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Optimizing Solid Waste Classification with Deep Learning: A Study on the Effectiveness of Pretrained Models

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Abstract:

The rapid growth in population, urbanization, and economic activities has led to a significant increase in solid waste generation, raising critical environmental concerns. Proper disposal and recycling of municipal solid waste are vital for sustainable development, aligning with the United Nations Sustainable Development Goals. Previous studies in this domain faced challenges such as the unavailability of real-world waste data and insufficient model generalization for diverse waste categories. This study explores the optimization of solid waste classification by employing transfer learning with pre-trained convolutional neural network models to address these limitations. The study utilizes the RealWaste dataset, consisting of 4,752 images categorized into nine waste classes (paper, plastic, glass, vegetation, food organics, cardboard, textile trash, metal, and miscellaneous trash), to assess the performance of three pre-trained convolutional neural network models: ResNet50, DenseNet121, and EfficientNet-B0. Originally trained on the ImageNet dataset, these models were fine-tuned to classify waste materials. The ResNet50 model achieved an impressive training accuracy of 100% and a validation accuracy of 92.24%, followed by DenseNet121 with a training accuracy of 99.99% and a validation accuracy of 91.82%, and EfficientNet-B0 with a training accuracy of 99.83% and a validation accuracy of 91.19%. Among the evaluated models, DenseNet121 achieved the highest test accuracy of 94.33%, followed by ResNet50 at 91.82% and EfficientNet-B0 at 91.4%, demonstrating the superior performance of DenseNet121 in the waste classification task. These results underscore the capability of deep learning to automate waste categorization with high precision. The research findings highlight the potential of transfer learning with pre-trained convolutional neural networks for reliable waste classification across multiple categories, fostering efficient recycling systems and contributing to a circular economy, thereby supporting global sustainability efforts.

Keywords: Convolutional Neural Network, Transfer Learning, Solid Waste Classification, Deep Learning.

1. Introduction

Solid waste encompasses a wide variety of waste types, including household waste, industrial waste, biomedical waste, agricultural waste, and electronic waste. Municipal Solid Waste (MSW), in particular, consists of everyday items such as paper, plastic, glass, vegetation, food organics, cardboard, metals, textiles, and miscellaneous trash. With the increasing urbanization and industrialization rate, solid waste generation has reached alarming levels, posing significant environmental and societal challenges (Malik et al., 2022).MSW generation is projected to increase dramatically from 2.3 billion tonnes in 2023 to 3.8 billion tonnes by 2050, highlighting a pressing global challenge. Despite this surge, only 19% of MSW is recycled worldwide, reflecting a critical gap in effective waste management practices (Iván, 2024).

Solid waste management is a multifaceted problem involving collection, segregation, recycling, and disposal. Proper management of MSW has become a critical challenge, with improper waste disposal leading to environmental degradation, resource wastage, and health hazards. Unsustainable waste management practices like open dumping and incineration often exacerbate these effects by releasing harmful pollutants into the environment. Traditional waste treatment methods, including landfilling and combustion, while reducing visible waste, often contribute to greenhouse gas emissions and leachate formation, undermining efforts to achieve global sustainability. Moreover, handling solid waste exposes workers and nearby populations to various health risks, including respiratory diseases from inhaling toxic fumes, skin infections from direct contact, and vector-borne diseases caused by pests breeding in waste (Vinti et al., 2021). Effective waste management strategies, such as recycling and composting, are essential to minimize these adverse impacts. Recycling, in particular, aligns with several United Nations Sustainable Development Goals (SDGs), including SDG 12 (Responsible Consumption and Production) and SDG 13 (Climate Action), by promoting resource efficiency, reducing landfill dependency, and curbing environmental contamination (Lenkiewicz, 2016). Furthermore, by reducing waste accumulation and pollution, recycling helps mitigate the adverse effects of solid waste disposal on public health and fosters a cleaner, healthier society.

