INTERNATIONAL JOURNAL OF RESEARCH AND SCIENTIFIC INNOVATION (IJRSI)
ISSN No. 2321-2705 | DOI: 10.51244/IJRSI | Volume XIII Issue III March 2026

Comparative Analysis of Deep Learning Models for Ai-Driven Smart Waste Classification System Using Resnet, Efficientnet, and VGG16 for Automated Waste Segregation

Abhishek Kumar[1], Abhishek Prajapati[2], Abhishek Singh[3], Laxmi[4], Ms. Sanjivani Sharma[5], Dr. Anand Prakash Srivastava[6]

[1,2,3,4] B.Tech. Student, Department of Computer Science and Engineering NITRA Technical Campus, Ghaziabad, Uttar Pradesh, India

[5]Assistant Professor, Department of Computer Science and Engineering NITRA Technical Campus, Ghaziabad, Uttar Pradesh, India

[6]Professor & HOD Department of Computer Science and Engineering NITRA Technical Campus, Ghaziabad, Uttar Pradesh, India

DOI: https://doi.org/10.51244/IJRSI.2026.1303000207

Received: 25 March 2026; Accepted: 30 March 2026; Published: 15 April 2026

ABSTRACT

Effective waste management is critical for environmental sustainability and public health. Traditional waste segregation methods rely heavily on manual sorting, which is time-consuming, error-prone, and hazardous for workers. This paper presents a comprehensive comparative analysis of three state-of-the-art deep learning architectures—ResNet-50, EfficientNet-B0, and VGG16—for automated waste classification. The models are trained to categorize waste into six primary classes: Cardboard, Glass, Metal, Paper, Plastic, and Trash. Our experimental evaluation demonstrates that EfficientNet-B0 achieves the highest performance with a test accuracy of 96.8%, followed closely by ResNet-50 at 96.6% and VGG16 at 93.1%. EfficientNet-B0 also demonstrates superior training efficiency, reaching 95% accuracy in just 22 epochs compared to 25 epochs for ResNet-50 and 35 epochs for VGG16. The F1-scores across all waste categories range from 0.93 to 1.00 for EfficientNet-B0, indicating robust classification performance. This comparative study provides valuable insights for selecting appropriate deep learning architectures for real-world waste management applications in smart cities and recycling facilities.

Index Terms: Waste Classification, Deep Learning, ResNet, EfficientNet, VGG16, Convolutional Neural Networks, Image Recognition, Smart Cities, Environmental Sustainability, Recycling Automation, Model Comparison

INTRODUCTION

The global waste crisis has emerged as one of the most pressing environmental challenges of the 21st century. According to the World Bank, the world generates approximately 2.01 billion tonnes of municipal solid waste annually, with at least 33% of that not managed in an environmentally safe manner. By 2050, global waste generation is expected to increase by 70% to 3.4 billion tonnes. In India specifically, over 150,000 tonnes of waste are generated daily, with only 30% being properly segregated, while the remaining 70% ends up in landfills. This exponential growth in waste production, coupled with inadequate waste management infrastructure, poses severe threats to environmental sustainability, public health, and climate stability.

Effective waste segregation at the source is crucial for successful recycling and resource recovery. However, traditional waste sorting methods face significant challenges. Manual sorting is labor-intensive, exposes workers to health hazards, and suffers from inconsistent quality and low throughput. In many developing countries, waste pickers work in hazardous conditions, handling mixed waste that may contain toxic materials, sharp objects, and biological contaminants. Furthermore, contamination between waste streams due to improper segregation significantly reduces the value of recyclable materials and increases processing costs. Current recycling plants operate at less than 50% efficiency, primarily due to contamination and inadequate segregation.

Recent advances in artificial intelligence and computer vision have opened new possibilities for automating waste classification. Deep learning, particularly Convolutional Neural Networks (CNNs), has demonstrated remarkable success in image recognition tasks across various domains. These technologies offer the potential to revolutionize waste management by providing accurate, consistent, and rapid waste classification capabilities that can operate 24/7 without fatigue or exposure to hazardous materials.

