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Deep Learning-Based Waste Classification with Transfer Learning Using EfficientNet-B0 Model

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Abstract

Recycling of waste is a significant challenge in modern waste management. Conventional techniques that use inductive and capacitive proximity sensors exhibit limitations in accuracy and flexibility for the detection of various types of waste. Indonesia generates approximately 175,000 tons of waste per day, highlighting the urgent need for efficient waste management solutions. This study develops a waste classification system based on deep learning, leveraging the powerful EfficientNet-B0 model through transfer learning. EfficientNet-B0 is designed with a compound scaling method, which uniformly scales network depth, width, and resolution, providing an optimal balance between accuracy and computational efficiency. The model was trained on a dataset containing six classes of waste—glass, cardboard, paper, metal, plastic, and residue—totalling 7014 images. The model was trained using data augmentation and fine-tuning techniques. The training results show a test accuracy of 91.94%, a precision of 92.10%, and a recall of 91.94%, resulting in an F1-score of 91.96%. Visualisation of predictions demonstrates that the model effectively classifies waste in new test data. Implementing this model in the industry can automate the waste sorting process more efficiently and accurately than methods based on inductive and capacitive proximity sensors. This study underscores the significant potential of deep learning models, particularly EfficientNet-B0, in industrial waste classification applications and opens opportunities for further integration with sensor and robotic systems for more advanced waste management solutions.

Keywords: *waste classification; transfer learning; EfficientNet-B0*

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1. Introduction

Waste management is a significant global issue, particularly in densely populated countries like Indonesia. In 2020, the country generated more than 175,000 tons of waste daily [1]. Much of this waste is not properly managed, leading to environmental pollution. One potential solution is the automation of waste sorting systems to enhance the efficiency of recycling processes [2].

Previous research has extensively explored the development of automated waste sorting systems using various sensors. For example, an automatic waste sorting machine based on proximity sensors employed several sensors such as PIR, LDR, inductive and capacitive proximity sensors, and ultrasonic sensors to detect and classify different types of waste. However, these systems still exhibited high error rates [3], [4]. Similarly, an automatic waste classification system that still used inductive and capacitive proximity sensors combined with modern algorithms like the binary tree concept and the Naïve Bayes algorithm showed limited performance [5], [6]. These systems continued to face errors in sorting waste due to sensor limitations and classification mechanisms.

On the other hand, in the current era, deep learning has emerged as a powerful technology capable of handling complex classification tasks by learning hierarchical representations of data [7], [8]. Transfer learning, a technique within deep learning, allows models pre-trained on large datasets to be fine-tuned on specific tasks, significantly reducing the need for extensive data and computational resources [9] - [11].

Recent research has begun to employ deep learning technologies to address the limitations of proximity sensor-based systems. Although these studies have

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demonstrated improvements in classification accuracy, Zhou et al.'s research was limited to classifying only medical waste [12]. Additionally, another study applied deep learning specifically to classify plastic waste, achieving significant results but focusing solely on plastic waste [13]. Other studies have attempted to apply deep learning to various types of waste using the Resnet-50 model, but the achieved accuracy has remained unsatisfactory [14].

Furthermore, several previous studies as shown in Table 1 have demonstrated the effectiveness of one of the deep learning models, EfficientNet-B0, in various classification tasks. For instance, in a study conducted by Kansal et al., EfficientNet-B0 achieved higher accuracy in classifying various lung abnormalities compared to the ResNet-50 model [15]. Additionally, research by Shaikh et al. indicated that EfficientNet-B0 can be effectively used for medical image classification, delivering highly satisfactory results [16].

