

AI-Based E-Waste Classification Using Deep Learning

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Abstract

Electronic waste (e-waste) management remains a critical environmental challenge due to increasing volumes and inefficient manual sorting practices. This study develops and evaluates an AI-based e-waste classification system using deep learning with transfer learning on the MobileNetV2 architecture. The proposed model classifies images into 10 common e-waste categories and achieves an overall accuracy of 95%, with strong per-class performance (F1-scores ranging from 0.89 to 0.98). The system demonstrates high potential for practical deployment in recycling facilities, supporting automated sorting, resource recovery, and sustainable waste management.

Keywords — E-waste classification, deep learning, MobileNetV2, transfer learning, image classification, electronic waste, automated sorting, lightweight neural network

1: Introduction

1.1 Background of the Study

Electronic waste (e-waste) encompasses discarded electrical and electronic equipment such as batteries, keyboards, microwaves, mobile phones, computer mice, printed circuit boards (PCBs), media players, printers, televisions, and washing machines. Global e-waste generation reached approximately 62 million metric tons in 2022 and is projected to grow by more than 30% by 2030 [1]. In India—one of the largest producers of e-waste in Asia—collection and recycling rates remain below 20–25%, with much of the processing occurring in the informal sector under unsafe conditions [2].

Manual sorting of e-waste is labor-intensive, inconsistent, prone to human error, and exposes workers

to hazardous substances including lead, mercury, cadmium, and brominated flame retardants [3]. Recent advances in computer vision and deep learning have shown significant promise in automating object classification tasks. Transfer learning using lightweight convolutional neural network architectures (such as MobileNetV2) enables high-accuracy image classification even with moderate-sized datasets when combined with appropriate data augmentation strategies [4]. This work leverages such techniques to develop an efficient and accurate e-waste image classification system tailored to real-world recycling needs.

1.2 Problem Statement

Inefficient classification and sorting of e-waste contribute to low recycling rates, resource loss, environmental pollution, and occupational health risks. Existing automated sorting solutions are often computationally heavy, require large labeled datasets, or perform poorly on diverse real-world images affected by varying lighting, angles, backgrounds, and object conditions. In the Indian context, where informal recycling predominates, there is an urgent need for cost-effective, lightweight, yet highly accurate classification models that can be deployed on edge devices or integrated into sorting conveyor systems. The challenge is to achieve robust multi-class performance across visually similar yet materially distinct e-waste items while maintaining computational efficiency suitable for practical implementation.

1.3 Research Objectives

The main objectives of this study are to design and implement a deep learning-based classification model utilizing transfer learning with MobileNetV2 for accurate identification of 10 major e-waste categories from images.

1.4 Scope of the Study

This research focuses on single-object image classification of 10 e-waste categories using a dataset containing 2,700 images (2,400 training + 300 validation), with equal representation per class. The MobileNetV2 architecture is employed as the feature extractor due to its balance between accuracy and computational efficiency [4]. Data augmentation (rotation, zoom, horizontal flip) is applied during training. Evaluation is performed on a separate validation set using standard multiclass classification metrics.

1.5 Significance of the Study

The developed model achieves **95% overall accuracy** with per-class F1-scores ranging from **0.89 (Player)** to **0.98 (Mouse, PCB)** on the validation set, demonstrating strong discriminative capability across visually and semantically diverse e-waste items. This performance level indicates practical viability for integration into automated sorting lines, mobile recycling apps, or smart bins.

The work contributes to:

- Improved resource recovery rates by enabling more accurate material-specific sorting
- Reduction of occupational hazards in informal recycling sectors [3]
- Support for compliance with India's E-Waste (Management) Rules, 2022 [5]
- Advancement of lightweight deep learning applications in environmental sustainability
- Progress toward UN Sustainable Development Goal 12: Responsible Consumption and Production

By using a computationally efficient architecture and achieving high classification performance with a relatively modest dataset, this study offers a replicable and scalable approach for e-waste classification in resource-constrained settings.

