorization of coins, including those from Denmark and China.

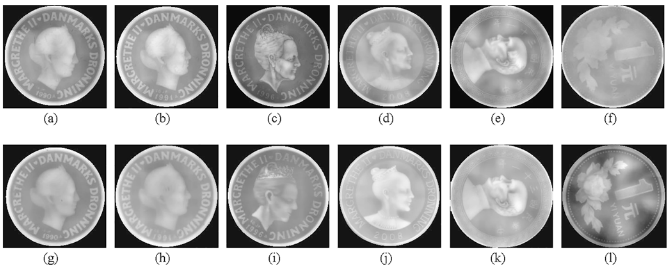


Figure 2.4: Examples of genuine and fake Danish and Chinese coin images: (a) Danish 1990, (b) Danish 1991, (c) Danish 1996, (d) Danish 2008, (e) Chinese 1942, (f) Chinese 1997; and (g), (h), (i), (j), (k), and (l) were the fake counterparts of the coins (Khazaee et al., 2021).

2.8.2 HOG and SVM Algorithm Coin Identification and Counting System

The study article by Naveen Kumar et al., (2018) aimed to develop an automated system that accurately identifies and measures Indian Rupee coins using histogram of oriented gradients (HOG) and SVM algorithms. The Histogram of Oriented Gradients (HOG) method was utilised to extract specific details and contours of coin pictures. This was achieved by dividing the image into smaller sections called cells and generating histograms, which were then used to create a feature vector. The features that were retrieved were subsequently utilised for coin categorization using Support Vector Machines (SVM). The system consists of two modules, namely HOG and SVM, which are used for the classification of head and tail images, respectively. The efficiency of the system in speedy and precise automatic coin recognition was proven through cross-validation on a partitioned database. Nevertheless, there has been discussion regarding the suitability with different currencies. Furthermore, the absence of rotational invariance in the HOG algorithm presented a difficulty in reliably detecting rotated coins, indicating the necessity for additional research on scalability.

2.8.3 RFR Technique Based Coin Recognition System

Kim et al., (2015) introduced a novel method for recognising coins based on images. Their methodology specifically tackled the problem of rotation-invariance in histogram data. The technique implemented region binary patterns (RFR) by considering the spatial configuration of coins. The procedure of computing gradient magnitudes in specific parts of coin pictures involves utilising the Sobel operator. This process involved dividing the images, calculating the gradient magnitudes, encoding them as binary patterns and concatenating them into an RFR feature vector. Nevertheless, the study recognised certain criticisms and areas of research that need further investigation, such as the absence of a direct comparison to well-established benchmarks when evaluating a single dataset, concerns regarding the application of the findings in different circumstances, and limits in accurately representing the variety of real-world coins. The computational complexity of the suggested approach was not evaluated, requiring additional research to comprehend its requirements and performance on larger datasets for future real-time applications.

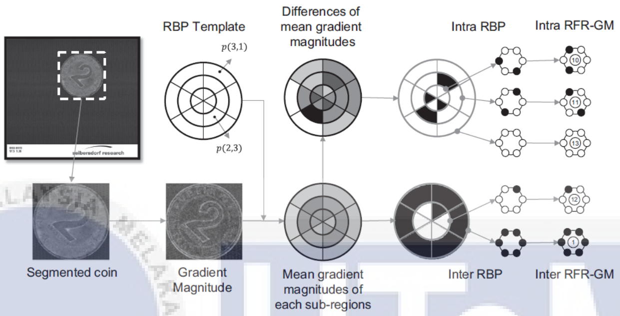


Figure 2.5: RFR extraction method for coin recognition (Kim et al., 2015).

2.8.4 Edge Detection Coin Categorization and Counting System

Salehittal et al., (2019) categorised and counted coins using a multilayer continuous neural network (MLCPNN) and edge detection techniques. An image was formed by applying Gaussian filtering and grey level thresholding. The features were then retrieved using the Harris-Hassian detector. Additionally, circles were recognised using Hough Transform to improve edges and extract features. In addition, many differentiating factors including as shape, size, surface and weight were utilised during training to accurately identify coin attributes, resulting in an identification accuracy of 99.5%. Nevertheless, obstacles such as dependence on high-resolution images and difficulties in accurately detecting edges were presented. Also, the study emphasised the need for standardisation in currency identification, as there are variances in coins across different nations.

Kushwaha et al., (2023) employed edge detection algorithms to properly delineate the perimeters of the coins and later correlated them with established coin types to correctly ascertain the total worth of the coins represented in the image. The technique was employed to identify regions in a picture where there were rapid variations in intensity, typically indicating the boundaries of distinct objects in the image. Various edge detection methods, such as the Laplacian of Gaussian edge detector, the Sobel edge detector, and the Canny edge detector, can be employed. The overall value was determined by matching the size and characteristics of the observed edges with a database of recognised coin types and their corresponding values.

2.8.5 Machine Vision Based Coin Detection and Counting System

The research by Dīnēshchandra Jōshī et al., (2016) focused on achieving accurate and effective coin classification through the use of dynamic images collected by a camera. The system successfully classified moving coins by employing machine vision algorithms and thresholding techniques. Conducting a test using ₹5 coins at a rate of 50 coins per minute and a frame rate of 30 FPS resulted in an accuracy of 89%. However, the accuracy was influenced by the state of the coins. The system achieved a count of 330 coins per minute with no mistakes when operating at a frame rate of 30 frames per second (FPS). However, it encountered inaccuracies when operating at greater speeds, suggesting the requirement for optimising the algorithm and using cameras with a higher frame rate. Future suggestions involve enhancing the training dataset and investigating sophisticated methods to enhance both accuracy and speed.

Rangan, (2018) suggested a system with the objective of automating the separation and counting of coins, hence minimising the need for manual intervention and saving time. The system utilised digital image processing techniques with a LabVIEW-controlled embedded system. It employed a camera to capture images of coins and compared them with templates to accurately separate them. The procedure entailed the utilisation of a vibrating grill to create movement, capturing images, detecting edges, matching templates, employing a servo system for segregation and utilising infrared sensors for counting. The results were presented on an LCD screen, using a template file to teach the software in identifying and increasing coin values. There was a distinct receptacle specifically designated for counterfeit or fraudulent coins. The automation was achievable by utilising easily accessible components and supported by its high precision, all while requiring a reasonable initial expenditure. The system provided efficient time management, cost-effective automation, accurate operation, and human control via a digital display. Nevertheless, the implementation necessitated a substantial upfront capital outlay and the possibility of sensor malfunctions could result in mistakes.

2.8.6 Vision System for Coin Identification from Scarp Metals

Kumar et al., (2022) devised a machine learning-driven visual method for discerning coins from scrap metal. The vision system classified pictures of coins using libraries that were configured with parameters for categorising and organising discarded parts. The algorithm excluded fragments resembling coins, such as circular cutouts, in order to prevent incorrect categorization. The challenges encompassed the requirement for a significant amount of training data, obstacles in obtaining the data, and the necessity for frequent updates and maintenance to achieve optimal performance. Possible enhancements in the future may include the incorporation of other machine learning libraries or algorithms, integration with robots and automation systems, and the development of a modular and scalable system capable of handling various types of scrap metal and sorting needs.

2.8.7 Coin Classification by using OpenCV and Arduino

The proposed system by Kavitha et al., (2022) utilised computer vision techniques and embedded programming using Arduino to automate the process of identifying and sorting coins. The system employed OpenCV algorithms and Arduino-controlled hardware to capture and analyse images, facilitating the categorization of coins based on their denominations. The system demonstrated remarkable expertise in accuracy, automation, and integration, but its performance depended on the quality of photographs and the characteristics of the currency, leading to challenges with foreign or damaged coins. The findings exhibited the effective detection and segregation of coins in substantial quantities with a notable degree of accuracy. Future recommendations could involve enhancing the ability to identify various types of coins and improving the speed and efficiency of processing by utilising advanced software and hardware components.

2.9 COMPARISON BETWEEN VARIOUS TYPES OF COIN HANDLING TECHNOLOGIES

Table 2.1: Summary Table of Comparison between Different Coin Handling Technologies.

Authors	Year	Key Techniques	Findings	Controversies
Mechanical Based Coin Handling Systems				
Zhao et al.	2017	Coin Radius/Diameter	-An inclined vibrating sieve plate effectively sorted and counted coins.	-Limited to certain currency denominations. -Sensitive to coin conditions, requiring regular maintenance.
Tsuchida et al.	2013	Coin Sorter based on Magnetic Properties	-Movable magnet to distinguish low magnetic coins, which reduced costs and allowed for easy adjustments.	-Precision influenced by coin velocity, potentially leading to misclassification.
Sensor Based Coin Handling Systems				
Borg et al.	2017	Optical Coin Discrimination System	-Optical sensor captures coin images, algorithm calculate diameters and uses Fourier transform to sort coins.	-Reliance on high-quality images and need precise spectral peak characteristics.
Martin	2013	Coin Counting System by using Auto-Positioning Sensor	-Autonomously adjusts position to coincide with the coin's centre in its path.	-
Microcontroller Based Coin Handling Systems				
A. Paramasivam et al.	2021	Coin Sorting Machine with Arduino UNO	-Lining mechanism quantifies coin denominations, avoid mixing via picture sensor and servo actuators.	-
Jayanthi et al.	2021	Coin Sorting and Counting System by Maker NANO	-Slope-like configuration for different coin denominations, with four infrared sensor modules.	-
Electromagnetic Based Coin Handling Systems				
Dao et al.	2022	EMAT Counterfeit Coin Identification System	-Novel counterfeit coin identification method and achieves 98.5% accuracy in coin classification.	-System cost, complexity, wear impact, and precision equipment need.
Digital Based Coin Handling Systems				
Krishna et al.	2019	FPGA Based Coin Recognition and Counting System	-Counts diverse Indian coins by size, shape, colour, grime and scratches. -Uses FPGA block memory, Verilog image enhancement, Basys 3 FPGA, and OV7670 camera.	-
Deep Learning Based Coin Handling Systems				
Roomi & Rajee	2015	MLBPN Technique Coin Recognition System	-Fourier approximation of rotational invariant coin images and achieves accuracy of 98.5% in identifying Indian coins.	-Concerns about generalizability to coins and lack of comparative analysis.

Kaur & Kaur	2015	ANN with PHT Coin Recognition System	-Achieves high accuracy of 98% in identifying coin denominations with rotational invariance.	-System's generalization to other countries' coins due to the limited dataset.
Rosidi et al.	2022	Deep Pre-trained CNN Models Coin Recognition System	-GoogLeNet stands out with accuracy of 99.2% for identifying Malaysian coins, surpassing AlexNet and MobileNetV2.	-Integration with embedded systems and clinical testing on visually impaired people.
Fanca et al.	2022	Coin Detection and Counting System using Tensorflow and Keras	-TensorFlow and Keras enhanced model sophistication, simplified training with transfer learning support, and improved accuracy through scalability and flexibility. -Attained 85% high accuracy in coin classification task.	-Brightness, luminosity, and reflective backgrounds affected accuracy, necessitating diverse training data. -Overfitting and overlapping coins reduced model precision and performance.
Putra	2023	CNN Algorithm Coin Classification System	-Two convolution layers and effective in differentiating same coins by achieving accurate predictions.	-Dataset size limitations with only five-coin classes on Indonesian Rupiah coins.
Image Processing Based Coin Handling Systems				
Dīnēshchandra Jōshī et al.	2016	Real Time Coin Detection and Counting System via Machine Vision Based	-Accurately classified and counted coins based on dynamic imaging at high speed by differentiating denominations based on their features.	-Accuracy impacted by quality of training set (differentiation between valid and invalid values) -Algorithms missed coins and miscounted at higher FPS.
Rangan	2018	Coin Counting System via Machine Vision Based	-LabVIEW-controlled for currency coin separation, integrating edge detection, template matching, servo mechanism, and IR sensors.	- Challenges include one-time high investment and potential sensor failures leading to inaccuracies.
Salehittal et al.	2019	Edge Detection Coin Categorization and Counting System	-ML-CPNN and edge detection methods (Robert's, Laplacian of Gaussian and Canny) for shape, size, surface and weight achieves 99.5% accuracy on diverse dataset.	-Reliance on high-quality images. -Trade-off between efficiency and accuracy in edge detection.
Kavitha et al., (2022)	2022	Smart Coin Classification System through OpenCV and Arduino	-Computer vision techniques and embedded programming using Arduino to automate the identification and sorting of coins.	-System's generalization to other countries' coins.

				-Speed could be improvised through updated software and hardware improvements.
Kushwaha et al.	2023	Edge Detection Algorithms Coin Identification System	-Edge detection algorithms (Laplacian of Gaussian, Sobel, Canny) through database matching, replacing manual methods and locating coin edges in rapidly changing intensity regions.	-Potential challenges in acquiring substantial training data for accurate recognition of valuable waste items.

Table 2.1 presents a comparison of several coin handling systems, focusing on their methods, discoveries, and disputes. Mechanical methods primarily emphasise physical attributes such as coin radius and magnetic characteristics, although they have constraints in terms of maintenance and precision. Sensor-based systems include optical and auto-positioning sensors, placing significant emphasis on picture quality and accurate calibration. Microcontroller-based methods utilise Arduino and infrared sensors to perform sorting and counting tasks. Electromagnetic systems provide a high level of precision in detecting counterfeit items, yet they are characterised by their intricate nature and substantial expenses. FPGA technology is utilised in digital systems for the purpose of recognising various types of coins. Deep learning systems utilise sophisticated neural networks to achieve high levels of accuracy. However, they encounter challenges in terms of generalizability and constraints of the dataset. Image processing systems utilise machine vision and edge detection techniques to achieve a high level of accuracy. However, these systems frequently necessitate a significant amount of training data and encounter difficulties related to image quality and system speed.

2.10 SUMMARY

The literature review meticulously examines a diverse array of coin handling technologies, including mechanical, sensor-based, microcontroller-based, advanced, digital-based, algorithm-based, and image processing-based systems. Mechanical methods offer simplicity but face limitations in applicability, while sensor-based and microcontroller-based approaches provide precision and adaptability with certain constraints. Advanced systems, employing electromechanical and digital technologies, raise concerns about costs and counterfeit detection challenges. Digital-based solutions showcase multifunctionality but may have limitations in real-world recognition and algorithm-based systems boast accuracy but face challenges with datasets and algorithm-specific concerns. Image processing technologies offer precision but encounter applicability issues and limitations in recognizing rotated coins. The purpose of the project is to pioneer a cutting-edge coin counting system using machine vision, addressing the challenges identified in existing technologies. The system aims to enhance precision through feature extraction, enable efficient automation and ensure adaptability in recognizing diverse coin attributes, thereby minimizing human involvement. The subsequent methodology chapter will serve as a practical roadmap for implementing this novel coin counting system. It will delve into system design, outlining the selection of machine vision algorithms and programming development using Python. Additionally, the chapter will articulate evaluation criteria to measure the system's performance, setting a benchmark for precision, automation, and adaptability in coin counting technology.

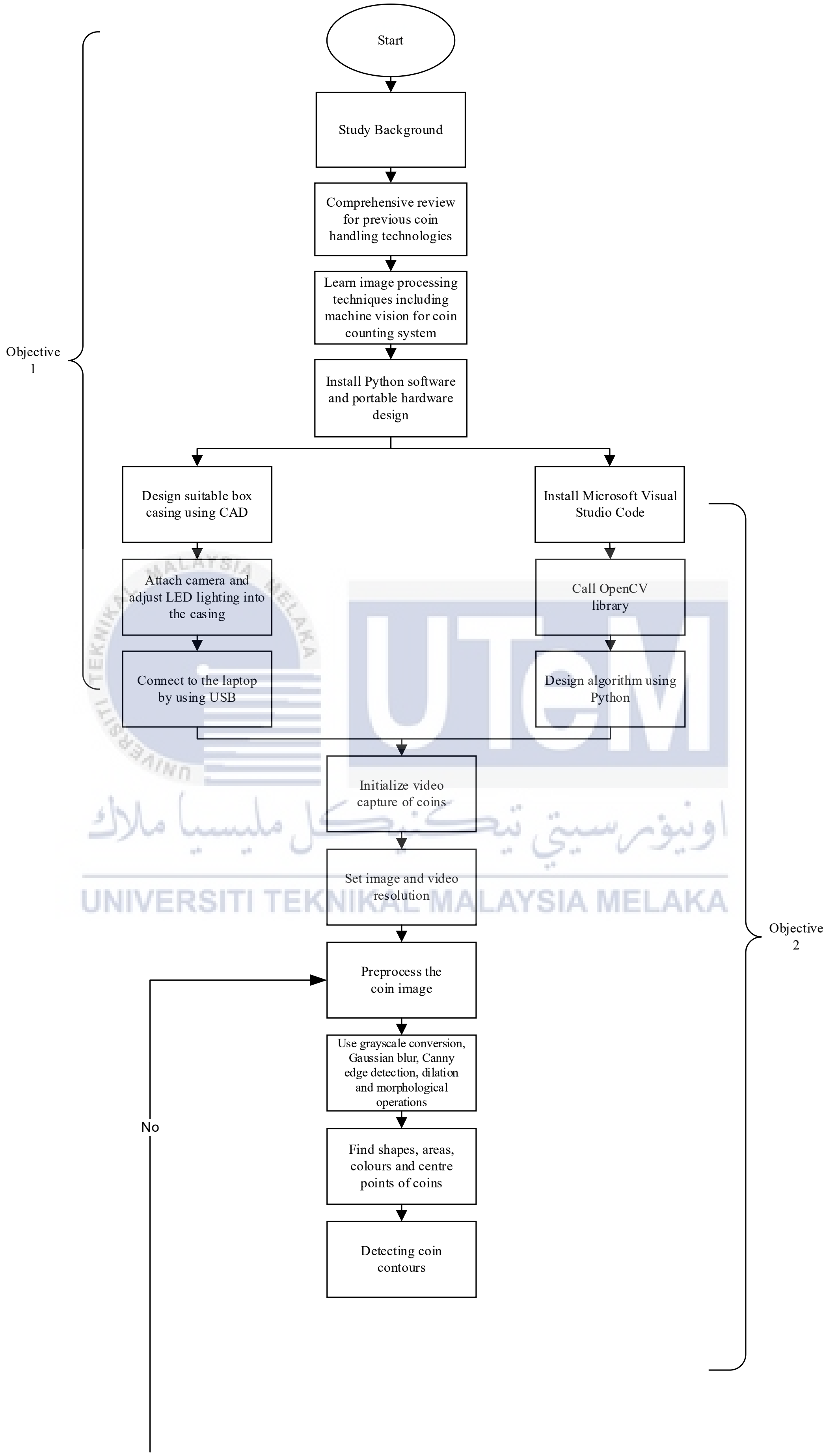
CHAPTER 3

METHODOLOGY

3.1 INTRODUCTION

This chapter will focus on the methods for creating a coin counting system using machine vision. The flowchart depicted in Figure 3.1 will be utilised to demonstrate the entire progression of the project, starting with its inception and continuing until the conclusion of the process flow.

According to the flowchart in Figure 3.1, to accomplish Objective 1, the process will begin with studying the background and end with displaying the ultimate result, which is the total value of coins. Objective 2 will involve constructing an algorithm using Python to present the end result, which is the total value of coins. Additionally, it will examine if the system is capable of accurately calculating the coins without any errors. Objective 3 will entail analysing and comparing the existing coin counting technology with the coin counting system developed in this project. The comprehensive analysis of the primary techniques employed in this project will be further upon in the subsequent sub-sections.


Start
Study Background
Comprehensive review for previous coin handling technologies
Learn image processing techniques including machine vision for coin counting system
Install Python software and portable hardware design
Design suitable box casing using CAD
Attach camera and adjust LED lighting into the casing
Connect to the laptop by using USB
Install Microsoft Visual Studio Code
Call OpenCV library
Design algorithm using Python
Objective 1
Objective 2
Initialize video capture of coins
Set image and video resolution
Preprocess the coin image
Use grayscale conversion, Gaussian blur, Canny edge detection, dilation and morphological operations
Find shapes, areas, colours and centre points of coins
Detecting coin contours
No

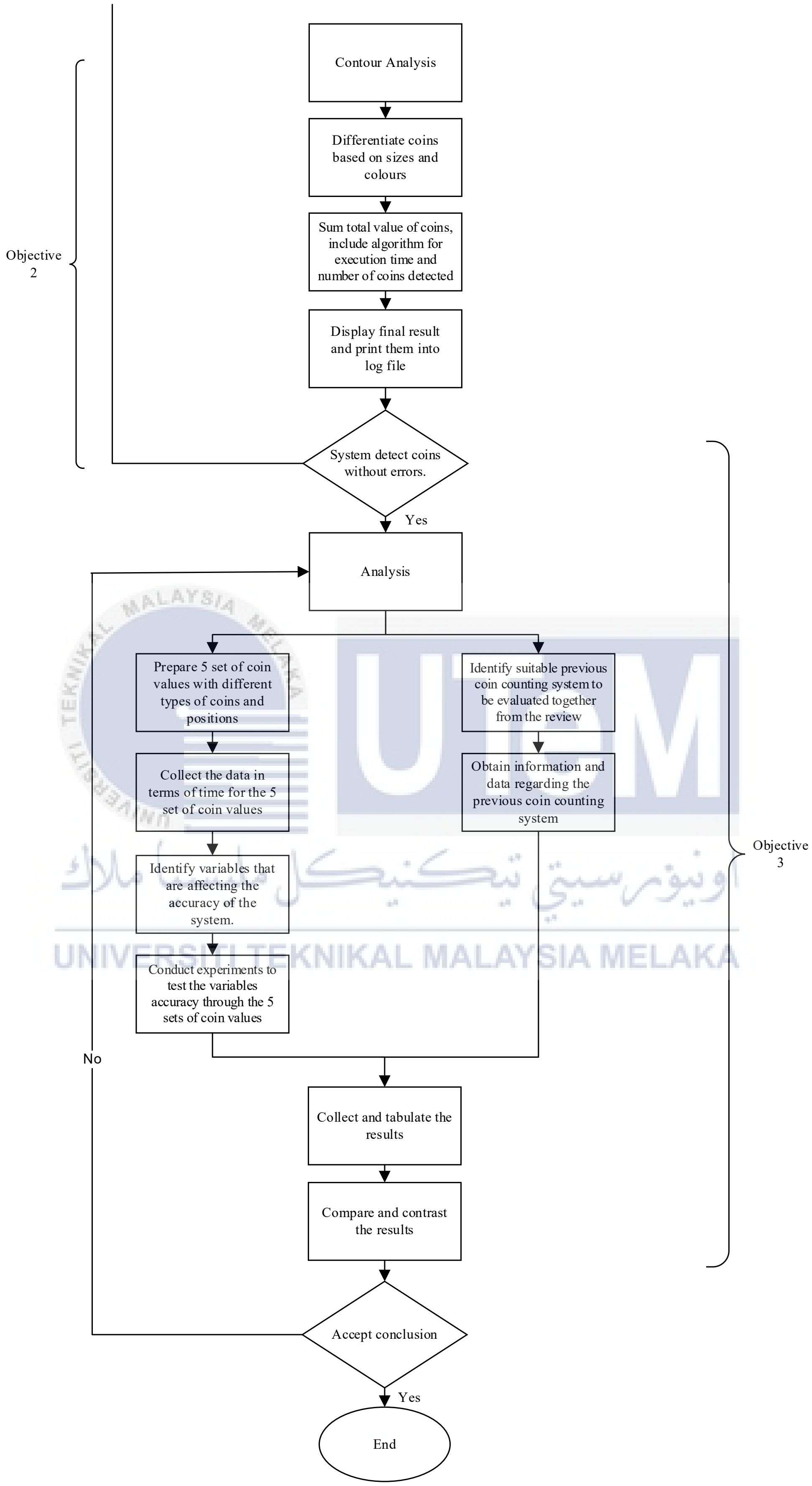


Figure 3.1: Flow Chart of Machine Vision Coin Counting System

3.2 TOOLS AND EQUIPMENT USED

In this topic, the tools and equipment used which are the hardware and software required in creating the coin counting system via machine vision will be described in detail.

3.2.1 Python Programming Software and Open CV Package Library

First of all, Python is an excellent choice for various applications, especially in computer vision when used alongside OpenCV, due to its versatility and extensive library collection. OpenCV offers a wide range of features for manipulating pictures and videos, making it essential for developers working on computer vision tasks. Python and OpenCV collaborate in a coin counting system to modify and analyse images of coins. This collaboration facilitates the execution of activities such as picture augmentation, filtering, and thresholding, which are aimed at extracting crucial information. OpenCV offers a range of features including contour and edge detection, which ensure precise identification and positioning of coins based on their unique characteristics.

The collaboration between Python and OpenCV involves complex calculations and measurements on recognised coins, streamlining the process of determining the total value based on denominations and dimensions. This connection facilitates the creation of advanced coin counting systems that may be utilised in various sectors, such as retail, banking, and vending machines. These methods streamline the process of calculating coins.

The project will employ Python software version 3.9.7 (32-bit) and OpenCV 4.9, utilising script creation through Microsoft Visual Studio Code (VSCode). The incorporation of VSCode with robust tools such as `pip install` in its terminal streamlines package management and script execution, ensuring prompt feedback and efficient resource utilisation. In addition, the functionalities of VSCode, such as automated code validation, personalised shortcuts, and seamless integration with Git, enhance the overall quality of code and streamline cooperation. Afterwards, the project will give priority to the construction of a portable coin counting prototype and the creation of the coin counting algorithm.

3.2.2 Camera and Lighting

The project uses the Sony PS3 Eye Webcam as the primary sensor for capturing images and videos of coinage. By utilising Python and OpenCV, the camera enables the immediate identification of coins through computational analysis. In order to enhance adaptability to different surroundings, the camera's position and orientation can be adjusted based on the lighting conditions. The camera is positioned in parallel with the surface of the coin resting on top of the box, and a ring lamp is used as the primary light source. This setup improves the sharpness of the images, making it easier to accurately identify and count coins in a controlled lighting situation. Adequate lighting is crucial for capturing sharp and accurate images, while also preventing inconsistencies, shadows, and reflections. It enhances the distinction between different elements and reduces inaccuracies in the process of tallying. This configuration ensures accurate coin counting. The camera and ring light specs are depicted in Figure 3.2 and Table 3.1 as well as Figure 3.3 and Table 3.2 respectively.

Figure 3.2: Sony PS3 Eye Webcam

Table 3.1: Camera Specification

Name of Model	Sony PS3 Eye Camera
Developer	Sony Computer Entertainment
Product Family	PlayStation
Type	Gaming Webcam
Release Date	October 2007
Generation	7^{th} Generation Era
Driver	Third Party Apps
Camera	640x480 pixels @ 60 Hz
Connectivity	USB 2.0 (Type A)
Price	RM 59.90

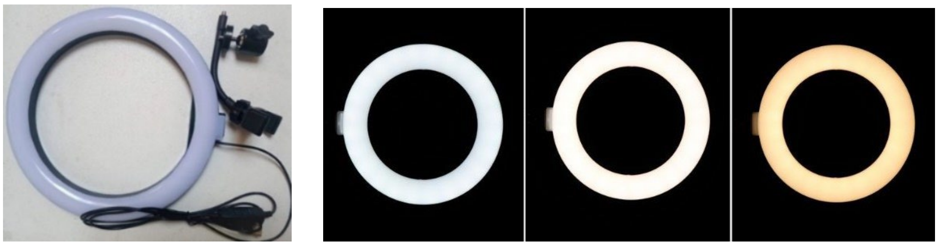


Figure 3.3: Commercial Ring Light

Table 3.2: Ring Light Specification

Name	LED Ring Light
Video Light Size	10 inch
Light Modes	Warm (3000-3500 K), Cool (4200-4500 K) and Day (6000-6500 K)
Brightness Range	10 levels, 10-100%
Power	8W
Power Supply	USB 5V DC Input
Connectivity	USB 2.0 (Type A)
Price	RM 39

3.2.3 Laptop Processor

The Acer Aspire 5 laptop is a dependable and adaptable option for creating a coin counting system, providing sturdy hardware components at a cost-effective price. The efficient CPU and substantial memory capacity allow for the quick execution of complex algorithms, resulting in immediate coin detection and improved system performance and responsiveness. The laptop's large RAM and storage capacity efficiently handle data flow, facilitating precise coin detection from high-resolution photos and movies. Integrating a camera improves the efficiency of data transmission and processing, especially when using Python algorithms. The laptop's portability makes it well-suited for use as the main processor in a coin counting system, as it can easily be adapted to varied contexts. The Acer Aspire 5 is a midrange CPU that offers a cost-effective solution for coin counting system.

Figure 3.4: Acer Aspire 5 Laptop

Table 3.3: Laptop Specification

Model	Acer Aspire 5 A515-44-R645 R5 Laptop
Operating System	Windows 11 Home 64Bit
Processor	AMD Ryzen 5
Memory	8 GB (1 x 4 GB + 4 GB (soldered))
Graphics	AMD Radeon Graphics
Storage	512 GB SSD-Western Digital
Price	RM 2,899.00

3.2.4 Timer

Integrating a timer into a machine vision coin counting project is crucial for enhancing productivity, accuracy, and reliability. The system quantifies the duration of each stage, encompassing image capture, image processing, coin detection, and coin counting. This guarantees that the system's performance stays satisfactory and precise. Accurate timing is particularly crucial for applications that necessitate real-time processing, thus impacting overall efficiency. Furthermore, it facilitates the ongoing evaluation of performance, prompt identification of potential problems, and enables modifications to uphold system stability and effectiveness.

3.2.5 Excel

Microsoft Excel is the primary software utilised for organising and managing project data as well as collecting information from experimental results. The structured architecture of the system facilitates efficient data entry by incorporating separate columns for different criteria. Moreover, its functions and algorithms ensure precise calculations. Excel's sorting and filtering capabilities provide focused analysis, while its integration with graphing tools provides advanced visualisation options, facilitating the comparison of system performance measurements. This integration enables thorough and succinct analysis, hence aiding in the assessment and comparison of findings for the coin counting system.

3.2.6 Setup

The Sony PS3 Eye webcam, functioning as the main visual input device, is directly connected to the laptop through a USB connection to facilitate immediate data transfer. The laptop utilises a Python script and the OpenCV library, supported by VSCode, to evaluate incoming data. It employs machine vision algorithms to recognise coins and perform calculations. The results are subsequently and effortlessly documented on Microsoft Excel, which is already installed on the same laptop, simplifying the process of gathering, organising, and analysing data. This integrated configuration allows for a comprehensive method of counting coins, encompassing image acquisition and analysis, data organisation, and interpretation. This enhances the overall system's efficiency and accuracy. The procedures and instructions for setting up are shown in Figure 3.2.

