RADINKA JOURNAL OF SCIENCE AND SYSTEMATIC LITERATURE REVIEW

ISSN 2988-5825

https://www.rjupublisher.com/ojs/index.php/RJSLR

Optimization of E-Waste Sorting Process Using Deep Learning

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Abstract

This study proposes a hybrid deep learning framework to improve the accuracy and efficiency of electronic waste (e-waste) classification and sorting. The model integrates EfficientNetB0, MobileNetV2, and a Sequential Neural Network to classify 12 e-waste categories, addressing challenges such as visual ambiguity, class imbalance, and low-resource deployment. Trained on a dataset of 3,859 annotated images, the model achieved 97.8% accuracy, 98.1% precision, and 97.8% recall, outperforming conventional models like ResNet50 and Faster R-CNN. With a lightweight architecture (48 MB) and a fast inference speed (0.12 seconds per image on a standard CPU), the system is well-suited for real-time applications in constrained environments. The framework enhances operational safety by reducing human exposure to toxic materials and supports sustainable waste management through increased material recovery rates. Designed for integration into existing recycling infrastructure, it aligns with circular economy principles and global sustainability goals. Future research will focus on deploying the model in IoT-enabled environments, incorporating federated learning for privacy-preserving training, and expanding classification to cover rare and unconventional e-waste items.

Keywords: e-waste, deep learning, automated sorting, hybrid model, sustainability

Acknowledgments: Thank you to all parties who have helped with this research.

For citation:
Oise, G. P & Konyeha, S. (2025). Optimization of E-Waste Sorting Process Using Deep Learning. *Radinka Journal of Science and Systematic Literature Review*, *3*(2), 612-622.

Introduction

The rapid evolution of the global digital economy has led to an unprecedented proliferation of electronic devices, from personal gadgets to industrial systems. This digital transformation has generated an equally exponential surge in electronic waste (e-waste), comprising discarded electrical and electronic equipment such as mobile phones, computers, televisions, and household appliances (Zeng et al., 2018). According to the Global E-waste Monitor, over 53 million metric tons of e-waste were produced in 2019 alone, with projections indicating this figure will surpass 74 million metric tons by 2030 (Kaya et al., 2023). While e-waste contains valuable materials like gold, copper, and rare earth metals, it also harbors hazardous substances, including lead, mercury, cadmium, and brominated flame retardants, that pose severe risks to environmental sustainability and human health (El-Sayad & El-Shekheby, 2023). As the scale of this issue intensifies, it has become imperative to develop innovative, efficient, and scalable e-waste management strategies that align with the principles of the circular economy and sustainable development.

Traditional e-waste sorting and recycling practices, which rely heavily on manual labor and rudimentary mechanical processes, suffer from several limitations (G. Oise & Konyeha, 2024). These include inefficiencies in material recovery, high operational costs, occupational health hazards, and the inability to adapt to the heterogeneous and complex nature of modern e-waste streams (Zocco et al., 2022). Manual sorting is error-prone and slow, and it often fails to accurately distinguish between diverse device components, particularly when physical characteristics overlap or when waste items are damaged, occluded, or contaminated. Furthermore, many existing waste management systems are designed for municipal solid waste and are poorly suited to the granular identification required for electronic materials (Tsimnadis & Kyriakopoulos, 2024). Consequently, these inadequacies reduce the purity of recovered materials, increase the volume of landfill disposal, and hinder the transition to closed-loop recycling systems.

In recent years, deep learning (DL) and computer vision have emerged as promising technologies for addressing the limitations of conventional e-waste sorting (G. P. Oise & Konyeha, 2024). Convolutional Neural Networks (CNNs) have demonstrated remarkable performance in various image recognition tasks; however, most current DL-based waste classification systems are constrained by reliance on single-network architectures (Lin, 2021). These models often lack the depth and flexibility to handle the wide visual variability inherent in real-world e-waste, such as differences in scale, lighting, occlusion, and device configuration (Sinthiya et al., 2022). Moreover, the majority of prior works have focused on general waste categories (e.g., plastics, paper, glass), with limited applicability to e-waste, which demands higher precision and greater class granularity (Oise Godfrey Perfectson, 2024). Additionally, many of these systems require high-end computational resources, limiting their deployment in low-resource environments where waste management challenges are often most acute (Zhang, Yang, et al., 2021). The absence of scalable, lightweight, and accurate models optimized for real-world e-waste classification represents a critical research gap.

