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Raspberry Pi 4 and Ultrasonic Sensor for Real-Time Waste Classification and Monitoring with Capacity Alert System

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ABSTRACT

The problem of waste management creates daily rubbish buildup due to thorough sorting. garbage sometimes accumulates in public garbage receptacles due to officials' ignorance of bin capacity and collectors' schedules, causing unclean conditions and the development of deadly diseases. Internet of Things technology was used to create a smart waste classification system with a notification mechanism in this study. This system classifies waste into plastic, metal, B3, and organic using a Raspberry Pi 4, camera module, and deep learning model. The classification uses a Convolutional Neural Network to speed up waste processing and separation. This research can be linked with research on separating trash types in one container and then allocated to garbage bins by type. Ultrasonic sensors and Raspberry Pi 4 can continuously monitor waste levels by sending data to the Ubidots IoT platform over HTTP. Based on experimental device data, system analysis shows 90% classification accuracy for all four waste categories. A Wireshark network analysis showed 61,098 bytes/s of throughput, 16 ms of delay, and zero data loss, demonstrating the system's ability for real-time monitoring and alerting. This research provides a realistic, cost-effective, and minimal solution to improve garbage classification and reduce collection costs to promote sustainability.

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1. INTRODUCTION

The world's growing population brings with it a mounting challenge waste management [1]. As waste generation increases, the environmental impact becomes increasingly significant [2], with large quantities of diverse waste materials requiring proper handling and disposa [3]. Efficient and timely waste management is crucial to mitigate these negative consequences [4], which can include pollution, resource depletion, and public health risks if waste is not managed effectively [5]. Traditional waste management systems, however, often struggle to keep pace [6]. Despite efforts to encourage waste separation at the source, such as designated bins for different waste types, improper disposal remains a persistent issue. To address this, researchers have explored the potential of emerging technologies, such as the Internet of Things, to enhance waste management processes [7], [8] This lack of source separation leads to significant challenges at final disposal sites, were waste must be manually sorted, slowing down the entire process [9]. Additionally, fixed collection schedules often result in overflowing bins, further compounding the problem [10], [11].

To address these challenges, this study proposes a smart waste management system inspired by recent advancements in the field [12], [13]. In existing research [34], waste is separated into organic and inorganic using a Raspberry Pi 4 as a microprocessor. In other studies, such as [35], waste classification is divided into Recycled Waste, Kitchen Waste, Hazardous Waste and other waste. To create a more specific waste classification, this research introduces a minimum system that includes a Raspberry Pi 4 and a camera, using image processing and deep learning methodology to classify waste independently [14] into four categories: Metal, Plastic, B3 (hazardous waste), and Organic, utilizing Convolutional Neural Network (CNN)[41]-[44]. A camera acts as the primary sensor [15], trained on a dataset of 50 images to accurately identify and classify waste items [16], The shooting was done by photographing the garbage in the surrounding environment and sorting it into 4 categories. The trash can that is made is designed to have four holes according to the type of waste which will be separated by a waste separator actuator using a servo [16].

In each hole an ultrasonic sensor [17]-[19] is installed to measure the waste capacity and the waste capacity is sent to the API IoT platform periodically using the Internet of Things [20] so that users can monitor the waste capacity in real-time such as system in [21]. Network analysis using Wireshark will be conducted to evaluate the system's data transmission efficiency, measuring key Quality of Service parameters such as throughput, delay [22], and packet loss [23] using formula (1)-(3). To solve the problem of overflowing bins, this research proposes early warning that rubbish bins are almost full with direct notification to officers so that rubbish collection officers can immediately act to collect rubbish. When the ultrasonic sensor reads the volume of waste disposal capacity of 90% using formula (5), the Raspberry Pi 4 will send notify to the user via telegram [24]-[25] to warn that the waste must be picked up immediately and provide information on the trash can's location. with a delay in sending data and sending notifications of 16 ms, then with this delay it can be concluded that the speed of receiving data and notifications is fast so that the response from the garbage collector will be faster.