Figure 3.5: Arrangements and setups of the coin counting system

3.3 DESIGN A SUITABLE BOX CASING FOR PROTOTYPE USING CAD

To create a portable coin counting system, the initial stage involves designing and constructing a prototype box case using computer-aided design (CAD) software like Solidworks. The prototype will be created using a blend of several manufacturing processes and 3D printing technology. When designing the case, various crucial factors are considered. One factor is the construction of a fully enclosed container that ensures a stable environment for the operation of detecting and calculating coins. Furthermore, the system will include a specialised platform that is fitted with a tray designed specifically for the purpose of feeding coins. The device will also feature an LED ring light as the main illumination source and a webcam which will function as the main sensor. In addition, the inclusion of an adjustable height mechanism will allow for optimal distance adjustment to provide the highest image quality. These improvements will boost the illumination conditions and raise the overall efficiency of the system. A camera mount with adjustable features is essential for achieving optimal camera orientation by allowing for vertical alterations.

Once the box prototype has been designed and produced, the next step is to establish a link between the camera sensor and the laptop processor via a USB cable. The incorporation of the design elements in this connection produces a functional and efficient portable coin counting system. The camera mount can be modified to position the camera at the optimal distance from the tray, guaranteeing the acquisition of impeccable coin photos. To summarise, the incorporation of these design elements simplifies the coin counting process and enhances the efficiency and user-friendliness of the system.

3.4 PREPROCESS THE COINS

The process of coin recognition requires the implementation of several essential steps in image preprocessing. Firstly, the image is converted from RGB to grayscale by consolidating the colour information into a single channel. This simplifies the processing operation while preserving important features like edges. Afterwards, adjustments to contrast and brightness are employed to enhance the sharpness of objects inside the image. These procedures are crucial for improving the quality of the image and getting it ready for accurate coin identification.

Since only the perimeters of the coins need to be identified in the image for this coin counting approach, hence any additional boundary that is recognised could potentially be mistaken as a coin that will contribute to errors. Therefore, the coin counting system employs a Canny edge detection function to accurately recognise the edges of coins in pre-processed photos. This method utilises a blurred image as its input and calculates the gradient intensity of the image by assessing the first derivative in both the horizontal and vertical directions for each pixel. The Canny method utilises two criteria to detect edges that are strong and weak, while also considering weak edges that are connected to strong edges. This stage is essential for discerning the outlines of coins. To guarantee the algorithm operates as intended, it is necessary to assess a range of choices until the application is content with the outcomes. A track bar allows for the changing of thresholds in real-time, which helps in continuously improving performance and eliminates the need for time-consuming trial and error. By iteratively modifying the threshold, this method guarantees accurate coin segmentation by eliminating unwanted noise, hence minimising the requirement for time-consuming trial and error during the stages later on.

However, prior to that, the Gaussian blur technique is performed on the images of the coins to provide smoother edges and minimise problems with detecting noise. The technique employs a Gaussian kernel to average pixel values, therefore diminishing high-frequency noise components.

Next, the dilation image processing technique is used to increase the thickness of edges by expanding the borders, closing gaps between segments, and boosting their visibility. This operation utilises the kernel. Next, the process of morphological closing is used to fill small gaps and breaks in the image. This involves expanding and shrinking the image to close gaps and join edges that are not connected. The same kernel used in the expansion stage is also used in this process.

In brief, this comprehensive preprocessing pipeline enhances the quality of information in a coin image, making it well-suited for further analysis or use in tasks like coin identification and quantification.

3.5 FIND SHAPES, COLOURS, AREAS AND CENTRE POINTS OF COINS, DETECTING COIN CONTOURS AND CONTOUR ANALYSIS

Contour detection is a technique that employs an algorithm to recognise and categorise contours in pre-processed images, producing a collection of additional data for each contour, making them ready for subsequent analysis.

The subsequent stage entails conducting a thorough analysis of contours, making approximations, filtering shapes, and computing properties such as area, bounding box, and colour. Contour approximation reduces the complexity of contours, while form filtering emphasises the significant number of vertices in a contour. In addition, area computation is useful for determining the borders of contours. Additionally, a cropped image is generated by extracting a specified region, so isolating a certain coin for subsequent study. Colour extraction is achieved via a sophisticated algorithm specifically designed for colour analysis.

Before completing this stage, it is essential to locate the central points of contours in order to accurately determine the spatial position of coins in a picture. The centroids of each coin are derived from either bounding frames or straight from the contours. By precisely identifying these locations, it will assist in thorough contour analysis, obtaining crucial data about each coin for subsequent activities such as coin calculating.

3.6 DIFFERENTIATE THE COINS BASED ON SIZES AND COLOURS

The primary objective of this stage is to distinguish the 10 sen coin, which is in silver colour, from the 20 and 50 sen coins, which are in gold colours. Subsequently, the distinction between 20 and 50 sen will be determined based on their sizes. The spatial dimensions of each coin are determined by calculating the area of each contour. Consequently, specific ranges of area are defined to differentiate between coins of varying size. These ranges serve as thresholds for classifying shapes according to their sizes. Consequently, it is essential to carefully adjust these thresholds as they have a direct influence on the accuracy of the size-based categorization.

By extracting colour information from coins, the differentiation process is much improved as it introduces an additional layer of precision. Specialised algorithms are employed to assess qualities such as colour, saturation, and value, which are dependent on the colour space utilised. This method offers valuable insights into distinct colour profiles, particularly beneficial when coins of the same dimensions exhibit colour differences that correlate to different denominations.

The capacity of the system to take into account geometric aspects and colour characteristics strengthens its ability to distinguish between coins, precisely categorising them into various denominations. This, in turn, improves the precision of coin recognition and establishes a solid groundwork for future attempts.

3.7 DISPLAY FINAL RESULT OF ITERATION, TOTAL MONEY, NUMBER OF COINS DETECTED AND EXECUTION TIME

During this step, an algorithm will be used to showcase the total value of coins on an output image. A rectangle is strategically positioned to enclose both the total worth of the coins and the text. The appearance of the rectangle can be adjusted by setting its position, size, distance from the original position, and thickness. This graph provides a clear representation of the total monetary value obtained from the various dimensions of the detected coins. Visualization aids users in quickly evaluating the cumulative worth of the coinage, enhancing the interpretability of the outcomes. Also, to ease the data collection and interpretation stage later, algorithm to display iteration number, number of coins detected, total money and execution time will be included, printed and logged to a file for further interpretation and analysis.

3.8 ANALYSIS

The analysis stage evaluates the accuracy of a machine vision coin counting system. The project's success depends on meeting all goals and providing good feedback throughout the process. A good coin counting system should be effective in terms of accuracy and speed in counting all coin values provided.

3.8.1 Data Collection

To collect data, the coin counting system will undergo tests using machine vision with various coin values. It must be verified to calculate total coin value accurately before results are recorded. If any errors occur during calculation, the image preprocessing steps will be reviewed and repeated to ensure accurate coin counting.

The experimental design for this project will include five fixed sets of coin values. The specific quantities of 10, 20, and 50 sen coins used as tabulated in Table 3.4 will be determined after the prototype is completed, as they depend on factors such as the camera's field of vision, the size of the coin tray, and the distance between the camera and the tray.

The speed of the machine vision coin counting system across the 5 set of coin values will be assessed by recording the time taken for the system to process and calculate the total value of coins presented to it. This includes measuring the execution time from the pre-processing step to the final summation of coin values. Setup time, or the time taken to feed coins into the system will also be recorded. The average calculation time for each set of coin values will be calculated and displayed. Additionally, the accuracy of the system will be evaluated based on coin detection and calculation. Factors affecting accuracy will be identified during the prototype development and coding phases. Mean error and mean absolute error (MAE) will also be used to assess coin calculation accuracy. Data collection will involve 2000 iterations and graphical representations such as box plots and bar charts will be used for further analysis and to visualize the results. Table 3.7 and 3.8 display the sample data collection for the accuracy of the system.

The machine vision coin counting system will be compared with existing coin handling technologies to assess its speed and accuracy. Based on findings from journal articles or machine catalogue, the data on its speed and accuracy will be collected and analysed to serve as a benchmark. A comparative analysis will then be conducted to evaluate the performance of the machine vision coin counting system against the identified mechanical method or machine.

3.8.2 Data Interpretation

Data interpretation involves summarizing and presenting results in tables, graphs, and images to draw conclusions from the analysis. Based on these graphical representations, decisions are made regarding the validity of the conclusions. If the conclusion is accepted, the project concludes. However, if the conclusion is not accepted, the analysis stage is revisited until a valid conclusion is reached.

Figure 3.6: Amount of 50, 20 and 10 sen Across 5 Coin Set Values

Coin Set Values	50 sen	20 sen	10 sen
Set 1			
Set 2			
Set 3			
Set 4			
Set 5			

Table 3.4: Setup Time for Coin Counting System

Coin Set Values	Setup Time/s
Set 1	
Set 2	
Set 3	
Set 4	
Set 5	

Table 3.5: Average Time Taken for Coin Calculation Across 5 Coin Set Values by System

Coin Set Values	Average Time Taken for Coin Calculation/s
Set 1	
Set 2	
Set 3	
Set 4	
Set 5	

Table 3.6: Accuracy of Machine Vision Coin Counting System

Accuracy Criteria	Factor		
Coin Detection Average Accuracy			
Coin Calculation Average Accuracy			

Table 3.7: Error in Coin Calculation for Machine Vision Coin Counting System

Error Metrics	Factor		
Mean Error			
Mean Absolute Error (MAE)			

3.9 SUMMARY

Chapter 3 of the involves eight subchapters, including flowcharts detailing the project flow from FYP 1 to FYP 2. It details the tools and equipment used for creating a coin counting system via machine vision, as well as design considerations for the box casing. The flowcharts are further described in Chapters 3.4 to 3.7, providing a clear vision for obtaining results. Chapter 3.8 discusses the expected results to achieve project objectives. The methodology chapter is crucial as it outlines the structured approach used to address research objectives. The clarity of this section allows readers to understand the reliability of study findings and provides a roadmap for future research, contributing to knowledge advancement. A well-crafted methodology establishes the rigor and validity of the FYP, making it a crucial component of the overall research process.

CHAPTER 4

RESULTS

4.1 INTRODUCTION

Chapter 4 outlines the results of the study conducted to create a coin counting solution that utilises machine vision technology. It provides a comprehensive account of the design, implementation, and assessment of the portable system. The chapter commences by incorporating the Sony PS3 Eye webcam, ring light, and 3D printed components to establish a reliable detection setting. Next, it discusses the Python coding script, emphasising image processing techniques and algorithms for distinguishing between different coins. The text provides a detailed description of the experimental design and setup, which encompasses the testing environment and the calibration method. The evaluation of system performance is based on its speed and accuracy, providing insights into its real-time capabilities and error analysis. The text presents a comparison between the newly designed machine vision system and the current coin handling technologies, with a focus on highlighting the new system's mobility, cost-effectiveness, speed, and accuracy. The chapter finishes by showcasing the practicability and efficiency of machine vision technology in counting coins, while also pinpointing areas that require further enhancement.

4.2 PORTABLE COIN COUNTING SYSTEM

4.2.1 Design and Fabrication of Prototype for Portable Coin Counting System

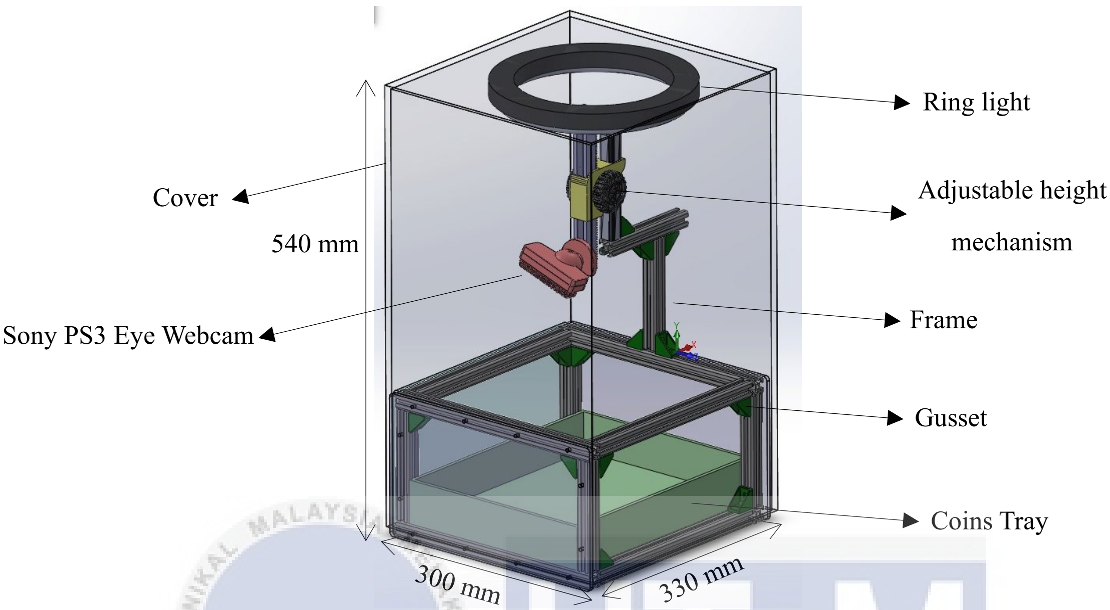


Figure 4.1: Assembly View of 3D CAD Model of Portable Coin Counting System Together with Dimensions

Figure 4.2: Setup of Portable Coin Counting System

The prototype was designed by using 3D CAD modelling software named Solidworks and Figure 4.1 displayed the assembly view of 3D CAD model of the portable coin counting system together with its dimensions for the box casing. On the other hand, Figure 4.2 portrayed the setup of the prototype of the portable coin counting system.

For the fabrication process of the prototype, first of all, it consists of the main frame which was made up of aluminium 2020 profile of different lengths at 140 mm, 280 mm, 300 mm and 320 mm respectively. The aluminium profile was cut by using a miter saw. The main frame of the prototype was then connected by using gusset, capscrew M4 and washer M4 for 2020 aluminium profile with the aid of an allen key.

Next, the components for 3D printing were designed. Firstly, the 3D model and stl.file for the adjustable height mechanism was referred and obtained from(A Fully Printable Microscope by Kwalus - Thingiverse, 2013) so that it was able to move up and down in the z direction to determine the best height to locate the camera as the main sensor to detect the coins as shown in Figure 4.2. Hence, upon several trials, the best height was fixed to be at 30 cm from the camera to the coin tray. After that, the mounting of the camera as shown in Figure 4.3 was also designed based on the 3D model and stl.file from (Free 3D File Tripod Mount for PS3 Eye ・3D Printer Design to Download・Cults, 2023) so that it can hold the camera in place during coin detection and calculation. Then, the camera in its mounting and then drilled to the adjustable height mechanism at the desired height. At the meantime, the coins tray was also designed so that it can contain all the coins for the coin counting system. Upon testing with the system, the tray had to be designed in two layers since the area of coin detection was limited by the field of vision of the camera as the initial first layer of tray was designed according to the dimension of the main frame. The new area for the second layer will be 284 x 214 mm and both of these two layers will be sticked together by using adhesive glue. The detection of coins will be carried out on the second layer of tray as shown in Figure 4.4. Nonetheless, the area of detection of coins must be in black colour matte background so that it will increase the contrast between the coins from the background as well as ensuring that the surface of the tray will not reflect the light.

Apart from that, after fixing all the components onto the main frame, the prototype was also covered by using the black PP corrugated board in order to create a fixed enclosed environment for the coin counting system as well as to minimize the impact of shadow. This is because shadows can result in false boundaries, incomplete or extra contours, distorted shapes and sizes and incorrect colour detection in the coin counting system.

Last but not least, due to the reflection of coins resulting from the metallic and shiny surface of the coins, the LED ring light had to be modified to obtain the best optimal lighting condition before being mounted onto the top of the box casing. It was wrapped with a few layers of translucent film as well as white A4 papers in order to reduce the effect of glare and increase the diffusion of light so that it can be uniform to shine towards all directions onto the coins.

Figure 4.3: Adjustable Height Mechanism 3D Printed

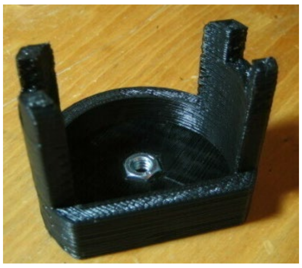


Figure 4.4: Sony PS3 Eye Webcam Mounting 3D Printed

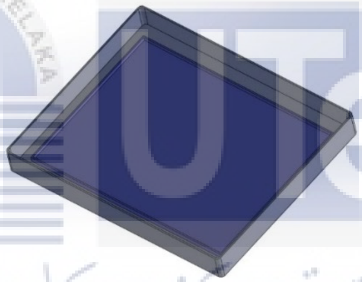


Figure 4.5: 3D CAD model for Coins Tray (blue colour will be the main area for coin detection)

4.2.2 Cost Analysis for Portable Coin Counting System

Table 4.1: Bill of Materials and Costs of Components for Portable Coin Counting System

No	Components	Quantity	Cost/RM
1	10 inch commercial ring light	1	22
2	Sony PS3 Eye Camera	1	59.90
3	Adjustable Height Mechanism	1	26
4	Coins Tray (Outer: 318 x 258 mm + Inner: 284 x 214 mm)	1	60
5	Aluminium 2020 Profile (140 mm)	4	72.60
	Aluminium 2020 Profile (280 mm)	4	
	Aluminium 2020 Profile (300 mm)	5	
	Aluminium 2020 Profile (320 mm)	2	
6	Gusset 2020 Profile	34	74.80
7	Rhombus Nut M4 2020	68	40.80
8	Washer M4 2020	68	13.60
9	Capscrew M4 2020	68	13.60
10	Black PP Corrugated Board Cover A3 Size	9	22.50
11	Camera Mounting	1	20
12	Translucent Film	3	3
13	Black Cloth Tape	1	2.50
14	Acrylic Foam Tape	1	9.30
Total Cost:			440.60

4.3 IMAGE PROCESSING ALGORITHMS IN PYTHON

The system was developed in Python using computer vision techniques to accurately count coins. It relied on libraries like OpenCV, cv2, cvzone, numpy, pyautogui, math, and ColorFinder for various tasks such as image manipulation, computer vision capabilities, mathematical calculations, and color detection. The goal was to identify, categorize, and quantify coins in real-time from a video stream.

The program initialized video capture using `cv2.VideoCapture(1)` to open the camera with an index of 1 and adjusted the frames per second (FPS) to 20 for smooth processing. Variables were initialized to track the total amount of money counted, the total execution time, and the number of iterations. The system used the ColorFinder object and hsvVals dictionary to define precise HSV values for color detection.

A function called `empty` was defined for use with trackbars to interactively set image processing parameters. Trackbars were created within a settings window to fine-tune thresholds for preprocessing procedures such as edge recognition and morphological operations. The `preProcessing` function handled image preprocessing, transforming images into grayscale, adjusting contrast and brightness, applying Gaussian blur to reduce noise, and using Canny edge detection to identify edges. Dilation and morphological closing procedures were performed to fill gaps and enhance identified edges.

The main loop continuously acquired frames from the camera, monitored performance by measuring execution time for each iteration, cropped images to remove unnecessary parts and emphasize the coin region, and preprocessed cropped images. Contours were detected using `cvzone.findContours`, and each contour was analyzed to determine if it corresponded to a coin. The perimeter and shape of each contour were calculated, and the algorithm excluded non-round shapes. Silver and gold coins were categorized based on the quantity of white pixels within the masked region. Monetary value and coin count were adjusted accordingly.

Execution time for each iteration was computed and rounded, and iteration data were displayed and recorded in a file. The original, blurred, pre-processed, and contoured images were combined and displayed to create a visual representation of the processing steps. If the stacked image was larger than the screen size, it was automatically adjusted. The graphic displayed the total amount of money and the duration of execution. The composite image was displayed using the `cv2.imshow` function, and the iteration continued until a keyboard input was detected, at which point the video capture resource was terminated. Overall, the system effectively demonstrated the use of image processing algorithms for object detection and categorization, specifically for coins. Preprocessing stages improved picture characteristics and colour detection aided in categorizing coins, providing an efficient method for distinguishing between various denominations.

4.4 EXPERIMENTAL DESIGN AND SET-UP

4.4.1 Coin Set Values

Upon completion of the prototype, various trials had been done to determine the maximum number of coins that can be fitted inside the coin tray after cropping the image to ensure 100% coin detection and calculation within that area. Hence, with, the 5 set of coin values that had been came up with are shown in Table 4.1 and Figure 4.6(a) to (e).

Table 4.2: Amount of 50, 20 and 10 sen Across 5 Coin Set Values

Coin Set Values	50 sen	20 sen	10 sen
Set 1: RM 4.60	6	6	4
Set 2: RM 3.90	4	6	7
Set 3: RM 5.50	9	3	2
Set 4: RM 2.30	2	2	9
Set 5: RM 1.90	2	2	6


(a)


(b)


(c)


(d)


(e)

Figure 4.6: (a) Set: RM 4.60, (b) Set 2: RM 3.90, (c) Set 3: RM 5.50, (d) Set 4: RM 2.30 and (e) Set 5: RM 1.90

4.4.2 Observation of Analysis

In this experiment, the effectiveness of coin counting system by using machine vision was measured based on three main variables:

a) Observing Variables:

i. Speed of the coin counting system measured in the form of setup time together with execution time.

ii. Accuracy of coin counting system measured in the form of coin detection as well as coin calculation.

b) **Fixed Variables:**

i. The camera will be set at a fixed 30 cm distance from the coin tray.

ii. To maintain consistent alignment, the camera will be set at a 90-degree angle relative to the coin tray via an adjustable height mechanism.

iii. Enclosed Environment: The experiment will take place in a fully enclosed box casing to eliminate the influence of shadows and external lighting.

iv. The ring light will be positioned on top of the box casing to ensure consistent illumination for the coin counting system.

v. Throughout the experiment, coins will only be deposited on the second layer of the coins tray.

vi. The background of the coins tray will be set to black to ensure a distinct contrast between the gold and silver coins and the background.

vii. The system will use a laptop with fixed processing power by using an AMD Ryzen 5 5500U processor, which runs at 2.1 GHz to 4 GHz and has 6 cores and 12 threads. The laptop will contain 8 GB of memory and a 512 GB Western Digital SSD.

During the development of the prototype as well as image processing techniques algorithms, there were several factors found to be impacting the accuracy of the coin counting system as shown in the following.

c) Changing Variables:

i. Brightness Level: Low, Medium and High
ii. Light Intensity: 6 lux (light in red or yellow tone), 9 lux (light in more pure white tone) and 10 lux (light with white tone together with a blue hue)
iii. Area of Image Detection of Coins: Before Cropped and After Cropped

4.4.3 System Performance Evaluation

In order to evaluate the speed of the coin counting system in the form of time taken to calculate the coins as well as accuracy which will be divided into two criterias, namely coin detection accuracy as well as coin calculation accuracy, the following list of equations will be utilized to help in the data interpretation of the analysis.

$$\textbf{Average Time Taken to Calculate Coins (s)} = \frac{\text{Total Time Taken}}{\text{Total number of iterations}} \qquad \text{Equation 4.1}$$

Equation 4.1 provided an accurate measure of the speed of a coin counting system using machine vision by calculating the average time per iteration. This metric was crucial for assessing the system's efficiency and performance, with a lower average time indicating a faster system. Regular measurement and analysis of this average time were necessary to evaluate the system's ability to handle large coin volumes and identify areas for improvement to enhance speed and efficiency.

$$\textbf{Coin Calculation Absolute Error} = |Value\ Actual - Value\ Calculated| \qquad \text{Equation 4.2}$$

$$\textbf{Coin Calculation Mean Absolute Error}(\textbf{MAE}) = \frac{\text{Coin Calculation Absolute Error}}{\text{Number of iterations,where coin calculation absolute error>0}} \quad \text{Equation 4.3}$$

The Mean Absolute Error (MAE) formula, as depicted in Equation 4.3, measures the discrepancies between paired observations in a system by calculating the average of the absolute mistakes in coin calculation. This statistic aids in evaluating the importance of errors, offering valuable understanding of the system's performance throughout the dataset. A reduced Mean Absolute Error (MAE) indicates a higher level of accuracy. A MAE close to zero suggests that the model is highly accurate and closely aligns with the actual numbers on average (Elesin, 2023).

$$\textbf{Coin Calculation Error} = \text{Value Calculated} - \text{Value Actual} \quad \text{Equation 4.4}$$

$$\textbf{Coin Calculation Mean Error} = \frac{\text{Coin Calculation Error}}{\text{Total number of iterations,where coin calculation error>0}} \quad \text{Equation 4.5}$$

Equation 4.4, which defines coin calculation error, is essential for assessing the accuracy of a coin counting system. It quantifies the discrepancy between the estimated and actual values of the coins. Positive mistakes signify an overestimation, whereas negative errors signify an underestimating, enabling the detection of biases and accuracy levels. The mean error, computed by averaging all mistakes using Equation 4.5, assists in evaluating the system's inclination to overestimate or underestimate. This aids in diagnosing issues, monitoring performance, and improving the system's accuracy compliance.

$$\textbf{Coin Calculation Accuracy}\ (\%) = \frac{(\text{Total number of times value calculated=value actual})}{\text{Total number of iterations}} \times 100\% \quad \text{Equation 4.6}$$

$$\textbf{Coin Calculation Mean Accuracy}\ (\%) = \frac{\text{Coin Calculation Accuracy}}{\text{Total number of iterations}} \quad \text{Equation 4.7}$$

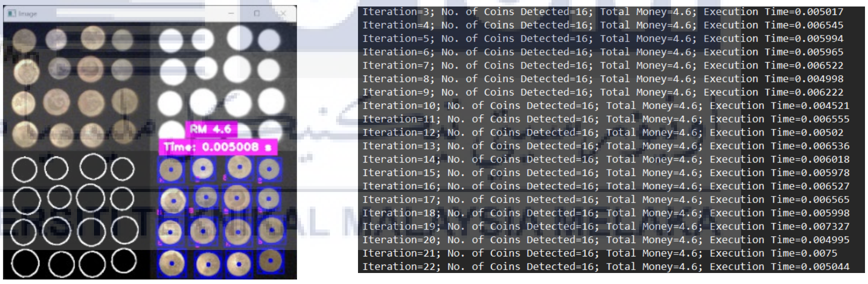
Equation 4.6 allows the comparison between the estimated and actual coin values, which in turn determines the accuracy of the system by calculating the proportion of correct computations. Equation 4.7 computes the mean accuracy of coin calculations each iteration, which serves as a measure of the precision and reliability of the system over numerous iterations. These measures collectively assess the performance of the system, dependability and applicability for activities that necessitate precise coin counts.

$$\textbf{Coin Detection Accuracy } (\%) = \frac{\text{Number of Coins Actual}}{\text{Number of Coins Detected}} \qquad \text{Equation 4.8}$$

$$\textbf{Coin Detection Mean Accuracy } (\%) = \frac{\text{Coin Detection Accuracy}}{\text{Total number of iterations}} \qquad \text{Equation 4.9}$$

Equation 4.8 assessed the coin counting system's accuracy by comparing the actual number of coins to the detected number, with higher percentages indicating greater accuracy. Equation 4.9 calculated the average accuracy over multiple iterations, evaluating system consistency, with higher mean accuracy indicating better reliability and precision.

4.5 SYSTEM PERFORMANCE EVALUATION ON SPEED



(a) (b)

Figure 4.7: (a) Sample Time Test for Set 1: RM 4.60, (b) Part of Raw Data Shown from 2000 Iterations for Time Test in Set 1: RM 4.60

Table 4.3: Setup Time for Machine Vision Coin Counting System Across 5 Coin Set Values

Coin Set Values	Setup Time/s
Set 1: RM 4.60	86
Set 2: RM 3.90	94
Set 3: RM 5.50	116
Set 4: RM 2.30	98
Set 5: RM 1.90	44

Table 4.4: Average Processing Time for Coin Calculation Across 5 Coin Set Values by System

Coin Set Values	Average Time Taken for Coin Calculation/s

Set 1	0.013337
Set 2	0.005884
Set 3	0.005452
Set 4	0.004661
Set 5	0.001966

Table 4.5: Average Total Time Taken for Coin Calculation Across 5 Coin Set Values by System Together with Setup Time

Coin Set Values	Average Time Taken for Coin Calculation/s
Set 1	86.013337
Set 2	94.005884
Set 3	116.005452
Set 4	98.004661
Set 5	44.001966

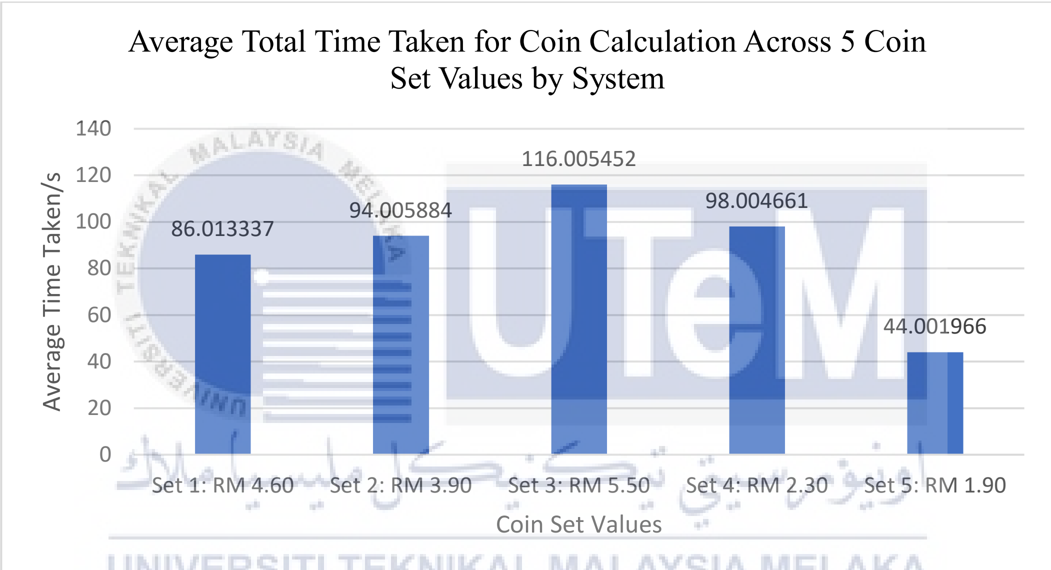


Figure 4.8: Graph of Average Total Time Taken for Coin Calculation Across 5 Coin Set Values by Machine Vision Coin Counting System

Based on Figure 4.8, the graph illustrates the mean duration required for coin computation across five distinct coin set values, including both the initial setup time and the time for 2000 iterations of coin calculations.