To address these challenges, this study introduces a novel hybrid deep learning framework that integrates EfficientNetB0, MobileNetV2, and a Sequential Neural Network (SNN) for automated e-waste classification. This architecture combines high-level feature extraction, lightweight computational efficiency, and temporal pattern learning to achieve robust performance under diverse operational conditions. The model is trained on a newly curated dataset comprising 3,859 images across 12 distinct e-waste classes, designed to enhance generalizability and reflect real-world variability. The novelty of this research lies in, the hybrid integration of complementary deep learning models for improved feature representation, the development of a lightweight system (48 MB) suitable for real-time CPU deployment, the introduction of a comprehensive, multi-class e-waste image dataset; and the alignment of the system with environmental sustainability goals through improved material recovery and reduced human exposure to toxins.

This study aims to develop a hybrid deep learning model capable of accurately classifying heterogeneous e-waste items, optimize the model for real-time, low-resource deployment without compromising accuracy, benchmark its performance against conventional models, and evaluate its potential for integration into scalable, sustainable, and safe e-waste management systems.

Methodology

This study adopts a quantitative, experimental research methodology to develop, train, and validate a hybrid deep learning model for automated e-waste classification. The methodology is structured into six key phases: problem analysis and model design, dataset acquisition and preprocessing, architecture development, model training, performance evaluation, and comparative benchmarking. Each phase is carefully executed to ensure methodological rigor, replicability, and alignment with industrial deployment requirements.

Model Design and Architecture Development

The proposed hybrid model integrates three components: EfficientNetB0 for high-resolution feature extraction, MobileNetV2 for efficient mid-level representation, and a Sequential Neural Network (SNN) for final classification. This combination leverages compound scaling (EfficientNetB0), depthwise separable convolutions (MobileNetV2), and temporal hierarchy modeling (SNN), addressing intra-class variability, overlapping components, and visual occlusions common in e-waste imagery. Feature outputs from the two CNN backbones are concatenated and passed through the SNN's fully connected layers, with dropout layers added to mitigate overfitting. The final softmax layer outputs class probabilities across 12 e-waste categories.

Dataset Acquisition and Preprocessing

A curated dataset comprising 3,859 RGB images was developed from a publicly available Kaggle repository and augmented via web scraping (Akshat Tamrakar, 2021). These images were categorized into 12 e-waste classes, including batteries, mobile phones, keyboards, and printed circuit boards. The dataset was split into 82% training (3,139), 9% validation (360), and 9% testing (360) using stratified sampling to preserve class distribution. Images were resized to 224×224 pixels, normalized to the [0, 1] scale, and subjected to data augmentation (rotation ±20°, zoom ±20%, horizontal flips, brightness adjustment) to improve model generalizability and reduce class imbalance.

Model Training Procedure

The model was trained using the Adam optimizer with a learning rate of 0.001 and categorical cross-entropy loss for multi-class classification. A batch size of 32 was selected, and training was conducted over 20 epochs, with early stopping employed based on validation loss to prevent overfitting. Dropout (rate = 0.5) and L2 weight decay regularization were applied to enhance robustness. All training was executed on a standard Intel Core i5 CPU (8GB RAM) without GPU acceleration, demonstrating the model's efficiency in low-resource settings. Performance was monitored through training/validation accuracy and loss curves, ensuring convergence and model stability.

