Faculty of Electronics and Computer Technology and Engineering

HARDWARE DEVELOPMENT OF NUT COUNTING SYSTEM USING COMPUTER VISION METHOD

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Bachelor of Computer Engineering Technology (Computer Systems) with Honours

2024

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A project report submitted
in partial fulfillment of the requirements for the degree of
Bachelor of Computer Engineering Technology (Computer Systems) with Honours

Faculty of Electronics and Computer Technology and Engineering

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

2024

UNIVERSITI TEKNIKAL MALAYSIA MELAKA
FAKULTI TEKNOLOGI DAN KEJURUTERAAN ELEKTRONIK DAN KOMPUTER

BORANG PENGESAHAN STATUS LAPORAN
PROJEK SARJANA MUDA II

Tajuk Projek : Hardware Development of Nut Counting System Using Computer Vision Method

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Supervisor Name : Dr. Suhaila Binti Mohd Najib

Date : 14/1/2024

DEDICATION

To my beloved mother, Rahimah Binti Ramly, and father, Zaini Bin Mohd Noor who gave me so many words of encouragement as I completed my final year project.

ABSTRACT

Counting system manually is very diffcult this is because of small metal and need to memorize for a long time. There is pressing need to develop an optimized hardware solution that utilizes computer vision techniques This project focuses on creating a system to count hexagon nuts on a conveyor belt. By utilizing Raspberry Pi as the main controller, the aim is to automate the nut counting process in industrial environments, leading to improved efficiency and accuracy. The system employs computer vision algorithms to detect and track individual nuts as they move along the conveyor. By combining the hardware capabilities of Raspberry Pi with object detection, the system achieves real-time nut counting with a high level of accuracy. The project covers various aspects such as capturing images, preparing them for analysis, detecting objects, and implementing counting algorithms.. This work contributes to the field of computer vision and offers a practical solution for automating nut counting in industrial settings.

ABSTRAK

Sistem pengiraan secara manual adalah sangat sukar ini kerana logam yang kecil dan perlu menghafal dalam jangka masa yang lama. Terdapat keperluan mendesak untuk membangunkan penyelesaian perkakasan yang dioptimumkan yang menggunakan teknik penglihatan komputer Projek ini memberi tumpuan kepada mencipta sistem untuk mengira hexagin nut pada tali pinggang penghantar. Dengan menggunakan Raspberry Pi sebagai pengawal utama, matlamatnya adalah untuk mengautomasikan proses pengiraan nut dalam persekitaran industri, yang membawa kepada kecekapan dan ketepatan yang lebih baik. Sistem ini menggunakan algoritma penglihatan komputer untuk mengesan dan mengesan nut individu semasa ia bergerak di sepanjang penghantar. Dengan menggabungkan keupayaan perkakasan Raspberry Pi dengan pengesanan objek, sistem ini mencapai pengiraan nut masa nyata dengan tahap ketepatan yang tinggi. Projek ini merangkumi pelbagai aspek seperti menangkap imej, menyediakannya untuk analisis, mengesan objek, dan melaksanakan algoritma mengira.. Kerja ini menyumbang kepada bidang penglihatan komputer dan menawarkan penyelesaian praktikal untuk mengautomasikan pengiraan nut dalam tetapan industri.

ACKNOWLEDGEMENTS

First and foremost, I would like to express my gratitude to my supervisor, Dr Suhaila Binti Mohd Najib for their precious guidance, words of wisdom and patient throughout this project.

I am also thanks to my father Zaini Bin Mohd Noor for the financial support which enables me to accomplish the project. Not forgetting my fellow roommates for the willingness of sharing her thoughts and ideas regarding the project.

My highest appreciation goes to my parents, and family members for their love and prayer during the period of my study. An honourable mention also goes to my parent for all the motivation and understanding.

Finally, I would like to thank to my supervisor Dr.Suhaila Binti Mohd Najib for always advised and helped me. Thanks to all my friends who are not listed here for being co-operative and helpful.

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CHAPTER 1

INTRODUCTION

1.1 Background

The performance of the workforce plays a vital role in evaluating the ongoing production of industrial goods in relation to the desired output. If the performance falls below or exceeds a certain threshold, it is likely to lead to a corresponding decline in productivity.(Rozikin et al., 2021). Currently the work of nut counting at production establishment is done manually, easy to lose and difficult for operator when they have to count and memorize for a long time. Next, for safety requirements, operators don't need to stand near the moving conveyor belt to count nuts one by one. Advancements in counting algorithms, computer technology, and camera technology have recently led to the development of counting using imaging methods. Computer vision techniques have been suggested and applied in automated count systems to effectively count objects. Computer vision encompasses a wider range of technologies, including three-dimensional imaging and spectral imaging, while machine vision typically refers to computer vision used in conjunction with conveyor-based machinery. The trend of counting objects using image processing and machine vision has gained momentum due to its automatic, cost-effective, and non-destructive measurement capabilities (Baygin et al., 2018). The purpose of the project aims to create a conveyor-based automated counting system that could calculate the number of nuts present. The computer vision technology used for the counting procedure included the detection and counting of images of nuts. In order to do this, a counting algorithm was designed and implemented into application using the Python programming language, with Raspberry Pi operating as the basis of the algorithm. An important factor to take into consideration is the connectivity between the processing unit and the cameras.

1.2 Safety Issues in Industry

Every year, a considerable number of life-altering injuries and fatalities occur due to direct interaction with machinery and powered equipment. Many of these incidents occur in relation to conveyor systems (*Best Practices on Conveyor Safety*, n.d.).To count manually on moving conveyor belt is very dangerous for a several reason, for first of all, the conveyor's moving nature increases the possibility of accidental contact with the counting equipment, which can result in damage to workers or damage to the equipment itself. Furthermore, the existence of other machinery and equipment near the conveyor might add to the possible risks and increase the chance of an accident. It is essential for industries to prioritize the well-being of their workers by maintaining a safe and hazard-free factory environment. Counting nuts can be done automatically by this system.

1.3 Problem Statement

In industrial settings, manually counting small objects like nuts is labor-intensive, slow, and prone to inaccuracies(Pearson et al., 2012). Accurate counting is crucial in industries such as manufacturing, electronics, agriculture, medicine, and food, where precise quantification of items like hardware, electronic components, and other standardized materials is necessary. (Xiao et al., 2021).The manual counting of nuts in industrial settings pose significant challenges, including time-consuming processes, error-prone operations, and labor-intensive tasks that impede productivity and introduce inefficiencies(Xiao et al., 2021). Consequently, there is a pressing need to develop an optimized hardware solution that utilizes computer vision techniques to overcome these limitations. This solution aims to accurately detect nuts on a conveyor belt by leveraging a pre-trained model, specifically YOLOv5, and seamlessly integrating it into a Raspberry Pi for real-time nut counting. This project aim is to design and implement an automated nut counting system that enhances productivity, reduces errors, and streamlines production processes in industrial settings. By addressing these challenges, its offer an innovative and efficient approach to nut counting, improving the overall operational efficiency and performance within industrial environments.

1.4 Project Objective

This thesis aims to achieve the goal of creating an optimized hardware solution for a nut counting system through the utilization of computer vision techniques.

a) To detect nuts on the conveyor based on pre-trained model YOLOv5.

b) To deploy the model into the Raspberry Pi for real time nut counting

1.5 Scope of Project

The scope of this project are as follows:

a) Nut detection on moving conveyor belt

b) Nut detection is based on hexagon shape.

c) The 510 dataset split into three categories.

d) 90% of images are the training dataset, 3% images is the validation dataset and 6% is test.

1.6 Summary

To put it simply, this project aims to create a hardware system that employs computer vision techniques for automated nut counting. By addressing the limitations of manual counting, this purposed system improves accuracy, efficiency, and cost-effectiveness, offering significant advantages to industries relying on precise nut counting in their everyday activities.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

A literature review provides a summary of existing journal articles and research papers. For this chapter focuses on the project's theory on the detection and counting using difference application. In industry there are many types of applications that have been used to detect and count objects. Object detection and counting are also used in a variety of industries, production, logistics, retail, food and beverage and others (Rozikin et al., 2021). This is used to monitor inventory levels, track the movements of goods, and ensure that the correct number of products are being manufactured and shipped to the supplier. In object detection it can also detect the size, shape, and location of an object. To make sure all projects are successful the project also needs to be clearly and make sure it This information can be used to optimize production processes, improve quality control, and identify potential issues or anomalies in the manufacturing process.

2.2 Understanding Safety Issues in The Literature

A safety system must be developed in each project to guarantee that it can be used properly. Accidents and injuries can be reduced or prevented entirely by installing an adequate safety system. This includes detecting workplace dangers, assessing risks, and putting appropriate preventative measures in place. Furthermore, thorough safety training and an advanced level of knowledge of safety practises are essential for including all stakeholders in the project. By putting safety first, projects may go smoothly and without interruptions, protecting the well-being of everyone involved.

2.3 Previous work on counting objects on various applications.

2.3.1 Convolutional Neural Network for Counting Fish in Fisheries Surveillance Video.

This article introduces a computer vision tool designed to analyze video footage from CCTV systems on fishing trawlers, specifically to monitor discarded fish. The system aims to assist expert observers in verifying the number, species, and sizes of the discarded fish. However, the operational environment presents challenges such as fish being processed below deck with varying lighting, random orientations, and occlusions.

To address these challenges, the article proposes an approach that uses the N 4 - Fields algorithm for segmenting the scene and counting fish. Extensive tests on a dataset with 443 frames from 6 belts demonstrate a relative count error ranging from 2% to 16% for individual fish. This system is considered the first to handle footage from operational trawlers.(French et al., 2015)

2.3.2 Object detection and Counting in Image

This paper implemented object detection using OpenCV and TensorFlow in Python. This focused on counting different types of fruits on a tree using the YOLO (You Only Look Once) framework. This paper learned about algorithms like Convolutional Neural Networks (CNN), Artificial Neural Networks (ANN), and YOLO for object detection and counting. Algorithm identifies specific fruits on a tree and calculates the total count of each fruit with an accuracy of around 97%. This paper made necessary content and organizational edits before final formatting. The code utilized a blob detection network and integrated the YOLO framework for accurate counting. This paper tested the code on an image of apples on a tree in Figure 2.1, and the resulting count is shown in Figure 2.2. This paper ran the code using

Anaconda Prompt and utilized YOLO libraries for configuring different layers and weights.(Shah et al., 2021)

Figure 2.1: Apple detection and count using YOLO (Shah et al., 2021)

Figure 2.2: Output count (Shah et al., 2021)

2.3.3 A system for a Real-Time Electronic Component Detection and Classification on a Conveyor Belt.

Several studies have proposed deep learning solutions for object detection on printed circuit boards (PCBs), but their practical implementation in embedded systems and real-time applications is not well-explored. Additionally, there is a need for diverse and regularly updated datasets to effectively train these models.

