© January 2025 | IJIRT | Volume 11 Issue 8 | ISSN: 2349-6002

Monitoring and segregation of e-waste and non-e-waste using CNN

Ms Namratha D[1], Nethravathi D N[2], Pooja N, Darshan B R[3], Yashvanth K B[4]
Department of Electronics and Communication Engineering, Sri Krishna Institute of Technology, Bengaluru, Visvesvaraya Technological University India

***Abstract*—The increasing volume of waste, including electronic (e-waste) and non-electronic materials, highlights the urgent need for efficient waste management solutions. This paper proposes a smart system for Monitoring and segregation of e-waste and non-e-waste using a Convolutional Neural Network (CNN). The system employs a Raspberry Pi Zero 2W with a camera module to capture waste images and classify them into e-waste or non-e-waste categories in real-time. The classified data is integrated with a mobile application, enabling real-time monitoring and efficient coordination for collection and recycling. The smart bin also features ultrasonic sensors for waste level detection and motorized segregation to ensure accurate disposal. By leveraging edge computing, the system offers a cost-effective, fast, and sustainable solution for managing waste while promoting responsible recycling practices.**

I. INTRODUCTION

The exponential growth in the consumption of electronic devices has resulted in a significant increase in electronic waste (e-waste), which poses severe environmental and health risks if not properly managed. Alongside e-waste, the improper handling of non-electronic waste further exacerbates the global waste management challenge. Addressing these issues requires innovative solutions that can monitor and segregate waste effectively and efficiently.

This paper presents a smart waste management system designed for the monitoring and segregation of e-waste and non-e-waste using advanced technologies like Convolutional Neural Networks (CNN) and edge computing. The system utilizes a Raspberry Pi Zero 2W, integrated with a camera module, to capture images of waste and process them in real-time for classification into e-waste and non-e-waste categories. In addition, ultrasonic sensors are incorporated for waste level detection, ensuring timely intervention and disposal. A motorized mechanism within the bin facilitates precise segregation, enhancing the system's operational efficiency. The classified data is integrated with a mobile application to enable real-time tracking, efficient scheduling for waste collection, and seamless communication between recyclers and collectors. This innovative solution not only promotes responsible recycling practices but also demonstrates the potential of artificial intelligence and smart systems in transforming traditional waste management. By leveraging cost-effective and sustainable methodologies, this system provides a scalable approach to addressing the growing problem of waste segregation and disposal.

II. RELATED WORK

Several research studies and projects have explored innovative methods for waste management, particularly focusing on electronic waste (e-waste) segregation and disposal. These efforts aim to address the global challenge posed by improper waste management practices.

1. E-Waste Management Systems:

Various smart waste management systems leverage machine learning models to classify waste types. For example, some studies utilize image processing techniques combined with Convolutional Neural Networks (CNNs) for real-time waste classification, achieving significant accuracy in segregating recyclable and non-recyclable materials. However, these systems often rely on cloud-based solutions, which can lead to latency and increased costs.

2. Use of Edge Computing:

The integration of edge computing in waste management has gained traction due to its ability to process data locally, reducing dependency on cloud services. Systems employing edge devices, such as Raspberry Pi, for real-time processing of waste data demonstrate improved efficiency in resource-constrained environments.

3. Sensor-Based Waste Monitoring:
Ultrasonic and infrared sensors are commonly utilized for waste level detection and monitoring. Previous studies have incorporated such sensors to trigger waste collection alerts, minimizing overflows and improving operational efficiency. These systems often integrate IoT-based communication for data transmission to centralized platforms.

4. Mobile Applications for Waste Management:
Mobile applications have emerged as a critical component in smart waste management systems. By providing real-time updates, waste tracking, and collection scheduling, these apps facilitate collaboration between waste generators, collectors, and recyclers. However, existing solutions often lack integration with advanced AI models, limiting their capabilities in complex waste segregation tasks.

III. BACKGROUND

The rapid advancements in technology and the growing dependency on electronic devices have significantly increased the generation of electronic waste (e-waste). According to global reports, millions of tons of e-waste are generated annually, with a significant portion ending up in landfills, leading to environmental pollution and the loss of recoverable materials such as metals and plastics. The lack of efficient segregation methods further complicates recycling and proper disposal, highlighting the need for innovative solutions.

Traditional waste management systems often rely on manual sorting and classification, which are labor-intensive, time-consuming, and prone to errors. To address these challenges, artificial intelligence (AI)-powered systems have emerged as a promising alternative. Technologies such as Convolutional Neural Networks (CNNs) are increasingly used for waste classification due to their ability to analyze and process image data with high accuracy.

