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WASTE CLASSIFICATION USING TRANSFER LEARNING WITH MOBILENETV2 TO SUPPORT ENVIRONMENTAL MANAGEMENT

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Abstract— *Efficient waste management requires an accurate automatic classification system for organic and recyclable categories. This study aims to develop a deep learning-based waste classification model using the MobileNetV2 architecture with a transfer learning approach. The main contribution of this study lies in the modification of the architecture through fine-tuning techniques and the integration of a 0.5 dropout layer specifically designed to address the problems of overfitting and class imbalance in waste image data. Test results show that the optimized MobileNetV2 model significantly improves classification performance, achieving an accuracy of 93%. This proposed model is proven to be more adaptive and substantially superior compared to standard architectures and comparable architectures such as ResNet.*

Keywords: *Deep Learning, MobileNetV2, Transfer Learning, Waste Classification, Image Classification.*

Intisari— *Pengelolaan sampah yang efisien memerlukan sistem klasifikasi otomatis yang akurat untuk kategori organik dan daur ulang. Penelitian ini bertujuan mengembangkan model klasifikasi sampah berbasis deep learning menggunakan arsitektur MobileNetV2 dengan pendekatan transfer learning. Kontribusi utama penelitian ini terletak pada modifikasi arsitektur melalui teknik fine-tuning dan integrasi lapisan dropout 0,5 yang secara spesifik dirancang untuk mengatasi masalah overfitting serta ketidakseimbangan kelas pada data gambar sampah. Hasil pengujian menunjukkan bahwa model MobileNetV2 yang dioptimalkan berhasil meningkatkan performa klasifikasi secara signifikan dengan mencapai akurasi sebesar 93%. Model usulan ini terbukti lebih adaptif dan unggul secara substansial dibandingkan arsitektur standar maupun arsitektur pembanding seperti ResNet.*

Kata Kunci: *Klasifikasi Sampah, MobileNetV2, Transfer Learning, Pembelajaran Mendalam, Klasifikasi Citra.*

INTRODUCTION

The uncontrolled growth of global waste volume poses a serious challenge to environmental sustainability [1], [2], [3]. Conventional waste management, which relies on manual sorting, is often inefficient, time-consuming and subject to high human error [4], [5], [6], [7], [8], [9], [10]. Therefore, a fast and accurate automated classification system is needed to differentiate organic and recyclable waste [11], [12], [13], [14], [15], [16]. Several previous studies have explored the use of Deep Learning architectures for automatic waste classification. For example, research conducted by Akbar et al. [17] utilized the DenseNet169 architecture and achieved an accuracy and F1 score of 82%. Meanwhile, Bustamin et al. [18] applied transfer learning techniques using the ResNet-50 architecture with the Adam optimizer, resulting in an accuracy of 87.73%. Although these heavy-duty architectures are capable of detecting inorganic waste quite effectively, significant challenges remain in terms of computational efficiency, the risk of overfitting, and imbalanced accuracy performance in minority classes, particularly in balancing the organic and recyclable categories.

This is where the research gap, the primary focus of this study, lies. Large-scale models like ResNet-50 and DenseNet169 require high computational resources, but are not yet fully optimal in overfitting when faced with the characteristics of waste datasets with high visual imbalance. To address these limitations, this study provides a key contribution in the form of developing a lightweight yet high-performance waste classification model using a modified MobileNetV2 architecture.

The specific contribution of this study focuses on the application of transfer learning combined with fine-tuning techniques and the integration of a 0.5 dropout layer. This modification is intentionally designed to mitigate the risk of overfitting and align precision and recall performance for the organic and recyclable classes. Through this approach, this study offers an automatic classification solution that not only excels in accuracy but is also efficient and adaptive to support sustainable environmental management systems.

This research aims to develop an efficient waste classification system using a transfer learning approach. The main focus of this study is to modify the architecture of MobileNetV2 to improve the model's accuracy and generalization capabilities [19], [20], [21], [22], [23]. The contribution of this research lies in the use of fine-tuning techniques and the addition of dropout layers, which have proven effective in addressing the problems of overfitting and class imbalance in waste datasets.