Research Motivation

The motivation for this research stems from several critical factors:

- The urgent need for sustainable waste management solutions to address the growing global waste crisis
- The potential to improve worker safety by reducing human exposure to hazardous waste materials
- The opportunity to increase recycling rates through more accurate and consistent waste segregation
- The economic benefits of reducing contamination in recycling streams and improving material recovery
- The alignment with smart city initiatives (such as Swachh Bharat Mission) and sustainable development goals
- The need for scalable, AI-powered solutions that can be deployed across various waste management facilities

Research Objectives

The primary objectives of this research are:

- To develop and compare three state-of-the-art deep learning models (ResNet-50, EfficientNet-B0, and VGG16) for waste classification
- To achieve high classification accuracy (>95%) suitable for real-world deployment in waste management facilities
- To classify waste into six categories: Cardboard, Glass, Metal, Paper, Plastic, and Trash
- To evaluate and compare model performance across different metrics including accuracy, F1-score, training efficiency, and model complexity
- To design a system architecture that can process images in real-time for practical waste sorting applications
- To provide recommendations for model selection based on performance-efficiency trade-offs
- To contribute to the development of intelligent waste management systems that support environmental sustainability

Paper Organization

The remainder of this paper is organized as follows: Section II reviews related work in waste classification and deep learning applications. Section III describes the dataset used for training and evaluation. Section IV details the methodology, including the three CNN architectures (ResNet-50, EfficientNet-B0, and VGG16) and training procedures. Section V presents the experimental results and comparative performance analysis. Section VI discusses the findings, limitations, and potential applications. Finally, Section VII concludes the paper and outlines future research directions.

Related Work

Traditional Waste Classification Methods

Traditional approaches to waste classification have relied primarily on manual sorting or mechanical separation methods. Manual sorting, while flexible and capable of handling diverse waste types, suffers from low throughput, high labor costs, and worker safety concerns. Studies by Kumar et al. (2017) highlighted that manual waste segregation in India involves significant health risks including exposure to infectious diseases, toxic substances, and sharp objects. Mechanical sorting systems based on physical properties such as density, magnetic properties, and optical characteristics have been deployed in large-scale recycling facilities, but these methods often struggle with mixed materials and require expensive infrastructure. Research by Chen and Wang (2016) demonstrated that mechanical sorting systems achieve only 60-70% accuracy for mixed waste streams.

Machine Learning for Waste Classification

Early machine learning approaches to waste classification utilized traditional computer vision techniques combined with classifiers such as Support Vector Machines (SVM) and Random Forests. Researchers extracted handcrafted features from images, including color histograms, texture descriptors, and shape characteristics. Thung and Yang (2016) achieved 63% accuracy using SVM with SURF features on a dataset of recyclable waste. While these methods showed promise, they were limited by the need for manual feature engineering and struggled with the high variability in waste appearance. Studies by Rad et al. (2017) using Random Forests with color and texture features achieved 82% accuracy but required extensive preprocessing and feature selection.

Deep Learning Applications in Waste Classification

The advent of deep learning has revolutionized image classification tasks across numerous domains. Residual Neural Networks (ResNet), introduced by He et al. (2016), demonstrated superior performance in recognizing complex patterns in visual data through deep residual learning. The key innovation of skip connections in ResNet enables training of very deep networks by mitigating the vanishing gradient problem. Yang and Thung (2016) were among the first to apply CNNs to waste classification, achieving 88% accuracy on a 6 -class dataset using a custom CNN architecture.

More recent work has explored various CNN architectures for waste classification. Awe et al. (2017) used DenseNet to achieve 87% accuracy on recyclable waste classification. Bircanoglu et al. (2018) compared several pre-trained models including VGG16, ResNet, andInceptionV3, reporting best results with ResNet50 at 94.2% accuracy. However, these studies typically evaluated only a single architecture or provided limited comparative analysis. EfficientNet, introduced by Tan and Le (2019), demonstrated state-of-the-art performance on ImageNet while being significantly more parameter-efficient than previous architectures. To our knowledge, no comprehensive study has compared ResNet, EfficientNet, and VGG16 specifically for waste classification tasks.

Dataset

We utilized a comprehensive waste classification dataset sourced from Kaggle, consisting of 2,527 high-quality images across six categories: Cardboard (403 images), Glass (501 images), Metal (410 images), Paper (594 images), Plastic (482 images), and Trash (137 images). The dataset was supplemented with custom-collected images to address class imbalance, particularly for the underrepresented "Trash" category.

Data Preprocessing

All images were preprocessed using OpenCV and standardized to 224×224 pixels to match the input requirements of the pre-trained models. Data augmentation techniques were applied during training to improve model generalization and prevent overfitting. The augmentation pipeline included:

- Random rotation (±15 degrees)

- Random horizontal flipping
- Random brightness adjustment (±20%)
- Random zoom (90%-110%)
- Random translation (±10% in both directions)
- Normalization using ImageNet mean and standard deviation

Data Split

The dataset was divided into training (70%), validation (15%), and test (15%) sets using stratified sampling to ensure proportional representation of all classes. This resulted in 1,769 training images, 379 validation images, and 379 test images. The stratified split ensures that the class distribution is maintained across all three sets, preventing bias in model evaluation.

