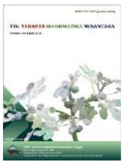

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Implementation of an Automatic Waste Sorting System using YOLOv5s with TFLite Conversion on Raspberry Pi

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Abstract–Waste management remains a major environmental challenge in Indonesia, particularly due to the low level of public awareness in sorting waste based on its type. This research aims to design and implement an image-based automatic waste sorting system using the YOLOv5s algorithm with TensorFlow Lite conversion on a Raspberry Pi 3B+. The research was conducted through a system development approach without involving human respondents, focusing on performance evaluation using an image dataset consisting of three categories: paper and tissue, plastic bottles, and cans. The proposed system integrates hardware components, including a camera, servo motors, an ultrasonic sensor, and an LCD, with software components such as YOLOv5s, OpenCV, and TensorFlow Lite. The model performance was evaluated using precision, recall, and mean Average Precision (mAP), while system functionality was assessed through hardware testing. The results show that the model achieved a precision of 0.986, recall of 0.978, and mAP@0.5 of 0.99, indicating excellent detection performance. In addition, the implementation of TensorFlow Lite significantly improved computational efficiency, with the system achieving a processing speed of 173.9 frames per second (FPS). These results demonstrate that the proposed system is capable of performing accurate and efficient real-time waste classification on resource-constrained devices. This research contributes by providing an efficient and practical implementation of real-time waste sorting using a lightweight deep learning model on embedded hardware.

Keywords: Waste Classification; YOLOv5s; TensorFlow Lite; Raspberry Pi; Object Detection

1. INTRODUCTION

Waste management remains one of the most critical environmental issues in Indonesia. Waste is defined as residual material from human activities or natural processes that is no longer useful and is discarded by its producer (Dewi, 2021). It can exist in solid, liquid, or gas forms depending on the generating activities (Hasibuan, 2023). In general, waste is classified into two main categories: organic and inorganic waste. Organic waste, such as food scraps and dry leaves, can decompose naturally but may produce unpleasant odors and become a source of disease if not properly managed. In contrast, inorganic waste, including plastic, metal, and glass, is difficult to decompose and requires special processing or recycling methods (Hasibuan, 2023).

Along with population growth and increasing human activities, the volume of waste continues to rise significantly. However, this increase is not accompanied by adequate public awareness in sorting waste based on its type, resulting in mixed waste that complicates management and recycling processes (Rahman, 2021). Effective waste management can begin with proper sorting at the source, which not only reduces waste accumulation but also extends the lifespan of disposal sites and preserves the economic value of recyclable materials (Wahyuningsih et al., 2023). According to data from the National Waste Management Information System (SIPSN) by the Ministry of Environment and Forestry (KLHK) in 2025, Indonesia generates approximately 27.20 million tons of waste annually, of which only 34.21% is properly managed while 65.79% remains unmanaged. This condition highlights the urgent need for more effective and innovative waste management solutions.

One promising solution is the application of Artificial Intelligence (AI), particularly in image processing through object detection techniques, which enable systems to automatically identify and locate objects within images or videos (Fauzi et al., 2020). The development of object detection has evolved from traditional feature-based approaches such as SIFT and HOG to deep learning-based models that significantly improve detection accuracy and efficiency (Gui et al., 2024). In deep learning, models learn from data during the training process by minimizing prediction errors using optimization techniques such as backpropagation (Rizqolima & Widhiantoro, 2025). This capability enables models to automatically extract important features from images, making them highly effective for object detection tasks. Among various algorithms, YOLO (You Only Look Once) has gained significant attention due to its ability to perform fast and efficient object detection in a single stage, making it suitable for real-time applications (Jiang et al., 2022).

In addition, image processing and object detection systems are commonly supported by the Open Source Computer Vision Library (OpenCV), which is an open-source library designed to simplify the development of computer vision applications (Wibysono et al., 2022). OpenCV was initially developed by Intel to enable computers to process visual data similarly to human vision (Zulfachmi et al., 2024). It provides various functions for image and video processing, including object detection, tracking, transformation, and integration with machine learning models, making it a powerful tool for real-time applications.

Several previous research efforts have investigated the application of object detection techniques for waste classification. Hendri & Utaminingrum (2022) applied the YOLOv3 algorithm using a relatively large dataset and achieved accuracy above 90%; however, the model required longer computation time, making it less suitable for real-time applications. Abdillah et al. (2024) implemented YOLOv5 in a web-based system and achieved an accuracy of 86%, although the research was limited by a relatively small dataset. Santoso et al. (2025) utilized YOLOv4-Tiny on a

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Raspberry Pi and obtained a mean Average Precision (mAP) of 86.43%, but the detection speed was relatively low, ranging from 3 to 5 frames per second (FPS). In another research, Fajar et al. (2025) developed an automatic plastic waste sorting system using a Raspberry Pi, camera, and servo motors; however, the system only achieved an accuracy of 47.5%, indicating the need for further improvement.

