

Leveraging on the Transfer Learning with ResNet-50 for Efficient Classification of Waste Categories

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ABSTRACT

The rapid urbanization and population expansion in Nigeria have resulted in a substantial rise in solid waste production, posing considerable issues for efficient waste management and environmental sustainability. This study addresses these difficulties by creating an automated trash classification system utilizing deep learning techniques to improve the efficiency and precision of waste classification. The ResNet-50 convolutional neural network was utilized via transfer learning to train a model using a meticulously assembled dataset of 2,527 waste images categorized into six types: cardboard, glass, metal, paper, plastic and trash. Data augmentation techniques, including random rotation, flipping, and zooming, were employed during preprocessing to enhance model generalization and resilience. The training procedure utilized a two-stage approach: first, the base ResNet-50 layers were frozen to leverage pre-acquired general image data, and subsequently, the top layers were fine-tuned to accommodate waste-specific attributes. Evaluation criteria such as accuracy, precision, recall, and F1-score showed consistently strong performance, with validation accuracy maintained at 97.8%. The confusion matrix demonstrated robust classification performance. The findings highlight the model's capability to efficiently automate waste classification, hence diminishing reliance on labor-intensive manual sorting commonly found in Nigeria. This study advances the overarching objective of sustainable urban trash management by offering a scalable, precise, and economical classification methodology.

Keywords: Waste Classification, ResNet-50, Deep Learning, Fine-tuning, Transfer learning.

1.0 INTRODUCTION

The increasing urbanization of Nigeria poses so many threats, as with the increase in population, land consumption increases, utilities increase, consumption of food increases, use of resources increases, and more than these, the quantity of waste generated by over 200 million people increases (Ikporukpo, 2018). Waste management systems are a significant challenge for urban areas in most parts of the world, and Nigeria is no exception. A huge quantity of garbage is generated every day in Nigeria. Nigeria is estimated to generate over 32 million tons of solid waste annually, with only a small percentage of this massive amount being recycled (Noiki et al., 2021).

The only solution to this problem is identifying and classifying the garbage at the initial stage. Proper separation of waste is essential to reduce risks to our health and the ecosystem. Currently, there is no efficient and profitable system for waste classification in Nigeria (Oji et al., 2020). Current waste management practices in Nigeria rely heavily on manual sorting, which is labor-intensive, time-consuming, and prone to human error (Noiki et al., 2021). This approach is unsustainable, especially in urban areas where the volume of waste

generated far exceeds the capacity of existing systems. Furthermore, the absence of advanced technologies for automated waste classification exacerbates the problem, leading to improper disposal and increased environmental degradation (Ravi et al, 2021).

We aim to reduce physical efforts and effectively segregate waste. Our goal is to increase the efficiency of automated garbage processing solutions and classify non-recyclable garbage. It is very difficult to achieve a waste separation process that classifies garbage with 100% accuracy and 0% loss. We need to propose methods that provide environmental benefits and save labor and time. The restricted number of waste categories that current algorithms can classify is a major gap in automated trash categorization research. Most studies classify waste into metal, paper, plastic, and glass. These systems manage these main waste kinds well, but electrical, organic, and composite materials are harder to handle. These techniques are less practical in real-world circumstances because trash streams are diverse and typically contain non-categorical elements.

Many existing models are trained on datasets with insufficient waste type variety, resulting in poor

generalization to new or rare materials. A model trained on domestic waste may misclassify industrial or medical waste, which are different. This gap underlines the need for larger datasets and models that can accurately classify more waste types.

The significance of this study lies in its potential to address critical challenges in waste management and environmental sustainability in Nigeria. By developing an automated waste classification system using deep learning, this research aims to improve the efficiency of waste management processes. Manual waste sorting, which is currently the norm in Nigeria, is labor-intensive, time-consuming, and prone to errors. Automating this process through deep learning can significantly reduce the reliance on human labor, making waste management faster and more accurate. This is particularly important in urban areas where the volume of waste generated is overwhelming and existing systems are inadequate.