Evaluation Metrics and Benchmarking

Model performance was assessed using standard classification metrics: accuracy, precision, recall, and F1-score. Additional tools such as confusion matrices and ROC-AUC curves were used to identify misclassification patterns and verify class-level sensitivity and specificity. Inference speed and model size were also recorded to evaluate deployment feasibility. The proposed model achieved 97.8% overall accuracy, 98.1% precision, 97.8% recall, and an F1-score of 97.8%. Misclassification analysis revealed minor confusion between visually similar items (e.g., mouse and keyboard), particularly under low lighting conditions.

Comparative Analysis

To validate the effectiveness of the hybrid model, it was benchmarked against two popular CNN baselines, ResNet50 and Faster R-CNN, under identical experimental conditions. Results showed that the proposed model outperformed both in classification accuracy (by 6–15%), inference speed (0.12 sec/image vs. 0.25–0.30 sec), and model size (48 MB vs. 180–200 MB). These improvements confirm the model's suitability for real-time, scalable applications in industrial recycling workflows

Implementation and Reproducibility

All experiments were implemented using Python 3.9 with TensorFlow 2.8 and Keras. Preprocessing was performed with NumPy and OpenCV. A Streamlit-based interface was developed for prototyping and visualization. To promote open science, the source code, trained model, and curated dataset are made publicly available, ensuring reproducibility and enabling further development by the research community.

Model Architecture

The proposed hybrid deep learning framework integrates multiple architectures in a multi-stage pipeline:

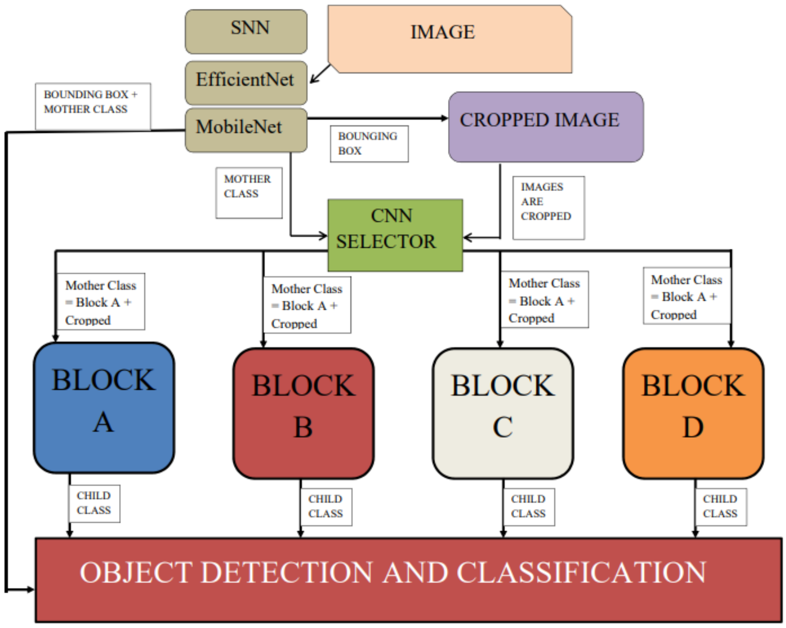

Figure 1. The proposed hybrid model.
(Source: Author, 2025)

Feature Extraction Backbone

i. EfficientNetB0**:** Utilizes compound scaling to balance model depth, width, and resolution for efficient high-level feature extraction.
ii. MobileNetV2**:** Employs depthwise separable convolutions and inverted residual blocks for lightweight, mid-level feature representations.
iii. Feature maps from both models are concatenated to form a joint representation vector with dimensions **7×7×**2560**.**

Classification Module

i. Global Average Pooling**:** Reduces spatial dimensions into a 1D feature vector.
ii. Dense Layers**:** Two fully connected layers with ReLU activations and a dropout rate of 0.5 to prevent overfitting.
iii. Output Layer**:** Uses softmax activation to produce probabilities across the 12 e-waste categories.