The emergence of the Internet of Things has paved the way for smart waste management systems that offer real-time monitoring and automated solutions. These systems leverage technologies like image processing and deep learning for waste detection and classification [26]. Several studies have demonstrated the potential of IoT-enabled smart waste management systems in addressing the challenges of traditional approaches [27]. This system offers many benefits, including increased waste sorting accuracy, reduced collection frequency, and optimal resource allocation. In addition, the IoT system can provide real-time information on current waste capacity so that users can check anywhere and anytime [28].

This paper presents the design and implementation of a smart waste classification prototype integrated with a warning system, based on the Internet of Things technology [36]-[40]. The key contribution of this research is the development of a practical and efficient solution for optimizing waste management processes, promoting sustainability through improved waste classification and reduced collection overheads

2. METHODS AND SYSTEM

2.1. Flowchart and System

Raspberry Pi 4 and ultrasonic sensors have essential tasks in this study. Raspberry Pi4 is a core system as this research [45]-[47] that can connect to the internet without additional modules, and its ability to manage image data is good enough to sort four types of waste. The sorting is supported by a servo such this study [48], [49] integrated with Raspberry Pi 4 to deliver every kind of waste to the proper trash can. In addition, ultrasonic sensors [50], [51] that can read distances are managed so that Raspberry Pi 4 can read the volume of waste, a reference for early warnings sent to users. The system workflow is illustrated through two flow diagrams. Fig. 1(a) depicts the waste classification and sorting process within the smart trash can, while Fig. 1(b) outlines the workflow of the early warning system triggered when the waste level reaches 90% capacity.

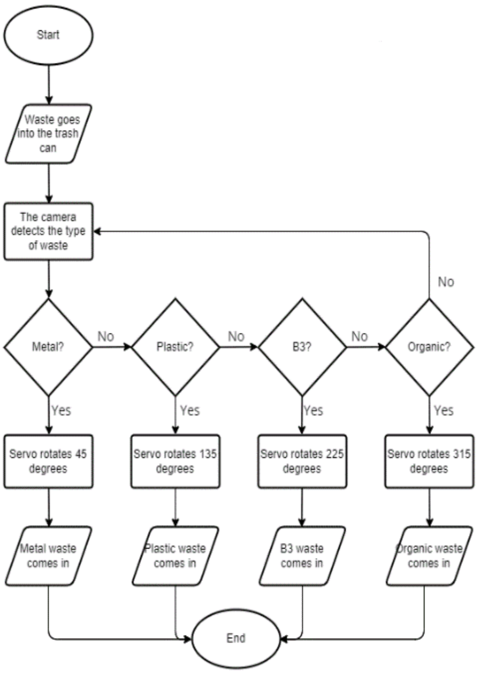
Waste is deposited into the designated intake area of the smart trash can. The integrated camera then captures an image of the waste item, and image processing techniques are applied to analyze the image and identify the waste type. Based on the determined waste type, the image processing and classification algorithm directs the servo motor to rotate the waste separator to the corresponding compartment: Metal (45 degrees), Plastic (135 degrees), B3 (225 degrees), or Organic (315 degrees). Finally, the waste item is deposited into the appropriate compartment.

Fig. 1(b) shows the flow of the process of sending data to an API IoT platform Ubidots which uses the HTTP protocol and an early warning system is a novel part of this research; it works when an ultrasonic sensor connected to a Raspberry Pi 4 detects a trash can volume of 90%. so that it can calculate the values of throughput, delay and packet loss, following the (1)-(3).

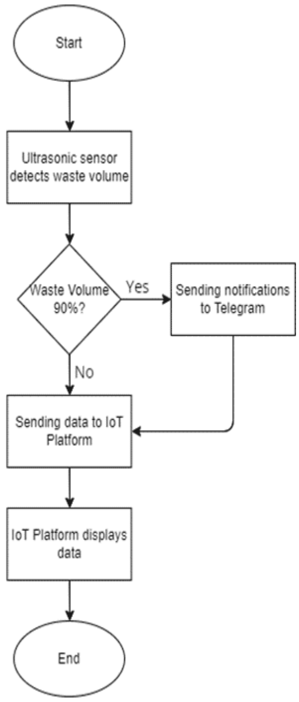
$$Packet\ loss = \frac{Packet\ Transmitte - Packet\ Received}{Packet\ Transmitte} \times 100 \tag{1}$$

$$Delay = \frac{Total\ Delay}{Total\ Packet\ Received} \tag{2}$$

$$Delay = \frac{Packet\ Received}{Time\ Transmitted} \tag{3}$$



(a)



