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Comparative Optimization of EfficientNetB3, MobileNetV2, and ResNet50 for Waste Classification

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Abstract

Waste management is an important challenge in protecting the environment and public health. Improperly managed waste can cause pollution and hinder the recycling process. This study aims to classify waste based on images by optimizing three deep learning architectures, namely EfficientNetB3, MobileNetV2, and ResNet50, to determine the model with the best performance. The dataset comes from the Kaggle platform, consisting of 4,650 images in six categories: battery, glass, metal, organic, paper, and plastic. The research stages include preprocessing, data augmentation, model development, and evaluation using accuracy, precision, recall, and F1-score metrics. The results show that EfficientNetB3 with the Adam optimizer achieved the best performance with 93% accuracy, followed by ResNet50 with 91%, while MobileNetV2 ranged from 70–73% depending on the optimizer. Variations in optimizers were found to affect model performance, while data augmentation improved generalization capabilities, especially in classes with limited samples. This research confirms the potential of deep learning methods in supporting automatic waste classification systems and provides a basis for the development of technology-based waste management systems in the future.

Keywords: Deep Learning, Optimization, Waste Classification

1. Introduction

Waste management in Indonesia is becoming an increasingly urgent issue due to rapid population growth and urbanization. Poorly managed waste can cause air, soil, and water pollution, reduce quality of life, and hinder the recycling process (Julia Lingga et al., 2024). One crucial aspect of waste management is the process of sorting waste, which is still mostly done manually and inefficiently. Improper sorting has a direct impact on the effectiveness of recycling (Aziz et al., 2025).

In this context, artificial intelligence (AI)-based technology, particularly Deep Learning, has shown great potential for automating the waste classification process (Pieters, 2025). Deep Learning architectures such as Convolutional Neural Networks (CNN) are capable of accurately and efficiently recognizing and classifying waste types from images (Muslihati et al., 2024), although model performance is greatly influenced by data variation, lighting conditions, shape, and texture of the waste (Sihabillah et al., 2025).

Previous studies have demonstrated the application of CNNs for waste classification using various architectures, ranging from AlexNet, LeNet, and VGG16 for basic models (Muslihati et al., 2024), to pre-trained models through transfer learning such as ResNet50, InceptionV3, and MobileNetV2 (Akbar, 2024). The transfer learning and fine-tuning approaches have been proven to significantly improve accuracy compared to training from scratch, while the use of lightweight models such as MobileNet and EfficientNet enables implementation on devices with limited computational resources (Pieters, 2025). In addition to static image classification, an object detection-based approach was also developed using the TensorFlow Object Detection API and transfer learning (Fathurrahman & Akbar, 2024). Data augmentation techniques are also widely used to overcome limited dataset constraints and improve model generalization capabilities (Syaifudin, 2024). In addition, experiments with various optimizers, such as Adam, AdamW, and SGD, have been shown to affect model performance (Anggara et al., 2023; Irfan et al., 2022; Sarasuartha Mahajaya et al., 2024), making the selection of the appropriate optimizer an important part of the optimization process (Sarasuartha Mahajaya et al., 2024).

However, most studies still have limitations, such as a limited number of waste classes, small dataset sizes, or a focus on only one architecture without comparing the performance of several models at once. There have not been many studies that systematically optimize and compare several Deep Learning architectures with various optimizers to determine the best combination for multi-class waste classification. This is the research gap addressed by this study.

Based on this, this study aims to implement and compare three popular Deep Learning architectures, namely EfficientNetB3, MobileNetV2, and ResNet50, in a multi-class waste classification task. In addition, this study also evaluates the effect of using various optimizers, such as Adam, AdamW, and SGD, on the performance of each architecture. Thus, this study focuses on finding the best combination of architecture and optimizer that can produce optimal performance. The results of this study are expected to contribute to the selection of the appropriate architecture and optimization strategy for building an automatic waste classification system, which in turn can support more effective and efficient waste processing.

2. Research Methods

The methods used in this study include several main stages, namely data collection, data pre-processing, data augmentation, model architecture, Optimization, and model evaluation.