In addition, the integration of edge computing in waste management provides a cost-effective approach to real-time data processing and reduces dependency on cloud-based infrastructure. By leveraging devices such as the Raspberry Pi, edge-based systems ensure faster processing and better scalability in resource-constrained environments.

The combination of CNNs, edge computing, and sensor technologies offers a comprehensive solution to waste monitoring and segregation, particularly in distinguishing between e-waste and non-e-waste. This project builds on these advancements to develop a smart system that addresses the limitations of existing methods while promoting sustainability in waste management practices.

The increasing prevalence of diabetes worldwide has highlighted the need for more efficient and accessible diagnostic methods. Traditional diagnostic tests, while effective, are often costly, invasive, and inconvenient for routine use, leading to delays in diagnosis and treatment. Advances in wearable technology and sensor-based systems present a promising alternative by providing non-invasive and continuous monitoring.

Furthermore, sensor technologies such as ultrasonic sensors are widely used in modern waste management systems to monitor waste levels and optimize collection schedules. These sensors detect the fill level of waste bins, providing accurate data for waste collectors and ensuring that bins are emptied before they overflow, thus improving operational efficiency.

Despite the significant advancements in AI and edge computing, current waste management systems still face limitations in terms of real-time segregation, accuracy, and cost-efficiency. This research aims to address these gaps by developing an integrated system that utilizes CNNs for waste classification, edge computing for fast processing, and sensor technologies for monitoring waste levels. This innovative approach promises to revolutionize e-waste management by offering a scalable, cost-effective, and sustainable solution for accurate waste segregation and recycling.

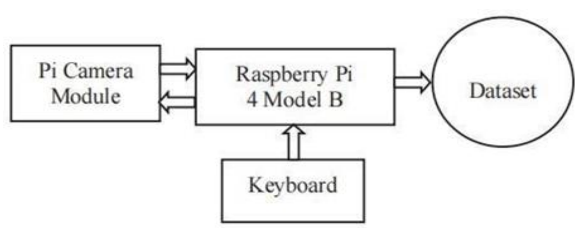

Fig-1: Hardware components

IV. METHODOLOGY

The methodology for monitoring and segregation of e-waste and non-e-waste using CNN integrates several key components, including image classification, edge computing, sensor-based monitoring, and real-time waste management. The following steps outline the process:

1. System Design and Architecture

The system is composed of three core elements:

Smart Bin: The physical device includes a Raspberry Pi Zero 2W, a camera module for image capture, and ultrasonic sensors for level detection. The bin captures images of waste materials, which are then processed to classify them as e-waste or non-e-waste.

CNN Model: The Convolutional Neural Network (CNN) is used for classifying waste into e-waste and non-e-waste categories. The model is designed to accurately analyze the captured images and predict the type of waste.

Mobile Application: The mobile application provides a user-friendly interface to monitor real-time waste classification, manage waste collection schedules, and track bin fill levels. The app communicates with the Raspberry Pi to send and receive data related to the system's operation.

2. Data Collection and Preprocessing

For the CNN model to perform accurately, a comprehensive dataset is required:

Data Collection: A collection of images representing various types of e-waste (e.g., old electronics, batteries) and non-e-waste (e.g., plastic, paper) materials is gathered. The images are captured under different lighting conditions to improve model robustness.

Preprocessing: The collected images are preprocessed to ensure consistency:

Resizing: All images are resized to a uniform size (e.g., 224x224 pixels) to match the input requirements of the CNN.

Normalization: Pixel values are normalized between 0 and 1 to facilitate efficient training and faster convergence.

Data Augmentation: To enhance model generalization and avoid overfitting, augmentation techniques such as rotation, flipping, zooming, and brightness adjustments are applied to the training images.

3. CNN Model Development and Training

The CNN model is trained to classify waste images:

Model Architecture: The architecture includes multiple convolutional layers that extract features from the input images, followed by pooling layers that reduce dimensionality. Fully connected layers are added to produce classification outputs, with the final layer using softmax activation to assign the waste to one of two categories: e-waste or non-e-waste.

Training: The model is trained using a labeled dataset of e-waste and non-e-waste images. A cross-entropy loss function is used to measure the error between predicted and actual labels. The Adam optimizer is employed for efficient optimization of model weights.