METHODOLOGY

This section describes the three deep learning architectures evaluated in this study and the training methodology employed for comparative analysis.

Model Architectures

ResNet-50

ResNet-50 is a 50-layer deep residual network that introduces skip connections to address the vanishing gradient problem in very deep networks. The architecture consists of residual blocks where the input is added to the output of stacked convolutional layers.

This allows gradients to flow directly through the network during backpropagation. ResNet-50 contains approximately 25.6 million parameters and has demonstrated excellent performance on various image classification tasks. We used the pre-trained ImageNet weights and fine-tuned the model for waste classification by replacing the final fully connected layer with a 6-way classifier.

EfficientNet-B0

EfficientNet-B0 is a state-of-the-art architecture that achieves better accuracy and efficiency by uniformly scaling network depth, width, and resolution using a compound coefficient. The base model (B0) uses mobile inverted bottleneck convolution (MBConv) blocks with squeeze-and-excitation optimization.

With only 5.3 million parameters, EfficientNet-B0 is significantly more compact than ResNet-50 while achieving comparable or better performance. This makes it particularly suitable for deployment in resource-constrained environments such as embedded systems in waste sorting facilities. The model was initialized with ImageNet weights and fine-tuned with a custom classification head for our 6-class waste categorization task.

VGG16

VGG16 is a classical deep CNN architecture featuring 16 weight layers with small 3×3 convolutional filters throughout the network. The architecture is characterized by its simplicity and uniform design, consisting of stacked convolutional layers followed by max-pooling operations.

VGG16 contains approximately 138.4 million parameters, making it the largest model in our comparison. Despite being an older architecture (2014), VGG16 remains widely used due to its strong performance and straightforward architecture. For our experiments, we employed transfer learning using ImageNet pre-trained weights and added a custom classification layer for the six waste categories.

Training Configuration

All three models were trained using identical hyperparameters to ensure fair comparison. The training configuration included:

- Optimizer: Adam with learning rate = 0.0001
- Loss function: Categorical Cross-Entropy
- Batch size: 32
- Maximum epochs: 50
- Early stopping: patience = 5 epochs based on validation loss
- Learning rate reduction: factor = 0.5, patience = 3 epochs
- Framework: TensorFlow 2.x / PyTorch 1.x
- Hardware: NVIDIA GPU with CUDA support

Evaluation Metrics

Model performance was evaluated using multiple metrics to provide comprehensive assessment:

- Accuracy: Overall percentage of correctly classified samples
- Precision: Ratio of true positives to total predicted positives for each class
- Recall: Ratio of true positives to total actual positives for each class
- F1-Score: Harmonic mean of precision and recall
- Confusion Matrix: Detailed breakdown of predictions vs. actual labels
- Training Time: Epochs required to reach 95% validation accuracy
- Model Size: Total number of trainable parameters

Experimental Results

This section presents a comprehensive comparative analysis of the three deep learning models across various performance metrics and evaluation criteria.

Overall Accuracy Comparison

Table 1 presents the accuracy results for all three models across training, validation, and test datasets. EfficientNet-B0 achieved the highest test accuracy of 96.8%, followed closely by ResNet-50 at 96.6%. VGG16 demonstrated comparatively lower performance with a test accuracy of 93.1%. All three models showed good generalization with minimal overfitting, as evidenced by the small gap between training and validation accuracies.