Table 1. Summary of Previous research

Topic	Performance
Sensor-Based (inductive and capacitive proximity) Waste Classification [3], [4]	High error rates due to sensor limitations.
Inductive and capacitive proximity sensors combined with binary tree algorithm. [5]	Inconsistent results for some types of waste
Proximity sensors combined with Naïve Bayes algorithm. [6]	Limited performance; difficulty in accurate classification of diverse waste types.
Deep Learning for Medical Waste Classification [12]	Improved accuracy but limited to medical waste only.
Deep Learning for Plastic Waste Classification [13]	High accuracy for plastic waste; limited scope and not generalizable to other types of waste.
Deep learning for various types of waste [14].	Accuracy is still below 90

Therefore, this study aims to explore a waste categorization system based on deep learning, using the EfficientNet-B0 model through a transfer learning strategy. By utilizing a dataset encompassing six waste categories, including glass, cardboard, paper, metal, plastic, and residue, this study brings forth notable advancements in precision and effectiveness for waste segregation within the sector. The novelty of this research lies in the integration of EfficientNetB0's advanced architecture with transfer learning to enhance classification capabilities, effectively addressing the limitations of previous sensor-based and single-class deep learning methods. The contribution of this research is manifested in a reliable, expandable resolution for automated waste segregation, surpassing conventional approaches by providing heightened precision and operational efficiency.

2. Research Methods

To achieve high accuracy in classifying waste, we utilized the EfficientNet-B0 model, known for its balance between performance and computational efficiency. EfficientNet-B0 leverages compound scaling, which uniformly scales the dimensions of depth, width, and resolution using a set of fixed scaling coefficients [17]. The model was fine-tuned with additional layers tailored to our specific dataset using the concept of transfer learning. Figure 1 shows the steps involved in our research methodology.

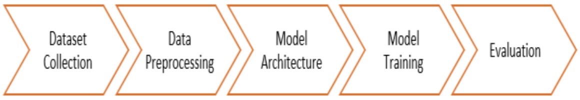


Figure 1. Research Methodology [18]

The dataset used in this study is the "Klasifikasi Sampah" dataset, which consists of six classes: glass, cardboard, paper, metal, plastic, and residue. The dataset includes a total of 7014 images, divided into 4907 images for training, 1052 images for validation, and 1055 images for testing. The following is an example of an image in the dataset in Figure 2.

Figure 2. Example of an image in the dataset

The dataset is sourced from Kaggle at this link: https://www.kaggle.com/datasets/fathurrahmanalfarizy/sampah-daur-ulang. It is divided into 70% for training, 15% for validation, and 15% for testing. The distribution of the dataset is presented in Table 2.

Table 2. The distribution of the dataset

Class	Training Set	Validation Set	Testing Set	Total
Glass	779	166	165	1110
Cardboard	437	93	94	624
Paper	1264	271	272	1807
Metal	847	182	181	1210
Plastic	879	189	189	1257
Residue	701	151	154	1106
Total	4907	1052	1055	7014

Before training the model, several data preprocessing steps were conducted to ensure consistency and quality across the dataset. Initially, the dimensions of all images were adjusted to 224 x 224 pixels, in accordance with the input size specifications of the EfficientNet-B0 model [19]. This adjustment guaranteed consistency throughout the dataset and compatibility with the architectural requirements of the model. Furthermore, the pixel values underwent normalization to a scale ranging from 0 to 1 through division by 255.0. This normalization step played a vital role in expediting the convergence process during model training by standardizing the intensity levels of pixels, thereby enhancing the model's capacity to effectively learn from the data.

This research utilizes the EfficientNet-B0 model, recognized for its optimal balance between performance and computational efficiency. EfficientNet-B0 uses compound scaling to proportionally increase the network's depth, width, and resolution through fixed scaling coefficients. Figure 3 provides an illustration of the EfficientNet-B0 architecture.

