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Edge-Deployed Waste Classification System Using Transfer Learning on Custom IoT Camera Data with Data Augmentation

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Abstract

Rapid urbanization and inefficient waste segregation have intensified the global waste management crisis, with Municipal Solid Waste projected to reach 3.8 billion tonnes annually by 2050. This study proposes a smart automated waste classification system integrating a lightweight MobileNetV2 convolutional neural network with an IoT-based Raspberry Pi 4 platform to enable real-time, cloud-independent automated waste sorting across five categories which are Metal, Plastic, Paper, Organic, and None (not_waste). A dataset of 671 manually collected images was used to train and compare two models: a baseline model achieving 71.20% accuracy and an augmentation-enhanced model achieving 93.60% accuracy with a macro F1-score of 0.9344, where offline data augmentation proved to be the single most important factor, dramatically improving Organic class recall from 0.22 to 0.96. The deployed system captures waste images in real time, classifies them on-device, and automatically activates a sorting mechanism, confirming that lightweight CNN architectures combined with balanced training data offer a practical and low-cost solution for smart waste management in resource-constrained real-world environments.

Keywords: Smart Waste Management, Waste Classification, MobileNetV2, Convolutional Neural Network (CNN), Internet of Things (IoT), Raspberry Pi 4, Data Augmentation, Image Classification, Automated Waste Sorting

1. Introduction

Consider a rapidly growing neighborhood in Kathmandu, where mixed household waste is collected and transported to already dumped landfill sites. In such situations, organic wastes are mixed with plastics and papers, thrown without proper separation. Oftentimes where they could be recovered and recycled, most of them turn out unrecoverable. In such environments, inefficient waste management is not just an environmental concern but a systemic urban challenge.

Waste management is a vital environmental issue of the 21st century. Driven by rapid urbanization, global Municipal Solid Waste (MSW) is projected to reach 3.8 billion tonnes annually by 2050 [1]. Currently, open dumping reports for nearly 33% of global waste, causing severe soil degradation and greenhouse gas emissions [1]. This crisis is worsened by on-site ineffective separation, resulting in the loss of up to 80% of recyclable materials to overflowing landfills [2].

The situation is particularly severe in rapidly growing urban regions such as Kathmandu Metropolitan City (KMC), which generates approximately 620 tonnes of waste daily [3]. A major challenge in Nepal lies in waste categorization where organic waste comprises 51% to 68% of the total and frequently contaminates ingorganic recyclables like plastics (19%) and paper (5-8%) [3] [4]. With nearly 49% municipalities relying

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on primitive landfilling methods [5], unmanaged organic waste makes recycling economically impractical and environmentally hazardous, highlighting the urgent need for automated sorting solutions [5].

While developing digital technologies have transformed multiple sectors, waste management systems remain largely manual and inefficient. Integrating Machine Learning (ML) and the Internet of Things (IoT) offers a good approach to waste segregation. Computer vision models enable reliable waste classification, while IoT-based actuators and sensors can automatically direct items into their desired containers. Such systems can improve efficiency by up to 40% and reduce operational costs by 25–35% [6], supporting economic goals [1]. However, although prior studies demonstrate deep learning-based classification in controlled environments [7] [8] [9], few studies address real-world deployment challenges in developing nations, particularly with the integration of lightweight Convolutional Neural Networks (CNNs) with low-cost edge hardware.

To address these limitations, we propose an automated waste classification and sorting system that combines lightweight computer vision with IoT-based actuation. The system is designed for real-time operation using affordable edge hardwares also enabling practical deployment in resource limited environments. This work is guided by the following research questions:

- RQ1: How can lightweight CNN architectures be optimized for accurate, real-time waste classification on low-cost edge devices?
- RQ2: How can IoT-integrated systems enable reliable, automated waste sorting in real-world, resource-constrained environments?