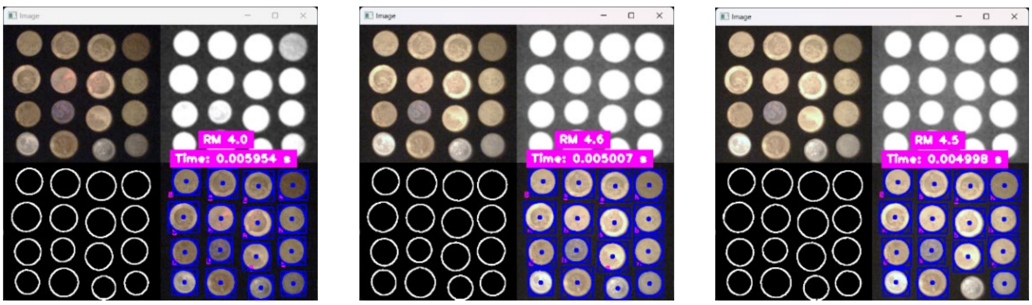
Firstly, for Set 1, RM 4.60 showed an average total time of 86.013337 seconds for 16 coins, resulting in a time per coin of about 5.375 seconds. The short time per coin indicated efficient processing, with an average computation time of 0.013337 seconds excluding setup time. For Set 2, RM 3.90, the time per coin was 5.529 seconds for 17 coins, slightly higher than Set 1, with an average computation time of 0.005884 seconds. As for Set 3, RM 5.50, had a duration per coin of 7.733 seconds for 15 coins while the mean computation time was 0.005452 seconds. Similarly, Set 4, RM 2.30, showed a time per coin of 7.538 seconds for 13 coins, with an average computation time of 0.004661 seconds. Lastly, Set 5, RM 1.90, had the lowest time per coin at 4.889 seconds for 9 coins, with a mean computation time of 0.001966 seconds, indicating the highest efficiency.

The average total time for coin calculation including setup time showed a minimal increase from Set 1 to Set 2 due to only one extra coin but increased significantly from Set 2 to Set 3 since larger coin set values required longer setup times to prevent overlapping. This highlighted the need for sufficient spacing when feeding coins to avoid misinterpretation as a single coin (Fanca et al., 2022). The time then decreased gradually from Set 3 to Set 4, as there were numerous small coins involved despite the smaller total number of coins and values. It decreased drastically from Set 4 to Set 5 due to fewer coins involved, which improved simplicity in coin feeding. Set 1 had the highest processing time, possibly due to initial buffering, but processing times generally decreased from Set 2 to Set 5, indicating that the total number of coins was the primary factor affecting processing speed rather than the coin values. The machine vision coin counting system exhibited exceptional speed, averaging less than 0.013 seconds per coin assuming stable setup. Manual feeding compromised performance, but despite this, the system still considered to be performing well by automating calculations efficiently through image processing. Overall, optimizing setup for high-value and numerous small coins could further enhance system performance.

4.6 SYSTEM PERFORMANCE EVALUATION ON ACCURACY

4.6.1 Brightness Level

a) Set 1: RM 4.60



(a) (b) (c)

Figure 4.9: Impact of Different Brightness Level in Set 1: RM 4.60; (a) Low Brightness, (b) Medium Brightness, (c) High Brightness

Table 4.6: Impact of Different Brightness Level on Coin Detection and Calculation Average Accuracy of System for Set 1: RM 4.60 (6 x 50 sen + 6 x 20 sen + 4 x 10 sen)

Accuracy Criteria	Brightness Level		
	Low	Medium	High
Coin Detection Average Accuracy	100.00%	100.00%	98.10%
Coin Calculation Average Accuracy	0.00%	100.00%	69.50%

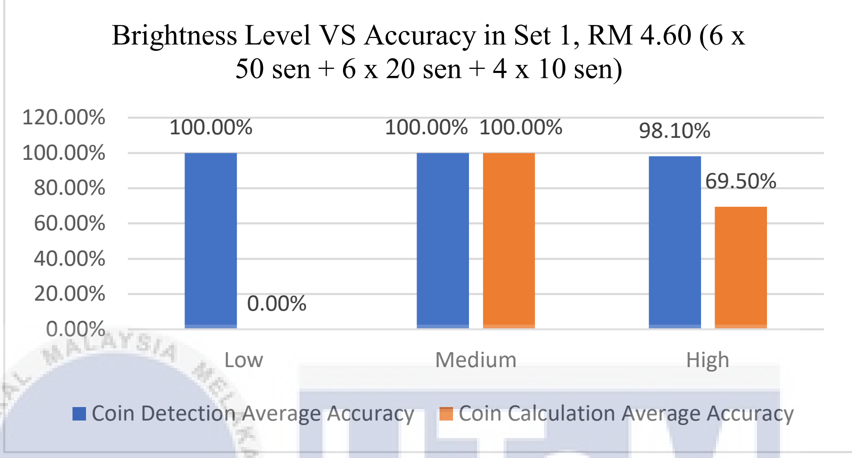


Figure 4.10: Graph of Brightness Level VS Accuracy of Coin Counting System for Set 1, RM 4.60

Table 4.7: Error Metrics of Different Brightness Level on Coin Counting System for Set 1: RM 4.60 (6 x 50 sen + 6 x 20 sen + 4 x 10 sen)

Error Metrics	Brightness Level		
	Low	Medium	High
Mean Error	-0.5788	0	-0.0305
Mean Absolute Error (MAE)	0.58	0	0.1

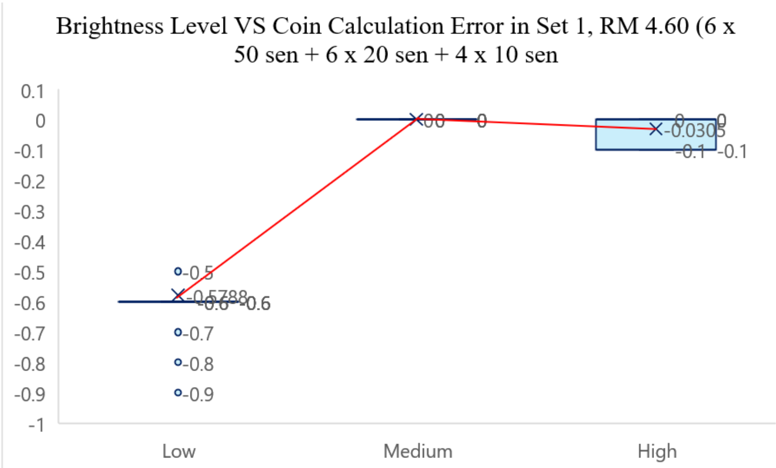


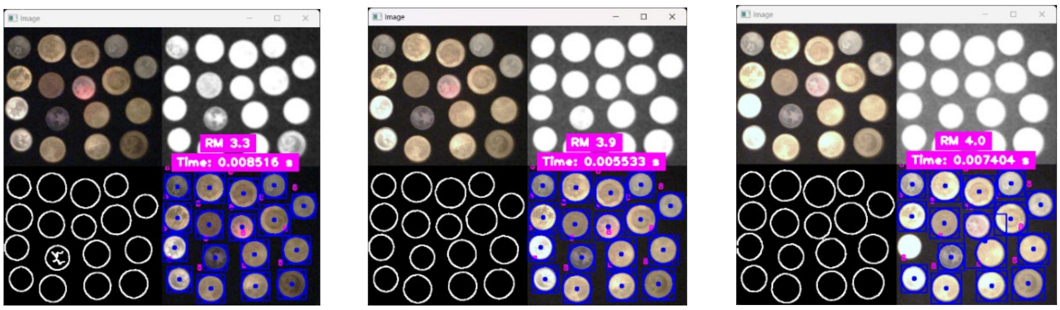
Figure 4.11: Graph of Error Distribution for Different Brightness Level on Coin Counting System in Set 1, RM 4.60

Table 4.6 and Figure 4.10 illustrated how different brightness levels affected the average accuracy of coin detection and calculation for Set 1: RM 4.60, which included 6 x 50 sen, 6 x 20 sen, and 4 x 10 sen as shown in Figure 4.9. Furthermore, Table 4.7 and Figure 4.11 displayed the error metrics for coin calculation at three different brightness levels.

Firstly, the accuracy of coin identification was consistently high throughout all levels of brightness, reaching 100% at low and medium brightness, and slightly lowering to 98.10% at high brightness. However, the accuracy of coin computation varied significantly: 0% in low brightness conditions, 100% in medium brightness conditions, and 69.50% in high brightness conditions.

In addition, the error metrics provided more evidence to support these differences. At low levels of brightness, there was a notable tendency to underestimate, with an average error of -0.5788 and a mean absolute error (MAE) of 0.58. This suggested that the computations tended to fall largely within the range of RM 4 to RM 4.10 instead of RM 4.60. In contrast, when the brightness was set to a medium level, the accuracy was flawless, as indicated by both the mean error and MAE being 0. This demonstrated that the system performed optimally. Intense luminosity led to a slight underestimation, with an average error of -0.0305 and a mean absolute error (MAE) of 0.1. These calculations, ranging from RM 4.50 to RM 4.60, indicated the presence of overexposure problems. The error distribution supported these findings, with low brightness errors ranging from -0.9 to -0.4, mid brightness errors being zero, and high brightness errors ranging from 0 to -0.1.

b) Set 2: RM 3.90



(a) (b) (c)

Figure 4.12: Impact of Different Brightness Level in Set 2: RM 3.90; (a) Low Brightness, (b) Medium Brightness, (c) High Brightness

Table 4.8: Impact of Different Brightness Level on Coin Detection and Calculation Average Accuracy of System for Set 2: RM 3.90 (4 x 50 sen + 6 x 20 sen + 7 x 10 sen)

Accuracy Criteria	Brightness Level		
	Low	Medium	High
Coin Detection Average Accuracy	100.00%	100.00%	100.00%
Coin Calculation Average Accuracy	0.00%	100.00%	1.90%

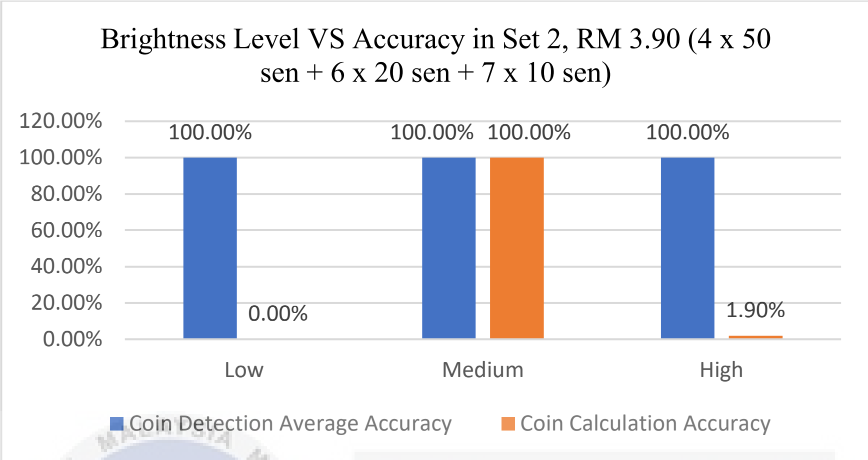


Figure 4.13: Graph of Brightness Level VS Accuracy of Coin Counting System for Set 2, RM 3.90

Table 4.9: Error Metrics of Different Brightness Level on Coin Counting System for Set 2: RM 3.90 (4 x 50 sen + 6 x 20 sen + 7 x 10 sen)

Error Metrics	Brightness Level		
	Low	Medium	High
Mean Error	-0.6494	0	0.13325
Mean Absolute Error (MAE)	0.65	0	0.15

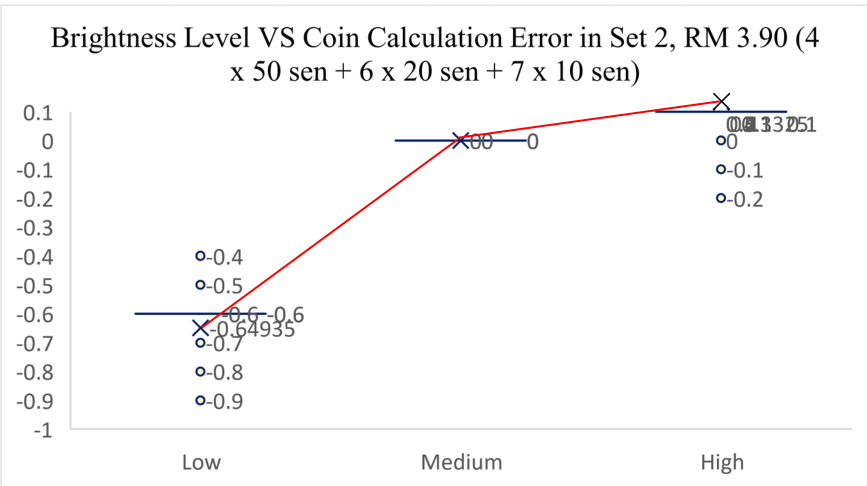


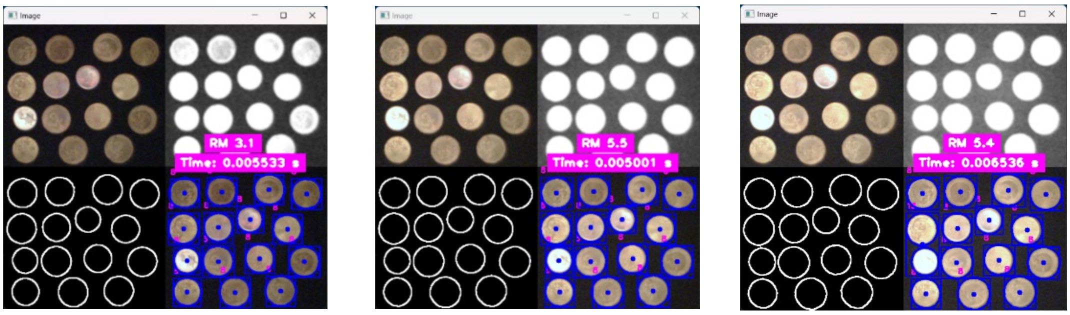
Figure 4.14: Graph of Error Distribution for Different Brightness Level on Coin Counting System in Set 2, RM 3.90

Table 4.8 and Figure 4.13 display the impact of brightness levels on the coin detection and calculation accuracy for Set 2: RM 3.90, comprising 4 x 50 sen, 6 x 20 sen, and 7 x 10 sen, as shown in Figure 4.12. Table 4.9 shows the error metrics for coin calculation across three different brightness levels, with the error distribution illustrated in Figure 4.14. The analysis reveals that brightness levels significantly influence the efficacy of the machine vision coin counting system for Set 2: RM 3.90.

Coin detection accuracy remains at 100% across all brightness levels. However, coin calculation accuracy varies: it is 0% at low brightness, 100% at medium brightness, and 98.1% at high brightness. Low brightness results in substantial underestimation, with a mean error of -0.6494 and a high MAE of 0.65, with calculated values of RM 3, RM 3.10, RM 3.30, and RM 3.40 instead of RM 3.90. Medium brightness achieves flawless calculations with no error (mean error and MAE of 0). High brightness causes a modest overestimation with a mean error of 0.13325 and an MAE of 0.15, with calculated values ranging from RM 3.80 to RM 4.60.

The error distribution indicates significant calculation errors at low brightness (-0.9 to -0.4), zero errors at medium brightness (optimal conditions), and slight inaccuracies at high brightness (0 to 0.2). Thus, the accuracy of the system increases from low to high brightness, with medium brightness providing the optimal conditions for precise coin detection and calculation.

c) Set 3: RM 5.50



(a) (b) (c)

Figure 4.15: Impact of Different Brightness Level in Set 3: RM 5.50; (a) Low Brightness, (b) Medium Brightness, (c) High Brightness

Table 4.10: Impact of Different Brightness Level on Coin Detection and Calculation Average Accuracy of System for Set 3: RM 5.50 (9 x 50 sen + 3 x 20 sen + 2 x 10 sen)

Accuracy Criteria	Brightness Level		
	Low	Medium	High
Coin Detection Average Accuracy	100.00%	100.00%	96.96%
Coin Calculation Average Accuracy	0.00%	100.00%	55.45%

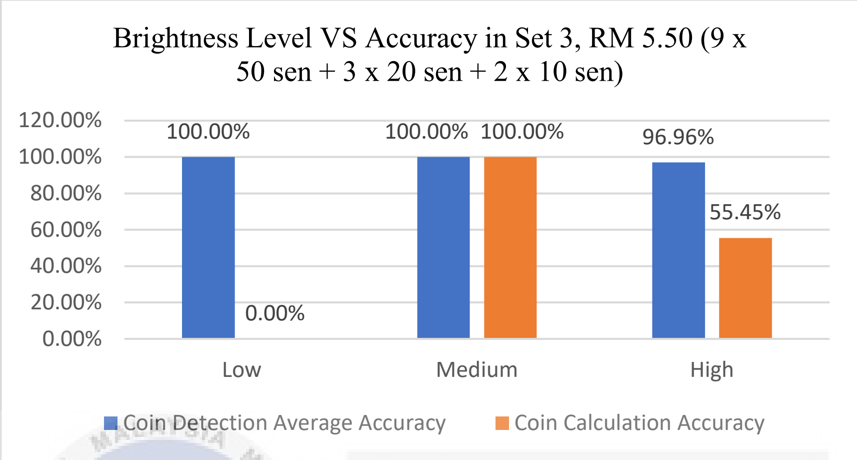


Figure 4.16: Graph of Brightness Level VS Accuracy of Coin Counting System for Set 3, RM 5.50

Table 4.11:Error Metrics of Different Brightness Level on Coin Counting System for Set 3: RM 5.50 (9 x 50 sen + 3 x 20 sen + 2 x 10 sen)

Error Metrics	Brightness Level		
	Low	Medium	High
Mean Error	-0.6023	0	-0.0492
Mean Absolute Error (MAE)	0.6	0	0.11

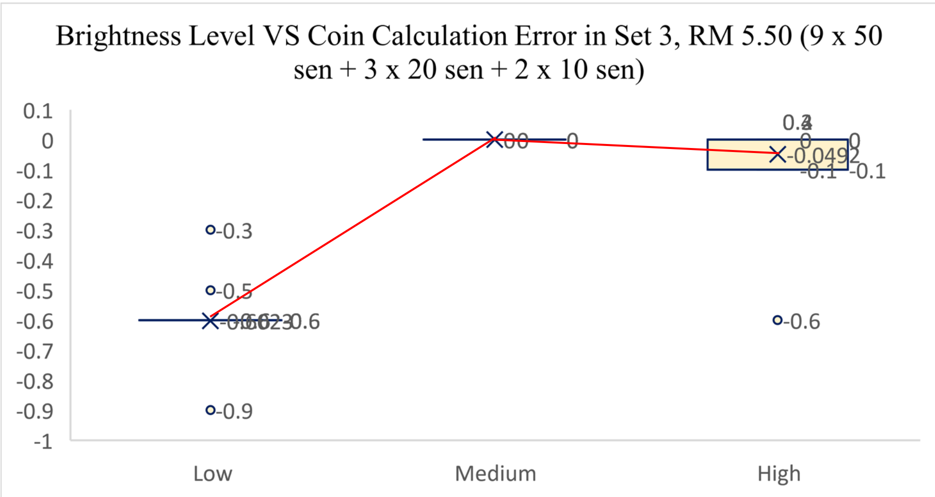


Figure 4.17: Graph of Error Distribution for Different Brightness Level on Coin Counting System in Set 3, RM 5.50

Table 4.10 and Figure 4.16 displayed the impact of brightness levels on coin detection and calculation accuracy for Set 3: RM 5.50, which comprised 9 x 50 sen, 3 x 20 sen, and 2 x 10 sen, as shown in Figure 4.15. Table 4.11 illustrated the error metrics for coin calculation across three brightness levels, with the error distribution in Figure 4.17.

The analysis revealed that coin detection maintained 100% accuracy in low and medium brightness, with a slight drop to 96.96% in high brightness. Coin calculation accuracy varied significantly, with 0% under low brightness, 100% under medium brightness, and 55.45% under high brightness, indicating struggles in extreme lighting.

Error metrics showed a mean error of -0.6023 and MAE of 0.6 under low brightness, consistently underestimating values at RM 3.90 instead of RM 5.50. Medium brightness had zero errors, while high brightness had a mean error of -0.0492 and MAE of 0.11, with values around RM 5.40 to RM 5.50. Error distributions confirmed these results: low brightness errors ranged from -0.9 to -0.3, medium had zero errors, and high ranged from 0 to -0.1, highlighting medium brightness as optimal for accurate detection and calculation.

d) Set 4: RM 2.30

(a) (b) (c)

Figure 4.18: Impact of Different Brightness Level in Set 4: RM 2.30; (a) Low Brightness, (b) Medium Brightness, (c) High Brightness

Table 4.12: Impact of Different Brightness Level on Coin Detection and Calculation Average Accuracy of System for Set 4: RM 2.30 (2 x 50 sen + 2 x 20 sen + 9 x 10 sen)

Accuracy Criteria	Brightness Level		
	Low	Medium	High
Coin Detection Average Accuracy	100.00%	100.00%	98.10%
Coin Calculation Average Accuracy	0.00%	100.00%	0.00%

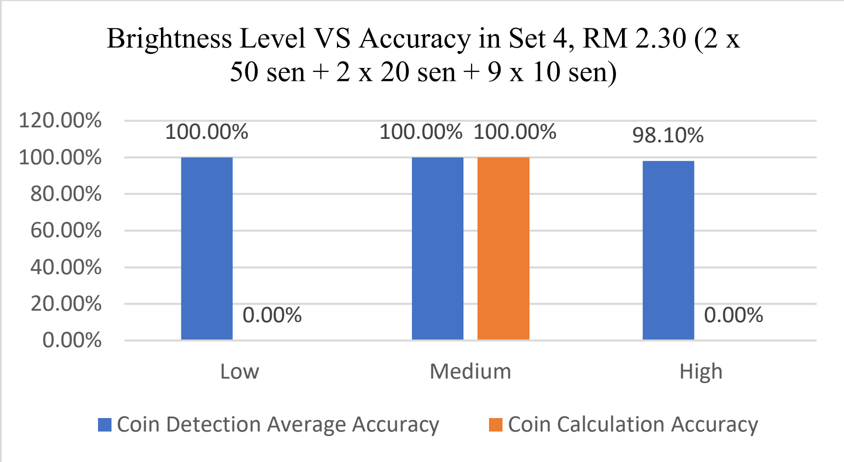


Figure 4.19: Graph of Brightness Level VS Accuracy of Coin Counting System for Set 4, RM 2.30

Table 4.13: Error Metrics of Different Brightness Level on Coin Counting System for Set 4: RM 2.30 (2 x 50 sen + 2 x 20 sen + 9 x 10 sen)

Error Metrics	Brightness Level		
	Low	Medium	High
Mean Error	-0.3	0	-0.1
Mean Absolute Error (MAE)	0.3	0	0.1

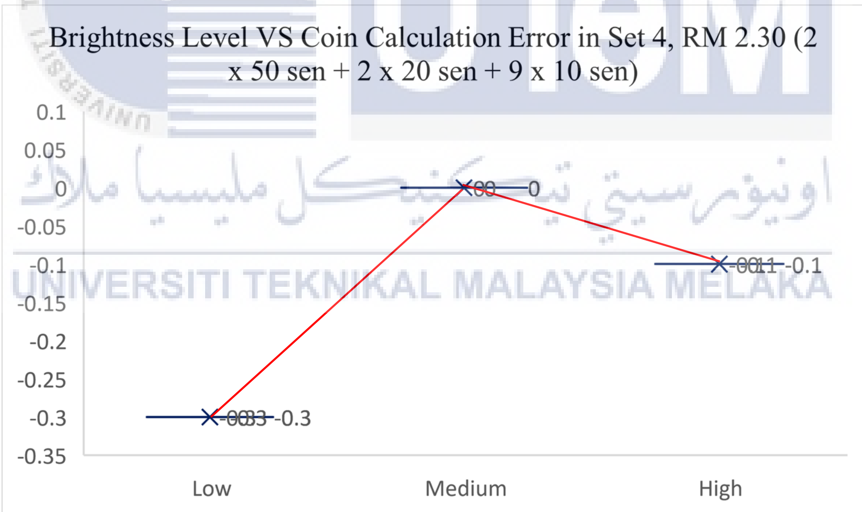


Figure 4.20: Graph of Error Distribution for Different Brightness Level on Coin Counting System in Set 4, RM 2.30

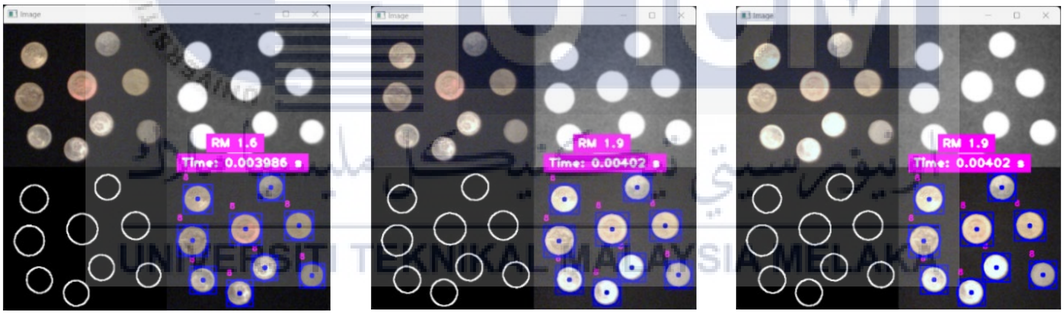
Table 4.12 and Figure 4.19 demonstrated the influence of different brightness levels on the accuracy of coin detection and calculation for Set 4: RM 2.30, which consisted of 2 x 50 sen, 2 x 20 sen, and 9 x 10 sen, as shown in Figure 4.18. Additionally, Table 4.13 presented the error metrics for coin calculation in Set 4, while Figure 4.20 visually represented the distribution of these errors.

Coin detection accuracy remained strong, achieving 100% in low and medium brightness conditions, and slightly lowering to 98.10% in high brightness. The modest decrease under high brightness was attributed to glare or reflections on the camera.

However, coin calculation accuracy showed a clear disparity. At both low and high brightness levels, the system completely failed, resulting in a 0% accuracy rate. This indicated that both low and high brightness hindered the system's ability to accurately compute the overall coin value. In contrast, medium brightness ensured a flawless calculation accuracy of 100%.

The error metrics and error distribution graph provided additional clarity. Low brightness yielded a mean error of -0.3 and MAE of 0.3, consistently calculating the coins at RM 2 instead of RM 2.30. High brightness had a mean error of -0.1 and MAE of 0.1, slightly underestimating the value to RM 2.20 due to overexposure. Medium brightness exhibited exceptional performance with a mean error and MAE of 0, indicating no variation from the true value and confirming its suitability for precise coin counting.

e) Set 5: RM 1.90



(a) (b) (c)

Figure 4.21 Impact of Different Brightness Level in Set 5: RM 1.90; (a) Low Brightness, (b) Medium Brightness, (c) High Brightness

Table 4.14: Impact of Different Brightness Level on Coin Detection and Calculation Average Accuracy of System for Set 5: RM 1.90 (2 x 50 sen + 2 x 20 sen + 6 x 10 sen)

Accuracy Criteria	Brightness Level		
	Low	Medium	High
Coin Detection Average Accuracy	100.00%	100.00%	100.00%
Coin Calculation Average Accuracy	1.90%	100.00%	100.00%

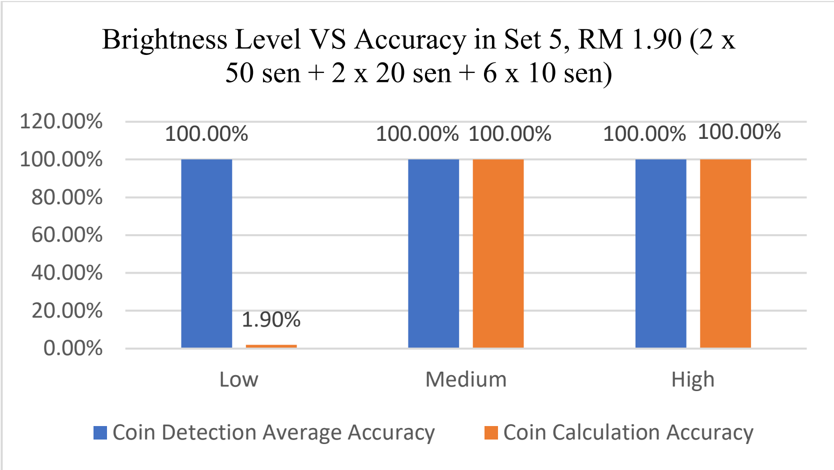


Figure 4.22: Graph of Brightness Level VS Accuracy of Coin Counting System for Set 5, RM 1.90

Table 4.15: Error Metrics of Different Brightness Level on Coin Counting System for Set 3: RM 2.30 (2 x 50 sen + 2 x 20 sen + 6 x 10 sen)

Error Metrics	Brightness Level		
	Low	Medium	High
Mean Error	-0.3	0	0
Mean Absolute Error (MAE)	0.3	0	0

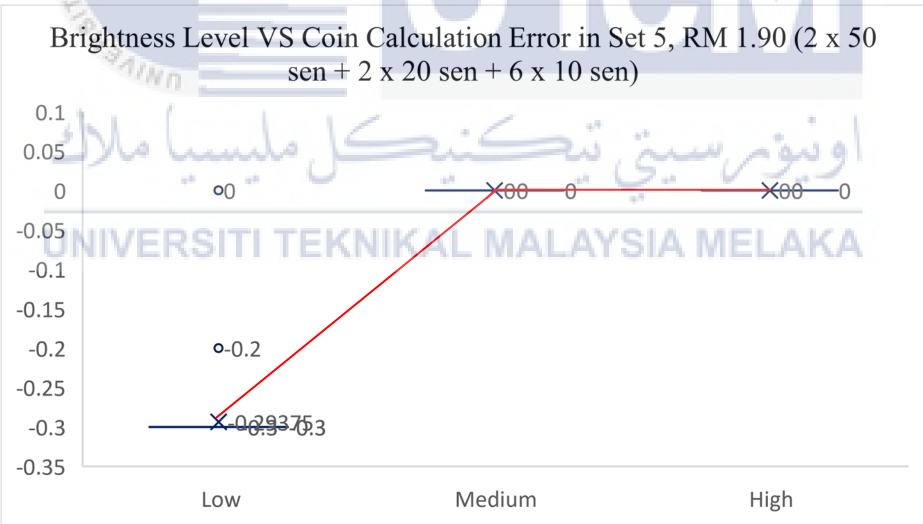


Figure 4.23: Graph of Error Distribution for Different Brightness Level on Coin Counting System in Set 5, RM 1.90

Table 4.14 and Figure 4.22 illustrated how varying brightness levels affected the precision of coin detection and calculation for Set 5: RM 1.90, as displayed in Figure 4.21. This set included 2 x 50 sen, 2 x 20 sen, and 6 x 10 sen. Furthermore, Table 4.15 displayed the error metrics for coin calculation in Set 5 at three different brightness levels, while Figure 4.23 visually illustrated the distribution of these errors.

