Automatic Waste Segregation System Based on Image and Audio Data

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***Abstract*: This paper explores the creation of an Automated Waste Segregation System intended to make waste management more efficient through real-time waste material classification and disposal. The system applies machine learning models, executed using TensorFlow Lite, in audio and image-based classification of waste. The hardware architecture includes a Raspberry Pi 4 as the central processing unit, which communicates with sensors and actuators for automatic waste recognition and sorting. The hardware structure of the system is made of PVC pipes and PVC sheets so that the overall structure of the waste compartments remains lightweight, inexpensive, and long-lasting. The mechanized segregation system is driven by servo motors and an efficient motor system to route waste to corresponding bins. The analytical system combines sensor-based data acquisition, real-time processing, and AI-based decision-making logic to segregate waste into types like biodegradable, recyclable, and non-recyclable. The new system will provide higher precision and effectiveness of garbage disposal in both domestic and commercial areas, leading to enhanced sustainability and garbage handling techniques.**

***Keywords*: Automated Waste Segregation, Machine Learning, Raspberry Pi 4, Image Classification, Audio Classification.**

1. Introduction

With high urbanization rates and growing waste generation, efficient waste management has become an issue globally. Manual waste segregation methods are inefficient, time-consuming, and labor-intensive, resulting in incorrect disposal and environmental pollution. Automation and AI address these issues to enhance the efficiency and accuracy of waste segregation. An Automatic Waste Segregation System based on machine learning audio and image classification to recognize and categorize waste into various categories is proposed here. The provided system is implemented with Raspberry Pi 4, TensorFlow, YOLO V8 and servo motors for automated segregation. The frame and compartments are made of PVC and PVC sheets, which make the system light in weight, strong, and affordable. The system to be proposed uses computer vision and audio analysis to differentiate between different types of waste.

A camera module takes pictures of the waste, which are then processed through a machine learning model. There is also an audio sensor that picks up audio signals from waste objects (e.g., metal objects making different sounds when tapped) to enhance the accuracy of classification. Once the waste is detected, a motorized system sorts the waste into the right compartment. Through the use of automated waste segregation, the system hopes to make waste management more efficient, minimize human involvement, and encourage eco-friendly waste disposal practices. The application of IoT and AI in waste management offers an expandable solution that can be applied for diverse waste collection and recycling processes.

2. Literature Review

[1] The article proposes an IoT-based system for self-sorting and bin monitoring waste to tackle the problem of waste management in cities. The system segregates the waste into degradable and non-degradable categories and keeps a track of bin levels to avoid overfilling with the help of ultrasonic and color sensors and a servo motor and Node MCU ESP8266 module for cloud communication. The 24x7 system monitoring and alert system of the system promote a cleaner atmosphere by means of reduced pollution and disease spread. The authors describe the hardware configuration and prove the efficiency of the system through data visualization in real time. It suggests future development, such as image processing for bulk waste segregation, and is a valuable contribution to smart waste management, complementing India's Swachh Bharat Scheme and offering a scalable, affordable solution to urban waste problems.

[2] The paper suggests a modified form of Mel Frequency Cepstral Coefficients (MFCC), which is conventionally used in voice recognition. MFCC is conventionally optimized to emphasize the low-frequency components of the sound, and therefore it is suitable for human speech. As the recycling wastes' sounds also contain strong high-frequency components, the authors generalize MFCC to extract higher-dimensional frequency components. The modified MFCC achieves better discrimination between the materials like aluminum cans, steel cans, plastic bottles, and glass bottles. Machine learning, i.e., Support Vector Machines (SVM), is utilized in the automatic sorting system to discriminate waste materials from each other based on sound. The edge-based sound recognition reduces the

use of cloud processing, and therefore it is suitable for real-time processing. The evaluation system uses a microphone and an embedded processor (Raspberry Pi) to detect and discriminate the free-fall sounds of the waste.

