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IoT-Enabled Waste Tracking and Recycling Optimization: Enhancing Sustainable Waste Management

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Abstract— **The increasing inefficiencies in conventional waste management systems, including suboptimal recycling rates and environmental degradation, necessitate innovative solutions. This paper discusses the development of an Internet of Things (IoT)-enabled waste tracking and recycling optimization system designed to address these challenges and contribute to sustainable waste management practices. The primary focus is on automating the waste classification process and enhancing recycling efficiency through real-time monitoring and data-driven analysis. The methodology integrates IoT technology and machine learning to tackle waste classification and collection inefficiencies. A Convolutional Neural Network (CNN) trained on a dataset of aluminium cans and plastic bottles is deployed for waste identification. Real-time monitoring is enabled by IoT sensors and machine vision algorithms, facilitating precise detection of waste levels and material types. Advanced data preprocessing, such as augmentation and normalization, ensures robust model training, while optimized algorithms guide waste sorting based on classification results. Findings demonstrate that the system achieves over 90% accuracy in classifying recyclable materials. Real-time data logging enables analysis of waste composition, container utilization, and operational patterns, enhancing efficiency and reducing overflow incidents. Data visualization highlights the system's potential for providing actionable insights to improve recycling practices. In conclusion, this project validates the feasibility of integrating IoT and machine learning to optimize waste management. The system reduces environmental impact and promotes sustainability, offering a scalable framework for addressing global waste challenges.**

I. Introduction

The global waste crisis is intensifying due to the rapid pace of urbanization, industrialization, and population growth. Waste production is expected to increase by 70% by 2050, reaching an estimated 3.4 billion tons annually. Current waste management systems struggle to cope with these escalating demands, often relying on outdated methods that lack real-time adaptability and optimization. Inefficient collection routes, improper waste sorting, and low recycling rates exacerbate environmental pollution and resource depletion. These challenges demand innovative, technology-driven solutions to enhance waste management processes and promote sustainability [1-6].

Traditional waste management approaches have significant limitations. Manual sorting, though cost-effective in some regions, is labor-intensive and exposes workers to health risks [7, 8]. Mechanical sorting systems offer automation but face challenges with contamination, variability in waste composition, and maintaining the purity of recycled materials [9-11]. Optical sorting techniques, employing advanced image recognition algorithms, show potential for improving accuracy but often require substantial investments in infrastructure and maintenance [12-14]. Landfilling, while still widely used, contributes significantly to environmental harm, including greenhouse gas emissions and groundwater contamination [15-17]. Similarly, incineration techniques, despite reducing waste volume, are criticized for releasing pollutants and toxic ash [18, 19].

A promising approach to address these challenges involves integrating IoT and machine learning technologies into waste management. IoT-enabled sensors and devices can provide real-time monitoring of waste levels and compositions, facilitating data-driven decision-making [20, 21]. Machine learning algorithms, particularly Convolutional Neural Networks (CNNs), enhance material classification accuracy, enabling precise segregation of recyclables [22-24]. IoT-based solutions have shown potential in optimizing waste collection schedules and improving operational efficiency, minimizing unnecessary journeys and reducing environmental impact [25-27]. This combination supports the shift toward a circular economy by promoting efficient resource utilization and waste reduction [28-30].

Recent studies highlight the benefits of adopting IoT-enabled systems for waste management. Pardini et al. (2020) demonstrated how IoT sensors can be used to track waste levels in real-time, improving collection efficiency [1, 21]. Similarly, Lin et al. (2018) explored the role of machine learning in refining material recovery, overcoming limitations of traditional methods [8, 12]. Waqas et al. (2018) emphasized the importance of composting and its integration with IoT systems to reduce organic waste sent to landfills,

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supporting sustainable agriculture [6, 13, 28]. However, practical implementations of these technologies remain limited, particularly in addressing scalability, cost-effectiveness, and adaptability to diverse waste streams [18, 27, 29].