Effective waste classification is a pivotal step in sustainable waste management as it enables targeted recycling processes, reduces contamination, and minimizes the volume of waste sent to landfills. Traditional methods of waste sorting are often labor-intensive, error-prone, and inefficient, especially given the sheer volume and diversity of waste materials. Artificial intelligence (AI), machine learning (ML), and deep learning (DL) have emerged as transformative technologies for automating and optimizing various aspects of waste management (Majchrowska et al., 2022). Image classification is a fundamental task in computer vision, involving automatically categorizing images into predefined classes. In the context of waste management, image classification plays a pivotal role in identifying and sorting various types of waste materials, such as paper, plastic, glass, and organic matter. Deep learning, a subset of ML, uses neural networks with multiple layers to automatically learn features from data, mimicking the human brain's ability to recognize patterns (Yu, 2023). Convolutional neural networks (CNNs), a specialized class of deep learning models, excel in processing image data, making them ideal for tasks like waste classification (Chen et al., 2021).

Employing machines powered by deep learning not only reduces the dependency on manual labor but also ensures consistent, scalable, and high-accuracy performance. This transformative approach is a critical step toward efficient waste management systems, enabling real-time sorting and recycling while minimizing human error and health risks. However, prior research in waste classification has encountered notable challenges, such as the lack of real-world waste datasets, and inadequate model generalization across diverse waste categories. This study aims to address these challenges by utilizing a dataset comprising real waste items captured in authentic landfill environments, ensuring greater relevance and applicability to real-world scenarios. To further improve model generalization, the research leverages transfer learning with pre-trained CNN models, which have already demonstrated exceptional performance on large-scale image datasets. Pre-trained CNNs are chosen over custom-built models because of their ability to extract rich, hierarchical features while reducing training time and performing well even with limited labeled data, making them ideal for complicated tasks such as waste classification. The study specifically aims to evaluate and compare the performance of ResNet50, EfficientNet-B0, and DenseNet121 models in accurately categorizing waste materials.

The structure of the paper is as follows: Section 2 provides an extensive review of related work in waste classification. Section 3 details the methodology employed for addressing waste classification tasks. Section 4 presents the results along with a discussion of the findings. Finally, Section 5 concludes the study and highlights potential directions for future research.

2. Literature Review

This section provides an overview of related works, focusing on the application of deep CNNs, the role of transfer learning, and the effectiveness of pre-trained models in addressing the challenges associated with automated waste classification.

Ramírez et al. (2020) employed transfer learning with Google's Inception-V3 CNN and a novel semi-supervised learning approach to achieve high accuracy with minimal human image labeling. Their method uses a three-round retraining process, comparing a baseline approach to two improved methods: half-worst and Gaussian Mixture Model (GMM). The system achieves 88% accuracy, which represents 94% of the performance achieved using a fully labeled dataset, demonstrating the effectiveness of their approach.

Feng and Tang (2020) proposed an intelligent garbage classification system using a convolutional neural network. The authors utilized transfer learning with the Inception-v3 model, achieving a 95.33% accuracy in classifying six types of office waste. The study addresses the growing problem of garbage pollution and offers a cost-effective solution for automated waste sorting. Parameter optimization for the embedded system was also explored to maximize efficiency and accuracy.

Atikuzzaman et al. (2021) trained and compared different CNN architectures: ResNet (ResNet34, ResNet50, ResNet101, ResNet152) and VGG (VGG11, VGG16, VGG19), using a dataset of 1989 trash images categorized into six classes (cardboard, glass, metal, paper, plastic, and trash). ResNet152 achieved the highest accuracy (93.86%) among all ResNet models, while VGG16 achieved the highest accuracy (90.49%) among the VGG models. The study highlights the potential of CNNs for automating waste management and suggests future improvements by expanding the dataset and handling multiple trash items within a single image.

Ling and Tianyi (2021) proposed designing and implementing a smart trash can leveraging CNNs and transfer learning for automated waste sorting. The system integrates image recognition capabilities, utilizing a fine-tuned Inceptionv3 model trained on a custom dataset comprising 1,200 images of various garbage types. Experimental results highlight the system's high accuracy and operational efficiency, with CNNs achieving an average recognition rate between 82.64% and 89.6%. The application of transfer learning further improved the performance, increasing accuracy from 85.32%

to 92.2%. These findings underscore the effectiveness of transfer learning in optimizing waste classification systems.

Srivatsan et al. (2021) applied transfer learning, leveraging the pre-trained weights of MobileNetV2, ResNet34, and DenseNet121 models on the CompostNet dataset, to achieve exceptional waste classification accuracy across seven categories. DenseNet121 achieved the highest accuracy at 96.43%, closely followed by ResNet34 and MobileNetV2, which both recorded accuracies of 96.27%. This research addresses the pressing global issue of inefficient waste management, striving to improve resource recovery and support sustainable practices.