This paper presented a real-time system for counting moving electronic components on a conveyor belt. It compared the performance of different deep learning models (InceptionV3, SSD, YOLO) in terms of mean average precision (mAP) and inference time.

The authors collected and augmented a dataset using MATLAB, implemented the algorithms using PyTorch and Keras, and conducted experiments on Google Colab and Nvidia Jetson.

The results demonstrated that the proposed system, utilizing a camera and CNN model, met the requirements for real-time object detection and counting of surface-mount device (SMD) components on a conveyor belt. Different algorithms and hardware setups achieved the highest mAP scores for various component types.

In conclusion, this paper showed the feasibility of a low-cost integrated system for real-time object detection and counting of SMD components in an industrial environment. It provided insights into the performance and suitability of different deep learning models. The authors emphasized the need for diverse datasets and regular updates to ensure practical implementation of object detection methods.(Varna & Abromavičius, 2022)

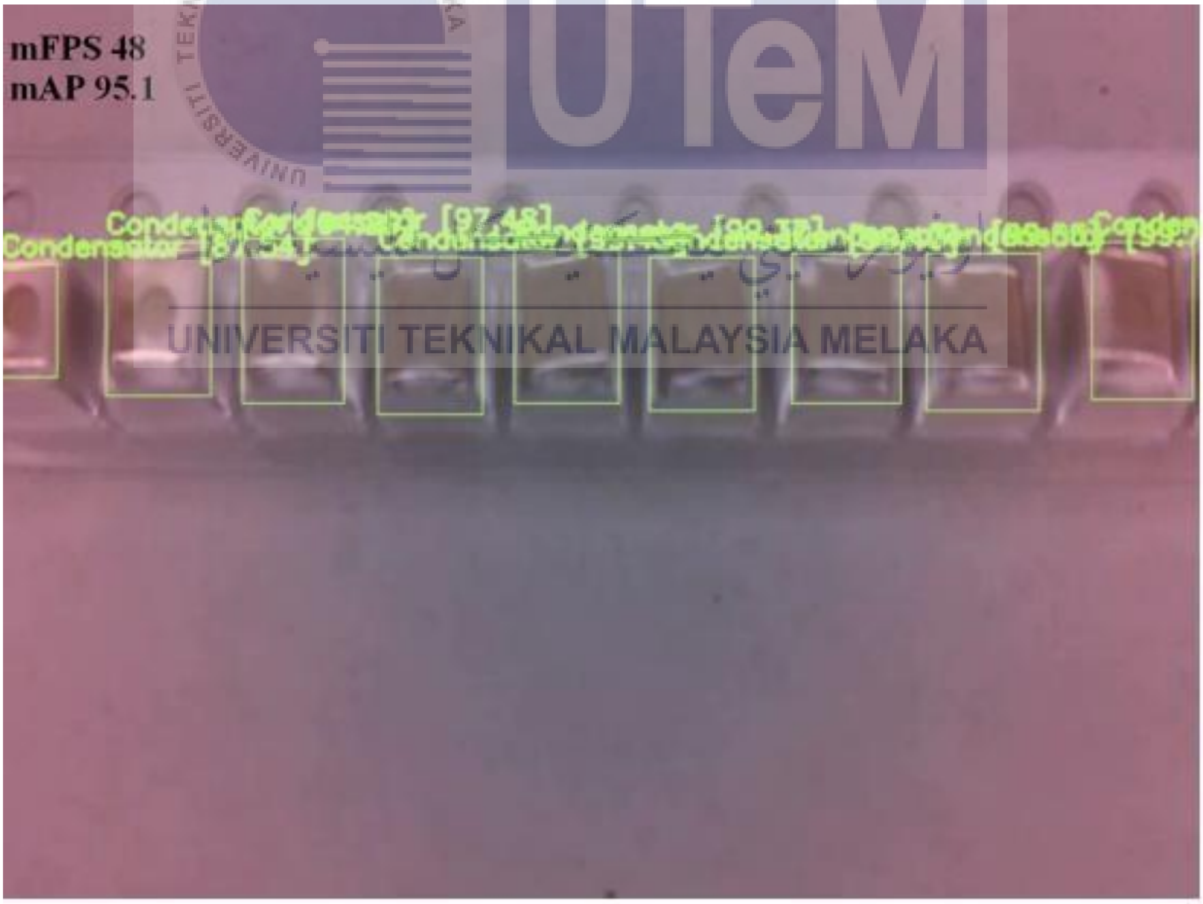


Figure 2.3: Frame of electronic component detection input using YOLOv4 architecture (Varna & Abromavičius, 2022)

2.3.4 Object Detection, Segmentation & Counting Using Deep Learning.

This project proposes a simple method for automatically detecting objects, segmenting them using pixel-wise masks, and determining the count of objects in an image. The approach utilizes the Mask R-CNN method, which is easy to train and operates at a speed of 5 frames per second. The method builds on established techniques like Faster R-CNN and FCN, which offer flexibility and efficiency in target recognition and semantic segmentation. The aim is to develop a similarly effective framework for instance segmentation.(S & Nataraj, 2018)

2.3.5 Efficient Fruit and Vegetable Classification and Counting for Retail Application Using Deep Learning.

Efficient Fruit and Vegetable Classification and Counting Retail Application using Deep Learning is a system that present hybrid model, which resolves classification and counting using data collected from a simple camera added to a scale. More specifically, while ongoing operation, the product image and associated weight are collected. Without a bar code, the model can swiftly identify products crossing the scale in a matter of seconds. As a result, object classification is possible on CPUs with just one core or even in real time Coral Ai Edge TPU.(Bogomasov & Conrad, 2021)

2.3.6 Design and Implementation of PLC Based Item Counting Sytem

The paper presents a machine designed for automated counting of items during manufacturing processes. This machine replaces the need for manual counting, resulting in time savings and reduced human labor. It consists of photoelectric sensors, a Programmable Logic Controller (PLC), and a 12V DC Gear Motor.

The photoelectric sensors provide information to the controller, while the DC gear motor moves the conveyor belts based on commands from the control system. The sensors feed data to the control system, and the conveyor belt transports items to be placed into specific paper boxes.

Control of the hardware system is achieved using a Kinco-K2 series PLC device, and a Ladder Diagram is employed for the counting system. The system has five inputs (push buttons, two photoelectric sensors, and a limit switch) and four outputs (DC gear motor, indicators, and a buzzer), as illustrated in the block diagram.

In the prototype, a CDD11N photoelectric sensor is positioned beneath the upper belt to detect and count items before they are deposited into the box. When the conveyor is in operation, a filled box reaches the end, triggering the limit switch. This signal prompts the PLC to halt the conveyor and activate the buzzer.

The item counting system demonstrates precise counting results and is suitable for both small-scale and complex production lines. It finds applications in various industries such as food packaging, tablet counting, and bottle filling, where PLC control is prevalent. PLC programs allow for systematic planning, and the widely adopted Ladder Diagram simplifies programming for electronic and electrical engineers.

By implementing this automated counting system using a PLC, the paper's approach achieves time savings, reduces human effort, and enhances counting accuracy through automation. The system offers high effectiveness and precision in item counting tasks.(Thae et al., n.d.)

2.3.7 Automated Conveyor Belts for Object Counting In Small Scale Industries.

The paper emphasizes the significance of precise quantity measurements in product manufacturing, specifically in small-scale and large-scale industries. It proposes an IR sensor and microcontroller-based system to count objects on a conveyor and display the count on an LCD screen. The objective is to enhance production statistics and ensure accurate quantity measurements.

Industrial automation techniques like Artificial Neural Networks (ANN), Distributed Control System (DCS), Supervisory Control and Data Acquisition System (SCADA), Human Machine Interface (HMI), and Programmable Logic Control (PLC) are mentioned as classification methods. The use of IR sensors enables accurate monitoring of objects on the conveyor, processed by the microcontroller to determine the count displayed on the LCD screen.

The paper aims to enhance counting operations in manufacturing by providing an accurate count of objects on a conveyor belt after production and before packing. It addresses the industry's need for error-free production and faster production speed. The proposed system ensures precise quantity measurements, contributing to improved efficiency and quality control in the manufacturing process.

This system proposed in the paper finds application in industries requiring precise quantity measurements of objects on a moving conveyor. It can be utilized in sectors such as food processing, packaging, assembly lines, and manufacturing facilities where accurate counting is critical for production monitoring and quality management.(Lahari & Venkatesan, n.d.)

2.3.8 Vision-based Vehicle Detection and Counting System Using Deep Learning in Highway Scenes.

This research presents a system that uses vision-based technology to detect and count vehicles on highways. It introduces a new dataset specifically designed for highway vehicle detection, focusing on small objects in images. The system employs a segmentation method to separate the road surface into distant and nearby areas, enabling effective vehicle detection using the YOLOv3 network. By applying the ORB algorithm, the system tracks vehicle trajectories, determines their driving direction, and provides accurate vehicle counts. Experimental results confirm enhanced detection accuracy, particularly for small objects. The proposed system finds applications in highway management, traffic analysis, and calibration of surveillance cameras in European settings.(Song et al., 2019)

2.3.9 An Advanced Deep Learning Approach For Multi-Object Counting In Urban Vehicular Enviroments.

This research paper presents an efficient method for counting and tracking objects, specifically focusing on vehicles in smart city transportation systems. The method combines deep learning and correlation filters, utilizing the YOLOv5 model for object detection and the CSRT tracker for tracking and counting objects. The system's performance is evaluated using a dataset of 16 videos with varying object densities, image qualities, angles of view, and motion speeds. The results demonstrate promising accuracy in different scenarios, surpassing existing approaches.

The proposed system finds applications in urban planning, traffic monitoring, security, surveillance, wildlife conservation, and agriculture. It provides precise information about object counting and tracking, assisting in infrastructure planning, traffic control, access point management, and detecting abnormal events. In wildlife conservation, it enables counting and tracking various species, while in agriculture, it aids in analyzing plant health, assessing productivity, and detecting diseases.