Based on these previous research findings, it can be concluded that YOLO-based methods demonstrate strong potential for waste classification. However, several challenges remain, including limited datasets, suboptimal accuracy, and constraints in real-time implementation on resource-constrained devices. To address these limitations, deep learning models are commonly optimized through conversion into lightweight formats such as TensorFlow Lite, which is specifically designed for efficient execution on edge devices such as smartphones and single-board computers (Dai, 2020). This conversion process plays an important role in reducing model size, accelerating inference speed, and enabling real-time performance on devices with limited computational resources such as the Raspberry Pi.

In this research, the system is developed using a Raspberry Pi 3B+ as the main controller, which is a low-cost and energy-efficient single-board computer equipped with a quad-core ARM Cortex-A53 processor, 1 GB RAM, and built-in Wi-Fi and Bluetooth connectivity (Papakyriakou & Barbounakis, 2023). These specifications make it suitable for implementing real-time image-based object detection systems on edge devices, although optimization is required due to its limited resources. By integrating the YOLOv5s algorithm with TensorFlow Lite conversion and utilizing OpenCV for image processing, this research aims to improve both detection accuracy and computational efficiency for real-time waste classification.

Therefore, this research aims to develop an image-based automatic waste sorting system that can operate efficiently on resource-constrained devices. The system integrates object detection, hardware actuation, and real-time monitoring to support automatic waste classification in practical environments. This research makes several important contributions by developing an efficient and practical system for intelligent waste management. It implements a lightweight object detection model based on YOLOv5s, optimized with TensorFlow Lite to achieve real-time performance on a Raspberry Pi 3B+. The study also integrates image-based classification with hardware components such as servo motors and ultrasonic sensors, enabling automatic waste sorting and accurate volume monitoring. Furthermore, it presents a complete Internet of Things based system that facilitates real-time data visualization and monitoring. This integrated approach enhances system usability and demonstrates strong potential for scalable deployment in real-world environmental management applications.

2. RESEARCH METHODOLOGY

2.1 Basic Research Framework

This research is categorized as applied research, which aims to design and implement an image-based automatic waste sorting system using the YOLOv5s algorithm with TensorFlow Lite conversion on a Raspberry Pi. The purpose of this research is to develop a system capable of classifying waste types accurately and efficiently in real-time conditions, particularly on resource-constrained devices. This research adopts the Waterfall method, which consists of sequential stages including requirements analysis, system design, implementation, and testing. In the requirements analysis stage, system needs are identified, including hardware and software components. The design stage defines the system architecture and workflow. The implementation stage involves system development and individual component testing. Finally, the testing stage ensures that the system works properly as an integrated unit. The research does not involve human respondents, as the evaluation focuses on system performance and model accuracy. The variables consist of input (waste images), process (object detection using YOLOv5s and TensorFlow Lite optimization), and output (waste classification results and system responses). System performance is evaluated using precision, recall, and mAP metrics, along with functional testing of hardware components.

It is hypothesized that the implementation of YOLOv5s with TensorFlow Lite conversion can improve computational efficiency while maintaining high detection accuracy on a Raspberry Pi.

2.2 Research Stages

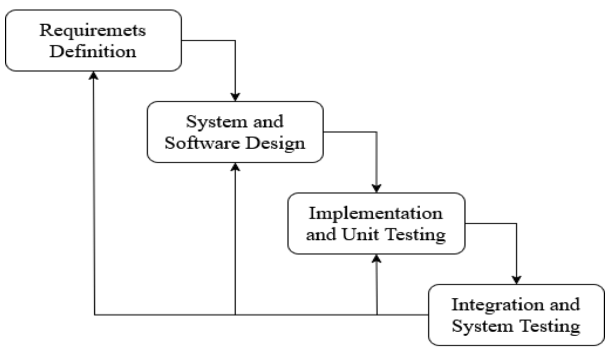

Figure 1. Research Stages of Waterfall Method

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The Waterfall model used in this research is illustrated in Figure 1 and consists of several sequential phases: requirements definition, system and software design, implementation and unit testing, and integration and system testing. In the requirements definition stage, all system needs are identified, including both hardware and software components required for the automatic waste sorting system. The system and software design stage focuses on defining the system architecture, workflow, and data processing mechanisms. Next, in the implementation and unit testing stage, the system is developed and each component is tested individually to ensure proper functionality. Finally, in the integration and system testing stage, all components are combined into a complete system and tested to ensure that they work together effectively and operate as expected.

2.3 Requirements Definition

The requirements analysis phase is the initial step in the Waterfall method, which aims to identify and define all system requirements that must be fulfilled. In this stage, system requirements are collected and analyzed comprehensively to ensure that the developed system aligns with the intended objectives and user needs. The requirements document produced in this phase serves as the primary reference throughout the system development lifecycle. Therefore, any ambiguity or errors in defining requirements may lead to issues in subsequent stages, particularly during system design and implementation (Swasotomo, 2025).