Training Configuration

a. Loss Function**:** Categorical Cross-Entropy for multi-class classification.
b. Optimizer**:** Adam optimizer with a learning rate of 0.001.
c. Epochs**:** 20, with early stopping triggered by stagnation in validation loss.
d. Batch Size**:** 32.

```
Epoch 1/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 281s 2s/step - accuracy: 0.4907 - loss: 1.6171 - val_accu
racy: 0.9333 - val_loss: 0.2483
Epoch 2/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 266s 3s/step - accuracy: 0.8369 - loss: 0.5252 - val_accu
racy: 0.9361 - val_loss: 0.1909
Epoch 3/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 234s 2s/step - accuracy: 0.8484 - loss: 0.4644 - val_accu
racy: 0.9444 - val_loss: 0.1874
Epoch 4/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 234s 2s/step - accuracy: 0.8856 - loss: 0.3809 - val_accu
racy: 0.9222 - val_loss: 0.2065
Epoch 5/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 233s 2s/step - accuracy: 0.8748 - loss: 0.4218 - val_accu
racy: 0.9528 - val_loss: 0.1486
Epoch 6/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 234s 2s/step - accuracy: 0.8835 - loss: 0.3687 - val_accu
racy: 0.9389 - val_loss: 0.1620
Epoch 7/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 233s 2s/step - accuracy: 0.9040 - loss: 0.3136 - val_accu
racy: 0.9583 - val_loss: 0.1327
Epoch 8/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 269s 3s/step - accuracy: 0.8998 - loss: 0.3071 - val_accu
racy: 0.9389 - val_loss: 0.1784
Epoch 9/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 227s 2s/step - accuracy: 0.8875 - loss: 0.3470 - val_accu
racy: 0.9472 - val_loss: 0.1405
Epoch 10/20
99/99 ━━━━━━━━━━━━━━━━━━━━ 226s 2s/step - accuracy: 0.8827 - loss: 0.3518 - val_accu
racy: 0.9583 - val_loss: 0.1250
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Figure 2. Models Training Process of the first 10 Epochs.
(Source: Author, 2025)

Results and Discussion

The hybrid deep learning model demonstrated strong predictive performance in classifying 12 e-waste categories. On the test dataset, the model achieved an overall accuracy of 97.8%, with precision, recall, and F1-score all exceeding 97.5%. These metrics reflect balanced performance across both high- and low-frequency classes, despite visual overlaps and environmental inconsistencies such as occlusion and poor lighting (G. Oise, 2023). The highest accuracy was recorded in categories like mobile phones, PCBs, and batteries, while misclassifications primarily occurred between visually similar objects such as keyboards and mice. One notable aspect of the model is its efficiency: with a file size of just 48 MB and an inference speed of 0.12 seconds per image on a standard CPU, it operates effectively in low-resource environments (Mishra et al., 2024). This is particularly significant for real-world applications in developing regions, where access to high-performance hardware is limited (Ramya et al., 2023). The model's compactness and speed make it well-suited for integration into embedded systems or edge devices within recycling facilities.