Masand et al. (2021) introduced ScrapNet, a new, larger, and more diverse dataset for trash classification, addressing the limitations of existing datasets. The authors compare various deep learning architectures, including ResNet, ResNext, and EfficientNet, finding that a modified EfficientNet B3 model achieves state-of-the-art accuracy (92.87%) on ScrapNet and 98% on the standard TrashNet dataset. The study also explores sub-classifying plastic waste as recyclable or non-recyclable using deep learning, achieving 89.21% accuracy. The improved accuracy and efficiency of the proposed model offer a viable solution for the recycling industry's challenges in waste classification. The ScrapNet dataset is intended to become a new benchmark for future research in this area.

Yuan and Liu (2022) proposed a novel hybrid deep learning model for trash classification. The model uses a two-stream approach, initially categorizing images into broader groups (metal, paper, plastic; or cardboard, glass, trash) before final classification. It leverages transfer learning from a pre-trained ResNeXt model and achieves a 98.5% accuracy on the TrashNet dataset, surpassing existing methods. The authors analyze the model's performance using class activation maps, explaining its superior accuracy.

Chazhoor et al. (2022) benchmarked six pre-trained CNN architectures: AlexNet, ResNet50, ResNeXt, SqueezeNet, MobileNetV2, and DenseNet for classifying plastic waste types based on their resin codes using transfer learning. The study utilized the WaDaBa dataset, addressing class imbalance through under-sampling. ResNeXt achieves the highest accuracy (87.44%) within 13 minutes. MobileNetV2 demonstrated comparable accuracy with faster training. AlexNet and SqueezeNet exhibited lower accuracy and struggled with validation loss reduction. The models were evaluated based on accuracy, loss, Area Under Curve (AUC), and Receiver Operating Characteristic (ROC) curve.

Dawood (2023) explored the application of deep convolutional neural networks (DCNNs), focusing on CNN and VGG-16 models with transfer learning, to enhance the accuracy of garbage classification for sustainable waste management. Utilizing the TrashNet dataset, the research evaluates the performance of these models in terms of accuracy, loss, and computational efficiency. The results indicate that while VGG-16 achieves higher training accuracy (99.55%) compared to CNN (96.29%), it comes at the cost of increased computational complexity. In contrast, CNN provides a balanced approach, offering competitive accuracy with greater efficiency. This study aims to advance more effective and sustainable waste sorting solutions by addressing the trade-offs between accuracy and computational requirements.

Poudel and Poudyal (2023) explored CNNs and transfer learning to classify waste images into seven categories: cardboard, glass, metal, organic, paper, plastic, and trash. The study utilized the Stanford

TrashNet dataset, augmented with an organic class, totaling 3242 images for training and validation. The researchers compared the performance of several pre-trained CNN models (InceptionV3, InceptionResNetV2, Xception, VGG19, MobileNet, ResNet50, and DenseNet201), finding that DenseNet201 achieved the highest validation accuracy (95.05%) and performed well in classifying most waste categories. Their work aims to improve waste management efficiency by automating waste sorting, ultimately contributing to a cleaner environment.

Sayed et al. (2024) introduced an intelligent waste classification model built on the InceptionV3 deep learning architecture, enhanced with a multi-objective beluga whale optimization algorithm for hyperparameter tuning. The model employed random oversampling and data augmentation techniques to address the class imbalance in the TrashNet dataset. It achieved a remarkable accuracy of 97.75% in waste material classification, outperforming existing state-of-the-art models. A comprehensive evaluation of the model's performance and components highlights substantial improvements in efficiency and accuracy, contributing to advancements in sustainable waste management practices.

The literature review highlighted the potential of pre-trained CNN models for waste classification tasks, demonstrating their ability to achieve impressive accuracy in categorizing waste materials. However, most existing studies predominantly rely on datasets of six waste categories in pristine forms, limiting their applicability to real-world scenarios and affecting model generalization across diverse waste categories. To address these gaps, this research utilizes techniques such as transfer learning, fine-tuning, and data augmentation to improve model performance and robustness. In addition, the study utilizes a dataset comprising real waste images from actual landfill environments to enhance model applicability in practical scenarios.