(b)

Fig. 1. (a)Flowchart Waste (b)Flowchart Early Warning System of Waste

The process begins with an ultrasonic sensor installed in each hole in the trash can that detects the volume of waste from a distance by means of ultrasonic work in accordance with (4). The distance is read by the sensor and then converts it into volume using (5). After that, if the waste volume is less than 90%, then the waste volume data is sent from the Raspberry Pi 4 using the WIFI network and HTTPS protocol communication to the Ubidots IoT platform. If the trash volume reaches 90%, Raspberry Pi 4 will notify Telegram users using the WIFI network and send the trash volume data to the Ubidots IoT Platform. Furthermore, the Ubidots IoT platform will display real-time Waste Volume data on the Dashboard. The IoT-based system connects the IoT device in this research with the Ubidots IoT platform for monitoring waste volume and user social media, namely Telegram, for early warning notifications that the waste volume is almost full.

$$s = \frac{v \times t}{2} \tag{4}$$

where s is Distance, v is Speed of sound = $0.034\frac{cm}{\mu s}$ and t is Duration of sensor read. And the distance is read by the sensor and then converts it into volume using the following equation:

$$\frac{Sensor\ Reading}{Bin\ Height} \times 100 \tag{5}$$

2.1. Preprocessing

Before the waste classification process, the captured images undergo preprocessing techniques to enhance their features and improve the accuracy of the waste classification algorithm [15]. This research employs a median filter, a non-linear digital filtering technique, to reduce noise in the captured images. The use of a median filter in this study aims to improve image quality by removing noise without damaging important information. This is important so subsequent processes, such as feature extraction or classification with CNN, can run more accurately. The median filter replaces each pixel's value with the median value of its neighboring pixels within a defined kernel size, using the following formula:

$$Ifiltered(x, y) = median(\{I(i, j): (i, j) \in N(x, y)\}) \tag{5}$$

where $I(x, y)$is the original pixel value at position (x, y), $Ifiltered(x, y)$ is the new pixel value after applying the median filter, and $N(x, y)$ represents the neighborhood (kernel) around the pixel.

This approach effectively reduces impulsive noise, such as salt-and-pepper noise, while preserving crucial edges and details for accurate waste classification. The median filter is ideal for this task as it removes unwanted noise without compromising important visual features, ensuring reliable data for classification algorithms.

By improving image quality through selective noise removal, the median filter enhances the performance of the waste classification algorithm, leading to more accurate and reliable results. In turn enables the system to provide more reliable and accurate results in identifying the different waste types, which is a crucial step in the smart waste management process. And the preprocessing phase of this research was represented in Fig. 2.

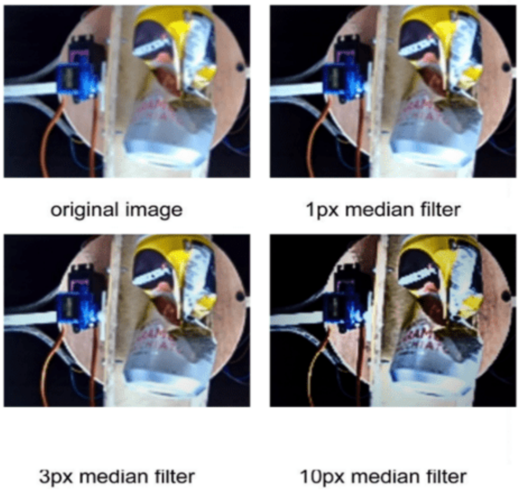


Fig. 2. Preprocessing using Median Filter

2.2. Training Data Set

So that the tool can differentiate between each type of waste, data training using machine learning is needed. The amount of training data is 50 data for 5 input classes, namely empty class, metal waste class, plastic waste class, B3 waste class, and organic waste class. Apart from that, the training data consists of Epochs 50 times, Batch Size 16, and Learning Rate 0.001. The data is displayed in Fig. 3. The five classes are trained and then produce a file with the extension .h5.

