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Automated Detection of Loose Palm Fruit for Quality Inspection

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Abstract

Palm oil plays a significant role in driving the global economy due to the versatile nature of its fruit, which has led to increasing demand worldwide. However, several processes such as quality inspection and documentation—are still performed manually. This project aims to enhance the effectiveness of quality inspection procedures. It addresses current limitations by implementing object detection and recognition methods to support the sorting process. The system utilizes Artificial Intelligence (AI) to improve the efficiency of palm fruit quality evaluation. It is specifically designed to detect and classify loose palm fruits based on their ripeness level. The method used in creating the project is implementation of Huskylens that is used to detect and recognize the palm fruit ripeness level by its colour. The project utilizes the Firebase console for documentation and control, while the ESP32 acts as the central processing unit. Results show that detection and recognizing accuracy could be influenced by the conveyor speed where accuracy percentage increases as conveyor speed decreases. The results show, at 22V the conveyor moves at 0.075 m/s, yielding an average accuracy of 70%. However, the project is constrained by the camera's field of view and resolution, which may affect its object detection capability. Additionally, the detection speed depends on the processing capabilities of the microcontroller used. This system is intended to benefit small-scale entrepreneurs and organizations who require a reliable and affordable solution to improve their workflow efficiency.

1. Introduction

Although palm fruit production has improved over the years, the industry still faces challenges in maximizing their outputs. Current segregation and monitoring method struggle to meet production method and require human intervention regularly which decrease its productivity. By implementing the methods and technologies previously studied a more efficient system could be develops. This developed system could, monitor the palm fruit quality inspection, uses AI and IoT technologies for monitoring and documentation and provide a effectives quality inspection system for the industry.

Palm fruit has played a critical role in Malaysia's economy. As of 2022, Malaysia's export products were valued at 17.7 billion dollars, with the palm oil industry contributing 4.69 percent of the total value (Golden Agri-Resources, n.d.). Palm fruit is a highly productive crop, delivering up to 10 years of optimum yield during its 28-year lifespan. A single oil palm tree can produce 12 to 14 fruit bunches annually, each weighing between 10 kg and 25 kg (Golden Agri-Resources, n.d.). Given its economic and agricultural significance, various technologies have been developed to enhance fruit quality and sorting efficiency.

In 2019, a segmentation process using Otsu thresholding was employed to determine palm fruit ripeness levels (Septiarini et al., 2019). This method utilized hue, saturation, and value (HSV) color analysis to assess ripeness, providing a foundational step for further automation (Hong et al., 2021). In recent years, Artificial Intelligence (AI) integration has significantly improved classification accuracy and productivity. AI models such as Convolutional Neural Networks (CNN), Support Vector Machines (SVM), and Artificial Neural Networks (ANN) have enabled more precise ripeness detection and classification (Krizhevsky et al., 2017; Hong et al., 2021).

In most palm processing facilities, conveyor systems are implemented to reduce manual labour (Groover, 2020). Belt conveyors are commonly used in tandem with synchronous motor control systems. Advanced control frameworks such as Distributed Control Systems (DCS) now dominate these operations by offering integrated computer control, real-time data transmission, and process monitoring. Additionally, Programmable Logic Controllers (PLC) remain prevalent in managing conveyor activities (Yue & Lu, 2024). Beyond control mechanisms, the physical conveyor architecture also plays a vital role. Efficient sorting is essential to categorizing palm fruit, and one proven method is the bomb bay sorter. This technique uses an electric motor or pneumatic actuator to open a hatch beneath the product, making it ideal for sorting various-sized items with high-speed throughput (Rahman et al., 2024; Boysen et al., 2017; Boysen et al., 2019; Hompel & Schmidt, 2006; Johnson & Russell, 2018; Furmans & Bohl, 2008; Gue & Meller, 2009).