[3] They propose an innovative alternative: automated recycling bin with machine learning-based waste sorting. The paper is supported by existing datasets, including TrashNet, and offers a new dataset of 1,800 images to maximize model accuracy.The article compares two embedded platforms, Jetson Nano and K210, with excellent classification accuracies of 95.98 percentage and 96.64 percentage, respectively. Notably, the K210 platform is very energy efficient, consuming just 0.89 W, and hence a viable implementation option in reality. The article also discusses commercialization prospects and utilizing renewable energy sources, like solar panels, to power the bins. Overall, the paper makes a contribution in the field of intelligent waste management through the integration of cutting-edge image classification techniques with practical, energy-saving applications.

[4]Plastic detection and segregation are essential in today's society due to fast urbanization and technological developments. Manual segregation is dangerous and time-consuming, which is why automation is required. There are several methods available, such as manual, optical, and floating waste segregation. This project designs a mechanical system with a sensing unit that separates plastic according to audio signals generated while crushing. Based on machine learning and Mel Frequency Cepstral Coefficients (MFCC), the system learns to detect plastic from materials such as wood, steel, and metal, enhancing segregation efficiency.

[5] Raspberry Pi, an efficient and powerful minicomputer having the dimension approximately equal to the size of a credit/debit card. It was invented by the United Kingdom Raspberry Pi foundation with the hope of enlightening and empowering the generation of learners to be more creative and efficient. Since its launch, many open-source communities have contributed towards open-source operating systems (OS), apps and various other forms of computers which are similar to Raspberry Pi. Moreover, various embedded system scholars and researchers across the globe are constantly involved in the development of innovative projects using this module which is observed to have out-of-the-box application. Since its inception, Raspberry Pi is under constant up-gradation both in terms of both software and hardware which is thereby making it a “Full-Fledged Computer” with a possibility to compute intense task within a specific timeframe. This review paper shall lay a foundation stone to numerous open-source community and will enable the embedded students to develop projects to a whole new level

[6] As cities produce more waste, traditional waste management is hampered by inefficiencies and environmental issues. This article proposes a Smart Recycling Bin that combines cameras, voice detection, and sensors with machine learning for maximum waste sorting. At the household and public levels, it sorts waste accurately to enhance recycling rates and minimize contamination, making recycling more efficient and responsive.

3. Automatic Waste Segregation System

A. Comparison With Existing systems

1) Manual Waste Segregation

Manual segregation of wastes relies heavily on human labor and visual inspection to segregate different wastes. It is cheap for small operations since it requires minimal initial investment and can be accommodated in different materials. Manual segregation, however, is time-consuming, labor-intensive, and extremely prone to human error, which affects both the efficiency and accuracy of the segregation process. Manual sorting has an average accuracy of about 60-70 percent and is normally classified as low-efficiency, hence not employed in large-scale operations. Due to its limitations manual segregation is gradually being replaced by automated methods in high-volume plants.

2) Traditional Mechanical System

Mechanical waste sorting systems use methods such as optical sorting, magnetic separation, and air jets to automatically sort waste procedures of separation [7]. These systems come with high capability for throughput while treating huge waste volumes, suitable for industrial large-scale facilities since high-throughput is a prerequisite. Mechanical systems are, in general, more appropriate to given types of wastes, such as plastics and metals, which can be separated using magnetism or optic sensors. The cost of maintenance is also relatively high since the systems incorporate complicated machinery and periodic maintenance. Regardless of these limitations, classical mechanical systems are capable of achieving accuracy of approximately 80 percent and are usually found to be very effective for large buildings.

3) Single-Input ML Systems (Image-Based Only)

Machine learning has brought new prospects for waste management by enhancing the accuracy of classification through image recognition with algorithms like Convolutional Neural Networks (CNNs) or Support Vector Machines (SVMs) [10]. Image-based ML systems perform well in identifying visual materials, e.g., plastics and metals, based on attributes like color, shape, and texture. However, these systems may be constrained by environmental conditions, e.g., lighting, and can have problems classifying non-visual refuse (e.g., some kinds of paper or organic waste) accurately. Typical accuracy for individual-input image-based ML systems can be 85-90 percent, with a medium level of efficiency, because their accuracy varies depending on environmental conditions.