The input for this process is images according to class with 10 images for each class, so the total is 50 images. The image collection process for the dataset is carried out by photographing the waste in the surrounding environment and dividing it into four categories of waste: plastic, metal, B3, and organic. Then the training data is carried out 50 times and divided into 3 batches once each. The 3 batches are the result of 50 images: 16 batch sizes. And finally, the learning rate is 0.001. After the data training process is carried out, the training data results will be produced in the form of a file with the extension .h5.

The data training process commences with collecting and processing data from five primary categories (Empty, Metal, Plastic, B3, and Organic), wherein the data is labeled, normalized, and prepared for the deep learning model. Subsequently, the data is input into the model, which is trained using specific parameters, including a maximum of 50 epochs (the training process is reiterated 50 times), a batch size of 16 (data is processed in groups of 16 samples), and a learning rate of 0.001. The model generates predictions based on the input data through forward propagation, while backward propagation calculates the error using the loss function. The model is then refined with an optimizer, such as Adam (Adaptive Moment Estimation), until optimal weights are achieved. Upon completion, the trained model is preserved in a .h5 file for new data classification or testing.

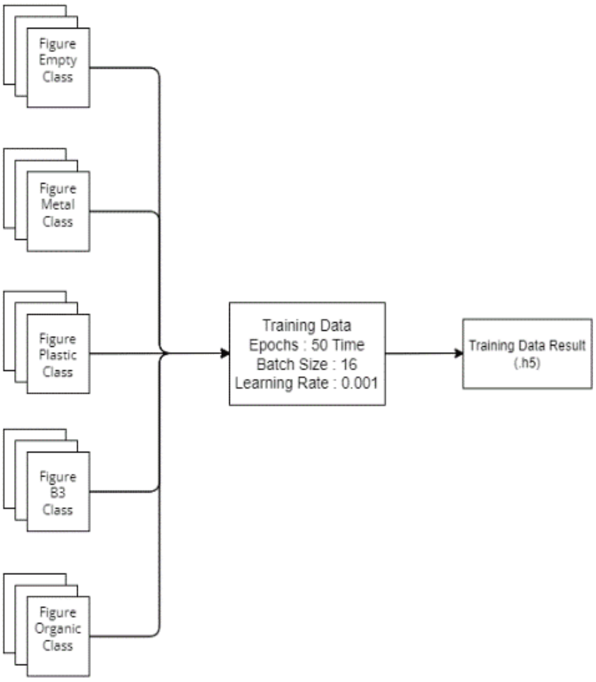


Fig. 3. Training Data Setup

2.3. Classification Image Method

The results of the training data will be entered into the main program so that the camera automatically carries out classification Images to determine the type of waste recorded. The libraries used to utilize the training data results are the TensorFlow, cvzone, and cv2 libraries. c shows the flow of the Machine Learning-based decision-making process for classifying types of waste read by the camera.

Fig. 4 shows the Classification of Waste based Machine Learning process. The process begins when the camera reads where the trash is placed, then the system performs feature extraction to see the characteristics of the trash that is placed into a value, then the value is matched with the training data file, and after that, it is classified according to the type of waste and the output produces whether it is trash. These are Empty (no waste at the location where the waste is placed) or No Empty, Metal or No Metal Waste, Plastic or No Plastic Waste, B3 or No B3 Waste, and Organic or No Organic Waste.