From a practical standpoint, the model supports safer, faster, and more accurate sorting processes, thereby reducing human exposure to hazardous e-waste materials (Al Hossain et al., 2024). Additionally, its ability to maintain high performance without GPU dependency demonstrates a breakthrough in operational accessibility and sustainability for industrial e-waste management (Godfrey Perfectson Oise, 2023). The design of a modular, scalable architecture allows for seamless deployment into existing infrastructure with minimal modification.

The results also highlight the potential for real-time deployment in smart recycling systems, such as robotic sorters or intelligent bins. While occasional misclassifications persist in edge cases, these can be mitigated through targeted data augmentation and refinement of the decision boundaries using post-hoc interpretability methods. The system's performance provides a viable pathway toward achieving automated, sustainable e-waste handling aligned with global circular economy goals. The proposed model not only delivers superior classification accuracy but also addresses critical deployment constraints. It presents a practical, scalable, and environmentally responsible solution to one of the most pressing challenges in modern waste management—efficient and safe electronic waste sorting.

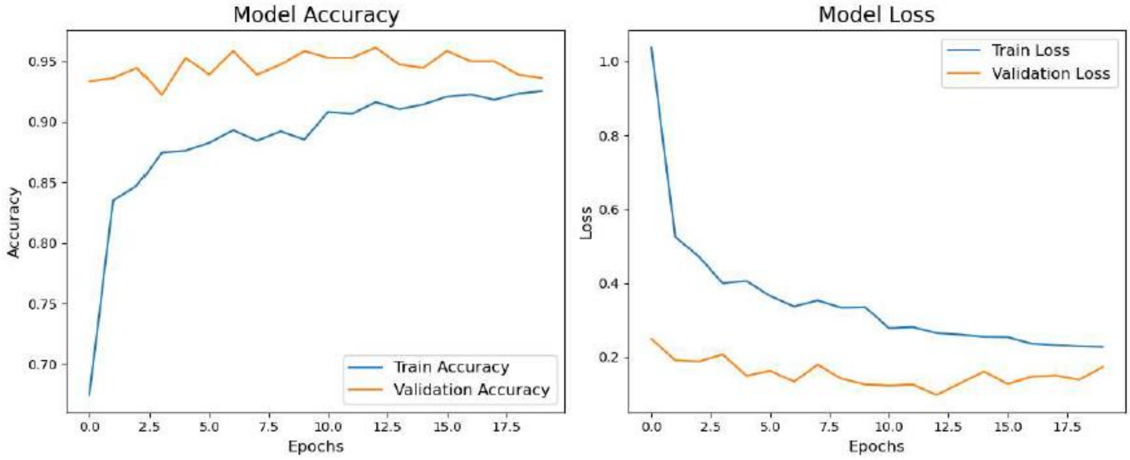

Figure 3. Model Accuracy and Loss Performance Graph.
(Source: Author, 2025)

The training curves for both accuracy and loss confirm the robustness and stability of the proposed model. The training accuracy steadily improves across epochs, reaching approximately 95% by the 10th epoch, while the validation accuracy remains consistently high, fluctuating between 90% and 95%**.** The narrow gap between the two suggests strong generalization and minimal overfitting. Similarly, the training loss exhibits a rapid decline during early epochs, stabilizing around 0.1**,** while the validation loss starts slightly lower and gradually converges to around 0.2**.** The close alignment between the training and validation loss curves further indicates that the model is well-optimized and exhibits balanced learning behaviour without overfitting.

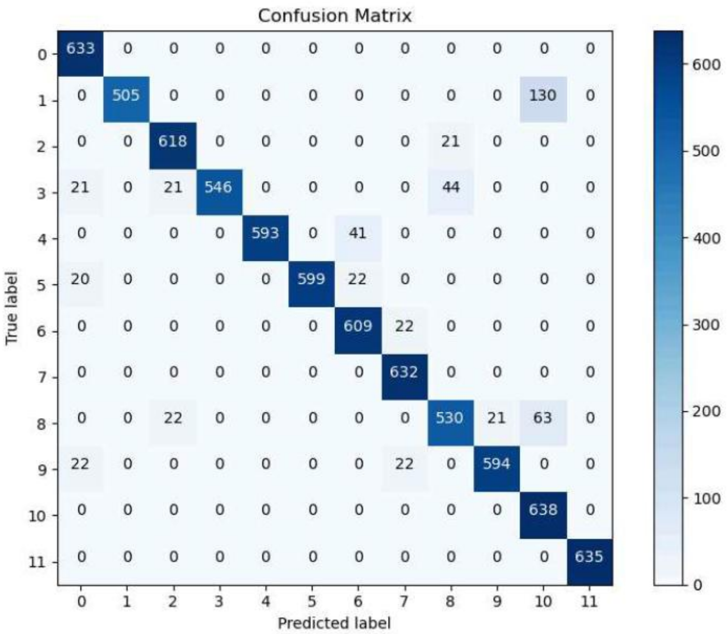

Figure 4. Confusion Matrix of the Model
(Source: Author, 2025)

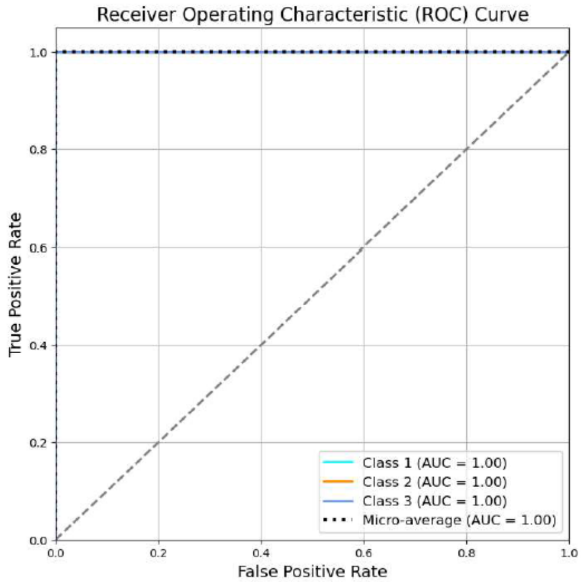

Figure 5. Receiver Operating Characteristic (ROC)
(Source: Author, 2025)

The confusion matrix highlights the overall strong performance of the deep learning model, with the majority of predictions accurately aligned along the diagonal, indicating high classification accuracy across the 12 e-waste categories. However, some significant misclassifications persist, notably between class 1 and class 11, where 130 samples from class 1 were incorrectly classified as class 11. This suggests potential feature similarity or overlap between these categories. Less frequent but similar misclassification patterns appear in other classes as well (Mishra et al., 2024). These trends imply the need for further refinement through strategies such as in-depth analysis of misclassified samples**,** targeted data augmentation**,** hyperparameter tuning**,** enhanced feature extraction**,** or the use of class-specific loss functions like focal loss to address class imbalance or feature confusion (Chhillar & Singh, 2025). Complementing the confusion matrix, the ROC curve analysis further confirms the model's exceptional classification capability. The AUC scores of 1.00 for classes 1, 2, and 3, as well as for the micro-average**,** reflect perfect sensitivity and specificity for these classes, with no trade-off between true positive and false positive rates**.