2: Literature Review

2.1 Introduction to Literature Review

The rapid growth of electronic waste (e-waste) has prompted extensive research into automated classification and sorting systems. Deep learning,

particularly convolutional neural networks (CNNs) and transfer learning techniques, has emerged as the dominant approach for image-based waste and e-waste recognition due to its superior feature extraction capabilities compared to traditional machine learning methods. This section reviews key theoretical foundations, prominent studies on waste/e-waste classification (with emphasis on deep learning and transfer learning), and identifies persistent research gaps that the current study addresses.

2.2 Theoretical Framework

The theoretical foundation of this work rests on **transfer learning** and lightweight CNN architectures. Transfer learning leverages knowledge learned from large-scale datasets (e.g., ImageNet) to fine-tune models on domain-specific tasks with limited data, significantly reducing training time and improving performance on small-to-medium datasets [6].

MobileNetV2 (Sandler et al., 2018), the base architecture adopted in this study, employs inverted residuals and linear bottlenecks to achieve high accuracy with low computational cost and few parameters (~3.4 million), making it suitable for edge deployment in resource-constrained environments such as recycling facilities or mobile applications [4]. Compared to heavier models (e.g., ResNet [17], DenseNet [18], VGG), MobileNetV2 balances efficiency and accuracy, which is critical for real-world e-waste sorting systems where inference speed and energy consumption matter.

Data augmentation (rotation, zoom, flipping) and fine-tuning of later layers further enhance generalization, addressing common issues like lighting variations, viewpoint changes, and limited labeled e-waste images [7].

2.3 Review of Previous Research

Numerous studies have applied deep learning to general waste classification, with a growing subset focusing specifically on **e-waste**.

- General waste classification studies frequently utilize transfer learning on architectures such as MobileNetV2, ResNet [17], DenseNet [18], and EfficientNet, reporting accuracies between 92–99% on datasets like TrashNet, TACO, and custom garbage sets [8], [9].

- E-waste-specific classification remains less explored but is gaining momentum. Several studies have applied CNNs and object detection models (YOLOv5/v7/v8 [19], [20], [21]) to identify e-waste components (e.g., PCBs, copper, steel, aluminum, glass, plastic), reporting F1-scores near 1.0 for dominant materials and mean average precision (mAP) of ~0.96 [10], [11].
- Transfer learning approaches dominate recent e-waste work. Models such as DenseNet121 [18], MobileNetV2, and custom sequential CNNs have been fine-tuned on custom e-waste datasets, achieving 83–98% accuracy depending on the number of classes and dataset size [12], [13]. Lightweight models are favored for practical deployment; one study reported MobileNetV2 achieving ~89% on a 5-class rural e-waste dataset [14].
- Multi-stage pipelines and hybrid approaches (e.g., parallel depthwise-separable CNN + ensemble ELM) have pushed performance to 96% in binary recyclable vs. non-recyclable tasks and 85–91% in fine-grained multi-class settings (up to 36 classes) on large combined datasets (~35,000 images) [15].
- Surveys and reviews highlight the shift toward lightweight, real-time-capable models (YOLO [19], MobileNet families) and the importance of domain-specific datasets that include e-waste categories [16].
- Additional frameworks like PyTorch [24] and architectures such as Xception [25] have been explored in related waste classification tasks, often leveraging datasets like PASCAL VOC [22] and COCO [23] for benchmarking object detection and segmentation in cluttered environments.

Despite these advances, most high-accuracy results (>97%) are reported on either general waste or binary/multi-material detection tasks rather than fine-grained multi-class e-waste appliance classification (e.g., distinguishing Mobile vs. Printer vs. Washing Machine).

2.4 Research Gaps Identified

Despite significant progress, several gaps persist in the literature:

- Limited focus on fine-grained appliance-level e-waste classification — Most studies target material components (PCB, metal, plastic) or broad waste categories rather than specific end-of-life products [10], [11].

- Heavy reliance on object detection (YOLO [19]) rather than pure classification — While detection is useful for cluttered scenes, many recycling conveyor systems benefit from simpler, faster classification models when items are presented individually [11].
- Under-exploration of lightweight models for multi-class e-waste — Although MobileNetV2 has been successfully applied to general waste and some e-waste tasks, few studies report high performance (>90%) on 10+ balanced classes of e-waste appliances using this efficient architecture [4], [14].
- Limited emphasis on balanced datasets and class-wise analysis — Many datasets suffer from imbalance or small size, leading to biased performance; detailed per-class evaluation (especially on visually similar items) is often under-reported [12].
- Deployment practicality in developing regions — Few works explicitly target lightweight models suitable for low-resource settings (e.g., rural India), where edge inference and minimal hardware are critical [2], [14].