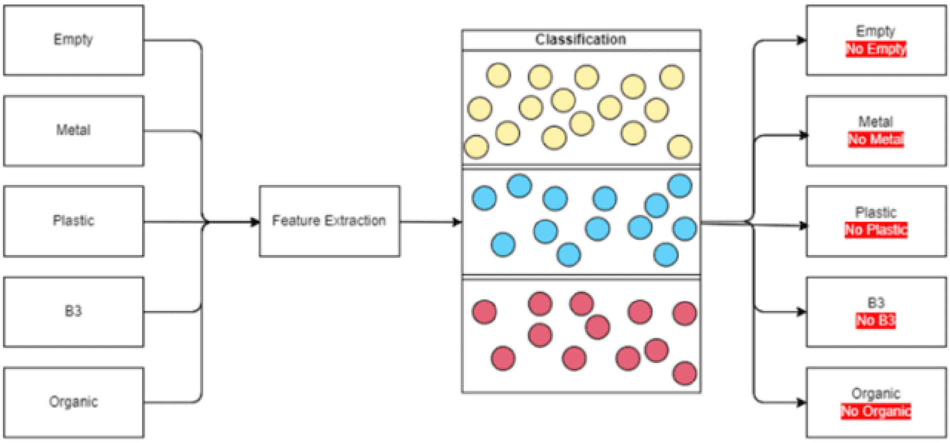


Fig. 4. Classification of Variation Waste

The system receives material images (such as metal, plastic, B3, organic, or empty) through a camera. The material image is fed into the system and processed through preprocessing to improve quality with Noise reduction, Normalization, and resizing to match the standard input of the CNN model. It is then analyzed by CNN using convolutional layers for complex feature extraction such as pattern, texture, and color, then through pooling and fully connected layers for final classification, producing an output that accurately identifies the material category such as plastic, metal, or organic.

2.4. Hardware Design

The IoT device utilizes a Raspberry Pi 4 [27], a camera, servos, and ultrasonic sensors, as shown in Fig. 5. The Raspberry Pi 4 features a Broadcom BCM2711 Quad-core Cortex-A72 (ARM v8) 64-bit SoC @ 1.8GHz, 2.4/5.0 GHz wireless, Bluetooth 5.0, 2 USB 3.0 ports, 2 USB 2.0 ports, Gigabit Ethernet, and 4 GB SDRAM. These specifications enable it to process images for identifying four types of waste [28]. The camera, connected via a USB 3.0 port, handles image and video processing, using a 5V power source and TX/RX for data exchange. Two servos sort and drop waste, while four ultrasonic sensors monitor trash capacity. These sensors are linked to the Raspberry Pi's GPIO header, with each Trig and Echo pin connected via a 220Ω resistor as shown in Table 1.

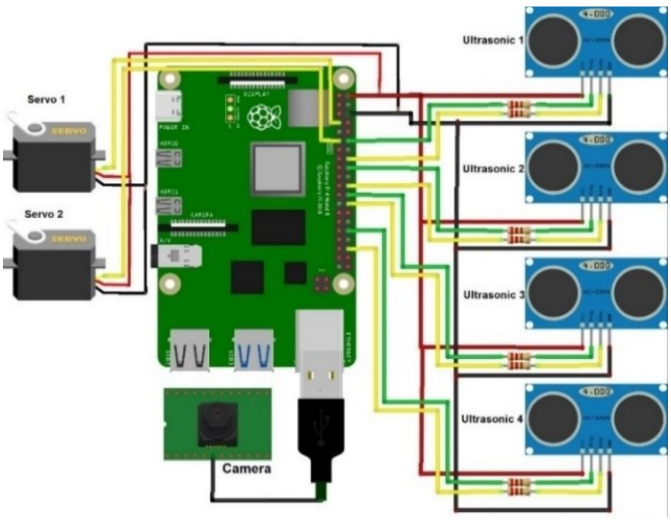


Fig. 5. Hardware Design

Table 1. Raspberry Pi 4 Connection with Sensors

	Servo 1				Servo 2			
	Red Wire	Black Wire	Purple Wire		Red Wire	Black Wire	Purple Wire	
GPIO Raspberry Pi 4	5V	GND	GPIO 4		5V	GND	GPIO 17	
	Ultrasonic 1				**Ultrasonic 2**			
	VCC	GND	Trig	Echo	VCC	GND	Trig	Echo
GPIO Raspberry Pi 4	5V	GND	GPIO 18	GPIO 23	5V	GND	GPIO 24	GPIO 25
	Ultrasonic 3				**Ultrasonic 4**			
	VCC	GND	Trig	Echo	VCC	GND	Trig	Echo
GPIO Raspberry Pi 4	5V	GND	GPIO 8	GPIO 7	5V	GND	GPIO 12	GPIO 16

The hardware that is made is specially designed and refers to 3D design with slight adjustments so that the placement of sensors and actuators can be precise. Fig. 6. is a picture of a trash bin made according to a 3D design and each side has a marker for the type of waste also shows the position of the camera above the trash can cover. For camera placement, its location can be raised further so that the camera can capture a wider area of incoming waste. Then shows the location of the servo and the holes on each side for the 4 types of waste and also the placement of the waste when inserted.