In recent years, emerging technologies have become more accessible to the broader engineering and agricultural communities. The ESP32-CAM, for example, has been increasingly adopted as a low-cost AI vision system. When integrated with image recognition frameworks like YOLO and OpenCV, it supports real-time object detection in low-power environments (Tien & Nguyen, 2019; Chen & Li, 2024). You Only Look Once (YOLO) is valued for its speed and detection accuracy, while OpenCV provides a versatile image processing library compatible with multiple programming environments. Hafidz et al. (2024) demonstrated the effectiveness of ESP32-CAM in building stereo vision systems for object detection. Another tool, the HuskyLens AI camera, supports real-time object and colour recognition. Its simplicity and compatibility with microcontrollers make it suitable for both educational and applied uses in fields such as robotics and agriculture (DFRobot, 2023; Liu & Wang, 2022). In smart farming contexts, HuskyLens has been successfully utilized in tasks like colour-based crop monitoring and autonomous fruit sorting (Chen & Musa, 2023).

2. Methodology

Figure 1 shows the flowchart of the loose palm fruit quality inspection system. The system begins when Huskylens is initialized and set into colour recognition mode and establishes connection with ESP32. After confirming connection, the system begins connecting to Firebase console through ESP32 Wi-Fi connection. During operation, Huskylens scan for recognized colour for example colour_id: 1, colour_id2, colour_id:3, and colour_id: 4. If Huskylens find a matching colour id, ESP32 will trigger an action – colour_id:4 trigger bomb bay sorter while colour ID 1 to colour ID 3 do not. All recognized colours will be sent to Firebase console for documentation. This process is running continuously until any interruption is introduced to the system.

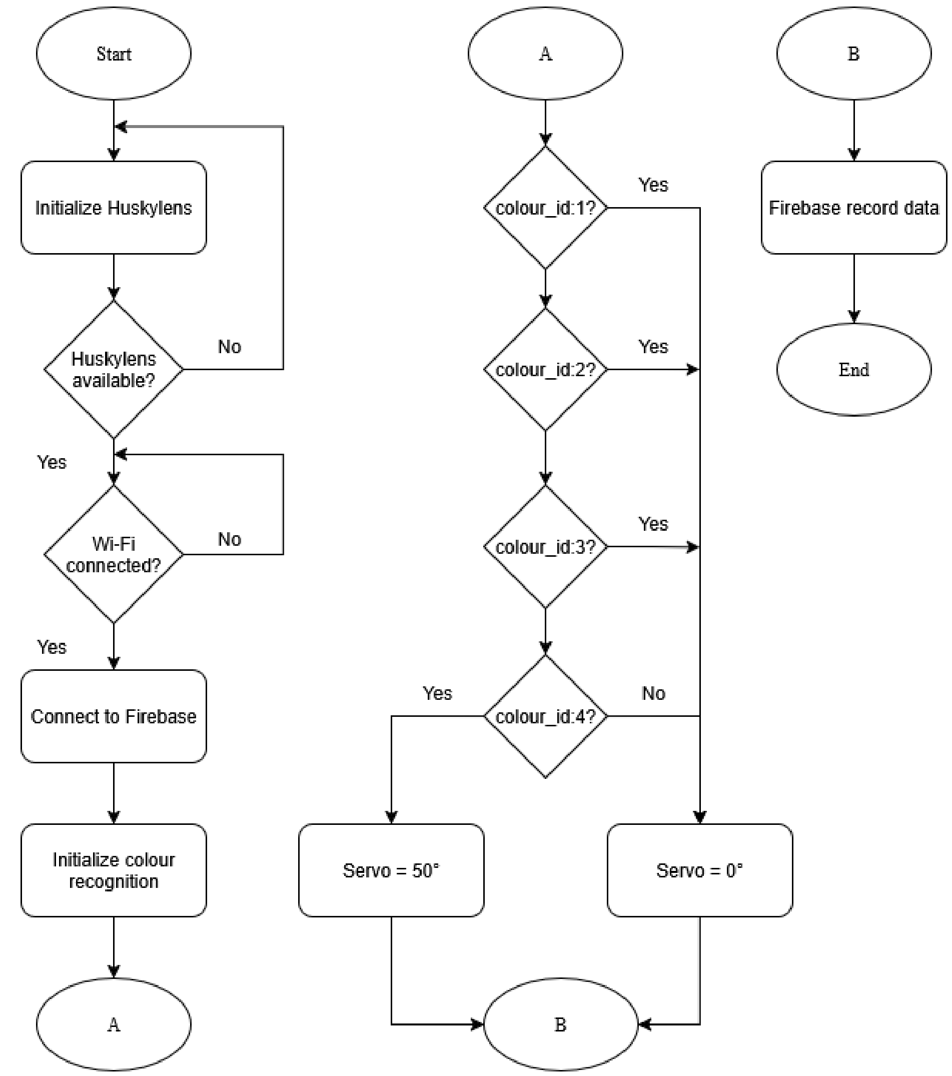


Fig 1: *System Flowchart*

Figure 2 shows the block diagram for the project. The Huskylens act as the sole input for the system. It will provide information regarding the colour to ESP32, which acts as the system controller. ESP32 is used to control the actuation for bomb bay via servo motor and act as the main communicator with Firebase. A 24VDC power supply is used to power the whole system.