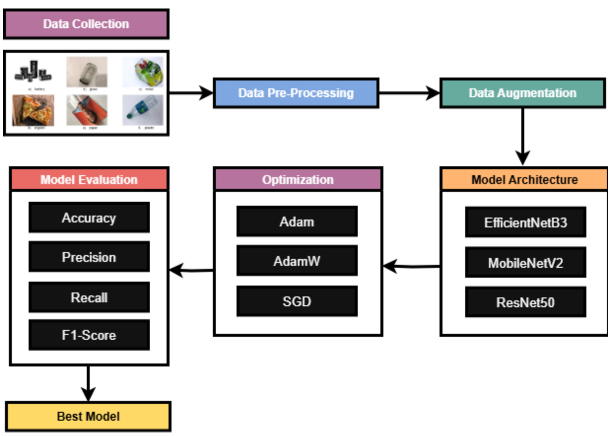

Figure 1. Research Methods

1. Data Collection

The dataset used in this study was obtained from the Kaggle platform. This dataset consists of images of waste classified into several categories, namely batteries, glass, metal, organic, paper, and plastic, as shown in Figure 2. The total dataset consists of 4,650 images, with each category having 775 images, the details of which are shown in Table 1.

For model training and validation purposes, the dataset was divided into 80% for training data, 10% for testing data, and 10% for validation data.

Figure 2. Samples in each Class

Table 1. Image Distribution

Class	Number of Images
Battery	775
Glass	775
Metal	775
Organic	775
Paper	775
Plastic	775
Total Number	4.650

2. Data Preprocessing

The preprocessing stage is carried out to improve data quality and prepare images so that they can be optimally processed by deep learning models. All images are resized to 224 × 224 pixels to match the input dimensions of EfficientNetB3, MobileNetV2, and ResNet50, converted to RGB format, and normalized to the range [0,1] to aid training stability and accelerate convergence. In addition, the waste category labels are converted to one-hot encoding format so that they can be used in multi-class classification.

3. Data Augmentation

To increase the diversity of training data and prevent overfitting, this study applies data augmentation to waste images. Augmentation is especially important when the dataset is limited, as it provides additional visual variation so that the model can learn more generally from new data (Rianto & Santosa, 2025).

The augmentation techniques used include random rotation to generate different orientations, zooming for scale variation, horizontal flipping so that the model recognizes objects in mirror orientation, shear transformation to add shape variation, and brightness adjustment to improve the model's resilience to lighting differences.

4. Model Architecture

The model architecture stage in this study includes the application of deep learning architecture and configuration for the classification of six categories of waste. The three architectures used are EfficientNetB3, MobileNetV2, and ResNet50, each of which has different characteristics in terms of parameter efficiency and network depth.

EfficientNetB3 was chosen because of its efficient architecture with compound scaling, which provides high accuracy with fewer parameters (Agustina, 2025). MobileNetV2 was chosen because of its lightweight design, which is ideal for real-time applications on devices with limited resources (Agustin et al., 2025). ResNet50 was chosen because of its residual block's superior ability to extract complex features from multi-varied images such as waste (Munthe & Akbar, 2025).

5. Optimization Model

Model optimization is performed to improve training performance and stability in each deep learning architecture. This study tests three optimization algorithms, namely Adam, AdamW, and Stochastic Gradient Descent (SGD), to compare their effectiveness in accelerating convergence while producing the best accuracy. Adam is known to converge quickly and be stable on various datasets (Khadafi & Zer, 2025), AdamW separates weight decay from gradient updates, providing more effective regularization (Pranatha et al., 2024), while SGD provides good control over the parameter update process and supports model generalization (Saptadi et al., 2025).

In addition to optimizer selection, this study also applies a regularization strategy by adding a dropout layer at the end of the network to reduce the risk of overfitting. The training process is regulated through hyperparameter tuning with a learning rate configuration of 0.0001, a batch size of 64, and a maximum of 200 epochs. To prevent overfitting, the early stopping technique is used with monitoring of the validation loss, so that training can be stopped early when the model performance does not show significant improvement. This combination of optimization, regularization, and hyperparameter adjustment strategies is expected to produce an optimal model capable of generalizing well to the test data.

6. Model Evaluation

Model evaluation was conducted to assess the performance of each architecture in classifying six categories of waste. The evaluation process used separate validation and test data to ensure the model's generalization ability to new data. The metrics used included accuracy, precision, recall, and F1-score, which were the main indicators of classification performance. Here are the formulas and their explanations (Jannah et al., 2025).