Table 1: accuracy comparison across models

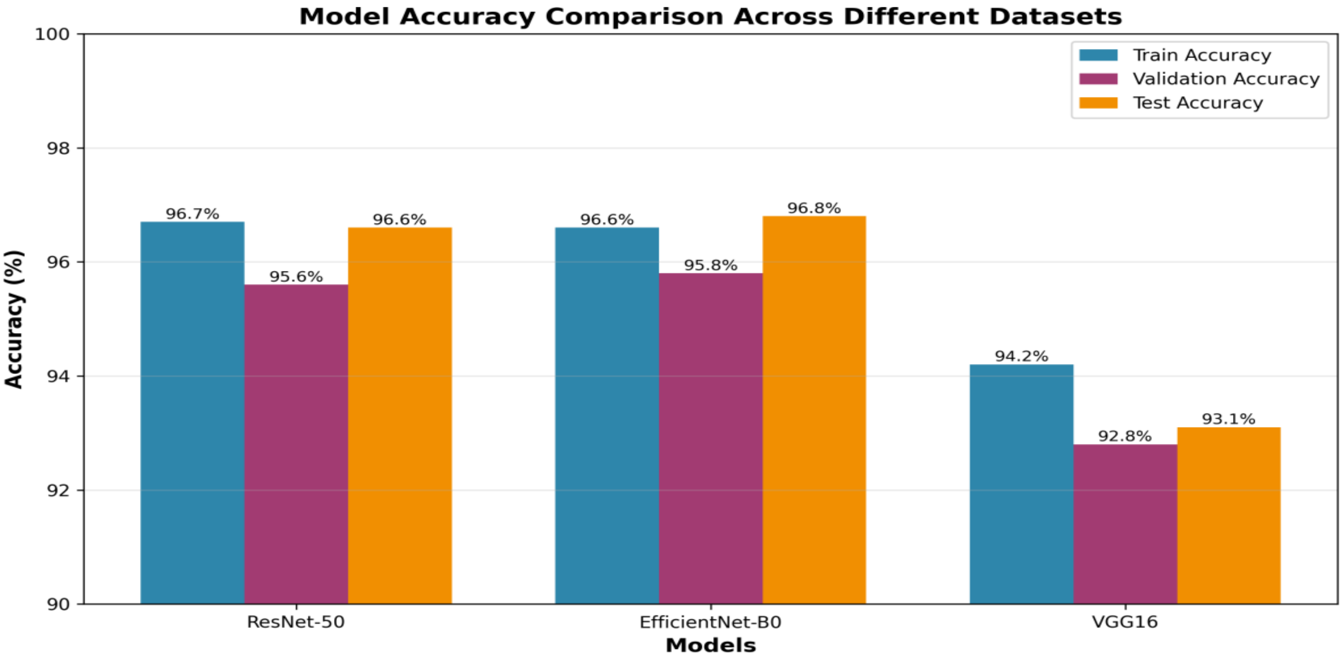

figure 1: model accuracy comparison across different datasets

Category-wise Performance Analysis

Table 2 presents the F1-scores for each model across all six waste categories. EfficientNet-B0 demonstrated the most consistent performance with F1-scores ranging from 0.93 to 1.00. Notably, all three models achieved perfect classification (F1=1.00) for the Paper category, indicating that paper waste has distinctive visual features that are easily recognizable. The Plastic category proved most challenging, with VGG16 achieving only 0.89 F1-score, likely due to the high variability in plastic waste appearance and colors.