(a) (b) (c)

Fig. 6. View of trash can (b) Camera placement (c) Servo placement

3. RESULTS AND ANALYZES

3.1. Classification Processing Result

Classification Processing is a process to distinguish five classes, namely the empty class or the condition when the camera reads that there is no trash can at the location where the waste is placed, such as Fig. 7(a). Then the metal class or the condition when the camera reads metal waste (b). Then the plastic class, namely the condition when the camera reads plastic waste (c). Next is class B3, namely when the camera reads B3 waste (d), and finally the organic class, namely when the camera reads organic waste (e). Each figure displayed is the result of Python 3 programming. Every time the system reads the garbage that enters the device, the dashboard will show the type of garbage that is detected, as shown in Fig. 7(b)-Fig. 7(e). and will not show anything when it is empty. This makes the dashboard easy to use and read by anyone.

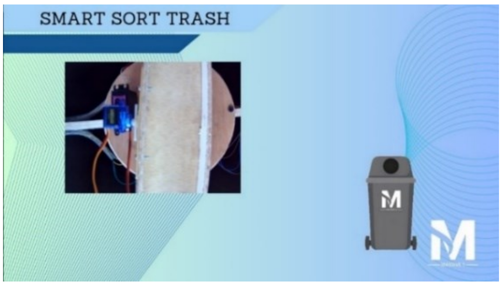


Fig. 7. (a) Classification Empty Capture

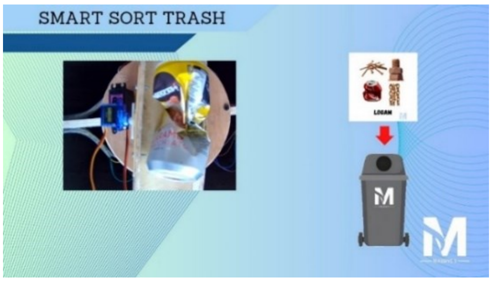


Fig. 7. (b) Classification Metal Capture

Fig. 7. (c) Classification Plastic Capture

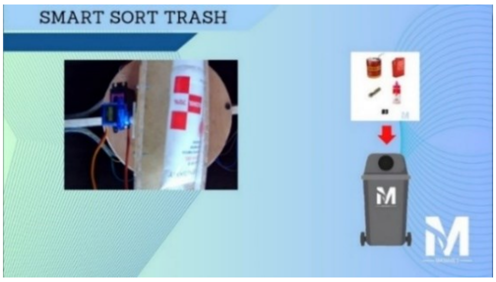


Fig. 7. (d) Classification B3 Capture

Fig. 7. (e) Classification Organic Capture

The model accuracy during training (accuracy) against the number of epochs passed show in Fig. 8. The X-axis (Epochs) is the number of training epochs, which is the number of complete iterations of the model over the dataset. The Y-axis (Accuracy) is the model accuracy (proportion of correct predictions) in the interval

[0,1]. The blue line (acc) is the model accuracy on the training data during training. The orange line (test acc) is the model accuracy on the test data (untrained data) during training.

