European Journal of Engineering Science and Technology
ISSN 2538-9181

Modified Deep Learning Model for Efficient Recyclable Waste Classification: A Comparative Study of Convolutional Network Architectures

Tamuno-Omie J. Alalibo[1*], Nkolika O. Nwazor[2] and Lawrence Oborkhale[3]

[1] Computer Engineering Department, Rivers State University, Port Harcourt, Nigeria
[2] Electrical/Electronic Engineering Department, University of Port Harcourt, Nigeria
[3] Electrical/Electronic Engineering Department, Michael Okpara University of Agriculture, Abia, Nigeria

ARTICLE INFO

Keywords:
Solid Waste Classification,
Convolutional Neural Network,
ResNet50,
Deep Learning,
Image Classification

ABSTRACT

Solid waste recycling management in Nigeria remains a challenge, necessitating efficient waste classification for environmental sustainability. This study proposes CiteWasteRN50, a modified ResNet50 Convolutional Neural Network (CNN), to classify waste into six groups. Key modifications include input image rescaling for enhanced feature extraction, three fully connected layers with dropout, and a SoftMax layer for probabilistic output. The model was trained and validated in MATLAB environment using the TrashNet dataset—75% for training over 7, 15, 30, and 45 epochs, and 25% for validation. CiteWasteRN50 was compared to eight other CNN models under identical conditions. At 15 epochs, CiteWasteRN50 achieved the highest classification accuracy of 98.09%, outperforming ResNet50, ResNet-18, DenseNet201, ResNet-101, EfficientNetB0, VggNet16, VggNet19, and InceptionV3 by 6.04%, 6.98%, 4.12%, 4.29%, 5.39%, 8.24%, 13.17%, and 5.08%, respectively. It also recorded the highest precision (0.9821), recall (0.9838), and F1-score (0.9819). Findings highlight CiteWasteRN50's strong accuracy and applicability for real-world waste classification.

1. Introduction

The global waste crisis, driven by rapid urbanisation, population growth, and economic development, continues to pose serious environmental and public health challenges (Fontaine et al., 2024). According to the United Nations Environment Programme (UNEP, 2024), annual municipal solid waste (MSW) generation is projected to rise from 2.1 billion tonnes in 2023 to 3.8 billion tonnes by 2050. In low-income countries, over 60% of waste goes uncollected, and a large portion of the collected waste is mismanaged and disposed of in landfills (UNEP, 2024; Samreen et al., 2024). In Nigeria, more than 70% of collected solid waste is neither sorted nor recycled, often ending up in open dumps or being burned (Ike et

---

* Corresponding Author's E-Mail Address: tamuno-omie.alalibo@ust.edu.ng, ORCID: 0000-0002-0547-7399

Cite this article as:
Alalibo, T-O. J., Nwazor, N. O. & Oborkhale. L. (2025). Modified Deep Learning Model for Efficient Recyclable Waste Classification: A Comparative Study of Convolutional Network Architectures. *European Journal of Engineering Science and Technology, 8*(2): 1-23. https://doi.org/10.33422/ejest.v8i2.1586

al., 2018; Okafor et al., 2022). Fakunle (2024) and Obani et al. (2025) further emphasise that the composition of waste in both formal and informal dumpsites reflect a lack of waste segregation practices. These ineffective waste management strategies contribute to widespread health risks, water contamination, and increased flood vulnerability, ultimately endangering local communities and ecosystems (Abraham et al., 2025; Nsirim et al., 2018).

Effective solid waste management, particularly through segregation and classification of recyclable materials, is essential for alleviating landfill pressure, conserving resources, and fostering circular economy practices (Samreen et al., 2024; Zisopoulos et al., 2023). To support this process, Aleena et al. (2016) and Wang et al. (2021) advocate for source-level segregation—sorting waste at the point of generation—to improve recycling efficiency and minimise material contamination. In Nigeria, a significant portion of recyclable waste is recovered by informal recycling networks, comprising waste pickers and small-scale collectors, who focus on materials such as metals, glass, paper, and plastic. While these systems assist in the collection and segregation of MSW, they remain under-regulated, poorly resourced, and largely unrecognized by official authorities, as noted by Ogwueleka & Naveen (2021) and Obani et al. (2025), contributing to continued socioeconomic marginalization of workers within the sector. Globally, informal waste collection provides livelihoods for many individuals, yet the predominant reliance on manual sorting or hand-picking methods, which expose workers to health risks, is time-consuming and often leads to low sorting accuracy due to fatigue and human error (Ogwueleka & Naveen, 2021; Sharma et al., 2024; Zisopoulos et al., 2023).

Addressing these limitations calls for scalable, technology-enabled solutions that improve sorting efficiency while minimising health hazards linked to manual waste handling. Deep learning (DL) and computer vision, especially Convolutional Neural Networks (CNNs), have emerged as effective tools for automating image-based classification tasks with high precision due to their excellent feature extraction capabilities (Xia et al., 2022; Li et al., 2025). Integrated within smart bins or automated sorting systems enhanced by Internet of Things (IoT) and wireless communication technologies such as Wi-Fi, LoRaWAN, and 5G, CNN-based models can deliver real-time waste identification and classification (Orike & Alalibo, 2019; Rahman et al., 2022). These innovations offer safer, faster, and data-driven alternatives to manual sorting and are paving the way for more sustainable MSW management practices (Malik et al., 2022).

This paper evaluates CiteWasteRN50, a modified ResNet50 model optimised for classifying common residential solid waste into six categories: cardboard, glass, metal, paper, plastic, and trash. The model was trained and validated using the publicly available TrashNet dataset compiled by Yang and Thung (2016). Emphasis is placed not only on classification accuracy but also on computational efficiency, with an aim of achieving high performance using fewer training epochs. CiteWasteRN50's performance is compared with eight other CNN architectures under uniform experimental conditions in MATLAB 2022. The comparative results highlight the model's potential for deployment in real-world waste management applications, contributing to safer and more efficient waste recovery efforts within both formal systems and informal recycling networks. This research is an effort to develop a practical, easy-to-deploy DL model for point-of-generation waste sorting and small-scale recycling initiatives aimed at sustainable waste management.

2. Literature Review

2.1 Understanding Convolutional Neural Networks (CNNs)

CNN is a deep learning architecture that processes grid-based data, such as images, by identifying shapes and unique features (Alzubaidi et al., 2021; Xia et al., 2022). It extracts patterns directly from image input using filters or kernels across layers, segmenting data into pixel blocks and mimicking human visual processing for effective classification (Chen et al., 2021). A typical CNN consists of interconnected layers: convolutional, pooling, fully connected (dense), and loss/classification layers (Dhillon & Verma, 2019), shown in Figure 1.

Each convolutional layer uses K filters of size (F×F×C) to extract features, generating K feature maps (Alalibo & Nwazor, 2023; Xia et al., 2022). The convolution operation involves element-wise multiplication between filters and input data (Equation 1), with the output size determined by Equation 2 and the stride controlling the movement (Alzubaidi et al., 2021). Activation functions like ReLU, commonly used with convolution layers, add non-linearity by setting negative values to zero (Equation 3). Pooling layers downsample feature maps to reduce complexity (Dhillon & Verma, 2019; Malik et al., 2022), and the final pooled features are passed to fully connected layers for prediction. In the classification layer, the SoftMax function converts the final outputs into class probabilities. The categorical loss function then updates weights and biases via backpropagation to minimise error and improve accuracy (Chen et al., 2021; Dhillon & Verma, 2019). Equations 4 to 7 outline the operations for the FC layer, SoftMax, loss calculation, and parameter updates.

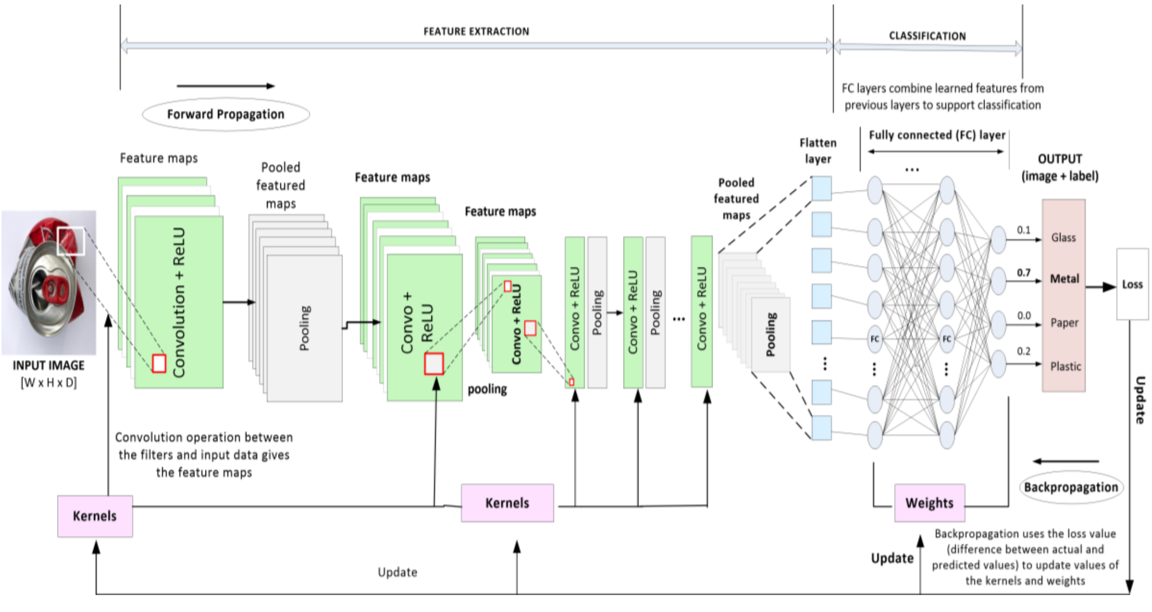


Figure 1. Typical CNN architecture (Alalibo & Nwazor, 2023)

$$Y_{t,v,k} = Conv(W,X) + b = \sum_{q=1}^{F}\sum_{s=1}^{F}\sum_{c=1}^{C}\left(W_{q,s,c,k} \cdot X_{t+q,s+v,c}\right) + b_k \tag{1}$$

$$O = \left(\frac{I + 2G - F}{S}\right) + 1 \tag{2}$$

$$\mathrm{A}_{\mathrm{ReLU}} = \max(0, Y_{t,v,k}) = \mathrm{Re}\,LU(Y_{t,v,k}) \tag{3}$$

$$H_l = A_l\left(b_l + \sum\nolimits_{q=1}^{Q} \left(W_{l,l-1}^{q} \cdot x_{l-1}\right)\right) \tag{4}$$

$$A_{softMax} : x_j = \frac{\exp(x_j)}{\exp(x_1) + \exp(x_2) + \ldots + \exp(x_z)} = \frac{\exp(x_j)}{\sum\nolimits_{z=1}^{N} \exp(x_z)} \tag{5}$$

$$\text{Cross-entropy Loss (E)} = E(Y, D) = -\sum\nolimits_{n=1}^{N} Y_{i,n} \log(D_{i,n}) \tag{6}$$

$$W_l = W_l - \alpha \cdot \partial E / \partial W_l \quad \text{and} \quad b_l = b_l - \alpha \cdot \partial E / \partial b_l \tag{7}$$

Where *b* is the bias value, *F* is the filter/kernel size, and *C* indicates the number of input channels/feature maps/filters of a layer's input. $Y_{t,v,k}$ is the output value found at coordinates (t,v) within the *k*-th output feature map after the convolution process. $W_{q,s,c,k}$ signifies the weight of the convolution filter at a specific position (q,s) within the filter, corresponding to a particular input channel (*c*) and the k-th output channel or feature map; $X_{t+q,s+v,c}$ indicates the pixel value situated at position *(t+q, v+s)* within the input data for a specific input channel; *A(.)* stands for the activation function; *O* denotes output feature size [$O^H \times O^W \times C$]; *I* denotes input size (height = I^H; width = I^W); *S* denotes the stride; *G* defines the padding size; *l* denotes the FC layer; $H_l, b_l, A_l(\cdot)$ denote the output, bias value and activation function of each layer; $W_{l,l-1}^{q}$ is the weight value of the *q*-th neuron between the current layer *l* and the previous layer *l-1*; x_{l-1} is the input from the last layer; *Q* is the number of neurons on each layer; e^{x_j} is the exponential (*exp*) of the j-th element of the input vector; *z* is the number of neurons in the output layer; $Y_{i,n}$ denotes the true class if class label *n* denotes correct classification for the i-th sample; *D* is the class probability for a sample prediction similar to Equation 5; *log* is the natural logarithm; *N* is the number of classes; the symbol α is the learning rate.