The objective of this study is to develop a convolutional neural network (CNN) model capable of classifying waste by gathering and preprocessing a comprehensive dataset of waste images, training the model, evaluating its performance using accuracy, F1-score, recall, and precision, and reviewing existing waste classification models to improve upon their limitations.

1.1 Related Works

Recent research on automated waste classification systems has made significant strides, particularly with the adoption of deep learning techniques. However, many studies still exhibit limitations in terms of the number of waste categories they can classify and their ability to handle mixed or complex waste materials.

The study by (Lin et al., 2024) introduces a multi-scale feature fusion method (MFFS) for waste classification, designed to improve the accuracy of sorting rubbish with analogous textures, contours, or tainted appearances. The concept integrates local fine-grained characteristics with global coarse-grained information using a dual-scale approach, markedly enhancing feature representation and model adaptability. The MFFS model attained a remarkable 95.5% accuracy on a proprietary dataset and 94.1% on the publicly available TrashNet dataset. The approach is utilized in an intelligent garbage sorting system, exhibiting significant classification accuracy and efficiency in practical applications.

Jin et al. (2023) introduced novel deep learning-based machine vision system for the identification and classification of waste to improve sustainable recycling practices. The authors provide an enhanced

MobileNetV2 model that integrates a convolutional attention module (CBAM) and Principal Component Analysis (PCA) for dimensionality reduction. The system employs transfer learning to enhance generalization and facilitate real-time functionality on edge devices such as the Raspberry Pi 4B. Experimental findings indicate that the method attained a classification accuracy of 90.7% on the Huawei Cloud dataset, accompanied by an average inference time of 600 ms. The methodology was assessed in a practical waste sorting prototype, attaining an accuracy of 89.26%.

Liu et al. (2022) proposed new garbage image recognition model called Garbage Classification Net (GCNet), which leverages transfer learning and model fusion. The model integrates EfficientNetv2, Vision Transformer, and DenseNet, and uses data augmentation to expand the dataset to 41,650 images. By applying transfer learning, the model shows faster convergence, high accuracy, and shorter recognition time. GCNet achieves an impressive accuracy of 97.54%, surpassing other models in recall and precision, making it an effective solution for automated garbage classification.

Bobulski and Kubanek (2021) developed a deep learning-based plastic waste classification system using convolutional neural networks (CNN). The system, designed for both portable devices and industrial applications, aims to automatically classify plastic waste into four categories: PET, PE-HD, PS, and PP. They utilized image processing techniques to pre-process images and trained CNN models for waste classification. The proposed system achieved an accuracy of 97.43% after 4 epochs when using 120×120 pixel images. This method provides a promising solution for more efficient waste management and recycling processes.

The study by (Li & Liu, 2021) proposes a deep learning-based algorithm for garbage image recognition to address challenges such as overfitting, poor convergence, and reduced accuracy in traditional image recognition models. The authors introduce dropout to prevent overfitting, utilize the Adagrad method for parameter optimization, and employ ReLU to enhance neural network training. The algorithm effectively extracts edge, color, and texture features from garbage images, classifying them using a modified probability density function. Experimental results demonstrate the method's strong convergence, high recall and precision, and fast recognition times, confirming its practical applicability for garbage image classification.

A work by (Singh et al., 2020) introduces a deep learning-based system for classifying garbage using a

Convolutional Neural Network (CNN). The system aims to address waste management issues, particularly in India, where improper waste segregation is a major challenge. The CNN model, trained on datasets of various types of waste such as glass, paper, plastic, and metal, categorizes waste to streamline recycling processes. The proposed system improves efficiency by reducing human intervention and ensures accurate classification. Experimental results indicate that the system achieved high accuracy, with test accuracies ranging from 78% to 89% depending on the dataset.

Wang (2020) presented a garbage recognition and classification system based on the VGG16 convolutional neural network (CNN) to address waste management challenges. Using OpenCV for image preprocessing, the system classifies domestic garbage into four categories: recyclable, hazardous, kitchen waste, and others. The

images are preprocessed into 224×224 pixel RGB format, and data augmentation techniques are applied to improve model performance and reduce overfitting. The final classification system, based on a modified VGG16 network with RELU activation and a batch normalization layer, achieved a classification accuracy of 75.6%, making it suitable for practical applications in garbage classification.