In summary, this research paper introduces an enhanced system that combines advanced techniques to improve object detection accuracy and reduce counting errors. Its versatility makes it valuable in diverse domains beyond transportation and traffic management.(Dirir et al., 2021)

2.3.10 Machine Vision System for Counting Small Metal Parts in Electrodeposition Industry

This research addresses the need for an efficient method to count small metal parts on a galvanic frame in the fashion industry. The aim is to avoid material waste by electroplating only the necessary amount of precious metals. Existing manual counting methods are prone to errors and inefficiencies. Traditional counting machines on the market are not suitable for counting items on a galvanic frame. To overcome this challenge, the study proposes a new machine vision-based approach that uses an acquisition system and image processing algorithms. This system accurately separates the metal parts from the reflective background and counts them. The proposed machine helps optimize the electroplating process by determining the right parameters and reducing material waste. It brings cost savings, especially in the high fashion industry where valuable materials are used. The approach is different from conventional counting machines because of the specific requirements for counting items on a galvanic frame. The research demonstrates the effectiveness of using machine vision and rear projection for accurate counting. A dedicated counting machine incorporating this system has been successfully developed.(Furferi et al., 2019)

Figure 2.4: Galvanic frame with items placed in a fixed position. (Furferi et al., 2019)

2.3.11 A Novel Algorithm OF Rebar Counting on Conveyor Belt Based on Machine Learning.

The paper introduces a new algorithm for automatically counting rebars on a production line using video analysis. It has two main parts: partitioning the video frame and applying heuristic rules and using sequence matching between frames.

In the first part, the video frame is divided into three areas, and rules are created based on these areas to count the rebars. If the rules don't cover a situation, the second part of the algorithm kicks in.

In the second part, the algorithm compares sequences of rebars between frames to find new arrivals and calculate their count. This ensures accurate counting even when the rules don't apply.

The algorithm allows for faster conveyor belt speeds, reduces rolling of rebars, and provides a clear indication of the last counted rebar. The paper describes the hardware used and shows the algorithm's effectiveness through experiments.

To summarize, the paper presents a novel algorithm for counting rebars using video analysis, with a partitioning and rule-based approach, as well as sequence matching. It offers advantages like faster counting and reduced rolling of rebars.(Nie et al., 2016)

Figure 2.5 Counting result (Nie et al., 2016)

2.3.12 Build Coconut Counting System Using Image Technology.

Vietnam's coconut industry, concentrated in regions such as Ben Tre, Tra Vinh, Kien Giang, and Ca Mau, faces productivity challenges due to small-scale operations and manual counting processes. To address this, there is a need for automation in coconut fruit counting. Existing studies primarily focus on counting fruits on tree images or estimating crop yield, which are costly and more suitable for large-scale farming. This study proposes a novel image processing algorithm that involves preprocessing, object-background separation using the Otsu method, center area determination through distance transform, contour identification, and the use of watershed segmentation to separate overlapping objects. The proposed method achieves a high counting productivity of over 2000 fruits per hour. Additionally, the study includes the design of a conveyor system with a fixed velocity and essential components for motor protection.(Nguyen et al., 2022)

2.3.13 The Detection and Counting of Object Bottles in The Boxs Based on Image Processing Watershed Algorithm

This research focuses on improving quality control in the production line, specifically in the bottled beverage industry. It proposes using the watershed algorithm to detect and count bottles accurately. Traditional methods like thresholding struggle to separate closely arranged bottles in boxes. The watershed algorithm, which analyzes images based on topographic surfaces, offers a solution to this problem. Previous studies have shown its success in segmenting various objects. The paper aims to introduce a new quantity control method using the watershed algorithm and assess its accuracy in bottle detection and counting. Accurate counting is crucial for ensuring proper product delivery to consumers. The paper acknowledges the possibility of over-segmentation with the watershed algorithm and suggests selecting regions of interest based on specific criteria. Further research is recommended in natural environments using conveyors and comparing the algorithm with other segmentation methods to evaluate accuracy, time, and resource requirements.(Rozikin et al., 2021)

2.3.14 Couting of Oil Palm Fresh Fruit Bunches Using Computer Vision

Accurate fruit counting is crucial for efficiency and cost-saving purposes. Traditional methods have limitations, but advancements in computer vision technology have provided reliable and non-destructive solutions. By utilizing computer vision, fruit counting can be automated for both pre-harvest estimation and postharvest sorting. This technology can also be applied in the oil palm industry to count fresh fruit bunches, aiding in yield estimation and processing capacity calculations. Overall, computer vision and artificial intelligence offer innovative and cost-effective approaches to fruit counting and sorting.(SHIDDIQ, 2022)

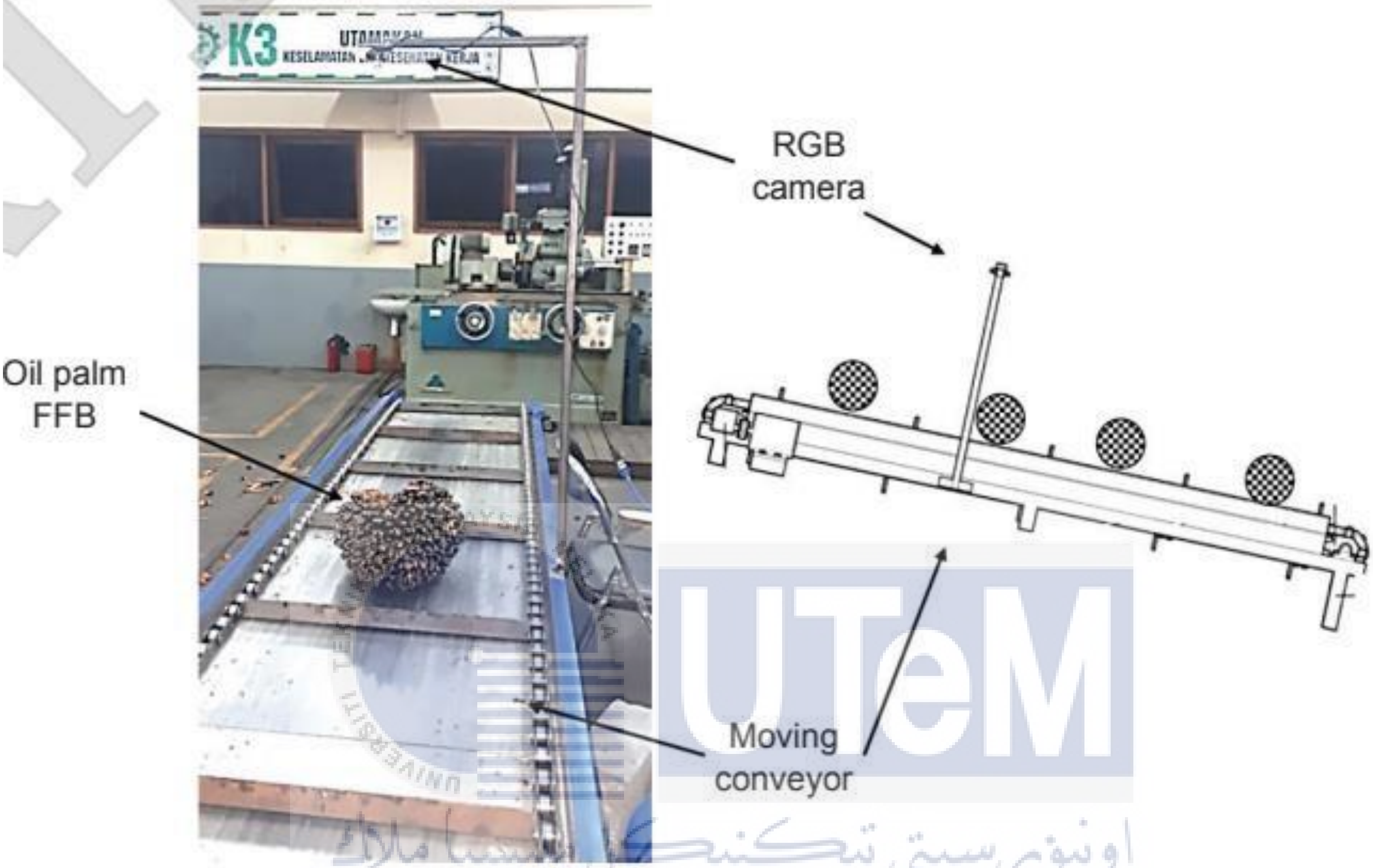


Figure 2.6: Counting system for palm fresh fruit bunches(SHIDDIQ, 2022)

2.3.15 Application of Computer Vision to Egg Detection on a Production Line In Real Time.

This study focuses on creating a real-time system for detecting, tracking, and counting eggs on a production line. Different methods and models were tested, highlighting the inefficiency of template matching and the effectiveness of CNN methods for eggs of similar size and good resolution. Hardware parameters, especially using a dedicated GPU, significantly impact performance. As a result, the proposed implementation involves utilizing YOLOv3 and GPU for industrial egg detection and counting. These findings offer valuable insights into the practical use of computer vision methods in this specific field.(Ulaszewski et al., 2021)

2.3.16 Automatic counting system for zebrafish eggs using optical scanner.

The paper introduces a new system for accurately counting live zebrafish eggs in a petri dish. Manual counting is time-consuming and prone to errors. The system captures an image of the dish and uses image processing to classify and count the live and dead eggs based on their color and shape. Previous systems didn't differentiate between live and dead eggs. This new system is cost-effective and provides a faster and more accurate alternative to manual counting.(Al-Saaidah et al., 2018)

2.3.17 Literature Review on Object Counting using Image Processing Techniques.

Object counting is essential in various industries, but manual counting methods are time-consuming and prone to errors. To overcome these limitations, the paper highlights the need for automated object counting using computer vision techniques. Automation improves accuracy and efficiency by eliminating human errors and ensuring consistent results.

The paper discusses the wide range of applications for object counting, such as cell counting in medical and biological research, blood count tests, fish population estimation, and scenarios where objects are difficult to distinguish or have a noisy background.

The proposed method utilizes image processing techniques for object counting. The algorithm takes into consideration factors like camera quality, object size, proximity, and lighting conditions to ensure accurate object recognition. By automating the counting process, the goal is to reduce the time required for counting while maintaining high accuracy.