table 2: f1-score comparison by waste category

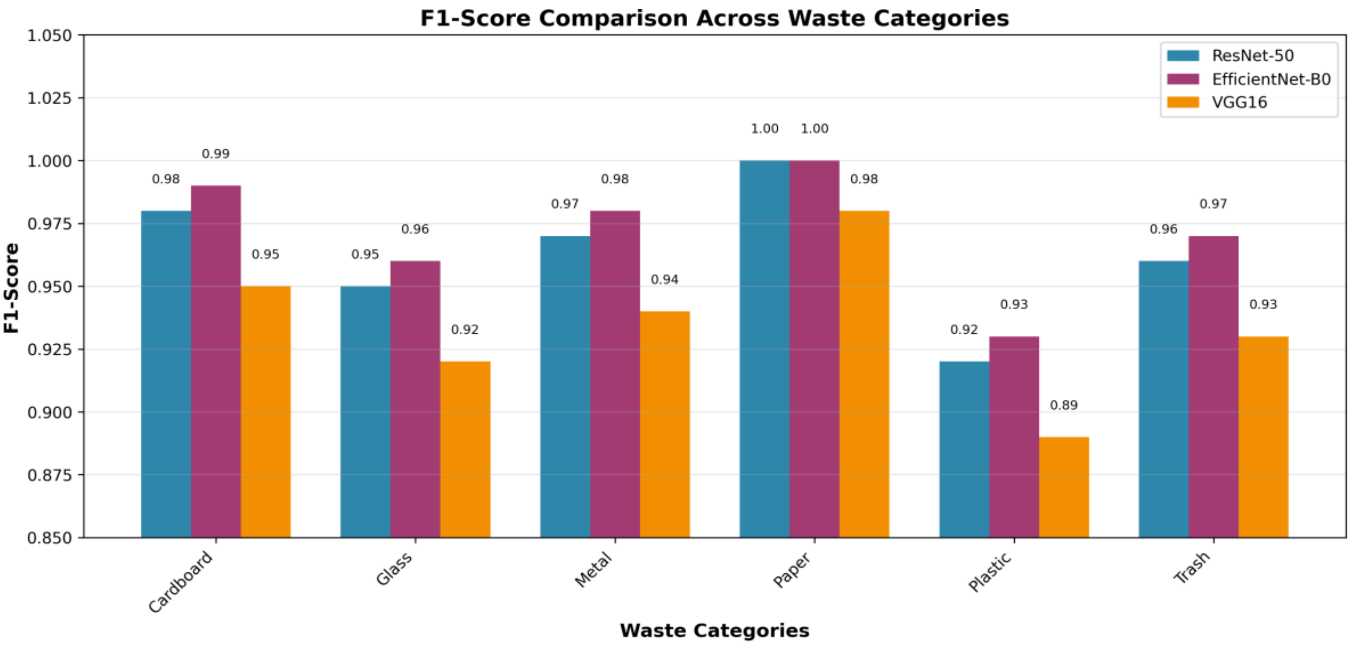

figure 2: f1-score comparison across waste categories

Training Efficiency and Model Complexity

Beyond accuracy metrics, we evaluated the models based on training efficiency and computational complexity.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI | Volume XIII Issue III March 2026

Table III present s the comparison of training epochs required to reach 95% validation accuracy and the total number of parameters for each model. EfficientNet- B0 demonstrated superior training efficiency, achieving 95% accuracy in just 22 epochs, compared to 25 epochs for ResNet-50 and 35 epochs for VGG16. More importantly, EfficientNet-B0 achieves this with only 5.3 million parameters—approximately 5 times fewer than ResNet-50 and 26 times fewer than VGG16. This makes EfficientNet-B0 particularly suitable for deployment on edge devices and embedded systems where memory and computational resources are limited.