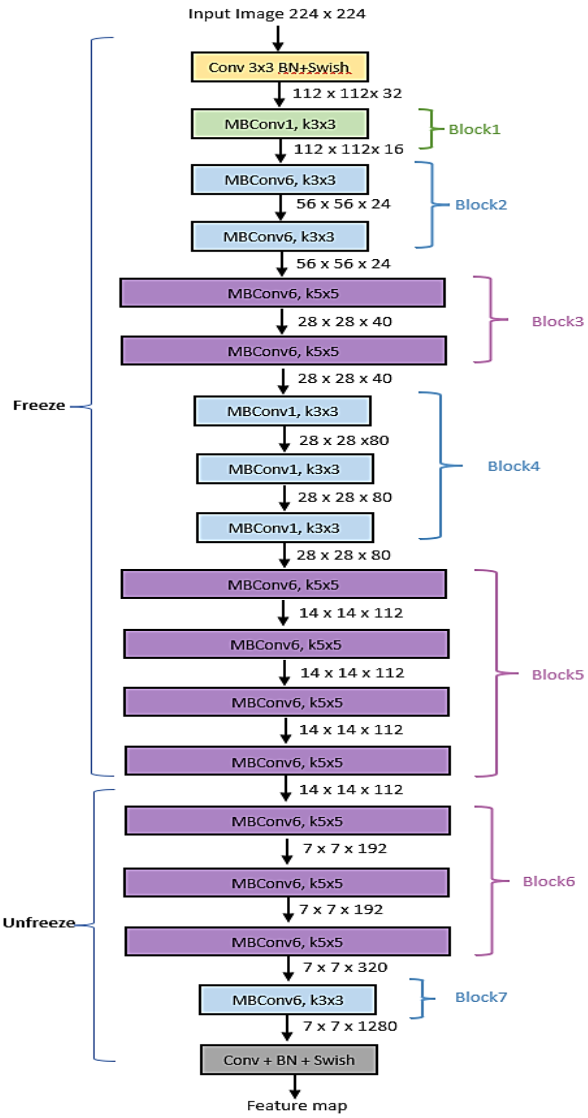


Figure 3. EfficientNet-B0 architecture [19]

Figure 3 illustrates the architecture of the EfficientNet-B0 model, an efficient convolutional neural network (CNN) designed for image classification tasks. The model starts with an input image sized 224x224 pixels, which is then processed through an initial convolutional layer with a 3x3 kernel, batch normalization (BN), and the Swish activation function, resulting in feature maps sized 112x112 pixels. This downsampling occurs due to the stride used in the convolutional layer. The core of EfficientNet-B0 consists of several Mobile Inverted Bottleneck Convolution (MBConv) blocks [20]. These blocks vary in kernel size and stride to maintain computational efficiency while enhancing performance.

To utilize transfer learning, the initial layers from the input to block 5 are frozen to prevent retraining. These foundational layers capture fundamental features such as edges, textures, and simple patterns, which are applicable across various image classification tasks [21]. By preserving these layers, the model leverages robust, pre-trained features from large datasets like ImageNet [22].

The final layers, from block 6 to block 7, and newly added fully connected layers integrate seamlessly with EfficientNet-B0. These include a global average pooling layer that converts spatial dimensions into a single vector per feature map, three dense layers with 512, 256, and 128 units using ReLU activation, and batch normalization and dropout layers to reduce overfitting [23]. The output layer has six units with softmax activation to produce a probability distribution over the classes.

The use of EfficientNet-B0 is motivated by its state-of-the-art performance in balancing accuracy and efficiency. Unlike traditional CNNs, EfficientNet-B0 is designed to maximize both accuracy and computational efficiency through a scalable architecture that adjusts dimensions proportionally. This makes it particularly suitable for deployment in resource-constrained environments typical in industrial applications [24], [25].

Transfer learning is employed to tailor the pre-trained EfficientNet-B0 model specifically for waste categorization. This approach offers notable advantages by enabling the model to utilize insights derived from broad and varied datasets. Consequently, it reduces the requirement for extensive data and computing resources for training on our specific dataset. Moreover, transfer learning accelerates the training process and enhances model performance, particularly when the available dataset is limited or not as comprehensive as the original training dataset.

This framework ensures that the model can effectively capture intricate waste attributes while remaining practically viable for real-world applications. By integrating these elements, a sturdy structure for precise and efficient waste classification is established, effectively overcoming the constraints associated with conventional proximity sensor-driven methods. The additional layers incorporated in the model are depicted in Figure 4.

Figure 5 shows the implementation of these additional layers in the program. This setup allows the model to adjust its learned features to the waste classification dataset, enhancing its ability to accurately classify waste types while leveraging pre-trained weights from the EfficientNet-B0 model. This approach optimizes the model's learning capability by retaining general image features in the early layers and specializing in waste classification in the latter layers.