Overall, the paper emphasizes the importance of object counting using image processing and its potential benefits in industrial systems, research fields, and situations where objects are small or challenging to differentiate.(Pandit & Rangole, 2007)

2.3.18 Object Counting Using Deep Learning.

The paper aims to automate the task of counting objects, which is commonly done in various places. Counting objects accurately in images or videos is important, and automatic counting provides consistent and reliable results. The paper suggests using deep learning, a type of machine learning, to achieve this.

The proposed method involves several steps:

1. Input Image: Images or videos are captured in real-time, but the counting process focuses on analyzing individual frames.
2. Object Detection: Objects are detected by comparing two images: the background and the image with moving objects. If the difference between them surpasses a certain threshold, it is assumed that objects are present. The size of the objects is estimated using the camera's height and previously collected size information.
3. Object Counting: The number of objects is determined through image analysis techniques, specifically by matching patterns. By detecting and matching these patterns, the count of moving objects in the frames can be obtained.
4. Reporting: The counted objects are recorded in an Excel file for further examination and analysis.

The paper highlights the advantages of deep learning for accurate and efficient object counting. It reduces the time required for counting and ensures high accuracy. Proper object detection is crucial for successful counting.(Atchaya et al., 2021)

2.3.19 Review On Object Counting.

Image processing and computer vision play a crucial role in identifying objects in various fields such as agriculture, research, and medical diagnosis. However, categorizing pictures and counting objects can be challenging, particularly when dealing with a large number of objects or a crowded scene. Manual counting has limitations, which is why computer systems are proposed for improved accuracy and efficiency.

Different algorithms are utilized, including traditional machine learning approaches like SVM, as well as deep learning-based methods such as CNN, R-CNN, Faster-RCNN, Fast-RCNN, Mask R-CNN, R-FCN, and anchor-based single-shot detection algorithms like MultiBox, SSD, and YOLO. These algorithms find applications in various scenarios, such as using drones to locate lost or injured individuals in remote areas or implementing traffic monitoring systems to reduce congestion in cities.

Object counting is also relevant in agriculture for tasks like detecting crop leaves and fruits, as well as counting active bodies in smart farms. Algorithm accuracy depends on factors such as camera quality, object size, image clarity, object proximity, and lighting conditions.(Dhaval et al., 2022)

2.3.20 Smart Count System Based On Object Detection Using Deep Learning.

A small-sized smart counting system is proposed, integrating image processing techniques and deep learning object detection to achieve accurate counting in manufacturing and management tasks. The system comprises a low-cost hardware device and a cloud-based object counting software server. The software utilizes a novel DBC-NMS technique and hyperparameter tuning to ensure high-performance object counting. The system achieves precise counting results on both public datasets and a custom dataset of small pills, with a mean absolute error (MAE) of 1.03 and a root mean squared error (RMSE) of 1.20 on the

Pill dataset. By combining low-cost hardware with cloud-based software, the proposed system offers an affordable and effective solution. Unlike previous counters limited to counting a single product type, this system provides a versatile counting solution suitable for various objects. To overcome the challenge of high object density, existing object-detection models are enhanced with the DBC-NMS technique. The hardware device plays a vital role in the counting process and can be operated on low-cost embedded platforms. Users can easily verify results through a web-based interface accessible on mobile devices. The system streamlines counting with a semi-automated process that surpasses the speed and accuracy of manual counting. Overall, the small-sized counting system demonstrates competitive performance in accurately counting and collecting small-sized objects.(Moon et al., 2022)

2.4 Limitation of previous Project

Paper (Nguyen et al., 2022) by need to count of over 2,000 fruits per hour achieved by the proposed system could be affected by factors such as the speed and stability of the conveyor belt. Higher speeds or unstable movement of the coconuts may impact the system's accuracy and productivity. (Atchaya et al., 2021) One limitation of this project is that it focuses on counting objects in images or live video streams without specifically addressing the challenges associated with different object recognition scenarios. Objects that are difficult to distinguish, vary in size, or are surrounded by noisy environments may pose challenges for accurate counting using this methodology. (Bogomasov & Conrad, 2021) One limitation of this project is that the evaluation and testing were mainly done using a CPU, without utilizing GPUs due to retail guidelines. Although the obtained results were satisfactory, additional research and testing are necessary to determine how well the proposed solution performs in real-world production settings.

Table 2.1: Summary of related projects

No	Year	AUTHOR	TITLE	APPLICATION
1	2015	Dr.M.H Fisher	Convolutional Neural Networks for Counting Fish in Fisheries Surveillance Video	This project is using computer vision application and existing cctv to counting fish.
2	2021	Prince Shah,Pratham Shah, Mit Thakkar	Object Detection & Count in Image	This paper implemented object detection using OpenCV and TensorFlow in Python. Additionally, we thoroughly studied YOLO (You Only Look Once) and its applications. This knowledge allowed to implement the YOLO framework, which detects various objects and counts them. The primary goal was to count the different types of fruits on a tree.
3	2022	Dainius Varna Vytautas Abromaviˇcius	A System for a Real-Time Electronic Component Detection and Classification	Detecting and counting small moving objects. Specifi to surface mount. Using deep learning methods. This project is implement real time system to detect and count objects on conveyor belt.

			on a Conveyor Belt	
4	2018	Dr.K R Nataraj, Nandini.	Object Detection, Segmentation & Counting Using Deep Learning.	It uses a technique called Mask R-CNN, which is easy to train and works at a speed of 5 frames per second. The method builds on existing methods like Faster R-CNN and FCN, which are known for their flexibility and efficiency in recognizing and segmenting objects in image
5	2021	Kirill	Efficient Fruit and Vegetable Classification and Counting for Retail Applications Using Deep Learning	This paper is specific fruit and vegetable . Using deep learning , MobileNetV2 Hybrid architecture which is an ensemble of EfficientNet for image classification. Presenting an efficient and innovative solution for classifications and counting of fruits and vegetables for retail.
6	2019	Thae thae Ei Aung	Design and implementati	Mainly used photoelectronic sensors and plc. Used push start and stop button also provide emergency stop button. Buzzer to generate sound. Press push start button to start running the

		Hnin Ngwe Yee Pwint, Thiri Kywe	on of plc-based item counting system	conveyor belt. For example, we tested three samples. If the item in the box is counted by photoelectric the sensor gives information to plc. And the conveyor belt will be bringing another box to package it.
7	2017	M.N.S Lahari Dr.P Venkatesan	Automated conveyor belts for object counting in small-scale industries	The paper is not specific to any object, it could be applicable for any product such as water bottle,container,etc. Used plc,ir sensor and lcd display.Microcontroller AT89C51 is enough for small scale industry.Used IC regulator that provided divided supply of 36V and +5V separately to the controller. This project aim to counting the number of objects place on moving conveyor that helps improving the statistics of production.
8	2022	Huaiyu Li Zhe Dai Xu Yun Huansheng Song	Vision-based vehicle detection and counting system using deep learning in highway scenes	This study established a high-definition vehicle object dataset from the perspective of surveillance cameras and proposed an object detection and tracking method for highway surveillance video scenes.vision-based vehicle object detection is divided into

		Haoxing Liang		
9	2021	A. Dirir H. IgnatiousH. Elsayed M. Khan, M. Adib A. Mahmoud M. Al-Gunaid	An Advanced Deep Learning Approach for Multi-Object Counting in Urban Vehicular Environments	The proposed system is evaluated using a dataset of 20 different videos with various characteristics, and it was found to identify and count objects with high accuracy in different scenarios. The document also discusses the influence of predefined parameters on the accuracy of the system, such as object density and image quality. Additionally, this paper provides a review of various techniques and frameworks for object tracking and counting in urban vehicular environments, including deep learning-based approaches such as YOLO and RCNN. The system uses the latest YOLO deep learning model for object detection and integrates it with the Channel and Spatial Reliability Tracker (CSRT) to track and count objects within a narrow region
10	2019	Rocco Furferi Lapo Governi Luca Puggelli Michaela Servi Yary Volpe	“Machine Vision System for Counting Small Metal Parts in Electro-Deposition Industry”	The system is implemented on a counting machine to help manufacturers avoid waste by depositing only the necessary amount of material. Next various computer vision-based approaches and their limitations for this specific task. The method uses a rear projection-based acquisition system and image processing-based routines to count the number of items on the frame.

11	2016	Zuoxian Nie Mao-Hsiung Hung Jing Huang	A novel algorithm of rebar counting on conveyor belt based on machine vision	This paper describes a new algorithm that uses machine vision to count rebar objects on a production line. The algorithm is divided into two parts: image segmentation and counting algorithm. It does not use a detection window, allowing for faster conveyor. The advantages of video-based counting system include: 1) no modification of conveyor belt for installing the counting system, 2) ability to accomplish a preset number of bundles. 3) no effect of the running speed of conveyor belt due to the counting
12	2021	Nguyen Huu Quang Ngo Quang Hieu Truong Qouc Bao	Build coconut counting system using image technology	The document discusses a study that proposes an efficient processing algorithm to automatically count the number of dried coconuts moving on a conveyor belt. The proposed method has an average accuracy of over 95% with a productivity count of over 2,000 fruits/hour. The study also includes the design of a wiper mechanism to solve the problem of overlap between coconuts. The study's results can be a prerequisite for developing an automated agricultural product counting and classification system.
13	2021	Mohamad iqbal suriansyah	The detection and counting of object bottles in the	This paper used watershed algorithm for detecting and counting bottles in boxes on a platform with high accuracy and minimal computer resources.