To address these limitations, we propose a smart waste classification that integrates lightweight computer vision with IoT-based automation. Our core contributions are:

- A dataset consisting of 671 images was collected across five categories: metal, plastic, paper, organic, and none (No Waste). The images were captured using the camera integrated into the prototype device developed for this study.
- We optimize a MobileNetV2 architecture using transfer learning, which can reduce the number of trainable parameters to approximately 362,000, enabling efficient real-time inference on resource-constrained hardware such as the Raspberry Pi 4.
- The training dataset was augmented while keeping this test data unchanged, resulting in a total dataset size of 2,500 samples. The model was then retrained using the same MobileNetV2 architecture, and its performance was compared to evaluate the impact of the augmented training data.
- We design and implement an integrated IoT prototype in which a webcam captures waste images, performs on-device classification on the Raspberry Pi, and actuates a sorting mechanism to automatically direct waste into the appropriate container.

Our work bridges high-accuracy computer vision with low-cost IoT deployment, demonstrating a practical system for real-world smart waste classification.

2. Related Works

Traditional waste classification relies heavily on manual sorting, processing only 30 to 40 items per minute while exposing unskilled workers to significant health risks [7] [9] [10]. Other conventional methods, such as chemical analysis or RFID technology, are resource-intensive or require costly pre-tagging, making them unsuitable for real-time processing [10]. Overall, these traditional approaches suffer from low accuracy (typically under 80%), high labor costs, inconsistent classification results, and poor scalability for increasing waste volumes [9] [11] [12].

Contemporary waste management systems integrate artificial intelligence and IoT for automated, real-time classification. Modern AI models demonstrate superior performance, with CNN architectures and hybrid approaches consistently exceeding 95% accuracy [7] [13], and specific VGG-19 implementations reaching up to 99.7% [11]. Furthermore, AI-powered IoT systems can process waste at up to 160 items per minute, representing a four to five-fold improvement over manual methods [7]. By eliminating labor-intensive requirements and integrating real-time monitoring, these automated systems drastically reduce operational costs and safety risks, positioning them as highly scalable solutions for sustainable smart city infrastructure [8] [12] [14]. Unlike these established models which often require huge training cycles, this project introduces an optimized training process that achieves over 93% F1-score in just 15 epochs. This work provides a more computationally efficient solution that maintains high reliability under the unpredictable lighting and positioning conditions common in real-world scenarios.

A few recent works have investigated waste classification through edge-based systems using lightweight deep learning models. For instance, a Raspberry Pi-based system using a ResNet-50 architecture achieved approximately 96% accuracy in real-time waste classification tasks [15]. Similarly, an improved MobileNetV2 model deployed on Raspberry Pi demonstrated around 90% accuracy with an inference latency of approximately 600 ms per image, highlighting the trade-off between efficiency and performance in embedded environments [16]. Another study integrating EfficientNet-based models into an intelligent waste bin system reported an accuracy of 93.38% under real-world conditions [16].

Despite these advancements, many existing approaches either rely on deeper architectures or require higher computational overhead for training and deployment. On the other hand, the technique introduced here has an F1-score of more than 93% in 15 training epochs, providing an approach that is highly efficient when it comes to computation.