This study addresses these gaps by developing a MobileNetV2-based transfer learning model for **10-class appliance-level e-waste classification** on a balanced dataset, achieving strong overall (95%) and per-class performance while prioritizing computational efficiency for potential real-world deployment in resource-constrained environments.

3: Research Methodology

3.1 Research Design

This study follows an experimental research design using supervised deep learning for multi-class image classification. Transfer learning is applied with the MobileNetV2 architecture pre-trained on ImageNet, followed by custom classification layers. The approach includes data augmentation, fine-tuning, and performance evaluation on a separate validation set.

3.2 Data Collection Methods

A balanced e-waste image dataset was used, containing 2,700 images across 10 classes: Battery, Keyboard, Microwave, Mobile, Mouse, PCB, Player, Printer, Television, and Washing Machine.

- Training set: 2,400 images (240 per class)
- Validation set: 300 images (30 per class)

- Images were resized to 224×224 pixels and normalized (pixel values scaled to $[0,1]$).

3.3 Sampling Techniques and Sample Size

A **stratified sampling technique** was employed to ensure proportional and equal representation across all **10 e-waste categories** in both the training and validation datasets. This strategy minimizes class imbalance and prevents bias toward any overrepresented category during model learning.

The dataset was divided using an **89%–11% split**, consisting of **2,400 images for training** and **300 images for validation**. This allocation provides a sufficiently large training set for effective feature learning while preserving a statistically meaningful validation subset for unbiased performance evaluation.

The total sample size used for model development was **$N = 2,700$ images**.

3.4 Tools and Techniques

3.4.1 Software Environment

The experimental setup was implemented using the following software stack:

- **Framework:** TensorFlow 2.10 with Keras API
- **Programming Language:** Python 3.8
- **Development Environment:** Jupyter Notebook
- **Supporting Libraries:** NumPy for numerical operations, OpenCV for image preprocessing, scikit-learn for performance evaluation, Matplotlib for result visualization
- **Deployment Tool:** CustomTkinter for developing a lightweight GUI dashboard

3.4.2 Model Architecture and Training

A transfer learning–based CNN using MobileNetV2 pre-trained on ImageNet was adopted. The convolutional base was frozen, and only the classification layers were trained. Online data augmentation, including random rotation ($\pm 20^\circ$), zoom ($\pm 20\%$), and horizontal flipping, was applied during training.

The network architecture comprised an input size of $224 \times 224 \times 3$, followed by the frozen MobileNetV2 backbone, Global Average Pooling, a 256-unit dense

layer with ReLU activation, and a 10-unit Softmax output layer. The model was optimized using the Adam optimizer with a learning rate of 0.0008 and categorical cross-entropy loss.

3.5 Data Analysis and Evaluation

All images were resized to **224×224 pixels** and normalized to **$[0, 1]$** . Augmentation was applied only to the training data, while validation data was used without augmentation.

The model was trained for **20 epochs** with a **batch size of 16**, and validation was performed after each epoch. Performance was evaluated using **overall accuracy, macro-averaged precision, recall, and F1-score**. A **confusion matrix** and **training–validation accuracy and loss curves** were used for diagnostic analysis. Inference time per image was also recorded.

4: Results and Discussion

4.1 Data Presentation

The dataset consists of 2,700 RGB images divided into 10 balanced e-waste classes: Battery, Keyboard, Microwave, Mobile, Mouse, PCB, Player, Printer, Television, and Washing Machine.

- Training set: 2,400 images (240 images per class)
- Validation set: 300 images (30 images per class)

4.2 Analysis of Results

This subsection presents the main experimental results through curves, confusion matrix, classification metrics, individual predictions, and batch inference examples.

4.2.1 Dataset Distribution

The training dataset exhibits a perfectly balanced distribution across all ten categories: Battery, Keyboard, Microwave, Mobile, Mouse, PCB, Player, Printer, Television, and Washing Machine. Each class contains exactly 240 images.