2.4 System and Software Design

This section describes the system and software design process used in the research. The design is carried out to illustrate the system workflow, the relationships between components, and the data processing mechanism from input to output.

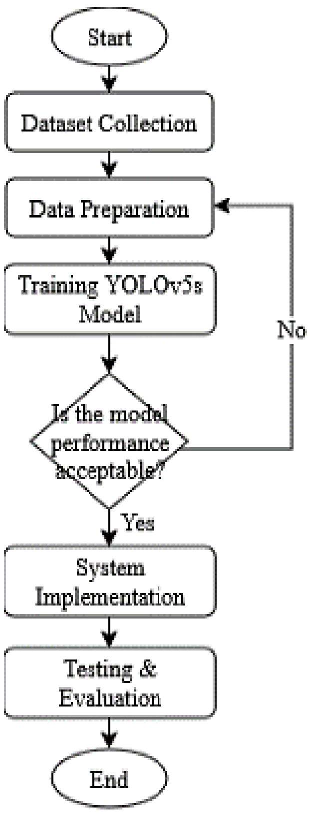

Figure 2. Workflow of Object Detection System

The flowchart illustrates (Figure 2) the workflow of developing a YOLOv5s-based waste detection system. The process begins with dataset collection, followed by data preparation, including annotation and data splitting. Next, the YOLOv5s model is trained using the prepared dataset. The model is then evaluated to determine whether its performance meets the required criteria. If the performance is not satisfactory, the process returns to the data preparation stage for improvement. If it meets the requirements, the model is implemented into the system, followed by testing and evaluation until the system is ready for use.

The system design is carried out to develop an image-based automatic waste sorting system capable of detecting and classifying different types of waste in real-time. The proposed system integrates both hardware and software components that are interconnected to achieve an optimal detection and sorting process.

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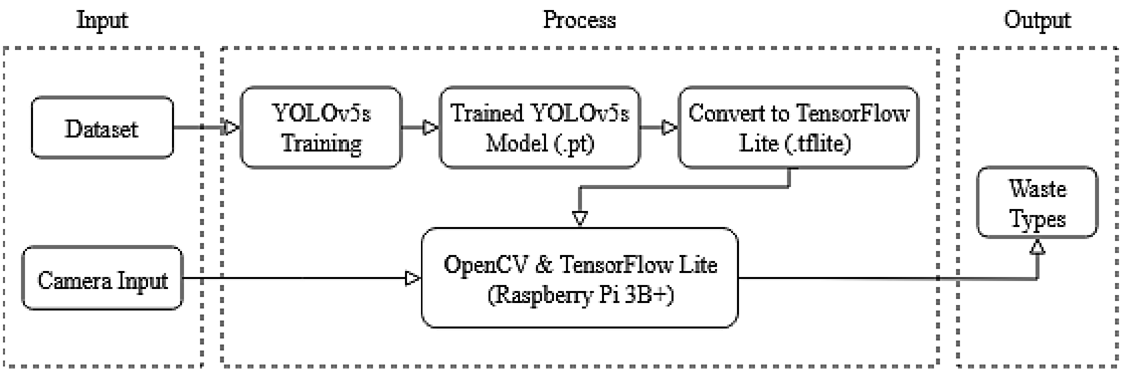

Figure 3. Block Diagram of Object Detection System

Figure 3 illustrates the architecture of the automatic waste sorting system, which consists of three main components: input, process, and output. In the input stage, the system utilizes a dataset for training the YOLOv5s model, as well as real-time image input captured from a camera. In the processing stage, the trained model is converted into TensorFlow Lite (TFLite) format to enable deployment on the Raspberry Pi 3B+. The captured images are then processed using OpenCV and the TFLite model to perform object detection. The output of this process is the identified waste type, which is displayed and can be integrated with an IoT-based system for monitoring purposes.