3. Methodology

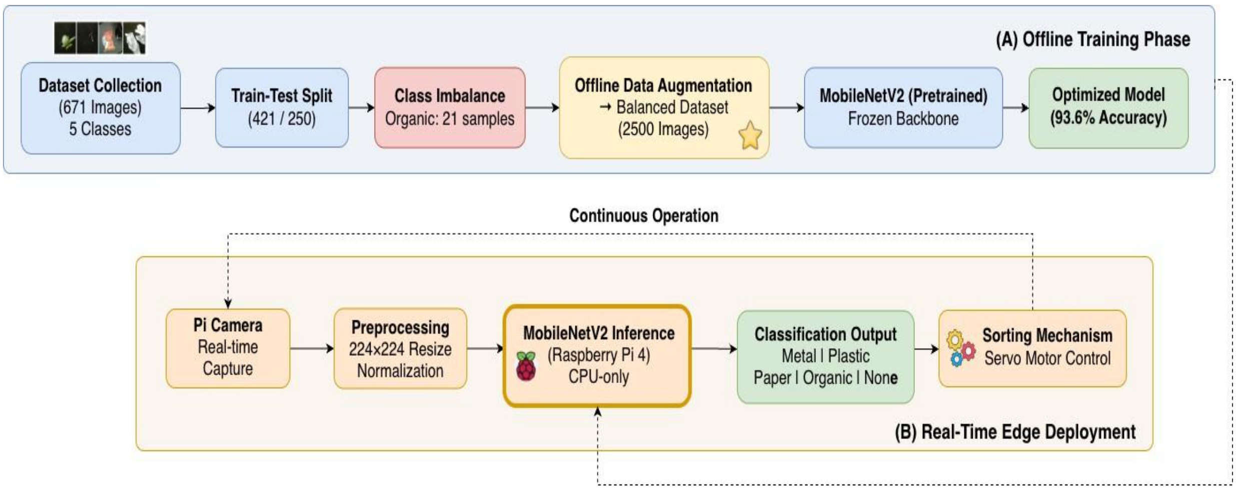

Figure 1. Overview of the proposed system. The top section shows the offline training pipeline, where data augmentation addresses class imbalance and improves models performance. The bottom section illustrates real-time edge deployment on a Raspberry Pi 4, enabling continuous waste classification and automated sorting without cloud dependency.

3.1 Data Acquisition and Partitioning

We manually collected the dataset to simulate realistic operating conditions. A camera sensor integrated into the developed waste classification prototype captured the images, ensuring natural variations in object orientation, lighting, and background. We gathered a total of 671 images across five predefined classes: metal, plastic, paper, organic, and none (only background). The sample images are shown in Figure 2.

To ensure unbiased evaluation, we partitioned the dataset into mutually exclusive training and test subsets using a fixed random seed. We reserved a fixed allocation of 50 images per class to form a perfectly balanced test set of 250 images. The remaining 421 images formed the baseline training set, as shown in

Table 1. This partitioning revealed a severe class imbalance in the training data, particularly for the ‘organic’ class which retained only 21 training samples. This imbalance directly motivated the data augmentation strategy we applied to our second model.

Table 1. Total dataset collected and its train-test split

Class	Total Images Collected	Train Images	Test Images
Metal	150	100	50
None (Background)	162	112	50
Organic	71	21	50
Paper	182	132	50
Plastic	106	56	50
Total	671	421	250

Figure 2. Sample images from each class (Paper, Plastic, Organic, Metal)

3.2 Data Preprocessing and Augmentation

We resized all input images to 224 × 224 pixels, converted them to PyTorch tensors, and normalized them using the ImageNet channel-wise statistics (Mean: [0.485, 0.456, 0.406], Std: [0.229, 0.224, 0.225]). We applied only deterministic transformations (resizing, center cropping, and normalization) to this test set to ensure consistent evaluation.

For training, we evaluated two different approaches:

- **Model 1 (Baseline):** We employed lightweight online data augmentation during training using PyTorch’s torchvision.transforms module. We included random resized cropping, horizontal and vertical flipping, rotation, perspective shifts, color jitter, Gaussian blur, and random erasing.

Model 2 (Augmentation-Enhanced): We addressed the extreme class imbalance by applying offline data augmentation. We generated this new data directly from our original baseline training set. We repeatedly applied random rotations, horizontal flips, color jitter, and resized crops to the existing images in our underrepresented classes, saving these new visual variations to the disk until we reached a target of 500 images per class. This expanded the balanced training dataset to 2,500 images, representing a 5.94x increase in volume.

No augmentation was applied to this test set at any stage, ensuring unbiased evaluation.

3.3 Model Architecture and Transfer Learning

The system employs MobileNetV2, which we chose for its depth wise separable convolutions and low parameter count, making it ideal for resource-constrained IoT deployments [19]. We used a pre-trained ImageNet backbone as the feature extractor and froze all base convolutional layers to prevent catastrophic forgetting and mitigate over fitting on our small dataset.