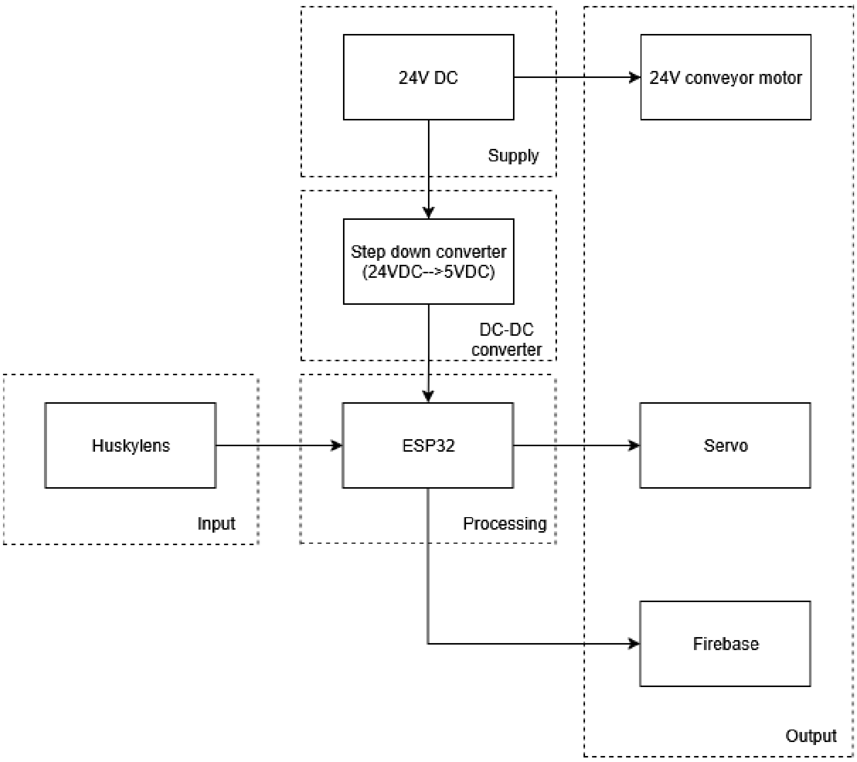


Fig 2: *Block diagram of the project*

Next, the experimental setup is arranged as in Figure 3 and Figure 4. The Huskylens is connected to the ESP32 for data input. The ESP32 then will process the data and feed the data to Firebase for data records and provide a necessary output for the servo motor. 24VDC power supply is connected to step down converter bringing voltage drop from 24V to 5V for ESP32 operation while conveyor system is directly connected to the 24V power supply.