		Nurlana sanjaya Chaerur rozikin Aries suharso	boxes based on image processing using watershed algorithm	This paper aims to propose a new method to do quantity control in the production line using a watershed algorithm and show the accuracy watershed algorithm can do bottle in the boxes detection and counting. The expected result of this paper would be how a good watershed algorithm can perform bottle detection and counting. This paper is used machine vision Machine vision provides a less-contact application and functions effectively to deliver fast output without errors
14	2022	Dodi sofyan arief Vicky vernando dasta Minarni shiddiq	Counting of oil palm fresh fruit bunches using computer vision	The conclusion section discusses the potential of using a computer vision method for counting moving oil palm FFB on a conveyor. The study found that the counting system has reached an accuracy of 100% depending on the oil palm FFB surface colors and the intensity of the room light. The program used video frames to detect and track oil palm FFB moving on a conveyor. The computer vision system used in the study, which consisted of a moving conveyor, an RGB camera, and a Python-based counting program with OpenCV library. The system used Hue-Saturation-Value (HSV) color space for image processing and a detection algorithm that

				included the color and fruit shape of the oil palm FFB (FRESH FRUIT BUNCH) to differentiate them from other fruits
15	2021	Andrzej Janowski Maciej Ulaszewski Robert Janowski	Application of computer vision egg detection on production line in real time.	Since this paper aimed at evaluating the process of visual egg detection, tracking, and counting, we defined events and related metrics that helped us assess its effectiveness. For events, the natural choice was as follows: a correctly detected egg, an unrecognized object, a false positive egg detection. However, since after a successful egg detection we track the position of this egg, the following events related to the effectiveness measure were introduced: a loss of an egg being tracked, a multiple detection of the same egg. The methods include template matching and neural network-based methods such as YOLOv3, FR-CNN, and SSD-MobileNet v2. This paper also highlights the sensitivity of the template matching method to the number of objects in the video frame and the effectiveness of the egg detection and tracking process
16	2018	Bayan Alsaaidah Moh'D hadidi Waleed Al-Nuaimy	An automatic counting system for zebrafish egg using optical scanner	From this paper, if we count using this system, counting will be more accurate than counting manually. The system also can count all the eggs in a petri dish making it a throughput solution for egg counting.

				The method used in this paper is an automatic counting system for zebrafish eggs using a low-cost imaging device. The system involves capturing images of the eggs with a scanner, processing the images to identify and count live eggs, and filtering out unwanted objects such as food powder and debris. The system uses color and shape features to distinguish between live and dead eggs and filter out unwanted objects. This method is used in aquaculture
17	2014	Amruta Pandit Jyoti Rangole	Literature Review on Object Counting using Image Processing Techniques	This paper reviews different methodologies for object counting using image processing techniques. It discusses various approaches for object counting, including blob analysis, connected components analysis, and statistical area measurements. Applications of object counting include packaging, quality control, medical diagnosis, and biological research. The accuracy of the algorithm depends on several factors such as camera quality, object size, and illumination conditions. The document also provides a list of research papers on various methods of automatic counting of cells, microorganisms, fish, and other objects using image processing and computer vision techniques.
18	2021	S.Atchaya D.Dhiliban R.Ragavi M.Supraja	Object Counting using Deep Learning	Purposes a method for object counting using deep learning techniques. The method includes image acquisition, object detection, object counting and reporting. This paper used a deep learning-based system for object counting that uses pre-trained data and can be used for real-time applications.

		K.Vinitha		
19	2022	Tejaswini Dhaval Tejas Kadam Sudhir Gupta Prof.Varsha Salunkhe	Review on object counting	This paper provides some information about methods and algorithms for object counting, image processing and computer vision. This method includes traditional machine learning and deep learning algorithms. It also discusses real-world applications of object counting. This paper also provides some information about YOLOv4 and the advantages and disadvantages.
20	2022	Jiwon Moon Sangkyu Lim Hakjun Lee Seungbum Yu Ki-Baek Lee	Smart Count System Based on Object Detection Using Deep Learning	The document reviews related works on counters and deep-learning-based object detection, evaluates the object-detection models used in the proposed system, and concludes that the proposed system shows competitive performance as a device specializing in counting and collecting small-sized objects. The document discusses a novel object-counting system that combines an existing deep learning object-detection model with a new object-counting technique called DBC-NMS. The system is cloud-based and can count various object types by fine-tuning the object-counting server with a specific task dataset. The system also includes a semi-automated object-collecting process to help remove excessive objects.

2.5 Summary

This chapter reviews existing research in a specific field, summarizing and analyzing scholarly articles, books, and other sources. It identifies important themes, trends, and gaps in literature. The chapter critically evaluates the current state of knowledge and provides a basis for future research in the field.

CHAPTER 3

METHODOLOGY

3.1 Introduction

This chapter elaborates in detail about hardware and software development such as equipment used for example, conveyor, raspberry pi, camera module. Procedure and application that will be used to develop automated counting nut. Next, cost analysis for creating the prototype for this project is also highlighted in this chapter.

3.2 System design

3.2.1 Experimental Setup

Experimental setup utilized a Raspberry Pi as the main controller and a camera module for detecting nuts on the conveyor. The hardware setup involved connecting the camera module to the Raspberry Pi. The camera module, specifically chosen for its compatibility with the Raspberry Pi, captured real-time images of the conveyor belt. These images will be then processed using computer vision algorithms to identify and count nut on the conveyor. Figure 3.1 shows the picture for experimental setup.

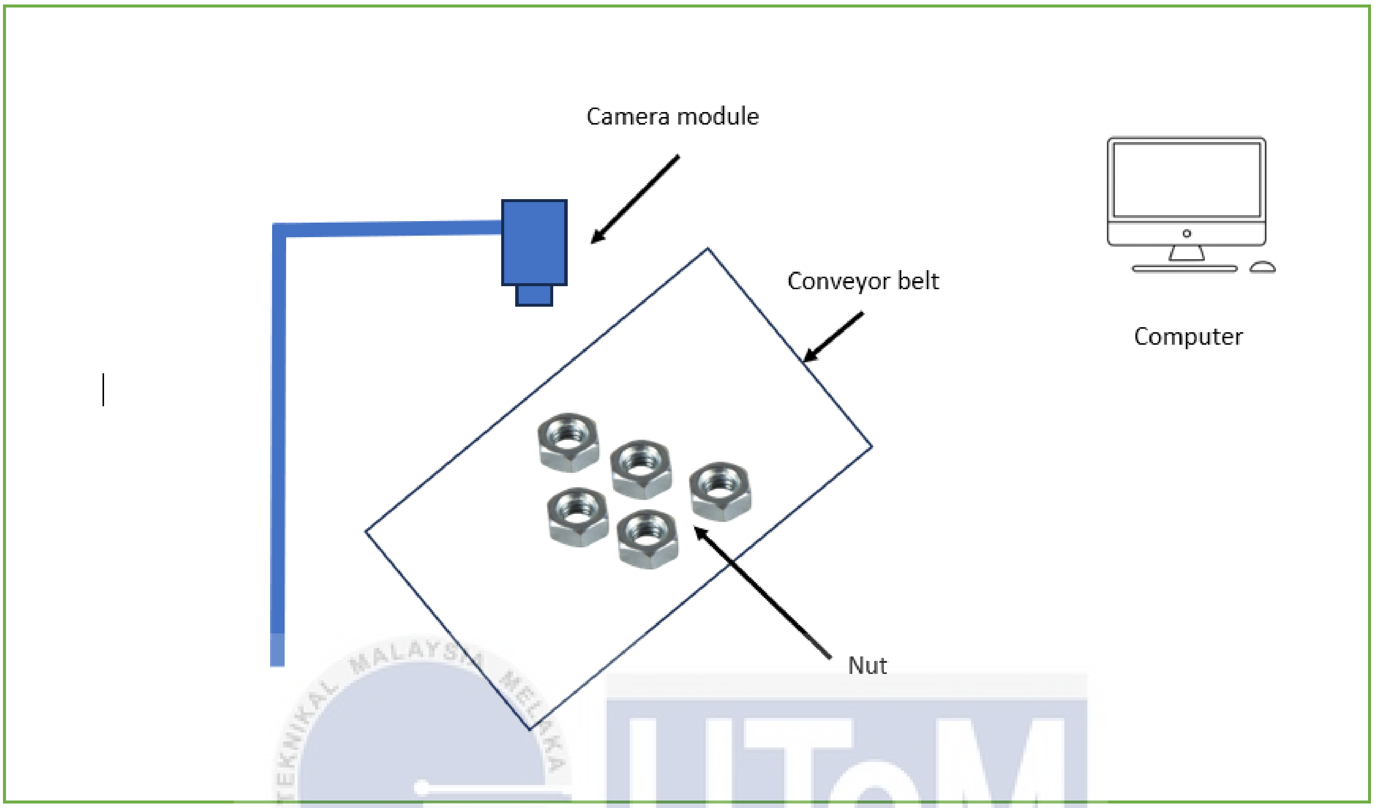


Figure 3.1: Experimental setup

3.2.2 Purposed system

The flowchart for the training process is shown in Figure 3.4. For the first process is data collection from various sources such as RoboFlow Universe. RoboFlow website is free, and dataset can be downloaded without any charges. The dataset was divided into three groups, namely the training dataset, the validation dataset and testing dataset in Figure 3.2 shown how many datasets that collected. Image annotation in the training dataset involves adding labels to indicate regions of interest. This can help train machine learning models to accurately identify and classify objects in new images. Images augmentation involves making changes to existing nut to create new and different nut. These changes can include things like rotating, resizing, to the nut. For the last step is, model testing on dataset. After the annotation process then generate the dataset after that download the dataset in term of yolov5 model.

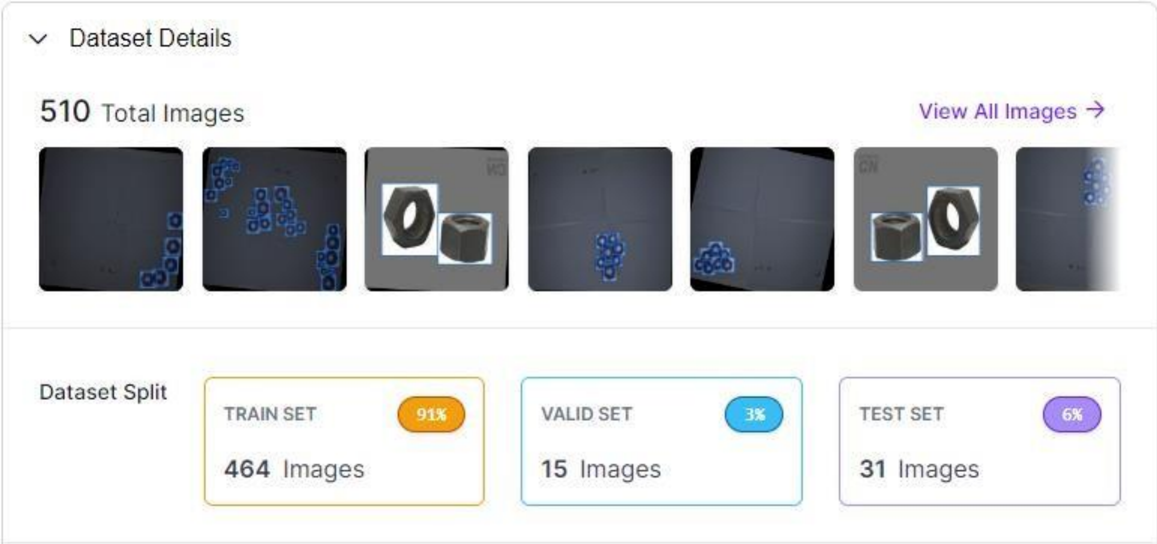


Figure 3.2: Dataset splitted into three groups

For trainning is used google colab refer Figure 3.3: Interface for google colab to succesfull the trainning processes. In google collab download the folder for yolov5 and paste the coding from roboflow in google collab. Its is to make sure that trainning process is used the correct dataset and to make sure the machine known the dataset. In trainning process epoch is must. Epoch function are like rounds of learning for a machine learning model. Each epoch involves the model going through the entire training data, adjusting its understanding. The number of epochs is crucia it's like deciding how many learning rounds the model needs. Too few, and the model might not learn enough; too many, and it might memorize the training data. For this trainning proccess used 30 epoch

For testing process is used visual studio code. In visual studio code used the best.pt from google colab and insert into folder yolov5 to make sure this testing process known the same thing from the trainning process. Next run the code, python detect.py and the result will be save in run/detect.