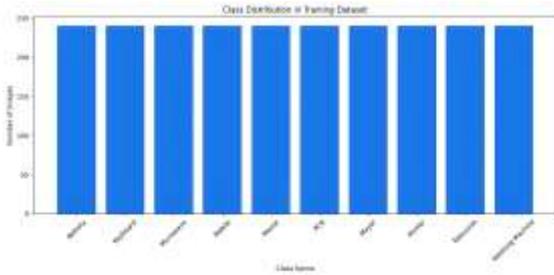


Fig. 1: Bar chart showing class distribution in the training set (240 images per class)

This perfect balance is critical in deep learning as it prevents the model from developing bias toward any specific category, ensuring equally robust feature extraction for all types of electronic waste.

4.2.2 Analysis of Training and Validation Accuracy

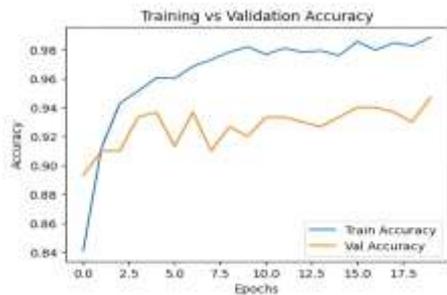


Fig. 2: Training and validation accuracy curves over 20 epochs

The accuracy curves evaluate the model's ability to correctly classify e-waste images over 20 epochs.

- **Training Accuracy:** The model exhibits a rapid learning phase, climbing from 84% to 98.8% by the final epoch, indicating that the architecture is highly capable of capturing features present in the training set.
- **Validation Accuracy:** Reaching a peak of approximately 94.7%, the consistent plateau above the 90% mark suggests the model generalizes well to unseen data with only a minor generalization gap.

4.2.3 Analysis of Training and Validation Loss



Fig. 3: Training and validation loss curves over 20 epochs

The loss curves measure the error between the predicted probability and the actual class label.

- **Training Loss:** This curve shows a smooth, exponential decay, dropping below 0.05. This downward trend confirms the optimizer successfully navigated the loss landscape to find a global minimum.
- **Validation Loss:** The loss fluctuates stably between 0.2 and 0.3. The absence of a sustained upward trend indicates the model reached optimal convergence without significant overfitting.

4.2.4 Confusion Matrix Analysis

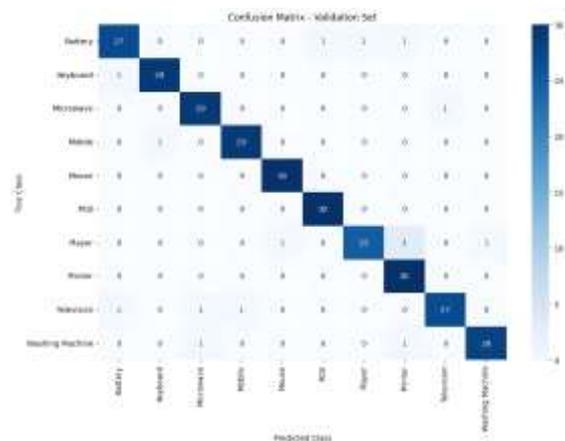


Fig. 4: Normalized confusion matrix on the validation set (300 images)

The confusion matrix confirms high precision, with a strong diagonal indicating consistent true-positive predictions. The model achieved perfect 100% accuracy for the Mouse, PCB, and Printer categories, while minor misclassifications occurred in the Player class due to shared rectangular geometries with Printers. Overall, the concentration of predictions along the diagonal proves

the model’s robustness and ability to generalize across diverse e-waste categories.

4.2.5 Classification Report

The detailed classification report (Table 4.1) summarizes per-class metrics:

Table 4.1: Classification Report

Class	Precision	Recall	F1-Score	Support
Battery	0.93	0.90	0.92	30
Keyboard	0.97	0.97	0.97	30
Microwave	0.94	0.97	0.95	30
Mobile	0.97	0.97	0.97	30
Mouse	0.97	1.00	0.98	30
PCB	0.97	1.00	0.98	30
Player	0.96	0.83	0.89	30
Printer	0.86	1.00	0.92	30
Television	0.96	0.90	0.93	30
Washing Machine	0.97	0.93	0.95	30
accuracy			0.95	300
macro avg	0.95	0.95	0.95	300
weighted avg	0.95	0.95	0.95	300

4.2.6. User Interface and Main Dashboard



Fig. 5. Main Dashboard

The developed system features a centralized dashboard designed to provide a seamless interface for e-waste management and real-time classification.