We replaced the original classification head with a custom sequential block tailored for five classes, consisting of Dropout, Linear (hidden units), ReLU, BatchNorm1d, and a final Linear mapping layer. This transfer learning strategy reduced the model's 2.5 million total parameters to approximately 362,000 trainable parameters, ensuring computationally efficient training while maintaining high accuracy.

3.4 Training Configuration

We trained both models for 15 epochs with a batch size of 32 using the Adam optimizer (initial learning rate of 0.0001) and CrossEntropyLoss. We employed a ReduceLROnPlateau scheduler to dynamically decrease the learning rate when validation loss plateaued. To optimize memory consumption and speed, we enabled Automatic Mixed Precision (AMP) training via PyTorch's GradScaler. The system automatically saved the model state dictionary whenever test accuracy exceeded the previous best1.

3.5 Hardware Integration and Deployment

We accelerated model training using a CUDA-enabled GPU via Google Colab. We then deployed the highest-performing model on a low-cost Raspberry Pi 4 Model B (quad-core ARM Cortex-A72 at 1.5 GHz, 64-bit ARMv8 architecture) for cloud-independent edge inference.

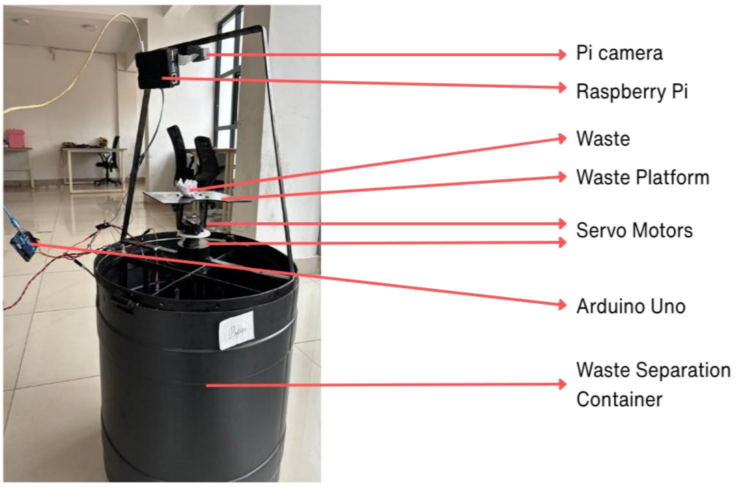

Figure 3. Hardware setup of the smart waste classification system.

During real-time operation, the connected Pi camera captures waste images, the CPU processes the lightweight MobileNetV2 classification, and the system actuates a sorting mechanism to direct items into appropriate containers. The hardware implementation is shown in Figure 3. While the Raspberry Pi 4 offers excellent energy efficiency (approximately 15W), its lack of dedicated GPU acceleration limits parallel processing [20]. We must account for sequential I/O bottlenecks from microSD storage and potential thermal throttling if CPU temperatures exceed 80°C during deployment [21].

4. Result

4.1 Training Performance - Model 1 (Baseline)

We trained Model 1 on the raw 421-image dataset for 15 epochs. The training progressed gradually, showing consistent improvement in both loss reduction and accuracy gain. The average epoch training time was approximately 72 to 87 seconds, with the first epoch requiring 423 seconds due to initial overhead.