4) Single-Input ML Systems (Audio-Based Only)

Audio ML systems are dependent on audio classification algorithms, including Mel-Frequency Cepstral Coefficients (MFCCs) and CNNs, to process sound data generated when waste material strikes a surface [4]. Audio ML systems are efficient in classifying materials with unique sounds, like metals, which have recognizable audio profiles. The limitation in audio-based systems is where they have difficulty in complex or noisy conditions where the background noise can confound proper classification. In spite of these problems, audio-only systems attain 80-85 percent accuracy and provide moderate efficiency, giving a plausible solution in environments where visual information is lacking.

5) Dual-Input ML Systems (Audio and Image)

Dual-input ML models that both make use of audio and image classification methods are the balanced approach and deliver high accuracy for varied categories of waste material. Audio and visual inputs blended together help classify a wide array of materials successfully, so such systems are solid in setups where there is variation in types of waste as well as their condition. Dual input systems commonly yield accuracy in the range of 90-95 percent and are rated very efficient. They do, however, need greater computational capacity and a more complicated installation, since they need to combine both image and audio processing modules, thus being better suited for sophisticated waste management applications.

B. Block Diagram

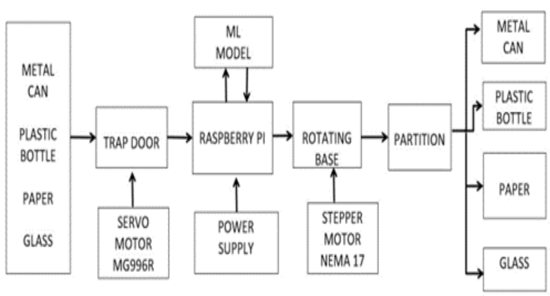

Fig. 1. Block diagram of the proposed system

Figure 1 presents the block diagram for the workflow of the automatic waste segregation system proposed. The waste is initially put into a primary collection box with a Pi camera and microphone. The Pi camera takes a picture of the waste, and the microphone records any clear sounds generated upon insertion. These inputs are subsequently processed to determine the type of waste, classifying it as paper, plastic, metal, or other. This dual-sensory system involves image processing and audio classification for increased precision in waste identification to enable smooth and trustworthy sorting. Once the waste is properly identified, the system triggers a sequence to guide the waste into the proper category bin. A stepper motor turns the collection box to place it above the appropriate compartment, and a servo motor is triggered to dispense the waste into its respective bin. The sorting process is done automatically with minimal human intervention, making it error-free and efficient. By enhancing waste sorting speed and accuracy, the Automatic Waste Segregation System helps facilitate improved recycling processes and drives environmental sustainability towards a cleaner, more organized waste management system.

4. Working Progress

A. System Workflow

1) Waste Input Section

The Waste Input Section is the beginning of the waste segregation process in its entirety. It is the area where users can deposit waste materials, whether these are metal cans, plastic bottles, paper, or glass. The section is made to fit different shapes and sizes of waste materials so that they can be compatible with most types of domestic and industrial waste. The main purpose of this section is to allow for the initial introduction of waste materials into the system in a controlled environment, allowing each material to be segregated so that it may be properly classified. After the item has been introduced into this section, it proceeds onward to be analyzed by the machine learning model.

2) Raspberry Pi With Machine Learning Model

The Raspberry Pi, integrated with a machine learning model coded in Python, is a compact and effective platform for real-time data processing and decision-making across different applications. With a camera module or sensors, the Raspberry Pi takes in input data, images or sensory inputs, which are processed by the trained machine learning model to recognize patterns, classify objects, or predict. Python frameworks such as TensorFlow facilitate smooth model integration and deployment on the Raspberry Pi. After analyzing data, the Raspberry Pi produces control signals to actuate hardware components attached to it, like motors or actuators, and perform tasks autonomously. This configuration is highly flexible, with the ability to retrain the model to improve accuracy or solve new problems, making it a perfect application for waste sorting.