The machine vision coin counting system demonstrated consistent and flawless coin identification accuracy of 100% across all brightness levels for Set 5. However, the accuracy of the coin calculations varied considerably. At low brightness levels, the accuracy of coin calculations was only 1.90%, with significant underestimation. This was proven by a mean error of -0.3 and MAE of 0.3, suggesting that insufficient light negatively affected the precision of the system, resulting in calculations of RM 1.60 instead of RM 1.90.

Under medium and high brightness conditions, the system attained flawless precision in both detection and calculation, without any mistakes, making these the most favorable lighting conditions. The MAE values suggested that the precision of the coin counting system increased in the following order: medium, high and lastly, low brightness.

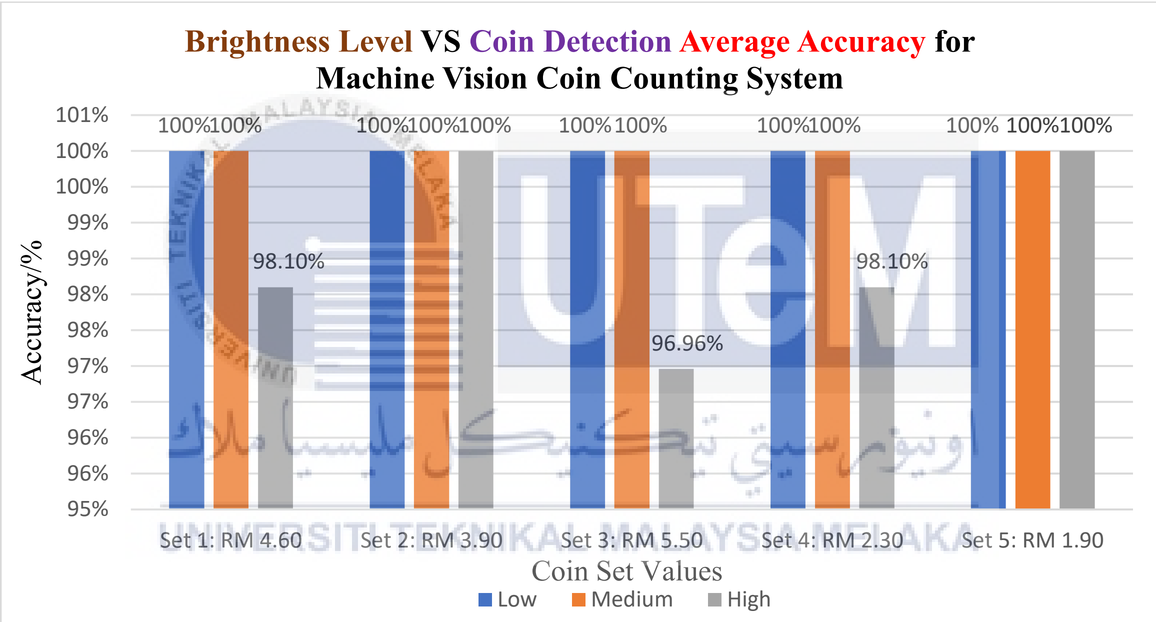


Figure 4.24: Graph of Brightness Level VS Coin Detection Average Accuracy for Machine Vision Coin Counting System across 5 Coin Set Values

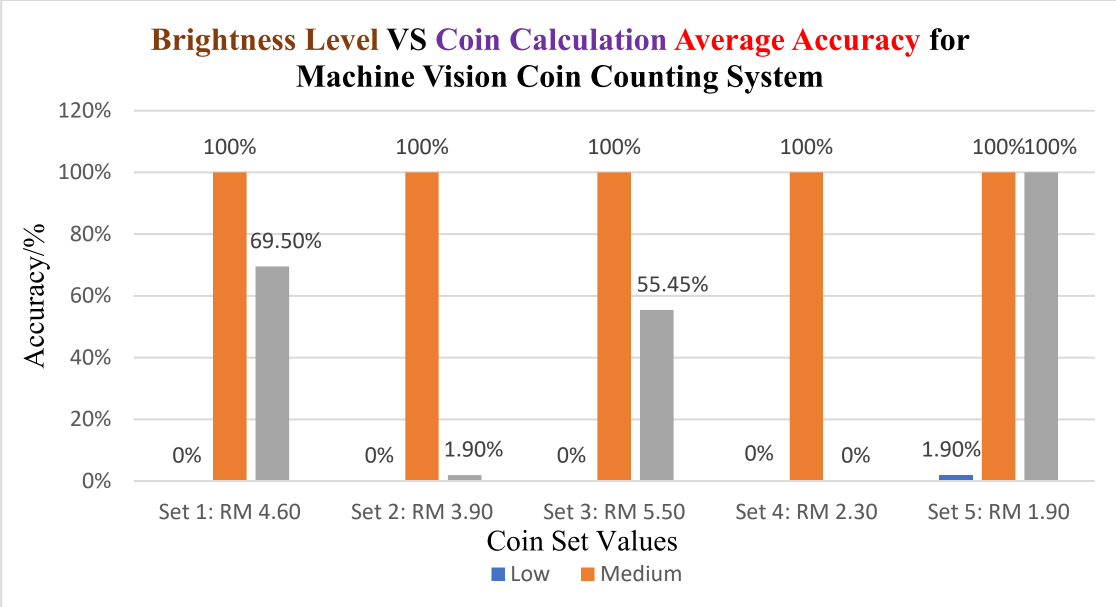


Figure 4.25: Graph of Brightness Level VS Coin Calculation Average Accuracy for Machine Vision Coin Counting System across 5 Coin Set Values

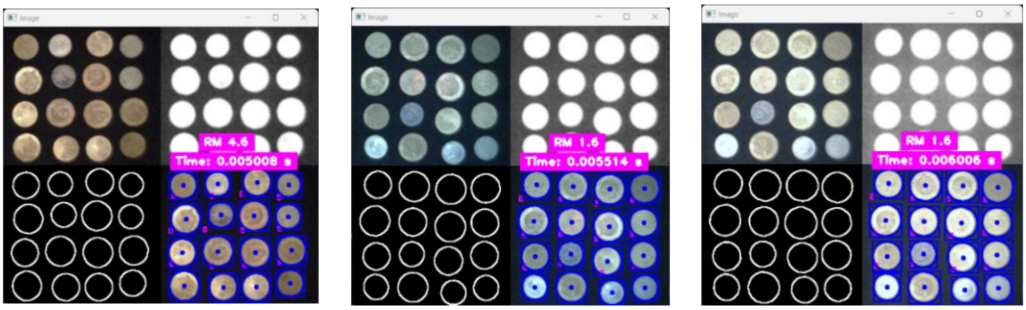
Figure 4.24 and 4.25 illustrated the overall impact of different brightness levels on coin detection and coin calculation average accuracy, respectively, across the five sets of coin values. In general, it could be concluded that varying brightness levels affected coin calculation more than coin detection, as the system could detect the coins better than computing their values without deviation from true values across the five sets of coin values.

Moreover, it was also observed that, over the five sets of coin values, low brightness impacted the coin calculation average accuracy more than high brightness, even though high brightness did not achieve 100% accuracy. Hence, generally, the accuracy of the system decreased from medium to high to low brightness levels.

Overall, from the five sets of coin values, it could be said that medium brightness was the most optimal brightness for the coin counting system, achieving 100% accuracy in both coin detection and coin calculation.

4.6.2 Light Intensity

a) Set 1: RM 4.60



(a) (b) (c)

Figure 4.26: Impact of Different Light Intensity in Set 1: RM 4.60; (a) 6 lux (Warm Yellow or Red Tone), (b) 9 lux (Pure White Tone), (c) 10 lux (White Tone with Blue Hue)

Table 4.16: Impact of Different Light Intensity on Coin Detection and Calculation Average Accuracy of System for Set 1: RM 4.60 (6 x 50 sen + 6 x 20 sen + 4 x 10 sen)

Accuracy Criteria	Light Intensity		
	6 lux	9 lux	10 lux
Coin Detection Average Accuracy	100.00%	99.85%	99.38%
Coin Calculation Average Accuracy	100.00%	0.00%	0.00%

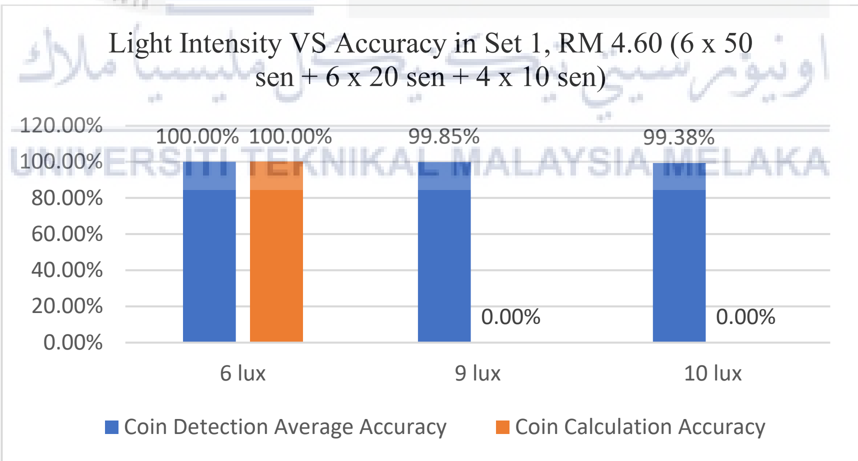


Figure 4.27: Graph of Light Intensity VS Accuracy of Coin Counting System for Set 1, RM 4.60

Table 4.17: Error Metrics of Different Light Intensity on Coin Counting System for Set 1: RM 4.60 (6 x 50 sen + 6 x 20 sen + 4 x 10 sen)

Error Metrics	Light Intensity		
	6 lux	9 lux	10 lux
Mean Error	0	-3.004	-3.004
Mean Absolute Error (MAE)	0	3	3

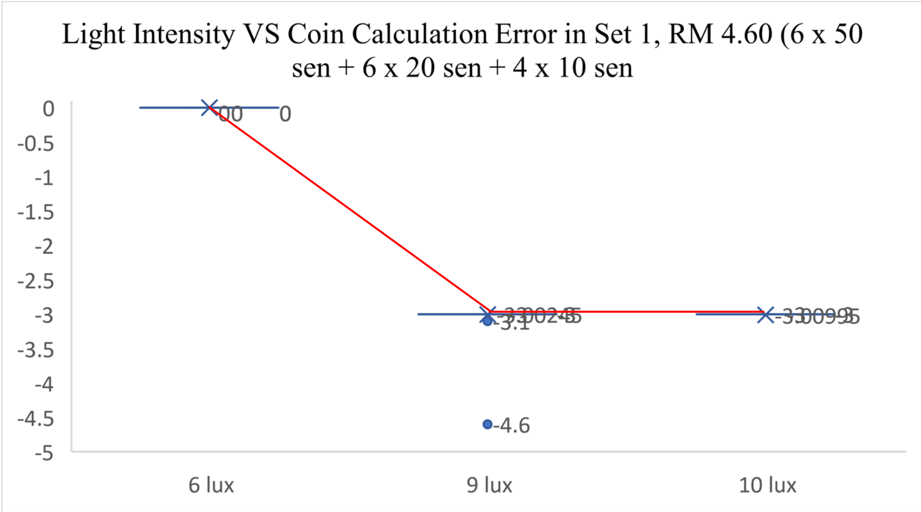


Figure 4.28: Graph of Error Distribution for Different Light Intensity on Coin Counting System in Set 1, RM 4.60

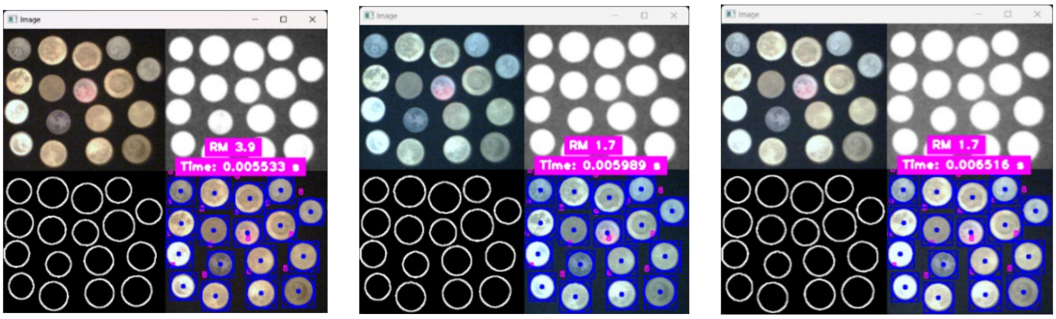
The average accuracy of coin detection and calculation for Set 1: RM 4.60, consisting of 6 x 50 sen, 6 x 20 sen, and 4 x 10 sen, was examined under varying light intensities, as shown in Table 4.16 and Figure 4.27. Figure 4.28 illustrates the error distribution for coin calculation in Set 1 across different light intensities, as detailed in Table 4.17.

First of all, the results indicated a notable performance difference based on light intensity. At 6 lux with a warm yellow tone, the system achieved a flawless 100% accuracy in both detecting and calculating coins, indicating optimal functioning. However, under 9 lux and 10 lux, detection accuracy decreased slightly to 99.85% and 99.38% respectively.

In contrast, calculation accuracy dropped to 0%, with a mean error of -3.004 and a MAE of 3, indicating significant underestimation in computed values. The error distribution also showed an increase from 6 lux to 9 lux and then to 10 lux. Under 9 lux and 10 lux conditions, the system frequently calculated RM 1.60 instead of the true value RM 4.60, as indicated by the negative mean error and MAE values.

These results suggest that while the system consistently identifies coins in different light intensities, its accuracy in calculating values significantly diminishes in brighter light, especially with pure white or blue-hued light.

b) Set 2: RM 3.90



(a) (b) (c)

Figure 4.29: Impact of Different Light Intensity in Set 2: RM 3.90; (a) 6 lux (Warm Yellow or Red Tone), (b) 9 lux (Pure White Tone), (c) 10 lux (White Tone with Blue Hue)

Table 4.18: Impact of Different Light Intensity on Coin Detection and Calculation Average Accuracy of System for Set 2: RM 3.90 (4 x 50 sen + 6 x 20 sen + 7 x 10 sen)

Accuracy Criteria	Light Intensity		
	6 lux	9 lux	10 lux
Coin Detection Average Accuracy	100.00%	99.96%	97.29%
Coin Calculation Average Accuracy	100.00%	0.00%	0.00%

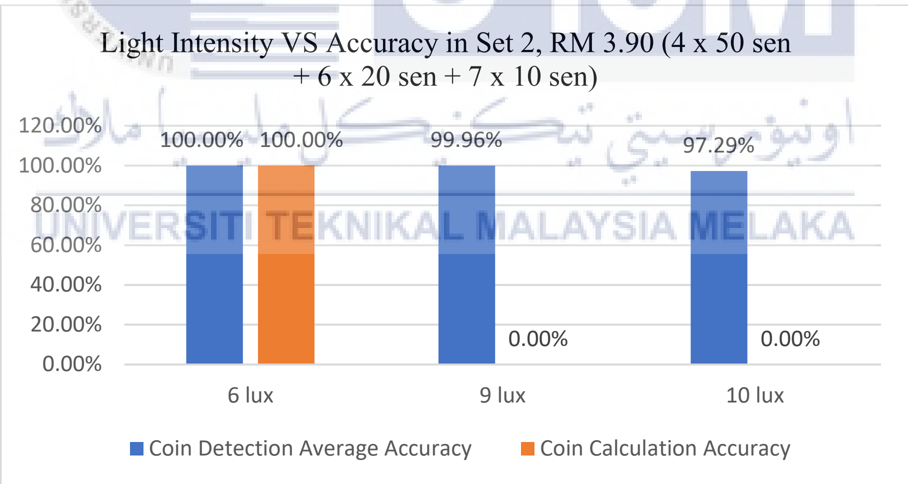


Figure 4.30: Graph of Light Intensity VS Accuracy of Coin Counting System for Set 2, RM 3.90

Table 4.19: Error Metrics of Different Light Intensity on Coin Counting System for Set 2: RM 3.90 (4 x 50 sen + 6 x 20 sen + 7 x 10 sen)

Error Metrics	Light Intensity		
	6 lux	9 lux	10 lux
Mean Error	0	-2.2006	-2.2461
Mean Absolute Error (MAE)	0	2.2	2.25

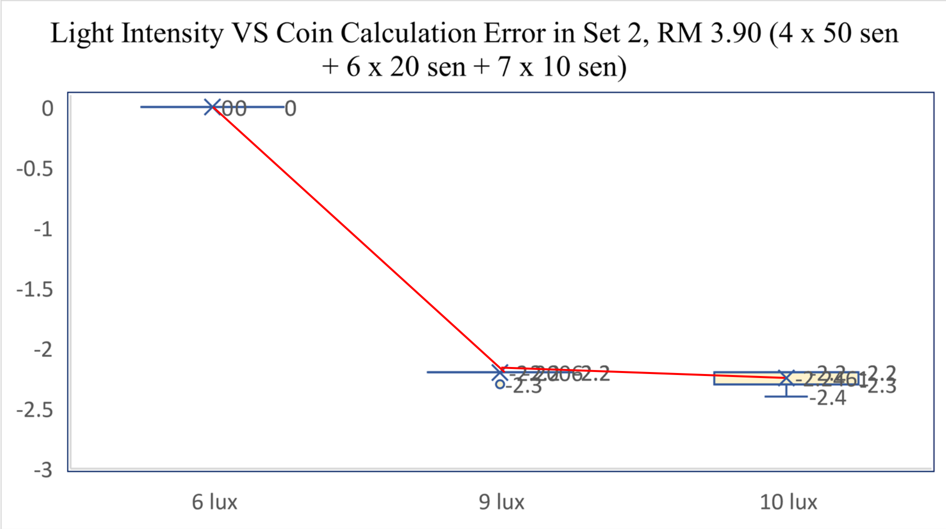


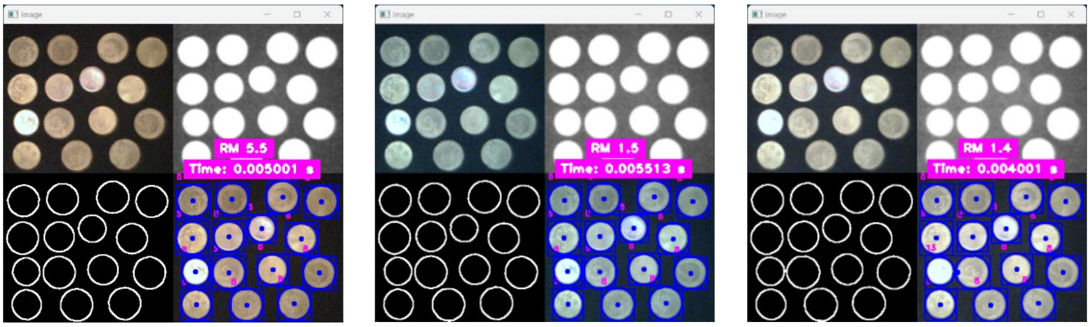
Figure 4.31: Graph of Error Distribution for Different Light Intensity on Coin Counting System in Set 2, RM 3.90

Table 4.18 and Figure 4.30 illustrated the impact of different light intensities on the average accuracy of coin detection and calculation for Set 2: RM 3.90, which consisted of 4 x 50 sen, 6 x 20 sen, and 7 x 10 sen as shown in Figure 4.29. At 6 lux, the system achieved optimal performance, with 100% accuracy in both coin detection and calculation and obtained no errors.

However, at 9 lux and 10 lux, detection accuracy slightly decreased to 99.96% and 97.29%, respectively, while calculation accuracy dropped to 0%. The error metrics for 9 lux and 10 lux indicated mean errors of -2.2006 and -2.2461, respectively, and MAEs of 2.2 and 2.25 respectively, indicating significant underestimation.

The error distribution showed that at 6 lux, errors were centred around zero with no variability. Conversely, at 9 lux, errors were consistently negative, ranging from approximately -2.3 to -2.2, indicating systematic underestimation. Similarly, at 10 lux, errors were consistently negative, ranging from -2.4 to -2.2, suggesting significant underestimation. These results highlight that as light intensity increased, the system's calculations were consistently and significantly underestimated.

c) Set 3: RM 5.50



(a) (b) (c)

Figure 4.32: Impact of Different Light Intensity in Set 3: RM 5.50; (a) 6 lux (Warm Yellow or Red Tone), (b) 9 lux (Pure White Tone), (c) 10 lux (White Tone with Blue Hue)

Table 4.20: Impact of Different Light Intensity on Coin Detection and Calculation Average Accuracy of System for Set 3: RM 5.50 (9 x 50 sen + 3 x 20 sen + 2 x 10 sen)

Accuracy Criteria	Light Intensity		
	6 lux	9 lux	10 lux
Coin Detection Average Accuracy	100.00%	99.31%	95.66%
Coin Calculation Average Accuracy	100.00%	0.00%	0.00%

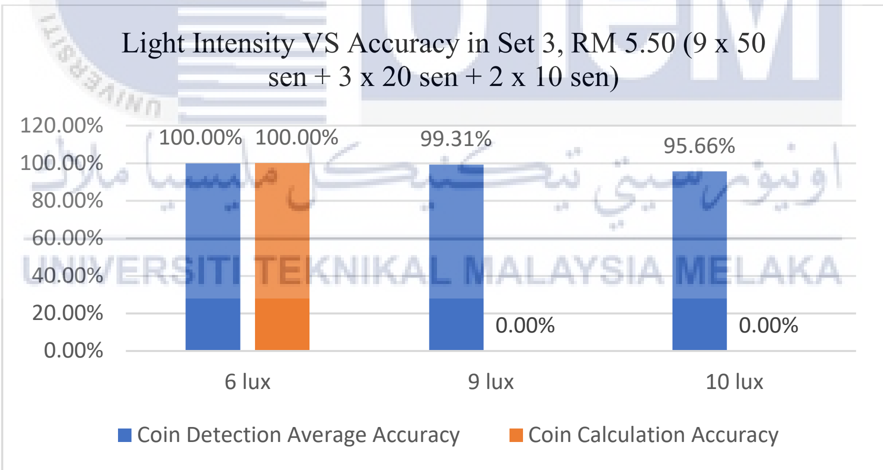


Figure 4.33: Graph of Light Intensity VS Accuracy of Coin Counting System for Set 3, RM 5.50

Table 4.21: Error Metrics of Different Light Intensity on Coin Counting System for Set 3: RM 5.50 (9 x 50 sen + 3 x 20 sen + 2 x 10 sen)

Error Metrics	Light Intensity		
	6 lux	9 lux	10 lux
Mean Error	0	-4.0101	-4.0648
Mean Absolute Error (MAE)	0	4.01	4.06

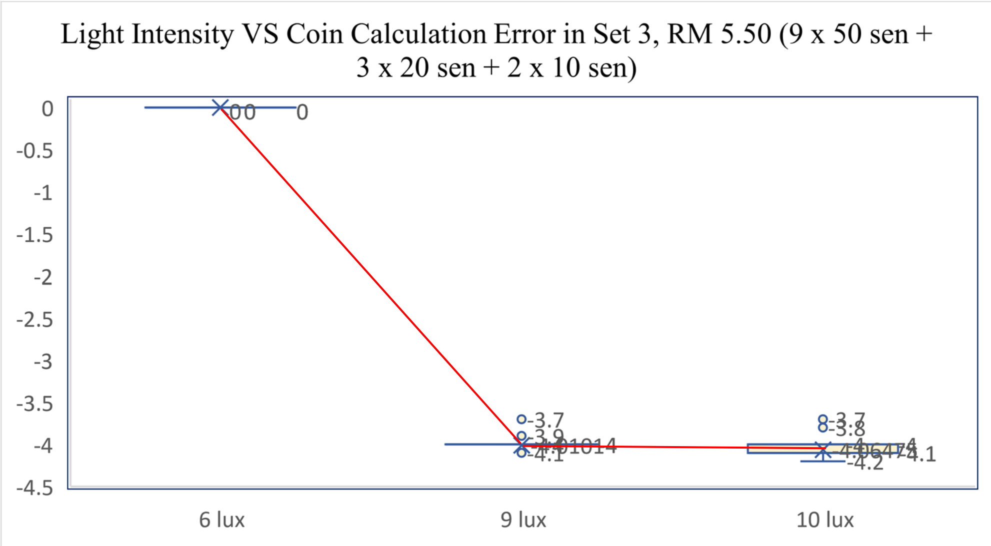


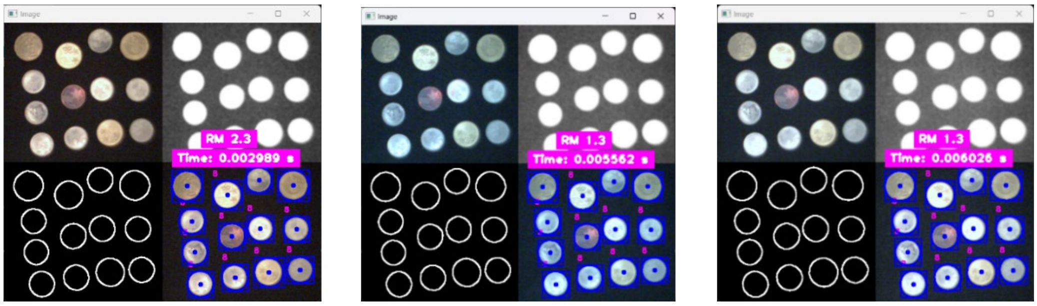
Figure 4.34: Graph of Error Distribution for Different Light Intensity on Coin Counting System in Set 3, RM 5.50

Table 4.20 and Figure 4.33 depicted the effect of different light intensities on coin detection and the average accuracy of calculations for Set 3: RM 5.50, which included 9 x 50 sen, 3 x 20 sen, and 2 x 10 sen as shown in Figure 4.32. At 6 lux, the system achieved 100% accuracy in both detection and calculation, indicating optimal conditions.

However, at 9 lux and 10 lux, detection accuracy decreased to 99.31% and 95.66%, respectively, while calculation accuracy dropped to 0%. The error metrics at 9 lux showed an average error of -4.0101 with a MAE of 4.01, and at 10 lux, the mean error was -4.0648 with a MAE of 4.06, indicating a significant tendency to underestimate coin values in the coin calculation.

The error distribution graph indicated that at 9 lux, the computed value of the system ranged from approximately RM 1.40 to RM 1.50, and at 10 lux, it ranged from approximately RM 1.30 to RM 1.50. Overall, the system's ability to detect coins was not significantly affected by increased light intensity, but the precision of its calculations was notably impacted, particularly under pure white and blue tones.

d) Set 4: RM 2.30



(a) (b) (c)

Figure 4.35: Impact of Different Light Intensity in Set 4: RM 2.30; (a) 6 lux (Warm Yellow or Red Tone), (b) 9 lux (Pure White Tone), (c) 10 lux (White Tone with Blue Hue)

Table 4.22: Impact of Different Light Intensity on Coin Detection and Calculation Average Accuracy of System for Set 4: RM 2.30 (2 x 50 sen + 2 x 20 sen + 9 x 10 sen)

Accuracy Criteria	Light Intensity		
	6 lux	9 lux	10 lux
Coin Detection Average Accuracy	100.00%	100.00%	100.00%
Coin Calculation Average Accuracy	100.00%	0.00%	0.00%

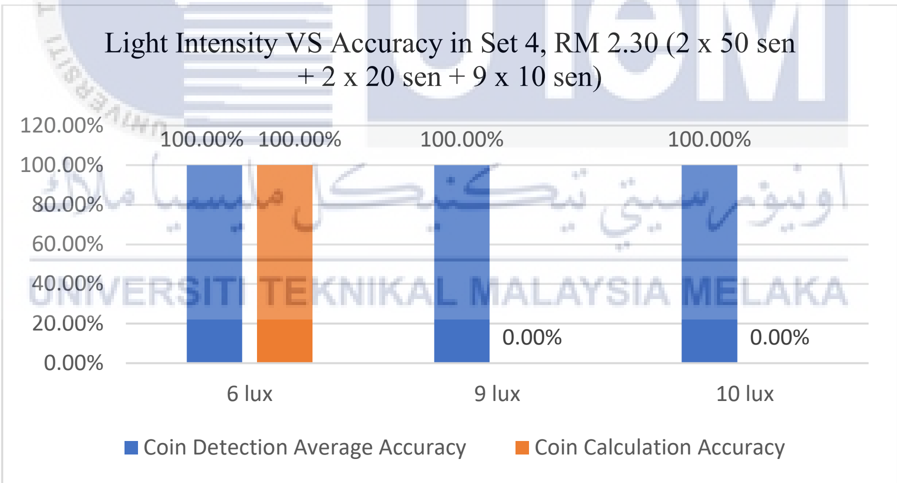


Figure 4.36: Graph of Light Intensity VS Accuracy of Coin Counting System for Set 4, RM 2.30

Table 4.23: Error Metrics of Different Light Intensity on Coin Counting System for Set 4: RM 2.30 (2 x 50 sen + 2 x 20 sen + 9 x 10 sen)

Error Metrics	Light Intensity		
	6 lux	9 lux	10 lux
Mean Error	0	-1	-1
Mean Absolute Error (MAE)	0	1	1

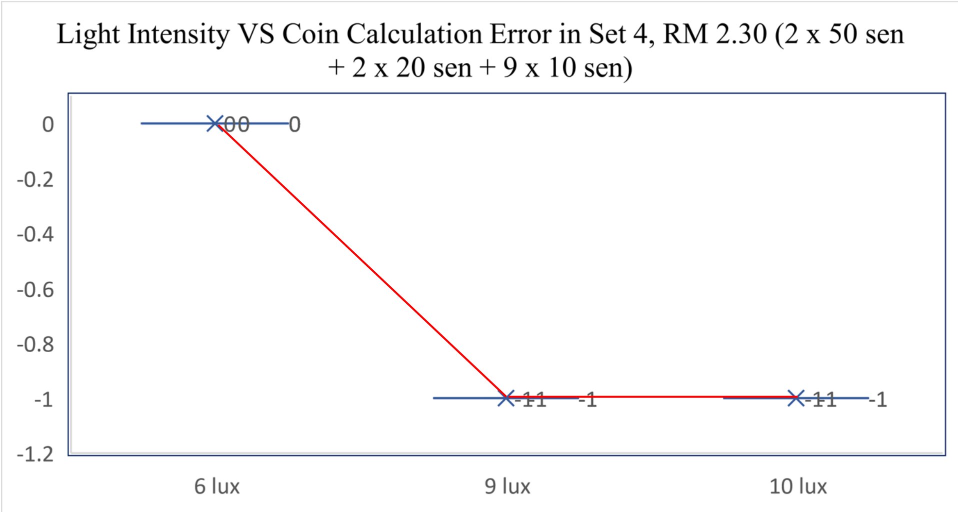
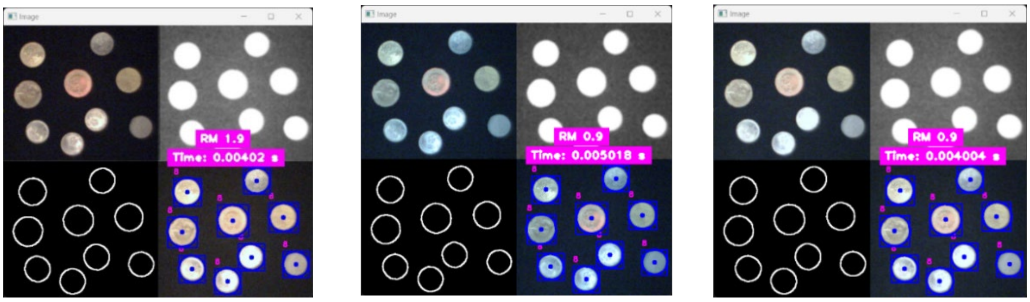


Figure 4.37: Graph of Error Distribution for Different Light Intensity on Coin Counting System in Set 4, RM 2.30

Table 4.22 and Figure 4.36 illustrated the impact of light intensities on coin detection and calculation average accuracy for Set 4: RM 2.30, which consisted of 2 x 50 sen, 2 x 20 sen, and 9 x 10 sen as shown in Figure 4.35. Additionally, Table 4.23 presented the error metrics for coin calculation in Set 4 across three different light intensities, with the error distribution shown in Figure 4.37.