The methodology used involved a comparison between three main models standard MobileNetV2, ResNet, and an enhanced MobileNetV2. Experimental results showed significant performance improvements. The standard MobileNetV2 model initially achieved only 52% accuracy. Meanwhile, ResNet performed better with 73% accuracy. However, the optimized MobileNetV2 model in this study achieved a peak accuracy of 93%. This improvement demonstrates that with appropriate parameter tuning, lightweight models can outperform more complex models in automatic waste classification tasks.

MATERIALS AND METHODS

This study employs the MobileNetV2 Convolutional Neural Network (CNN) to perform waste classification through hyperparameter adjustment. The research workflow is divided into five main phases, which include the following:

Data Collection

The study utilized a waste image dataset obtained from Kaggle, categorized into two distinct classes: organic and recycled. Each class consists of 13,966 organic images and 11,111 recycled images, resulting in a total of 25,077 images. These images then underwent preprocessing to ensure data quality before being used in model training and testing.

Data Processing

The initial step in the data collection process is obtaining images from [this Kaggle dataset](https://www.kaggle.com/datasets/eldadvikorian/dataset-sampah-organik-dan-anorganik). This study focuses on two classes of waste: Organic (O) and Recyclable (R). The total number of images used is 8,750, with the distribution in Table 1.

Table 1. Number of Images

No	Type of Waste	Number of Images
1	Organic	13966
2	Recycle	11111
	Total	25077

Source: (Research Results, 2025)

The data in Table 1 is sourced from Kaggle, where it has already been categorized based on waste type. Below are example images used for each type of waste.

(a) Organic (b) Recycle

Source: (Research Results, 2025)

Figure 1. Image of Waste Types

Research Stages

To ensure that the results are scientifically accountable, this research is conducted empirically, logically, and systematically, starting from problem formulation to report writing [24]. Figure 1 illustrates the structure of the proposed research stages. In Figure 2, the main issue in this study is class imbalance in waste classification, where organic waste is more dominant than recyclable waste, leading to reduced accuracy in the minority class. Although transfer learning models such as MobileNetV2 and ResNet have been used for waste classification, they have not been fully optimized to address class imbalance. This research proposes the development of an enhanced MobileNetV2

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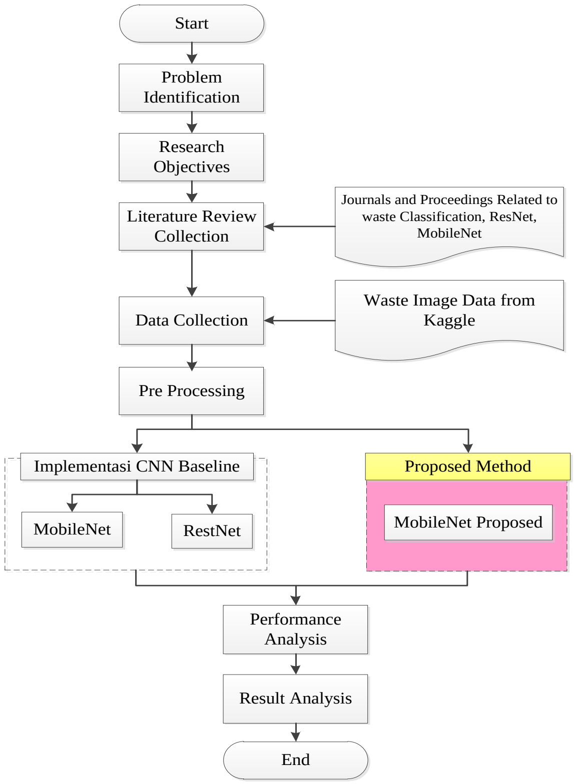
(proposed method), which is more efficient and lightweight, and compares it with ResNet to improve classification balance and accuracy, particularly for the recyclable waste category.