3) Trap Door Mechanism

The Trap Door Mechanism is the initial phase of physical movement within the system. It is regulated by a servo motor (DS3225), which is controlled by signals from the Raspberry Pi after the waste item has been sorted. Workflow of the Trap Door Mechanism is as follows,

- *Signal Reception*: The Raspberry Pi provides a signal to the servo motor to make the trap door
- *operational. Opening and Closing*: The trap door is opened by the servo motor so that the waste item can drop on the rotating base.

After a brief moment, the trap door shuts ready to accept the next object. This system is designed to deliver a controlled drop of the waste object onto the rotating base in order to avoid misalignment or accidental drops. The trap door also serves to block any object from outside to fall into the sorting compartment and interfere with the system.

4) Partitioned Compartments

The Partitioned Compartments are the ultimate receptacle for waste materials, compartmentalized into distinct sections for metal cans, plastic bottles, paper, and glass. Every compartment is reserved for a particular type of waste, making segregation efficient and well-organized. Characteristics of the Partitioned Compartments are,

- *Divided sections*: Physically separated in that they prevent waste types cross-contamination and streamline subsequent collection to recycle or get rid of it.
- *Simple Collection Facility*: The compartments are designed with simple access to facilitate collection by waste management staff to collect segregated waste effortlessly and rapidly.

With each item sorted properly, these compartments help make the system efficient and effective in segregation.

B. Circuit Diagram

Figure 2 illustrates the circuit of a waste segregation system with a Raspberry Pi as the central controller. The stepper motor serves as a device for pushing or turning waste materials into respective bins according to the instruction from the Raspberry Pi. The Pi camera takes pictures of the waste product and transmits them to the Raspberry Pi to process images, where the type of item is determined (e.g., recyclable, non-recyclable). The microphone may pick up sounds related to the waste product being dropped, which would initiate the camera to take pictures and the motor to turn on. The power supply unit provides stable DC power to the Raspberry Pi and other elements. LED lights offer visual feedback regarding the state of operation, including the camera's readiness or motor operation, and improve the functionality and usability of the waste segregation process. The circuit, by this configuration, automates the waste sorting, thus aiding in effective waste management and recycling processes.

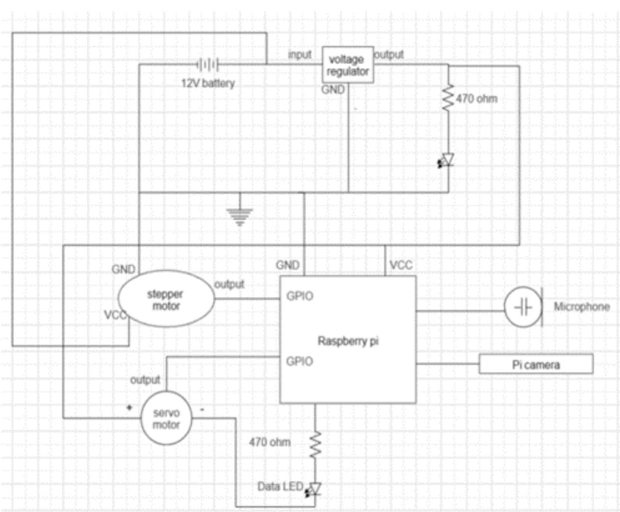

Fig. 2. Circuit schematic

C. 3D CAD Model

Figure 3, Figure 4, Figure 5, Figure 6, shows the 3D CAD models for key parts of the Automated Waste Segregation System, which serves as a vital tool for visualizing the physical layout and spatial arrangement of the system's components. This was made using solidworks software. The CAD model provides a comprehensive representation of how the various elements such as the waste platform, trapdoor, bins, and sensors are positioned in relation to each other and the motors that facilitate movement. By creating a detailed and accurate digital prototype, the model aids in understanding the assembly process and practical feasibility of the design. It not only highlights the design's functionality but also allows for adjustments and optimizations before physical implementation, ensuring that all components work together effectively for efficient waste sorting. This visualization enhances the overall comprehension of the system's operational workflow and serves as a reference point for further development and troubleshooting.