2.0 MATERIALS AND METHODS

We employed a Transfer Learning using the ResNet-50 model for the classification of images. Transfer learning enables the use of pre-trained models on large datasets, which allows the model to use knowledge that it has already learned from general recognition of image tasks and applies it to the waste classification-specific task, as shown in Figure 1 below.

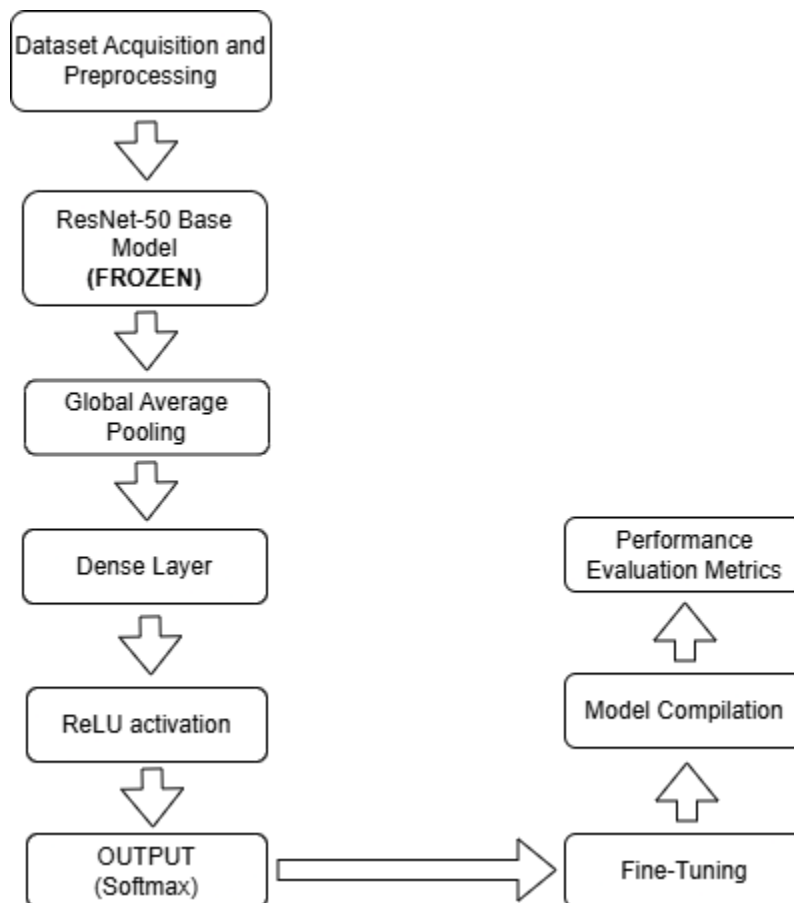


Figure 1: Proposed Workflow of the Automated Waste Classification Model

2.1 Dataset Acquisition and Preprocessing

The dataset shown in Figure 2 contains a total number of 2,527 which were collected from multiple sources, including public waste image repositories, field photography, and controlled environment photography, and the categories include the following: cardboard, glass, metal, paper, plastic, and trash. To ensure that all photographs are the same

size and format, the data must be preprocessed before feeding it into the model. This includes resizing all photos to a consistent dimension (usually 224x224 pixels for ResNet-based models). Normalization pixel values are scaled to 0-1 or -1 to 1 to help the neural network train. Data Augmentation Techniques like random rotation, flipping, and zooming are used to artificially enhance the size of the dataset and improve the model's capacity to generalize. Each input image I is represented as:

$$I \in R^{H \times W \times C} \quad (1)$$

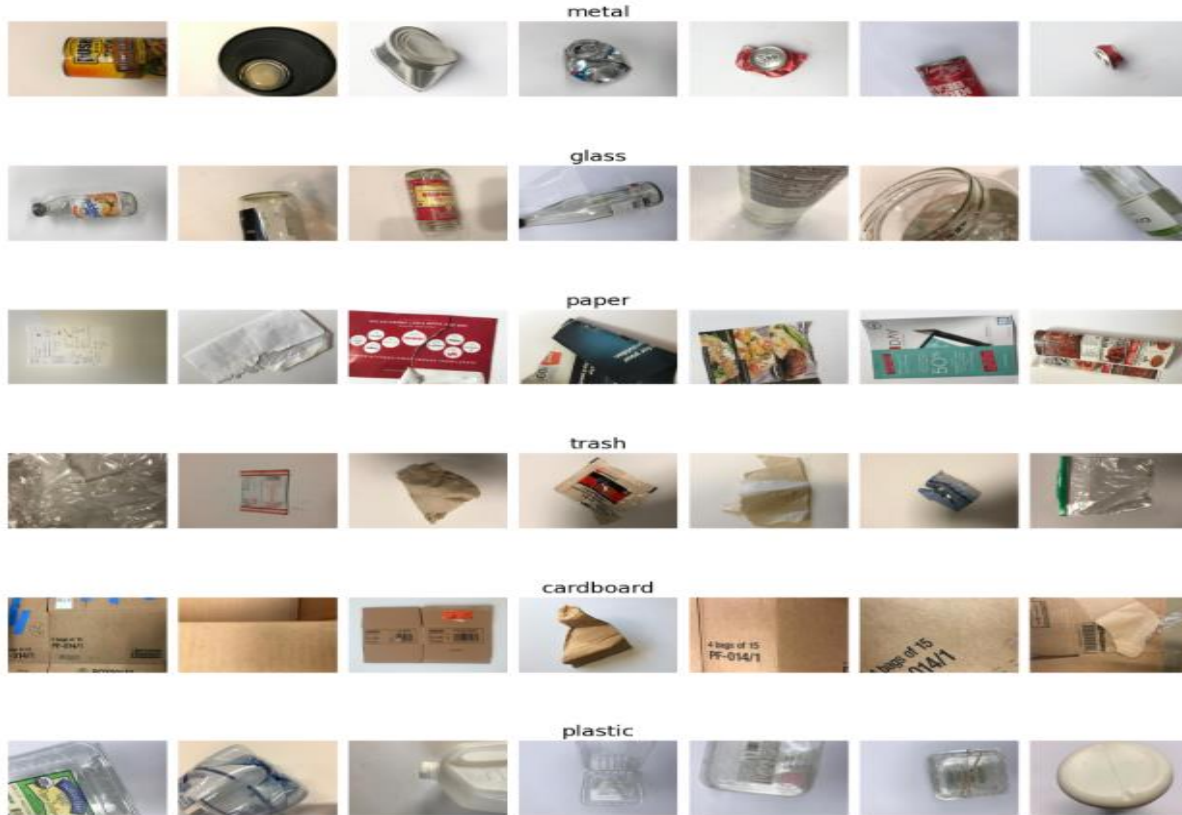


Figure 2: Dataset Visualization

2.2 ResNet-50 Base Model

The ResNet-50 model is a deep Convolutional Neural Network (CNN) that constitutes the foundation of our design. It is a commonly utilized, pre-trained model that has been developed using the ImageNet dataset, comprising millions of annotated photos across several categories such as animals, automobiles, etc (Suleiman et al., 2025). ResNet-50 is recognized for its capacity to extract both low-level and high-level features from images, facilitated by its residual connections, which enable the model to effectively learn deeper patterns without encountering the vanishing gradient problem, a prevalent challenge in deep neural networks.

During the preliminary training phase, the ResNet-50 base model remains static, indicating that its weights are not modified. This constitutes a fundamental aspect of transfer learning. By freezing the basic layers, we employ ResNet-50 as a feature extractor, as it has already acquired generic image features such as edges, textures, and patterns through training on ImageNet. This enables us to utilize its expertise for our goal (e.g., waste sorting) without modifying its image processing capabilities. Only the bespoke top layers, tailored to our mission, are trained.