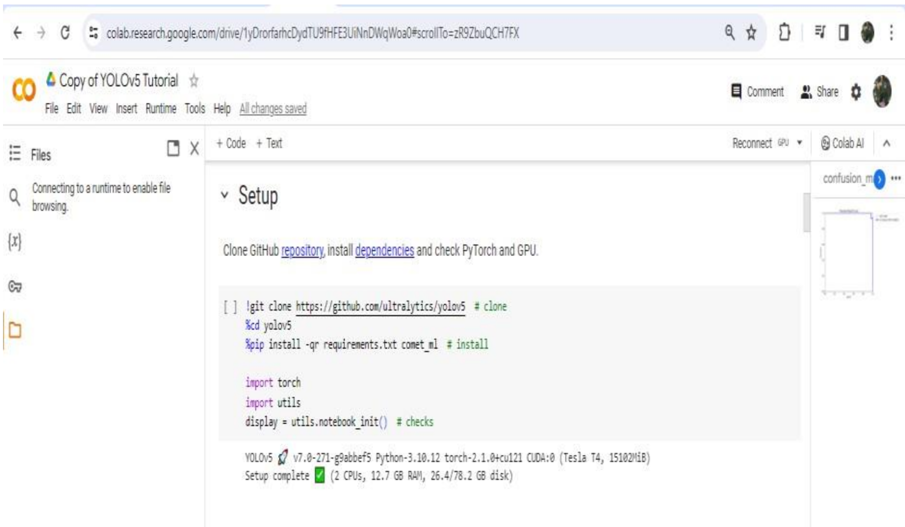


Figure 3.3: Interface for google colab

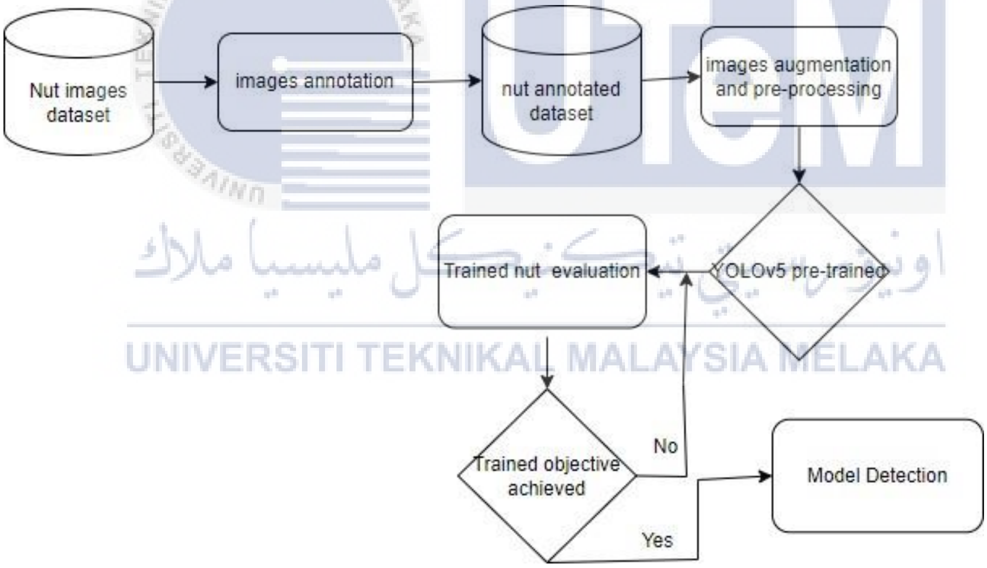


Figure 3.4: Trainning process using YOLOv5 flowchart

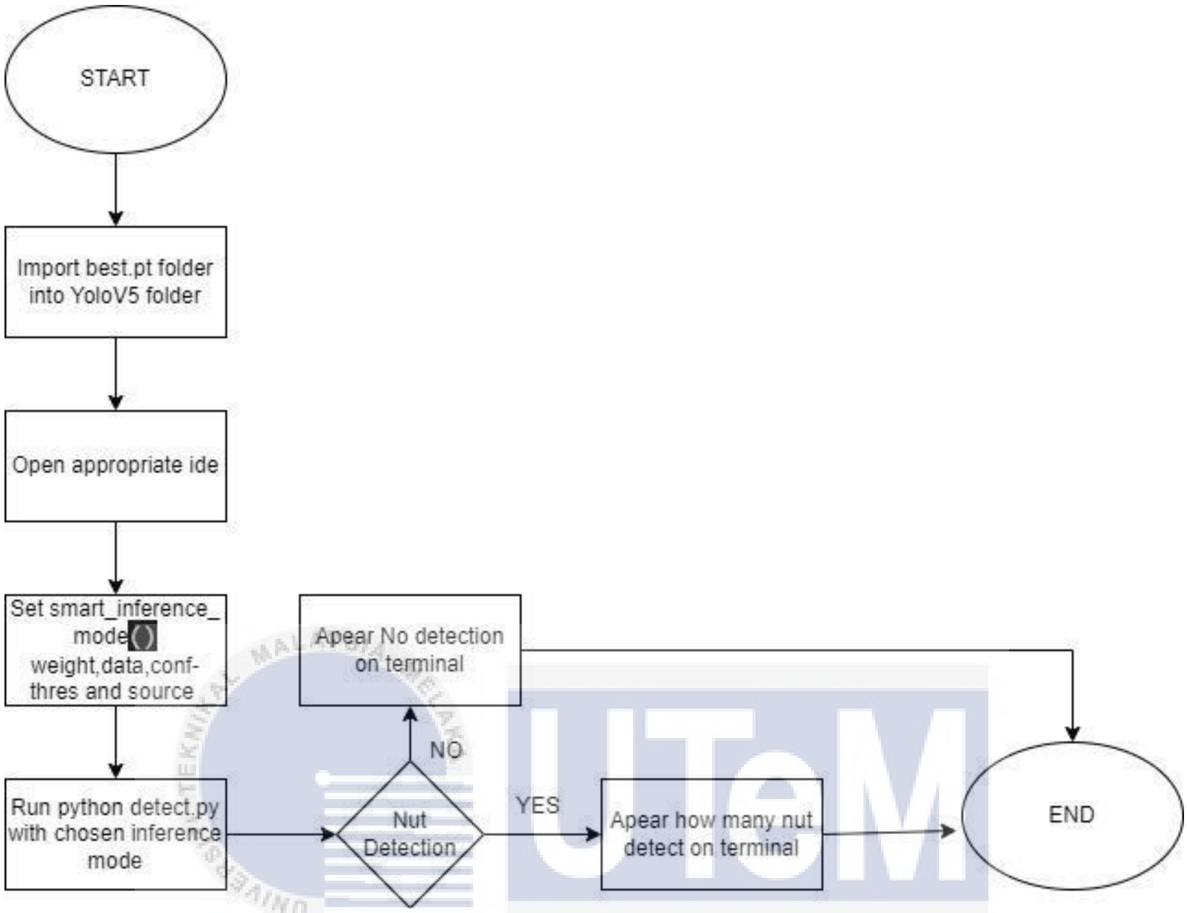


Figure 3.5: Testing process flowchart

If nuts are detected in the frame, the count variable is incremented, and the current count is displayed. If no nuts are detected, no detection is displayed. The algorithm then waits for the next frame from the conveyor belt and repeats the process.

3.2.3 Programming language

Python is a popular and easy-to-use programming language that is widely used for different purposes. When it comes to Raspberry Pi, a small and affordable computer, Python is a great choice for creating projects.

Python works well with Raspberry Pi because it has a simple and flexible syntax. It also has a wide range of libraries and modules that can be easily used with Raspberry Pi's hardware features.

Raspberry Pi 4 comes with the Thonny IDE pre-installed. Thonny is a user-friendly development environment specifically designed for Python. It has features like code completion and debugging tools, which make writing Python code easier. Thonny provides a simple interface that enhances the coding experience on Raspberry Pi.

In conclusion, Python is a versatile and beginner-friendly programming language that works well with Raspberry Pi. By using Python and the pre-installed Thonny IDE on Raspberry Pi 4, it can control and interact with its hardware components smoothly.

3.2.4 Raspberry Pi 4

The processing power of Raspberry Pi boards varies, with some having quad-core or even octa-core CPUs. Due to these features, the board can handle challenging computer vision tasks like object identification, tracking, and image recognition. Raspberry pi used linux-based operating systems, such as Raspbian, which the Raspberry Pi runs on, offer flexibility and a variety of software tools for developing computer vision systems. For the Raspberry Pi, you can use OpenCV, or PyTorch libraries to create computer vision algorithms. Overall , the processing power, networking options, small size, low cost, and robust community support of the Raspberry Pi make it a great alternative for computer vision projects.

3.2.5 5mp Camera Board For Raspberry Pi 4

An official camera module created especially for the Raspberry Pi 4 and other Raspberry Pi boards that are compatible is the 5MP Camera Board for Raspberry Pi 4. It gives users a way to take pictures and videos straight from the Raspberry Pi for use in a variety of project and apps. The camera board is supported by Raspbian, the official operating system for the Raspberry Pi (now called Raspberry Pi OS). This guarantees compatibility and offers software frameworks and APIs for simple camera module integration and control. Applications for the 5MP Camera Board for Raspberry Pi 4 include photography, video surveillance, robotics, computer vision projects, and more.