4.1.1 Convergence Analysis and Learning Curves

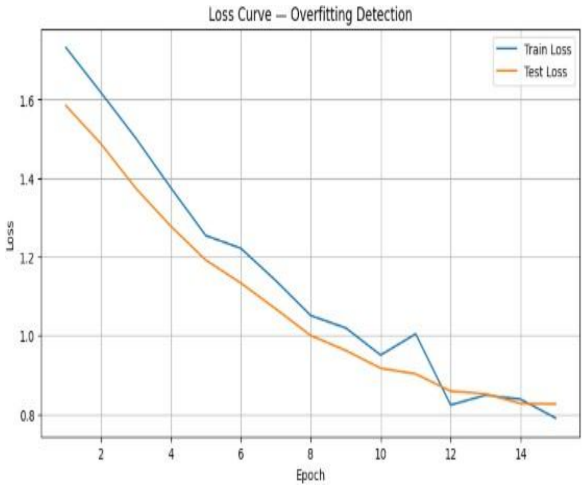

Figure 4. Training and testing loss curve of model 1

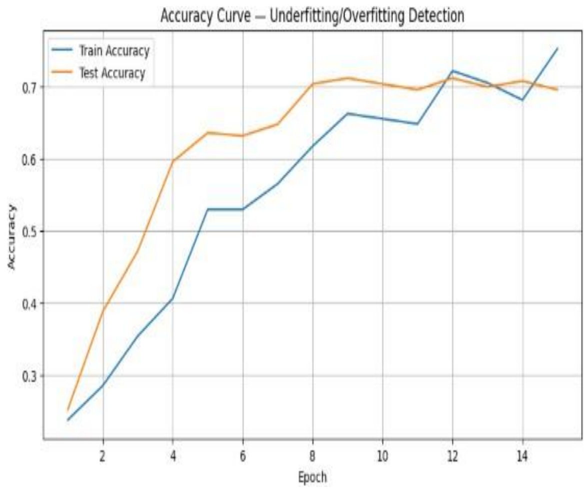

Figure 5. Training and testing accuracy of model 1

We observed a clear convergence pattern divided into three learning stages. In the initial phase (epochs 1 and 2), the model improved from near-random performance (approximately 25% accuracy) to 38.8% accuracy. During the accelerated learning phase (epochs 3 to 5), the model experienced its most significant improvement, with test accuracy jumping to 63.6% as the classification head effectively utilized the backbone's feature representations. In the final phase (epochs 6 to 15), performance plateaued as the model approached the generalization limit imposed by the small dataset.

Both the loss and accuracy curves (Figures 4 and 5) reflect this trend. The training loss decreased from 1.73 to 0.79, while test loss decreased from 1.58 to approximately 1.15. A small but consistent gap between the training and test loss indicates mild, controlled overfitting, which is typical when training deep learning models on small datasets. The model ultimately achieved its best test accuracy of 71.20% at epoch 12.

4.1.2 Final Evaluation and Per-Class Performance

Evaluating the best checkpoint on the 250-image test set revealed a significant asymmetry in model behavior. The model achieved a relatively high macro precision of 78.53% compared to a lower macro recall of 71.20% and a macro F1-score of 67.17%.

This asymmetry stems directly from the class-imbalanced training data. The 'none' and 'metal' classes achieved perfect recall (1.00), likely due to their larger representation in the training set and visually distinctive features. However, the severely underrepresented 'organic' class achieved perfect precision (1.00) but a dismal recall of 0.22. This indicates that the baseline model simply learned to avoid predicting organic waste altogether unless it was highly confident, misclassifying the vast majority of organic samples.

4.2 Training Performance - Model 2 (Augmentation-Enhanced)

We trained Model 2 on the augmented 2500-image balanced dataset for 15 epochs under identical hyperparameters.

4.2.2 Convergence Analysis and Learning Curves

Model 2 demonstrated drastically faster convergence. By utilizing the balanced dataset, it achieved 74.80% test accuracy in the very first epoch, instantly surpassing the baseline model's peak performance. The training and testing loss curves (Figures 6 and 7) exhibit a steady downward trend, with test loss decreasing significantly from 0.95 to 0.28.

The close alignment between the training and test accuracy curves indicates strong generalization performance with no severe overfitting. The model reached near convergence around epochs 8 to 10, ultimately achieving its best test accuracy of 93.60% at epoch 15.