In CNN-based waste classification, there is ongoing debate around balancing model complexity and accuracy. Deep architectures like ResNet, DenseNet, InceptionV3, and EfficientNet achieve high accuracy by capturing intra-class variability (Risfendra et al., 2024; Srivatsan et al., 2021), but these performance gains often come with larger model sizes, longer training times, and increased computational requirements, which may limit use in real-time or low-power settings. On the other hand, lightweight models like MobileNetV2 are faster to train and require fewer resources, making them a good fit for real-time applications (Howard et al., 2017; Jin et al., 2023), yet often underperform with complex or noisy data. A comparison study by Khan et al. (2024) highlighted this trade-off, noting that deeper models need more resources but perform better, while lighter ones suit embedded systems but may compromise accuracy. The study also emphasised that model selection should be based on the intended deployment platform, and the analysis showed ResNet50 as a middle ground, providing reasonable accuracy without being too resource-heavy. Building on these insights, this study introduces the CiteWasteRN50 model, developed to maintain high classification accuracy while reducing the number of training epochs. Instead of pushing for either deeper models or very minimal ones, CiteWasteRN50 focuses on improving a moderately complex, well-established ResNet50 model, making it a practical and scalable solution for real-time waste classification.

2.2 ResNet Architecture: Rationale for Applicability in Waste Classification

Residual Network (ResNet) is a convolutional neural network (CNN) architecture that transformed deep learning by introducing residual learning and skip connections, which significantly ease the training of deep networks (He et al., 2016). Rather than strictly learning a direct layer-by-layer mapping from inputs to outputs, ResNet focuses on learning residual functions—effectively capturing the difference between input and target output. This approach means that once a feature is learned, the ResNet model can focus on learning new features rather than re-learning existing ones. This innovation enables the model to have more layers without performance degradation, providing more efficient feature learning and mitigating common issues such as vanishing gradients (Alzubaidi et al., 2021). Among its many variants, ResNet50 has become a preferred model in image classification tasks, offering a favourable balance between architectural depth and computational efficiency. It consists of 49 convolutional layers followed by a fully connected output layer, arranged in five stages of bottleneck residual blocks. These structures reduce parameter redundancy and computational cost while maintaining high accuracy. The standard ResNet50 operates on 224×224×3 input images, making it suitable for waste image data with diverse visual features.

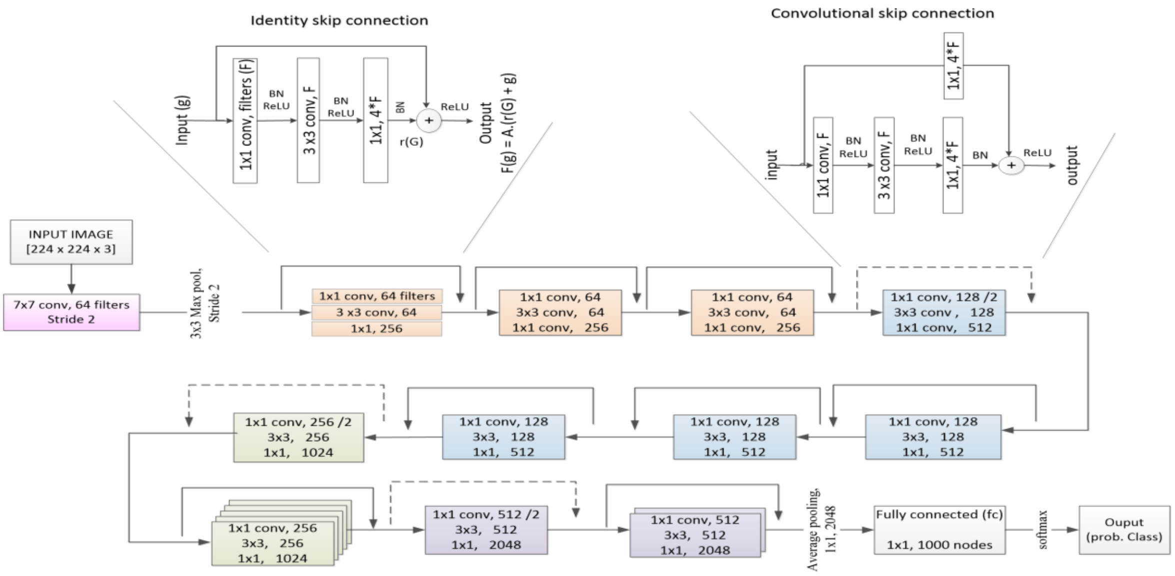


Figure 2. Architecture of ResNet50 CNN Model

In this study, ResNet50 was selected as the foundation for developing the CiteWasteRN50 model, a modified version aimed at improving classification accuracy while reducing training time and computational overhead. The choice of ResNet50 was based on the well-documented architectural strengths:

1. **Effective vanishing gradient mitigation** through identity skip connections that ensure the flow of information through deep network models without degradation in performance.
2. **Improved convergence and training stability**, even in large and noisy datasets, due to residual learning.
3. **Moderate parameter count** compared to deeper models like ResNet101, enabling deployment in resource-constrained environments, such as smart bins, mobile apps, or embedded waste classification systems.

These characteristics make ResNet50 technically sound for waste classification, directly contributing to reduced training time, lower computational cost and improving accuracy for practical relevant for real-world applications The CiteWasteRN50 model builds on these strengths by introducing targeted architectural enhancements (e.g., image resizing, additional fully connected layers, dropout regularization, and optimized training schedules) to deliver comparable or superior performance in fewer training epochs. Figure 2 shows the architecture of the ResNet50 model.

2.3 Review of CNN-based Waste Classification

Early efforts in automated waste classification primarily relied on conventional machine learning (ML) techniques such as Support Vector Machines (SVM), Random Forests, and Decision Trees, often in conjunction with handcrafted feature extraction. While these approaches offered initial improvements over manual sorting, they struggled with the high-dimensional and noisy nature of real-world imagery, limiting their scalability and robustness. For instance, Sami et al. (2020) compared multiple machine learning (ML) algorithms and found that CNNs significantly outperformed traditional methods, achieving around 90% accuracy, compared to 85% for support vector machines (SVMs) and 55%–65% for tree-based models. Jangsamsi (2023) employed CNN-SVM classifiers with a double fusion approach achieved 80% accuracy. These results underscore a growing consensus: traditional ML, though computationally efficient, has limited representational capacity to generalise across diverse waste categories.

As waste classification tasks increasingly demand scalability, real-time capability, and adaptability to complex visual inputs, the field has experienced a paradigm shift toward deep learning (DL). DL methods like CNN offer automatic hierarchical feature extraction, eliminating the dependency on manual feature engineering and achieving robust performance even under challenging conditions. These methods also have more adaptability, suitable for integration in smart systems (Sharma et al., 2024). Abood and Al-Talib (2023) emphasised deep CNN superiority in large-scale classification tasks, especially with transfer learning, against both traditional ML and shallow CNNs, highlighting deep CNNs' practicality in waste sorting and monitoring systems.

Several studies have demonstrated the effectiveness of CNN architectures in waste classification, particularly its ability to maintain performance while being adaptable to real-world implementation in waste management systems. As demonstrated in Amin et al. (2021), the efficiency of various CNN models for classifying waste via transfer learning achieved up to 90% accuracy using ResNet50, suggesting feasibility for microprocessor- or camera-based mobile applications. Srivatsan et al. (2021) explored the effectiveness of DenseNet121, MobileNetV2, and ResNet34. After training for 60 epochs, the models achieved impressive accuracies of 96.42%, 96.27%, and 96.273%, respectively. These results demonstrate the potential of CNNs to classify waste materials with high precision, suggesting that deeper and more complex models can capture intricate patterns in waste images. In Mohammed et al. (2022), an artificial neural network (ANN) with feature fusion techniques achieved an accuracy of 91.7%, proving its ability to sort and classify the waste as per the recycling requirements automatically. In Ma et al. (2022), the standard ResNet-50 model was trained on the TrashNet dataset for 250 epochs, resulting in an accuracy of 84.46%, which was then compared with two improved variants—ResNet-50-A and ResNet-50-B—which achieved higher accuracies of 88.4% and 92.08%, respectively, highlighting the potential of ResNet-50 and its modification to significantly improve classification accuracy in waste sorting applications. In Rahman et al. (2022), ResNet50 was applied in a mobile application for IoT bin segregation and monitoring, where it achieved 94.15% accuracy after 32 epochs, highlighting its practicality for edge-based smart waste solutions.

Mu et al. (2023) optimised ResNet50 by reducing kernel sizes, widening layers, and training for 200 epochs, achieving 95.19% accuracy with faster convergence on a real-world recycling dataset. Tamuno-omie et al. (2023) introduced a modified ResNet50 model utilising transfer learning, which resulted in an impressive accuracy after training on the TrashNet dataset, surpassing AlexNet, GoogleNet, and MobileNetV2 by margins of 19.69%, 8.26%, and 7.31%, respectively, highlighting the success of transfer learning potential for leveraging pre-trained models to improve classification tasks. Kaya (2023) developed Xception_CutLayer and InceptionResNetV2_CutLayer models yielded accuracies of 89.72% and 85.77% after 50 epochs. These models outperformed five other CNN models, showcasing the competitive nature of newer architectures in waste classification. Alalibo & Nwazor (2023) trained various CNN models on the TrashNet dataset. ResNet50 achieved 92.06% accuracy after 7 epochs, while ResNet101 reached 92.38% after 10 epochs. The results indicate that even with fewer training epochs, certain architectures can yield competitive performance, suggesting a potential for faster training times without sacrificing accuracy. Risfendra et al. (2024) utilised the EfficientNet-B0 CNN model with transfer learning to achieve a test accuracy of 91.94%, precision of 92.10%, and recall of 91.94%, leading to an F1-score of 91.96%. These metrics indicate a well-rounded performance, emphasising the importance of not just accuracy but also the balance between precision and recall in classification tasks. Hossen et al. (2024) applied the RWC-Net model to the TrashNet dataset, achieving an overall accuracy of 95.01%. This performance surpassed that of DenseNet201 and MobileNetV2 models, illustrating the potential of new architectures to push the boundaries of what is achievable in waste classification. Li et al. (2025) extended ResNet50 by integrating feature fusion and depthwise separable convolutions, trained for 400 epochs, attained 94.13% accuracy, and reduced model complexity, which is crucial for deployment in embedded systems and municipal recycling centres.