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN}\ x\ 100\% \quad (1)$$

$$Precision = \frac{TP}{TP+FP}\ x\ 100\% \quad (2)$$

$$Recall = \frac{TP}{TP+FN}\ x\ 100\% \quad (3)$$

$$F1 - Score = \frac{2\ x\ (Recall\ x\ Precision)}{(Recall+Precision)}\ x\ 100\% \quad (4)$$

In addition, the best model is evaluated in more depth using a confusion matrix, which visualizes the distribution of predictions between classes, and ROC-AUC, which assesses the model's ability to distinguish between classes. The results of this evaluation form the basis for selecting the best model to be implemented in the automatic waste classification system.

3. Results and Discussion

This section presents the results of image classification experiments using three deep learning architectures—EfficientNetB3, MobileNetV2, and ResNet50—combined with several optimizers (Adam, AdamW, and SGD). The performance of each model is evaluated based on accuracy, precision, recall, and F1-score metrics to provide a comprehensive overview of its effectiveness.

1. Model Evaluation Results

Testing was conducted on all combinations of architectures and optimizers. The evaluation results are shown in Figures 3, 4, and 5, which visualize the comparison of model performance based on accuracy, precision, recall, and F1-score metrics. This presentation facilitates analysis of the performance differences between the tested architectures.

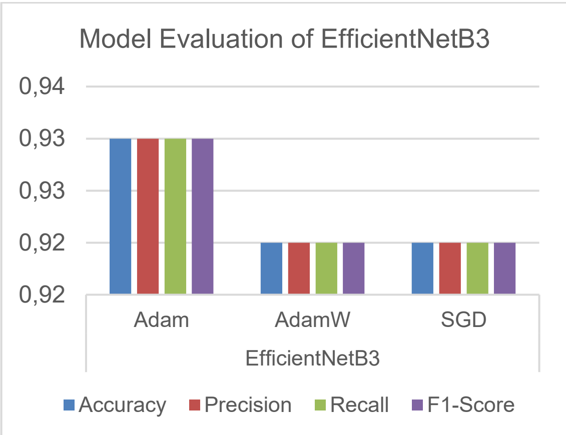

Figure 3. Model Evaluation of EfficientNetB3

Figure 3 shows the results of evaluating the performance of the EfficientNetB3 model with three optimizers. The results show that the Adam optimizer provides the best performance with accuracy, precision, recall, and F1-score values of 0.93. Meanwhile, AdamW and SGD produce slightly lower but consistent values, namely 0.92 on all evaluation metrics. This consistency indicates that the EfficientNetB3 architecture is quite stable. Although Adam provides a slight improvement, all three optimizers still produce competitive performance.

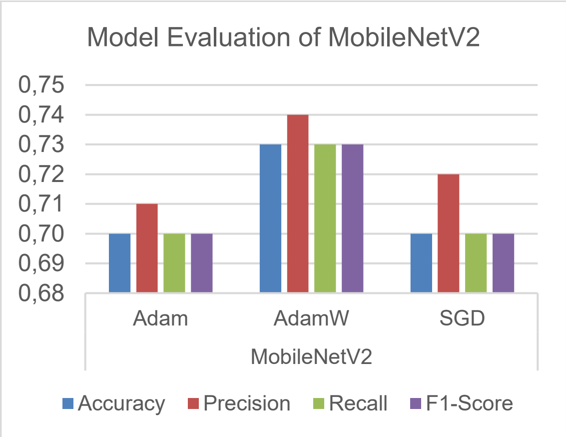

Figure 4. Model Evaluation of MobileNetV2

Figure 4 shows the results of evaluating the performance of the MobileNetV2 model with three types of optimizers. The graph shows that AdamW provides the best performance, with accuracy, recall, and F1-score values of 0.73, and precision of 0.74. Meanwhile, the Adam and SGD optimizers show relatively stable performance, each producing accuracy, recall, and F1-score of 0.70, with precision of 0.71 for Adam and 0.72 for SGD.

These results indicate that the choice of optimizer affects the performance of MobileNetV2, where AdamW is able to improve the model's ability to extract image features, resulting in more accurate predictions.