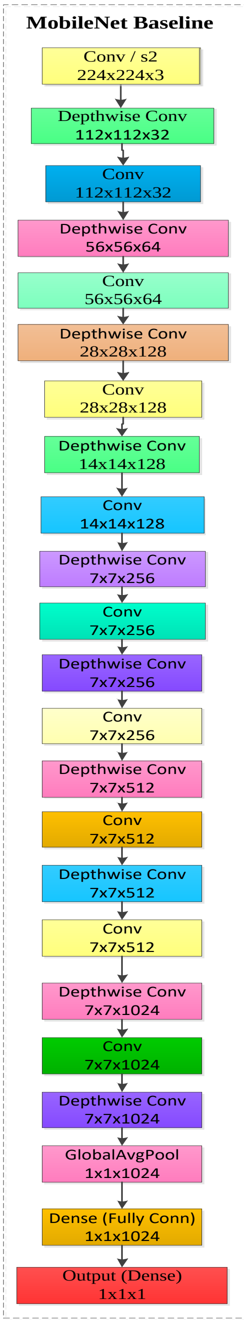


Source: (Research Results, 2025)
Figure 2. Research Phases

The objective of this study is to evaluate and compare the performance of MobileNetV2, ResNet, and the proposed method (an enhanced version of MobileNetV2) in waste classification tasks. This research aims to identify the most effective model for addressing class imbalance and improving accuracy and recall, particularly for the recyclable waste category. In the literature review phase, this study will identify and analyze previous research related to waste classification using CNN models, MobileNetV2, ResNet and transfer learning methods. This literature review will serve as the foundation for developing the Statement of Data Analysis (DA), which underpins the model selection and provides a deeper understanding of the strengths and weaknesses of each model in waste classification tasks, particularly in addressing class imbalance.

CNN Algorithm for Image Classification

MobileNetV2 is a convolutional neural network (CNN) architecture designed for high computational efficiency on resource-constrained devices, such as mobile devices [25], [26], [27]. By utilizing depthwise separable convolutions, MobileNetV2 is able to decrease the total number of parameters and computational operations compared to traditional CNN architectures, enabling faster processing and lower power and memory consumption [28], [29], [30]. Due to its efficiency, MobileNetV2 is widely used in real-time applications requiring image processing with limited resources, such as object recognition, image classification, and other recognition systems [31], [32].



Source: (Research Results, 2025)
Figure 3. MobileNetV2 Architecture

Proposed Method

Source: (Research Results, 2025)
Figure 4. Comparison of MobileNetV2 with Proposed Method

The main difference between the standard MobileNetV2 and the proposed architecture lies in the integration of dropout techniques and the addition of extra components, where the baseline model does not apply dropout to the fully connected layer, while the proposed model inserts a dropout layer with a value of 0.5 before the fully connected layer to reduce the risk of overfitting while adding a new Dense layer to strengthen the final feature extraction capability and improve classification accuracy. To ensure the reproducibility of the study, the model training process is strictly configured using hyperspecific parameters, including adjusting the input image dimensions to 224 x 224 pixels with 3 color channels (RGB), a batch size of 32 images per iteration, and weight optimization through the Adam optimizer algorithm with a low learning rate of 0,0001 (10^4)to maintain the stability of the fine-tuning transition.

In addition, although the maximum training limit is set at 20 epochs, this study integrates an Early Stopping mechanism with a patience value of 3 epochs that monitors the decrease in validation loss, so that the training process will be stopped automatically to lock the best model weights if there is no consecutive decrease in loss to prevent saturation or overfitting of the model is shown in Figure 4 as follows. In Figure 4, the basic architecture of MobileNetV2 is enhanced by adding several additions such as fully connected and dropout 0.5 which are useful for improving the performance of the MobileNetV2 algorithm in garbage classification.

RESULTS AND DISCUSSION

In this section, we present research results related to the refinement of the modified MobileNetV2 method and the standard CNN architecture. The discussion includes an examination of the implementation results, a comparison between the baseline and optimized models and an assessment of model performance.