At 6 lux, the system achieved 100% accuracy in both coin detection and calculation, indicating optimal performance. However, at 9 lux and 10 lux, while detection accuracy remained at 100%, calculation accuracy dropped to 0%. The error metrics for both 9 lux and 10 lux showed a mean error of -1 and a MAE of 1, indicating consistent underestimation. The error distribution graph further illustrated that at 9 lux and 10 lux, the system consistently underestimated the total value by RM 1, computing the value as RM 1.30. This had shown that the pure white tone and white tone with blue hue were not suitable to be used in the current project since it caused errors.

e) Set 5: RM 1.90



(a) (b) (c)

Figure 4.38: Impact of Different Light Intensity in Set 5: RM 1.90; (a) 6 lux (Warm Yellow or Red Tone), (b) 9 lux (Pure White Tone), (c) 10 lux (White Tone with Blue Hue)

Table 4.24: Impact of Different Light Intensity on Coin Detection and Calculation Average Accuracy of System for Set 5: RM 1.90 (2 x 50 sen + 2 x 20 sen + 6 x 10 sen)

Accuracy Criteria	Light Intensity		
	6 lux	9 lux	10 lux
Coin Detection Average Accuracy	100.00%	100.00%	100.00%
Coin Calculation Average Accuracy	100.00%	0.00%	0.00%

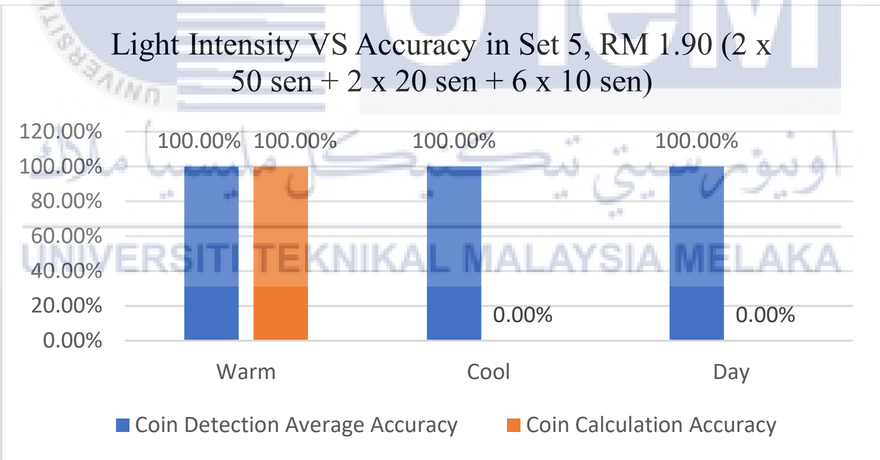


Figure 4.39: Graph of Light Intensity VS Accuracy of Coin Counting System for Set 5, RM 1.90

Table 4.25: Error Metrics of Different Light Intensity on Coin Counting System for Set 5: RM 1.90 (2 x 50 sen + 2 x 20 sen + 6 x 10 sen)

Error Metrics	Light Intensity		
	6 lux	9 lux	10 lux
Mean Error	0	-1	-0.6122
Mean Absolute Error (MAE)	0	1	0.61

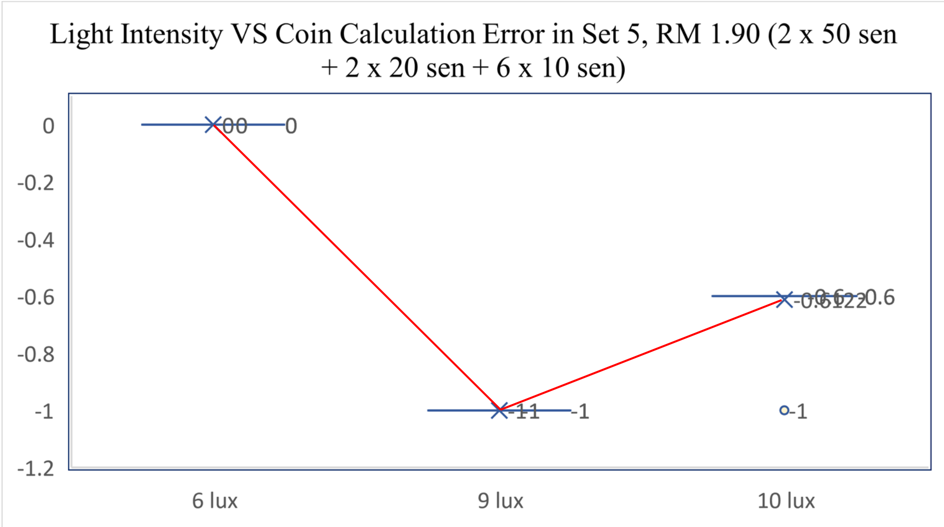


Figure 4.40: Graph of Error Distribution for Different Light Intensity on Coin Counting System in Set 5, RM 1.90

The average accuracy of coin detection and calculation for Set 5: RM 1.90, comprising 2 x 50 sen, 2 x 20 sen, and 6 x 10 sen as shown in Figure 4.38, was analyzed based on various light intensities. Table 4.24 and Figure 4.39 illustrated these findings. Additionally, Table 4.25 presented the error metrics for coin calculation in Set 5 across three different light intensities, with the error distribution depicted in Figure 4.40.

Under warm light conditions at 6 lux, the system achieved 100% accuracy in both coin detection and calculation, indicating optimal performance. At 9 lux, under cool light conditions, the system maintained 100% accuracy in coin detection but dropped to 0% accuracy in calculation, resulting in a mean error of -1 and a MAE of 1. This indicated a consistent underestimation of the total value by RM 1. Under a light intensity of 10 lux (equivalent to daylight), the system detected coins with 100% accuracy but calculated the total value with 0% accuracy. The mean error was -0.6122 with a MAE of 0.61, showing a slight underestimation, with values computed between RM 0.90 and RM 1.30.

The error distribution graph illustrated a consistent tendency to underestimate values at higher light intensities. Overall, while the system could detect coins accurately under varying light intensities, calculating their values accurately was challenging, especially under cool and daylight conditions.

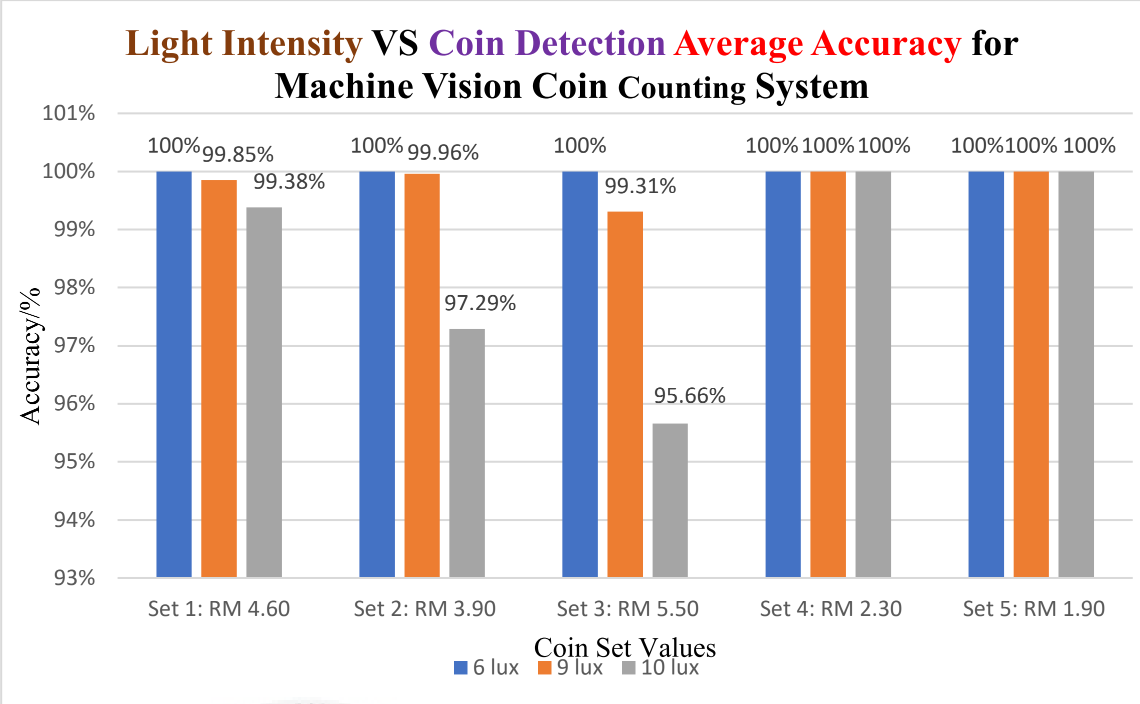


Figure 4.41: Graph of Light Intensities VS Coin Detection Average Accuracy for Machine Vision Coin Counting System across 5 Coin Set Values

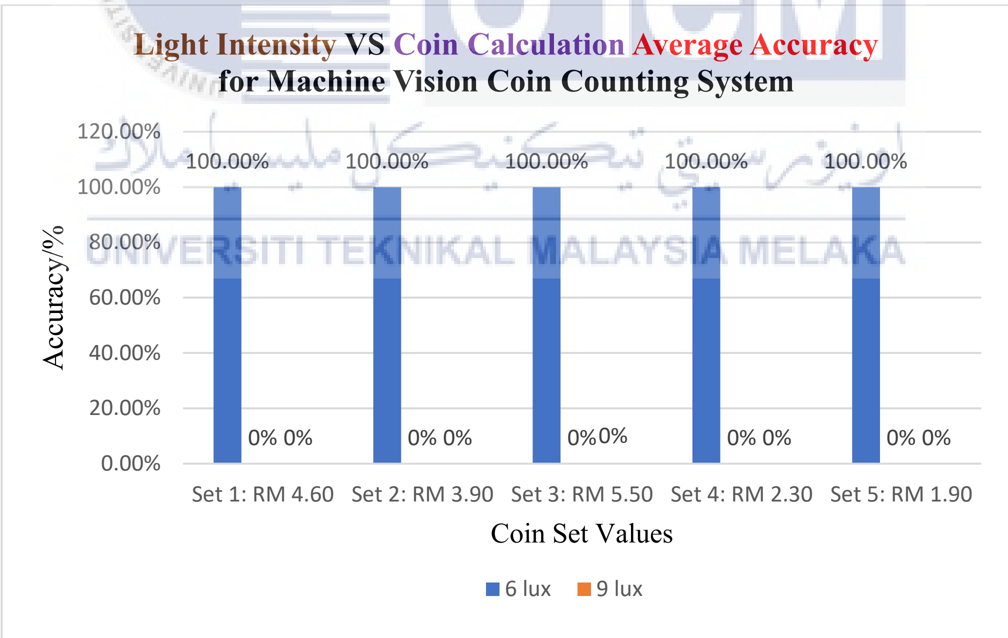


Figure 4.42: Graph of Light Intensities VS Coin Calculation Average Accuracy for Machine Vision Coin Counting System across 5 Coin Set Values

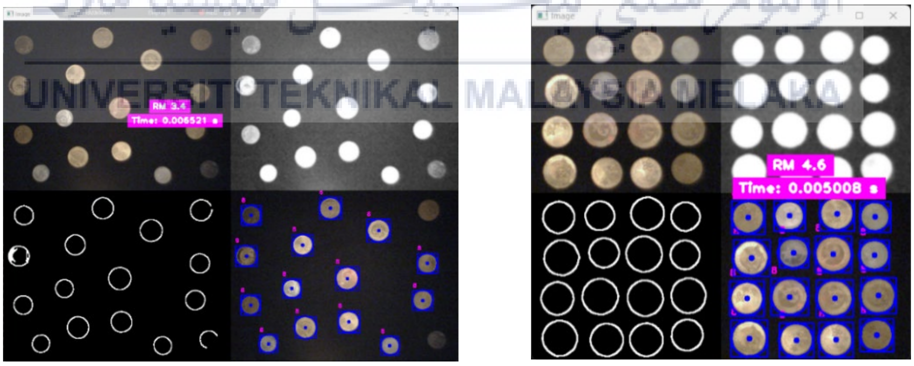
Figure 4.41 and 4.42 illustrated the overall impact of different light intensities on the coin detection and coin calculation average accuracy respectively across the 5 sets of coin values together. In general, it could be concluded that the varying brightness levels affected the coin calculation more than the coin detection as the system could detect the coins better than computing the value of coins that showed no deviation from the true value across the 5 sets of coin values.

Moreover, it could also be seen that over the 5 sets of coin values, 10 lux in the tone of white light with a blue hue impacted the coin calculation average accuracy more than 9 lux, which was cool light in the tone of pure white light. Based on the above results, it could be concluded that these findings indicated that the system could accurately detect coins in different light intensities. However, its ability to calculate accurately was significantly reduced when the light intensity was strong, especially with pure white and blue hues.

All in all, from the 5 sets of coin values, it could be said that 6 lux, which is in warm yellow tone, would be the most optimal light intensity to be chosen for the coin counting system since it achieved 100% accuracy in both coin detection and coin calculation.

4.6.3 Area of Image Detection

a) Set 1: RM 4.60



(a) (b)

Figure 4.43: Impact of Different Area of Image Detection in Set 1: RM 4.60; (a) Before Cropped, (b) After Cropped

Table 4.26: Impact of Different Area of Image Detection on Coin Detection and Calculation Average Accuracy of System for Set 1: RM 4.60 (6 x 50 sen + 6 x 20 sen + 4 x 10 sen)

Accuracy Criteria	Area of Image Detection	
	Before Cropped	After Cropped
Coin Detection Average Accuracy	94.73%	100.00%
Coin Calculation Average Accuracy	0.00%	100.00%

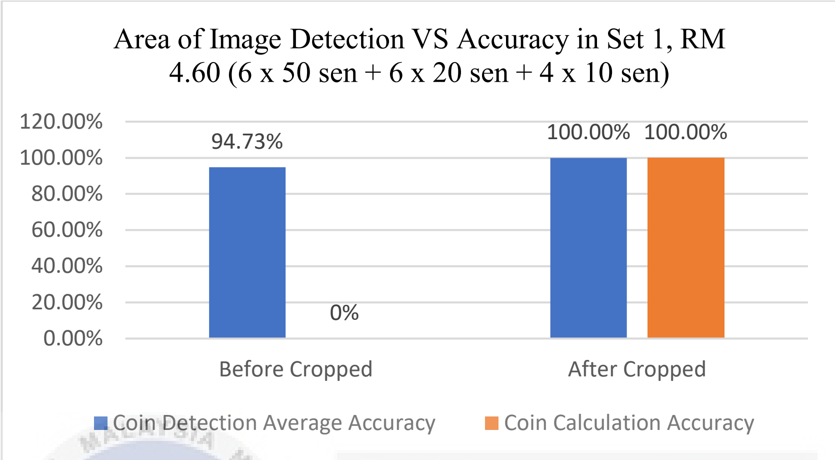


Figure 4.44: Graph of Area of Image Detection VS Accuracy of Coin Counting System for Set 1, RM 4.60

Table 4.27: Error Metrics of Different Area of Image Detection on of Coin Counting System for Set 1: RM 1.90 (6 x 50 sen + 6 x 20 sen + 4 x 10 sen)

Error Metrics	Area of Image Detection	
	Before Cropped	After Cropped
Mean Error	-0.9988	0
Mean Absolute Error (MAE)	1	0

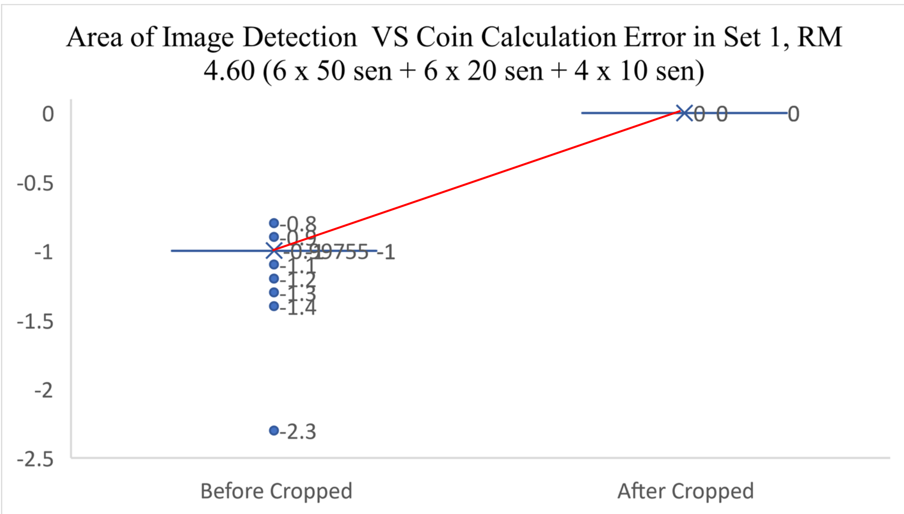


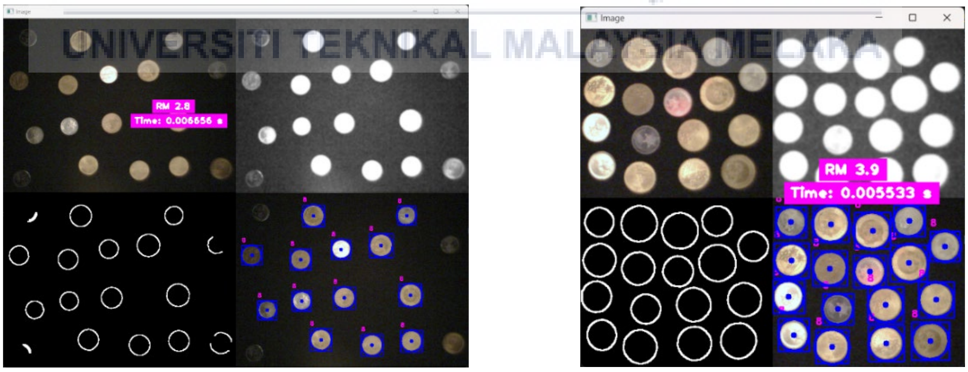
Figure 4.45: Graph of Error Distribution for Different Area of Image Detection for Coin Counting System in Set 1, RM 4.60

Table 4.26 and Figure 4.44 presented the impact of different areas of image detection on the average accuracy of detecting coins and calculating their value for Set 1: RM 4.60, which comprised 6 x 50 sen, 6 x 20 sen, and 4 x 10 sen as depicted in Figure 4.43. Additionally, Table 4.27 presented the error metrics for coin calculation in Set 1 for the image before and after cropping, while Figure 4.45 visually depicted the error distribution.

The evaluation revealed that the accuracy was greatly influenced by the size of the image detection region. Prior to cropping, the system exhibited an average accuracy of 94.73% in detecting coins, but the average accuracy in calculating the value of the coins was 0%. The error metrics revealed a mean error of -0.9988 and a MAE of 1, indicating a consistent tendency to underestimate the total value. On average, the computed values deviated lesser by RM 1 from the true value, which was RM 4.60.

The error distribution graph clearly illustrated the extent of this miscalculation, with errors ranging from -0.8 to -2.3. Following the cropping process, the accuracies of both coin detection and calculation reached 100%, and the error metrics demonstrated 0 mean error and MAE. The result clearly indicated that a concentrated detection region greatly improved the system's capacity to precisely identify and calculate the overall value of the coins.

b) Set 2: RM 3.90



(a) (b)

Figure 4.46: Impact of Different Area of Image Detection in Set 2: RM 3.90; (a) Before Cropped, (b) After Cropped

Table 4.28: Impact of Different Area of Image Detection on Coin Detection and Calculation Average Accuracy of System for Set 2: RM 4.60 (4 x 50 sen + 6 x 20 sen + 7 x 10 sen)

Accuracy Criteria	Area of Image Detection	
	Before Cropped	After Cropped
Coin Detection Average Accuracy	77.24%	100.00%
Coin Calculation Average Accuracy	0.00%	100.00%

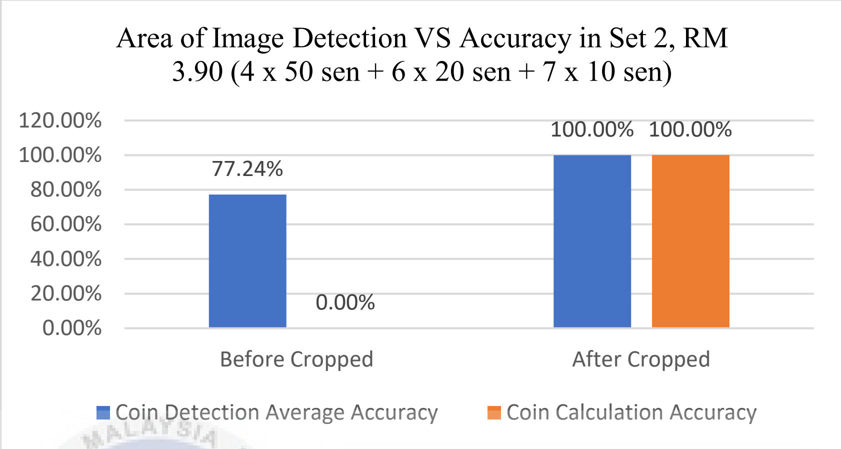


Figure 4.47: Graph of Area of Image Detection VS Accuracy of Coin Counting System for Set 2, RM 3.90

Table 4.29: Error Metrics of Different Area of Image Detection on Coin Counting System for Set 2, RM 3.90 (4 x 50 sen + 6 x 20 sen + 7 x 10 sen)

Error Metrics	Area of Image Detection	
	Before Cropped	After Cropped
Mean Error	-1.0963	0
Mean Absolute Error (MAE)	1.1	0

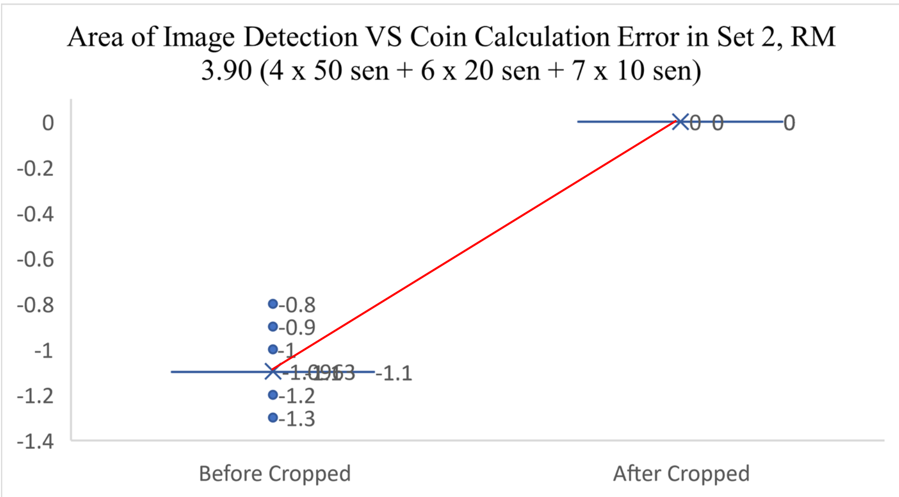


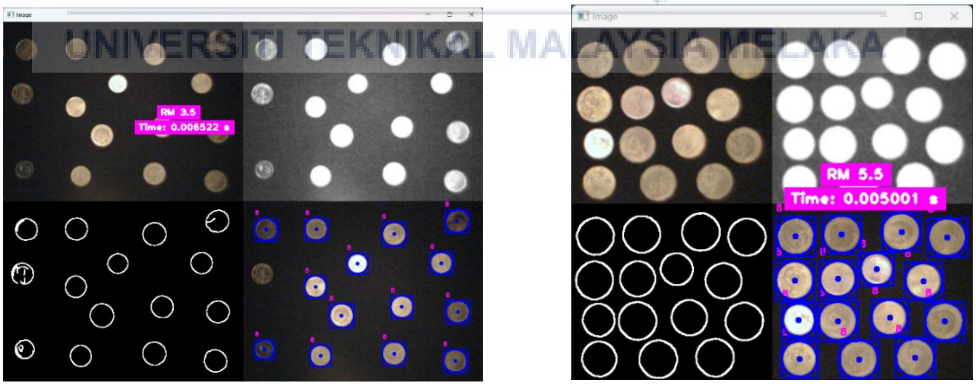
Figure 4.48: Graph of Error Distribution for Different Area of Image Detection for Coin Counting System in Set 2, RM 3.90

Table 4.28 and Figure 4.47 displayed the effect of the area of the image before and after cropping on the average accuracy of coin detection and calculation for Set 2: RM 3.90, consisting of 4 x 50 sen, 6 x 20 sen, and 7 x 10 sen as depicted in Figure 4.46. Additionally, Table 4.29 showed the error metrics for coin calculation in Set 2 across three different light intensities, with its error distribution illustrated in Figure 4.48. The results clearly demonstrated a substantial enhancement in both the recognition of coins and the accuracy of calculations after the specific area of image detection was cropped.

Initially, the average accuracy for coin detection was 77.24%, while the accuracy for coin calculation was 0%, with a mean error of -1.0963 and a MAE of 1.1. The error distribution exhibited a range of values from -0.8 to -1.3, indicating significant errors. Following the cropping process, the accuracies of both coin detection and calculation reached a perfect score of 100%, completely removing any mean error or MAE.