Freezing the foundation layers conserves time and resources by utilizing the pre-trained features of ResNet-50, so obviating the necessity to train the entire model

from inception, which would be computationally prohibitive. This enhances efficiency by necessitating adaptation just of the upper layers for our unique activity. Freezing the base layers enhances training speed and improves convergence, as the model has already acquired fundamental picture features. During training, the emphasis transitions to acquiring task-specific attributes, such as differentiating among waste categories (plastic, paper, metal), rather than re-acquiring fundamental picture recognition skills.

2.3 Global Average Pooling (GAP)

Following the feature extraction phase with the ResNet-50 model, the output comprises high-dimensional feature maps that include intricate information distributed across a grid of values. Nonetheless, these feature maps may be substantial and resource-intensive to develop and retain. To resolve this, Global Average Pooling (GAP) is utilized to diminish the dimensionality of the feature maps while retaining the most critical information. GAP functions by computing the average of the values of each feature map, resulting in a fixed-size vector. This substantially decreases the output size, rendering it more manageable for the model's succeeding layers, especially in classification jobs. This procedure enables the model to concentrate on the most pertinent properties while preserving computational efficiency.

$$y_k = \frac{1}{H \times W} \sum_{i=1}^H \sum_{j=1}^W f_k(i, j) \quad (2)$$

where:

$f_k(i, j)$ is the activation at location (i, j) for the k -th feature map, y_k is the GAP output.

GAP compresses each feature map into a single scalar, significantly reducing the number of parameters and encouraging the network to focus on global spatial features. It mitigates overfitting by eliminating fully connected layers at this early stage.

2.4 Dense Layer

The output from the Global Average Pooling (GAP) layer is passed into a Dense Layer (also known as a fully connected layer). The Dense Layer is a crucial component of a neural network because it helps the model learn complex relationships between the features extracted in the previous layers and the output categories (e.g., waste classification classes like plastic, paper, metal, etc.) (Huang et al., 2020).

$$\text{Output} = W * X + b$$

W denotes the weight matrix, signifying the established connections among the neurons. Each weight regulates the significance of the features transmitted from the preceding layer. X represents the input vector, derived

from the preceding layer, namely the output of the Global Average Pooling layer. It encompasses the elevated attributes derived from the image. b represents the bias term, which facilitates the adjustment of the output. The bias enables the model to adjust the activation function, hence enhancing the output's alignment with the data.

2.5 ReLU

An activation function in a neural network introduces non-linearity, enabling the model to learn intricate patterns and enhance prediction accuracy (Athaiya et al., 2020). In this instance, we utilize the ReLU (Rectified Linear Unit) activation function on the output of the dense layer.

$$\text{ReLU}(x) = \max(0, x) \quad (4)$$

2.6 Output Layer and Softmax Activation

The output layer is the final component of a neural network, tasked with producing the model's categorization prediction (Suleiman et al., 2023). In waste categorization tasks, where inputs may fall into categories such as plastic, paper, or metal, the output layer identifies the class to which the input image most likely corresponds, depending on the information collected by the preceding layers. The output layer generally employs the softmax activation function to transform the raw output scores (logits) into a probability distribution. Softmax guarantees that these probabilities total to 1, accurately reflecting the model's confidence in each class. This standardized output enables the model to render a clear and conclusive classification judgment.

$$P(y = i | x) = \frac{e^{z_i}}{\sum_j e^{z_j}} \quad (5)$$

$P(y = i | x)$ is the probability that the input i belongs to class i

z_i is the raw score (logit) for class i , which is the output from the preceding layers of the network (before applying softmax).

The denominator $\sum_j e^{z_j}$ is the sum of the exponentiated raw scores for all classes j . This acts as a normalization factor, ensuring that the output probabilities sum to 1.