3. Research Methodology

This section outlines a comprehensive methodology encompassing dataset details, preprocessing techniques, and the architectural specifications of the three CNN based pre-trained models utilized in this study. The approach leverages transfer learning to enhance model performance, ensuring efficient and accurate waste classification.

3.1 Dataset Description

For this study, we employed the RealWaste image classification dataset created by (Sam Single, 2023) , which contains 4,752 high-resolution (524x524 pixels) color images of waste materials collected in a landfill environment. The dataset is organized into nine distinct categories: Cardboard, Glass, Metal, Food Organics, Paper, Plastic, Miscellaneous Trash, Textile Trash, and Vegetation. This dataset provided a comprehensive and realistic basis for developing a solid waste classification model using transfer learning techniques. The total number of images in each class is shown in Table 1.

Table 1. Number of images in each class

Class	Image Count
Cardboard	461
Food Organics	411
Glass	420

Metal	790
Miscellaneous Trash	495
Paper	500
Plastic	921
Textile Trash	318
Vegetation	436

Fig. 1 illustrates the sample images from the RealWaste dataset utilized for training models with labels indicating the type of waste material.

Fig.1. Sample images from the RealWaste dataset

3.2 Data Preprocessing

To ensure that the train, validation, and test sets accurately represent all waste classes and avoid biases associated with image ordering, stratified sampling was employed. This method inherently shuffles and splits the dataset while preserving the proportional distribution of each class across the subsets. Initially, the dataset was divided into 80% training and 20% test sets. Subsequently, the training set was further divided into 70% training and 10% validation sets, maintaining the class label proportions throughout. The final split resulted in 70% for training, 10% for validation, and 20% for testing, ensuring a balanced representation for robust model evaluation and generalization. Given the limited number of images in the dataset, data augmentation was applied to the training set to mitigate the risk of overfitting. Augmentation techniques included random rotations, flips, zooming, and slight shifts, enhancing the model's generalization capability. Importantly, no augmentations were applied to the validation and test sets to ensure an unbiased evaluation of the models on unseen data. All images were resized to 384x384 pixels to maintain a consistent square shape, aligning with the input requirements of the ResNet50, DenseNet121, and EfficientNet-B0 architectures. This resizing step ensures compatibility across all three pre-trained models while preserving the structural integrity of the waste images. Class weights were generated and applied during training to correct dataset class imbalances and prioritize underrepresented classes. Additionally, class label mapping was implemented to accurately associate class weights with the corresponding one-hot encoded labels during training. This comprehensive preprocessing pipeline ensures optimal data preparation for leveraging the capabilities of ResNet50, DenseNet121, and EfficientNet-B0 in the solid waste classification task.

3.3 Model Architecture

This study employs three pre-trained CNN architectures—ResNet50, DenseNet121, and EfficientNet-B0—to enhance the performance of waste classification tasks. Pre-trained on the ImageNet dataset, these architectures are widely recognized for their robust feature extraction and strong performance across diverse image classification challenges. The deep neural network ResNet50, consisting of 50 layers, introduces residual connections to address the vanishing gradient problem, enabling the training of very deep networks (He et al., 2015). It excels at extracting hierarchical features through its layered design. DenseNet121, comprising 121 layers, connects each layer to every other layer in a feed-forward manner, promoting feature reuse and efficient gradient flow, which improves learning efficiency (Huang et al., 2018). Designed using a compound scaling method, EfficientNet-B0 balances network depth, width, and resolution, achieving high accuracy with fewer parameters and computational resources compared to traditional architectures (Tan & Le, 2020).

Building and training complex CNN models from scratch can lead to inconsistent performance on smaller datasets due to challenges like overfitting and uneven class distributions. To address this, transfer learning was employed, which allows pre-trained models to be fine-tuned to adapt to specific datasets. In transfer learning, earlier layers that capture general features are typically retained, while deeper layers are fine-tuned to learn task-specific features. This approach makes the models more robust and less prone to overfitting. For this study, ResNet50, DenseNet121, and EfficientNet-B0 architectures were loaded without their top classifier layers to accommodate the dataset's nine waste classes. The input shape was set to (384, 384, 3) to align with the dataset's image dimensions. A balanced strategy was adopted to freeze the earlier layers, which capture broad and general features while fine-tuning the latter layers to adapt to the specific waste classification task.