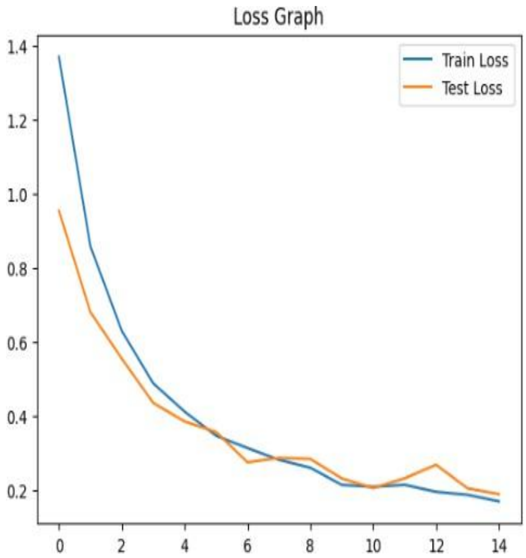

Figure 6. Train and test loss curve of model 2

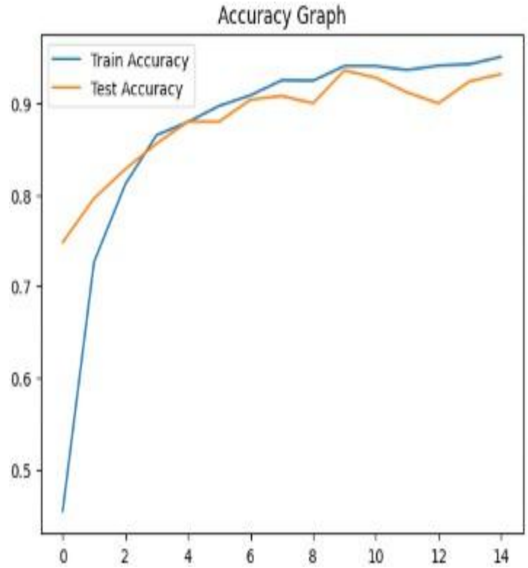

Figure 7. Train and test accuracy curve of model 2

4.2.2 Final Evaluation and Per-Class Performance

Model 2 completely resolved the precision-recall asymmetry observed in the baseline. It achieved near-equal overall metrics: 93.74% precision, 93.60% recall, and a 93.44% macro F1-score. This alignment confirms that Model 2 exhibits balanced prediction behavior and neither over-predicts nor under-predicts any specific class.

The balanced training data dramatically improved the per-class performance. Most notably, the 'organic' class F1-score increased from 0.36 to 0.97, and its recall surged from 0.22 to 0.96. The 'plastic' class recall improved from 0.46 to 0.78; while it remains the lowest-performing class due to its visual heterogeneity, an overall F1-score of 0.86 indicates strong practical performance

4.3 Comparative Results Summary

Table 2 illustrates the overall performance improvements from Model 1 to Model 2. The offline data augmentation strategy enhanced all classes without introducing any performance trade-offs.

Table 2. Overall evaluation comparison of both model

Metric	Model 1 (baseline)	Model 2(Augmented)	Absolute Improvement
Accuracy	0.712	0.936	**+0.224**
Macro Precision	0.785	0.937	**+0.152**
Macro Recall	0.712	0.936	**+0.224**
Macro F1 score	0.672	0.934	**+0.263**

Furthermore, Table 3 breaks down the category-wise comparison of the two models, highlighting the specific precision, recall, and F1-score improvements across all five waste categories.We observe the largest gain in the ‘organic’ class, which rises from an F1-score of 0.36 to 0.97. This surge is directly driven by the increase in training samples from 21 to 500. The ‘plastic’ category also improves significantly from an F1-score of 0.60 to 0.86, though it remains the lowest-performing class due to its visual heterogeneity. ‘Metal’ gains from 0.74 to 0.97, primarily through improved precision while maintaining perfect recall. The ‘none’ and ‘paper’ classes, already strong in Model 1, see further modest improvements. These results confirm that our offline data augmentation strategy successfully enhanced all classes without introducing any performance trade-offs.