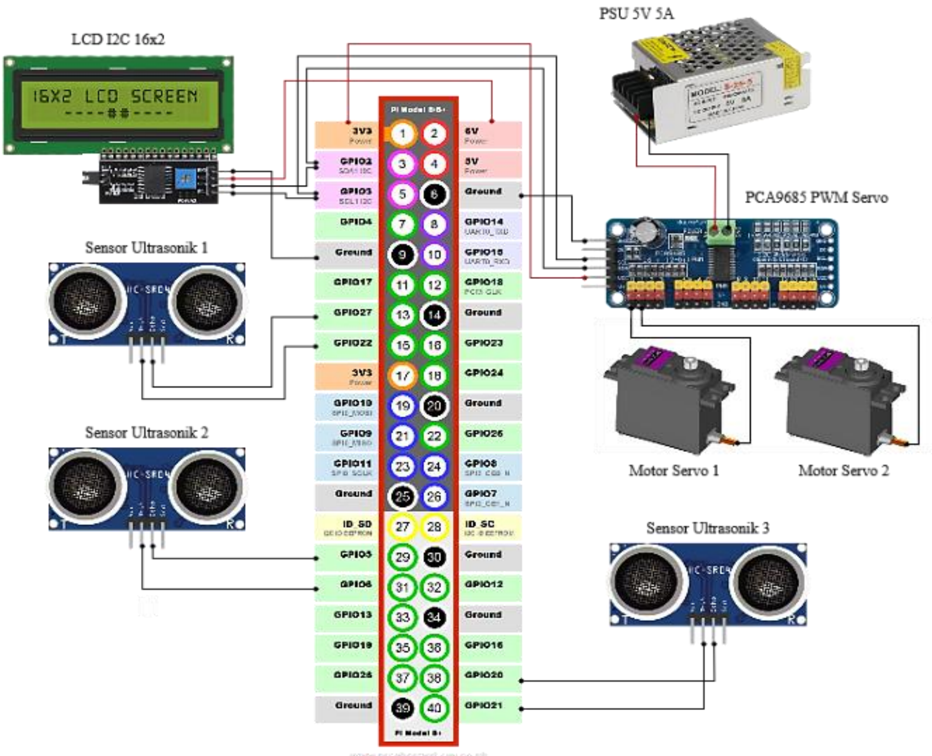

Figure 4. Hardware Circuit Design

Figure 4 illustrates the hardware design of the automatic waste sorting system. The Raspberry Pi 3B+ acts as the main controller that connects all components through its GPIO pins. A camera is used as the input device to capture images of the waste, while a servo motor functions to direct the waste into the appropriate bin based on the classification results. An ultrasonic sensor is utilized to detect the capacity or fill level of each waste container. In addition, an LCD is used to display the detection results directly to the user. All components are interconnected and operate in an integrated manner to support the automatic waste sorting process.

2.5 Implementation and Unit Testing

At this stage, the implementation of the automatic waste sorting system is carried out in a real-world form, including the integration of hardware and software components. Each component is tested individually to ensure that it functions according to the system design. Testing is performed on the sensor to detect object presence, the camera to capture waste images, the detection model to classify waste types, and the servo motor as the sorting actuator. This process aims to ensure that each part of the system operates properly before conducting overall system testing.

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2.6 Integration and System Testing

After all system components have been successfully tested individually, the next stage is to integrate them into a complete system. At this stage, comprehensive testing is conducted to ensure that all components, from waste detection by the camera, object classification by the model, servo motor actuation, waste volume measurement, to data transmission and display, can communicate and operate synchronously. This testing aims to evaluate whether the system workflow functions as designed and is capable of providing fast and accurate responses under real-world conditions.

3. RESULTS AND DISCUSSION

3.1 Data Collection and Preparation

The data collection process was carried out by gathering waste images from various sources to ensure dataset diversity. The collected data include several categories, namely paper and tissue, plastic bottles, and cans, as shown in Figure 5.

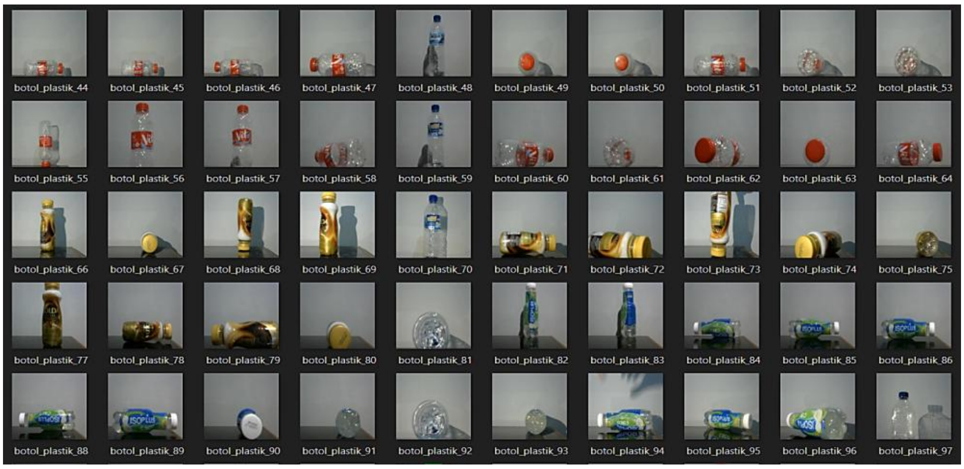


Figure 5. Data Collection

In this research, the dataset used consists of waste images categorized into several classes, namely paper and tissue waste, plastic bottles, and cans. The image data were obtained from publicly available online datasets as well as direct image acquisition to increase data variation. The use of diverse data sources aims to improve the model's ability to recognize objects under various conditions. The distribution of images in each class is presented in Table 1.