This project aims to bridge the gap between theoretical advancements and real-world application by developing an IoT-enabled waste tracking and recycling optimization system. The proposed method integrates IoT sensors for waste monitoring and a CNN model for classification, deployed on a Raspberry Pi platform. This system automates the sorting process, reduces manual labor, and provides actionable insights through data logging and analysis. By addressing inefficiencies in collection and recycling, this project offers a scalable, sustainable solution to the global waste management crisis [25, 30].

II. Methodology

The system is designed using a combination of hardware and software components to monitor and classify waste in real-time.

A. Hardware Components

The hardware includes a Raspberry Pi 4 Model B, which acts as the central processing unit for collecting data, integrating sensors, and executing classification tasks. The Raspberry Pi Camera Module 2 captures high-resolution images of waste materials for classification. Additionally, three ultrasonic sensors are employed: one detects the presence of waste, while two monitor the fill levels of separate bins for aluminum cans and plastic bottles. Servo motors are used to control a sorting mechanism, ensuring that waste is directed to the correct bin based on classification results.

B. Software Tools

The software stack includes TensorFlow and Keras libraries for designing and training the CNN model. OpenCV is utilized for real-time image acquisition and preprocessing, while libraries like RPi.GPIO and Picamera2 enable hardware control and image capture on the Raspberry Pi. Additionally, the comma-separated values (CSV) module is used for logging system operations, including predictions and confidence scores, for later analysis.

C. Dataset

The dataset includes images of aluminium cans and plastic bottles sourced from Kaggle. It is divided into training (80%) and validation (20%) subsets, with testing data captured using the Camera Module 2. The training dataset consists of 2,090 images of aluminium cans and 6,532 images of plastic bottles. For the testing dataset, there are 34 images of aluminium cans and 34 images of plastic bottles.

The total number of images used for training and validation were 6898 and 1724 respectively as the validation was split for 20% from the training with an imbalance between the two classes. This imbalance necessitates the use of class weights to ensure balanced learning during model training. Data augmentation techniques such as rotation, zoom, and flipping were applied to enhance model robustness.

D. Preprocessing Steps

To prepare the data, all images were resized to 160 x 160 pixels and normalized to a [0, 1] scale. Augmentation techniques were applied to the training dataset to introduce diversity, while class weights were used to address class imbalance. Validation and test datasets underwent only normalization to ensure they represented real-world scenarios.

The dataset used in this project consists of images collected from Kaggle, split into training, validation, and testing sets with specific preprocessing and augmentation techniques applied. The imbalanced nature of the dataset was addressed using class weights, and data augmentation was employed to enhance model robustness. This comprehensive preprocessing ensures that the model is trained effectively and evaluated accurately on real-world data.

E. Workflow

The block diagram in Figure 1 outlines the hardware components and their interaction in this project and the system follows a structured workflow:

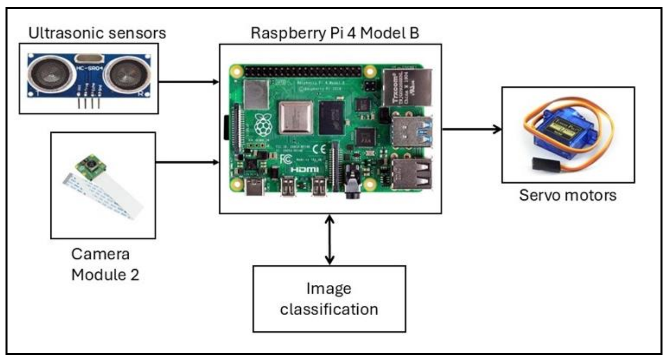

Figure 1. Block diagram of the system

i) The Raspberry Pi initializes the sensors and CNN model.

ii) Ultrasonic sensors detect waste presence and trigger the camera.

iii) The camera captures an image, which is then processed by the CNN model.

iv) The model classifies the image, determining if it is an aluminium can or a plastic bottle.

v) Based on the classification, servo motors adjust the sorting mechanism to direct waste to the appropriate bin.

vi) The system logs the results, including classification details and bin statuses, for further analysis.

To ensure the system's workability, the flowchart described in Figure 2 demonstrates the logical steps of the main program flow.