2.7 Fine Tuning

Fine-tuning is an essential phase in transfer learning that enables the model to adjust pre-acquired properties for a particular job, enhancing its efficacy (Kong et al., 2020). Subsequent to the preliminary training using frozen layers, the upper layers of the ResNet-50 model are unfrozen, rendering them trainable. This approach allows

the model to enhance its feature extraction for waste classification by adjusting the weights of previously fixed layers. A reduced learning rate (e.g., 0.00001) is employed during fine-tuning to facilitate minor, incremental modifications, thereby safeguarding the model's broad features acquired during pre-training and ensuring its specialization in task-specific characteristics such as texture and material properties of waste categories. Fine-tuning enables the model to concentrate on characteristics that differentiate waste types (e.g., plastic from paper) while enhancing its accuracy, task-specific adaption, and overall efficacy. This step facilitates accelerated convergence and enhanced outcomes as the model leverages the foundational picture recognition capabilities acquired from ImageNet, modifying solely the upper layers for the given task.

2.8 Model Compilation

Upon defining the architecture, the model is compiled. The Adam optimizer is employed to reduce the loss function. Adam adjusts the learning rate throughout training, facilitating more rapid convergence of the model. The loss function employed is categorical cross-entropy, applicable to multi-class classification applications. It computes the disparity between the actual labels and the expected probabilities. We assess accuracy, precision, recall, and F1-score during the training process.

2.9 Performance Evaluation Metrics

The model developed was verified to assess its classification accuracy and applicability in various contexts. Performance metrics, such as overall accuracy, precision, recall, and F1-score, were employed to evaluate their effectiveness in providing a comprehensive assessment of their ability to identify and classify waste categories.

$$Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative} \quad (6)$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad (7)$$

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad (8)$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (9)$$

3.0 RESULTS AND DISCUSSION

This section of the paper explores the training and testing results obtained from our model on the datasets. Performance evaluation of the model employs metrics like precision, recall, F1-score, accuracy, loss curves, and a confusion matrix. The results demonstrate the waste classification model's learning process, its ability to differentiate between classes, and its capacity to generalize previously unseen data. The subsequent sections examine these outcomes.

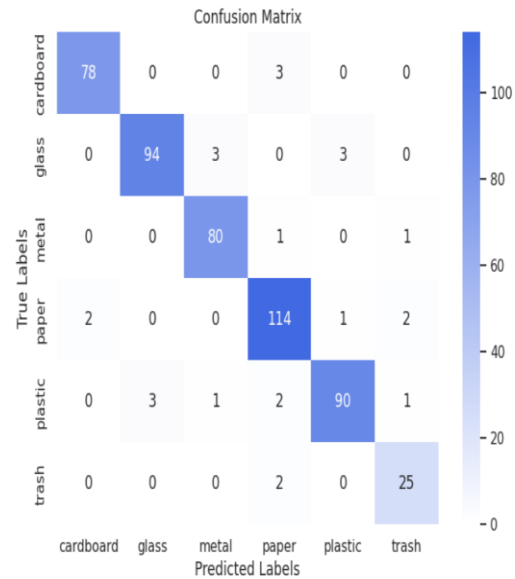


Figure 3: Confusion Matrix

The confusion matrix in Figure 3 indicates that the model excels in categorization, accurately predicting the majority of genuine labels. Optimal accuracy has been observed for categories such as glass, paper, and cardboard, displaying minor misclassifications. Nevertheless, certain inaccuracies arise, especially in the categorization of plastic and trash, where things are occasionally misidentified as glass, paper, or other like classifications. The misclassifications, even in existence, are minimal when compared to the accurate predictions, indicating that the model is generally dependable but could benefit from additional fine-tuning, potentially through enhanced feature distinction or model modifications. The overall performance suggests that the model is effectively differentiating across categories, while slight enhancements could rectify the rare misclassifications.