Table 1. Dataset Distribution

Class	Number
Paper and Tissue	229
Plastic Bottles	247
Cans	200

The data collection process was carried out by considering variations in object types, image capture angles, and lighting conditions. This is important to enhance the model's capability in accurately detecting objects in real-world scenarios. As shown in Table 1, the dataset consists of 229 images of paper and tissue waste, 247 images of plastic bottles, and 200 images of cans. The collected dataset is then used as the basis for training the YOLOv5s model.

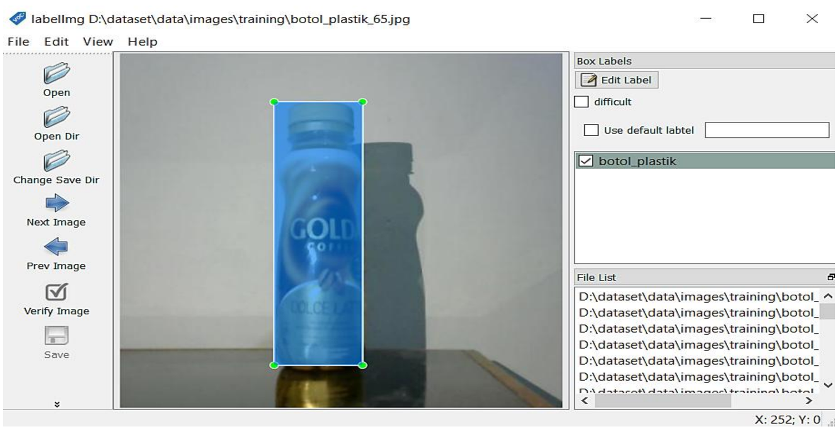
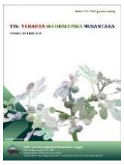


Figure 6. Data Annotation



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As shown in Figure 6, the initial stage of data preparation is carried out through an annotation process on each waste image. Image annotation is performed using LabelImg. LabelImg is a free and user-friendly image annotation tool that is widely used by researchers for creating datasets in object detection tasks (Ke et al., 2024). By using LabelImg, each waste object in the image can be labeled according to its category. This annotation process aims to identify the position of objects within the image and provide class information that will be used in the model training process.

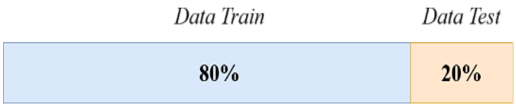

Figure 7. Data Splitting

Furthermore, the dataset is divided into two parts, namely training data and testing data, as illustrated in Figure 7. This data splitting is intended to train the model and evaluate its ability to recognize new data. In this research, the dataset is divided with a proportion of 80% for training data and 20% for testing data.

3.2 Model Training

The modeling process is carried out using the YOLOv5s algorithm as the main method for detecting and classifying types of waste based on images. YOLOv5s is one of the variants of YOLO (You Only Look Once) designed to have a lightweight model size with high detection speed, making it suitable for implementation on resource-constrained devices such as the Raspberry Pi. YOLOv5s operates using a single-stage detection approach, where the system directly predicts the object location (bounding box) along with its class in a single process. This enables YOLOv5s to perform real-time object detection with good efficiency. In this stage, the dataset that has undergone annotation and preparation is used to train the YOLOv5s model.

3.3 Training Results

The performance of the trained YOLOv5s model was evaluated to assess its ability in detecting and classifying waste objects. The evaluation results are presented in Figure 8.

Class	Images	Instances	P	R	mAP50	mAP50-95:
all	376	496	0.986	0.978	0.99	0.885
kertas_dan_tisu	376	198	0.974	0.963	0.982	0.876
botol_plastik	376	172	0.994	0.996	0.995	0.886
kaleng	376	126	0.988	0.976	0.993	0.895

Figure 8. YOLOv5s Model Training Results

Figure 8 shows the performance metrics obtained from the YOLOv5s model after the training process. Based on the evaluation results, the model achieved a precision of 0.986 and a recall of 0.978, indicating that it can accurately detect objects and successfully recognize most objects in the dataset. The mAP@0.50 reached 0.99 (99%), demonstrating excellent detection performance, while the mAP@0.50–0.95 of 0.885 indicates stable performance across varying IoU thresholds. In terms of individual classes, the model is able to recognize objects effectively.

The high precision and recall values indicate that the model is capable of accurately identifying waste objects with minimal false positives and false negatives. This performance is influenced by the diversity of the dataset, including variations in lighting conditions, object angles, and backgrounds. In addition, the use of YOLOv5s contributes to efficient feature extraction and detection speed, making it suitable for real-time systems. However, minor misclassifications may still occur due to similarities in object shapes or overlapping objects.