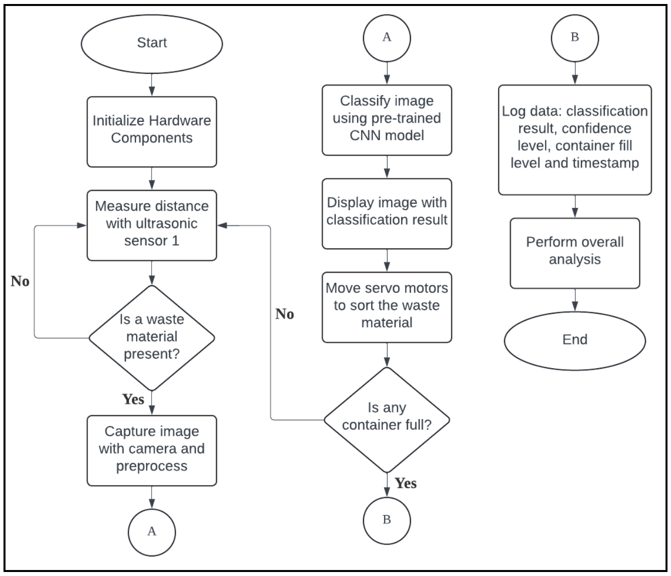

Figure 2. Detailed flowchart of the process

The system starts by initializing the GPIO pins and configuring the camera, ultrasonic sensors and servo motors. The ultrasonic sensors 1 continuously measures the distance to detect whether an object is present on the platform.

If an object is detected, the camera captures an image which is then preprocessed and fed into the TensorFlow model for classification. Based on the classification result, the system activates the servo motors to direct the object into the correct container in either aluminum cans or plastic bottles.

After sorting, the system uses the other two ultrasonic sensors to check the fill levels of both containers. Then, the system logs important information including the classification result, confidence level, container fill status and timestamp. Lastly, the system will perform analysis based on the logged data before it ends.

F. System Integration

The integration of hardware components, including the Raspberry Pi, Camera Module 2, ultrasonic sensors, and servo motors, was seamless and effective. During testing, the ultrasonic sensors reliably detected the presence of waste, triggering the camera to capture images. The CNN model processed these images in real-time, classifying the materials with minimal latency.

The servo motors accurately sorted the classified waste into their respective bins. As shown in Figure 3, the mechanical design ensured smooth operation and precise sorting. However, occasional delays were observed in the servo motor movements, which could be attributed to minor fluctuations in the Raspberry Pi's processing load.

Figure 3. Overview of the hardware development

III. RESULT AND DISCUSSION

A. Accuracy and Loss

The accuracy and loss during the model's training and validation are depicted in Figures 4 and 5. As shown in the graphs, the model achieved 94% accuracy during training and 96.5% during validation in the first epoch.