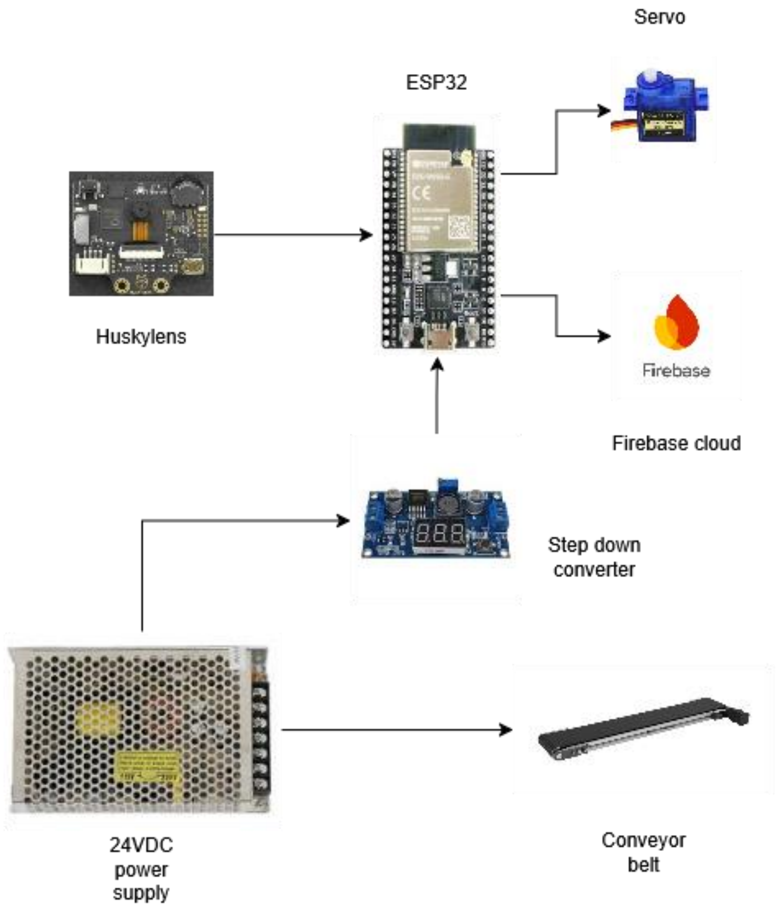


Fig 3: *Experiment setup of the project*

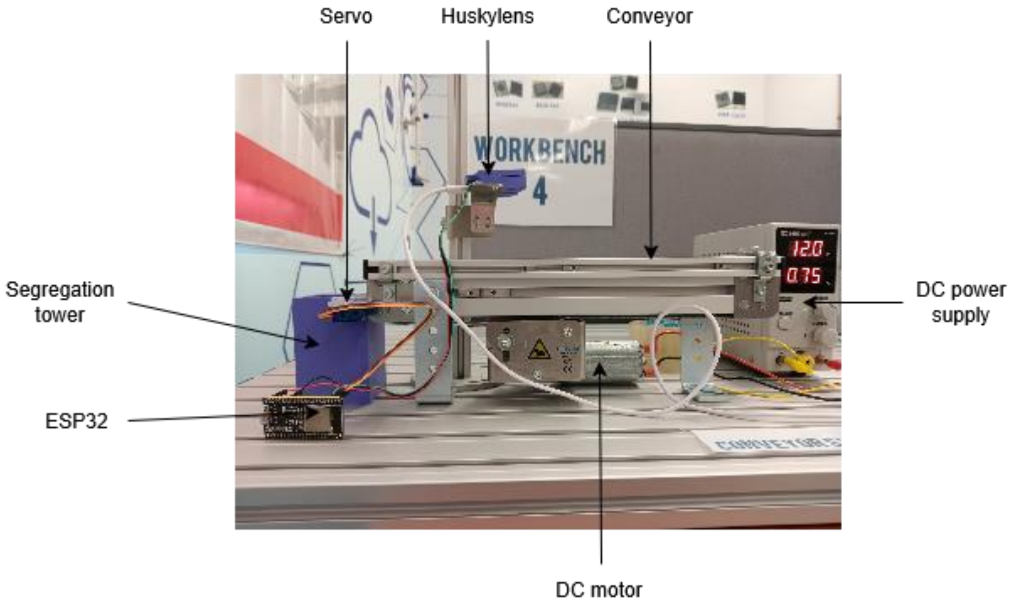
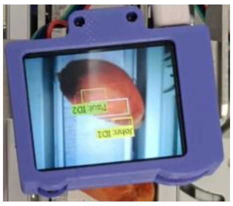
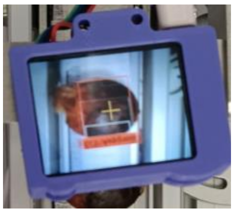


Fig 4: *Actual setup*

3. Results and Discussion

Once the setup is complete, a colour ID is assigned to each fruit to represent their ripeness level. This colour ID help simplify the data collected and provides a more systematic approach. Table 1 shows each colour ID along with their represented ripeness level.

Table 1: *Colour ID and ripeness level*

Colour ID	Colour	Fruit characteristics	Ripeness level
Colour_id:1	Orange		Overripe
Colour_id:2	Red		Ripe
Colour_id:3	Orange-red		Ripe
Colour_id:4	Black		Underripe

This table is used when assigning each colour ID to avoid any false data and action occurring in the system. This ID also includes information necessary for the Firebase storage. Figure 5 to Figure 7 shows how the Colour ID is used in the Firebase console.

