Internet of Things (IoT) - based Fruit Sorting Results Monitoring System

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Abstract. This research presents an experiment utilizing machine learning technology in an automatic simulator designed for sorting fruit by type and color conditions. The simulator is integrated with a real-time monitoring system that uses deep learning algorithms. The deep learning methods applied enable automatic monitoring of fruit sorting results, which can be transmitted via an Android-based application over the internet. The fruit sorting machine is equipped with a dashboard for monitoring and control, displaying both the quantity and quality of the fruit. This system can also be applied directly to fruit plants, allowing remote analysis of fruit production via an internet network. The real-time monitoring system provides accurate data and information on early fruit crop production. During software and hardware testing, the fruit sorting machine was able to detect the color quality of four different types of fruit using object detection technology based on the Tensor Flow Lite algorithm. The system's performance was evaluated using a confusion matrix, achieving a precision rate of 85.7%, an accuracy rate of 81.2%, and a recall rate of 72%. These results demonstrate that the detection system performs optimally in identifying fruit types.

Keywords: Algorithms, IoT, Machine learning, Monitoring, Tensor Flow

1 Introduction

Various types of fruit are popular for processing and consumption as food supplements, leading to the rapid growth of fruit cultivation (Hidayat et al., 2020). According to data from the Central Statistics Agency and the Directorate General of Horticulture in 2019, Indonesia produced 1,020,333 tons of fruit (Husein & Kharisma, 2020). Interest in apples, tomatoes, mangoes, and oranges is very high both in Indonesia and internationally, prompting farmers to maximize production while ensuring good quality (Rinaldi et al., 2023). However, the fruit sorting process in many industries is still predominantly manual (Suma, 2021). This has driven the development of machine learning technologies, allowing machines to sort various types of fruit automatically and efficiently, in contrast to manual methods, which can result in inconsistent sorting

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(Kristiawan et al., 2020). To inspect fruit destined for processing industries, export, traditional markets, and supermarkets, automatic sorting systems can be utilized (Afifah et al., 2024). These systems can leverage digital image processing technology, specifically object detection, a subset of computer vision that identifies and locates objects in images or videos (Dwiyatno et al., 2022).

Image processing refers to the manipulation of images to accelerate the detection process or make decisions based on trained data (Wiley & Lucas, 2018). Computer vision, also known as computer visualization, involves transforming data from sources such as images, videos from directories, or real-time camera feeds, and is essential for image processing tasks (Oktaviani et al., 2023). Various algorithms can be applied in object detection, including the Tensor Flow deep learning algorithm, with its lightweight version known as Tensor Flow Lite. Tensor Flow Lite utilizes the Efficient Det-Lite architectural model, a streamlined version of EfficientDet (Evita et al., 2022).

According to research conducted by Mingxing Tan, EfficientDet consistently achieves superior accuracy and efficiency compared to other architectural models (Tan et al., 2020). A study addressing this issue is Ihsan's research titled "Facial Expression Detection Using Tensor Flow" (Ihsan et al., 2021). Another relevant study is by Arbilah titled "Design and Implementation of Goods Sorting Tools on Conveyors with Image Processing" (Arbilah et al., 2021). Building on these studies, a fruit-sorting tool was developed using object recognition based on the Tensor Flow Lite algorithm. The mechanical setup for the fruit sorter includes a servo motor for sorting, a conveyor for moving the fruit, and a camera to detect the shape and type of fruit being sorted. The machine, capable of sorting four types of fruit, is equipped with a Raspberry Pi 4 Model B microprocessor and a Coral USB Accelerator. The fruit types green apples, red tomatoes, oranges, and mangoes are placed on a conveyor, where a camera or webcam detects the shape and color of the fruit in real-time. If the fruit's type and color match the trained dataset, the sorter directs the fruit to the appropriate container using a servo motor. The sorting system utilizes an infrared sensor to delay the camera and allow clear object detection. Better results are shown by the classification of banana fruit quality based on fruit images using Stochastic Gradient Descent (SGD) with hyperparameter variations (Armiady & Muslem R, 2023).

Various studies on object detection using deep learning algorithms in computer vision and sorting tools have been conducted. One such study was carried out by Mohamad Ihsan, Ratih Kumalasari Niswatin, and Daniel Swanjaya (Ihsan et al., 2021), and published in the Unisla Engineering Faculty Journal. Their research focused on facial expression detection in computer vision, titled "Facial Expression Detection Using Tensor Flow". The results demonstrated that the Tensor Flow algorithm, applied to detect seven different facial expressions using a real-time webcam, achieved an accuracy of 77%, precision of 72%, and recall of 74%. Testing on external data, different from the training sample, resulted in an accuracy of 67%, precision of 67%, and recall of 66%. A notable weakness of the study was the relatively high training loss value of 4.29% and validation loss of 3.96%. While both studies involve computer vision, they use different deep-learning algorithms. In this research, the Tensor Flow Lite algorithm will be used to detect objects via a webcam or camera in real-time. The objects to be detected are tomatoes, classified into four categories: super green tomatoes, non-super green tomatoes, super red tomatoes, and non-super red tomatoes.