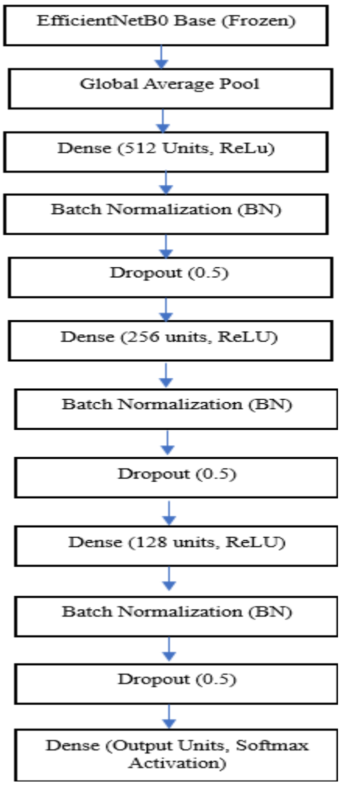


Figure 4. Additional architectural layers

```
# Add custom layers on top of the base model
x = base_model.output
x = GlobalAveragePooling2D()(x)
x = Dense(512, activation='relu', kernel_regularizer=l2(0.01))(x)
x = BatchNormalization()(x)
x = Dropout(0.5)(x)
x = Dense(256, activation='relu', kernel_regularizer=l2(0.01))(x)
x = BatchNormalization()(x)
x = Dropout(0.5)(x)
x = Dense(128, activation='relu', kernel_regularizer=l2(0.01))(x)
x = BatchNormalization()(x)
x = Dropout(0.5)(x)
predictions = Dense(train_generator.num_classes, activation='softmax')(x)
```

Figure 5. Program of Additional architectural layers

The model was compiled using the Adam optimizer with a learning rate of 0.0001, chosen for its efficiency in handling sparse gradients and dynamic learning rate adjustment [26]. Categorical cross-entropy was used as the loss function, which is ideal for multi-class classification tasks like waste type identification. Early stopping was employed to monitor the validation loss and terminate training if no improvement occurred over a set number of epochs, thus preventing overfitting. Additionally, a learning rate reduction on the plateau was implemented to decrease the learning rate when validation loss stagnated, facilitating finer adjustments during the latter training phases. The model underwent training for 100 epochs with a batch size of 32, which provided a balanced approach to utilizing computational resources effectively while ensuring stable and consistent gradient updates.

The performance of the model was evaluated using three metrics: accuracy, precision, and recall [27]. Accuracy measures the overall correctness of the model and is calculated as the ratio of correctly predicted instances to the total instances. Precision measures the correctness of positive predictions and is calculated as the ratio of true positive predictions to the sum of true positive and false positive predictions. Recall, also known as sensitivity, measures the model's ability to identify all relevant instances and is calculated as the ratio of true positive predictions to the sum of true positive and false negative predictions [28], [29]. The metric formula can be seen in Formulas 1-3.

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

$$\text{Precision} = \frac{TP}{TP + FP} \quad (2)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (3)$$

True Positive (TP) refers to the number of instances correctly identified as positive. True Negative (TN) denotes the number of instances correctly identified as negative. False Positive (FP) is the count of instances incorrectly predicted as positive, while False Negative (FN) represents the count of instances incorrectly predicted as negative.

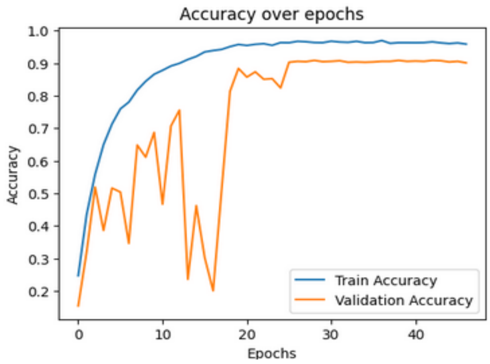
By evaluating the model using these metrics, we can gain a comprehensive understanding of its performance in terms of both accuracy and the ability to correctly identify and classify waste types. This evaluation helps ensure that the model not only performs well overall but also correctly identifies and distinguishes between different types of waste.