These studies show the effectiveness and versatility of CNN for waste classification. While previous studies have focused on developing robust models for waste classification, relatively little attention has been paid to optimising the number of training epochs. Many existing models, including those utilising transfer learning, often rely on prolonged training durations, which can lead to overfitting and reduced generalisation performance in real-world applications. To address this gap, this study introduces CiteWasteRN50, a modified ResNet50 architecture designed to maintain high classification accuracy while significantly reducing the number of required training epochs. By optimising for low-epoch convergence without compromising performance, CiteWasteRN50 enhances the model's practicality and deployability in scalable, real-time waste management systems.

3. Methodology

This study compares the performance of CiteWasteRN50, a modified ResNet50 model, against eight other CNN architectures—ResNet50, DenseNet201, EfficientNetB0, InceptionV3, ResNet18, ResNet101, VggNet16, and VggNet19—aiming to achieve high classification accuracy of solid waste with minimal training epochs. All models were fine-tuned to classify the specified waste categories using the same dataset, data augmentation techniques, training parameters, and evaluation criteria to ensure a fair comparison.

The CiteWasteRN50 model was built upon the architectural strengths of ResNet50 identified by He et al. (2016) and Tamuno-omie et al. (2023). Figure 3 depicts the overall methodology, outlining the training and validation process applied across all models. Each model was trained for 7, 15, 30, and 45 epochs, totalling thirty-six experiments. The experiments were conducted in MATLAB 2022 on a Lenovo laptop equipped with an Intel(R) Core(TM) i7 CPU @ 2.20GHz, 24GB RAM, and an Nvidia GF RTX 2060 GPU.

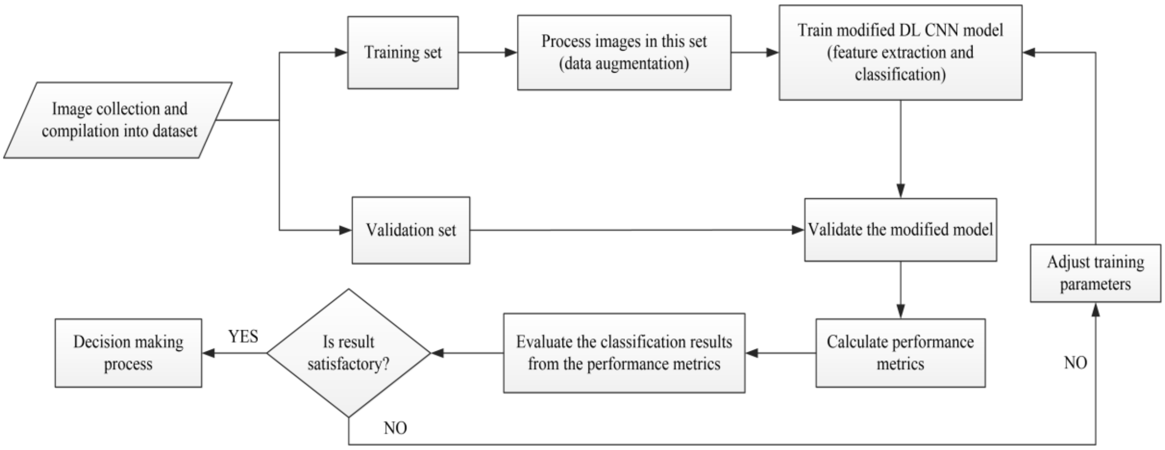


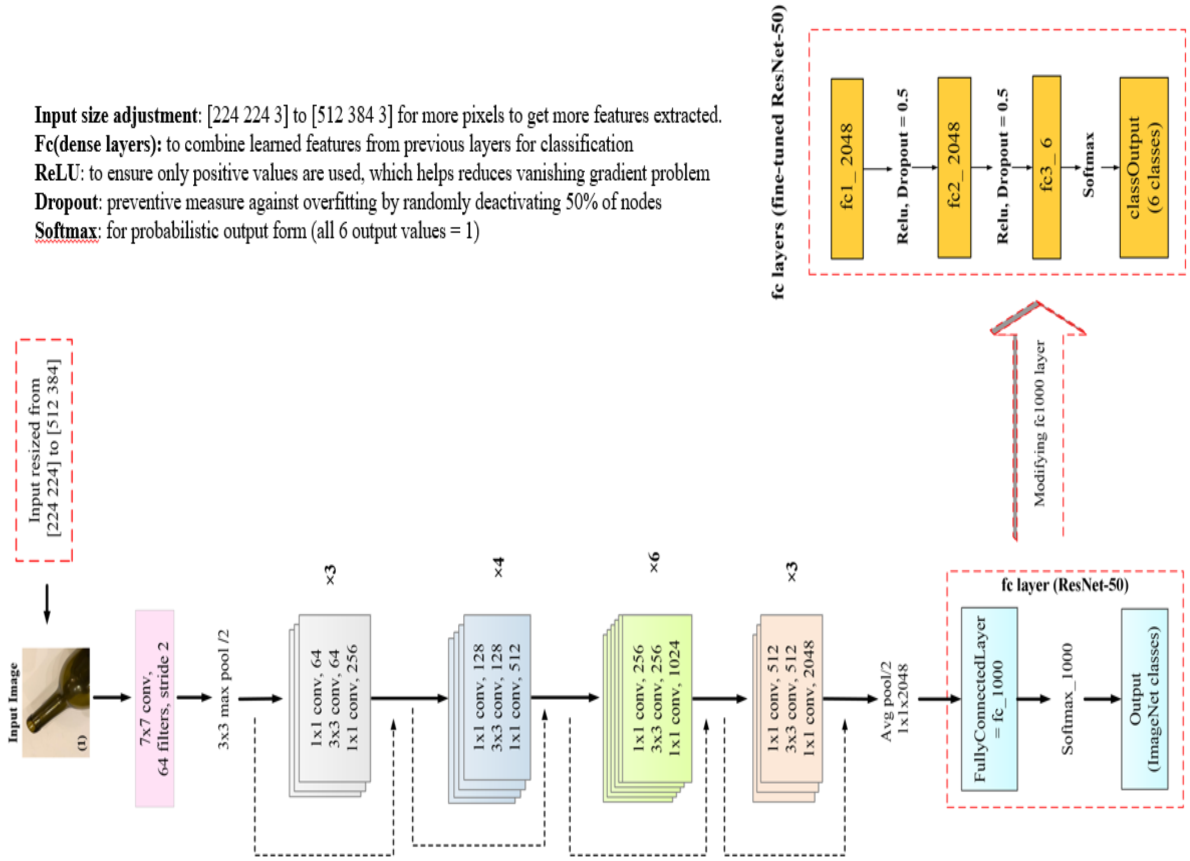
Figure 3. Methodology Steps used for the Training and Validation Process of CNN Models

3.1 CiteWasteRN50 Model for Solid Waste Classification

The architecture of CiteWasteRN50 is illustrated in Figure 4, highlighting the specific areas where modifications were implemented on the original pre-trained ResNet50 to obtain the CiteWasteRN50 model:

1. The default input image size was increased from [224,224,3] to [512,384,3] to capture and extract more detailed features from the larger pixel numbers.
2. The original fully connected layer (fc_1000) was replaced with a sequence of layers: fc1_2048, relu1, dropout1_0.5, fc2_2048, relu2, dropout2_0.5, fc3_6, SoftMax, and outputLayer
3. The dropout rate of 0.5 was implemented to mitigate overfitting conditions by randomly deactivating 50% of the nodes during training. The SoftMax layer converts the outputs from the fc3_6 layer to class probabilities.

These architectural changes were designed to improve both accuracy, generalisation capabilities, and training efficiency, critical for real-world application in automated waste sorting. The increased input resolution and refined fully connected layers with dropout reduce overfitting while enabling the model to better capture complex waste features. This leads to faster convergence and robust generalisation, enabling the CiteWasteRN50 model to support real-time deployment in automated waste sorting systems. Such practical applications can significantly enhance recycling efficiency by enabling rapid, precise classification that reduces reliance on labour-intensive manual sorting.



Input size adjustment: [224 224 3] to [512 384 3] for more pixels to get more features extracted.
Fc(dense layers): to combine learned features from previous layers for classification
ReLU: to ensure only positive values are used, which helps reduces vanishing gradient problem
Dropout: preventive measure against overfitting by randomly deactivating 50% of nodes
Softmax: for probabilistic output form (all 6 output values = 1)

Figure 4. CiteWasteRN50: The Modified ResNet50 Architecture

3.2 Settings for Dataset, Data Augmentation, and Training Option

The dataset used was the TrashNet dataset, which contains 2527 images of solid waste across six classes: cardboard (403), glass (501), paper (594), plastic (410), metal (482), and trash (137). This dataset was split randomly into training and validation sets, with 75% assigned to training for CNN models to learn image characteristics and labels. The validation set (25%), comprising unseen images not used in training, was assigned to assessing and validating model performance.

Dataset augmentation and pre-processing were then performed on the dataset before training the CNN models to enhance their diversity and reduce overfitting. Data augmentation techniques were applied using MATLAB's DL neural network library functions, including *imageDataAugmenter* and *augmentedImageDatastore*. Augmentation techniques applied to the training dataset are presented in Table 1.

Training options are the network's hyperparameters that govern the training process. Following augmentation, these parameters were configured using MATLAB's *trainNetwork* function. For each model, the training was repeated for 7, 15, 30, and 45 epochs, respectively, with each epoch consisting of 94 iterations. The validation frequency was configured to be every 50 iterations, utilising images from the validation set. The *outputNetwork* parameter was configured to "best-validation-loss" to store the model and its parameters at the stage of minimal validation loss. Table 1 shows the training options used for each CNN model.

Table 1. Settings for Data Augmentation and Training Option

Data Augmentation Setting	
Image Resize	Model's input size
Rotation Range	[-45 45]
Random Translation	[-10 10]
Scale Range	[1 2]
Random XScale	[1 1]
Random YScale	[1 1]
Random Reflection	[1 1]

Training options	
Optimizer	SGDM
Learning Rate	0.001
Number of Epochs	7, 15, 30, 45
Mini-Batch Size	20
Validation Frequency	50 iterations
Output Network	best validation loss
Shuffle	every epoch

3.3 Performance Metrics

To provide a comprehensive evaluation of model effectiveness, accuracy, precision, recall, F1-score, and the confusion matrix were used as performance metrics to assess CiteWasteRN50 and the other CNN models. These metrics provide insights not only into overall classification accuracy but also into the models' ability to identify each waste category correctly.

i. **Accuracy** measures the ratio of the correct predicted labels by the model to the total actual input samples (see Equation 8). Training accuracy assesses a model's ability to predict labels from training examples, while validation accuracy shows its performance on unseen images. High validation accuracy indicates reliable real-world performance.
ii. **Precision** quantifies a model's accuracy in positive predictions, minimising false positives (see Equation 9).
iii. **Recall** measures a model's proficiency in identifying positive cases, reducing false negatives, and capturing true positives (see Equation 10).
iv. The **F1 score** indicates a model's optimal balance between precision and recall, indicating its reliability and accuracy in classifying samples across different classes. This is mathematically expressed in Equation 11.
v. The **confusion matrix** provides a visual representation of the true and predicted values for the different waste classes. It shows the number of correct and incorrect predictions by a model. In this paper, a 6×6 confusion matrix was used.

$$Accuracy = (TP + TN)/(TP + TN + FP + FN) \tag{8}$$

$$precision = TP/(TP + FP) \tag{9}$$

$$recall = TP/(TP + FN) \tag{10}$$

$$F1 - score = \frac{2 \times precision \times recall}{precision + recall} = \frac{2TP}{(2TP + FP + FN)} \tag{11}$$

Where *TP* (True Positive) indicates the number of times the model correctly predicts that an image belongs to a class. *TN* (True Negative) is the number of times the model correctly predicts an image does not belong to a class. *FP* (False Positive) denotes the number of times the model incorrectly predicts an image belongs to a class when it does not. *FN* (False Negative) indicates the number of times the model incorrectly predicts an image does not belong to a class when it actually does.