Furthermore, research by Fajar Ridho Wicaksono, Angga Rusdinar, and Ig. Prasetya Dwi Wibawa focused on automatic goods sorting based on image processing Titled "Design and Implementation of Goods Sorting Tools on Conveyors Using Image Processing" (Wicaksono et al., 2018a; Wicaksono et al., 2018b). This study employed the HSV (Hue, Saturation, and Value) algorithm to sort goods based on color specifically red and blue on a conveyor. The system used a camera to detect the color of the goods, which was then processed by a single-board computer. The algorithm demonstrated effective performance, achieving 85% accuracy in sorting goods using a pusher arm to direct items to the distribution line. However, the study identified a shortcoming: an average error rate of 4.739% in distance readings of red and blue, primarily caused by light intensity fluctuations affecting pixel readings. The similarity between this study and the current research is the use of Raspberry Pi microprocessors and conveyors as the moving mechanism. The key difference lies in the object being detected and the algorithm used, with this research utilizing the Tensor Flow Lite deep learning algorithm.

2 Methodology

This research involved direct experimentation with a fruit sorting machine simulator, utilizing machine learning technology and the Tensor Flow algorithm. The research objective was to develop a fruit sorting monitoring and control system based on IoT. This system, powered by the Tensor Flow algorithm, is designed to automatically detect and control the condition of four types of fruit using machine learning. Reference data, stored in a database, will be collected for the four fruit types. To recognize objects in images, specific parameters are required to characterize each fruit. These characteristics are extracted and grouped into defined classes based on certain parameters. Image classification involves grouping all pixels in an image into classes, with each class representing an entity with specific attributes. The accuracy of the fruit detection system depends on the diversity of the training samples and images being analyzed. The classification method used is unsupervised classification, which operates by differentiating the gray levels of each pixel in the image.

3 Result and Discussion

3.1 Result

The hardware system was successfully implemented, featuring an aluminum main frame equipped with a conveyor belt to transport the fruit toward the detection camera. Upon detection, a servo motor attached to a solid plastic arm directs the fruit, adjusting by an angle of 200 degrees. This hardware setup is a key component in the detection process, as the fruit travels along the conveyor belt for identification. The fruit samples used for detection include Green Apples, Mangoes, Oranges, and Tomatoes. These samples were processed using a model trained in Google Colaboratory, with the output in.tflite format, which is specifically designed for running object detection methods in Tensor Flow Lite. The detection results from this model are presented in Table 1.

Table 1. Detection results

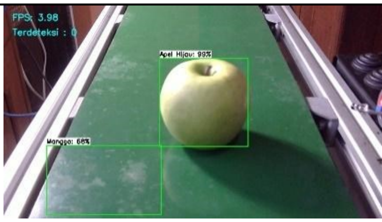
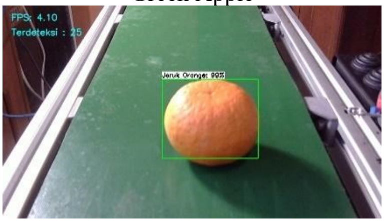
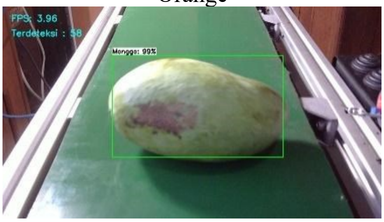
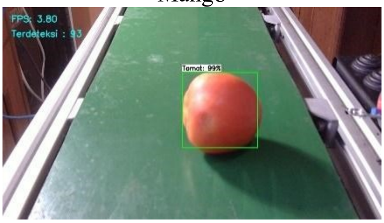
Actual condition	Test data	Result
Green Apple	 Green Apple	False Positive
Orange	 Orange	True Positive
Mango	 Mango	True Positive
Tomato	 Tomato	True Positive

Table 2. Detection results in the confusion matrix

Data result	True	False
Positive	36	6
Negative	0	8

The system's detection data is analyzed using a confusion matrix, which calculates recall, precision, and accuracy levels, as shown in Table 2. The detection status is monitored and sent to a dashboard viewable on an Android smartphone. This monitoring dashboard will display the detection results within the Android application. The system is designed with a Kodular creator and the files are in APK format. To ensure successful data transmission to the monitoring dashboard, the detection tool must meet specific connectivity requirements: it must be connected to the internet and configured with the correct database address. The database used is Google Firebase's Real-Time Database, which supports real-time data updates every second from the fruit sorting simulator. Firebase was chosen for its free authentication service, a unique feature among available databases. Once the database is successfully connected, all data will be sent to predefined variables within the database via API (Application Programming Interface) authentication. The dashboard display is illustrated in Figure 1.