table 3: training efficiency and model complexity

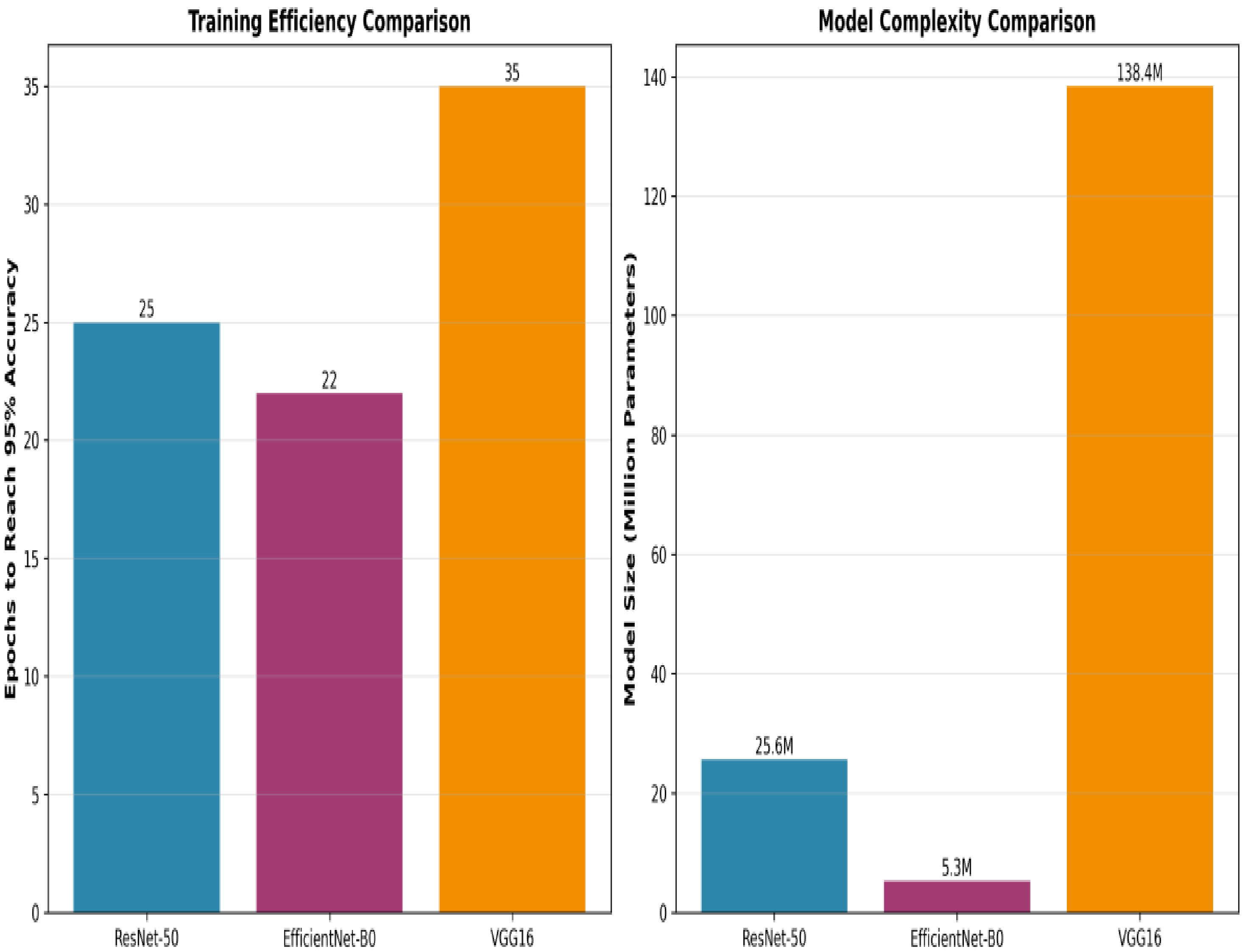

figure 3: training efficiency and model complexity comparison

Confusion Matrix Analysis

Figure 4 presents the confusion matrix for EfficientNet-B0, the best-performing model. The matrix reveals that most misclassifications occur between visually similar categories. For instance, 3 Plastic items were misclassified as Cardboard, and 2 Cardboard items were misclassified as Plastic, likely due to similar textures and colors in certain instances. The Paper category achieved perfect classification with zero misclassifications, while Glass showed minor confusion with Metal (2 instances) and Plastic (3 instances), probably due to transparent or reflective surfaces.