Table 3. Category-Wise Model Comparison

Class	Model 1 (Precision)	Model 2 (Precision)	Model 1 (Recall)	Model 2 (Recall)	Model 1 (F1-score)	Model 2 (F1-score)
Metal	0.59	0.94	1.00	1.00	0.74	0.97
Organic	1.00	0.98	0.22	0.96	0.36	0.97
Paper	0.67	0.89	0.88	0.94	0.76	0.91
Plastic	0.85	0.95	0.46	0.78	0.60	0.86
None	0.82	0.93	1.00	1.00	0.90	0.96

4.4 Hardware Integration Results

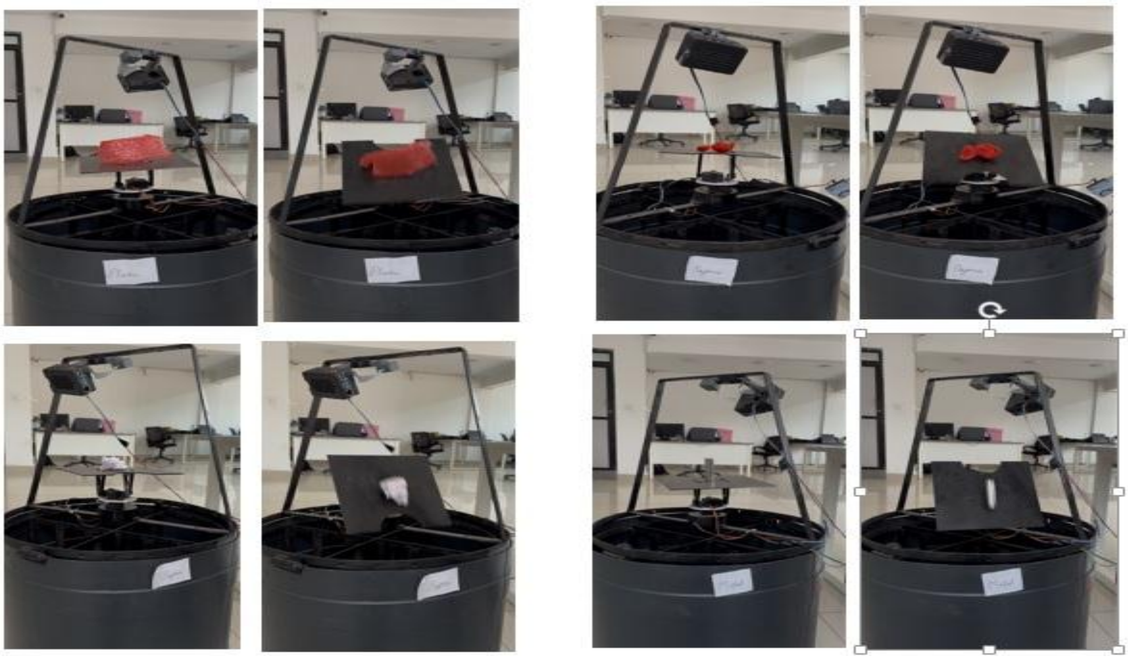

Figure 8. Hardware Integration Results. The waste is scanned by the pi camera and classified under the said classes.

During real-time physical testing, the Raspberry Pi 4 Model B successfully executed the full classification pipeline without cloud connectivity. The system captured live waste images via the camera sensor, executed local CPU inference using the trained MobileNetV2 model, and reliably actuated the physical sorting mechanism to direct items into the correct bins (Figure 8). The integration demonstrated low inference latency which as measured on Raspberry Pi 4 remained sub-second under low thermal load whereas increases approximately to around 1-2 seconds when ran for a operated time due to high thermal load, and stable end-to-end operation, proving that the trained lightweight architecture successfully translates high laboratory accuracy into practical, resource-constrained edge environments.

4.5 Evaluation on Real-World Distribution

In the first evaluation, the dataset used had equal samples in each category (50 samples per category). This is inconsistent with the actual world distribution, where the majority of waste is organic waste (approximately 51% to 68%). To overcome this problem, we created a distribution-aware test set to evaluate the baseline model.