Image Data Pre-Processing Results

At this stage, data preparation is carried out before processing with the model. This includes data cleaning and splitting the data into training and testing sets. The data distribution at this stage is as follows:

Table 2. Image Data Splitting

No	Data Splitting	Class	Amount
1.	*Training*	*Organic*	12565
2.		*Recycle*	9999
3.	*Testing*	*Organic*	1401
4.		*Recycle*	1112

Source: (Research Results, 2025)

Table 2 the data in this study is divided to ensure that the model can be trained and tested optimally. The model learns to identify patterns across waste classes using the training data, while the separate testing data assesses its ultimate accuracy on novel, unfamiliar examples. Each class has a balanced amount of data to prevent class imbalance, which could affect the model's

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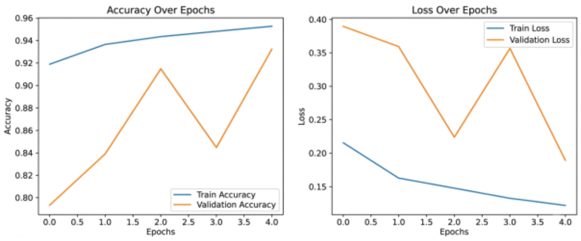
prediction accuracy. A total of 22,564 images are used for training and 2,513 images for testing, ensuring a fair representation of each class in the dataset. With this data-splitting strategy, the model is expected to achieve good generalization on real-world data.

Image Data Classification Results

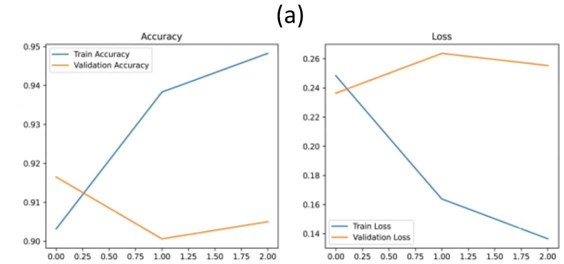
At the modeling stage, three Convolutional Neural Network (CNN) architectures are used MobileNetV2, ResNet, and the proposed MobileNetV2 method to train the model on waste images.

Loss and Accuracy Curve

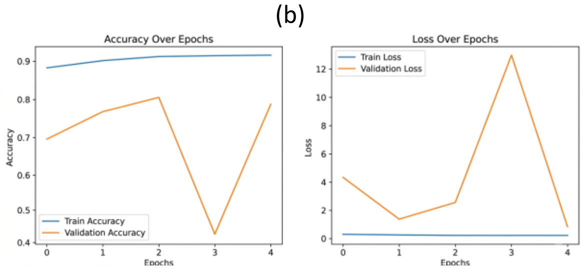
The training process is monitored through loss and accuracy values. Below are the results of the waste image classification training.



(a)



(b)



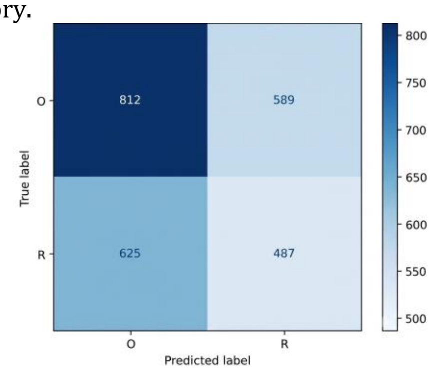
(c)

Source: (Research Results, 2025)
Figure 5. Training Loss and Accuracy Results of (a) MobileNetV2, (b) ResNet, (c) Proposed Method