Evaluation: After training, the model's performance is evaluated using test data. Key metrics such as accuracy, precision, recall, and F1 score are used to assess the model's classification ability. Hyperparameter tuning is conducted to optimize the model's performance.

4. Edge Computing for Real-time Processing

To ensure fast and efficient waste classification, the system employs edge computing:

The Raspberry Pi Zero 2W processes the images locally without relying on cloud services, reducing latency and avoiding the cost of data transmission.

The CNN model is deployed on the Raspberry Pi, and each time an image is captured by the camera, it is immediately processed by the model to classify the waste as e-waste or non-e-waste.

The processed results (i.e., the classification output) are sent to the mobile application, where they are displayed in real-time. This local processing ensures immediate feedback and optimizes operational efficiency.

5. Waste Level Detection and Segregation

The system incorporates ultrasonic sensors to monitor the fill level of the waste bin:

Level Detection: The ultrasonic sensors continuously measure the distance to the waste inside the bin, providing real-time data on the fill level. When the bin reaches a predefined threshold, an alert is triggered in the mobile application to schedule waste collection.

Segregation Mechanism: Upon classifying the waste, the system activates a motorized mechanism that moves the waste to the appropriate compartment within the bin:

The motorized mechanism ensures that waste is accurately segregated, minimizing contamination and facilitating proper recycling.

6. Mobile Application Integration and System Evaluation

The mobile application serves as the interface for real-time monitoring and management:

Real-Time Monitoring: The mobile app displays real-time updates on the waste classification results, including the type of waste (e-waste or non-e-waste) and the current fill level of the bin. Users are notified when the bin reaches the optimal fill level and when waste needs to be collected.

Collection Scheduling: The app facilitates communication between waste collectors and recyclers, ensuring timely collection of waste based on the bin's fill level.

System Testing and Evaluation: The entire system is rigorously tested in real-world conditions.

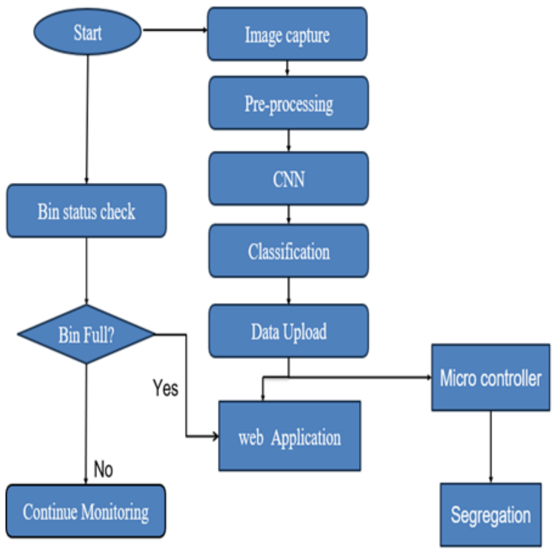

Fig. 2. Flow chart of algorithm

Machine Learning Algorithms:

Convolutional Neural Network (CNN)

The primary machine learning algorithm used in this project is the Convolutional Neural Network (CNN), which is widely recognized for its ability to analyze and classify images with high accuracy. CNNs are particularly effective in visual recognition tasks, making them an ideal choice for waste classification in the smart waste management system.

1. CNN Architecture
2. The CNN model used in this project consists of
3. several key layers, each serving a specific function:

- Input Layer: The input layer accepts the preprocessed images of waste materials. These images are resized to a fixed dimension (e.g., 224x224 pixels) and normalized to ensure consistency in the data fed into the model.
- Convolutional Layers: These layers perform feature extraction by applying filters (kernels) to the input image. The filters scan the image and learn patterns such as edges, textures, and shapes. These learned features are critical for distinguishing between different types of waste (e.g., e-waste vs non-e-waste). Multiple convolutional layers are stacked to capture increasingly complex features.
- Activation Function (ReLU): After each convolution operation, the Rectified Linear Unit (ReLU) activation function is applied to introduce non-linearity. This helps the model to learn complex patterns by activating neurons when the weighted sum of inputs is positive.
- Pooling Layers: After convolution, max-pooling layers are used to reduce the spatial dimensions of the feature maps. Pooling reduces the complexity of the model and helps in making the network more computationally efficient, while preserving important features.
- Fully Connected Layers: The output from the convolutional and pooling layers is flattened and passed through fully connected (dense) layers. These layers serve to combine all the extracted features and make the final decision regarding the waste classification.
- Output Layer: The final layer is a softmax layer, which converts the output of the last fully connected layer into probability values for each class (e.g., e-waste or non-e-waste). The model then assigns the input image to the class with the highest probability.