In this scenario, the accuracy, precision, recall, and F1 score of the model were found to be 71.20%, 78.53%, 71.20%, and 67.17%, respectively. On the other hand, there was a remarkable degradation in performance concerning the organic class with low recall at 0.22. Therefore, the model did not identify organic waste adequately.

5. Discussion and Recommendations

5.1 Impact of Data Augmentation on Model Performance

We found the most significant outcome of this study to be the 22.40 percentage point improvement in test accuracy (93.60% versus 71.20%). We attribute this entirely to the offline data augmentation strategy since we held all other experimental variables constant. This confirms a well-established deep learning principle: training data volume and class balance are just as important as architectural choices for small custom datasets. While MobileNetV2's pre-trained features provide a strong foundation, the custom classification head requires balanced training signals to learn reliable boundaries. The augmentation strategy successfully addressed the extreme class imbalance. By expanding the 'organic' training images from 21 to 500, we improved its recall from 0.22 to 0.96. This proves the baseline model had simply learned to avoid predicting organic waste due to a lack of data. Furthermore, Model 2 achieved 74.80% test accuracy at epoch 1. This rapid convergence demonstrates that balanced data enables the pre-trained backbone to transfer its representations much more effectively.

5.2 Class-Specific Behavior Analysis

Both models achieved perfect recall (1.00) for 'metal' and 'none'. We attribute this to their relatively large initial training sets and visually distinctive features, such as metallic reflections and uniform backgrounds, which the pre-trained detectors capture easily. Conversely, the severely imbalanced 'organic' class in Model 1 showed near-perfect precision but near-zero recall (0.22), meaning it misclassified most organic items. Model 2 completely resolved this, achieving 0.96 recall and 0.98 precision. 'Plastic' remained the most challenging category, capping at a 0.78 recall due to high visual variability among bottles, bags, and wrappers. We also found that Model 1 primarily erred toward the visually dominant 'metal' and 'paper' classes. Model 2 exhibits a reliable diagonal-dominant pattern, with remaining errors occurring mainly between visually similar mixed materials like plastic and paper.

5.3 Implications for Edge Deployment

Deploying the system on a Raspberry Pi 4 provides several practical advantages. Performing local inference eliminates cloud dependency, allowing immediate actuation of the sorting mechanisms. The low power consumption supports continuous, decentralized deployment in real-world collection environments. However, the system must navigate strict hardware limits. CPU-only inference requires lightweight architectures like MobileNetV2 to prevent severe latency. Additionally, prolonged high CPU usage can cause thermal throttling, which can reduce inference speed over time. Future deployments must incorporate reliable preprocessing to handle varying environmental lighting and careful thermal management to maintain classification reliability.

6. Conclusion

This study successfully demonstrates that combining a lightweight MobileNetV2 transfer learning model with low-cost IoT hardware creates a highly effective automated waste classification system. By applying offline data augmentation to balance the training dataset, we increased test accuracy to 93.60% and achieved a macro F1-score of 0.9344. These results confirm that data volume and class balance are just as necessary as model architecture when engineering solutions with limited data. Finally, our successful deployment on a Raspberry Pi 4 validates this architecture as a practical, low-latency solution for resource-constrained smart waste management.

7. Limitations

We acknowledge several limitations in the current system that highlight areas for future improvement. First, the relatively small raw dataset (671 images) and reliance on a single train-test split instead of k-fold cross-validation may limit generalization. We also collected images from a fixed camera angle under controlled lighting. Performance may degrade in cluttered or poorly lit real-world scenarios. Furthermore, the broad ‘plastic’ category fails to capture the visual diversity of mixed materials, leading to confusion with laminated paper or reflective transparent containers. Dirty or heavily worn items also obscure surface textures. Finally, hardware constraints on the Raspberry Pi 4, such as thermal throttling above 80 degrees Celsius and reliance on slower MicroSD storage, can throttle processing speeds during continuous operation.

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