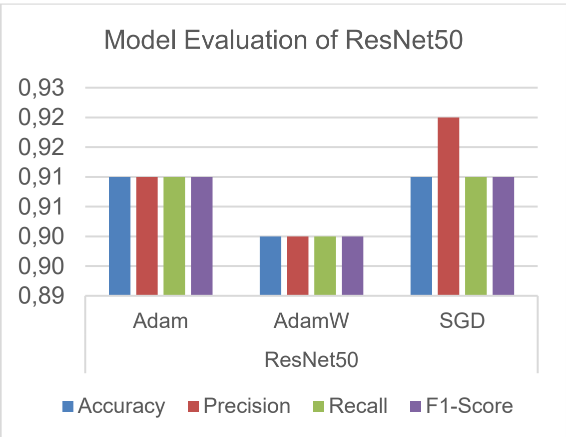

Figure 5. Model Evaluation of ResNet50

Figure 5 shows the performance of the ResNet50 model with three types of optimizers. For Adam, the model achieved an accuracy, recall, and F1-score of 0.91, with a precision of 0.91. Meanwhile, for SGD, the accuracy, recall, and F1-score were also 0.91, but the precision was slightly higher at 0.92. Meanwhile, AdamW shows consistent values for all metrics, namely 0.90. From these results, it can be seen that ResNet50 can perform classification well with all three optimizers, with SGD providing the best performance on the precision metric.

3. Optimizer Comparison Analysis

The use of the Adam optimizer provides consistently high performance on all three model architectures tested. EfficientNetB3 showed the best results with accuracy, precision, recall, and F1-score of 0.93, followed by ResNet50 with a score of 0.91, while MobileNetV2 lagged far behind with an accuracy of 0.70. This indicates that Adam is highly effective for more complex architectures such as EfficientNetB3 and ResNet50, while its performance is less optimal on lightweight architectures such as MobileNetV2.

The AdamW optimizer produces performance close to Adam on all models, but with a slight decrease in metric values. EfficientNetB3 recorded an accuracy of 0.92, ResNet50 recorded 0.90, and MobileNetV2 actually experienced an increase compared to Adam with an accuracy of 0.73. This shows that AdamW is more stable on lightweight architectures such as MobileNetV2, but is not as optimal as Adam on more complex models.

The SGD optimizer shows relatively stable performance on the EfficientNetB3 and ResNet50 models with accuracies of 0.92 and 0.91. However, the results on MobileNetV2 are less satisfactory with an accuracy of only 0.70. This indicates that the SGD optimizer requires more specific parameter adjustments, such as learning rate and momentum, in order to work optimally, especially on lightweight models. Compared to Adam and AdamW, SGD performance tends to be lower on this dataset.

4. Comparative Model Analysis

Based on the test results in Figures 3, 4, and 5, it can be seen that EfficientNetB3 with the Adam optimizer achieved the best performance with an accuracy, precision, recall, and F1-score of 0.93. ResNet50 ranks second with relatively stable performance in the range of 0.90–0.91, while MobileNetV2 shows much lower performance with an accuracy of around 0.70–0.73.

This difference can be explained by the complexity and representation capacity of each model. EfficientNetB3 is designed with a compound scaling approach that balances the depth, width, and resolution of the network so that it is more effective at capturing complex visual patterns in waste images. Meanwhile, MobileNetV2 is lighter and optimized for devices with computational limitations, so it tends to sacrifice accuracy. ResNet50 is still competitive because it has a residual learning architecture, but its performance is slightly below EfficientNetB3.

In terms of optimizers, Adam shows the best consistency in results for almost all models, especially EfficientNetB3. AdamW and SGD provide relatively similar performance, although slightly lower. This shows that the combination of the right architecture and the appropriate optimizer greatly affects the classification results.

Comparing the results of this study with previous studies is important to show the position and contribution of this study in the field of deep learning-based waste classification. Several previous studies have used various network architectures to solve similar problems, with varying accuracy results depending on the complexity of the architecture, the dataset used, and the training method. The following table summarizes a comparison of the accuracy of several studies relevant to this study.

Table 2. Comparison with Related Research

Researcher	Architecture	Accuracy
(Muslihati et al., 2024)	NasNet Mobile	82%
(Pieters, 2025)	CNN	52%
(Fathurrahman & Akbar, 2024)	SSD MobileNet V2 FPNLite 640x640	85%
(Akbar, 2024)	DenseNet169	92%
Proposed Method	**EfficientNetB3**	**93%**

Based on Table 2, it can be seen that the method proposed in this study, namely EfficientNetB3, is capable of providing the highest accuracy of 93%, surpassing previous studies that used DenseNet169 (92%), SSD MobileNet V2 FPNLite 640x640 (85%), NasNet Mobile (82%), and standard CNN (52%). This shows that the selection of the EfficientNetB3 architecture, which optimizes the balance between depth, width, and network resolution, is capable of providing better feature representation for waste classification tasks. Thus, this study makes a real contribution to improving the performance of deep learning-based waste classification, while strengthening its potential application in sustainable waste management systems.