4. Results and Discussion

This section presents the experimental results, providing a comprehensive evaluation of CiteWasteRN50's performance based on the metrics outlined in Section 3.3.

4.1 Result for the CiteWasteRN50 Model

Figure 5 illustrates the validation accuracy of the CiteWasteRN50 model over 7, 15, 30, and 45 training epochs. The model achieved impressive classification accuracies of 93.65%, 98.09%, 94.60%, and 96.03%, respectively. The peak validation accuracy of 98.09% at 15 epochs highlights the model's ability to generalise well, balancing training efficiency and classification performance. Although accuracy showed minor fluctuations beyond 15 epochs, the consistently high validation results suggest robust learning with no significant overfitting. This level of performance is important for real-world waste classification systems that require fast and reliable decision-making. Figure 6 compares training and validation accuracies, showing that at most epochs, validation accuracy lags training accuracy as expected. However, at 15 epochs, validation accuracy surpasses training accuracy, demonstrating strong generalisation and suggesting that CiteWasteRN50 does not overfit the training data at this stage.

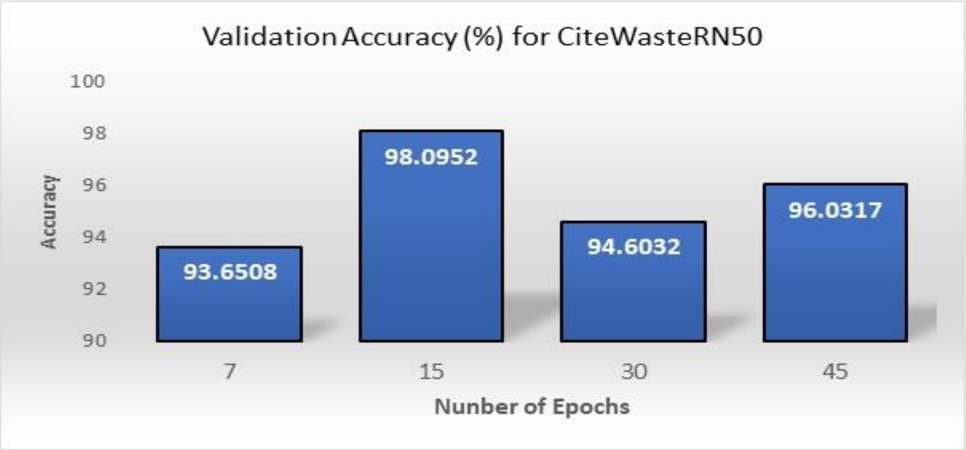


Figure 5. Validation Accuracy for CiteWasteRN50 Model (Epoch = 7,15,30, 45)

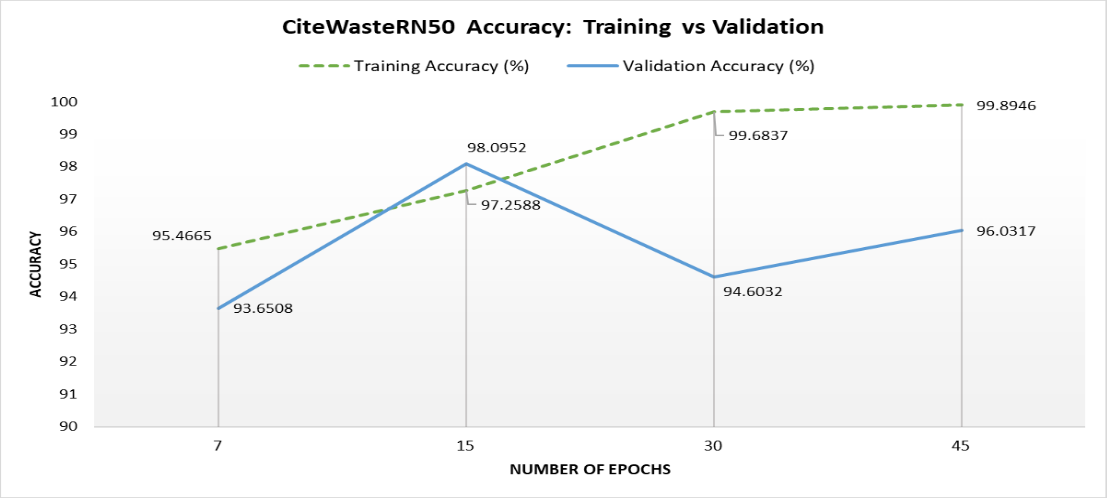


Figure 6. Validation vs. Training Accuracy for CiteWasteRN50 (Epoch = 7, 15, 30, 45)

The training curves in Figure 7 and the Receiver Operating Characteristic (ROC) curve in Figure 8 further reinforce the model's effectiveness. The diagonal line in ROC denotes random guessing with a 50/50 chance, while a curve above it indicates a model performing better than random guessing. The Model Operating Points denote the selected operating point for each class, typically determined by balancing the True Positive Rate and False Positive Rate. The micro-average Area Under the Curve (AUC) of 0.9989 is near perfect, confirming excellent discrimination across all six waste categories. Such high precision supports practical deployment where sorting accuracy directly impacts recycling purity and process efficiency.

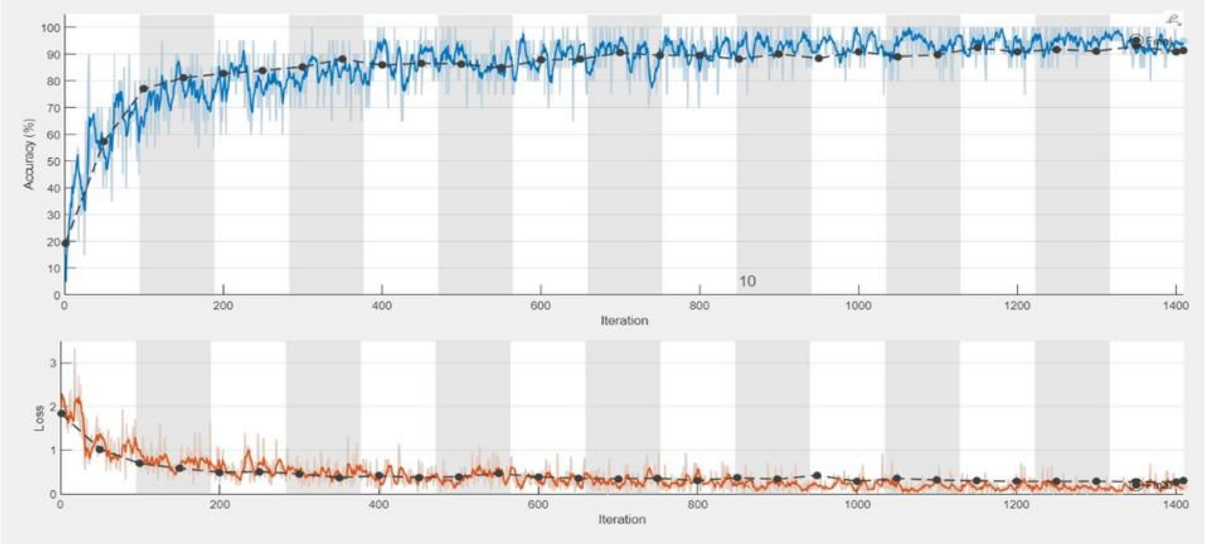


Figure 7. Accuracy and Loss Curves for CiteWasteRN50 (Epoch=15)

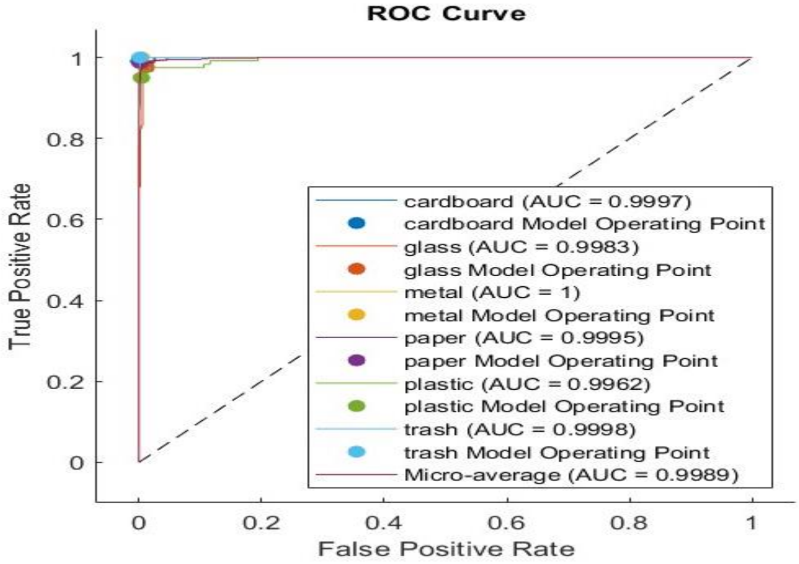


Figure 8. ROC Curve for CiteWasteRN50 (Epoch=15)

4.2 Comparative Result between CiteWasteRN50 and the Original ResNet50 Models

Figure 9 shows that CiteWasteRN50 consistently outperforms the original ResNet50 model by margins of 2.22%, 6.04%, 1.91%, and 2.06% for 7, 15, 30, and 45 epochs, respectively, with the highest improvement at 15 epochs. Validation accuracy and loss curves in Figures 10(a) and 10(b) highlight this gap at the critical 15-epoch mark, illustrating CiteWasteRN50's improved learning stability and reduced overfitting. Figure 11 presents detailed class-wise performance metrics—accuracy, precision, recall, and F1-score—demonstrating that CiteWasteRN50 outperformed the ResNet50 model across all waste categories. This result shows that the architectural modifications, such as increased input resolution and refined fully connected layers, translate into tangible gains in classification precision, critical for sorting systems to minimise contamination in recycling streams.

Practically, the enhanced classification accuracy reduces the need for human intervention, lowering labour costs and health risks associated with manual sorting of potentially hazardous waste. The improved model efficiency also supports faster throughput, making it viable for integration in small-to-industrial-scale sorting lines.