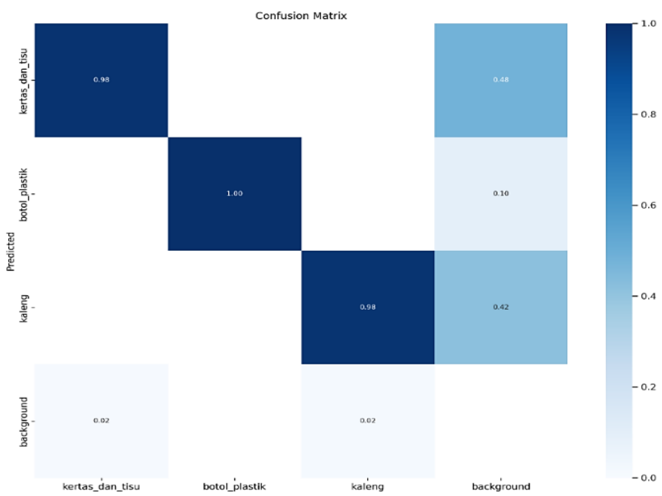

Figure 9. Confusion matrix of YOLOv5s model testing results

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As shown in Figure 9, most of the data were correctly classified. This is indicated by the values along the diagonal, which are close to 1, such as in the plastic bottle class, which reaches 1.00 or 100%. For the paper and tissue and can classes, values of 0.98 indicate that almost all data were accurately recognized. Meanwhile, misclassification errors are relatively minimal, as shown by the very low values outside the diagonal.

The confusion matrix results show that misclassification is very low, indicating strong class separability. This suggests that the model has successfully learned the distinguishing features of each waste category. The slight misclassification observed may be caused by similarities in texture or shape between certain objects, such as crumpled paper and certain plastic materials.

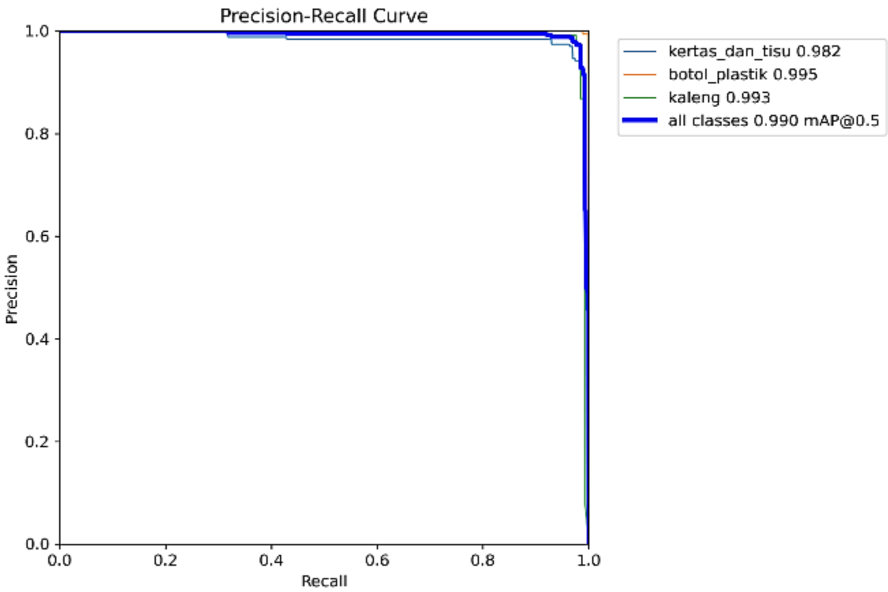

Figure 10. Precision-recall curve of YOLOv5s model testing results

Figure 10 illustrates the relationship between precision and recall in the object detection process using the YOLOv5s model. Precision indicates how accurate the model's detections are, while recall represents how many objects are successfully detected out of all actual objects in the test data. The Average Precision (AP) values for each class are very high, with 0.982 for paper and tissue, 0.995 for plastic bottles, and 0.993 for cans. In addition, the mean Average Precision (mAP@0.5) for all classes reaches 0.990 or 99%, indicating excellent overall detection performance.

The precision-recall curve demonstrates that the model maintains a high precision value even at higher recall levels, indicating a good balance between detecting as many objects as possible while maintaining accuracy. This is important in real-world applications where both false detections and missed detections must be minimized.

3.4 Conversion to TensorFlow Lite (TFLite)

After the modeling process is completed, the trained model is converted into the TensorFlow Lite (TFLite) format. This conversion process aims to optimize the model so that it can run efficiently on resource-constrained devices such as the Raspberry Pi 3B+. The converted model is then used in the system implementation stage to perform real-time detection and classification of waste types from camera input.