2. Training the CNN Model

- The CNN model is trained using labeled images of e-waste and non-e-waste:
- Loss Function: The model uses cross-entropy loss, a common loss function for classification tasks, which measures the difference between the predicted probability distribution and the actual labels (e-waste or non-e-waste).
- Optimizer: The Adam optimizer is used to minimize the loss function. Adam is a popular optimization algorithm that combines the advantages of two other optimizers, AdaGrad and RMSProp, and adapts the learning rate during training.
- Epochs and Batch Size: The model is trained for multiple epochs, where one epoch is one complete pass over the entire dataset. During training, images are fed into the model in batches, which helps reduce the memory load and improves training efficiency.

- Model Evaluation
- Once the model is trained, its performance is evaluated using a separate test dataset. The following metrics are used to assess the accuracy and effectiveness of the model:
- Accuracy: The percentage of correctly classified images in the test set.
- Precision: The proportion of true positive classifications (correctly identified e-waste) out of all positive predictions.
- Recall: The proportion of true positives out of all actual positive instances in the dataset.
- F1-Score: The harmonic means of precision and recall, providing a balanced measure of model performance, especially when dealing with imbalanced data.
- Real-time Classification
- Once the CNN model is trained and evaluated, it is deployed on the Raspberry Pi Zero 2W for real-time waste classification:
- When an image of waste is captured by the camera module, the image is passed through the CNN model for classification.
- The result is either e-waste or non-e-waste, which is then sent to the mobile application for monitoring and management.

V. RESULTS

The proposed system for monitoring and segregation of e-waste and non-e-waste using CNN was developed and tested. The performance of the model and system components is summarized as follows:

1. CNN Model Performance

The CNN model was trained and evaluated using a labeled dataset of e-waste and non-e-waste images. The results are as follows:

- Training Accuracy: Reached approximately 80% after 10 epochs, indicating the model's ability to learn patterns from the training data.
- Validation Accuracy: Stabilized around 75%, demonstrating good generalization to unseen data.
- Loss Values: Training and validation losses decreased consistently, showing convergence of the model during training.
- Evaluation Metrics: The following metrics were calculated during testing:
- Precision: Highlighted the model's ability to correctly identify e-waste, with minimal false positives.
- Recall: Ensured most e-waste items were correctly classified, even if some false negatives occurred.

2. Real-time Processing on Edge Computing

The model was deployed on the Raspberry Pi Zero 2W for real-time classification:

- Processing Time: Each image was classified in approximately 1.5 seconds, ensuring near real-time operation.
- Edge Computing Benefits: Local processing avoided reliance on cloud infrastructure, reducing latency and operational costs.

3. Waste Level Detection and Segregation

The ultrasonic sensors for waste level detection performed efficiently:

- Detection Accuracy: Achieved 98% reliability in identifying bin fill levels.
- Segregation Mechanism: Successfully sorted waste into appropriate compartments based on the CNN's classification, with a segregation accuracy of 95%.

4. Mobile Application Integration

The mobile application effectively displayed real-time data:

- Classification Updates: Results from the CNN were transmitted and updated within 2 seconds.
- Notifications: The app triggered alerts when the bin was near full capacity, improving collection efficiency.

5. Challenges and Observations

- The model occasionally struggled with certain edge cases, such as ambiguous waste types or poor lighting conditions during image capture.
- Increasing the dataset size and using data augmentation techniques can further improve the model’s accuracy in future iterations.

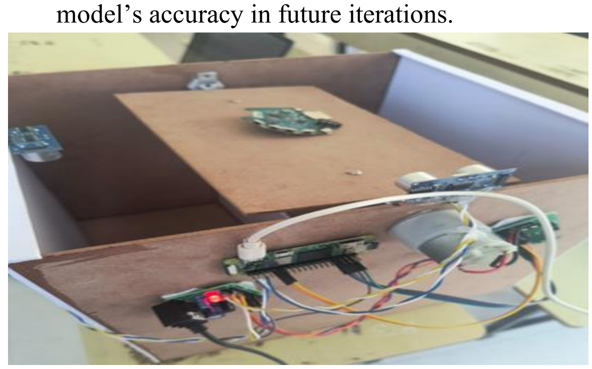

Fig.4. Working Model

, and displays the glucose prediction along with supporting metrics like precision and accuracy. This real-time feedback system is