The pre-trained models were extended with custom layers for enhanced task suitability. After feature extraction using the pre-trained models, a global average pooling (GAP) layer was added to reduce the spatial dimensions of the feature maps. To mitigate overfitting, a dropout layer was incorporated for regularization. Finally, a dense layer with a softmax activation function was added to classify the inputs into the nine distinct waste classes. The models were compiled using the Adam optimizer with a learning rate of 0.0001. The loss function was set to categorical cross-entropy, ideal for multi-class classification tasks like waste type identification. Early stopping was implemented to monitor validation loss and halt training if no improvement was observed within a specified number of epochs to further mitigate overfitting. Additionally, a learning rate reduction on the plateau was used to decrease the learning rate when the validation loss plateaued, enabling finer adjustments during the later stages of training. The models were trained for 30 epochs with a batch size of 32 to strike a balance between gradient stability and computational efficiency. Further, the performance of these models was evaluated using standard metrics, including accuracy, precision, recall, and F1-score.

4. Results and Discussion

The performance of the ResNet50, DenseNet121, and EfficientNetB0 architectures was systematically evaluated for the waste classification task, considering their training, validation, test accuracies, and the corresponding loss metrics.

Table 2. Accuracy comparison of three pre-trained models

Model	Train Accuracy	Validation Accuracy	Test Accuracy
ResNet50	100%	92.24%	91.82%
DenseNet121	99.99%	91.82%	94.33%
EfficientNetB0	99.83%	91.19%	91.40%

Table 2 compares the training, validation, and testing accuracies of ResNet50, DenseNet121, and EfficientNetB0. During training and validation, ResNet50 achieved a training accuracy of 100% and a validation accuracy of 92.24%, with corresponding losses of 0.0021 and 0.3450, respectively. Early stopping restored weights from the 9th epoch, indicating efficient convergence. DenseNet121 completed the full 30 epochs, restoring weights from the 21st epoch, and achieved a training accuracy of 99.99% and a validation accuracy of 91.82%, with training and validation losses of 0.0047 and 0.3001, respectively. EfficientNetB0, trained for 30 epochs with weights restored from the 28th epoch, attained a training accuracy of 99.83%, a validation accuracy of 91.19%, and training and validation losses of 0.0127 and 0.3254, respectively. Regarding test performance, DenseNet121 outperformed the other models with a test accuracy of 94.33% and the lowest test loss of 0.2586. ResNet50 followed closely with a test accuracy of 91.82% and a test loss of 0.2998, while EfficientNetB0 achieved a test accuracy of 91.40% and a test loss of 0.3552. The performance variation curves for ResNet50, DenseNet121, and EfficientNetB0 for training and validation data accuracy and loss with epochs are shown in Figures 2-4.