As a result, the calculations were precise and had no variance. The enhancement was clearly seen in the error distribution graph, where all mistakes were eliminated after cropping, suggesting a direct relationship between the decreased image detecting area and improved accuracy in the coin counting system.

c) Set 3: RM 5.50



(a) (b)

Figure 4.49: Impact of Different Area of Image Detection in Set 3: RM 5.50; (a) Before Cropped, (b) After Cropped

Table 4.30: Impact of Different Area of Image Detection on Coin Detection and Calculation Average Accuracy of System for Set 3: RM 5.50 (9 x 50 sen + 3 x 20 sen + 2 x 10 sen)

Accuracy Criteria	Area of Image Detection	
	Before Cropped	After Cropped
Coin Detection Average Accuracy	90.79%	100.00%
Coin Calculation Average Accuracy	0.00%	100.00%

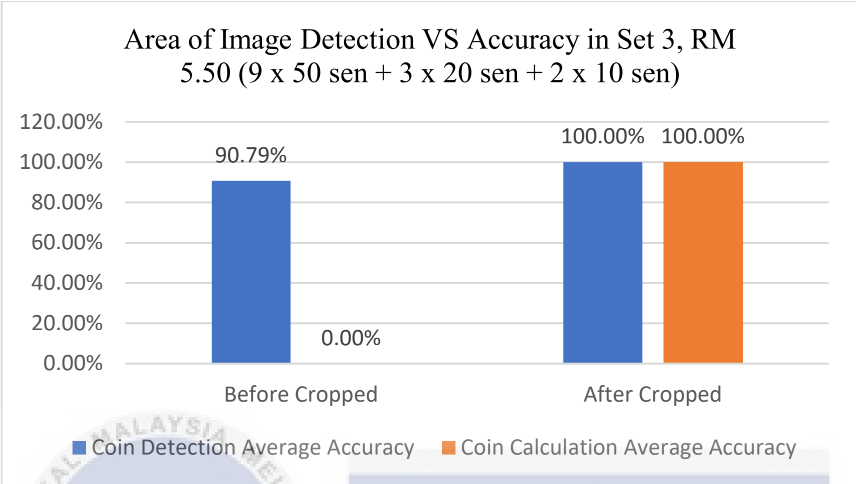


Figure 4.50: Graph of Area of Image Detection VS Accuracy of Coin Counting System for Set 3, RM 5.50

Table 4.31: Error Metrics of Different Area of Image Detection on Coin Counting System for Set 3: RM 5.50 (9 x 50 sen + 3 x 20 sen + 2 x 10 sen)

Error Metrics	Area of Image Detection	
	Before Cropped	After Cropped
Mean Error	-2.05	0
Mean Absolute Error (MAE)	2.05	0

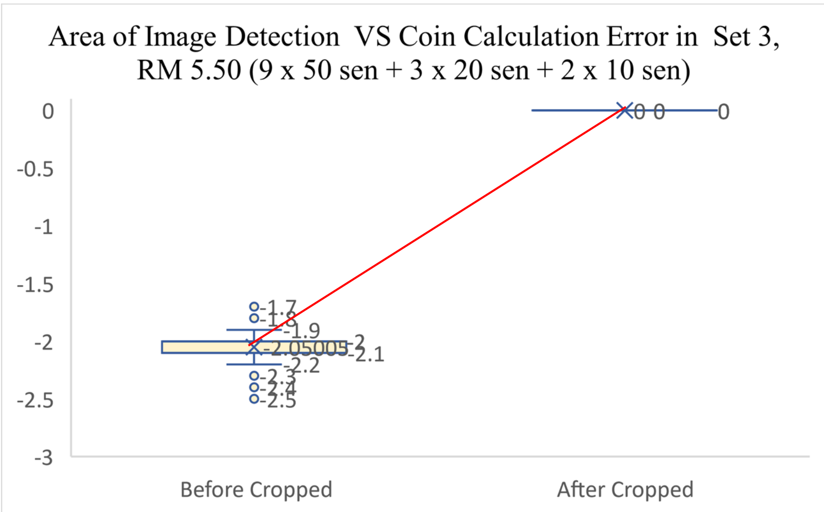


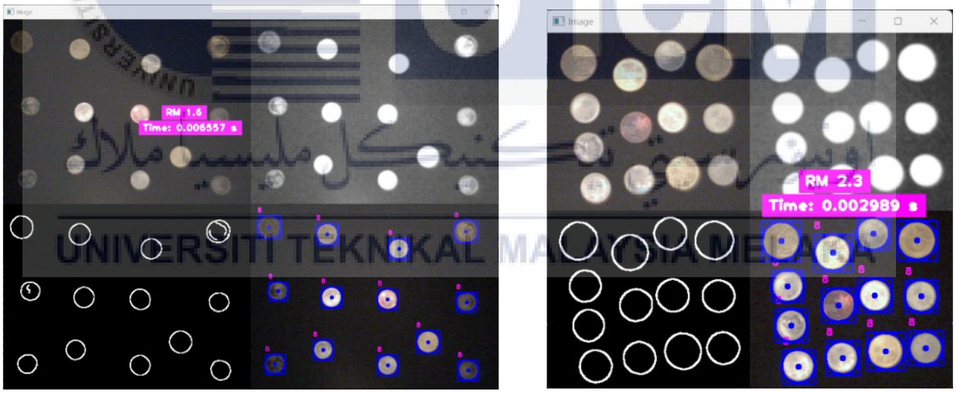
Figure 4.51: Graph of Error Distribution for Different Area of Image Detection for Coin Counting System in Set 3, RM 5.50

The average accuracy of coin detection and calculation based on the area of the image before and after cropping for Set 3: RM 5.50, which consisted of 9 x 50 sen, 3 x 20 sen, and 2 x 10 sen as portrayed in Figure 4.49, was illustrated in Table 4.30 and Figure 4.50. Additionally, Figure 4.51 illustrates the error distribution of the error metrics for coin calculation in Set 3 across three different light intensities, as shown in Table 4.31.

Before cropping, the coin detection average accuracy was 90.79% and the coin calculation average accuracy was 0.00%, with a mean error of -2.05 and a MAE of 2.05. This suggests that the system struggled to accurately detect and calculate the coins, leading to substantial underestimation. The error distribution showed a range of errors from -2.5 to -1.7, with the mean error clustering around -2.0.

After cropping, both the coin detection and calculation average accuracies improved to 100.00%, with the mean error and MAE dropping to 0. This was also evidenced by the error distribution, which showed no errors after cropping, reflecting optimal performance.

d) Set 4: RM 2.30



(a) (b)

Figure 4.52: Impact of Different Area of Image Detection in Set 4: RM 2.30; (a) Before Cropped, (b) After Cropped

Table 4.32: Impact of Different Area of Image Detection on Coin Detection and Calculation Average Accuracy of System for Set 4: RM 2.30 (2 x 50 sen + 2 x 20 sen + 9 x 10 sen)

Accuracy Criteria	Area of Image Detection	
	Before Cropped	After Cropped
Coin Detection Average Accuracy	96.02%	100.00%
Coin Calculation Average Accuracy	0%	100.00%

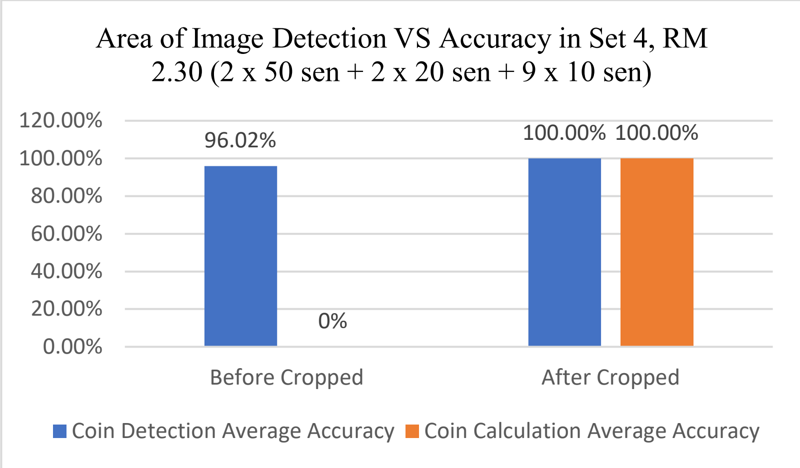


Figure 4.53: Graph of Area of Image Detection VS Accuracy of Coin Counting System for Set 4: RM 2.30

Table 4.33: Error Metrics of Different Area of Image Detection on Coin Counting System for Set 4: RM 2.30 (2 x 50 sen + 2 x 20 sen + 9 x 10 sen)

Error Metrics	Area of Image Detection	
	Before Cropped	After Cropped
Mean Error	-0.7515	0
Mean Absolute Error (MAE)	0.75	0

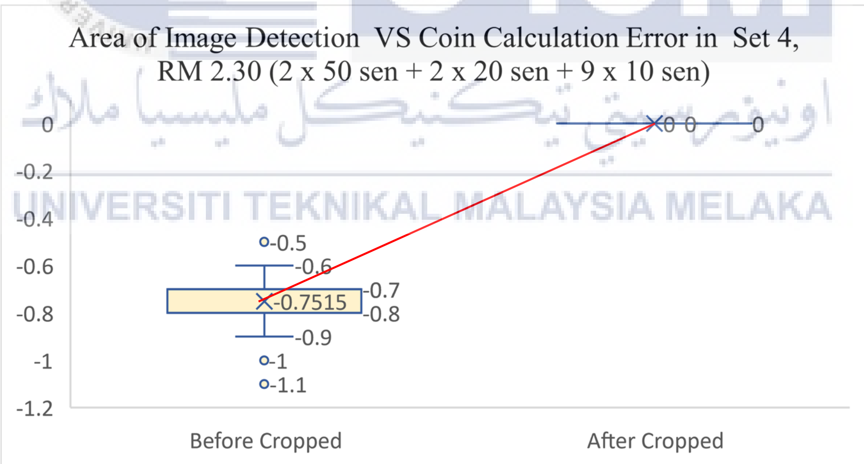


Figure 4.54: Graph of Error Distribution for Different Area of Image Detection for Coin Counting System in Set 4, RM 2.30

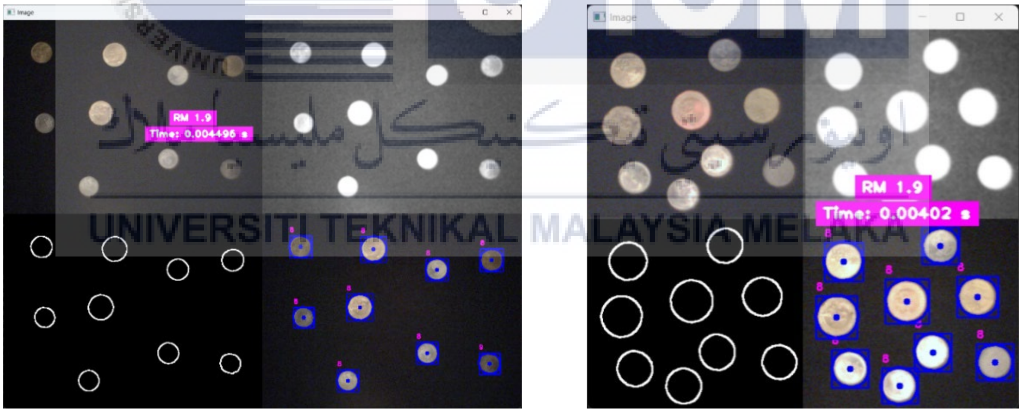
Table 4.32 and Figure 4.53 presented the impact of the area of the image before and after cropping on the average accuracy of coin detection and calculation for Set 4: RM 2.30, which consisted of 2 x 50 sen, 2 x 20 sen, and 9 x 10 sen as portrayed in Figure 4.52. Furthermore, Table 4.33 presented the error metrics for coin calculation in Set 4 under different areas of image detection, while Figure 4.54 visually depicted the distribution of these errors.

The coin detection average accuracy increased from 96.02% before cropping to 100.00% after cropping, indicating a more precise identification of coins. Similarly, the coin calculation average accuracy rose sharply from 0% to 100%, demonstrating the system's enhanced ability to correctly calculate the coin value post-cropping.

Before cropping, the mean error was -0.7515 with a MAE of 0.75, which was reduced to 0 after cropping. The error distribution, visualized in the box plot, showed that the range of errors before cropping included values between -1.1 and -0.5, with a mean error of -0.7515. In terms of the image after cropping, the errors were completely eliminated, reflecting a perfect calculation with no deviation.

This analysis clearly underscores the importance of proper image cropping in enhancing the accuracy of coin detection and calculation in machine vision systems.

e) Set 5: RM 1.90



(a) (b)

Figure 4.55: Impact of Different Area of Image Detection in Set 5: RM 1.90; (a) Before Cropped, (b) After Cropped

Table 4.34: Impact of Different Area of Image Detection on Coin Detection and Calculation Average Accuracy of System for Set 5: RM 1.90 (2 x 50 sen + 2 x 20 sen + 6 x 10 sen)

Accuracy Criteria	Area of Image Detection	
	Before Cropped	After Cropped
Coin Detection Average Accuracy	90.90%	100.00%
Coin Calculation Average Accuracy	18.10%	100.00%

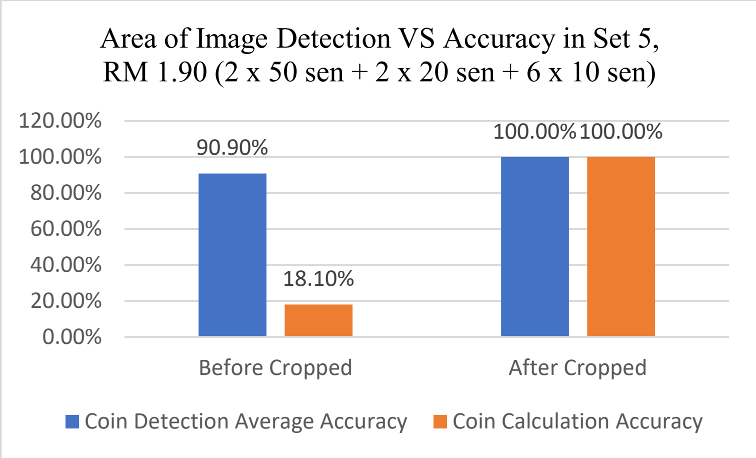


Figure 4.56: Graph of Area of Image Detection VS Accuracy of Coin Counting System for Set 5: RM 1.90

Table 4.35: Error Metrics of Different Area of Image Detection on Coin Counting System for Set 5: RM 1.90 (2 x 50 sen + 2 x 20 sen + 6 x 10 sen)

Error Metrics	Area of Image Detection	
	Before Cropped	After Cropped
Mean Error	-0.0817	0
Mean Absolute Error (MAE)	0.1	0

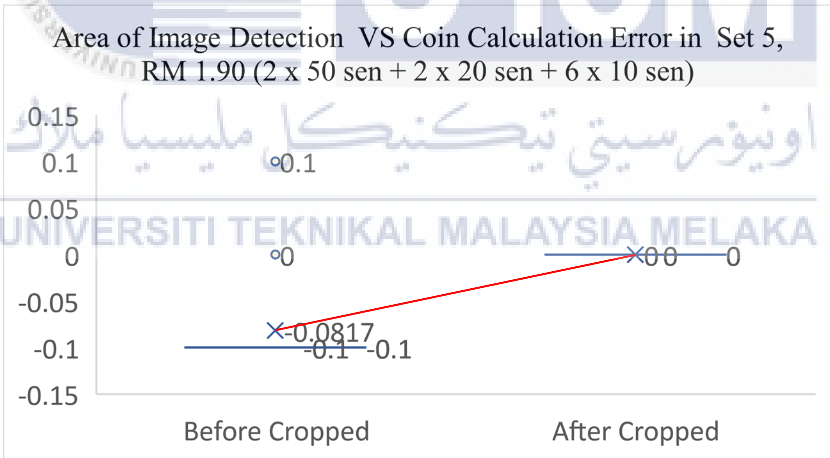


Figure 4.57: Graph of Error Distribution for Different Area of Image Detection for Coin Counting System in Set 5, RM 1.90

Table 4.34 and Figure 4.56 presented the impact of different areas of image detection on the average accuracy of coin detection and calculation for Set 5: RM 1.90, which consisted of 2 x 50 sen, 2 x 20 sen, and 6 x 10 sen as displayed in Figure 4.55. Furthermore, Table 4.35 presented the error metrics for coin calculation in Set 5 for the image before and after cropping, while Figure 4.57 visually depicted the distribution of these errors.

Before cropping, the coin detection average accuracy was 90.90%, and the coin calculation average accuracy was a mere 18.10%. This was coupled with a mean error of -0.0817 and a MAE of 0.1. The error distribution graph indicated a concentrated error around -0.1 with two outliers of 0.1 and 0, suggesting that the system sometimes computed lesser or extra value of coins before cropping. However, after cropping, both coin detection and calculation accuracies improved significantly to 100.00%, with the mean error and MAE both reducing to 0. This improvement was also evident in the error distribution graph, which showed no errors in the image after cropping, indicating perfect accuracy in coin calculation.

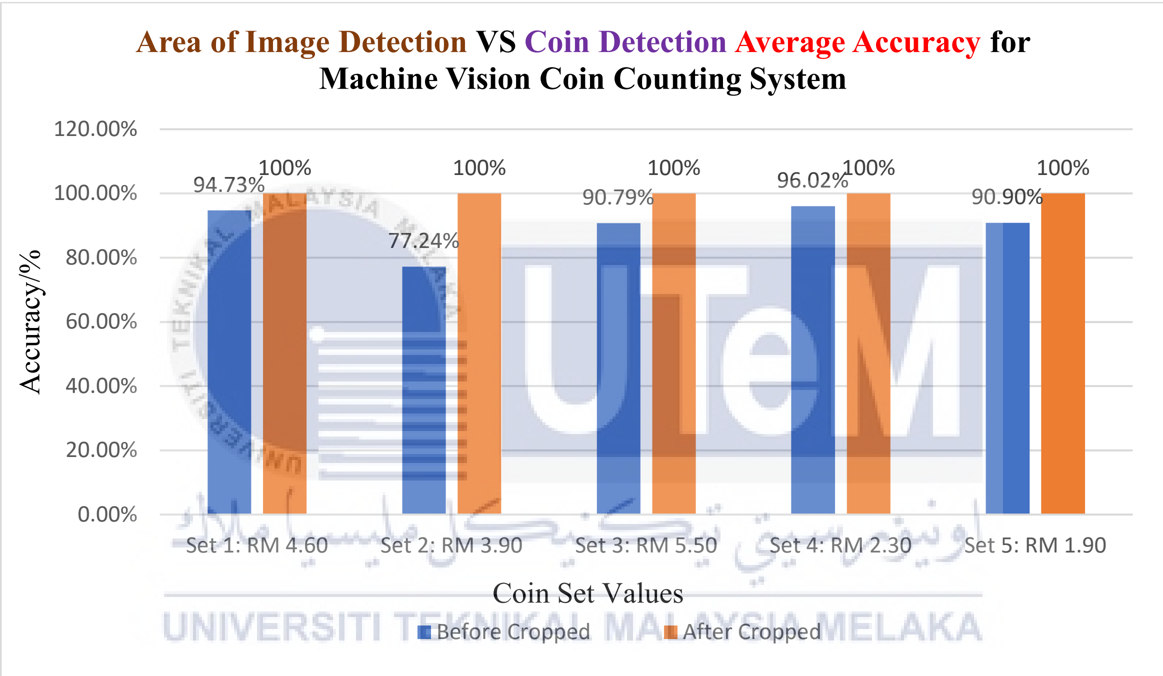


Figure 4.58: Graph of Area of Image Detection VS Coin Detection Average Accuracy for Machine Vision Coin Counting System across 5 Coin Set Values

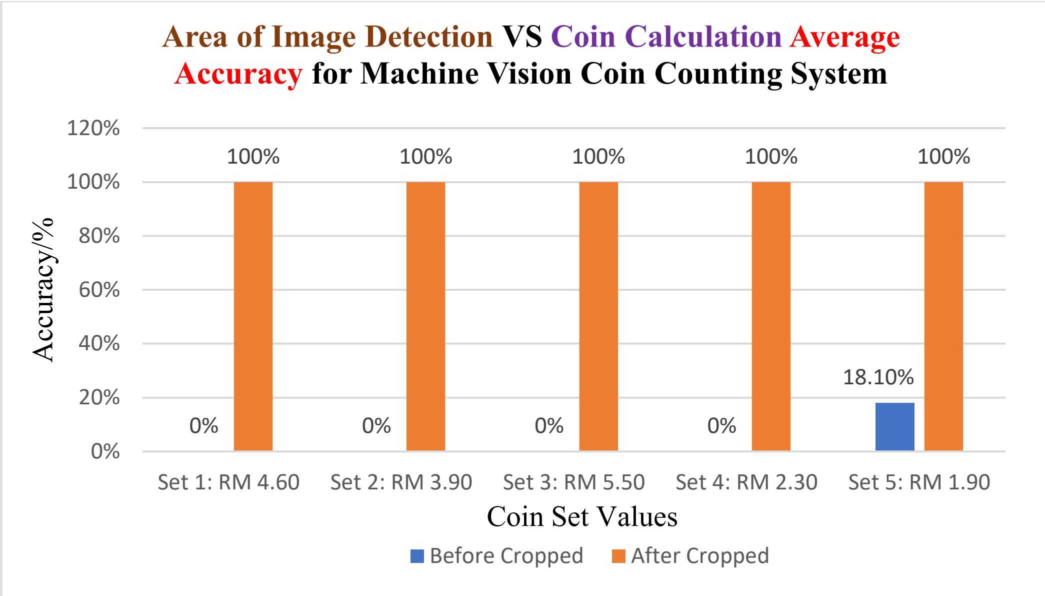


Figure 4.59: Graph of Area of Image Detection VS Coin Calculation Average Accuracy for Machine Vision Coin Counting System across 5 Coin Set Values

Figure 4.42 and 4.43 illustrated the overall impact of different areas of image detection on the coin detection and coin calculation average accuracy respectively across the 5 sets of coin values together. In general, it was concluded that the system displayed decreased accuracy in terms of coin identification and calculation for images before cropping compared to images after cropping.

The accuracy of images after cropping, with the area of detection of coins increased sharply to 100%, underscored the importance of precise image detection areas in enhancing the system's accuracy and reliability. Cropping effectively eliminated detection errors, ensuring that the coin counting process was accurate and consistent.

All in all, from the 5 sets of coin values, it could be said that the image after cropped should be used as the area of image detection, as this would be the most optimal area to be chosen for the coin counting system, since it achieved 100% accuracy in both coin detection and coin calculation.

4.7 COMPARISON BETWEEN EXISTING COIN COUNTING TECHNOLOGY VS MACHINE VISION COIN COUNTING SYSTEM

4.7.1 Existing Mechanical Coin Counter in Market VS Current Machine Vision Coin Counting System

Table 4.36: Comparison of Existing Mechanical Coin Counter in Market VS Machine Vision Coin Counting System (Syarikat Kichong Office Equipment Sdn Bhd, 2024)

Performance Evaluation	Coin Counter Model and Specifications			
	iTBOX iZ-Coin Coin Sorter Machine	*MONEYSCAN CS-850 Coin Counter*	*PRIMUS PRC-R6 Coin Sorter*	*Machine Vision Coin Counting System*
Portability	High (Weight=4.2 kg)	Moderate (Weight=10.5 kg)	Low (weight=40 kg)	High (Weight=3.7 kg)
Cost	RM800	RM3,515	RM10,915	RM440.60
Maximum Hopper Capacity	1100	11,000	400-1500 coins (varies according to coins of different countries)	70 coins (limited to the area of image after cropped for coin detection)
Slot Capacity	120-450 coins	N/A	N/A	N/A
Speed	0.17 s/coin	0.02609 s/coin	0.1 s/coin	0.0313 s/coin
Accuracy	Standard	Higher since user can adjust to the coin's thickness and diameter accordingly. Any smaller coins will fall into the rejection box while the large coins cannot pass through the hopper	99.96% or better for sorting precision	100% accuracy for coin detection and calculation for medium brightness, 6 lux light intensity (warm yellow tone) and detection of coins within area after cropped
Sorting Mechanism	N/A	Simple-to-use motor and belt system	Rail Sorting	Size and Colour Differentiation (Image Processing Techniques)
Counting Device	Electronic Sensor	Electronic Sensor	Comprehensive detection of coins by self learning	N/A
Counting Mode	Batching from 1-999	Batch (add, mix and continuous counting)	Batch (non-stop, mix and continuous counting)	N/A
Display	LED	LED	4.3-inch capacitive touch LCD	15" 1080p IPS laptop display
Integration with software	No	No	Yes (Software upgrade can be obtained online)	Python OpenCV algorithm
Built-In Sound Insulation System	No	Yes	Yes	N/A
Automatic Sorting after Summing	Yes	No	No	N/A
Report Quantity of Each Denomination	Yes	Yes	Yes	No
Report Total Value of Coins	Yes	No	No	N/A
In-built thermal printer	No	No	Yes	N/A
Data query and statistical analysis	No	No	Yes	Yes
Counterfeit Detection	N/A	Low	<=0.5%	N/A
Application	Suitable for businesses of all kinds including laundry shop, restaurant and charity organization	Bank, supermarkets and casino	Bank, cash center, transportation company and commericial organization	Suitable for home use and SMEs
Limitation	Coin stacking issue	Too expensive	Initial cost is too high	Strongly affected by lighting conditions
	Accuracy of sorting is not 100% (sometimes there will be wrong coin in different compartments and missed recognition)	Prone to wear and tear since it involves motor and belt system	Speed is compromised due to high volume of coins	Requires knowledge in Python OpenCV algorithms
	Prone to sensor failure	Risks of jamming is relatively high	Affected by working temperature and humidity	Coins per count is lesser than mechanical coin counter
	Risks of jamming is high	Frequent calibration is needed for different denominations of coins	Frequent maintenance required as rails are prone to jam	No counterfeit detection of coins due to the scope of the project
	Manual loading of coins as the batch size is not continuous and small	Manual separation of coins upon passing through the machine	Low portability suggests that it may occupy more space and not convenient to be carried around	Manual feeding of coins is still affecting the overall impact in terms of speed of the coin counting system.

Based on Table 4.36, to begin with, the mechanical coin counters, including the iTBOX iZ-Coin Coin Sorter Machine, MONEYSCAN CS-850 Coin Counter and PRIMUS PRC-R6 Coin Sorter, varied in portability and cost. The iTBOX was the lightest, while the PRIMUS was the heaviest. In terms of cost, the iTBOX was the most economical, priced at RM800, suitable for small-scale businesses. The MONEYSCAN, priced at RM3,515, offered advanced specifications for medium to large enterprises. The PRIMUS, priced at RM10,915, was specifically engineered for extensive operations despite its substantial expenses. On the other hand, the prototype of the machine vision coin counting system was quite inexpensive, priced at RM440.60, but it did require additional setup expenditures.

Regarding processing speed, the iTBOX exhibited the lowest performance, taking 0.17 seconds to process each coin. Additionally, its basic functions necessitated more manual effort. The MONEYSCAN demonstrated exceptional speed, processing each coin in a little 0.02609 seconds, making it highly suitable for high-volume settings. The PRIMUS has a coin processing speed of 0.1 seconds per coin, making it well-suited for large-scale environments. The machine vision system achieved a processing speed of 0.0313 seconds per coin, which is considered competitive for small to medium volumes. However, its performance is hindered by the need for hand feeding.

In terms of precision, mechanical currency counters typically had sophisticated sorting processes. The iTBOX exhibited consistent accuracy but occasionally had coin misplacement. The MONEYSCAN exhibited a high level of precision, albeit it necessitated regular calibration. The PRIMUS exhibited an accuracy rate of 99.96% and a false rate of less than or equal to 0.5% for detecting counterfeit coins. The machine vision system boasted a perfect accuracy rate of 100% while operating under ideal circumstances, thereby circumventing problems such as mis-sorting and jamming that are frequently encountered with mechanical counts.

To summarise, the machine vision system overcame the constraints of mechanical counters by employing non-contact image processing, which resulted in decreased mechanical failures and improved portability. Nevertheless, the success of the system relied on the presence of ideal lighting conditions and a high level of technical expertise in Python OpenCV, which might potentially lead to complications and additional expenses. However, the presence of abundant online tutorials for OpenCV helped to reduce the obstacle of technical expertise, hence improving accessibility and user-friendliness.

4.7.2 Electromagnetic Based Coin Handling System VS Current Machine Vision Coin Counting System

Table 4.37: Comparison of Electromagnetic Transducer (EMAT) Coin Classification System VS Machine Vision Coin Counting System

System Characteristcs	EMAT Coin Classification System	Machine Vision Coin Counting System
Components	Specialized equipment includes a spiral coil, NdFeB magnets, custom EMAT probe, microphone receiver, discharge capacitor circuit, control system with a microcontroller, and signal processing equipment.	Readily available off-the-shelf components (Sony PS3 Eye Webcam, ring light)
Signal Processing	Crucial for evaluating acoustic data and categorizing coins based on acoustic features.	Mainly differentiates coins based on image processing techniques.
Control System	Uses microcontroller and FETs for coil excitation management.	Integrates camera and processor via USB, relying heavily on software for image analysis.
Speed	Rapid, with the natural acoustic frequency calculated within 22 milliseconds and coin classification within 30 milliseconds	Calculates and counts each coin in less than 0.014 seconds after setup, but is slower overall due to setup time.
Accuracy	High precision for counterfeits, identifying coins with a SNR of 1425 and an inaccuracy of only 0.07%	100% accuracy in coin detection and calculation under medium brightness with 6 lux warm yellow light intensity within cropped images.
Practicality	Automated toll kiosks or vending machines which require rapid coin classification,	Appropriate for precise counting tasks in environments like SMEs or retail shops where moderate volume of coins are counted
Cost	Higher due to specialized equipment and complex signal processing algorithms	Lower due to the use of standard, readily available components
Environmental Impact	Less efficient in noisy environments, relying on maintaining a high SNR.	Unaffected by acoustic interference, can be optimized with proper lighting conditions

Table 4.37 indicated that the EMAT coin classification system developed by Dao et al., (2022) necessitated the use of specialised and expensive equipment. This included a spiral coil, NdFeB magnets, a custom EMAT probe, a microphone receiver, a discharge capacitor circuit, a control system and signal processing equipment. On the other hand, the machine vision system employed a less intricate and more economical components, hence diminishing the overall intricacy and expense.

Besides, the signal processing equipment of the EMAT system analysed acoustic data in order to classify coins, resulting in increased expenses as a result of intricate algorithms and software. The control system, overseen by a microprocessor equipped with components like as FETs contributed to its intricacy and cost. In contrast, the machine vision system depended heavily on software for analysing images and utilises straightforward USB connections, hence simplifying the procedure and decreasing expenses.

In addition, the EMAT system demonstrated high efficiency in terms of speed, as it could analyse acoustic frequencies within a mere 22 milliseconds and accurately identifying coins in less than 30 milliseconds. Nevertheless, the total processing time per coin, which included setup, was more in comparison to the machine vision system. The machine vision system, on the other hand, was capable of processing coins in less than 0.013 seconds after the setup was completed. The EMAT system was well-suited for efficient coin categorization jobs in automated environments, whilst the machine vision system was optimal for accurate counting tasks in small and medium-sized enterprises (SMEs) or retail shops.

Lastly, the EMAT system displayed exceptional precision in identifying counterfeit coins, boasting a signal-to-noise ratio (SNR) of 1425 and a mere 0.07% margin of error. Nevertheless, the presence of ambient noise could diminish its effectiveness. In contrast, the machine vision system was able to overcome this constraint. However, its capability to identify counterfeit coins was restricted within the current project's scope. Improving illumination conditions and integrating modern imaging technologies could possibly increase the accuracy of the machine vision system in coin classification activities.

4.7.3 Different Embedded Processor for Microcontroller Based VS Current Machine Vision Based Coin Counting System

Table 4.38: Comparison of Different Embedded Processor for Microcontroller Based VS Machine Vision Coin Counting System

Parameters	Arduino UNO	Arduino NANO	Raspberry PI	AMD Ryzen 5 (Laptop Processor)
Speed and Accuracy	Speed and Accuracy is lower.	Speed and Accuracy is high.	Speed and Accuracy is very high.	Speed and Accuracy is considerably high but may be compromised to environmental factors such as lighting
Design complexity	The design is more complex as it requires more hardware components	It does not require more components than UNO.	The design is not complex as it contains all inbuilt in it.	Simple hardware design as most of the components are readily available
Cost	Less expensive.	The cost is higher than UNO but lesser than Raspberry PI	As it contains advanced component, it is more expensive.	Cheaper than Raspberry PI
External Interfacing	More	Lesser	No	No
SD card	No	No	Yes	Use the computer storage, SSD
Cloud Computing	No	No	Yes	No
Programming Language	It uses Embedded C code using Arduino IDE.	It uses Arduino coding using C.	It uses Machine Learning Algorithm.	It uses Python OpenCV
Sensors	IR sensors	IR sensors	Metal sensors	Sony PS3 Eye Camera as the main sensor.

Based on Table 4.38, the survey analysis by Dr S.M. Shamsheer Daula et al., (2022) emphasised the unique characteristics and constraints of different coin classification methods. The Arduino UNO was well regarded for its portability due to its compact and lightweight design. This had made it useful for a wide range of applications and convenient to transport. Besides, it was the most cost-effective choice among the controllers listed, making it perfect for projects with limited budgets, educational endeavours, prototyping and straightforward tasks. Nevertheless, its restricted velocity and precision rendered it inappropriate for high-performance assignments. The precision of coin detection was further limited by the utilisation of IR sensors, as deviations in the material and surface of the coin could result in inaccuracies in detection.