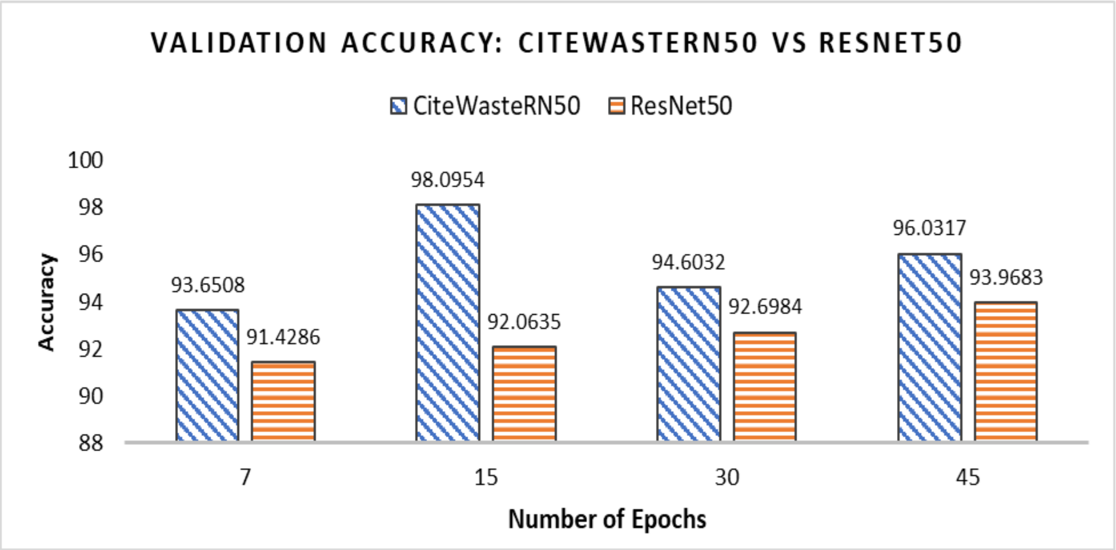
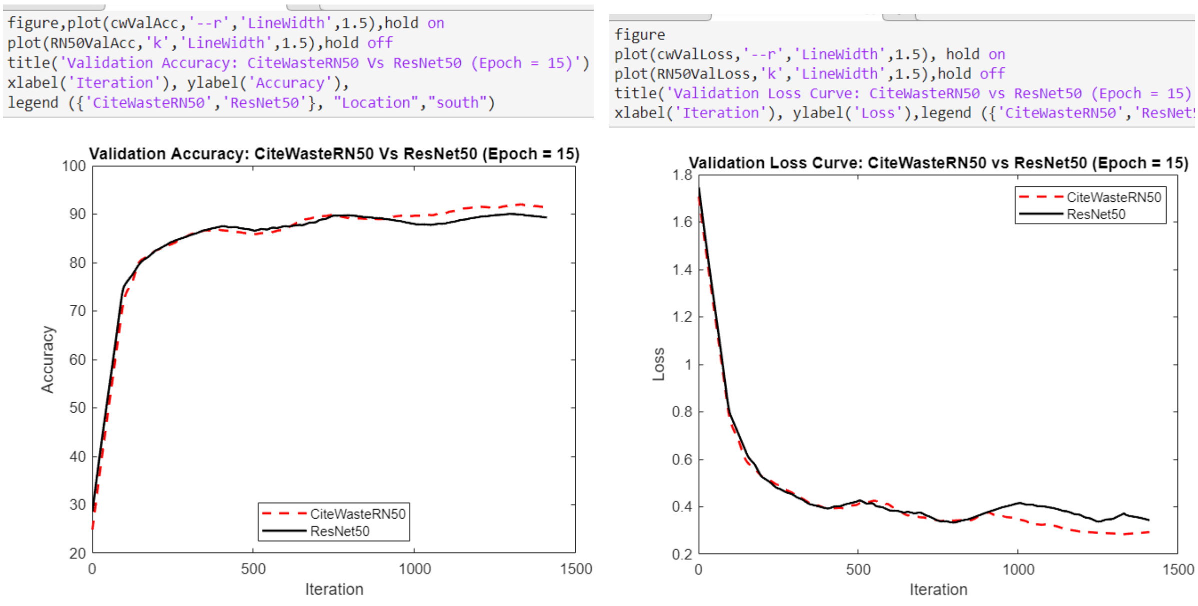


Figure 9. Accuracy Comparison for CiteWasteRN50 and ResNet50



```
figure,plot(cwValAcc,'--r','LineWidth',1.5),hold on
plot(RN50ValAcc,'k','LineWidth',1.5),hold off
title('Validation Accuracy: CiteWasteRN50 Vs ResNet50 (Epoch = 15)')
xlabel('Iteration'), ylabel('Accuracy'),
legend ({'CiteWasteRN50','ResNet50'}, "Location","south")
```

```
figure
plot(cwValLoss,'--r','LineWidth',1.5), hold on
plot(RN50ValLoss,'k','LineWidth',1.5),hold off
title('Validation Loss Curve: CiteWasteRN50 vs ResNet50 (Epoch = 15)
xlabel('Iteration'), ylabel('Loss'),legend ({'CiteWasteRN50','ResNet
```

10(a) 10(b)

Figure 10. CiteWasteRN50 vs ResNet50 **(a)** Validation accuracy **(b)** Validation loss

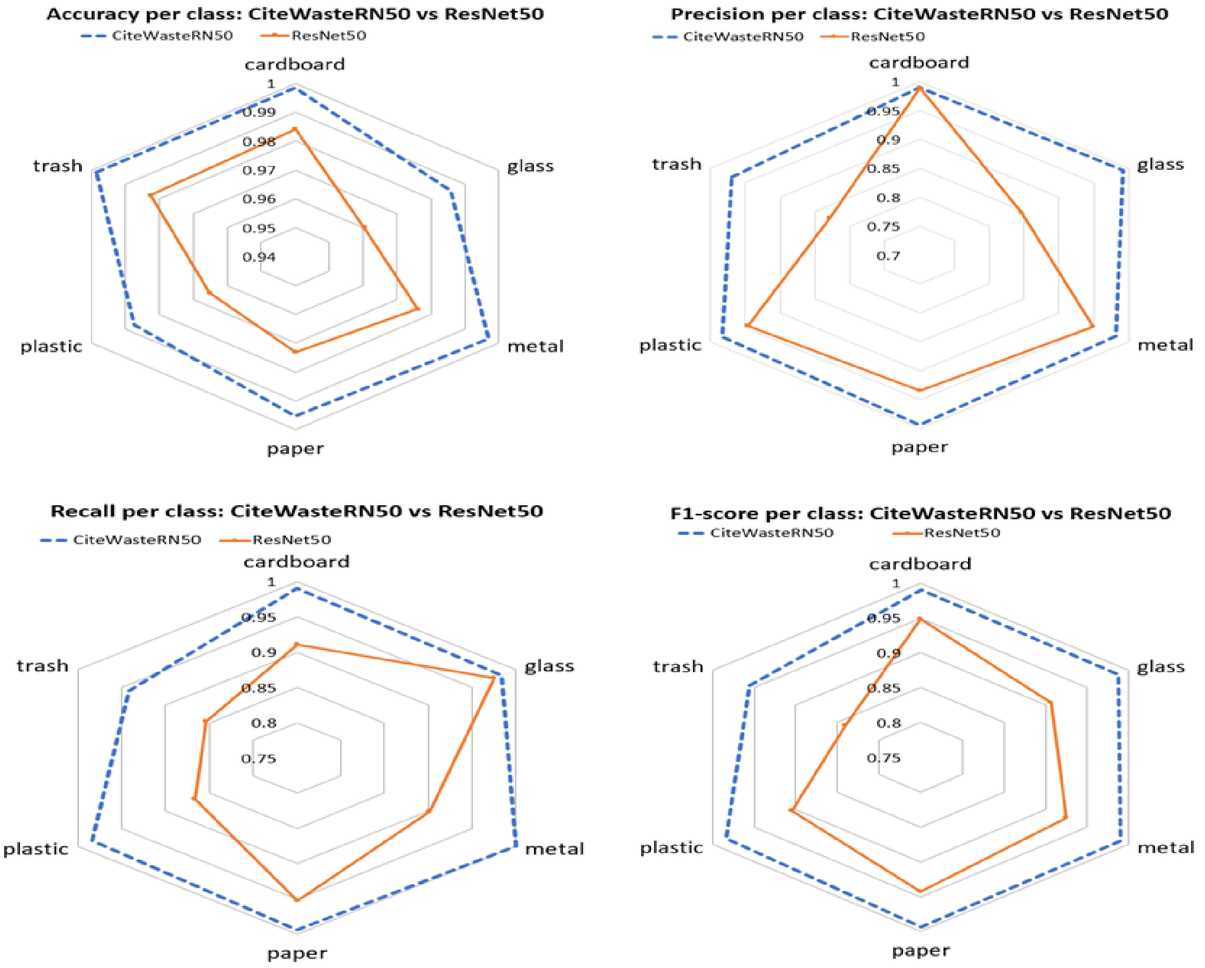


Figure 11. Performance Metrics Comparison (Epoch 15) - CiteWasteRN50 vs. ResNet50

4.3 Comparative Results for CiteWasteRN50 and the Eight CNN Models

Figures 12 and 13 present the validation accuracies and errors of CiteWasteRN50 compared to eight other CNN architectures, evaluated at 7, 15, 30, and 45 training epochs. CiteWasteRN50 consistently ranks highest in accuracy for three out of four epochs, peaking at 98.09% accuracy and a 1.91% error rate at 15 epochs. The validation loss curves in Figure 14 confirm that CiteWasteRN50 achieves lower loss, indicating better model fit and generalisation than its competitors.

At 15 epochs, CiteWasteRN50 outperformed DenseNet201, EfficientNetB0, InceptionV3, ResNet18, ResNet101, ResNet50, VggNet16, and VggNet19 by significant margins by margins of 4.12%, 5.39%, 5.08%, 6.98%, 4.29%, 6.04%, 8.24%, and 13.17%, respectively. This robust performance across a diverse set of architectures underscores the practical utility of the proposed model for real-time automated sorting

The results in Table 2 provide the values for precision, recall, and F1-score at 15 epochs for the nine CNN models. The closer these metrics are to one, the more accurate the model's predictions. CiteWasteRN50 gave the highest values for precision (0.9821), recall (0.9838), and F1-score (0.9819). This indicates that CiteWasteRN50 can correctly identify more true positive cases and avoid predicting false positive cases, demonstrating better prediction accuracy compared to the other eight CNN models evaluated for solid waste classification in this study.