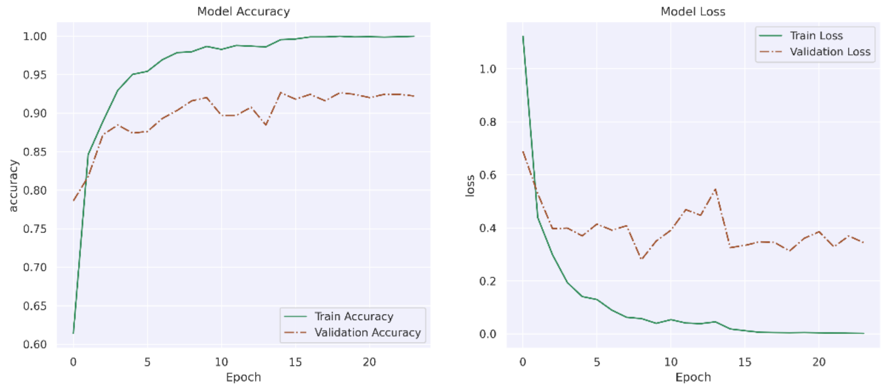

Fig. 2. Training and validation accuracy and loss curves for ResNet50

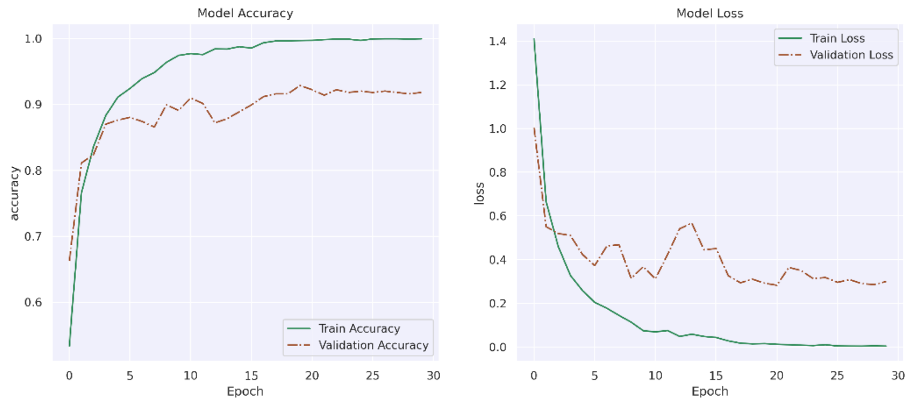

Fig. 3. Training and validation accuracy and loss curves for DenseNet121

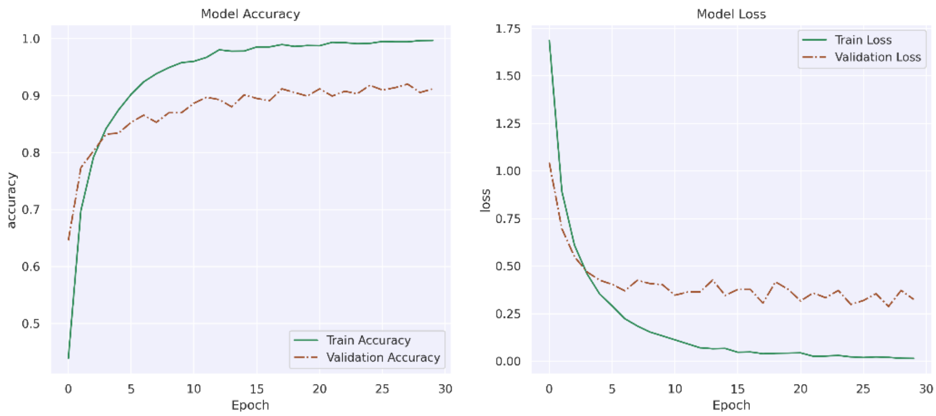

Fig. 4. Training and validation accuracy and loss curves for EfficientNetB0

Tables 3-5 show performance metrics for ResNet50, DenseNet121, and EfficientNetB0, including precision, recall, and F1-score. The classification report of test data for ResNet50 demonstrates a solid overall performance in waste classification, with balanced metrics across most categories. Classes like

Glass, Vegetation, and Food Organics exhibit high precision, recall, and F1-scores, indicating the model's strong ability to classify these categories. However, Miscellaneous Trash shows a notable drop in recall, suggesting that some instances were misclassified, likely due to overlaps with other categories. Similarly, Plastic and Cardboard show slight variability in precision and recall, reflecting occasional confusion. DenseNet121 consistently demonstrated better generalization, with high precision, recall, and F1-scores for key categories such as Cardboard, Glass, Textile Trash, and Paper. However, Food Organics and Miscellaneous Trash show slightly lower recall, suggesting that some instances were misclassified, likely due to shared features with other categories. EfficientNetB0 demonstrated satisfactory performance, achieving high F1-scores for categories such as Glass, Paper, and Vegetation indicating strong precision and recall for these waste types. Cardboard and Metal also performed well, though Cardboard showed slightly lower recall, suggesting occasional misclassification. However, it struggled in categories like Food Organics and Miscellaneous Trash, where lower recall impacted its overall performance. Overall, DenseNet121 slightly edges out the others in balancing precision and recall.

Table 3. Performance Metrics of ResNet50 Model

Class	Precision	Recall	F1-Score
Cardboard	0.88	0.96	0.92
Food Organics	0.97	0.90	0.94
Glass	0.98	0.95	0.96
Metal	0.92	0.93	0.92
Miscellaneous Trash	0.97	0.72	0.83
Paper	0.90	0.95	0.92
Plastic	0.88	0.95	0.91
Textile Trash	0.95	0.89	0.92
Vegetation	0.91	0.99	0.95

Table 4. Performance Metrics of DenseNet121 Model

Class	Precision	Recall	F1-Score
Cardboard	0.96	0.98	0.97
Food Organics	0.99	0.84	0.91
Glass	0.95	0.98	0.96
Metal	0.94	0.97	0.96
Miscellaneous Trash	0.90	0.88	0.89
Paper	0.97	1.00	0.99
Plastic	0.95	0.92	0.93
Textile Trash	0.98	0.91	0.94