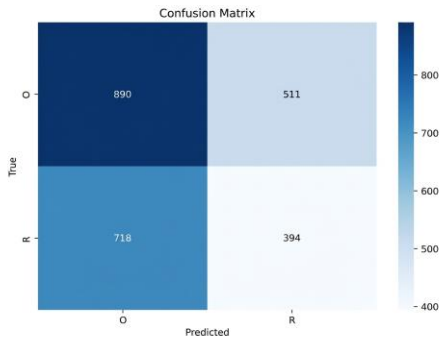
Figure 5 (a) The training process showed very stable, efficient results, and was free from any indication of overfitting. The optimization process was automatically stopped at the 5th epoch (epoch 4 on the X-axis) thanks to the Early Stopping mechanism after the model reached its best convergence point. In both the accuracy and loss graphs, the training and validation data curves moved consistently in tandem. Figure 5 (b) Both graphs indicate that the model is experiencing overfitting (memorizing too much of the training data). In the Accuracy graph, the training data accuracy (Train Accuracy) continues to increase rapidly from around 90% to nearly 95%, while the validation data accuracy (Validation Accuracy) actually decreases sharply at the beginning and plateaus at a much lower figure (around 90.5%). This pattern is reinforced by the Loss graph, where the training data error rate (Train Loss) consistently decreases drastically, but the validation data error (Validation Loss) actually increases and remains high. Figure 5. (c) This indicates a highly unstable training model and severe overfitting. The Accuracy Over Epochs graph shows the training data accuracy (Train Accuracy) as very stable and high, above 93%, but the validation data accuracy (Validation Accuracy) fluctuates sharply, even plummeting to 45% in the third epoch before rebounding. This instability pattern is clearly confirmed in the Loss Over Epochs graph.

Confusion Matrix

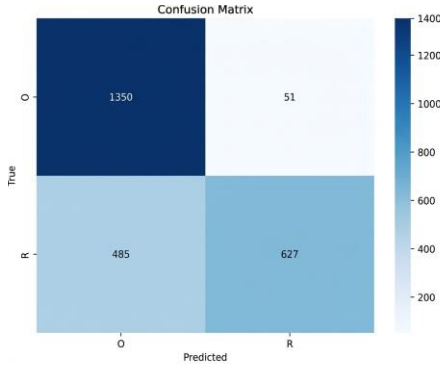
The classification evaluation results are analyzed using a confusion matrix, which measures how well the model classifies waste images. This analysis provides insights into the model's performance in identifying each class, including the number of correct predictions and errors in each category.



(a) MobileNetV2



(b) ResNet



(c) Proposed Method MobileNetV2

Source: (Research Results, 2025)

Figure 6. Confusion matrix for (a) MobileNetV2, (b) ResNet, and (c) Proposed Method MobileNetV2

Figure 6. Based on the evaluation results of the MobileNetV2 model, the overall accuracy obtained is 52%. The weighted average also shows a precision of 52%, recall of 52%, and an F1-score of 52%. These results indicate a suboptimal model performance, with strength in the organic waste class but highlighting areas for improvement, especially in the recycle class.

For the ResNet model evaluation, the overall accuracy obtained is 73%. The weighted average also shows a precision of 73%, recall of 74%, and an F1-score of 74%. These results demonstrate fairly good performance, particularly in the organic waste class, although the recycle class has slightly lower precision. Overall, the ResNet model outperforms the previous model, achieving significantly higher accuracy and a more consistent F1-score across most classes.

Meanwhile, the evaluation results of the MobileNetV2 Proposed model show an overall accuracy of 93%. The weighted average also indicates a precision of 92%, recall of 92%, and an F1-score of 92%. These results highlight outstanding performance, with the MobileNetV2 Proposed model successfully identifying almost all classes with high accuracy. This model consistently performs well across all classes, achieving very high precision, recall, and F1-score, ultimately delivering optimal results on this dataset.

Model Performance Evaluation

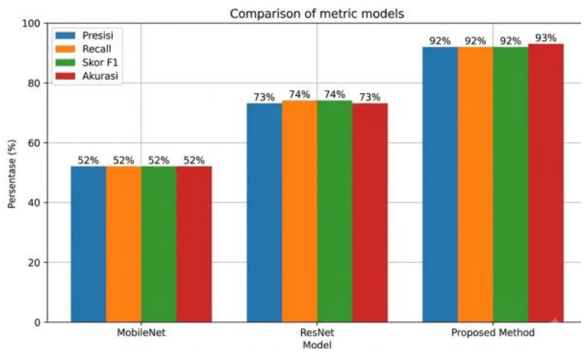
The results highlight the superiority of the MobileNetV2 Proposed model in handling complex datasets with high inter-class similarity. While Mob ileNetV2 provides a balance between performance and computational efficiency, the accuracy limitati ons of CNN emphasize the need for more advanced architectures for similar tasks. The comparison is s ummarized in Table 3.