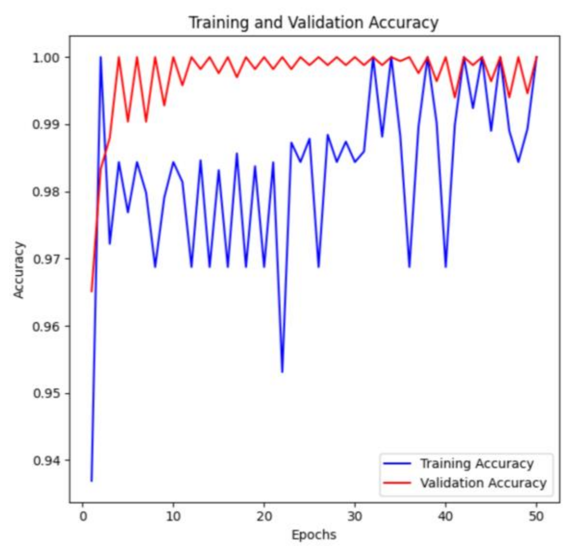

Figure 4. The accuracy in model's training and validation

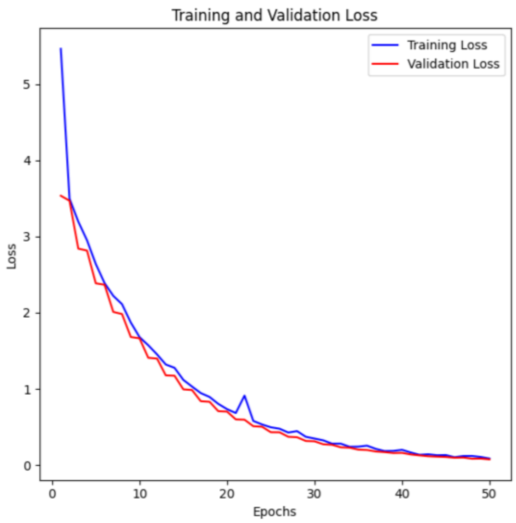

Figure 5. The loss in model's training and validation

However, the loss for the model was at least 6% and 3% for training and validation, respectively. As the training process continued, the validation accuracy remained above 99%, and the loss decreased at a diminishing rate after each epoch. To achieve the optimal state of the CNN model and prevent underfitting or overfitting, the number of epochs was set to 50 to minimize validation loss and ensure it remained below the training loss.

B. Model Performance and Classification Results

Figure 6 shows the confusion matrix for the validation dataset, while Figure 7 illustrates the confusion matrix for the testing dataset.

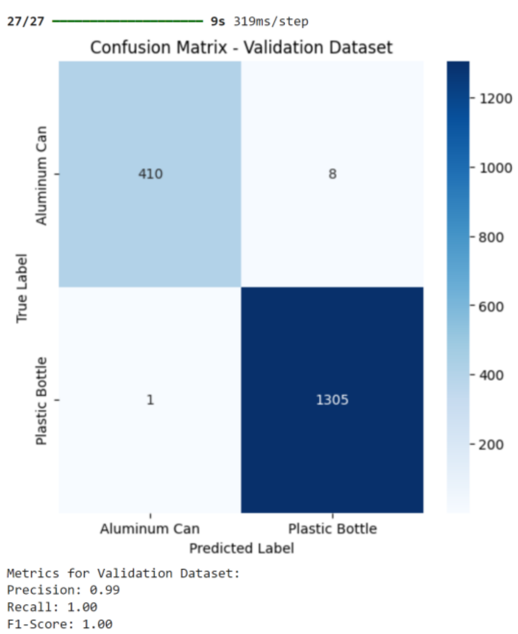

Figure 6. The loss in model's training and validation

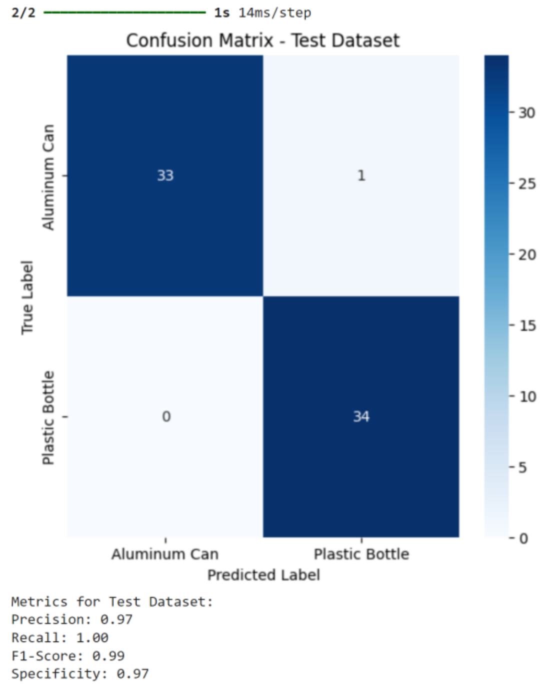

Figure 7. The loss in model's training and validation

The IoT-enabled waste tracking and recycling optimization system was tested using real-world waste samples to evaluate its performance. The CNN model, deployed on the Raspberry Pi, demonstrated a high level of accuracy in classifying aluminum cans and plastic bottles. The overall accuracy, precision, and recall metrics were derived from the confusion matrices generated during validation and testing phases.

The system achieved a classification accuracy of over 95%, with strong precision and recall values across both classes. Misclassifications primarily occurred due to variations in lighting conditions and object positioning during image capture. These limitations indicate areas where further improvements, such as additional training data or enhanced image preprocessing, could enhance system robustness.