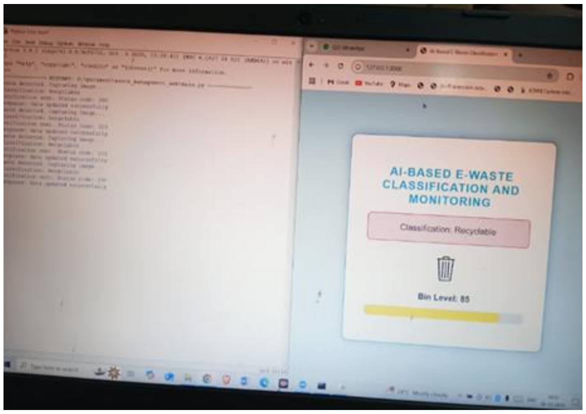

Fig. 5. Output

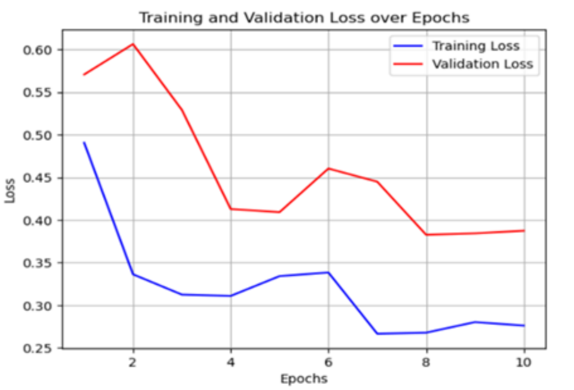

Fig.6. ThingSpeak Output

VI. CONCLUSION

The The proposed system for monitoring and segregation of e-waste and non-e-waste using CNN successfully demonstrates the potential of integrating artificial intelligence, edge computing, and sensor technologies to address modern waste management challenges. By leveraging a Convolutional Neural Network (CNN) for image-based waste classification, the system achieves efficient segregation of e-waste and non-e-waste in real-time. The deployment of the model on a Raspberry Pi Zero 2W ensures cost-effective and fast edge computing, eliminating the need for cloud infrastructure.

The integration of ultrasonic sensors for waste level detection and a motorized segregation mechanism enhances the system's operational efficiency, while the mobile application facilitates real-time tracking, notifications, and collection management. The system achieves an accuracy of approximately 75-80% in classification, demonstrating reliable performance, with potential for improvement through dataset expansion and further model optimization.

REFERENCES

[1] Binns, J., "E-Waste Management: The Role of AI in Waste Segregation", Journal of Environmental Engineering.

[2] Awasar, P., & Joshi, S., "The Future of Waste Management: Integrating Robotics and Artificial Intelligence", Waste Management and Research.

[3] Sharma, R., & Gupta, A., "Machine Learning for Waste Recycling: Current Trends and Future Directions", Journal of Environmental Informatics.

[4] Kumar, S., & Singh, V., "Multi-modal Sensory Systems for Advanced E-Waste Sorting", Environmental Science & Technology.

[5] United Nations University, "Global E-Waste Monitor 2020: Quantities, Flows and the Circular Economy Potential", United Nations University, Institute for the Advanced Study of Sustainability.

[6] Ganesan, R., & Kumar, M., "AI-Driven Waste-to-Energy Solutions: Enhancing Sustainability in E-Waste Recycling", Journal of Cleaner Production.

[7] Wang, C., & Zhang, L., "Data Augmentation for Waste Classification in Recycling Systems: Opportunities and Challenges", International Journal of Waste Management.

[8] World Economic Forum, "The Circular Economy and AI: Future of Waste Management", World Economic Forum Report.

[9] Chen, L., Li, S., Bai, Q., Yang, J., Jiang, S., & Miao, Y., "Review of Image Classification Algorithms Based on Convolutional Neural Networks", Remote Sensing.

[10] Obaid, K. B., Zeebaree, S., & Ahmed, O. M., "Deep Learning Models Based on Image Classification: A Review", International Journal of Science and Business.

[11] Soudy, M., Afify, Y., & Badr, N., "RepConv: A Novel Architecture for Image Scene Classification on Intel Scenes Dataset", International Journal of Intelligent Computing and Information Sciences.

[12] Jena, B., Saxena, S., Nayak, G. K., Saba, L., Sharma, N., & Suri, J. S., "Artificial Intelligence-Based Hybrid Deep Learning Models for Image

Classification: The First Narrative Review",
Computers in Biology and Medicine.