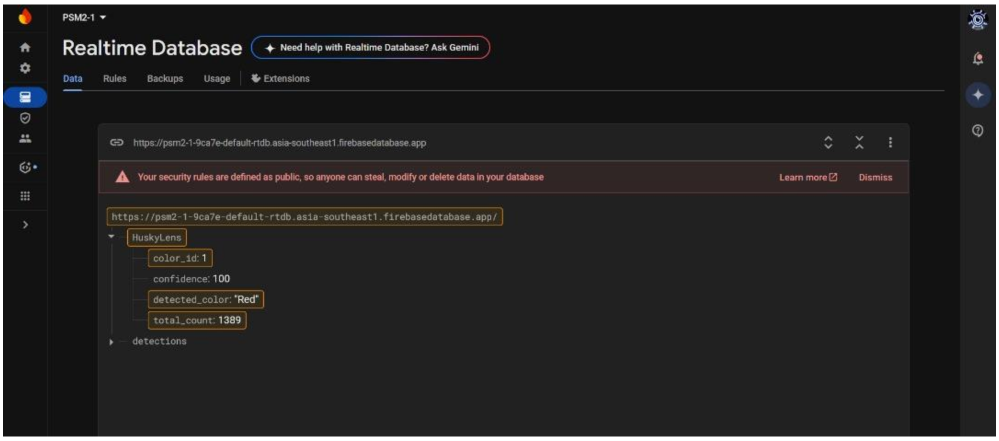


Fig 5: *Firebase login colour_id: 1*

Penerbit UTHM

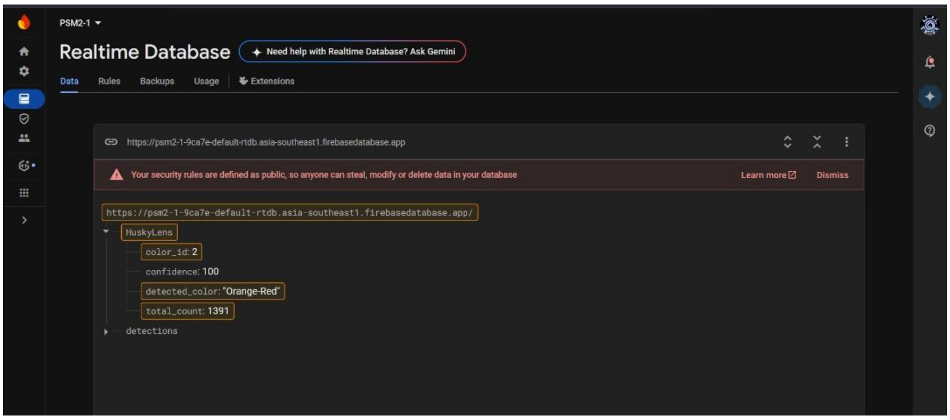


Fig 6: *Firebase login colour_id: 2*

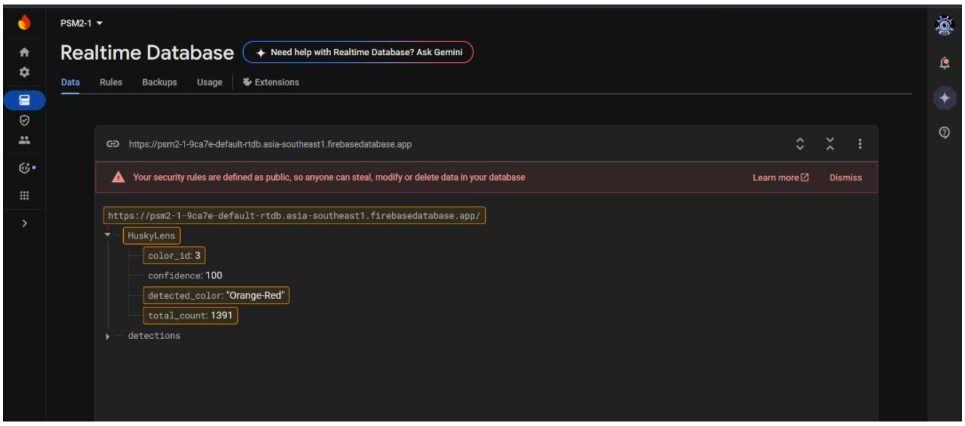


Fig 7: *Firebase login colour_id: 3*

Each colour ID contains a colour name and is used to count the total number of fruits detected by the system. This helps the system keep track of the fruit it detects and make data acquisitions and analysis easier. By implementing the colour ID, it also helps confirm the system able to communicate with Firebase console by eliminating a so-called ghost ID.