3.5 System Implementation

The system implementation is carried out by integrating both hardware and software components to enable the system to operate automatically. This implementation represents the application of the proposed method described in the previous section. To further explain how the proposed method is applied, the trained YOLOv5s model, which has been converted into TensorFlow Lite format, is deployed on the Raspberry Pi system. The model processes real-time image input captured by the camera, performs object detection, and generates classification results. Based on the detected class, control signals are sent to the servo motor to sort the waste automatically. At the same time, the ultrasonic sensor measures the container capacity, and the results are displayed on the LCD and can be monitored through the IoT system. This integration ensures that the entire process—from detection to sorting and monitoring—operates automatically in real-time.

The main device used is the Raspberry Pi 3B+ as the central controller, a camera as the image input, and a servo motor as the actuator for waste sorting. Additionally, an ultrasonic sensor is used to detect the fill level of the waste container, allowing the system to monitor its capacity in real-time. The hardware implementation of the system is illustrated in Figure 11.

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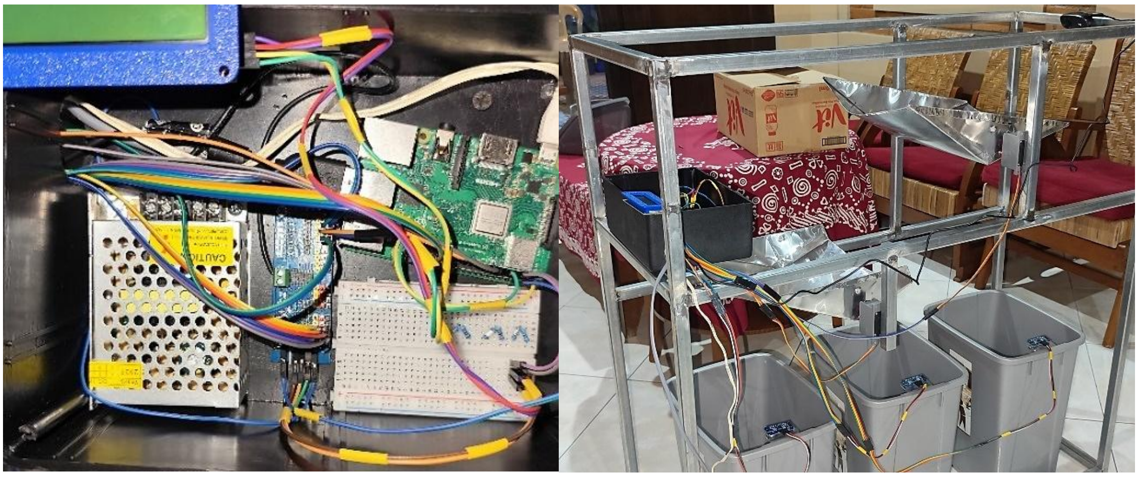

Figure 11. Hardware Design Implementation

3.6 System Testing

System Testing was conducted to ensure that each component of the system functions properly and operates in an integrated manner. The performance of the TensorFlow Lite (TFLite) model during real-time detection testing is presented in Figure 12.

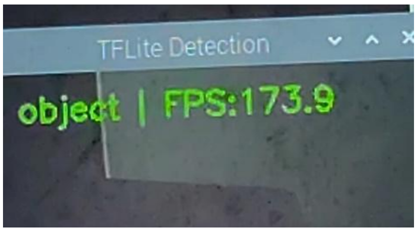

Figure 12. FPS of TFLite Real-Time Object Detection

As shown in Figure 12, the implementation of the TensorFlow Lite (TFLite) model demonstrates a significant improvement in inference speed when deployed on the Raspberry Pi. Based on the testing results, the system achieves a processing speed of 173.9 frames per second (FPS). This indicates that the converted TFLite model is highly efficient and capable of performing real-time object detection with very low latency. The high FPS value shows that the optimization process successfully reduces computational load while maintaining stable detection performance, making the system suitable for real-time waste sorting applications on resource-constrained devices.

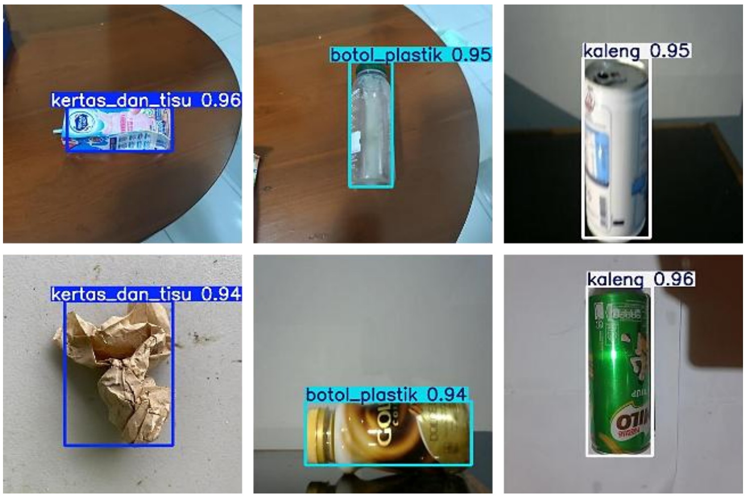

Figure 13. Successfully Detected Waste and Accuracy

Object detection testing was performed to evaluate the system's ability to detect and classify different types of waste based on images captured by the camera. The testing was carried out using several waste objects from each category, namely paper and tissue, plastic bottles, and cans. As shown in Figure 13, the system was able to correctly identify the tested objects according to their respective categories. The accuracy values ranged from 0.94 to 0.96, indicating that the model has good performance in detection tasks.