5. Evaluation of the Best Model

Based on the test results, the EfficientNetB3 model with the Adam optimizer was selected as the best model. This model was able to achieve an accuracy, precision, recall, and F1-score value of 0.93, which was superior to other combinations of models and optimizers.

```
Classification Report:
              precision    recall  f1-score   support

     battery       0.99      0.95      0.97        77
       glass       0.89      0.88      0.89        77
       metal       0.88      0.91      0.89        77
     organic       1.00      0.99      0.99        77
       paper       0.96      0.97      0.97        77
     plastic       0.88      0.90      0.89        77

    accuracy                           0.93       462
   macro avg       0.93      0.93      0.93       462
weighted avg       0.93      0.93      0.93       462
```

Figure 6. Classification Report

Figure 6 shows the consistency of values across all metrics, confirming that this model is not only accurate but also balanced in recognizing all waste classes. This consistency is important because each type of waste has different characteristics and needs to be predicted with the same level of reliability. Further analysis was conducted using a confusion matrix, which provides a detailed overview of the distribution of prediction results for each class.

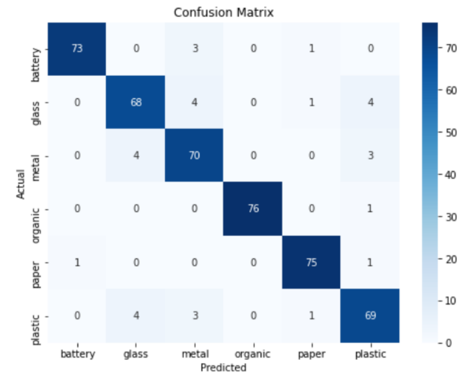

Figure 7. Confusion Matrix

The results show that most of the waste images were predicted correctly, although there were some classification errors in classes with similar visual characteristics. In addition, the model performance evaluation was also visualized through the ROC (Receiver Operating Characteristic) curve and AUC (Area Under Curve) values.

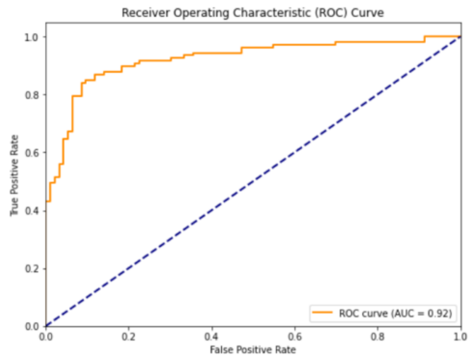

Figure 7. ROC Curve and AUC Value

Figure 7 shows the Receiver Operating Characteristic (ROC) curve of the EfficientNetB3 model, with an Area Under the Curve (AUC) value of 0.92. This high AUC value indicates that the model is able to distinguish between positive and negative classes with a very good level of reliability. The ROC curve, which is well above the baseline diagonal line, confirms that the model has balanced sensitivity and specificity, so it does not focus on just one specific metric. These results reinforce the findings from the confusion matrix that the model has consistent classification capabilities across various waste classes, making it reliable for implementation in automatic classification systems. As a supplement, several sample image predictions are also shown.

Table 1. Sample Results of Class Prediction

Prediction Class	Prediction Results
Battery	
Glass	
Paper	

Table 1 shows several examples of model prediction results on test images. It can be seen that the model is capable of classifying various types of waste with a high confidence level, reaching more than 95% in sample tests from three classes.

4. Conclusion

Based on the test results, several deep learning architectures, namely EfficientNetB3, MobileNetV2, and ResNet50, showed different capabilities in waste classification. EfficientNetB3 provided the best performance with the highest accuracy, precision, recall, and F1-score, indicating that this architecture is more effective in capturing complex waste image features. The use of different optimizers also affects model performance, with Adam and AdamW tending to converge faster than SGD. Thus, the combination of the EfficientNetB3 architecture and the appropriate optimizer can be implemented to build an accurate and efficient automatic waste classification system, supporting sustainable waste management.This study has several limitations, including the fact that the dataset used is still limited to six waste classes, the image variation in each class does not fully represent real conditions, and the computation time for some architectures is still quite high.

For further research, it is recommended to increase the number and variety of datasets to make the model more robust, explore other deep learning architectures or model combinations, and optimize computation time to facilitate the implementation of automatic waste classification systems in real-world environments.

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