Fig. 3. Solid work representation of the compartment

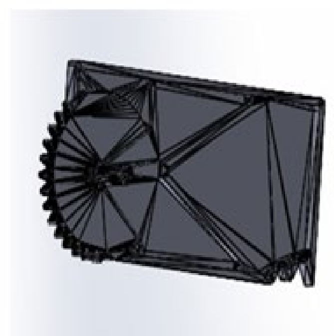

Fig. 4. Solid works representation of the main trapdoor

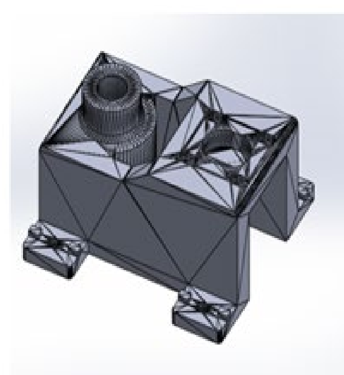

Fig. 5. Solid works representation of the rotating base

Fig. 6. Solid works representation of the base pulley

5. Machine Learning model

Two machine learning models for the automatic waste segregation system, an audio classifier and an image classifier, were developed. Both models were implemented to utilize different data sources audio signals and visual features to effectively classify waste materials such as metal, plastic, paper, and glass. With these two models combined, the system is able to utilize a dual input strategy, enhancing classification accuracy and reliability.Simulation experiments were performed in order to confirm the efficiency and accuracy of the ML model in categorizing various types of wastes.

A. Audio Classifier Model

The system is turned on and initialized. Initialize GPIO Pins. Raspberry Pi GPIO (General Purpose Input/Output) pins are set up to control sensors, motors, and other peripherals. A pre-trained machine learning algorithm for waste sorting is loaded and the system initializes to record audio input for processing. The stepper motor (rotation) and servo motor (sorting) are initialized and calibrated to operate. The system captures an audio signal that has features of the waste item to be classified. Mel-Frequency Cepstral Coefficients (MFCCs), which are popularly used for audio classification, are derived from the audio input to be used as input features for the ML model. The ML model classifies the extracted MFCC features and outputs the type of waste (Glass, Metal, Paper, or Plastic). on the prediction of glass servo motor opens the bin of disposal. For metal stepper motor rotates 90° to send the waste to the metal bin. For plastic stepper motor rotates 180° to send the waste to the it's bin. For glass stepper motor rotates 270° to send the waste to the it's bin. The classification result with timestamps and type of waste is stored for analysis and monitoring. Repeat the Process Ongoing until The system recurs to process the next waste item without interruption. The process stops when manually interrupted or turned off.

B. Image Classifier Model

The device is turned on and the execution starts. The GPIO pins of the Raspberry Pi have been set for motor control and sensor. The YOLO object detection model has been loaded, and the camera has been initialized to capture images The stepper motor has set up to drive the movement of the sorting mechanism. ultrasonic sensor constantly measures distance to find the existence of an object ahead of the camera. The system verifies if an object is found inside 15 cm. If no object exists, it returns to keep monitoring. If an object is found, the camera takes a picture to analyze. The taken image is analyzed using the YOLO model to detect objects in the image. on glass servo motor opens the disposal bin. For metal stepper motor rotates 90° to waste to metal bin. For plastic stepper motor rotates 180° to waste to plastic's bin. For glass stepper motor rotates 270° to waste to respective bin. The classification result, along with timestamps and waste type, are saved for analysis and tracking. Repeat the Process Ongoing until The system loops back to process the next waste item without interruption. The process concludes when powered down or manually stopped.