3. Results and Discussions

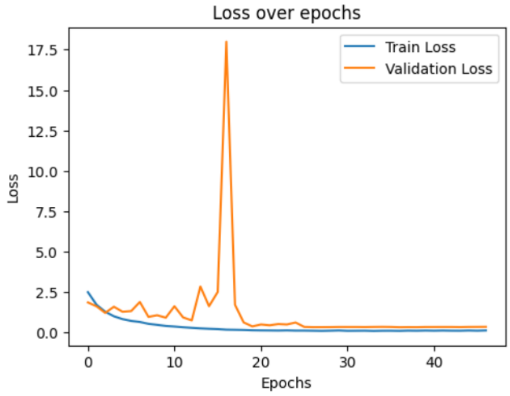
3.1 Results

This research uses the EfficientNet-B0 model for classifying six classes of waste: glass, cardboard, paper, metal, plastic, and residue. The model is trained using transfer learning techniques, where the initial layers (from input to Block 5) are frozen to retain the general features already learned, while the final layers and the newly added fully connected layers are retrained with a new waste classification dataset. The accuracy and loss graphs during training are shown in Figure 5.

The evaluation results from the training process reveal that the model achieved a test accuracy of 91.94% with a corresponding loss value of 0.2673. The accuracy graphs, as depicted in Figure 6 (a), illustrate that the model experienced a notable improvement in accuracy within the initial 30 epochs, subsequently stabilizing as the training progressed. This improvement reflects the model’s effective learning from the training data. The validation accuracy closely mirrors the trend of the training accuracy throughout the epochs, demonstrating consistency and indicating that the model is not significantly overfitting to the training data. This consistency between training and validation accuracy suggests a good generalization capability of the model.



(a)



(b)

Figure 6. Plot of (a) accuracy and (b) loss function on training

In Figure 6 (b), the graphical representation of the loss function demonstrates a significant decrease in training loss in the initial phases, indicating proficient learning and optimization. The validation loss exhibits a decreasing trend, albeit with periodic fluctuations, which are common and could be linked to variations in the validation data batches. These fluctuations, particularly prominent around the 20th epoch, are likely a result of the diversity and intricacy present in the validation dataset. Despite these slight variations, the overall pattern suggests that the model attains a satisfactory level of convergence, effectively reducing the loss over time. The consistent convergence in loss and the correlation between training and validation accuracy highlights the resilience of the model and its capacity to sustain performance across diverse datasets, ensuring dependable classification accuracy in practical scenarios.

The obtained model was subsequently tested on the test data, resulting in a confusion matrix in the output as in Figure 7.

Figure 7 shows the confusion matrix of the model's performance on the waste classification task. A confusion matrix visualizes the performance of a classification algorithm by displaying the actual versus predicted classifications. The diagonal elements represent correctly classified instances, while off-diagonal elements represent misclassifications.

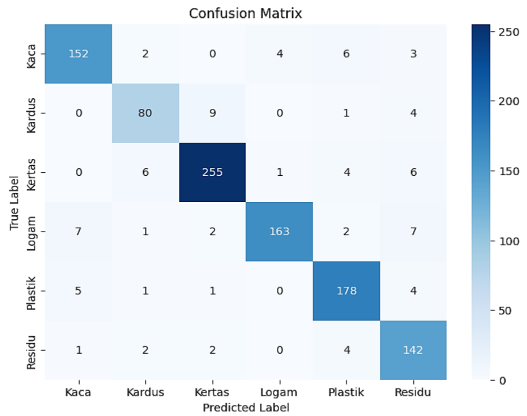


Figure 7. The plot of (a) accuracy and (b) loss function on the training process

The matrix indicates that the model accurately classified glass waste in 152 instances, with 15 incorrect classifications. For cardboard, 80 instances were correctly classified with 14 misclassifications. Paper waste saw 255 correct classifications and 17 misclassifications. Metal waste was correctly classified in 163 instances with 19 errors. Plastic waste had 178 correct classifications and 11 errors. Lastly, residue waste was accurately classified in 142 instances with 9 misclassifications. Detailed classification results are provided in the classification report in Table 3.