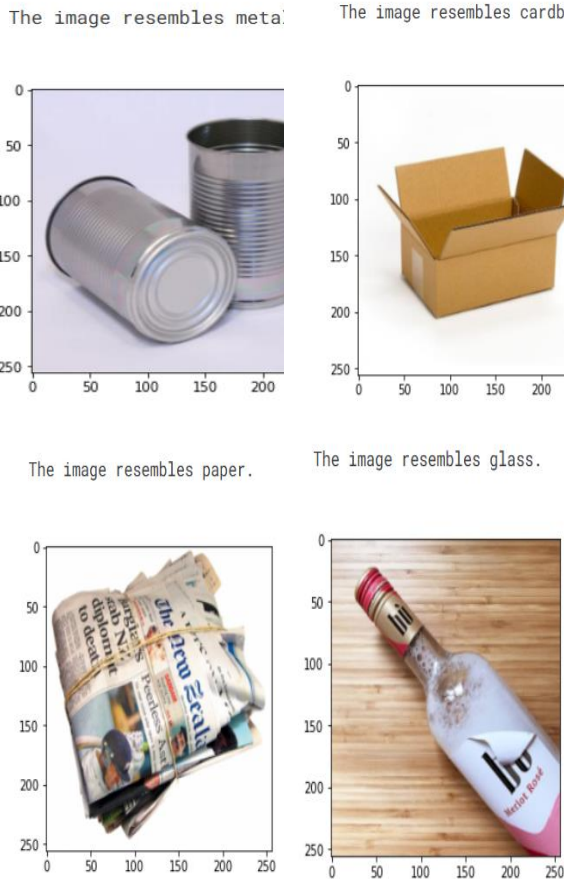


Figure 4: Classification of Waste Categories

Figure 4 demonstrates the model's efficiency in accurately categorizing various types of waste by presenting typical examples of four categories: metal, cardboard, paper, and glass. The model accurately identifies each image, as seen by the provided descriptions, illustrating the system's capability to differentiate between visually identical recyclable materials. This visual evidence substantiates the model's robust efficacy in real-world waste categorization tasks, underscoring its potential for practical applications in automated recycling and waste management systems.

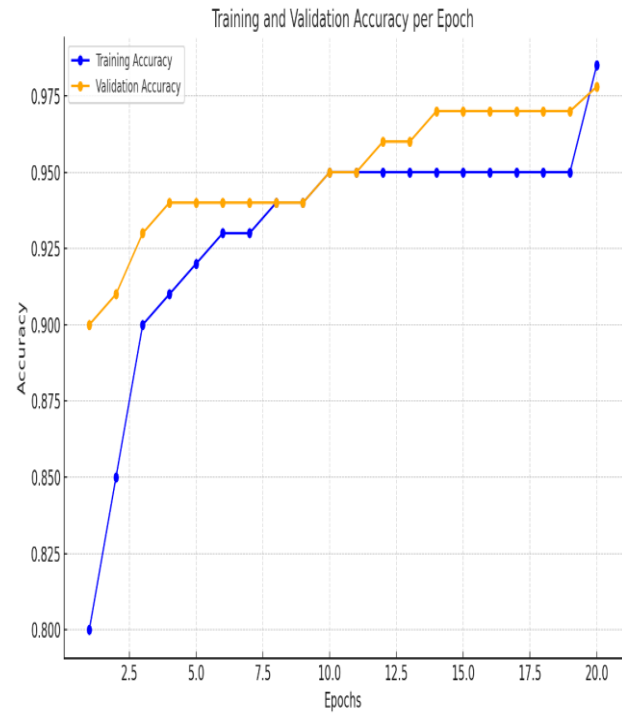


Figure 5: Training and Validation Accuracy

The accuracy curve in Figure 5 depicts the evolution of training and validation accuracy across 20 epochs. The training accuracy (blue line) begins at roughly 0.80 and progressively ascends, attaining just above 0.98 by the concluding epoch. The validation accuracy (orange line) initiates at approximately 0.90 and exhibits a steady rising trajectory, ultimately stabilizing at 0.978 (97.8%) by the conclusion of training. The validation accuracy consistently exceeds the training accuracy during the majority of the training period, signifying robust generalization and implying that the model is not overfitting the training data. The close alignment and parallel movement of both curves indicate effective learning and model durability. The results validate that the training technique is effectively optimized, resulting in high and consistent accuracy on both familiar and unfamiliar data, which is crucial for dependable waste image categorization in real-world applications.