Vegetation	0.88	1.00	0.94

Table 5. Performance Metrics of EfficientNetB0 Model

Class	Precision	Recall	F1-Score
Cardboard	0.96	0.88	0.92
Food Organics	1.00	0.80	0.89
Glass	0.98	0.94	0.96
Metal	0.87	0.98	0.92
Miscellaneous Trash	0.91	0.81	0.86
Paper	0.88	0.99	0.93
Plastic	0.92	0.89	0.90
Textile Trash	0.93	0.89	0.91
Vegetation	0.86	1.00	0.93

The confusion matrices for the ResNet50, DenseNet121, and EfficientNetB0 models shown in Figures 5-7 reveal strong classification performance across most waste categories, with some variations in accuracy and misclassifications. All three models excel in categories like Metal, Glass, and Vegetation, showcasing their ability to distinguish well-defined features. ResNet50 demonstrates high accuracy but struggles slightly with miscellaneous trash, confusing it with food organics and plastic. DenseNet121 achieves strong results in most categories, with minimal misclassifications, but shows confusion between Vegetation and Food Organics. EfficientNetB0 also performs well but exhibits slight difficulty in distinguishing plastic from cardboard and metal. Across all models, visually or texturally similar categories, such as food organics and vegetation or plastic and miscellaneous trash, pose challenges, indicating areas where fine-tuning or additional data preprocessing may improve performance.