3.2.6 Conveyor belt

The conveyor belt's main job in this project is to move nuts in a controlled way so that the computer vision system can count them accurately. It keeps the nuts flowing continuously, making it easier for the system to take pictures or videos and count the nuts with precision. The conveyor belt automates the nut counting process, eliminating the need for manual work. This improves efficiency by enabling the system to count a large number of nuts continuously without human involvement.

3.3 Cost analysis

Table 3.1: Cost analysis

Component	Quantity	Unit Price (RM)	Subtotal (RM)
Raspberry pi 4	1	RM695	RM695
Conveyor Belt	1	RM13.10	RM13.10
Rapsberry pi camera module	1	RM36.80	RM36.80
7 Inch LCD Touch Screen Module For Rasberry Pi	1	RM65	RM65
			Total : RM 809.9

3.4 Summary

The purpose for this project is to make an automated counting nut on conveyor with combination of computer vision technique. In this chapter have an explanation about the method for object detection training and testing process to make sure that computer vision known the right object to detect.

CHAPTER 4

RESULTS AND DISCUSSIONS

4.1 Introduction

In this chapter present the results of the hardware development of nut counting system using computer vision. The results for this chapter are from visual studio code and also from raspberry pi 4. For this chapter also have graph as analysis for this project.

4.2 Hardware Prototype

Figure 4.1, we can see how the raspberry pi 4 is placed on top of the conveyor belt. This design makes it simple for the raspberry pi to identify and count nuts as they move along the belt. The raspberry pi can easily detect the nuts.

Figure 4.1: Raspberry pi on the top of conveyor belt

4.3 Process Flow

In Figure 4.2 shown flowchart is shown to run the project on visual studio code. On visual studio code, when the project is running completely, the result will be show on the folder run/detect. It’s also the same with raspberry pi 4. When the project is deployed into raspberry pi 4, the process will be same but using different ide. Refer Figure 4.3 that shows how the process to run the project on raspberry pi 4.

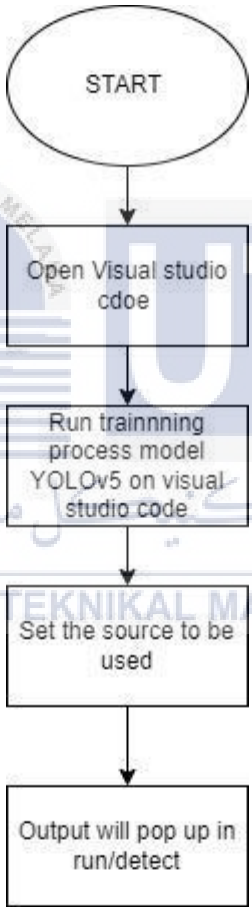


Figure 4.2: Flowchart to run the project on visual studio code

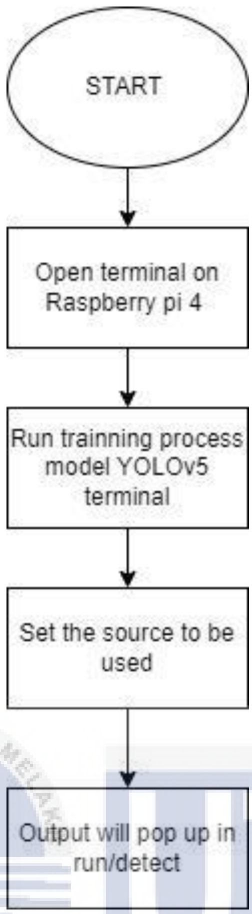


Figure 4.3 : Flowchart to run the project on raspberry pi 4

4.4 Result and Analysis

4.4.1 Training process from Google Colab

Figure 4.4 below shows the result of F1-Confidence Curve using 30 epochs and Figure 4.5 below shows the result F1-confidence Curve used 25 epochs. Graphs with 30 epochs have more confident rather than graph with 25 epochs. More confident can have the prediction results. Figure 4.6 shown output data for epochs 25 and Figure 4.7 shown output data for 30 epochs. Training epochs are used between two epochs only. From Figure 4.6 and Figure 4.7 the meaning of class is the denotes name of the object used “nut”. Images in figure means the metric to tell the number of images in the validation set that contain in object class. Next for instances it will tell how many times a specific class appears in all the images in the validation set. P and R are precision and recall. For the precision metric reflects the correctness of the objects identified by the detection model, while the recall metric measures the model's effectiveness in recognizing every instance of an object in the images. Object detectors play a crucial role in several recent computer vision tasks. Nevertheless, even the most advanced object detectors exhibit imperfections. When presented with two visually similar images, a single detector can yield dissimilar results due to minor image distortions, such as sensor noise from the camera or lighting changes.

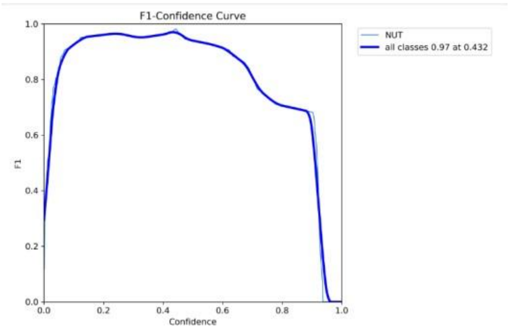


Figure 4.4: Training used 30 epochs.

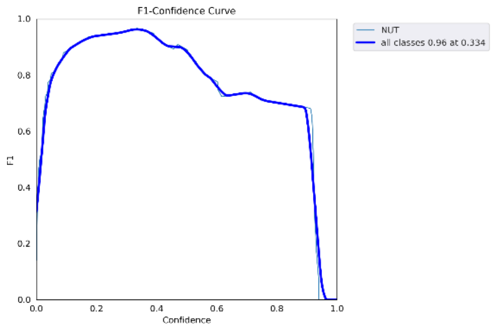


Figure 4.5: Training used 25 epochs.

```
Model summary: 157 layers, 7012822 parameters, 0 gradients, 15.8 GFLOPs
                 Class     Images  Instances          P          R      mAP50   mAP50-95: 100%|██████████| 1/1 [00:00<00:00,  5.41it/s]
                   all         15         29      0.935          1      0.976      0.732
```

Figure 4.6: Output for epochs 25

```
Model summary: 157 layers, 7012822 parameters, 0 gradients, 15.8 GFLOPs
                 Class     Images  Instances          P          R      mAP50   mAP50-95: 100%|██████████| 1/1 [00:00<00:00,  5.52it
                   all         15         29      0.852      0.994      0.957      0.657
```

Figure 4.7: Output for epochs 30

From Figure 4.8 and Figure 4.9 below shows the result for train_batch0 and val_batch0 after train pre-trained model process. Train_batch0" specifically refers to the very first batch of data loaded for training a model, and it is typically used as the initial batch to start the model training process. This initial batch is important as it initializes the training procedure. Val_batch0 serves as the initial segment of data drawn from the validation dataset and plays a vital role in evaluating and overseeing the YOLOv5 model's performance throughout the training process. Its primary purpose is to verify the model's ability to generalize effectively to previously unseen data, which, in turn, aids in making important training-related determinations, including the possibility of early termination and adjustments to hyperparameters for optimal results."

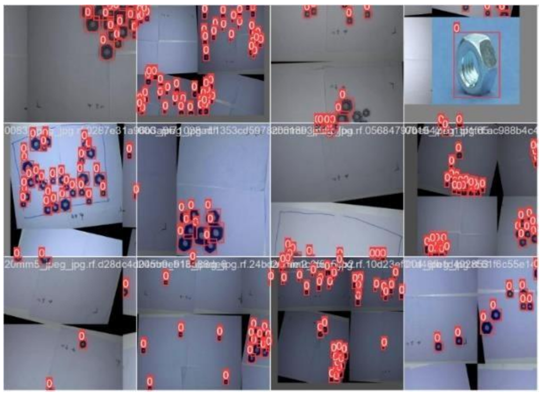
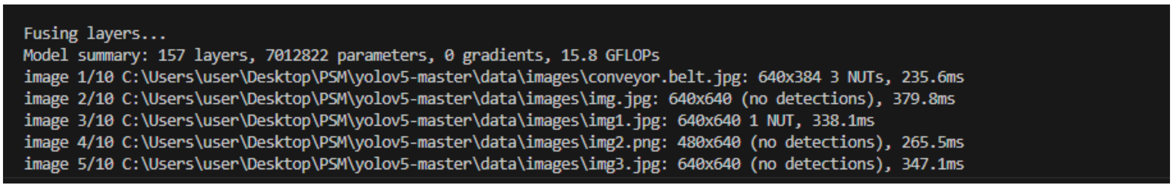


Figure 4.8: Train batch

Figure 4.9: Validation batch

4.4.2 Result From Visual Studio Code

Figure 4.10 shows the output for the object detection on visual studio code. On the visual studio code terminal show that how many objects on the images. For example, on conveyor belt images detect have 3 NUTS. Next images output is no detection because of the computer cannot detect images of nut on that image. Figure 4.11 shows the images on the conveyor belt, but the accuracy of the detection is still low because on the confidence graph still has loss. Figure 4.12 shows that images with no detection because of that image that is not the nut.



```
Fusing layers...
Model summary: 157 layers, 7012822 parameters, 0 gradients, 15.8 GFLOPs
image 1/10 C:\Users\user\Desktop\PSM\yolov5-master\data\images\conveyor.belt.jpg: 640x384 3 NUTs, 235.6ms
image 2/10 C:\Users\user\Desktop\PSM\yolov5-master\data\images\img.jpg: 640x640 (no detections), 379.8ms
image 3/10 C:\Users\user\Desktop\PSM\yolov5-master\data\images\img1.jpg: 640x640 1 NUT, 338.1ms
image 4/10 C:\Users\user\Desktop\PSM\yolov5-master\data\images\img2.png: 480x640 (no detections), 265.5ms
image 5/10 C:\Users\user\Desktop\PSM\yolov5-master\data\images\img3.jpg: 640x640 (no detections), 347.1ms
```

Figure 4.10 : Output after run python detect.py use image

Figure 4.11 : Nut detection on conveyor belt

Figure 4.12 : No detection images

4.4.3 Result From Raspberry Pi 4

In the Figure 4.13 shows the output in terminal and how many nut on the conveyor belt detecting an image using raspberry pi 4. This detection is functionally well after deploying the algorithm yolov5. The next Figure 4.14 shows the output on conveyor belt. Have boundary box around the nut detection. The detection is still not really accurate because the graph also shows that this training still has lost on result. Also, accuracy depends on the object; for example, if the object has more lighting it can affect the accuracy.