6. Results of Machine Learning Model

A. Image Classifier Model Results

1) Precision Confidence Curve Analysis

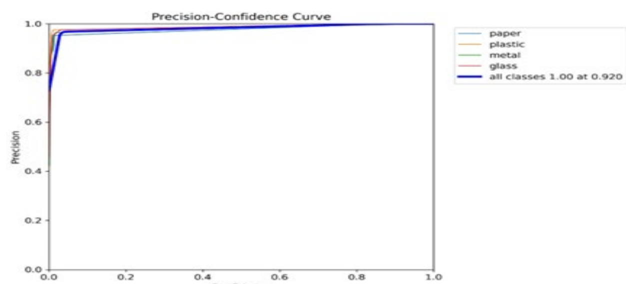

Fig. 7. Precision confidence curve

Figure 7 displays The Precision-Confidence Curve demonstrates the way precision changes with confidence levels for various waste types. Every line in the curve is a representation of a particular type of waste, illustrating how precision of the model increases as confidence levels are higher. The heavy blue line is the total precision over all categories and hits 1.00 at a confidence of 0.92, meaning that at greater confidence, the model achieves ideal precision. All classes except for the likes of coin, banana, and apple show high precision at lower thresholds of confidence. But the likes of watermelon and bottle have a tendency to improve gradually and hence optimizing classification confidence for these types might make the model more reliable.

2) F1-Confidence Curve Analysis

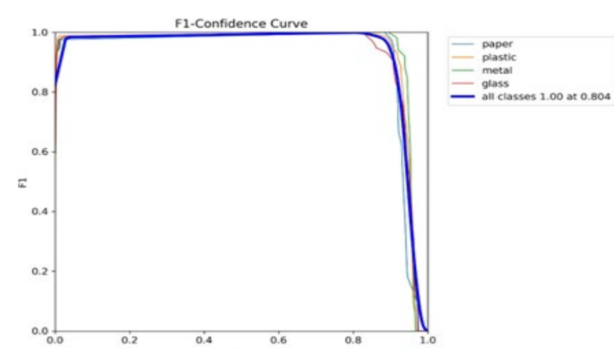

Fig. 8. F1-Confidence curve

Figure 8 depicts the F1-Confidence Curve plots the confidence score against the F1-score, a balanced evaluation of the precision and recall for various categories of wastes. The thick blue curve is the average performance over all classes and has a maximum F1-score of 0.804 when the confidence threshold is set to 0.553. Class curves show how various waste items respond to different confidence thresholds. Certain categories have high F1-scores over a large range of confidence, while others show a drastic drop-off at greater confidence levels.The analysis indicates that by choosing an optimal confidence threshold at about 0.55, precision and recall can be well-balanced for the majority of classes.

3) Training and Validation Performance Analysis

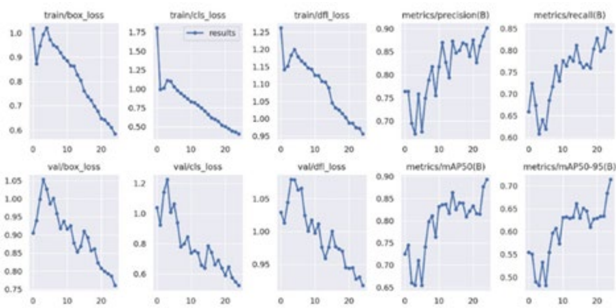

Fig. 9. Training and validation performance analysis

Figure 9 indicates the training and validation performance metrics follow the learning trajectory of the model across several training epochs. The trends of the training losses in bounding box regression (box loss), classification (cls loss), and distribution focal loss (dfl loss) all decrease steadily, which shows effective learning. The corresponding validation losses also reduce, which illustrates that the model generalizes to unseen data. Moreover, important performance measures like precision, recall, mean Average Precision (mAP) at IoU 0.5, and mAP over a variety of IoU values (0.5–0.95) improve consistently, validating that the model becomes more accurate and confident in its detections as training continues. These findings indicate that the model is learning to classify and detect waste objects with high precision and reliability.