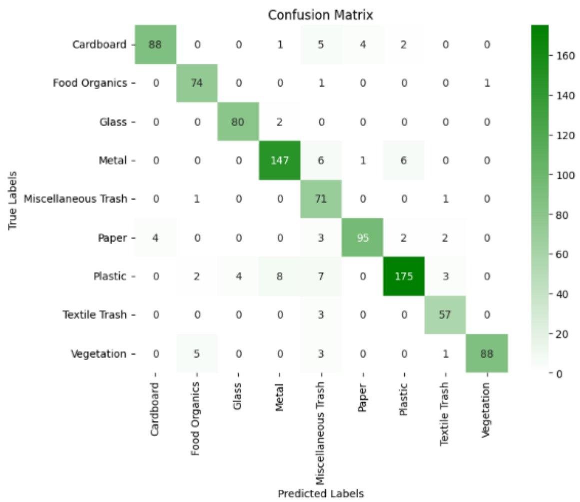

Fig. 5. Confusion matrix for ResNet50 model

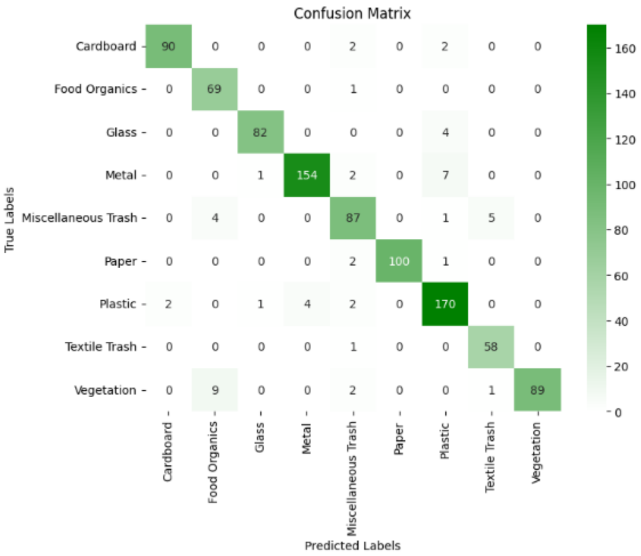

Fig. 6. Confusion matrix for DenseNet121 model

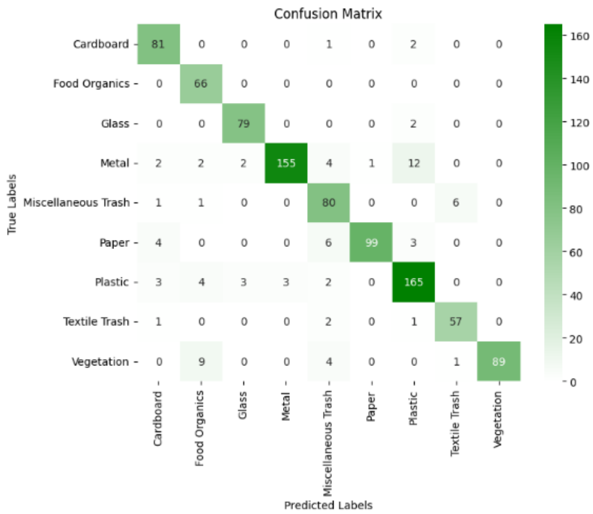

Fig. 7. Confusion matrix for EfficientNetB0 model

The results reveal several key insights into the comparative performance of the three pre-trained models. DenseNet121 emerged as the most robust model in the study, showing the highest test accuracy of 94.33% and the lowest test loss. Its strong generalization ability is attributed to its architecture, which preserves feature flow through dense connections, allowing for better feature reuse. The model did not exhibit early stopping, demonstrating stable learning even over prolonged training, which is particularly advantageous for tasks requiring comprehensive feature extraction. DenseNet121's balanced training and validation performance further underscore its reliability for waste classification. ResNet50 demonstrated efficient learning, benefiting from early stopping at an earlier epoch. This reflects its ability to capture meaningful patterns in the training data quickly. While ResNet50's test accuracy (91.82%) was competitive, its performance suggests that it is well-suited for scenarios where training time is critical, though further regularization could improve generalization. EfficientNetB0, known for its computational efficiency, performed well but slightly underperformed with a test accuracy of 91.40% and higher test loss compared to the other models. The validation and test results of EfficientNetB0 suggest it may be more sensitive to dataset variability, requiring additional optimization, such as better hyperparameter tuning or enhanced data augmentation, to improve its generalization. Nonetheless, its lightweight design makes it an appealing choice for resource-constrained environments.

The results demonstrate that the proposed DenseNet121 model outperformed state-of-the-art models discussed in the literature review, achieving an impressive accuracy of 94.33%. Unlike existing studies, which predominantly relied on datasets with limited waste categories, this research utilized a real-world dataset of 4,752 images categorized into nine diverse waste classes. In comparison, a fine-tuned InceptionV3 model proposed by Ling and Tianyi (2021), trained on a custom dataset of 1,200 images achieved an accuracy of 92.2%. Another study by Atikuzzaman et al. (2021) reported that a ResNet152 model obtained the highest accuracy of 93.86%, using a dataset of 1,989 trash images categorized into six classes. Other studies achieved an accuracy of 92.87% with an EfficientNet-B3 model proposed by Chazhoor et al. (2022) and 87.44% with a ResNeXt model proposed by (Masand et al., 2021). The superior performance of the DenseNet121 model underscores its ability to address real-world waste classification challenges effectively, demonstrating the benefits of employing transfer learning techniques.

5. Conclusion

This study evaluated the performance of three pre-trained models—ResNet50, DenseNet121, and EfficientNetB0—for the waste classification task using the RealWaste dataset. The dataset comprises 4,752 images collected in a real landfill environment, categorized into nine waste types. Among the three state-of-the-art pre-trained models, DenseNet121 emerged as the most suitable for waste classification due to its superior generalization capabilities and overall performance across training, validation, and testing phases. Its dense connectivity architecture enabled effective feature reuse and hierarchical feature extraction, resulting in the highest test accuracy of 94.33% and the lowest loss. This makes DenseNet121 particularly well-suited for real-world waste management scenarios that require precise and reliable classification.

ResNet50 demonstrated strong performance with rapid convergence, achieving competitive results efficiently. Its ability to learn effectively within fewer epochs makes it a practical choice for scenarios where computational time is critical. Meanwhile, EfficientNetB0 provided a lightweight and resource-efficient solution, offering solid performance with minimal computational requirements, making it an appealing option for deployment in environments with constrained resources.

This research highlights the strengths and trade-offs of these pre-trained models in waste classification. DenseNet121 is recommended for tasks requiring high accuracy and robust generalization, ResNet50 for applications needing quick training and deployment, and EfficientNetB0 for settings where computational efficiency is paramount. Future work could explore ensemble methods to combine the strengths of these models and expand the dataset to include images from diverse waste management environments. This would enhance the robustness and applicability of the models, further supporting advancements in automated waste sorting and management systems.

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