Table 3. Precision, Recall, F1-Score Per Class

Class	Precision	Recall	F1-Score	Support
Glass	0.92	0.91	0.92	167
Cardboard	0.87	0.85	0.86	94
Paper	0.95	0.94	0.94	272
Metal	0.97	0.90	0.93	182
Plastic	0.91	0.94	0.93	189
Residue	0.86	0.94	0.90	151

Table 4. Metric Summary

Metric	Value
Overall Accuracy	91.94 %
Precision	92.10 %
Recal	91.94 %
F1-Score	91. 96 %

Table 3 shows the classification report with precision, recall, and F1-Score metrics for each class, with the most notable results in the 'Metal' class, with a precision of 0.97 and a recall of 0.90. The 'Residue' class has lower precision compared to other classes but has a high recall of 0.94, indicating that the model tends to be more sensitive in detecting the residue class.

In addition to the class-specific metrics, the overall performance of the model is summarized in the Metric Summary as shown in Table 4. The model achieves an overall accuracy of 91.94%, indicating that approximately 92% of the predictions are correct across all classes. The precision across all classes averages to 92.10%, reflecting the model's ability to produce a high proportion of true positive identifications among all positive identifications. The recall is 91.94%, which underscores the model's effectiveness in identifying most of the actual positive cases in the dataset. The F1-

score, balancing precision and recall, stands at 91.96%, illustrating the model's overall competency in waste classification tasks.

Furthermore, Figure 8 shows the prediction results for sample images from each waste class, visualizing the model's ability to classify images from the test dataset accurately. Each image is labelled with the corresponding model prediction, and most of the prediction results match the actual labels, demonstrating high accuracy.

Figure 8. Example of image prediction results from the data test

Overall, the use of EfficientNet-B0 with transfer learning proves effective in waste classification. This model demonstrates strong performance and can be implemented in automated waste sorting systems, replacing traditional proximity sensor-based methods that tend to have limitations in accuracy and efficiency. With the achieved accuracy and the ability to handle various types of waste, this model offers the potential to improve waste management efficiency and recycling processes. However, there is still room for further improvement, such as addressing minor fluctuations in validation loss and testing the model with a more diverse dataset to enhance generalization.

3.2 Discussions and Future Work

The results of this study demonstrate the effectiveness of the EfficientNetB0 model with transfer learning in classifying waste into six categories: glass, cardboard, paper, metal, plastic, and residue. The model achieved high accuracy, precision, and recall, showing good generalization capabilities across various types of waste. These findings are consistent with the research by Shaikh et al., which demonstrated that EfficientNetB0 achieved high accuracy in medical image classification [16].

Additionally, this study shows that using the EfficientNet-B0 model performs better than the study by Adedeji and Wang, which used the ResNet-50 model in waste classification [14]. The study by Kansal et al. also supports these findings, where EfficientNet-B0 achieved higher accuracy in classifying various lung abnormalities compared to the ResNet-50 model [15].

The training graphs indicate a substantial improvement in accuracy during the initial 30 epochs, after which the accuracy stabilizes. The validation loss shows a consistent downward trend, though with occasional fluctuations. These patterns suggest that further stabilization of model performance could be achieved by implementing additional regularization techniques and increasing dataset diversity. The model was trained using the Adam optimizer with a learning rate of 0.0001, which has proven effective in managing sparse gradients and dynamically adjusting the learning rate, as supported by previous research [26].

However, applying this model in real-time waste classification systems faces challenges such as performance stabilization in dynamic operational environments and the need for fast inference, as discussed in the studies by Bhattacharya et al. and Lin, which emphasize the importance of inference speed and performance stability in real-time applications [30], [31]. Future research should focus on integrating this model into real-time waste sorting systems, developing direct data acquisition mechanisms, and improving inference speed.

4. Conclusions

This study successfully developed a waste classification system using the EfficientNet-B0 model, retrained through transfer learning techniques. The model demonstrated high test accuracy at 91.94% with satisfactory precision and recall across all waste categories (glass, cardboard, paper, metal, plastic, and residue). This system significantly improves waste sorting efficiency and accuracy compared to methods relying on inductive and capacitive proximity sensors, which are prone to high error rates. This approach sets the stage for further advancements in adaptive and efficient automated waste management systems.

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