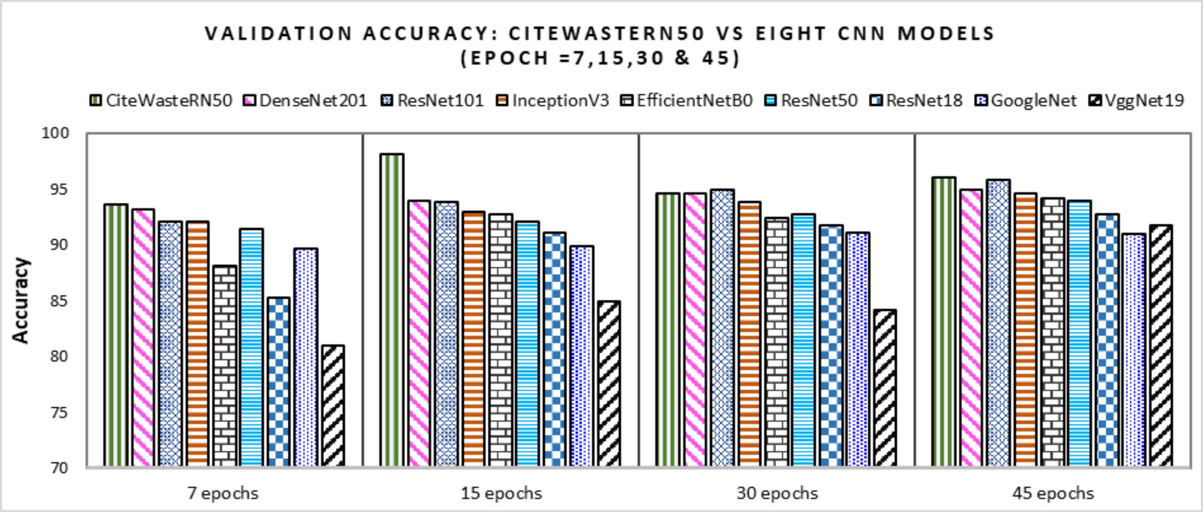
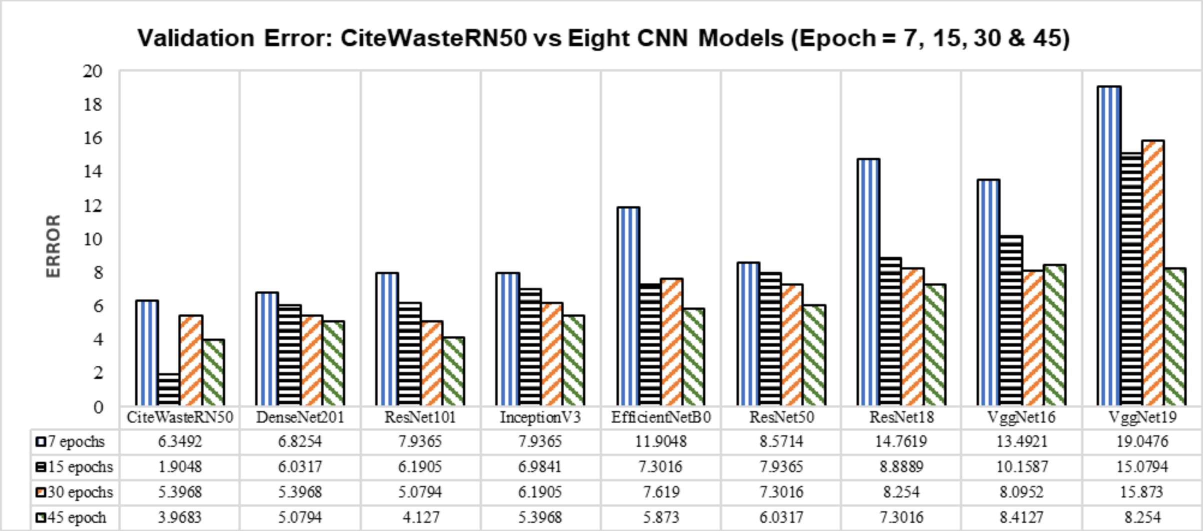


Figure 12. Accuracy Comparison for the Nine CNN models



	CiteWasteRN50	DenseNet201	ResNet101	InceptionV3	EfficientNetB0	ResNet50	ResNet18	VggNet16	VggNet19
◫ 7 epochs	6.3492	6.8254	7.9365	7.9365	11.9048	8.5714	14.7619	13.4921	19.0476
▤ 15 epochs	1.9048	6.0317	6.1905	6.9841	7.3016	7.9365	8.8889	10.1587	15.0794
▨ 30 epochs	5.3968	5.3968	5.0794	6.1905	7.619	7.3016	8.254	8.0952	15.873
▧ 45 epoch	3.9683	5.0794	4.127	5.3968	5.873	6.0317	7.3016	8.4127	8.254

Figure 13. Validation Error Comparison for the Nine CNN models (Epochs = 7,15, 30, 45)

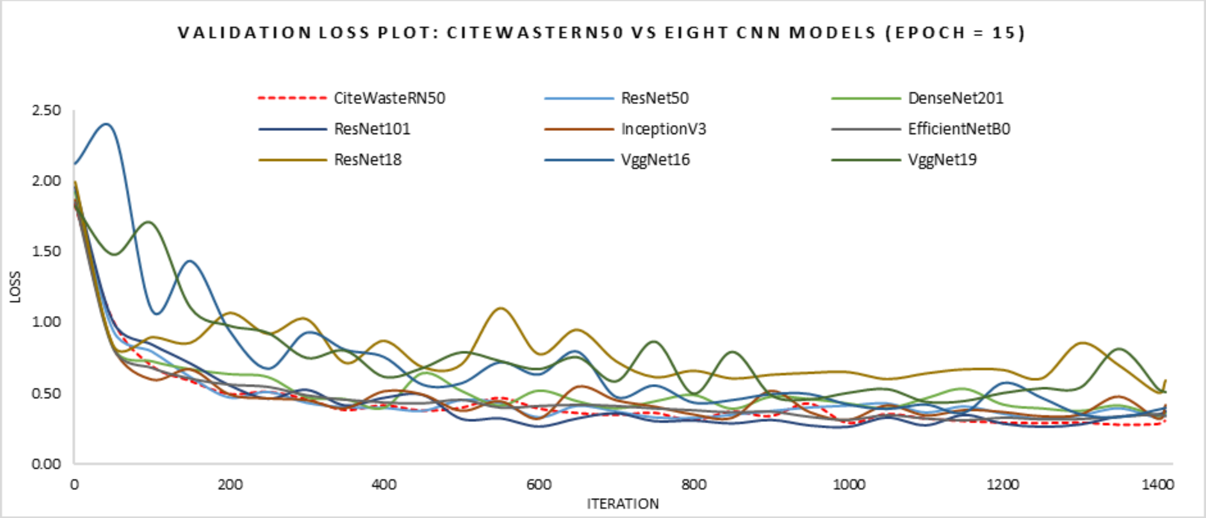


Figure 14. Validation Loss Curve for the Nine CNN models (Epoch = 15)

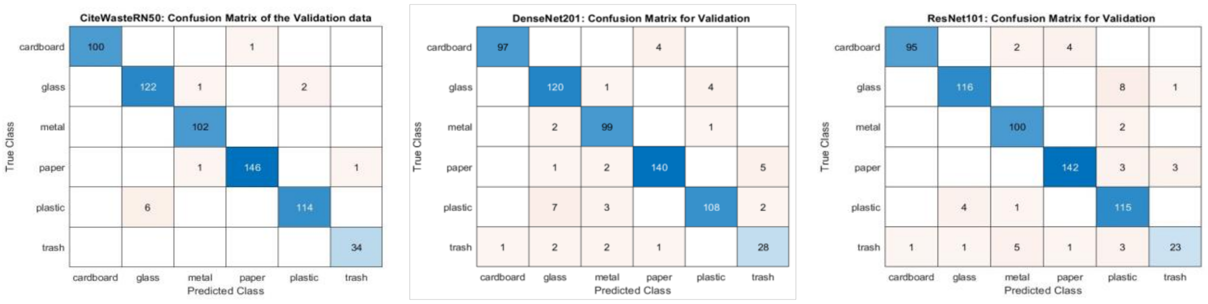
Table 2. Comparison of Precision, Recall, and F1-score Metrics for the Nine Models

cnn models (epoch = 15)	**accuracy**	**average precision**	**average recall**	**average f1-score**
citewastern50	0.9810	0.9821	0.9838	0.9819
densenet201	0.9397	0.9242	0.9267	0.9251
resnet101	0.9381	0.9283	0.9072	0.9155
inceptionv3	0.9302	0.9211	0.9139	0.9157
efficientnetb0	0.9270	0.9267	0.8892	0.9026
resnet50	0.9206	0.9155	0.9102	0.9114
resnet18	0.9111	0.8912	0.8993	0.8943
vggnet16	0.8984	0.8874	0.8792	0.8814
vggnet19	0.8492	0.8209	0.8202	0.8200

Qualitative Performance Analysis (Confusion Matrices): The CiteWasteRN50 model demonstrated strong robustness, with only **12 misclassifications** from the validation dataset. Those specific misclassified images are shown in Figure 15. A visual comparison of the confusion matrices for CiteWasteRN50 and the other eight CNN models at 15 epochs is presented in Figure 16. The diagonal cell values in the confusion matrices represent the number of correct predictions, whereas off-diagonal values indicate incorrect predictions. While CiteWasteRN50 has 12 misclassification, in comparison, EfficientNetB0 misclassified 46 images, ResNet50 had 50, and VGGNet19 had 94 misclassifications. This low error rate of CiteWasteRN50 highlights its high precision and effectiveness in distinguishing between visually similar waste categories.

Based on the overall results, the model achieved the objectives of attaining high classification accuracy with fewer training epochs and consistently outperformed the original ResNet50 and eight other CNN models across multiple evaluation metrics

Figure 15. The 12 Images from the Validation Set Misclassified by the CiteWasteRN50 model



CiteWasteRN50: Confusion Matrix of the Validation data

True Class	cardboard	glass	metal	paper	plastic	trash
cardboard	100			1		
glass		122	1		2	
metal			102			
paper			1	146		1
plastic		6			114	
trash						34

Predicted Class

(a) CiteWasteRN50 misclassification = 12

DenseNet201: Confusion Matrix for Validation

True Class	cardboard	glass	metal	paper	plastic	trash
cardboard	97			4		
glass		120	1		4	
metal		2	99		1	
paper		1	2	140		5
plastic		7	3		108	2
trash	1	2	2	1		28

Predicted Class

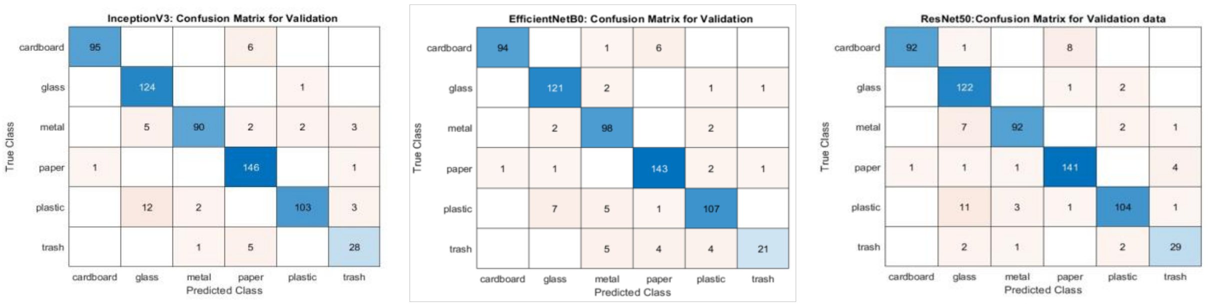
(b) DenseNet201 misclassification = 38

ResNet101: Confusion Matrix for Validation

True Class	cardboard	glass	metal	paper	plastic	trash
cardboard	95		2	4		
glass		116			8	1
metal			100		2	
paper				142	3	3
plastic		4	1		115	
trash	1	1	5	1	3	23

Predicted Class

(c) ResNet101 misclassification = 39



InceptionV3: Confusion Matrix for Validation

True Class	cardboard	glass	metal	paper	plastic	trash
cardboard	95			6		
glass		124			1	
metal		5	90	2	2	3
paper	1			146		1
plastic		12	2		103	3
trash			1	5		28