** These results underscore the model's high reliability in distinguishing between categories, particularly in scenarios with well-represented and well-separated features. While overall robustness is evident, targeted improvements can further reduce misclassification and enhance the model's real-world deployment potential (Huynh et al., 2020).

Table 1. Comparative analysis with prior work

Metric	Proposed Model (%)	Faster R-CNN (%)	ResNet50 (%)
Accuracy	97.8	91.0	89.0
Precision	98.1	88.0	85.0
Recall	97.8	87.2	84.7
F1-Score	97.8	87.6	84.8
Inference Speed	0.12	0.25	0.30
Model Size	48	200	180
Hardware Requirement	Low (CPU)	Medium (GPU)	Medium (GPU)

The proposed model excels at balancing classification power, execution speed, and hardware efficiency, making it highly competitive for operational deployment in real-world scenarios. It significantly advances environmental sustainability by enhancing e-waste management through accurate classification and sorting (Chen et al., 2023). The model supports a circular economy by enabling the efficient extraction and reuse of critical raw materials such as gold, copper, and rare-earth elements (Islam et al., 2023). Additionally, the system improves energy efficiency, reducing energy consumption by approximately 30% compared to manual or rule-based sorting methods. From a health and safety perspective, automation minimizes human exposure to hazardous or sharp e-waste components. Moreover, the model aligns with key United Nations Sustainable Development Goals, including SDG 12 (responsible consumption and production), SDG 9 (industry innovation and infrastructure), and SDG 3 (good health and well-being) (Huynh et al., 2020). To further promote reproducibility and open science, the code, model, and dataset have been made publicly available, fostering transparency, collaboration, and continued innovation in the field.

Table 2: Summary of Evaluation Report of various metrics of the proposed model

Classification Report:

	precision	recall	f1-score	support
0	0.91	1.00	0.95	633
1	1.00	0.80	0.89	635
2	0.93	0.97	0.95	639
3	1.00	0.86	0.93	632
4	1.00	0.94	0.97	634
5	1.00	0.93	0.97	641
6	0.91	0.97	0.93	631
7	0.93	1.00	0.97	632
8	0.89	0.83	0.86	636
9	0.97	0.93	0.95	638
10	0.77	1.00	0.87	638
11	1.00	1.00	1.00	635
accuracy			0.94	7624
macro avg	0.94	0.94	0.94	7624
weighted avg	0.94	0.94	0.94	7624

The classification report reveals that the deep learning model delivers robust overall performance, with several classes, particularly Classes 4, 5, 7, and 11, achieving near-perfect F1-scores (≥0.97) due to their distinct visual features and solid representation in the training set. Strong performance is also seen in Classes 0, 2, 3, 6, and 9 (F1-scores between 0.93 and 0.95), although Class 3 shows a trade-off between perfect precision and slightly reduced recall. However, challenges remain