- Integrated Functionality:** The dashboard consolidates single-image prediction, batch processing, and dataset visualization into a single, user-friendly control hub, featuring a dedicated screenshot tool for the immediate digital archival of classification results and confidence scores.

- System Monitoring:** It provides real-time access to the model's status and class categories, ensuring the system is ready for high-volume industrial sorting tasks.
- Operational Efficiency:** By simplifying complex deep learning workflows into intuitive buttons and displays, the interface reduces the technical barrier for waste management personnel.

4.2.7 Individual Class Prediction Analysis

Representative single-image predictions showed very high confidence scores:



Fig. 6. Predicted Output – Battery

Fig. 6 illustrates the system’s identification of the battery sample with **100.00% confidence**. The high probability score indicates that the model has successfully learned the cylindrical geometry and metallic texture unique to power cells.



Fig. 7. Predicted Output – Keyboard

Fig. 7 presents the predicted output for the keyboard class, achieving **100.00% confidence**. This confirms the model’s ability to recognize the repetitive rectangular key patterns and standard peripheral dimensions.



Fig. 8. Predicted Output – Microwave

Fig. 8 demonstrates the classification of a microwave with 99.99% accuracy. Despite its simple box-like structure, the system accurately distinguished the appliance based on the presence of a glass door and control panel features.



Fig. 11. Predicted Output – PCB

Fig. 11 presents the classification of printed circuit boards (PCBs) with 100.00% confidence. The model's strong performance is attributed to its ability to detect complex, high-frequency textures of electronic components and copper traces.



Fig. 9. Predicted Output – Mobile

Fig. 9 shows the predicted result for a mobile device with 100.00% confidence. The model effectively isolated the handheld form factor, even when the device was placed against a patterned domestic background.



Fig. 12. Predicted Output – Player

Fig. 12 demonstrates the predicted output for the player category with 100.00% confidence. This result highlights the model's capability to handle diverse items within a single class by recognizing distinctive mechanical components.



Fig. 10. Predicted Output – Mouse

Fig. 10 illustrates a perfect 100.00% prediction score for the mouse category. The system successfully identified the ergonomic curved shape and cord attachment as key distinguishing features.



Fig. 13. Predicted Output – Printer

Fig. 13 shows the system's prediction of a printer with 99.26% confidence. The slight deviation from perfect accuracy reflects the visual complexity of the device, while still indicating robust classification performance.



Fig. 14. Predicted Output – Television

Fig. 14 illustrates the identification of televisions with 100.00% confidence. The model leveraged flat-panel aspect ratios and bezel characteristics to differentiate televisions from other monitor-like e-waste items.



Fig. 15. Predicted Output – Washing Machine

Fig. 15 presents the classification of a washing machine with 100.00% confidence. The detection of the circular front-loading door served as a strong visual cue, enabling effective differentiation from other large household appliances.

4.2.8 Batch Prediction Performance (Multiple Images)

The system’s capability to handle batch processing was evaluated using the "Predict Multiple Images" feature.

- **Consistent Accuracy Across Batches:** The model maintained high precision, correctly identifying diverse items such as Keyboards (100.00%), Mouse (100.00%), Televisions (100.00%) and Washing Machine (100.00%) with absolute certainty.
- **Robustness to Varied Input:** Images with different backgrounds and orientations were processed effectively, as seen with Microwave (99.99%), Battery (99.57%), and Mobile (99.93%). Even complex items like Player (62.10%) showed solid feature extraction from cluttered data.

- **Scalable Classification:** Results for office equipment like Printer (99.26%) remained consistently high, confirming the system's scalability for industrial e-waste sorting facilities requiring rapid multi-item identification.