Figure 8 illustrates how conveyor speed responds to varying voltage values ranging from 5V to 24V. At 5V, the conveyor operates at minimum speed at 0.015 m/s, which also indicates its minimum operating voltage. At 0.015 m/s, it would reduce the system efficiency significantly. At the higher end, the conveyor achieves its maximum speed of 0.09 m/s when being supplied with 24V, but this could damage the conveyor over time make it unsuitable to be applied.

The graph also shows the optimal operating voltage for the conveyor shown by the dashed line. At 12V, the conveyor speed is 0.05 m/s that has a balanced trade-off between operational safety and efficiency. While speed is an important factor, a balance operation is crucial to ensure the system's reliability and longevity.

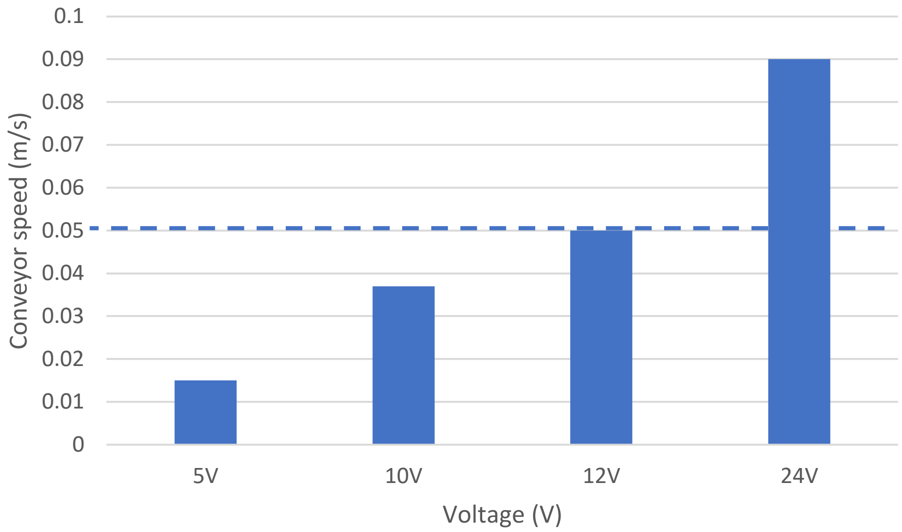


Fig 8: *Conveyor speed vs voltage*

Figure 9 shows the relationship between conveyor speed and camera accuracy was examined using 30 palm fruits. At a speed of 0.015 m/s, the camera successfully detected all fruit with 100% accuracy. However, this high level of accuracy comes at a cost of significantly slower system performance, making it impractical for real-life applications.

At 0.037 m/s, the accuracy drops slightly to 97% which remains acceptable but still too slow for practical implementation. At 0.05 m/s, the accuracy decreases further to 90% representing a small trade-off in precision for a considerably faster operation. Operating at 0.05 m/s provides a good balance between detection reliability and system efficiency, while still maintaining safe operation condition as stated in Figure 8.

Conversely, at 0.09 m/s the camera accuracy drops significantly from 90% to 33%. This makes the system unreliable for detection at high speed. This also implies that as the speed increases the camera accuracy decreases.