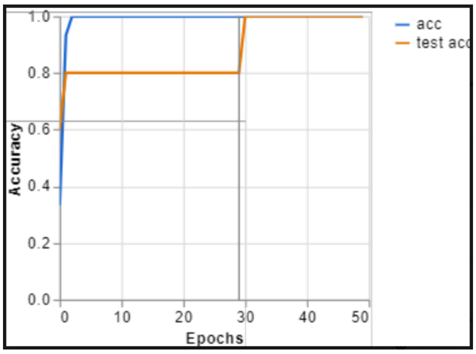


Fig. 8. Accuracy based on the number of epochs

The training accuracy (blue) rises rapidly, signifying that the model effectively assimilates patterns in the training data. The training accuracy attains a maximum of 100% approximately around epoch 15. The testing accuracy (orange) also rises at a comparable rate, albeit slower than the training accuracy. The testing accuracy rises until it stabilizes at approximately 0.9 (90%) and approaches 1 (100%). The model starts to comprehend the fundamental patterns in the training data, which can be generalized effectively to the testing data. The testing accuracy stabilizes at approximately 90% without notable declines.

Employing a sorting system of this nature will provide cleaners with more efficient waste handling in the subsequent phase. To facilitate further research, it is essential to augment the dataset to allow the system to categorize a diverse array of waste. This enhancement must accompany an increase in the precision of the outcomes.

3.2. Result of Monitoring and Early Warning System

This research produced highly encouraging results, highlighting the effectiveness of the newly developed smart waste management system. The system's monitoring capabilities, accessible through an intuitive web interface, offer real-time insights into waste accumulation patterns. The intuitive dashboard includes two separate visualisations for waste capacity data: a gauge display that offers an instant overview of current waste levels for each category (metal, plastic, hazardous, and organic) and a graphical representation that illustrates historical trash volume trends. The visualisations presented in Fig. 7 assist users in recognising long-term trends and formulating viable optimisation plans.

Accurate measurement of waste volume is a cornerstone of effective waste management. To achieve this, the system employs ultrasonic sensors to collect data, which is then processed using (5). This equation takes into account a predefined trash bin depth of 50 cm, translating sensor readings into precise volume measurements. This methodology not only ensures the reliability of the monitoring process but also enhances the accuracy of the system’s early warning capabilities.

One of the key achievements of this research is the development and implementation of a robust early warning system, as depicted in Fig. 9(b). When ultrasonic sensors detect that the amount of waste in a certain bin has reached 90% of its capacity, the Raspberry Pi 4 instantly sends out an alert using the Telegram messaging app, giving consumers timely notice that waste collection is urgently needed. Importantly, the notification includes the exact location of the nearly full bin, facilitating more efficient waste collection efforts and helping to prevent overflow. This proactive approach to waste management, characterized by real-time monitoring and an efficient notification system, highlights the practical value and effectiveness of the developed smart waste management system. By addressing both immediate and long-term waste management needs, this system represents a significant advancement in the field of waste management technology.

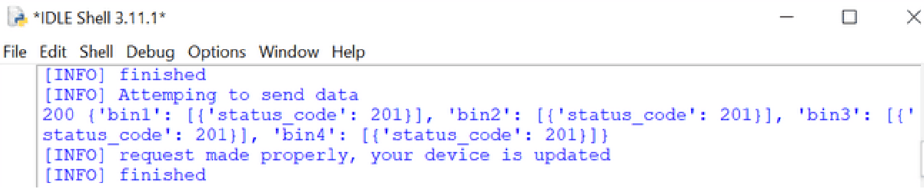
In existing research regarding tools that can sort types of waste, such as in [31] which can read types of metal and non-metal waste using a Proximity sensor. and can send notifications via telegram and in research [32] which can read types of non-organic waste using a camera based on AI detection. Of course, this research is an improvement from previous research which was able to read and sort 4 types of waste, namely metal, plastic, B3 and organic. Apart from that, you can also send notifications via telegram so that cleaning staff can act immediately and there will be no accumulation of rubbish.