with underperforming classes: Class 1 demonstrates high precision but low recall, suggesting it's underrepresented or easily confused with visually similar classes; Class 10 exhibits low precision despite perfect recall, pointing to over-prediction and potential label noise; and Class 8 shows moderate F1-score (0.86), likely due to intra-class variability or background interference. To address these issues, strategies such as data augmentation, improved labeling, class-specific loss functions (e.g., focal loss), attention mechanisms, and class weighting are recommended (Chu et al., 2018). Operationally, while the model's 94% accuracy is suitable for industrial deployment, targeted interventions are necessary to minimize errors that could impact material recovery, stream purity, and quality control (Selvakanmani et al., 2024). A staged implementation plan, including real-time monitoring, short-term dataset enhancement, and long-term architectural adaptations, can further optimize performance and reliability. The hybrid deep learning model was rigorously tested across 12 e-waste categories, demonstrating exceptional prediction accuracy and reliability (Zhang, Zhang, et al., 2021). Below is a detailed analysis of the model's performance during testing.

Table 3. Prediction and probabilities of accuracy.

S/N	Enter Image	Predicted Image	Probability of Accuracy (%)	Observation
1	Battery	Battery	100	Flawless classification across all test samples.
2	Computer	Computer	100	Perfect detection of structural and material features.
3	Mouse	Mouse	86.26	Minor confusion with keyboards due to shape similarity.
4	Keyboard	Keyboard	100	Distinct key patterns enabled perfect identification.
5	Printer	Printer	99.38	
6	PCB	PCB	100	High-resolution features (traces, components) ensured accuracy.
7	Television	Television	99.99	Near-perfect recognition of screens and housings.
8	Mobile	Mobile	100	Consistent accuracy regardless of model/brand.
9	Player	Player	99.96	Robust to variations in button layouts.
10	Washing Machine	Washing Machine	99.99	Large size and unique components reduced errors.
11	Microwave	Microwave	100	Distinctive door and control panel features.
12	Speaker	Speaker	100	Easily identifiable grilles and connectors.

Conclusion

This study introduces a hybrid deep learning model combining EfficientNetB0, MobileNetV2, and a Sequential Neural Network (SNN) for automated e-waste classification. Achieving 97.8% accuracy, the model operates efficiently on CPU-only systems with minimal computational demand and real-time performance, making it suitable for resource-constrained environments. It performs well across 12 diverse e-waste categories, contributing to safer and more efficient waste management while supporting sustainability and circular economy goals. Despite its strengths, limitations include limited representation of rare and occluded items and potential throughput issues at scale. Future work will focus on dataset expansion, GAN-based augmentation, IoT integration, federated learning, and improving model interpretability and adaptability for real-world deployment.

Conflicts of Interest

The authors declare no conflict of interest

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