Conversely, the Arduino NANO exhibited even greater portability as a result of its reduced dimensions. Despite being significantly pricier than the Arduino UNO, it nonetheless maintained affordability while providing enhanced performance for more intricate jobs. However, it still had drawbacks in terms of computational capacity for exceptionally demanding jobs. Similarly, the dependence on infrared sensors restricted its accuracy and adaptability, rendering it susceptible to incorrect categorization.

Furthermore, the Raspberry Pi was more substantial in size and necessitated supplementary peripherals, making it more cumbersome compared to the Arduino boards. Due to its superior capabilities, this controller was the most expensive, as it provided great speed and precision. It was well-suited for advanced applications that demanded significant computational capacity, such as machine learning and intricate automation activities. Utilising metal sensors enabled precise coin identification through analysis of their metallic properties. However, this approach was limited in its capacity to offer details regarding the coin's denomination or distinctive characteristics, therefore restricting its applicability.

Conversely, laptops equipped with an AMD Ryzen 5 processor were specifically engineered to be compact and easy to carry. While a laptop might not be a conventional controller, it could be a more economical option compared to a Raspberry Pi if one already possessed it. The AMD Ryzen 5 processor was capable of efficiently running complex software applications such as Python with OpenCV for advanced image processing tasks, providing exceptional performance for both speed and accuracy. This technology utilised advanced image processing techniques to capture high resolution images of coins, allowing for accurate analysis of their size, shape and colour. This technique had enhanced precision and flexibility in comparison to metal and IR sensors. Hence, the AMD Ryzen 5 processor was well-suited for a machine vision coin counting system, effectively managing complex image processing operations and providing dependable real-time performance, assuming the setup had already included ideal illumination conditions for precise coin calculation.

4.7.4 Digital Based Coin Handling System VS Current Machine Vision Based Coin Counting System

Table 4.39: Comparison of FPGA Based Coin Recognition System VS Machine Vision Coin Counting System

System Characteristcs	FPGA Based Coin Recognition System	Machine Vision Coin Counting System
Components	OV7670 Camera, Basys 3 FPGA Board, Block Memory and ChipScope Pro Logic Analyzer	Readily available off-the-shelf components (Sony PS3 Eye Webcam, ring light)
Working Principle	Uses MATLAB to convert coin images into coefficients, stores them in memory, and matches input images to display coin values, while comparing pixel values for better recognition.	Uses Python to apply preprocessing techniques, followed by operations to enhance shape and connectivity. The system extracts features for real-time coin classification and counting.
Control System	Uses FPGA as the core processing unit to implement the coin recognition algorithm in Verilog HDL.	Integrates camera and processor via USB, relying heavily on software for image analysis.
Speed	Capable of rapid coin recognition for real-time applications.	Calculates and counts each coin in less than 0.014 seconds after setup, but is slower overall due to setup time.
Accuracy	Lower as it mainly detect the coins based on its area or size	Higher accuracy since it differentiate the coins based on their sizes and colours.
Practicality	Application which requires high processing performance, flexibility and low development cost.	Appropriate for precise counting tasks in environments like SMEs or retail shops where moderate volume of coins are counted
Cost	Higher due to specialized equipment and knowledge requirements	More cost-effective due to flexibility
Limitation	Limited block memory	Sensitivity to environmental factors such as lighting and camera resolution.
	Sensitivity to environmental factors such as variations in light intensity, camera position and distance.	Speed is compromised due to manual feeding mechanism of coins.
	The static mode of operation restricts the system's ability to store and identify a wide range of coin images.	Issues with occlusion and overlapping or stacked coins

Based on Table 4.39, the comparison between FPGA-based coin identification system by Krishna et al., (2019) and the machine vision coin counting system is shown. Firstly, the FPGA-based system depended on specialised hardware, such as the Basys 3 FPGA board and block memory, which restricted its ability to be easily adapted for other purposes. Moreover, this system necessitated a robust setup, rendering it less flexible in accommodating different settings. On the other hand, the machine vision system utilised easily accessible components, including the Sony PS3 Eye Webcam, which improved its ability to be carried and deployed with simplicity.

In terms of cost, the FPGA-based system incurred higher expenses as a result of the requirement for specialised equipment and skills. In contrast, the machine vision system was more cost-effective, as it made use of widely available and affordable components such as a camera and ring light, which were easily obtainable for both development and maintenance purposes. The FPGA system had shown efficient coin identification capabilities; however, its performance was restricted by a limited block memory capacity, which decreased the number of pictures it could detect and save. Alternatively, the machine vision system accurately computed the number of coins by utilising the laptop's memory and RAM, successfully handling variations in coin flow.

The FPGA-based device was lacking in precision due to its single reliance on coin size for detection and its limitation to static mode. In contrast, the machine vision system provided exceptional accuracy by differentiating coins based on their size and colour in real time, rendering it appropriate for both fixed and mobile modes.

All in all, FPGA technology was highly valuable for industrial applications requiring high processing performance and flexibility. In contrast, the machine vision system was ideal for small and medium-sized organizations (SMEs) or retail establishments, requiring adaptability and scalability for accurate counting activities. Despite potential challenges like occlusion and illumination, the system was able to address these limitations through scalable computer memory, dynamic software calibration and advanced image processing algorithms. As a result, this had led to improved flexibility, streamlined configuration and upkeep, making it the optimal choice for managing dynamic coin counting situations.

4.7.5 Deep Learning Algorithm Based Coin Handling System VS Current Machine Vision Based Coin Counting System

Table 4.40: Comparison of CNN Algorithm Implementation Coin Classification System VS Machine Vision Coin Counting System

System Characteristcs	CNN Algorithm Implementation on Coin Classification	Machine Vision Coin Counting System
Working Principle	CNN classifies Indonesian Rupiah coins by using convolutional layers to learn and classify visual features into different denominations.	Preprocessing techniques reduce noise and identify coin edges, followed by operations to enhance shape and connectivity. The system extracts features for real-time coin classification and counting.
Speed	Slower in training phase but relatively fast in inference phase	Generally faster and consistent during real time operation
Accuracy	88% accuracy and a 91% F1-score on the validation set, with training accuracy peaking at 99% and validation accuracy peaking at 88%.	100% accuracy in coin detection and calculation under medium brightness with 6 lux warm yellow light intensity within cropped images.
Practicality	Appropriate for tasks to obtain high efficiency and accuracy of coin sorting systems	Appropriate for precise counting tasks in environments like SMEs or retail shops where moderate volume of coins are counted
Cost	Initial investment and development cost is higher	More cost effective
Limitation	Limited size of dataset	Sensitivity to environmental factors
	Rescaling of image reduced amount of information available	Concerns in terms of scalability
	Narrow classification limited to five coin classes limits scope of study	Less practical to be used to detect counterfeited coins
	CNN configuration may not be fully optimized for this model.	Image procesisng techniques algorithms may not be fully optimized.

Based on Table 4.40, the comparison between the CNN algorithm implementation for coin classification by Putra, (2023) and the machine vision coin counting system was depicted. Firstly, the CNN algorithm classified Indonesian Rupiah coins by resizing and normalizing pre-processed images, using convolutional, pooling and fully connected layers to learn visual features in which the approach learned complex patterns from large datasets. On the contrary, the machine vision coin counting system utilised traditional image processing techniques like Gaussian blur, grayscale conversion, edge detection, thresholding and morphological operations to reduce noise, identify edges and improve shape connectivity. Contour detection located edges and extracted distinctive characteristics for instantaneous coin counting.

In speed, the training phase of the CNN algorithm was characterised by high computational demands and time consumption, necessitating substantial resources. Nevertheless, the inference step, in which the trained model categorised novel coin images, was comparatively rapid but still contingent on the intricacy of the system. On the other hand, the machine vision coin counting system was capable of providing quicker and more reliable real-time operation by utilising predetermined image processing procedures that did not necessitate significant CPU power.

Furthermore, the CNN algorithm demonstrated a validation set accuracy rate of 88% and an F1-score of 91%, indicating its high level of precision. The accuracy of the training set reached its maximum at 99%, while the accuracy of the validation set reached its maximum at 88%. This suggested that the model performed with high precision and reliability in controlled conditions. As a comparison, the machine vision coin counting system attained a perfect accuracy rate of 100% in detecting and calculating coins, given ideal circumstances, such as medium brightness and a precise light intensity of 6 lux in a warm yellow hue. Both methods were only efficient in stable and regulated contexts.

Besides that, the CNN method incurred higher initial investment and development costs due to the requirement for prolonged training and continuous maintenance, which included the allocation of computational resources and the knowledge needed for model creation and fine-tuning. In contrast, the machine vision coin counting method was more economical, as it was straightforward and required fewer computational resources since it relied on well-established image processing algorithms.

However, the CNN algorithm was constrained by the size of the dataset, which could lead to inconsistencies and mistakes. Additionally, the resizing of images decreased the amount of information that could be used for learning. The restrictive reach of its classification, which was limited to only five coin types also limited its application. Not only that, the CNN configuration might not be fully optimised for the particular model. On the other hand, the machine vision coin counting method was susceptible to ambient conditions like as lighting and camera resolution that affected its accuracy. Additionally, the scalability of the system also raised concerns as it only contained three coin denominations in this. Moreover, it was not very practical for identifying fake coins because of the limited capabilities of standard image processing.

To summarise, whereas CNN algorithms offered advanced and precise coin categorization, their extensive processing requirements and intricate upkeep rendered them less feasible without substantial datasets or robust hardware. In contrast, conventional image processing methods used in machine vision coin counting systems, such as edge detection and contour analysis provided a more convenient and effective option. These approaches were deemed effective in stable lighting conditions, offered real-time processing at affordable prices, and could be adjusted to dynamic, high-traffic venues and SMEs. Therefore, conventional image processing methods were a pragmatic and economical option for dependable coin counting applications.

4.7.6 Existing VS Current Machine Vision Based Coin Handling System

Table 4.41: Comparison of Existing VS Current Machine Vision Coin Recognition and Counting System

Machine Vision Coin Recognition and Counting System	Existing	Current
Working Principle	Captured real-time images and processed them to classify denominations accurately while including a counting algorithm for real-time counting.	Preprocessing techniques reduce noise and identify coin edges, followed by operations to enhance shape and connectivity. The system extracts features for real-time coin classification and counting.
Portability	Less portable	More portable
Speed	Classification: 1.2 s/ coin Counting: 0.18 s /coin	0.0313 s/coin after setup
Accuracy	Classification: 89% Counting: 100%	100% accuracy in coin detection and calculation under medium brightness with 6 lux warm yellow light intensity within cropped images.
Practicality	Stores, banks and individuals	Appropriate for precise counting tasks in environments like SMEs or retail shops where moderate volume of coins are counted
Cost	Higher (additional and advanced feature such as special dedicated light sources and spot light holder plate)	Lower (most of the components were readily available)
Limitation	The accuracy decreases with higher FPS.	Sensitivity to environmental factors such as lighting and camera resolution.
	The class created was of insufficient quality to clearly distinguish between valid and invalid denominations.	Speed is compromised due to manual feeding mechanism of coins.
	At higher speeds, the Velcro tape was disturbed, which could cause coins to fall off the conveyor.	Issues with occlusion and overlapping or stacked coins
	The additional spotlights improved the coin image but also illuminated the Velcro tape, interfering with the detection algorithm.	Image procesisng techniques algorithms may not be fully optimized.

Based on Table 4.41, the comparison between the existing machine vision coin recognition and counting system by Dīnēshchandra Jōshī et al., (2016) and the current machine vision coin counting system revealed several key differences. Firstly, the working principles of both systems were similar, but the existing system separated coin recognition and counting into two tasks for better clarity. The existing system was less portable due to the use of a conveyor, which added complexity despite having the similar components.

In terms of speed, the existing system, which aimed to achieve 99.99% accuracy at high speeds (processing 1,000 coins per minute) was considered to be slower than the current system. This is due to the fact that the current system only took about 0.0313 seconds per coin during processing, assuming a stable setup and limited to a project scope of 70 coin sets.

Moreover, in the aspect of accuracy, the existing system achieved 89% accuracy in coin classification and 100% in counting tasks using 30 frames per second (FPS). However, higher FPS also increased the risk of missing coins. The current system, fixed at 20 FPS, achieved 100% accuracy in coin detection and calculation under specific conditions (medium brightness, 6 lux light intensity and a defined detection area), but it was highly sensitive to environmental changes. Also, the existing system avoided issues like occlusion or coin stacking due to the use of Velcro tape on the conveyor.

Besides, the current system was more limited in terms of practicality, as it was only appropriate for exact counting of moderate coin volumes and static graphics. On the other hand, the current technology had the capability to analyse and tally a greater number of coins by utilising a conveyor that operated continually. The processing capacity of the current system was also constrained by the coin tray size and the camera's field of vision.

Furthermore, the existing system incurred higher costs due to the exclusive dedicated light sources and advanced cameras, in contrast to the existing system which relied on a standard Sony PS3 Eye Webcam as the main image sensor only.

Overall, the current coin counting method could be considered as the most efficient model where cost and profitability were the main priorities in a stable setting. Given a consistent baseline configuration and optimised illumination conditions, the system could significantly achieve a higher level of speed and precision compared to the existing system.

CHAPTER 5

DISCUSSION

5.1 INTRODUCTION

Chapter 5 primarily centres on an extensive examination of the advanced machine vision coin counting system, highlighting its various elements including cost-effectiveness, portability, speed, accuracy, limitations, and prospective enhancements. Each of these factors is essential for comprehending the performance and suitability of the system in real-world situations. The chapter explores the utilisation of machine vision technology through a low-cost paradigm, with a focus on cost efficiency. This approach provides firms with a strategic edge. In addition, the concept of portability is being addressed to emphasise the system's ease of use and convenience in many settings. In addition, it is essential to analyse speed and accuracy as key indicators to showcase the system's efficiency in automating coin counting activities with exceptional precision. Moreover, this analysis openly examines restrictions to offer a deeper understanding of existing difficulties, thus creating a foundation for exploring possible enhancements. Every subject covered in this chapter enhances a comprehensive comprehension of the capabilities, difficulties, and future prospects in expanding the technology of coin counting in machine vision systems.

5.2 DISCUSSION IN TERMS OF COST EFFICIENCY

The prototype for the portable coin counting system was developed at low-cost being only at RM 440.60, machine vision technology offers high return of investment since it minimizes the need for periodic maintenance and calibration typically required by mechanical coin counting devices to ensure accuracy. For example, the coin separation and counting machine designed by Mohd Abu-Alfotouh Ahmad Qandel et al., (2023), there is issue of coins not falling into their designated boxes was attributed to the boxes being full. Therefore, the servo motors had to be adjusted to ensure the boxes were emptied before the subsequent coin was sorted. Additionally, the situation that IR sensor failed to detect some of the coins was also observed, indicating that the IR sensor required an unobstructed view of the coins. Not only that, since mechanical coin counters contain physical moving components such as the rotational coin sorting machine as shown in Han & Liu, (2021) which are prone to deterioration of wear and tear over time. In addition, this statement is also mentioned in the coin sorting machine designed by Dabhade et al., (2020) where it is crucial for the material used to exhibit excellent wear resistance and thus they had chosen the material to be mild steel. Machine vison technology employed in coin counting system maintained a consistent and reliable operation by reducing mechanical components which subsequently translates to fewer breakdowns and less frequent maintenance. Consequently, businesses benefit from reduced downtime and lower repair costs, leading to significant cost savings over the lifecycle of the machine vision system.

Apart from that, since the prototype of the current machine vision coin counting system was designed to be at low-cost, hence it only integrates the usage of a single camera as the main sensor, namely the Sony PS3 Eye Camera for capturing the images of coins as well as commercial ring light as the light source. As compared to the EMAT coin classification system, FPGA based recognition system as well as the existing machine vision coin recognition and counting system, all of them utilized various specialized and advanced equipment such as a custom-designed EMAT probe, Basys 3 FPGA board and block memory, special dedicated light sources in hollow circular shape and spot lights respectively which can incur higher cost since the current system is focused on using readily available components. Also, the wide range of data that must be obtained as well as the training time for the CNN algorithm may contribute to higher cost of the system. Therefore, it was clear that the simplicity of the design of current prototype will also contribute to its cheaper cost.

Moreover, the current machine vision coin counting system benefits from the use of an AMD Ryzen 5 processor and controller, outperforming other processors as shown in the comparison in Table 4.37. AMD Ryzen 5 processor which is readily integrated into the laptop causing it to be efficiently handling image processing tasks. This is due to its powerful processing capabilities and large memory to ensure quick and effective implementation of complex algorithms for instant coin identification. Besides, the substantial RAM and storage capacity manage data flow seamlessly, enabling accurate coin identification. Additionally, the graphical capabilities of the processor also support real-time monitoring and analysis, boosting the overall efficiency of the system. With this being said, the processor being used in this system can effectively overcome the issue of having limited block memory as depicted in the FPGA coin recognition system as well as extra interfacing as described in Table 4.37 in which all of these will result in implementing higher cost of the system. As evidence, Berglund et al., (2014) had stated that despite it should be an industrial PC equipped with a SSD for enhanced durability to carry out their research, however, this was not essential for the case, as the environment was not particularly demanding, indicating that the standard laptop or PC processor could be used if the environment is not highly varied.

Apart from that, the precision of this current system is able to eliminate the need for the owners of small businesses, medium enterprises or even individuals to burn a hole in their pockets by purchasing expensive mechanical coin counters in the market since the current system is compact enough to precisely sum small to moderate volume of coins by utilizing image processing techniques.

In summary, the cost-effectiveness of the current machine vision coin counting system lies in the long-term benefits in terms of simplicity, one-stop integration of components, reduced maintenance costs with enhanced operational efficiency.

5.3 DISCUSSION IN TERMS OF PORTABILITY

The prototype for the current machine vision coin counting system only weighed about 3.7 kg as it mainly utilized lightweight components such as the aluminium 2020 profile as the main frame. Not only that, by utilizing 3D printing technology for the adjustable height mechanism as well as coins tray, it also contributed to the lightweight of the system as mentioned by Mat Sahat et al., (2023) where significant weight reduction was able to be achieved through application of additive manufacturing. Hence, the current machine vision coin counting system was considered to be more portable, convenient and easier to carry around as compared to the mechanical coin counters such as MONEYSCAN CS-850 Coin Counter and lastly PRIMUS PRC-R6 Coin Sorter which weighed at 10.5 kg and 40 kg respectively due to additional components and advanced features that may be integrated into the machine, causing them to be more bulkier and heavier.

Next, if compared with the EMAT, FPGA or even the existing machine vision coin recognition, classification and counting system respectively, it was noted that the specialized equipment and advanced features that were present in their system contributed to the complexity of the hardware design of the system, limiting the ease of the system to be carried around which had resulted them to be less portable than the current machine vision coin counting system. For example, the utilization of conveyor in existing machine vision coin recognition and counting system may decrease the portability of the system to a certain extend since it was too intricate to be moved around to different settings (Dīnēshchandra Jōshī et al., 2016).

5.4 DISCUSSION IN TERMS OF SPEED

The current machine vision coin counting system displayed exceptional speed in calculating the coins presented in each coin set values. However, the performance of the system was compromised by the manual feeding of coins which might contribute to the setup time which will impact the calculation process to become slower. Nonetheless, the system was able to calculate the coins at an average time of less than 0.013 seconds across the 5 coin set values presented by assuming all setup was stable and done. This had clearly shown that the machine vision coin counting system was beneficial especially when compared to the mechanical coin counters as it was able to efficiently automate the whole calculation process based on image processing techniques with superior performance. This situation had been further supported by the (Rangan, 2018) where the study had stated that machine vision coin counting system offers less time consumption and there was no need for manual labour anymore with the utilization of machine vision coin counting system since the mechanical coin counters still required human intervention to certain extend to ensure the hopper is not jammed when too many coins are loaded into the hopper at once.

When comparing EMAT, FPGA, CNN and existing machine vision coin handling technologies with the current coin counting system, it is evident that each technology demonstrates high-speed performance in their specific environments. Firstly, EMAT systems are highly proficient in detecting objects without physical contact, offering rapid and precise measurements. However, they can be costly and necessitate specific expertise. Furthermore, FPGA and CNN offers remarkable computing velocity and flexibility, Nevertheless, both of these methods frequently need substantial computational resources and extensive training data. While these technologies have significant benefits, they also have limits in terms of complexity, energy consumption and cost. However, the machine vision coin counting system is the optimal solution due to its remarkable speed. Using advanced image processing techniques, it rapidly analyses high-resolution pictures and videos to promptly identify and count coins. The versatility of this product allows it to be easily integrated into various environments without requiring extensive customisation. Furthermore, machine vision systems are specifically engineered to be user-friendly, requiring minimal specialised knowledge for both installation and upkeep. As a consequence, there is a reduction in costs associated with training and operational activities. These solutions are highly cost-effective and have the capability to monitor and analyse in real-time. As a result, they significantly enhance overall efficiency, making them the most efficient and practical choice for current currency handling needs (Dan et al., 2013).

5.5 DISCUSSION IN TERMS OF ACCURACY

Despite the limits of the present machine vision coin counting system, it achieved 100% accuracy in detecting and calculating coins within certain parameters. The existing system's accuracy was affected by various elements, such as the brightness level and light intensity. Berglund et al., (2014) found that the accuracy of the vision system in a low-cost model is closely tied to the quality and consistency of lighting. Adequate brightness levels and controlled light intensity are crucial for improving the distinction of features, minimising irrelevant areas, and increasing the system's ability to withstand challenges. Fluctuations in luminosity and illumination strength can have an impact on the sharpness and differentiation of images, which in turn affects the accuracy of identification. Therefore, it is important to ensure that the system can adapt to different lighting conditions and maintaining consistent detection performance across various levels of brightness. The reason for this is because inadequate brightness negatively affects the picture's quality by causing an uneven distribution of light. As a result, the introduction of random noise, which in turn diminishes the contrast and accuracy of colours in the image will occur (Zhang et al., 2023). These challenges hindered the ability to accurately differentiate between coin edges and features, resulting in inaccuracies. Not only that, high brightness in images could lead to overexposure, causing the system to lose critical visual details and reducing the accuracy as it masked the edges and surface features of coins, leading to incorrect classifications and miscalculations (Wei et al., 2021) .

Also, the accuracy of the coin counting system will be somehow impacted by the area of detection of image of coins since the spatial resolution in machine vision has a substantial impact on the accuracy of object identification. Images with higher resolution provide more detailed information for detection models to analyse, resulting in better item localization and classification. On the other hand, images with lower resolution may lack sufficient detail to precisely identify items, resulting in decreased accuracy, particularly for smaller or intricate objects that depend on minute details for recognition, such as the coin counting system. Therefore, selecting an appropriate spatial resolution is extremely crucial in machine vision applications. (Hao et al., 2022). Cropping, even if it only includes removing excess image area around coins, significantly affects the efficiency and accuracy of the coin counting system. Before cropping, the enlarged detection region may include scattered coins, which might potentially result in the system processing an excessive quantity of data. By applying the technique of cropping, the system reduces the detecting area to focus exclusively on the coins, eliminating any extraneous space and allowing for optimal use of its greater spatial resolution. The focused methodology utilised in this procedure enhances the lucidity and intricacy of the coins portrayed in the image, leading to a more accurate enumeration of the coins. Furthermore, by analysing a smaller and more pertinent region, the system may function with greater efficiency, hence enhancing the overall speed and performance in the process of counting coins.

5.6 LIMITATIONS OF THE PROJECT

According on the analysis of the results obtained, despite the project could possibly be more advantageous over the different coin handling technologies as compared in Section 4.7, the current project still presented several shortcomings and constraints of the image processing-based system.

Due to the fact that the portable prototype was designed to be a low-cost model within budgetary constraints, hence it was able to operate effectively with readily available and basic components such as a Sony PS3 Eye webcam, ring light, coin tray, 3D printed adjustable height mechanism and constructed cardboard enclosure, which together established a stable, fixed and controlled environment for the system. Next, based on the experimental settings detailed in the previous section, it was evident that the optimal configuration for the machine vision coin counting system involved using medium brightness, light intensity of 6 lux with warm yellow colour tone and using image after cropped for the detection area image for all five sets of coin values. Nevertheless, this current project faces certain limitations and identifies research gaps, particularly concerning the factors influencing the accuracy of the machine vision coin counting system.

First and foremost, the camera resolution of the Sony PS3 Eye Webcam utilized in this project is low. Image sensors specifically CCD sensors, which consist of individual MOS diodes arranged in rows and columns, with each diode acting as a pixel. These sensors convert photons into electrons, where the number of electrons generated corresponds to the intensity at each pixel. The resolution of CCD sensors is determined by parameters such as the size of each pixel and the distance between pixels. (RadhaKrishna et al., 2021). Generally, conventional devices such as the Sony PS3 Eye Webcam have a pixel count of only 310,000, whereas higher-resolution ones often boast a minimum of 2 million to 5 million pixels. The number of pixels directly impacts the resolution of the camera, emphasising the crucial function of pixel arrays in recording intricate images. Zhu et al., (2022) had stated that high-resolution cameras offer detailed images that enable advanced image-processing algorithms to evaluate a larger dataset. This leads to improved precision in identifying and classifying tasks. Furthermore, high-resolution cameras provide precise and intricate images that enhance the visualisation of coin textures and hues. This facilitates the comprehensive analysis of the coin pictures at a superior level of quality.

In addition, the reflecting properties of the metallic elements used in Malaysian coins often result in glare and distortions in captured photographs. As a consequence, there is a decrease in the quality of the image and it impairs the effectiveness of machine vision checks. Norman et al., (2020) had stated that the brightness of a surface area, including reflective objects like coins is determined by multiplying its reflectance with the amount of illumination it receives. Shiny metallic items, like coins, have a high reflectance since the coins will reflect a significant amount of incoming light. Thus, determining the best and appropriate brightness for coins can be complex, as low brightness levels may cause inadequate illumination, resulting in images that lack contrast and detail. On the other hand, excessive brightness might create glare and overexposure, which can make it difficult to distinguish small details, such as coins, from the background. This can potentially cause the system to misread the objects. Overall, attaining a moderate degree of brightness achieves a harmonious equilibrium by improving the visibility of coin details while minimising negative effects like as glare and shadows (Rodríguez-Rodríguez et al., 2024).

Furthermore, the restricted white balance of the Sony PS3 Eye camera has a direct impact on the image quality, which in turn affects the accuracy of the coin counting mechanism. Based on the insights from Akazawa et al., (2021), it can be deduced that the limited ability to adjust white balance can impact both the brightness level and accuracy of a coin counting equipment. Accurate adjustment of white balance is crucial for achieving perfect colour depiction in images. The camera's restricted white balance choices might lead to inaccurate colour representation and inconsistencies in perceived luminosity across the image. Precise colour depiction is essential in a coin counting system to distinguish between various denominations of currency. The limited white balance option may cause variations in colour in captured currency photographs, making it challenging to precisely identify and count the amount of coins. Inaccurate light intensity levels can also affect the sharpness of coin details, potentially leading to inaccurate classification or enumeration. Therefore, the camera's limited ability to adjust white balance may cause colour distortions and reduced image clarity, which in turn might impact the accuracy of the coin counting process.

Apart from that, according to insights from the study of Manish R & Dr. S. Denis Ashok, (2016), the significance of the distribution of grey scale intensities in an image for the purpose of detecting coin edges based on pixel values was highlighted. Augmenting the luminosity of illumination induces a displacement of pixel values towards regions of higher brightness, thereby impacting the detection of coin boundaries. Erroneous edge detection may occur due to insufficient or excessive reflection induced by narrow distributions at the extreme ends of the grey scale range. To achieve optimal edge detection, it is necessary to use an appropriate range of lighting intensity. In addition, Bochen & Ambrożkiewicz, (2023) had clearly stated in their study that the intensity of light has a substantial impact on the operation of a vision system. The number of unsuccessful attempts in the system increases as the light intensity level increases. Therefore, it is essential to adjust illumination techniques to specific scenarios and areas in order to ensure system performance and reliability and achieve optimal results in image processing. Good illumination in object identification necessitates adhering to guidelines that prevent light distribution, reflections, shadows and glare. In industrial applications, it is essential to adjust lighting techniques and sustain appropriate light intensity levels to ensure the accurate operation of vision systems. This project utilizes light intensity of 6 lux which was made up of warm yellow tone or red tone is beneficial for vision systems when inspecting shiny coin surfaces due to its ability to reduce specular reflections, enhance contrast, minimize shadows, and optimize image processing. This selection improves efficiency and accuracy in detecting objects in challenging environments. However, 9 lux which was made up of pure white tone and 10 lux which was made up of white tone with blue hue lighting modes cannot be used because both of these modes would excessively brighten the image, causing overexposure and compromising the system's effectiveness in capturing clear and detailed images under these conditions Sciotex, (2023).

Due to limitations in camera resolution and the type of lighting available as well as specific illumination requirements, cropping the image area becomes necessary to ensure accurate detection and calculation, especially in the centre of the illuminated object. The ring light's design focuses light at an angle toward the centre of the object being illuminated, necessitating the adjustment of the detection area to optimize visibility and clarity for precise analysis and measurement. According to Microscan Systems, (2014), Ring lights are a popular choice in machine vision applications due to their cost-effectiveness and uniform light source around the camera lens. They are particularly effective for capturing images of subjects on matte or lacklustre surfaces, as they provide ample illumination. However, ring lights may not offer the best contrast for measuring highly shiny parts, resulting in low image quality and potentially affecting measurement accuracy. The overall quality of captured images can also be influenced by poor contrast from highly reflective surfaces. Additionally, ring lighting may result in diminished repeatability, negatively impacting the yield of high-quality components. Additionally, objects at the corner may not be successfully detected due to the uniform light only emitting around the middle area.