B. Audio Classifier Model Results

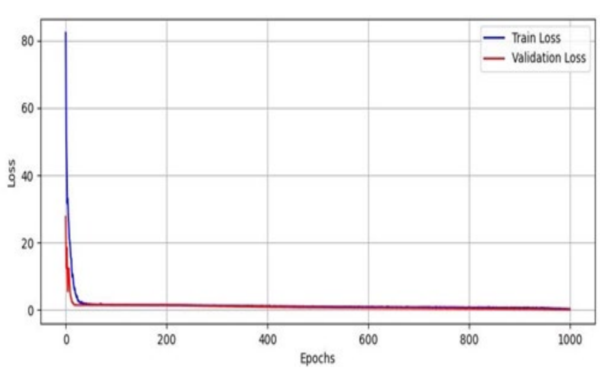

Fig. 10. Training Vs Validation loss curve

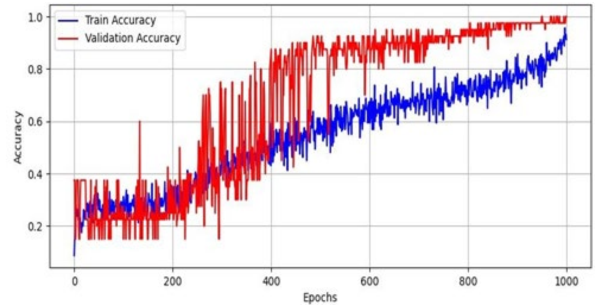

Fig. 11. Training Vs Validation accuracy curve

The Figure 10 illustrates training and validation loss curves of 1000 epochs of the audio classification model used in the system. Training loss indicated by blue line and validation loss indicated by red line both show a steep drop across the initial epochs, indicating rapid learning. Towards the latter stages of training, the losses settle down and approach near-zero levels, reflecting that the model is successfully reducing errors and establishing robust generalization. The close overlap of training and validation loss curves indicates little overfitting, making the model solidly reliable in unseen data. This pattern reaffirms that the model has indeed learned to properly classify waste objects with great precision and dependability.

The Figure 11 illustrates the training and validation accuracy patterns across 1000 epochs for the model. Both training accuracy (blue line) and validation accuracy (red line) increase steadily, reflecting ongoing model improvement. Accuracy is low at the beginning because of random initialization, but as training continues, the model improves its parameters, resulting in better performance. Validation accuracy outperforms training accuracy for some areas and may be related to batch shifts or regularization benefits. Validation accuracy, at late epoch points, nears 1, implying the model achieved perfect waste object classification accuracy. A growing tendency for training accuracy validates further rapid learning achievement with the model appropriating it as ideal for practice of real waste categorization duties.

7. Hardware

Fig. 12. Side view of hardware hardware prototype

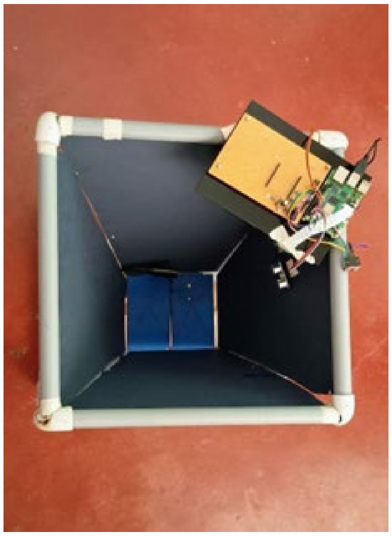

Fig. 13. Top view of hardware prototype

Figure 12 and Figure 13 shows the side view and top view of the prototype respectively. The hardware structure of the automated waste segregation system is made to be structurally strong, economical, and versatile. The system makes use of polyvinyl chloride (PVC) pipes and sheets, selected for their light weight character, resistance to corrosion, and economic feasibility. The PVC pipe structure offers necessary structural strength, providing stability while being easy to assemble and make changes. The PVC sheet enclosures are protective barriers that provide a smooth, non-reactive surface that adds durability and operational efficiency to the system. The system has compartmentalized waste segregation, where each compartment is specially designed with personalized slots to enable proper classification and disposal of various waste materials. The modular setup provides scalability and flexibility, and the setup is therefore suitable for use in different operating environments. In addition, the structure is supported by safe joints and fixings, allowing it to sustain operational loads without sacrificing structural stability.