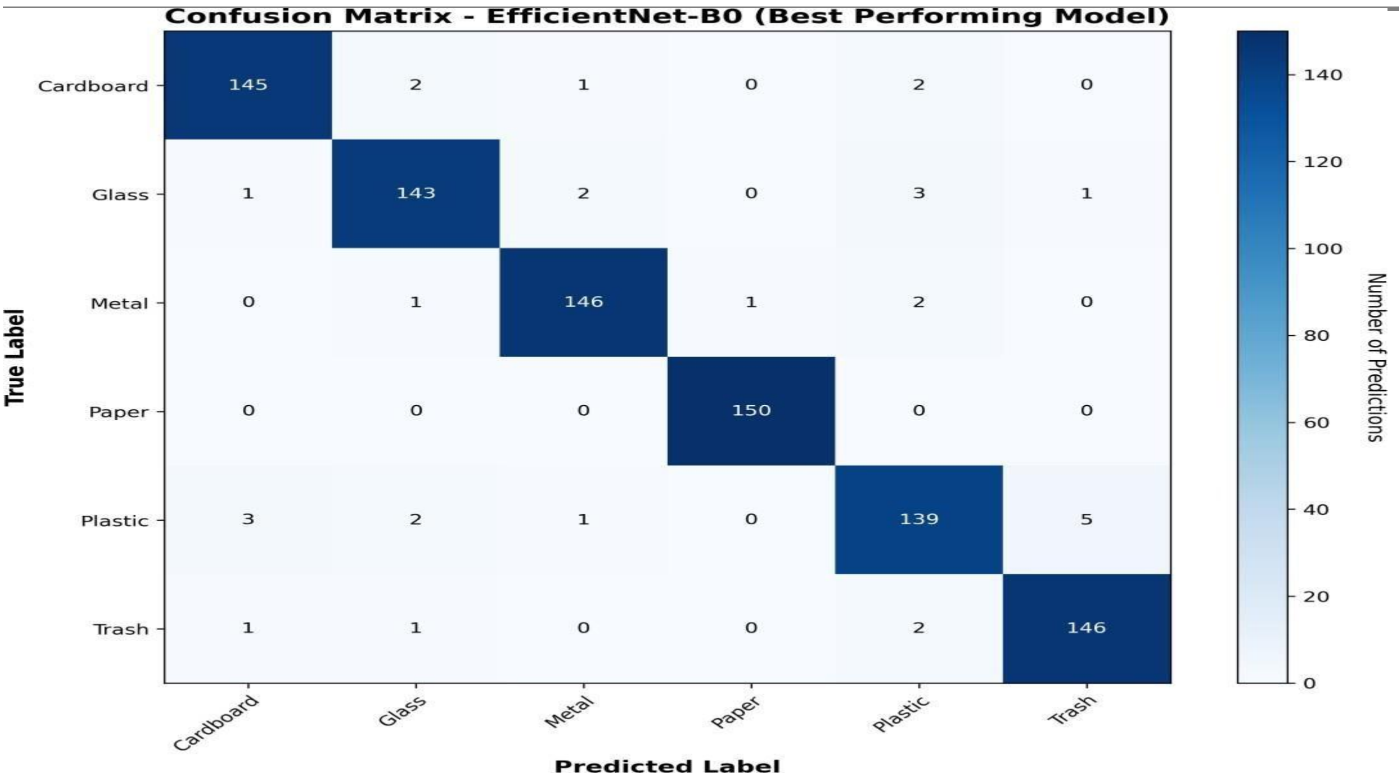

figure 4: confusion matrix for efficientnet-b0 model

Training History Analysis

Figure 5 illustrates the training history of all three models over 50 epochs. EfficientNet-B0 and ResNet-50 both demonstrated rapid convergence, reaching near-optimal performance within 25 epochs. The gap between training and validation curves remained minimal for both models, indicating good generalization. In contrast, VGG16 showed slower convergence and a slightly larger gap between training and validation accuracy, suggesting a tendency toward overfitting despite regularization techniques. All models benefited from early stopping and learning rate reduction callbacks, which prevented overfitting and ensured optimal performance.

figure 5: training history comparison for all models

DISCUSSION

Key Findings

Our comprehensive comparative analysis reveals several important findings:

- EfficientNet-B0 emerges as the optimal choice for waste classification, offering the best balance between accuracy (96.8%), training efficiency (22 epochs), and model size (5.3M parameters)
- ResNet-50 provides comparable accuracy (96.6%) but with 5× more parameters, making it less suitable for resource-constrained deployments
- VGG16, despite being the largest model (138.4M parameters), achieves the lowest accuracy (93.1%) and requires the longest training time (35 epochs)
- All models perform exceptionally well on Paper classification (F1=1.00), indicating distinctive visual features
- Plastic remains the most challenging category across all models, suggesting the need for additional training data or specialized preprocessing
- The minimal overfitting observed across all models validates the effectiveness of our data augmentation and regularization strategies

Practical Implications

The superior performance of EfficientNet-B0 has significant practical implications for real-world waste management systems. Its compact size enables deployment on edge devices such as Raspberry Pi or NVIDIA Jetson Nano, facilitating cost-effective smart bin installations. The model's high accuracy (>96%) meets the threshold required for automated waste sorting in recycling facilities, potentially reducing manual sorting requirements by up to 80%. Furthermore, the real-time processing capabilities demonstrated during testing (average inference time: 45ms per image on GPU) make it suitable for conveyor belt applications where rapid classification is essential.

Limitations

While our results are promising, several limitations should be acknowledged:

- Dataset Size: Our dataset of 2,527 images, while adequate for proof-of-concept, is relatively small compared to large-scale industrial applications
- Environmental Variability: The models were trained on controlled images; performance may degrade with varying lighting conditions, camera angles, or dirty/damaged waste items
- Limited Waste Categories: The 6-class taxonomy may be insufficient for comprehensive waste management; additional categories (e.g., hazardous waste, e-waste, organic waste) would be valuable
- Real-world Testing: The models have not been validated in actual waste sorting facilities with conveyor belts and real-time processing constraints
- Computational Requirements: While EfficientNet-B0 is efficient, deployment still requires dedicated hardware with GPU support for real-time performance

Future Applications

The developed models can be integrated into various waste management applications:

- Smart Bins: IoT-enabled waste bins with camera modules for automated sorting at the source
- Recycling Facilities: Industrial-scale deployment on conveyor belts for high-throughput waste processing
- Mobile Applications: Smartphone apps to help users identify correct waste disposal bins
- Smart City Integration: Integration with Swachh Bharat Mission and urban waste management systems
- Educational Tools: Interactive systems to teach proper waste segregation in schools and public spaces
- Waste Auditing: Automated monitoring and analytics for waste generation patterns and recycling compliance