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Figure 14. LCD 16x2 I2C Testing

The LCD functionality was also tested to ensure that information could be displayed correctly to users. The testing results are presented in Figure 14. When the system successfully detects the type of waste, the LCD displays the waste category on the first line. On the second line, it shows the volume information in percentage form along with the status of the waste container, such as empty, medium, or full. Furthermore, when no object is detected, the LCD displays the message "No object detected," indicating that the system is in standby mode.

Servo response testing was conducted to ensure that the servo motor moves according to the commands generated by the system after the object detection and classification process. This test aims to verify whether each detected waste category produces the correct servo movement in terms of direction and position. During the testing phase, several waste objects from each category were used. After classification, the servo movement was observed to determine whether it moved in the correct direction and returned to its initial position after the sorting process. The results are presented in Table 2.

Table 2. Servo Response Testing Results

Detection Input	System Comman	Servo Movement	Status
Paper and tissue	Servo 1 active	Moves to the left	Success
Paper and tissue	Servo 1 active	Moves to the left	Success
Plastic bottle	Servo 1 & 2 active (alternating)	Servo 1 moves right, then Servo 2 moves left	Success
Plastic bottle	Servo 1 & 2 active (alternating)	Servo 1 moves right, then Servo 2 moves left	Success
Can	Servo 1 & 2 active (alternating)	Servo 1 moves right, then Servo 2 moves right	Success
Can	Servo 1 & 2 active (alternating)	Servo 1 moves right, then Servo 2 moves right	Success

As shown in Table 2, the servo motor responded accurately to the system commands. For the paper and tissue category, servo 1 consistently moved to the left as designed. For plastic bottles and cans, servo 1 and servo 2 operated alternately to direct the waste into the appropriate bins, with correct and stable movements. No significant delay or instability was observed during testing. Therefore, it can be concluded that the servo system functions properly and supports the automatic waste sorting process effectively.

The ultrasonic sensor HC-SR04 was tested by comparing the actual distance with the sensor's measured distance over a range of 5 cm to 30 cm at 5 cm intervals. The measurement results are presented in Table 3.

Table 3. Ultrasonic Sensor Testing Results

Actual Distance (cm)	Read Distance (cm)	Error	Accuracy (%)
5	5.2	0.2	96
10	9.6	0.4	96
15	16.2	1.2	92
20	19.1	0.9	95.50
25	26.8	1.8	92.80
30	28.6	1.4	95.33

Based on Table 3, the sensor shows minor differences between the actual distance and the measured distance. Overall, the HC-SR04 sensor demonstrates relatively good performance in distance detection, with accuracy remaining consistently above 92%. However, it can be observed that as the distance increases, the measurement error tends to grow. This is caused by factors such as ultrasonic wave reflection conditions, the surface characteristics of the target object, and the sensor's resolution limitations. The results indicate that the sensor is still suitable for use, with a fairly reliable level of performance for short to medium-range distance measurements.

Overall, the integration of hardware and software components shows that the system is capable of performing automatic waste sorting effectively. The combination of object detection, servo actuation, and sensor monitoring enables

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the system to operate in a fully automated manner. This demonstrates the feasibility of implementing intelligent waste sorting systems in real-world environments, particularly in areas with limited human intervention.

4. CONCLUSION

The results of this research demonstrate that the proposed image-based automatic waste sorting system using the YOLOv5s algorithm with TensorFlow Lite conversion on a Raspberry Pi 3B+ is able to perform waste detection and classification effectively in real-time conditions. The model achieved high performance, with precision, recall, and mAP values indicating accurate detection across all waste categories, namely paper and tissue, plastic bottles, and cans. The conversion of the model into TensorFlow Lite format significantly improved computational efficiency, as evidenced by the system's ability to reach 173.9 FPS, making it suitable for deployment on resource-constrained devices. In addition, the integration of hardware components, including the camera, servo motors, ultrasonic sensor, and LCD, functioned properly and supported the automatic sorting process as designed. However, this research has several limitations, such as the relatively limited dataset size and the system's dependency on lighting conditions and object positioning. Therefore, future research can focus on expanding the dataset, improving model robustness under various environmental conditions, and enhancing system scalability by integrating IoT-based monitoring features. Overall, this research successfully answers the problem of developing an efficient and accurate automatic waste sorting system for real-world applications.

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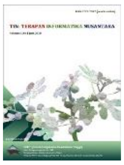

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