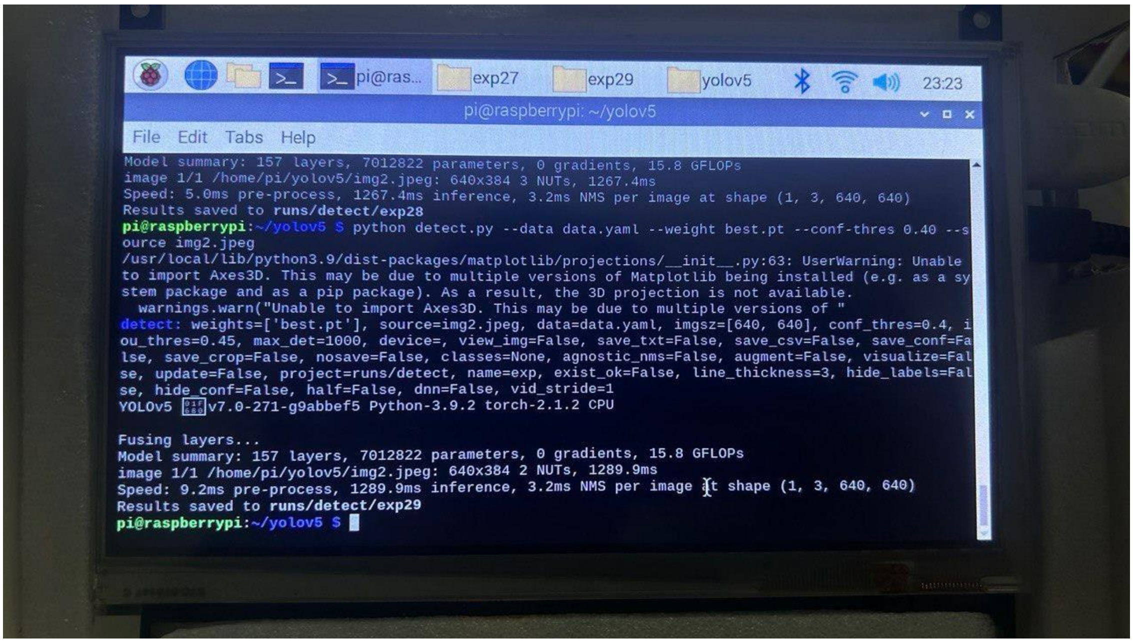


Figure 4.13 : Output on terminal

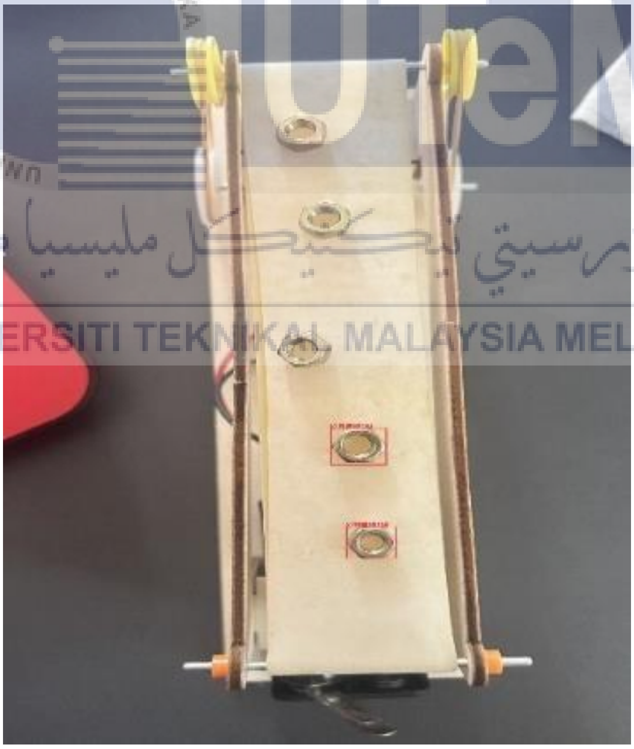


Figure 4.14 : Output on conveyor

In the Figure 4.15 shows the output of nut detection using video and for Figure 4.16 shows the output on terminal and the number of nut on conveyor. Same as image, using video also did not achieve the high accuracy.

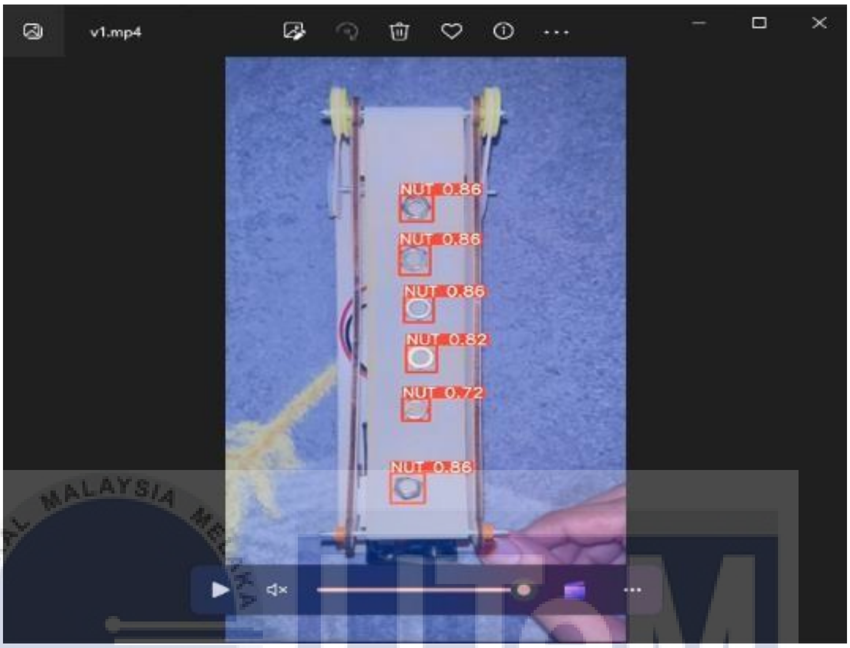


Figure 4.15 : Output for video in terminal

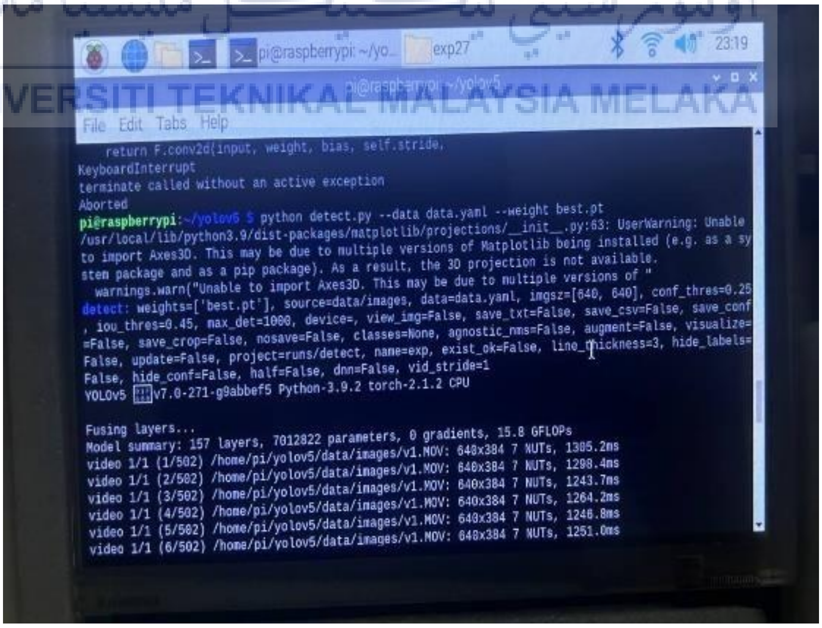


Figure 4.16 : Output in terminal

4.5 Summary

In this chapter primarily centers on the outcomes and evaluations stemming from our work with a pre-trained YOLOv5 model. Training and testing of dataset using Google Colab. Additionally, explored the results obtained from deploying this model on two different platforms, the Raspberry Pi 4 and Visual Studio Code.

Through this project, assessed the model's performance and effectiveness in detecting objects within the dataset. The insights gained from these evaluations are crucial for understanding the capabilities and limitations of YOLOv5 in real-world applications, especially when implemented on resource-constrained devices like the Raspberry Pi 4.

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

In conclusion, the performance of the workforce in industrial production is crucial for achieving the desired output. Deviations from the expected level of performance can have a significant impact on productivity. Currently, manual counting of nuts in production establishments is prone to errors, loss of count, and difficulties for operators who need to remember counts for extended periods. However, recent advancements in counting algorithms, computer technology, and camera technology have opened up new possibilities for counting using imaging methods.

The integration of technology for computer vision in nut counting improves efficiency, accuracy, and productivity in the production process. Companies could save precious resources and time by removing the need for manual counting, while also minimizing the possibility of human mistakes.

The aim of this project was to develop a conveyor-based automated counting system specifically for nuts. The counting procedure involved the detection and counting of nut images using computer vision technology. The implementation utilized a counting algorithm programmed in Python, with Raspberry Pi serving as the underlying platform. To ensure uninterrupted efficiency, it is important to establish reliable connectivity between the processing unit and the cameras.

To evaluate the precision and accuracy of the nut counting system, extensive testing will be conducted. This will validate the effectiveness of the developed system in accurately counting nuts in an automated manner.

Overall, the use of computer vision methods for automated counting of nuts on a conveyor offers significant benefits to manufacturers, including improved efficiency, accuracy, and quality control.

5.2 Future works

Future research in the field of industrial component detection and counting should concentrate on employing cutting-edge technology and methods to boost accuracy. Integrating these technologies with the Industrial Internet of Things (IIoT) can allow for instant data analysis and better decision-making. Overall, future studies should aim to merge these advanced technologies with practical uses in industry, leading to more precise, efficient, and flexible detection and counting systems.

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