A. Live Classification Results of Hardware Prototype

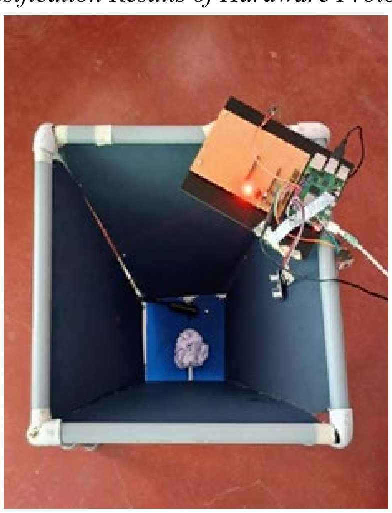

Fig. 14. When the input waste type is Paper

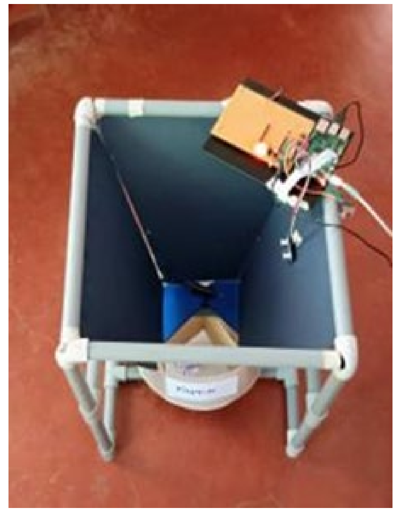

Fig. 15. Waste getting classified into right compartment

Figure 14 and figure 15 shows the real-time classification result when a waste type of paper is being fed into the system. The real-time image classification system used in the automatic waste segregation machine efficiently combines machine learning object detection with a hardware-based sorting process. The YOLO detection model handles real-time images of waste objects along with the audio classifier model, which allows for accurate classification into various categories. The hardware configuration, using an ultrasonic sensor for detecting objects and a servo motor-operated sorting system, ensures accurate and efficient separation. The outcomes exhibit high levels of classification accuracy with negligible processing delay, justifying the system's suitability for real-time waste sorting. Slight misclassifications are, however, seen for objects with comparable visual characteristics, suggesting possible areas for model improvement. In general, the live hardware classification results confirm the reliability of the system to boost automated waste management systems.

8. Conclusion

The design and implementation of an automated waste sorting system combining machine learning-based classification with hardware automation to optimize waste management efficiency is proposed. The system deploys a YOLO-based image classifier model and an audio classifier model for real-time waste detection and classification and uses an ultrasonic sensor for object detection as well as a servo motor-operated sorting unit to facilitate accurate waste sorting. The PVC-based hardware platform provides a light, robust, and economically friendly implementation that makes the system applicable for real-world deployment. The test results confirm excellent classification accuracy and stable sorting performance with very low latency in real-time execution. Nevertheless, issues like visually confusable object misclassification and requirement for better feature extraction in some categories point towards possible improvement areas. The validation and training performance analysis verifies that the model learns well, with consistent improvements in precision, recall, and mean Average Precision (mAP) across several training epochs. This adds to the body of knowledge in sustainable waste management by providing a scalable and automated method for waste segregation. Future development will concentrate on enhancing the accuracy of classification, increasing the dataset to achieve better generalization, and processing speed optimization. The system presented has great potential to minimize human effort, enhance recycling efficiency, and enhance environmental sustainability through intelligent segregation of waste.

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