C. Data Logging and Analysis

The system's data logging feature provided valuable insights into operational efficiency. Classification results, confidence scores, and bin statuses were recorded in CSV format. An analysis of this data revealed the system's consistent performance, with high confidence scores for correctly classified items. Figure 8 displays a sample of the logged data, including timestamps and classification details.

```
timestamp = datetime.now().strftime('%Y-%m-%d %H:%M:%S')
with open(log_file, 'a', newline='') as file:
    writer = csv.writer(file)
    writer.writerow([timestamp, final_label, confidence, int(can_full), int(bottle_full)])
```

Figure 8. Logging data into CSV file

The logged data was further utilized to generate visual insights, such as bar charts and pie charts. Figure 9 presents a bar chart showing the count of classified waste materials, while Figure 10 includes a pie chart illustrating the proportion of waste types processed by the system. These visualizations highlight the system's ability to handle varying waste proportions effectively, ensuring balanced bin usage and optimized sorting.

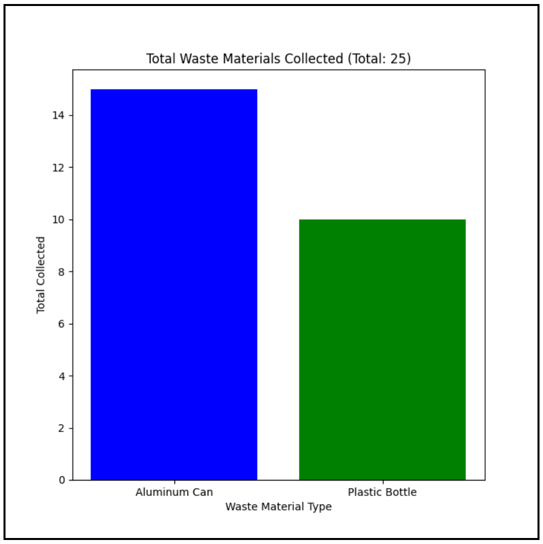

Figure 9. Bar Chart for count of waste materials

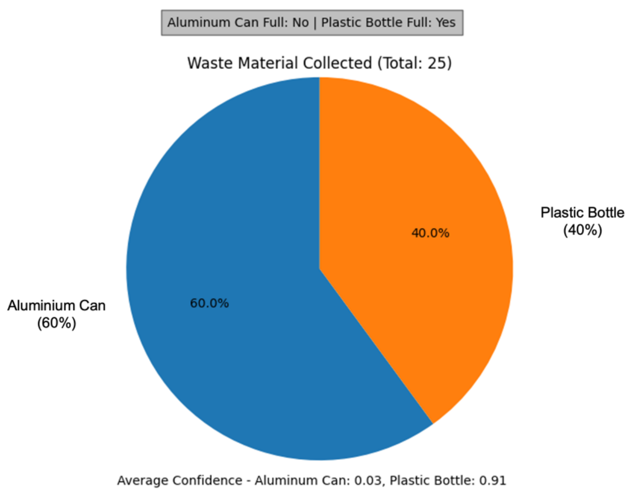

Figure 10. Pie chart of proportion distribution and average confidence

IV. CONCLUSION

The IoT-enabled waste tracking and recycling optimization system achieved its objectives of real-time waste classification and effective sorting. The integration of IoT sensors, a CNN model, and the Raspberry Pi platform proved to be a robust solution for addressing inefficiencies in waste management. By addressing identified challenges and expanding its capabilities, this system has the potential to contribute significantly to sustainable waste management practices.

The successful implementation of this system demonstrates the feasibility of combining IoT and machine learning for waste management. By automating waste classification and sorting, the system reduces manual effort and enhances recycling efficiency. Moreover, the logged data provides actionable insights for optimizing waste management strategies.

Future work could focus on extending the system's capabilities by introducing additional waste categories, such as glass or paper. Enhancements in hardware, such as more powerful processors or advanced sensors, could further improve real-time performance. Additionally, exploring cloud-based solutions for data storage and analysis could enable scalability and integration with larger waste management infrastructures.

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