In the connectivity process, potential issues include weak internet signals and data format discrepancies. To ensure smooth operation, the database accepts only strings and integers; thus, the displayed information is limited to the fruit names and their respective counts. The camera detection data is not shown in the application to maintain a responsive dashboard that focuses on delivering the most current data.

Figure 1. Monitoring dashboard (in Indonesia language)

3.2 Discussion

The system design features an aluminum frame and incorporates a conveyor belt for fruit transport. This conveyor belt is powered by a DC motor with a single direction of rotation. The camera is mounted above the conveyor and positioned to capture a comprehensive view of the fruits on the belt. The design has been tailored to accommodate the length of the conveyor lane, though the width has only been adjusted for the prototype. The system's performance has been tested with up to 5 fruits aligned in a single camera view. It successfully detects these fruits simultaneously without issues. This suggests that the detection system can handle more than 5 fruits without interference, assuming the design is scaled appropriately. However, the conveyor belt is limited to supporting a maximum weight of 5 kg. It is crucial to consider the weight of the fruits when designing the system, taking into account the anticipated number of fruits that will pass through the conveyor and be detected by the camera.

Based on fruit type detection tests, the system's performance can be evaluated by analyzing the detected fruit types as they pass through the conveyor belt. The system operates optimally when the camera is positioned 20 cm above the conveyor, ensuring a clear view of the fruits. The camera continuously detects fruits as they enter its frame. Out of 50 test runs, the system correctly identified fruit types 36 times, resulting in true positive results. This indicates the successful detection of the fruits. However, there were 6 false positive instances where non-fruits were incorrectly identified as fruits. These results are used to assess the detection system's performance using the confusion matrix formula.

In testing fruit detection, the objects classified as positive include mango, tomato, orange, and green apple. Objects that are not detected, or instances where no object is detected, are categorized as negative data. False positive data occur when the system incorrectly identifies a non-fruit object as a fruit. This error is often due to the system confusing a negative object with a positive one, which is reflected in a lower confidence level for false positives compared to true positives. False positive data is crucial for assessing the precision of the detection system, as it indicates how often the system misidentifies objects. False negative data, on the other hand, occurs when the system fails to detect an object that is present. This can result from suboptimal training datasets or visual disturbances such as poor lighting. The amount of false negative data impacts the system's recall level, which measures the system's success in detecting objects based on the created dataset. The performance of the detection system can be evaluated using the confusion matrix, which provides insights into precision and recall levels.

$$Recall\ Rate = \frac{TP}{TP+FN} = \frac{36}{36+8} = 0{,}812\ or\ 81{,}2\% \tag{1}$$

$$Precision\ Level = \frac{TP}{TP+FP} = \frac{36}{36+6} = 0{,}857\ or\ 85{,}7\% \tag{2}$$

$$Accuracy\ Level = \frac{TP+TN}{TP+FP+TN+FN} = \frac{36+0}{36+6+0+8} = 0{,}72\ or\ 72\% \tag{3}$$

The testing results indicate that the system operates optimally, achieving an 81.2% success rate in detecting objects. The system's precision is 85.7%, and its overall accuracy performance level is 72%. These results categorize the fruit sorting monitoring machine as performing well in object detection.

The system uses a real-time database, specifically Firebase, to determine the number and type of detected fruits. To identify fruit types, the system requires a dataset tailored to the specific fruits being detected. The detection frame is captured and sent to Firebase, which facilitates quick updates to the dashboard. Firebase's real-time capabilities are well-suited for this application as it only handles strings and integers, not visual data. The system continuously processes fruit sorting data as long as the detection frame is active. However, data is not saved automatically, meaning that once the fruit has passed the detection frame, the dashboard resets to its initial conditions. This setup ensures that the dashboard displays the most current data from the system.

4 Conclusion

The fruit sorting monitoring system utilizes machine learning technology with the Tensor Flow algorithm, enabling real-time data transmission of fruit object detection results via the internet. The monitoring dashboard displays the number and types of fruits successfully detected by the system. The fruit sorting machine exhibits optimal performance, with a system recall rate of 85.7%, an accuracy rate of 81.2%, and a precision rate of 72% in detecting four types of fruit.

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