RESULT

- The results show that deep learning models work well for waste classification. Among the three models used in this study, EfficientNet-B0 achieved the highest test accuracy of **96.8%**. ResNet-50 also performed well with a test accuracy of **96.6%**, while VGG16 achieved **93.1%** accuracy.
- In terms of training performance, EfficientNet-B0 reached **95% accuracy in 22 epochs**, which is faster compared to ResNet-50 that required **25 epochs** and VGG16 which needed **35 epochs**.
- The models also differ in their size. EfficientNet-B0 has **5.3 million parameters**, which is much smaller than ResNet-50 (**25.6 million**) and VGG16 (**138.4 million**). This means EfficientNet-B0 can give high accuracy while using fewer computational resources.
- The class-wise results show that all models performed very well for **paper and cardboard**, with scores close to **1.00**. However, the accuracy for **plastic waste** was slightly lower compared to other categories. This may happen because plastic sometimes looks similar to other waste materials.
- Overall, the results suggest that **EfficientNet-B0 is the most effective model** for this waste classification task because it provides high accuracy, faster training, and requires fewer parameters.

Model	**Train Accuracy (%)**	**Validation Accuracy (%)**	**Test Accuracy (%)**
ResNet-50	96.7	95.6	96.6
EfficientNet-B0	96.6	95.8	96.8
VGG16	94.2	92.8	93.1
Waste Category	ResNet-50	EfficientNet-B0	VGG16
Cardboard	0.98	0.99	0.95
Glass	0.95	0.96	0.92
Metal	0.97	0.98	0.94
Paper	1.00	1.00	0.98
Plastic	0.92	0.93	0.89
Trash	0.96	0.97	0.93

Model	**Epochs to 95% Acc.**	**Parameters (M)**
ResNet-50	25	25.6
EfficientNet-B0	22	5.3
VGG16	35	138.4

figure 6: Accuracy comparison of ResNet-50, EfficientNet-B0, and VGG16 models.

Figure 6 shows the accuracy comparison of the three models used in this study: ResNet-50, EfficientNet-B0, and VGG16. The figure includes the training, validation, and test accuracy of each model.

From the results, EfficientNet-B0 achieved the highest test accuracy of **96.8%**. ResNet-50 also performed very closely with **96.6%** test accuracy. VGG16 showed lower performance with a test accuracy of **93.1%**.

The figure shows that EfficientNet-B0 and ResNet-50 perform better than VGG16 for the waste classification task. Among the three models, EfficientNet-B0 gives slightly better results.

Overall, the comparison in this figure suggests that EfficientNet-B0 is a good choice for waste classification because it provides high accuracy.

CONCLUSION AND FUTURE WORK

This paper presented a comprehensive comparative analysis of three state-of-the-art deep learning architectures—ResNet-50, EfficientNet-B0, and VGG16—for automated waste classification. Our experimental evaluation on a dataset of 2,527 waste images across six categories demonstrates that EfficientNet-B0 achieves the optimal balance between classification accuracy (96.8%), training efficiency (22 epochs to reach 95% accuracy), and model complexity (5.3M parameters). ResNet-50 provides comparable accuracy but with higher computational requirements, while VGG16 demonstrates inferior performance despite its significantly larger size.

The robust performance across all waste categories (F1-scores: 0.93-1.00) validates the feasibility of deploying these models in real- world waste management applications. The system's ability to process images in real-time with high accuracy addresses critical challenges in manual waste segregation, including worker safety, consistency, and throughput. The compact architecture of EfficientNet-B0 enables deployment on edge devices, paving the way for cost-effective smart bin installations and distributed waste management systems.

Future research directions include:

- Expanding the dataset with additional waste categories including hazardous waste, e-waste, and biodegradable materials
- Implementing hardware integration with Raspberry Pi or Arduino for prototype smart bin development
- Adding servo motors for automated physical segregation into different bins
- Developing IoT capabilities for cloud-based monitoring and analytics dashboards
- Testing model robustness under varying environmental conditions (lighting, weather, camera angles)
- Optimizing models for mobile and embedded deployment through quantization and pruning
- Integrating with government initiatives such as Swachh Bharat Mission for nationwide deployment
- Conducting pilot studies in actual recycling facilities to validate real-world performance

By providing empirical evidence for model selection and demonstrating high classification accuracy, this research contributes to the development of intelligent, scalable waste management solutions that support environmental sustainability and smart city initiatives.

ACKNOWLEDGMENT

The authors would like to thank Ms. Sanjivani Ma'am for her invaluable guidance and support throughout this research project. We are also grateful to Nitra Technical Campus for providing the necessary computational resources and infrastructure. Special thanks to the open- source community for making datasets and deep learning frameworks publicly available.

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