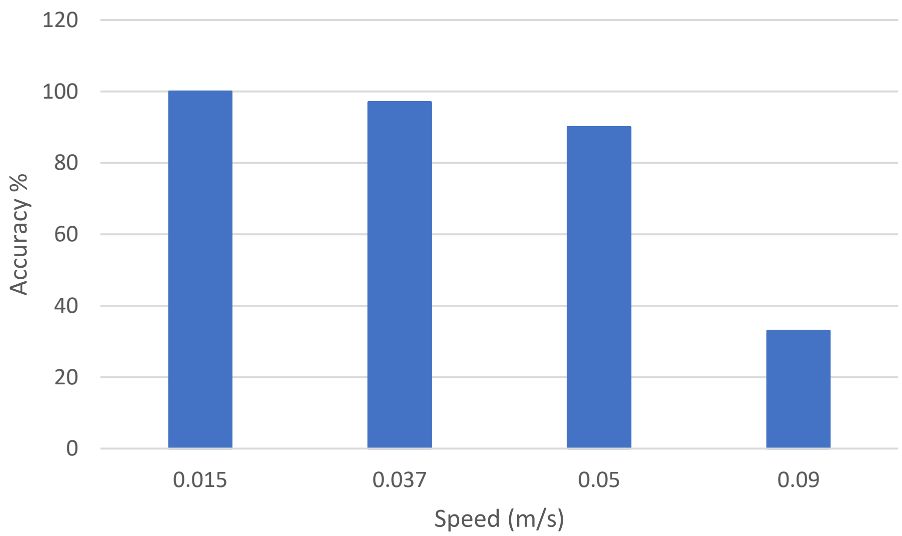


Fig 9: *Accuracy vs conveyor speed*

Figure 10 shows the relationship between conveyor speed and the number of fruits detected per minute is assessed. At 0.015 m/s, the camera is only able to detect four palm fruits within one minute, which correlates with the slow system pace. The graph shows that as the conveyor speed increases, the number of fruits detected per minute also increases.

At 0.037 m/s, the detection increases six times to 24 fruit/min and at 0.05m/s, camera able to detect 30 fruit/min achieving its goals. At 0.09 m/s, camera able to detect 52 fruit/min, surpassing its goals. But as stated in Figure 4.6, faster speed reduces the detection accuracy significantly. Thus 0.05 m/s remains the optimal speed that offer both speed and precision for colour detection

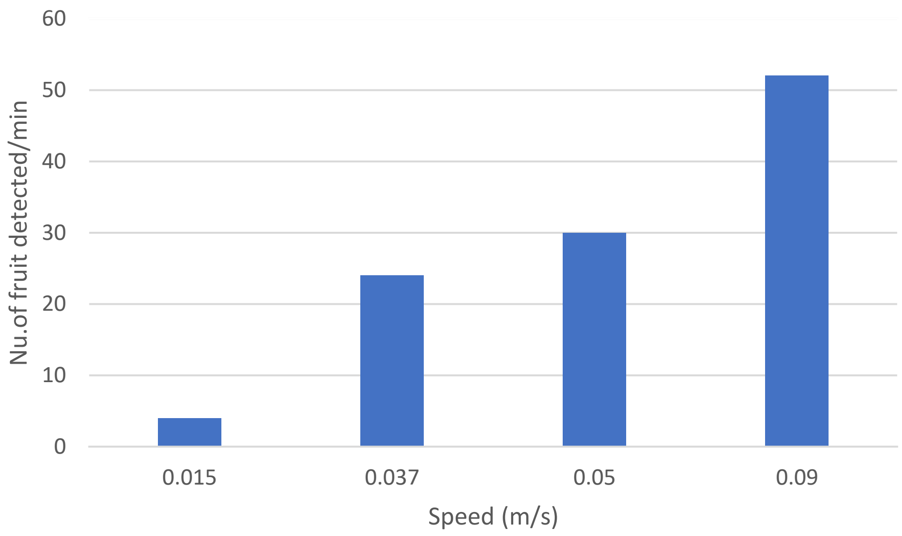


Fig 10: *No. of fruit detected per minute vs conveyor speed*

Figure 11 show the result for detection accuracy by colour at 22 V. The graph show oranges colour has the highest accuracy at 100%, indicating optimal detection and operation at 22V due to its bright and high contrast colour which makes it easier for the system to detect its colour. This also indicated at 22V, the system can detect orange colour consistently with high accuracy.

Red and orange red colour has second highest accuracy at 80%, due to be almost identical to each other both colour has the same accuracy when detected. Although their accuracy is 80%, it also suggests that the system has a hard time differentiating the colour which could affect system reliability when being scaled up.

Black exhibits the lowest accuracy at 22V at 20%. This value suggests the system is struggling to detect a dark colour object due to minimum reflection. This low value makes it unreliable to detect black or dark colour.