Table 3. Model Comparison Summary

Model	Precision	Recall	F1 Score	Accuracy
MobileNetV2	52%	52%	52%	52%
ResNet	73%	74%	74%	73%
Proposed Method	92%	92%	92%	93%

Source: (Research Results, 2025)

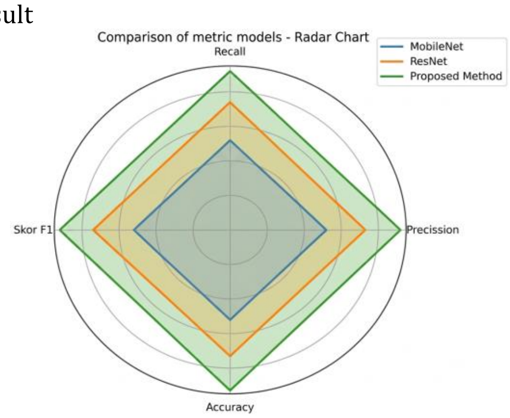
Table 3 Based on the data presented, the Proposed Method (proposed method) shows the most superior and dominant performance compared to the other two models, with an accuracy rate reaching 93% and other metric values consistently at 92%. In second place, the RestNet model (probably referring to ResNet) provides mid-range performance with 73% accuracy and an F1 score of 74%. Meanwhile, MobileNetV2 ranks lowest with quite poor performance, where all evaluation metrics are stuck uniformly at 52%, indicating that the newly proposed method has succeeded in providing a very significant performance improvement. Below is the comparison chart of the four methods used:



Source: (Research Results, 2025)

Figure 7. Comparison Chart of the Three Models' Results

From Figure 7, it can be seen that the Proposed Method yields better and more stable result



Source: (Research Results, 2025)

Figure 8. Model Comparison Radar Chart

Accredited Rank 2 (Sinta 2) based on the Decree of the Dirjen Penguatan RisBang Kemenristekdikti No.225/E/KPT/2022, December 07, 2022. Published by LPPM Universitas Nusa Mandiri

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Figure 8 Based on the radar chart comparison of the models, it is evident that the proposed method outperforms both MobileNetV2 and ResNet, as its connection lines approach a value of 100 at each point. MobileNetV2 Proposed achieves an accuracy of 93%, which is nearly perfect and significantly higher than MobileNetV2 (52%) and ResNet (73%). This high accuracy indicates that the model is highly effective in classifying test data, with minimal prediction errors. The Precision, Recall, and F1-Score, all reaching 93% in MobileNetV2 Proposed, demonstrate an excellent balance between accuracy and the model's ability to correctly detect classes without generating excessive false positives. MobileNetV2 Proposed provides more realistic results while maintaining exceptional performance.

CONCLUSION

This study successfully developed an efficient and lightweight waste classification model through optimization of the MobileNetV2 architecture with a transfer learning approach. The main scientific contribution of this study is the proof that structural modifications in the form of precise fine-tuning and the integration of a 0.5 dropout layer can act as a strong regularizer to overcome the problem of visual data imbalance and reduce the risk of overfitting, thus successfully boosting the model accuracy massively from only 52% (in the standard model) to 93%, while outperforming more complex architectures such as ResNet which only achieved an accuracy of 73%. Despite providing significant results, this study has limitations in terms of the variety of waste categories which are still limited to two large classes (organic and recyclable) and dependence on ideal image draft lighting conditions. Therefore, future work is recommended to expand the scope of classification into several more specific waste sub-categories (multi-class) and test the robustness of the model in real-world environments (real-time deployment) with more complex image backgrounds.

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