Predicted Class

(d) InceptionV3 misclassification = 44

EfficientNetB0: Confusion Matrix for Validation

True Class	cardboard	glass	metal	paper	plastic	trash
cardboard	94		1	6		
glass		121	2		1	1
metal		2	98		2	
paper	1	1		143	2	1
plastic		7	5	1	107	
trash			5	4	4	21

Predicted Class

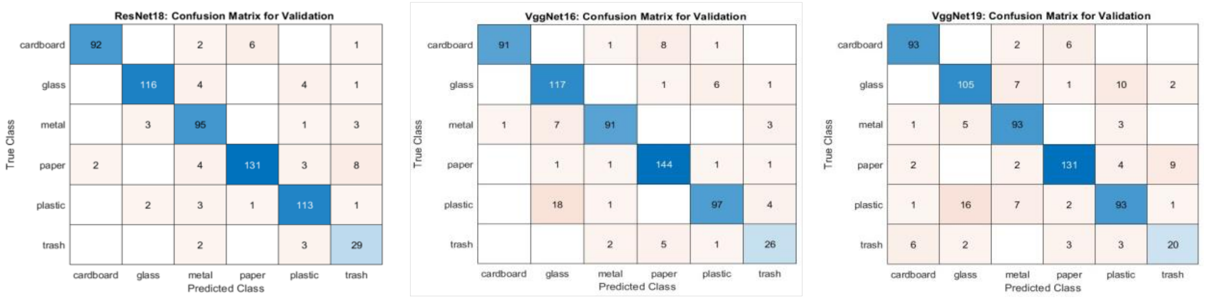
(e) EfficientNetB0 misclassification = 46

ResNet50:Confusion Matrix for Validation data

True Class	cardboard	glass	metal	paper	plastic	trash
cardboard	92	1		8		
glass		122		1	2	
metal		7	92		2	1
paper	1	1	1	141		4
plastic		11	3	1	104	1
trash		2	1		2	29

Predicted Class

(f) ResNet50 misclassification = 50



ResNet18: Confusion Matrix for Validation

True Class	cardboard	glass	metal	paper	plastic	trash
cardboard	92		2	6		1
glass		116	4		4	1
metal		3	95		1	3
paper	2		4	131	3	8
plastic		2	3	1	113	1
trash			2		3	29

Predicted Class

(g) ResNet18 misclassification = 54

VggNet16: Confusion Matrix for Validation

True Class	cardboard	glass	metal	paper	plastic	trash
cardboard	91		1	8	1	
glass		117		1	6	1
metal	1	7	91			3
paper		1	1	144	1	1
plastic		18	1		97	4
trash			2	5	1	26

Predicted Class

(h) VggNet16 misclassification = 64

VggNet19: Confusion Matrix for Validation

True Class	cardboard	glass	metal	paper	plastic	trash
cardboard	93		2	6		
glass		105	7	1	10	2
metal	1	5	93		3	
paper	2		2	131	4	9
plastic	1	16	7	2	93	1
trash	6	2		3	3	20

Predicted Class

(i) VggNet19 misclassification = 95

Figure 16. Confusion Matrices of CiteWasteRN50 and the other 8 CNN models (Epoch =15)

4.4 Practical Implications and Real-World Impact

A crucial aspect of this research was to assess the practical utility of our developed model. We envision our model for deployment within automated sorting conveyor lines or IoT bins, integrated with high-speed cameras for small-to-middle scale formal or informal recycling sectors. Thus, the functionality of the CiteWasteRN50 model was demostrated in the live MATLAB program output shown in Figure 17, revealing real-time solid waste classification. In addition, the CiteWasteRN50 model was used on unseen, real-world images of solid waste, simulating practical scenarios. Figure 18 shows the successful classification results from these real-world image tests, further validating the model's robustness and generalisation capabilities beyond the controlled dataset environment.

Building on this results, the model was integrated into a IoT bin to automate solid waste classification and enhance efficiency. Figure 19 shows the different sections of the bin – top view, circuitry and display units. The IoT bin featured a top-mounted ultrasonic sensor for touchless lid operation, enhancing hygiene. When a hand or object was detected within 15 cm, the ESP32 triggered a servo motor to open the lid. A camera module then scanned the contents; if no waste was detected, the lid closed after 10 seconds. If waste was present, the camera captured images and sent them to the Raspberry Pi, where the CiteWasteRN50 model was deployed for classification. Based on the classification result, a DC motor was activated to rotate the bin to the appropriate chamber (plastic, metal, or general), where the waste was deposited.

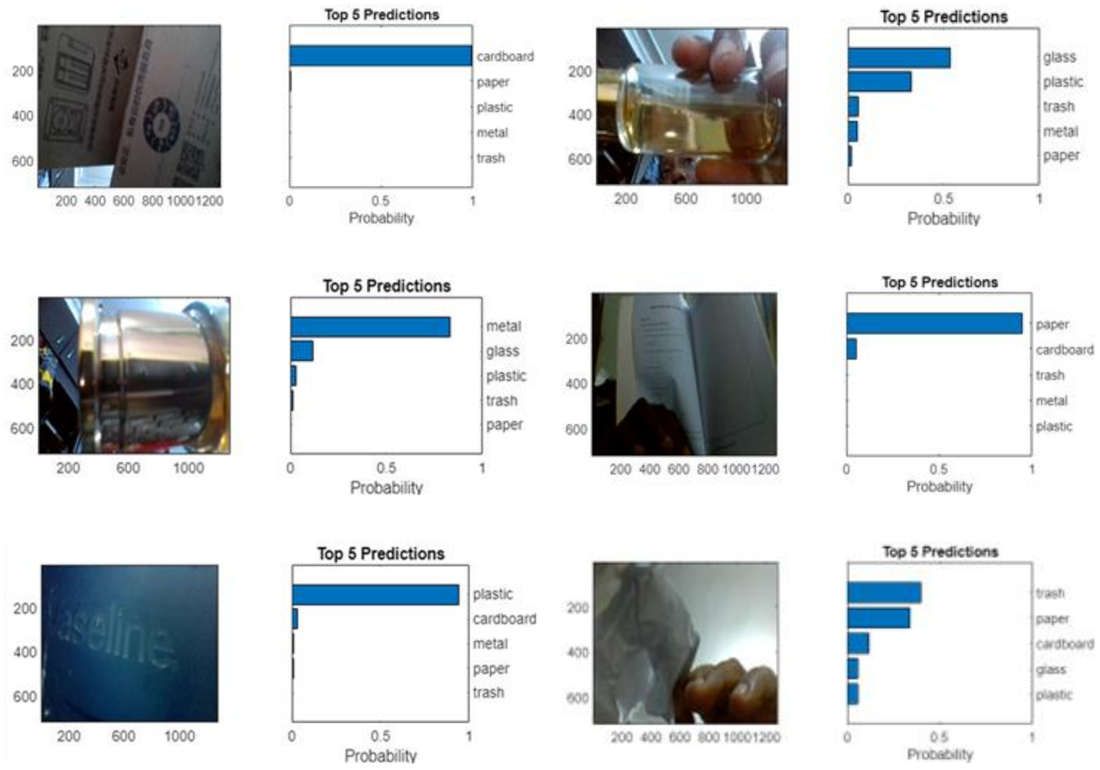


Figure 17. Real-time Image Processing Output in MATLAB

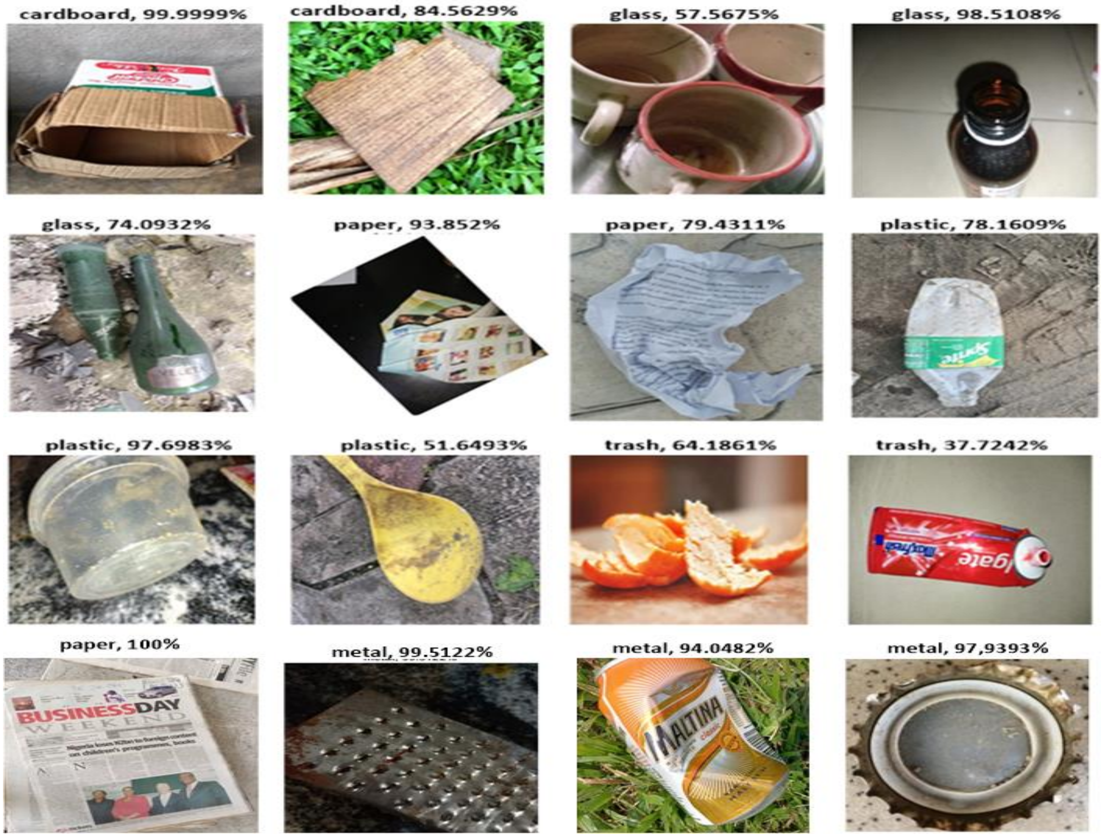


Figure 18. CiteWasteRN50 Classification of Real World Solid Waste Images

Figure 19. IoT bin – Top view, Circuitry and Display Units – for Solid Waste Classification using CitewasteRN50 model

Deep learning models like CiteWasteRN50 can address key challenges in conventional waste sorting by:

1. **Automating manual sorting** to reduce hand sorting, minimize errors, and improve recycling efficiency, thus helping reduce landfill overflow.
2. **Lowering health risks** by providing precise, automated sorting that limits exposure to hazardous waste, enhancing worker safety in places like Nigeria, where manual sorting is still common.
3. **Enabling real-time sorting** via integration with conveyors and edge devices, surpassing manual sorting speeds.
4. **Supporting smart waste systems** by combining with IoT sensors and computer vision for intelligent, data-driven waste management (including IoT-based waste monitoring and collection)
5. **Increasing recyclate purity** through high accuracy and low misclassification, raising recyclable market value and promoting sustainable investment.