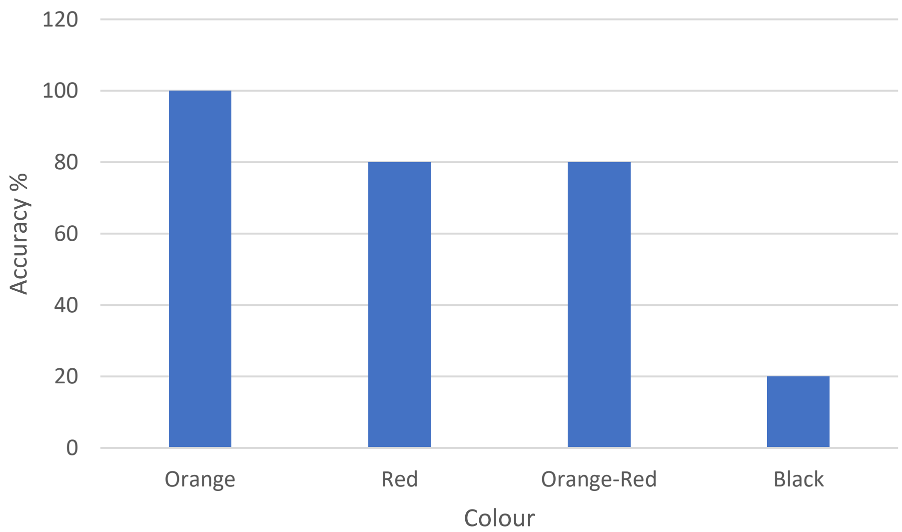


Fig 11: *Accuracy by colour at 22V*

Figure 12 evaluates the same four colours as in Graph 4.8, but under a 12V supply. The results show that the detection accuracy remains consistent with the 22V scenario. Orange is detected with 100% accuracy, red and orange-red at 80% and black at 20%. However, operating at 12V reduces the system speed and negatively affects overall performance. Although the detection accuracy is unaffected, the system experiences a decline in operational efficiency, making 12V operation unsuitable for high-speed or high-volume environment.

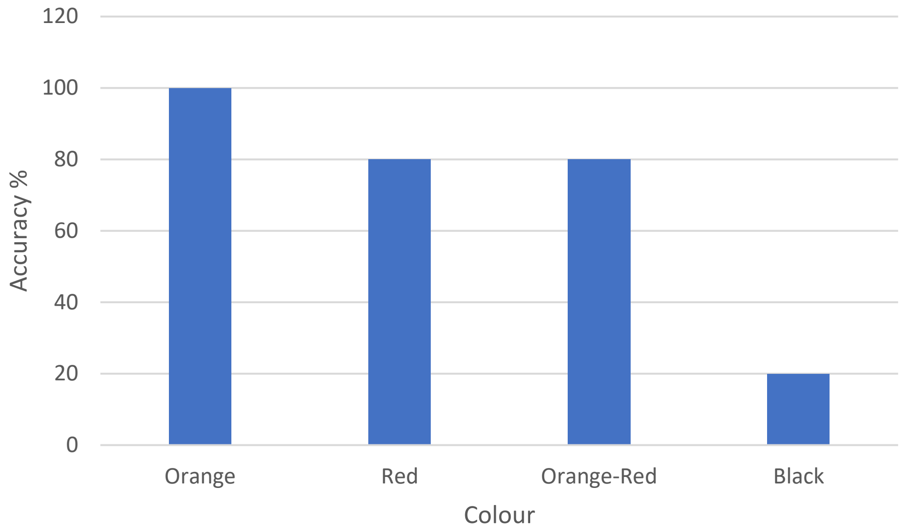


Fig 12: *Accuracy by colour at 12V*

4. Conclusion

In conclusion, this project successfully developed an automated palm fruit quality inspection system using AI-based image recognition and IoT technologies. Husklens was able to detect the colour reliably and ESP32 perform an excellent job in controlling the whole system. The system developed show an excellent result where the optimal conveyor system in between 0.048 m/s – 0.05 m/s which yield a balance trade-off between speed and precision. Testing shows the system able to detect and recognize 30 fruit per minute with 90% accuracy. Furthermore, the system shows excellent results when detecting and recognizing high-contrast colour like orange, red, and orange-red colour, while darker colour like black show lower detection value due to low contrast and reflectivity. Implementation of Firebase console also improves the data acquisition and monitoring process for the whole system.

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