(a) (b)

Fig. 9. Result of Web Monitoring (a) Result of Telegram Early warning notification (b)

3.3. Analyze of Quality of Service (QoS)

In this research, Quality of Service (QoS) testing was carried out using the Wireshark application on the IoT network to see the performance of the network [33] used to send data from 4 ultrasonic sensors which were used to see waste capacity. Table 2 shows samples uplink and downlink with Address A as the sender and Address B as the recipient with a data length of 330 bytes and sending every 15 seconds. Value and category for throughput, delay, and packet loss show in Table 3 and also some reviewed literature. Replies from the server which can be seen from the idle python shell in Fig. 10. The data is sent using the API (application programming interface) from the Ubidots IoT platform with the HTTP protocol Fig. 10. shows status code 201 which is the response from the server when data is received from the user. The HTTP protocol used by the Ubidot Platform uses an API address that will only be known to the user so that Ubidot guarantees data security.



```
*IDLE Shell 3.11.1*
File Edit Shell Debug Options Window Help
[INFO] finished
[INFO] Attemping to send data
200 {'bin1': [{'status_code': 201}], 'bin2': [{'status_code': 201}], 'bin3': [{'
status_code': 201}], 'bin4': [{'status_code': 201}]}
[INFO] request made properly, your device is updated
[INFO] finished
```

Fig. 10. Delivery status and response

Table 2. Uplink and Downlink of IoT Network

No	Address A	Address B	Protocol	Data Length (Bytes)	Duration (s)
1	Raspberry Pi 4	API Ubidosts	TCP	330	150.134
2	Raspberry Pi 4	API Ubidosts	TCP	330	150.409
3	Raspberry Pi 4	API Ubidosts	TCP	330	150.294
4	Raspberry Pi 4	API Ubidosts	TCP	330	150.339
5	Raspberry Pi 4	API Ubidosts	TCP	330	150.566
6	Raspberry Pi 4	API Ubidosts	TCP	330	15.062
7	Raspberry Pi 4	API Ubidosts	TCP	330	150.622
8	Raspberry Pi 4	API Ubidosts	TCP	330	150.385
9	Raspberry Pi 4	API Ubidosts	TCP	330	150.506
10	Raspberry Pi 4	API Ubidosts	TCP	330	150.498

Table 3. Perfomance Analysis of QoS of Result and Some Reviewed Literature

Ref	Packet loss (%)	Delay (ms)	Throughput (byte/s)
[29]	0	14	71.85
[33]	0	21	345
This Work	0	16	61.098

Table 3 shows the packet loss, delay, and throughput produced in this study, as well as a comparison with relevant references. In this study, based on the International Telecommunication Union (ITU) standard, namely

ITU-T G.1010, which is shown in Table 4 and Table 5, the delay category value with 0 is very good, and the delay category with a value of 16ms, which is still below 150 ms is the very good category.

Table 4. ITU Delay Category G.1010

Latency Category	Delay
Very Good	<150 ms
Good	150 – 300 ms
Medium	300 – 450 ms
Bad	>450 ms

Table 5. Packet Loss Category ITU G.1010

Degradation Category	Packet loss
Very Good	0%
Good	5%
Medium	15%
Bad	25%

The Quality-of-Service value obtained is based on one condition: good or sunny weather without any obstacles such as buildings or trees. In networking testing, this can be a reference for future research with multi-devices integrated into the same network and also testing in various weather and obstacles that can block and absorb signals.

4. CONCLUSION

This research effectively created a prototype of an intelligent waste management system capable of identifying and sorting four categories of waste: metal, plastic, hazardous (B3), and organic. It utilises a Raspberry Pi 4 and a camera, employing image processing and deep learning techniques for autonomous waste classification. System study indicates a categorisation accuracy of 90% across all four waste categories. This system is additionally equipped with a servo actuator that operates subsequent to the classification of waste, facilitating the entry of rubbish according to its type. The examination of the Quality-of-Service characteristics reveals a throughput of 61,098 bytes/s, a latency of 16 ms, and no data loss. These findings demonstrate exceptional network performance. Furthermore, the system has effectively shown the waste volume on the Ubidot platform dashboard and issued an early warning regarding waste capacity when the ultrasonic sensor indicates that it has surpassed 90% then Raspberry Pi will send notice to user telegram.

Future improvements could focus on enhancing the system's robustness and versatility. Expanding the training dataset with a wider variety of waste images for each category would improve the accuracy and reliability of the classification algorithm. Additionally, exploring alternative network protocols, such as Lora and Lorawan, known for their low-power, long-range capabilities, could further optimize the system for cost-effectiveness and energy efficiency. These enhancements would contribute to a more sustainable and scalable solution for smart waste management.

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