5. Conclusion

Over the years, CNN models have demostrated great potential in image classification. This paper focuses on CiteWasteRN50, a modified ResNet50 model, to classify solid waste images into six categories with high efficiency using fewer training epochs. A comparative analysis against eight other CNN models was performed using MATLAB on the TrashNet dataset. At 15 epochs, CiteWasteRN50 outperformed others, achieving 98.09% accuracy, 98.21% precision, 98.38% recall, and 98.19% F1-score, demonstrating strong pattern recognition and minimal errors. While models like DenseNet201 and ResNet101 also performed admirably, CiteWasteRN50 showed better generalisation and achieved top accuracy. Its ability to deliver high accuracy with limited training makes CiteWasteRN50 suitable for real-world waste management, where speed and efficiency are critical. To mitigate labour-intensive, error-prone manual sorting method that exposes workers to health risks, this model provides a scalable, automated solution that improves accuracy and reduces operational strain. Lower misclassification rates, robust generalisation, and faster inference support real-time sorting systems that ease human workload and enhance safety. These benefits contribute to reducing landfill overflow, increasing recycling rates, and lowering waste management's environmental impact. Future research can aim to optimise inference speeds, expand waste categories, test across diverse datasets, and address challenges such as lighting variability, overlapping waste, and contamination.

References

Abood, I. N., & Al-Talib, G. A. A. (2023). Waste classification using artificial intelligence techniques: Literature review. *Technium Science,* *5*, 49–59. https://doi.org/10.47577/technium.v5i.8345

Abraham, C. M., Ukoh, I. J., Jimmy, U., & Bassey, I. O. (2025). Solid waste management, surface water quality and river basin contamination in Akwa Ibom State: Case study of Ikpa River catchment. *International Journal of Social Sciences and Management Research, 10*(11), 263–283.

Aleena, V. J., Balakrishnan, K., Rosmi, T. B., Swathy, K. K. S., Sreejith, S., & Subha, T. D. (2016). Automatic waste segregator and monitoring system, *Journal of Microcontroller Engineering Applications*, 3(2), 1-7

Alalibo, T. O. J., & Nwazor, N. O. (2023). Comparative analysis of convolutional neural network models for solid waste categorisation. *Iconic Research and Engineering Journals, 6*(12), 1396–1405.

Alzubaidi, L., Zhang, J., Humaidi, A. J., Al-Dujaili, A., Duan, Y., Al-Shamma, O., Santamaría, J., Fadhel, M. A., Al-Amidie, M., & Farhan, L. (2021). Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions. *Journal of Big Data, 8*(1), 1–74. https://doi.org/10.1186/s40537-021-00444-8

Amin, Z., Sami, K. N., & Hassan, R. (2021). An approach of classifying waste using transfer learning method. *International Journal on Perceptive and Cognitive Computing (IJPCC), 7*(1), 41–52.

Chen, L., Li, S., Bai, Q., Yang, J., Jiang, S., & Miao, Y. (2021). Review of image classification algorithms based on convolutional neural networks. *Remote Sensing, 13*(22), e4712. https://doi.org/10.3390/rs13224712

Dhillon, A., & Verma, G. K. (2019). Convolutional neural network: A review of models, methodologies and applications to object detection. *Progress in Artificial Intelligence, 9*(2), 85–112.

Fakunle, S. O. (2024). Peculiarities in household solid waste management in Nigeria: A quick review. *Frontiers in Sustainability, 5*, 1–8. https://doi.org/10.3389/frsus.2024.1440758

Fontaine, L., Legros, R., & Frayret, J.-M. (2024). Solid waste generation prediction model framework using socioeconomic and demographic factors with real-time MSW collection data. *Waste Management & Research, 43*(2), 267–281. https://doi.org/10.1177/0734242X241231414

He, K., Zhang, X., Ren, S., & Sun, J. (2016, June 27–30). Deep residual learning for image recognition. In *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)* (pp. 770–778). Las Vegas, NV, USA. https://doi.org/10.1109/CVPR.2016.90

Hossen, M. M., Majid, M. E., Kashem, S. B. A., Khandakar, A., Nashbat, M., Ashraf, A., Hasan-Zia, M., Kunju, A. K. A., Kabir, S., & Chowdhury, M. E. H. (2024). A reliable and robust deep learning model for effective recyclable waste classification. *IEEE Access, 12*, 13809–13821. https://doi.org/10.1109/access.2024.3354774

Howard, A. G., Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T., Andreetto, M., & Adam, H. (2017). Mobilenets: Efficient convolutional neural networks for mobile vision applications. *ArXiv.* https://doi.org/10.48550/arXiv.1704.04861

Ike, C. C., Ezeibe, C. C., Anijiofor, S. C., & Daud, N. N. N. (2018). Solid waste management in Nigeria: Problems, prospects, and policies. *The Journal of Solid Waste Technology and Management, 44*(2), 163–172. https://doi.org/10.5276/jswtm.2018.163

Jangsamsi, K. (2023). Conventional machine learning approach for waste classification. In *Proceedings of the 2023 6th Artificial Intelligence and Cloud Computing Conference (AICCC 2023)* (pp. 7–12). ACM. https://doi.org/10.1145/3639592.3639594

Jin, S., Yang, Z., Krolczyk, G. M., Liu, X., Gardoni, P., & Li, Z. (2023). Garbage detection and classification using a new deep learning-based machine vision system as a tool for sustainable waste recycling. *Waste Management, 162*, 123–130. https://doi.org/10.1016/j.wasman.2023.02.014

Kaya, V. (2023). Classification of waste materials with a smart garbage system for sustainable development: A novel model. *Frontiers in Environmental Science, 11*, 1–9. https://doi.org/10.3389/fenvs.2023.1228732

Khan, H. A., Naqvi, S. S., Alharbi, A. a. K., Alotaibi, S., & Alkhathami, M. (2024). Enhancing trash classification in smart cities using federated deep learning. *Scientific Reports*, *14*(1), 1 – 12. https://doi.org/10.1038/s41598-024-62003-4

Li, L., Wang, R., Zou, M., Guo, F., & Ren, Y. (2025). Enhanced ResNet-50 for garbage classification: Feature fusion and depth-separable convolutions. *PLoS ONE, 20*(1), e0317999. https://doi.org/10.1371/journal.pone.0317999

Ma, X., Li, Z., & Zhang, L. (2022). An improved ReSNet-50 for garbage image classification. *Tehnicki Vjesnik-technical Gazette, 29*(5), 1552-1559 . https://doi.org/10.17559/tv 1552-155920220420124810

Malik, M., Sharma, S., Uddin, M., Chen, C.-L., Wu, C.-M., Soni, P., & Chaudhary, S. (2022). Waste classification for sustainable development using image recognition with deep learning network models. *Sustainability, 14*(12), 7222. https://doi.org/10.3390/su14127222

Mohammed, M. A., Abdulhasan, M. J., Kumar, N. M., Abdulkareem, K. H., Mostafa, S. A., Maashi, M. S., Khalid, L. S., Abdulaali, H. S., & Chopra, S. S. (2022). Automated waste-sorting and recycling classification using artificial neural network and features fusion: A digital-enabled circular economy vision for smart cities. *Multimedia Tools and Applications, 82*(25), 39617–39632. https://doi.org/10.1007/s11042-021-11537-0

Mu, A., Sun, X., & Zhang, W. (2023). Method for identification of recycled waste image based on deep residual neural network. *COJ Electronics & Communications, 2*(5), 1–9. https://doi.org/10.31031/cojec.2023.02.000550

Nsirim, H. U., Ochonogor, C. I., & Nwachukwu, F. G. (2018). Assessment of Rivers State Waste Management Agency's communication strategies for waste management in Port Harcourt metropolis, Nigeria. *International Journal of Innovative Research & Development, 7*(10), 69–79.

Obani, I. P., Obani, Z. I., Anaeto, F. C., & Akroh, T. O. (2025). Public-private collaborations in waste management: Evaluating policy effectiveness and governance models in Nigeria. *Journal of Integrity Ecosystems and Environment, 3*(2), 25–53.

Ogwueleka T. C., & Naveen, B. P. (2021, November). Activities of informal recycling sector in North-Central, Nigeria. Energy Nexus, 1, 100003. https://doi.org/10.1016/j.nexus.2021.100003

Okafor, C. C., Ibekwe, J. C., Nzekwe, C. A., Ajaero, C. C., & Ikeotuonye, C. M. (2022). Estimating emissions from open-burning of uncollected municipal solid waste in Nigeria. *AIMS Environmental Science, 9*(2), 140–160. https://doi.org/10.3934/environsci.2022011

Orike, S., & Alalibo, T. J. (2019). Comparative analysis of computer network protocols in wireless communication technology. *International Journal of Electronics Communication and Computer Engineering, 10*(3), 76–85.

Rahman, W., Islam, R., Hasan, A., Bithi, N. I., Hasan, M. M., & Rahman, M. M. (2022). Intelligent waste management system using deep learning with IoT. *Journal of King Saud University - Computer and Information Sciences, 34*(5), 2072–2087.

Risfendra, R., Ananda, G. F., & Setyawan, H. (2024). Deep learning-based waste classification with transfer learning using EfficientNet-B0 model. *Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi), 8*(4), 535–541. https://doi.org/10.29207/resti.v8i4.5875

Samreen, S., Agarwal, M. K., Gautam, A. K., & Khajanchi, Y. (2024). Comprehensive review of solid waste management strategies and disposal approaches. *Multidisciplinary Reviews, 6*, 2023ss076. https://doi.org/10.31893/multirev.2023ss076

Sami, K. N., Amin, Z. M. A., & Hassan, R. (2020). Waste management using machine learning and deep learning algorithms. *International Journal on Perceptive and Cognitive Computing, 6*(2), 97–106. https://doi.org/10.31436/ijpcc.v6i2.165

Sharma, D. K., Bharti, Upadhayay, U., & Pandey, T. (2024). Deep learning approaches for automated waste classification and sorting. *International Journal for Research in Applied Science and Engineering Technology, 12*(4), 3593–3600. https://doi.org/10.22214/ijraset.2024.60018

Srivatsan, K., Dhiman, S., & Jain, A. (2021). Waste classification using transfer learning with convolutional neural networks. *IOP Conference Series: Earth and Environmental Science, 775*(1), 1–9.

Tamuno-omie J. A., Oborkhale, L. I., & Omijeh, B. O. (2023). Leveraging transfer learning with a modified ResNet-50 model for enhanced solid waste classification. *Global Scientific Journal, 11*(10), 195–202.

UNEP - UN Environment Programme. (2024, February 24). *Global waste management outlook 2024*. Retrieved May 22, 2025, from https://www.unep.org/resources/global-waste-management-outlook-2024

Wang, C., Qin, J., Qu, C., Ran, X., Liu, C., & Chen, B. (2021). A smart municipal waste management system based on deep-learning and Internet of Things. *Waste Management, 135*, 20–29.

Xia, W., Jiang, Y., Chen, X., & Zhao, R. (2022). Application of machine learning algorithms in municipal solid waste management: A mini review. *Waste Management & Research, 40*(6), 609–624.

Yang, M., & Thung, G. (2016). Classification of trash for recyclability status. *CS229 Project Report*, 1–6. https://www.semanticscholar.org/paper/Classification-of-Trash-for-Recyclability-Status-Thung-Yang/c90811082924011c73fea6252f42b01af9076f28

Zisopoulos, F. K., Steuer, B., Abussafy, R., Toboso-Chavero, S., Liu, Z., Tong, X., & Schraven, D. (2023). Informal recyclers as stakeholders in a circular economy. *Journal of Cleaner Production, 415*, 137894. https://doi.org/10.1016/j.jclepro.2023.137894