Some other limitations from this research include the complexity in terms of coin differentiation between 20 and 50 sen since both of them are made up of the same colour and shared almost the same size. At times, it was a little hard to distinguish between both of them by using naked eyes thus contributing to the complexity to optimize the algorithm between the differentiation of these two coins. Next, the setting of the prototype in which the camera must be exactly 90 degrees when being attached to the frame in order to minimize the area gap between coins on the left hand side and right hand side when performing algorithm to differentiate the coins so that it can support the coins to be randomly placed at any location on the coins tray for detection. Furthermore, the distance of the camera from the coins must be always fixed and uniform at 30 cm within this project as the variation in distance between the coin and the camera during picture capture can have an impact on the quality and consistency of the photos, which may in turn affect the performance of the classification system Joshi et al., (2022). Not only that, but this project also exclude external lighting factors by thoroughly enclosing and covering the prototype. This is so that it could minimize the impact of shadow from external lighting which may introduce noise that impact the accuracy of the system. For example, Rodríguez-Rodríguez et al., (2024) had demonstrated in their studies that the efficacy of object detectors can be compromised by the presence of noise, which includes Poisson, Gaussian, salt-and-pepper and uniform noise. Object detection methods are generally less effective when they encounter higher levels of noise. Although a moderate quantity of noise may enhance detection in specific scenarios, excessive noise tends to decrease the model's confidence level and the number of detections. Moreover, the manual feeding mechanism of coins could possibly impact on the efficiency of the system as it will tend to make the calculation process slower. Last but not least, since the project only focused on three types of Malaysian coin denominations as well as being conducted in a single location, hence it somehow limits the scope of the study and the potential applications of the current coin counting system for small to moderate volume of coins that are typically seen in small or medium enterprises.

5.7 WAYS TO IMPROVE

In order to mitigate all the limitations that are currently faced by the machine vision coin counting system, firstly, the integration of a high-resolution camera, as described by Yang et al., (2022) will be useful for the precise identification and classification of various coin denominations based on their features since it is facilitated by the acquisition of detailed and clear images of coins through the use of a high-resolution camera in a coin counting system. Besides, the system is capable of accurately detecting and counting coins, even distinguishing between similar coins with subtle differences, due to the improved image quality. The camera's high sensitivity ensures precise coin identification, improving overall accuracy. It can record coin images quickly using a high-speed data transfer device like the spike camera. The system uses spiking neural networks (SNNs) for real-time analysis of visual information, allowing for accurate tracking and identification of coins. A dynamic connection gate with short-term plasticity (STP) eliminates irrelevant spikes. A three-layer fully linked SNN enhances precision in tallying and identifying coins, categorizing different types of coins. (Huang et al., 2023).

Lin Li et al., (2013) developed a diffuse light source to address specular and strong reflections on highly reflective surfaces like coins. This method reduces image highlights' brightness and ensures consistent lighting, enhancing clarity of coin features, decreasing picture saturation, and improving the machine vision coin counting system's ability to accurately count and recognize coins with reflecting surfaces.The above situation was also supported by D. Martin, (2013) where even, multi-directional illumination is provided by diffuse lighting, a frequently employed method in machine vision, which is particularly well-suited for objects with reflective or mixed reflectivity surfaces. Particularly effective for curved, specular surfaces and textured or topographic features on flat objects, it reduces shadows, enhances contrast and improves feature visibility. In general, diffuse lighting is essential for the accurate performance of machine vision inspections by improving image quality, reducing shadows and guaranteeing reliable illumination.

Moreover, in the context of a coin counting system, the utilization of a dome light would be advantageous over a ring light since it can offer even and scattered lighting across a wide surface. Utilizing dome lights is crucial for achieving precise coin identification and counting by reducing shadows, improving contrast and maintaining consistent lighting conditions. The omnidirectional characteristics of dome light minimize discrepancies in luminosity and shadows on the coins, hence enhancing the dependability of image analysis and counting outcomes D. Martin, (2013). Diffuse lighting is used to efficiently light glossy objects like coins, removing glaring highlights or shadows. This is achieved by using a dome lamp that casts light on the matte interior walls, enhancing the light intensity and providing a continuous level for the highest quality coin image, thus improving precision and effectiveness in coin counting. Lastly, in order to eliminate the manual feeding of coins into the machine vision coin counting system, the budget should be increased to ensure that it is automated to remove the setup time which will in turn enhance the efficiency of the coin counting system.

5.8 SUMMARY

Chapter 5 provides a detailed analysis of the machine vision coin counting system's thorough evaluation. The system's cost-effectiveness is emphasised by utilising affordable and easily accessible components, while also guaranteeing long-term durability and decreased maintenance expenses. In addition, the conversation about mobility highlights the system's emphasis on a lightweight design and the simplicity of transporting it, in contrast to larger mechanical alternatives. In addition, the system's speed and accuracy assessments demonstrate its capacity to rapidly and accurately count coins, but certain elements such as setup and ambient conditions need to be taken into account. The chapter also discusses constraints such as camera resolution and lighting difficulties, as well as the project's restrictions within the specified scope. It suggests enhancements such as using high-resolution cameras and optimised lighting sources to increase performance. In conclusion, the chapter reiterates the promise of machine vision systems to revolutionise coin counting operations due to their superior capabilities and adaptability.

CHAPTER 6

CONCLUSION AND RECOMMENDATION

6.1 DEVELOPMENT OF PORTABLE COIN COUNTING SYSTEM

At first, Solidworks aided in the construction of the portable coin counting device. The prototype was primarily constructed with aluminium 2020 profiles of varying lengths. The accurately shaped profiles were assembled using gussets, capscrews, and washers. The design of 3D printing components, such as an adjustable height mechanism and a camera attachment, was influenced by pre-existing models sourced from the internet. Next, the camera attachment was specifically engineered to secure the Sony PS3 Eye Webcam in position during coin detection. Besides that, precise positioning of the camera was enabled at a consistent height of 30 cm from the coin tray through the adjustable height mechanism. Moreover, a 10-inch commercial ring light was utilized as its main source of illumination. In addition, the coin tray was developed with a dual-layer structure to fit the limited field of vision of the camera. With that being said, the area where the camera could detect the coins ideally was located on the second layer. Also, the tray was specifically crafted with a black matte background to enhance contrast and minimize light reflection. In order to reduce the effects of shadows, the prototype was enveloped in black PP corrugated board, establishing a stable enclosed setting for the coin counting device. The LED ring light was altered to diminish glare and guarantee consistent illumination.

Following that, the Sony PS3 Eye webcam, functioning as the main visual input device was directly connected to the laptop through a USB connection to facilitate immediate data transfer. Subsequently, the laptop will utilise the computing power of AMD Ryzen 5 to execute machine vision algorithms in Python OpenCV for the purpose of coin identification and doing computations. Subsequently, Microsoft Excel processes, evaluates, and comprehends the outcomes. With the utilisation of this integration framework, it became possible to comprehensively quantify coins, encompassing the entire process from picture acquisition and processing to data arrangement and interpretation. System efficiency can be enhanced using specific tactics.

A portable coin counting system was built using the Sony PS3 Eye webcam, a 10-inch commercial ring light, and an AMD Ryzen 5 laptop processor. The device has specific design components to ensure effectiveness and efficiency in its operation. The system's usability and ability to efficiently connect visual input, data processing, and result recording were highlighted, hence enhancing its practical worth in many applications.

6.2 UTILIZATION OF IMAGE PROCESSING TECHNIQUES FOR MACHINE VISION COIN COUNTING SYSTEM THROUGH PYTHON OPENCV

First and foremost, Python OpenCV's image processing methods were utilised in a machine vision coin counting system, resulting in improved accuracy and efficiency in the automated coin counting process. The preprocessing procedures maintained crucial edge information by initially converting the image to grayscale. Subsequent adjustments to the brightness and contrast enhance the clarity of crucial components, hence aiding precise identification of coins.

The subsequent significant use of the Canny edge detection technique involves applying it to a blurred image, utilising gradient intensity and two thresholds to distinguish between strong and weak edges. Real-time threshold adjustments were utilised with a track bar to achieve precise segmentation, ensuring that only the edges of coins were detected and minimising potential errors. To enhance the precision of the system, Gaussian blur was employed prior to edge detection in order to refine edges and reduce noise.

After applying Canny's contour detection algorithm, we utilised dilation to increase the thickness of the detected edges. Subsequently, a morphological closing operation was performed to fill in any gaps and connect the edges. During this technique, the boundaries of the coins were accurately portrayed, thereby establishing the basis for precise analysis. Subsequently, the contour detection technique was discovered and the contours were classified in pre-processed images to provide a roster of contours for further scrutiny. The examination of every contour was conducted meticulously, employing approximating contours to simplify outlines and filtering forms based on the number of vertices. Each contour was analysed to determine its area, bounding box, and colour, providing essential information for identifying the coins.

The endurance of the system was proven by its ability to differentiate coins based on their weight and colour. The area of each identified contour was used as a measure of size variation, while colour information was utilised for the purpose of correctly categorising coins of different values. By integrating geometric information with colour attributes, this twin technique significantly enhanced the accuracy of coin identification and established a solid foundation for further research.

The final step in the coin counting system was to visually determine the aggregate worth of the coins displayed in the output image. A rectangle was superimposed on the shot to provide a distinct and visually evident depiction of the total monetary value of the discovered coins. In addition, enhancements were made to enhance the usability of the system and improve the clarity of the results. These enhancements include the ability to display and record the iteration number, the number of identified coins, the total amount of money, and the execution time.

The utilisation of image processing methods significantly improved the efficiency, accuracy, and utility of the machine vision coin counting system. This technological advancement represents a significant milestone in the automation of coin counting, since it offers enhanced speed and precision for various applications.

6.3 EVALUATION OF SPEED AND ACCURACY OF THE COIN COUNTING SYSTEM THROUGH VARIOUS SETS OF COIN VALUES

During the experimental phase, the system's performance, speed, and accuracy were evaluated by several tests, which were of crucial importance. The results demonstrated that the system's exceptional efficiency in analysing coin data allows it to calculate coins from five different sets with varying values in an average time of less than 0.013 seconds. Furthermore, under optimal circumstances, characterised by moderate brightness and a precise level of light intensity, the system achieved flawless accuracy of 100% in both coin detection and computation. This unequivocally showcases its reliability and robustness.

The machine vision coin counting system proved to be the most sophisticated option compared to other coin handling technologies. The coin handling system stands out due to its mobility, affordability, exceptional speed, and accuracy. It surpasses other technologies that were previously studied, making it the most optimal and best choice.

Despite its benefits, the system had specific limitations that might potentially undermine its functionality. These obstacles consisted of issues related to image quality caused by the camera's restricted resolution, as well as challenges regarding illumination and camera location. Various improvements were being considered to address these limitations and boost the system's performance. To improve image quality and achieve this goal, it is advisable to utilise a camera with a greater resolution. Additionally, a diffuse light source can be utilised to reduce glare and improve visibility. In order to enhance efficiency, it may be advantageous to automate the coin feeding system.

The speed and accuracy of the coin counting system were examined, highlighting its efficiency and potential in future applications. By addressing its limitations and implementing necessary improvements, the system has the potential to further boost its performance and serve as a valuable tool for counting coins in various environments.

6.4 FUTURE RECOMMENDATIONS

Primarily, this study establishes a solid foundation for future research and advancements in the field of coin recognition, differentiation, and computing. It is often recommended to incorporate a greater variety of coin values and denominations. This development has the potential to enhance the practicality of the current project in real-world scenarios, hence expanding its practical capabilities in various applications.

Furthermore, future initiatives could prioritise the identification and distinction of genuine and counterfeit coins. This is designed to help solve issues related to counterfeit coins. In conclusion, this research significantly impacts the field of coin detection and contributes to the development of more reliable and efficient coin recognition systems through its recommendations.

6.5 SUSTAINABLE DESIGN AND DEVELOPMENT

A coin counting system that utilises machine vision technology integrates sustainable design principles by prioritising environmental awareness, economic efficiency, and social responsibility. This method aims to meet consumer demands while reducing environmental impact and promoting long-term ecological balance. The project ensures that both the hardware and software components of the system are cost-effective, environmentally friendly, and easily accessible.

Firstly, through using a software-based solution and machine vision technology, the system greatly enhances the environmental sustainability. The portable coin counting system improves recyclability and material economy by using aluminium profiles in a compact and lightweight design. Its enclosed design also decreases the effect of outside elements like light and shadow, therefore saving energy and lessening the demand for high-power lighting. Not only that, the components that are fabricated through 3D printing can significantly reduce material waste, energy used and carbon emissions (Nadagouda et al., 2020).

Besides, economic sustainability is achieved through the creation of an affordable and efficient coin counting system that is easily adopted by small enterprises and companies. Traditional coin counting systems can be expensive, especially for small businesses that require accurate and reliable solutions. The project offers a cost-effective alternative by utilising inexpensive components such as the Sony PS3 Eye Camera and commercially available LED ring lights, along with open-source software like Python OpenCV. In addition, the system's portability enhances its economic viability by eliminating the need for several fixed installations and enabling flexible deployment across various locations.

Next, by designing a user-friendly and easily available coin counting system that streamlines coin management for different users, including those with minimal technological knowledge, social sustainability is addressed. Together with the obvious result visualisation, the system's simple design guarantees that users may count coins rapidly and precisely without extensive training to be undergone. Furthermore, dependence on software updates for enhancements and upkeep minimises the necessity for regular physical interventions, rendering it a sustainable solution in terms of both usability and long-term maintenance.

6.6 COMPLEXITY

The project encompasses a range of intricate engineering tasks, such as the development of advanced algorithms and the creation of accurate experimental settings. To distinguish between similar coins, it is necessary to use highly efficient algorithms and ensure that the camera is positioned accurately to reduce variations in image capture. In order to enhance accuracy and minimise interference, it is necessary to encapsulate the system to exclude external illumination factors. Each of these tasks requires meticulous planning, exacting control and sophisticated problem-solving skills in order to attain dependable and precise outcomes in the coin counting system.

The development of a coin counting system using machine vision presents significant engineering challenges, primarily due to hardware limitations and the nature of coins being analyzed. The use of a low-resolution Sony PS3 Eye Webcam restricts the quality of captured images, making it difficult to accurately identify and count coins. Additionally, the reflective properties of metallic coins create glare and distortions, further complicating image analysis. These limitations necessitate precise calibration and optimization of lighting conditions, such as achieving the right balance to avoid overexposure or inadequate illumination.

In order to surmount these obstacles, it is imperative to incorporate a high-resolution camera. High-resolution cameras produce intricate images, allowing sophisticated image-processing algorithms to enhance accuracy in coin identification and counting. In addition, the utilisation of diffuse lighting methods, such as dome lights, can diminish shadows and glare, hence improving image quality and guaranteeing uniform lighting conditions. Implementing automation in the coin feeding mechanism can enhance system efficiency hence enabling faster and more precise counting.

6.7 LIFELONG LEARNING AND BASIC ENTREPRENEURSHIP

The suggested enhancements for the coin counting system, such as the integration of high-resolution cameras and enhanced illumination techniques, greatly increase the long-term viability of the project. These enhancements not only tackle existing constraints but also lay the groundwork for future progress in machine vision technology. To continuously improve the system and keep it useful and relevant, practitioners should stay updated on the newest advancements in high-resolution imaging and diffuse lighting techniques. The dedication to continuous learning and adjustment emphasises the significance of lifelong learning in upholding the effectiveness and precision of the system, ultimately resulting in more resilient and enduring solutions.

The machine vision-based coin counting system has significant potential for implementation in small and medium-sized organisations (SMEs) as well as for individual users. This system provides an effective and precise solution for small and medium-sized enterprises, especially those that handle moderate amounts of coins, to optimise their cash handling procedures. Machine vision technology offers automated and precise capabilities that can effectively save labour expenses and minimise inaccuracies in counting. For individual users, the system can function as a simple tool for overseeing personal coin collections or conducting small-scale transactions. The system's scalability and versatility make it an appealing product for commercialisation, as it has the potential to serve a wide market segment that is looking for efficient and dependable coin counting solutions.

6.8 SUMMARY

The project successfully developed a portable coin counting system using Python OpenCV, showcasing the potential of image processing techniques in automating coin counting tasks. The system demonstrated exceptional speed, accuracy and usability, making it particularly beneficial for SMEs or even individuals which are dealing with small to moderate volume of coins daily. Despite notable limitations such as issues with image resolution, complex illumination conditions and the intricacy of the setup process, the system demonstrated exceptional performance, especially when compared to existing coin handling techniques. Future recommendations seek to enhance the ability of the coin counting system to identify counterfeited coins and broaden its scope to accommodate additional currency denominations, hence enhancing its application in the domain of coin recognition.

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APPENDICES

A Full Table of Comparison between Various Types of Coin Handling Technologies

Authors	Year	Key Techniques	Findings	Controversies
Mechanical Based Coin Handling Systems				
Zhao et al.	2017	Coin Sorting and Counting Based on Coin Aperture Sizes	-Inclined vibrating sieve plates for coin sorting and counting.	-Only applicable for currency and coin conditions sensitivity.
Dabhade et al.	2020	Diameter Based Coin Sorter	-Vertically positioned coin collecting receptacles sort coins by diameter using rollers or sensors.	-
Han & Liu	2021	Diameter Based Coin Sorting Machine	-Coin storage box with sieve plates for sorting by size.	-
Tsuchida et al.	2013	Coin Sorter based on Magnetic Properties	-Movable magnet to distinguish low magnetic coins, which reduced costs and allowed for easy adjustments.	-Precision influenced by coin velocity, potentially leading to misclassification.
Sensor Based Coin Handling Systems				
Borg et al.	2017	Optical Coin Discrimination System	-Optical sensor sorts coins by image-capturing, algorithm calculates diameters, log-polar transform aids checking and Fourier transform in spectral peaks analysis.	-Practical constraints may include the need for high-quality images and precise determination of spectral peak positions and intensities.
Martin	2013	Coin Counting System by using Auto-Positioning Sensor	-Coin sensor in mobile device for autonomous adjustment of position to coincide with the centre of a coin passing through the coin path.	-
Microcontroller Based Coin Handling Systems				
Goh	2016	Coin Sorting and Counting System by using Arduino UNO	-Security door with a password. -Sorts six Malaysian coins and rejects foreign or fraudulent ones and outcomes sent to a computer.	-
A. Paramasivam et al.	2021	Coin Sorting Machine with Arduino UNO	-Lining mechanism to quantify various coin denominations. -Prevents coin mixing through a picture sensor and servo actuators.	-
Jayanthi et al.	2021	Coin Sorting and Counting System by Maker NANO	-Slope-like configuration for various coin denominations. -Four infrared sensor modules detect coins and increment the tally.	-
Dr Daula et al.	2022	Comparison Between Arduino UNO, Maker	-Evaluates capabilities of the three microcontrollers.	-

		NANO, and Raspberry PI as the Embedded Processors	-Arduino UNO is chosen considering cost, design complexity, efficiency and precision.	
Electromagnetic Based Coin Handling Systems				
Dao et al.	2022	Electromagnetic Acoustic Transducer (EMAT) Counterfeit Coin Identification System	-Novel counterfeit coin identification method. -Achieves 98.5% accuracy in coin classification based on experimental results.	-Considers system cost, complexity, wear impact, and precision equipment needs, while facing challenges in detecting small cracks due to efficiency and signal-to-noise ratio issues.
Digital Based Coin Handling Systems				
Krishna et al.	2019	FPGA Based Coin Recognition and Counting System	-Counts diverse Indian coins by variations in size, shape, colour, grime and scratches. -FPGA block memory and Verilog image enhancement techniques, integrating Basys 3 FPGA with an OV7670 camera for portability.	-
Deep Learning Based Coin Handling Systems				
Putra	2023	CNN Algorithm Coin Classification System	-Two convolution layers, one subsampling layer, and two fully connected layers, effective for distinguishing similar coins and achieving accurate predictions for Indonesian Rupiah coins.	-Narrow classification task covering only five-coin classes. -Dataset size limitations and exclusive focus on Indonesian Rupiah coins.
Bawa & Modi	2011	ANN Technique Coin Recognition System	-ANNs address rotation invariance for recognizing Indian coins. -High identification rate of 97.74% with minimal false positives.	-Constraints in feature extraction documentation and potential adaptability issues for other coins.
Malik et al.	2014	ANN Technique Coin Recognition System	-ANN based on a multi-step approach for coin recognition. -Employs unequally spaced frequency Fourier transform for feature extraction and rotation-invariant neural network training.	-Lack of empirical testing, mainly relying on static image datasets. -Need for exploration of real-world implementations and testing accuracy.
Kaur & Kaur	2015	Artificial Neural Networks (ANNs) with Polar Harmonic Transform (PHT) Coin Recognition System	-ANNs and the PHT algorithm for rotation invariance. -Achieves high accuracy of 98% in identifying various coin denominations.	-Concerns in system's generalization to other countries' coins due to the limited dataset.

				- Insufficient practical evaluation.
Rosidi et al.	2022	Deep Pre-trained CNN Models Coin Recognition System	-Deep pre-trained CNN models for Malaysian coin recognition and show effectiveness. -GoogLeNet stands out with accuracy of 99.2%, surpassing AlexNet and MobileNetV2.	-Integration with embedded systems and potential clinical testing on visually impaired subjects suggested for future work.
Qiu et al.	2017	CNN Technique Coin Recognition System	- Uses Hough detection, radius ratio, colour features, and relative position constraints for identifying Chinese and Hong Kong coins. -Final recognition and classification performed using CNNs.	- Challenges related to coin recognition in real-world images. -Efficacy under complex illumination conditions or backgrounds.
Capece et al.	2016	CNN Technique Coin Recognition System	-Explores the application of CNNs, AlexNet, in automatic coin recognition on mobile devices within a client-server architecture. -Optimal training dataset size for high classification accuracy.	- Optimal model performance achieved when trained on 70–80 coin images with moderate to light wear.
Katariya et al.	2022	CNN Technique Coin Recognition System	-Deep learning approach by integrating LSTM cells and CNNs, to recognize Indian coins. -Addresses challenges related to illumination, scale, and orientation variations using CNNs and achieves a 98.5% accuracy.	- Drawbacks of CNN-based systems, particularly the fixed receptive field, acknowledged.
Fanca et al.	2022	Coin Detection and Counting System using Tensorflow and Keras	-TensorFlow and Keras enhanced model sophistication, simplified training with transfer learning support, and improved accuracy through scalability and flexibility. -Attained 85% high accuracy in coin classification task.	-Brightness, luminosity, and reflective backgrounds affected accuracy, necessitating diverse training data. -Overfitting and overlapping coins reduced model precision and performance.
Roomi & Rajee	2015	MLBPN Technique Coin Recognition System	-Rotationally invariant coin recognition through MLBPNN, with Fourier approximation of coin images to extract rotation-invariant features and achieves accuracy of 98.5% in identifying various denominations of Indian coins.	-Concerns about generalizability to coins from different locations and lack of comparative analysis with established algorithms.
Kim & Park	2020	DDR-Coin Algorithm Coin Handling System	-Probabilistic distributed trigger counting (DTC) algorithm in sensor-based	-

			monitoring systems, optimizing communication loads with superiority in received message load and complexity.	
Schlag & Arandjelovi´c	2017	Deep Convolutional Network for Face Profiles Recognition in Coins	-Profile face recognition with a deep convolutional network to determine the issuing authority on Roman Imperial coins, showcasing effectiveness in accuracy and robustness with annotated datasets.	-Further exploration on alternative coin types and potential datasets. -Additional attributes, like reverse designs or inscriptions.
Image Processing Based Coin Handling Systems				
Khazaee et al.	2021	3D Height Map Image Analysis Method Coin Identification System	-Utilizes 3D scanning, Fuzzy C-Means algorithms and an ensemble classifier for precise counterfeit coin detection, surpassing SVM, KN, and Random Forest by analyzing cliff-like borders on coin surfaces.	-
Kumar et al.	2018	HOG and SVM Algorithm Coin Identification and Counting System	-An automated system for precise identification and quantification of Indian Rupee coins by using HOG for feature descriptor and SVM for coin classification. -Achieves high accuracy in coin recognition through cross-validation.	-Explicit design of Indian coins raises questions about applicability. -Lack of rotation invariance in HOG poses challenges for rotated coins.
Kim et al.	2015	RFR Technique Based Coin Recognition System	-Addresses rotation-invariance challenges for accurate coin recognition regardless of orientation by using Sobel operator, Local Difference Magnitude Transform (LDMT) and concatenation of it for feature vectors.	-Potential objections and research gaps, including the lack of direct comparison with established benchmarks.
Salehittal et al.	2019	Edge Detection Coin Categorization and Counting System	-Comprehensive coin categorization and counting system using ML-CPNN and edge detection methods such as Robert's, Laplacian of Gaussian and Canny; achieves 99.5% accuracy when trained on diverse dataset. -Features like shape, size, surface and weight for coin classification.	-Reliance on high-quality images. -Debate on the trade-off between computing efficiency and accuracy in edge detection.
Kushwaha et al.	2023	Edge Detection Algorithms (Laplacian of Gaussian, Sobel, Canny) Coin Identification System	-Edge detection algorithms to identify and total Indian Rupee coins through database matching, replacing manual and error-prone methods, and locating coin edges in rapidly changing intensity regions.	-Potential challenges in acquiring substantial training data for accurate recognition of valuable waste items.

Dīnēshchandra Jōshī et al.	2016	Real Time Coin Detection and Counting System via Machine Vision Based	-Accurately classified and counted coins based on dynamic imaging at high speed by differentiating denominations based on their features.	-Accuracy impacted by quality of training set (differentiation between valid and invalid values) -Algorithms missed coins and miscounted at higher FPS.
Rangan	2018	Coin Counting System via Machine Vision Based	-LabVIEW-controlled for currency coin separation, integrating edge detection, template matching, servo mechanism, and IR sensors for accurate counting, causing time efficiency, cost-effective automation and precision.	- Challenges include one-time high investment and potential sensor failures leading to inaccuracies.
Zhang et al.	2019	Machine Vision Based Coin Sorting Device	-Image recognition, manipulators, suction nozzles, an industrial computer, stepper motors, and electromagnetic valves by coin denominations.	-Image recognition algorithms adaptability to diverse coin types needs to be improved.
Kumar et al.	2022	Vision System for Coin Identification from Scrap Metals	-Identify and categorize photos of coins from scrap pieces using a vision system with machine learning libraries which allows for rejection of classifications for scrap bits that resemble coins.	
Kavitha et al., (2022)	2022	Smart Coin Classification System through OpenCV and Arduino	-Computer vision techniques and embedded programming using Arduino to automate the identification and sorting of coins.	-System's generalization to other countries' coins. -Speed could be improvised through updated software and hardware improvements.

B Python Script Coding for Machine Vision Coin Counting System

~\Desktop\Development of Coin Counting System by Using Machine Vision.py

```python
import cv2
import cvzone
import numpy as np
import pyautogui
import math
import time
from cvzone.ColorModule import ColorFinder

cap=cv2.VideoCapture(1)
cap.set(cv2.CAP_PROP_FPS,20)

totalMoney=0
totalExecTime = 0
numIterations = 0

myColorFinder=ColorFinder(False)
hsvVals={'hmin': 6, 'smin': 48, 'vmin': 59, 'hmax': 37, 'smax': 163, 'vmax': 255}


def empty (a):
    pass

cv2.namedWindow("Settings")
cv2.resizeWindow("Settings",640,240)
cv2.createTrackbar("Threshold1" , "Settings" , 100,255, empty)
cv2.createTrackbar("Threshold2" , "Settings" , 206,255, empty)

def preProcessing(img):

    # Convert the image to grayscale
    imgPre = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

    contrast = 2.5; brightness=1.5    # TODO: adjust this if you want to increase the contrast & brightness
    imgPre = cv2.addWeighted(imgPre, contrast, np.zeros(imgPre.shape, imgPre.dtype), 0, brightness)


    imgPre=cv2.GaussianBlur(imgPre,(5,5),5)
    imgBlur = imgPre


    thresh1=cv2.getTrackbarPos("Threshold1", "Settings")
    thresh2=cv2.getTrackbarPos("Threshold2", "Settings")
    imgPre=cv2.Canny(imgPre, thresh1, thresh2)

    kernel=np.ones((3,3), np.int8)
    imgPre=cv2.dilate(imgPre,kernel,iterations=1)
    imgPre=cv2.morphologyEx(imgPre,cv2.MORPH_CLOSE, kernel)

    return imgBlur, imgPre

iterations = 1

while True:

    success, img=cap.read()

```

```
    #########
    start_time = time.time()    # start the time once the program successfully read the img

    # Crop Img

    x=180; w=330; y=90; h=290    # TODO: Adjust this to set the coins target region
    img = img[y:y+h, x:x+w]

    imgBlur, imgPre=preProcessing(img)
    imgContours, conFound=cvzone.findContours(img,imgPre,minArea=1000,retrType=cv2.RETR_EXTERNAL,approxType=cv2.CHAIN_APPROX_NONE)

    totalMoney=0
    coin_detected_count = 0
    imgCount = np.zeros ((480,640,3), np.uint8)

    if conFound:
        for contour in conFound:
            peri=cv2.arcLength(contour['cnt'], True)
            approx=cv2.approxPolyDP(contour['cnt'], 0.02 * peri, True)

            if len(approx)>5:
                area=contour['area']
                area_x, area_y, area_w, area_h = contour['bbox']

                # Detecting the amount of pixels with gold color
                imgCropArea = img[area_y:area_y+area_h, area_x:area_x+area_w]
                imgColor, mask = myColorFinder.update(imgCropArea, hsvVals)
                whitePixelCount = cv2.countNonZero(mask)

                # print(f'area = {area}; pixel count = {whitePixelCount}')

                if whitePixelCount<1000:  # silver: 0.10
                    totalMoney +=0.10
                else:  # gold: 0.20 / 0.50
                    if area>3100:
                        totalMoney +=0.50
                    else:
                        totalMoney +=0.20

                coin_detected_count += 1

    exec_time = (time.time() - start_time)

    totalMoney = round(totalMoney,2)
    exec_time = round(exec_time,6)
    # print("Total Money = ", totalMoney)
    # print("Time= ", exec_time)
    print(f"Iteration={iterations}; No. of Coins Detected={coin_detected_count}; Total Money={totalMoney}; Execution Time={exec_time}")

    with open('coin_counting_output.txt', 'a') as file:
        file.write(f"Iteration={iterations}; No. of Coins Detected={coin_detected_count}; Total Money={totalMoney}; Execution Time={exec_time}" + '\n')

    imgStacked = cvzone.stackImages([img,imgBlur,imgPre,imgContours], 2,1)
    height, width, _ = imgStacked.shape
    screen_width, screen_height = pyautogui.size()  # Set your desired screen dimensions

    # Resize the stacked image if it exceeds the screen size
    if height > screen_height or width > screen_width:
```

```python
        imgStacked = cv2.resize(imgStacked, (screen_width, screen_height))


    cvzone.putTextRect(imgStacked,f'RM {totalMoney}', (420,250), scale=1.7)
    cvzone.putTextRect(imgStacked,f'Time: {exec_time} s', (360,290), scale=1.7)


    cv2.imshow("Image", imgStacked)

    iterations += 1

    if cv2.waitKey(1) != -1:
        break

cap.release()
```

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