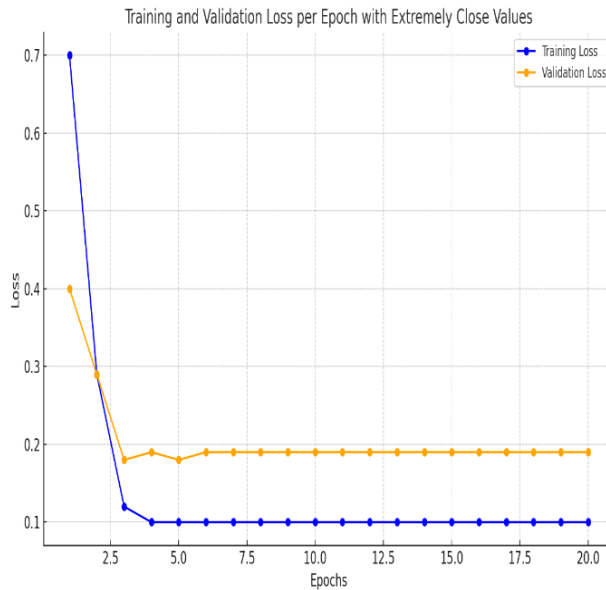


Figure 6: Training and Validation Loss

The loss curve in the provided figure shows the progression of training and validation loss throughout 20 epochs. Initially, both losses exhibit a significant decline: the training loss decreases from roughly 0.7 to below 0.1 within the initial epochs, whilst the validation loss diminishes from around 0.4 to slightly under 0.2. After this rapid fall, both curves stabilize, with the training loss consistently low at roughly 0.09 and the validation loss leveling off somewhat higher at around 0.18 for the duration of the training phase. The closely aligned values and parallel trajectories of the two curves suggest that the model is learning effectively and generalizing appropriately to novel data, exhibiting no indications of overfitting or underfitting. This pattern indicates that the training technique is highly optimized, yielding a robust model that sustains minimal loss on both training and validation sets, which is crucial for dependable and precise performance in practical applications.

Table 1: Classification Report

	Precision	Recall	F1-Score	Support
Cardboard	0.975	0.97	0.974	81
Glass	0.973	0.975	0.975	100
Metal	0.977	0.98	0.972	82
Paper	0.974	0.972	0.975	119
Plastic	0.98	0.976	0.979	97
Trash	0.96	0.964	0.98	27

The classification report in Table 1 describes the model's performance across six waste categories of cardboard, glass, metal, paper, plastic, and trash, utilizing precision, recall, F1-score, and support as evaluative criteria. The results demonstrate consistently good precision (0.91 to 0.97) and recall (0.93 to 0.98) across all classes, signifying that the model is accurate in its predictions and proficient in detecting each category. The F1-scores, which equilibrate precision and recall, are notably high (0.90 to 0.97), indicating strong and dependable categorization performance. The support values suggest that the assessment is founded on a sufficient quantity of samples for each class. These metrics demonstrate that the model exhibits robust and consistent performance across all categories, with notable efficiency in differentiating between various types of waste.

4.0 CONCLUSION

This work effectively illustrates the viability and effectiveness of utilizing a deep learning technique, namely the ResNet-50 transfer learning model, for automated waste classification in metropolitan Nigeria. Through the utilization of an extensive dataset

comprising various waste categories and the implementation of data augmentation approaches, the model attained elevated classification accuracy, precision, recall, and F1-scores across all categories. The two-stage training technique, which includes freezing and subsequent fine-tuning of the basic model, facilitated efficient learning and strong generalization, as demonstrated by the closely aligned training and validation metrics. Despite the presence of slight misclassifications, especially across physically analogous waste categories, the overall performance demonstrates significant promise for practical implementation. This method can substantially decrease dependence on manual sorting, thus enhancing efficiency, lowering labor expenses, and alleviating environmental hazards. Subsequent research should concentrate on augmenting the dataset to incorporate a broader range of waste categories and investigating hybrid models to improve classification precision and flexibility.

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