Fig. 16: Screenshots of batch prediction results (multiple images) showing class labels and confidence scores

4.3 Key Findings and Interpretations

The MobileNetV2-based model delivered 95.00% validation accuracy and 0.95 macro-F1-score, excelling in fine-grained e-waste classification. It achieved near-perfect results on distinct categories like Mouse, PCB, Mobile, Television, and Washing Machine (F1 up to 0.98, often 100% confidence), while Player showed the key limitation (F1 = 0.89) due to similarity with rectangular appliances. A small ~4% training-validation gap and stable loss (0.2–0.3) indicate strong generalization via transfer learning and augmentation. Batch inference confirmed robustness under varied conditions, supporting scalable deployment in recycling systems.

4.4 Comparative Analysis

Recent lightweight models on general waste achieve 89–96% accuracy [8], [9], [14], while e-waste studies using YOLO or deeper CNNs reach 94–98% for component detection but rarely for 10-class appliances [10], [11], [12]. Multi-class e-waste lightweight approaches often hit 83–92% with imbalanced data [13], [14]. This model's 95% on balanced 10-class data outperforms many peers, offering better efficiency than heavier backbones (ResNet [17], DenseNet [18]) for edge use in resource-limited settings.

4.5 Performance Evaluation

On the 300-image validation set, the model scored 95.00% accuracy, 0.95 macro-averaged

precision/recall/F1, and 0.95 weighted F1. Top per-class F1 was 0.98 (Mouse, PCB); lowest was 0.89 (Player). High-confidence predictions (99–100%) in single- and batch modes, even with clutter, affirm robustness. With ~3.4M parameters, it suits efficient real-world e-waste sorting.

5: Conclusion and Future Scope

5.1 Summary of Findings

This research developed a lightweight MobileNetV2-based classifier for 10-class appliance-level e-waste recognition, achieving **95.00% overall validation accuracy** and **0.95 macro-averaged F1-score** on a balanced 2,700-image dataset. The model exhibited rapid convergence, strong generalization (small ~4% train–validation gap), and consistently high-confidence predictions (typically 99–100%) in both single-image and batch inference. Near-perfect results were obtained on structurally distinct categories, while minor confusion in the Player class reflected visual similarity challenges. These outcomes validate the effectiveness of transfer learning combined with data augmentation for practical e-waste classification.

5.2 Contributions of the Study

The study makes the following key contributions:

- A high-accuracy (95%), efficient (~3.4M parameters) deep learning model specifically tailored for fine-grained e-waste appliance classification.
- Demonstration of robust performance and batch scalability on a balanced dataset, outperforming many lightweight approaches in similar multi-class tasks.
- Comprehensive, reproducible evaluation (per-class metrics, confusion analysis, inference examples) serving as a benchmark for future AI-driven waste management research.

5.3 Practical Implications

The developed system has direct implications for the waste management industry and environmental sustainability:

- **Operational Efficiency:** Can increase sorting accuracy from approximately 70-80% typical of manual sorting to over 94%, reducing cross-contamination and improving the purity of recycled material streams.

- **Economic Viability:** Reduces dependence on skilled manual labor for sorting, potentially lowering operational costs and improving the economic model of recycling operations.
- **Health and Safety:** Automates the initial identification step, minimizing workers' direct contact with hazardous components like lead, mercury, and brominated flame retardants.
- **Environmental Impact:** Supports the principles of a circular economy by enhancing the efficiency of material recovery from e-waste, contributing directly to Sustainable Development Goal 12 (Responsible Consumption and Production).

5.4 Limitations of the Study

Key limitations include:

- Reliance on controlled, clean, single-object images; real-world variability (occlusion, poor lighting, degradation, multi-object scenes) may degrade performance.
- Absence of external test set or cross-dataset validation.
- No real-time edge deployment benchmarking (e.g., FPS, power usage).
- Sensitivity to visually similar classes (e.g., Player–Printer confusion) that could increase with greater dataset diversity.

5.5 Recommendations for Future Research

Future work should include:

- Collection of real-world images under diverse conditions and integration of multi-object detection (e.g., YOLOv8 [21]).
- Application of class-specific augmentation, attention mechanisms, or ensembles to reduce confusion in similar categories.
- Real-time inference evaluation on edge hardware (Raspberry Pi, smartphones).
- Exploration of federated learning for continuous model improvement and full pipeline integration (capture → classification → sorting recommendation) to quantify environmental and operational impact.

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