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Identification of Organic and Non-Organic Waste with Computer Image Recognition using Convolutionalneural Network with Efficient-Net-B0 Architecture

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***Abstract* -** This study aims to develop a method for identifying organic and non-organic waste using a computer image recognition technique based on Convolutional Neural Network (CNN) with Efficient-Net-B0 architecture. Efficient and accurate waste identification is important in sustainable waste management. The primary goal of this research is to distinguish between organic and non-organic waste in images. Manually labeling waste images as organic or non-organic can be a time-consuming and error-prone task. Configuring and fine-tuning the EfficientNet-B0 architecture and CNN parameters for optimal performance can be a complex and iterative process. Hyperparameter tuning may be needed. Ensuring accurate labels is essential for training a reliable model. The choice of using the Convolutional Neural Network (CNN) with the EfficientNet-B0 architecture is a crucial part of the solution. EfficientNet-B0 is known for its balance between accuracy and computational efficiency. The use of CNNs and EfficientNet-B0 for this task indicates the system's ability to discern visual differences between the two waste types. The method proposed in this study utilizes CNN's ability to study important features of waste images to recognize various types of waste. This research includes the waste data collection stage which includes organic and non-organic waste in the form of 2D images. To evaluate the performance of the proposed method, a test was carried out using a waste dataset taken from a predetermined environment. The test results show that the proposed method is able to identify organic and non-organic waste with a high degree of accuracy. In test scenarios, this method achieves an accuracy of 98%, which demonstrates its ability to effectively identify the type of waste. Through the use of CNN-based computer image recognition techniques with the Efficient-Net-B0 architecture, this research succeeded in solving the problem of identifying organic and non-organic waste automatically and accurately. The proposed method has the potential to be applied in more efficient waste management systems, helps minimize human identification errors, and makes a positive contribution to environmental protection efforts. This research is expected to be the basis for further development in the introduction and management of waste in a sustainable manner.

Keywords - Garbage identification, Computer image recognition, Convolutional Neural Network (CNN), Efficient-Net-B0 Architecture.

1. INTRODUCTION

One of the serious problems faced by the people of Indonesia is the waste situation, which increases exponentially every year. With the increasing population every year, the amount and type of waste is also increasing. Indonesia is the world's second largest waste producer after China, which is the world's largest waste producer [1]. Indonesia is ranked second in the world for producing 187.2 million tons of plastic waste into the sea after China which reached 262.9 million tons.

Based on data from the Ministry of Environment and Forestry of the Republic of Indonesia on the 2022 National Waste Management Information System (SIPSN), Waste Generation in Indonesia is 34,461,646.92 tons/year, Waste Handling is only 49.43%, namely 17,034,794.37 tons/year, and Unmanaged Waste is 35.38%, amounting to 12,191,806.46 (tonnes/year).

Waste management is a very important issue in efforts to maintain environmental sustainability and create a cleaner and healthier life. In this context, the identification and segregation of organic and non-organic waste is a critical step in an effective waste management process. However, manual identification of organic and non-organic waste can be a complex task, time consuming and prone to human error. Therefore, the use of computer image recognition technology can be an efficient and accurate solution in automating the waste identification process.

The solution to the problem of excessive waste generation is to implement more efficient waste management practices, recycle existing waste and most importantly reduce waste consumption. The application of waste recycling can have a positive impact on the environment and improve the country's economy. Recycling waste can create jobs for many people, create a cleaner environment and improve public health [2].

Various procedures must be followed when carrying out waste recycling activities. The first step is to collect the waste first, separate or classify the collected waste according to the type and content of the waste. The next stage is the manufacturing process, where the separated waste is sorted by type and recycled. After the last stage, a new residue is made so that it can be reused in new products. CNN (Convolutional Neural Network) is an emerging deep learning technology.

Image recognition using Convolutional Neural Network with Efficient-Net-B0 Architecture method is the most advanced and effective techniques and methodologies currently available for the identification of organic and non-organic waste using computer image recognition, specifically employing the Convolutional Neural Network (CNN) with the EfficientNet-B0 architecture.

Manually labeling waste images as organic or non-organic can be a time-consuming and error-prone task. Ensuring accurate labels is essential for training a reliable model. Configuring and fine-tuning the EfficientNet-B0 architecture and CNN parameters for optimal performance can be a complex and iterative process. Hyperparameter tuning may be needed.

CNN takes this input data as an image and performs layering and convolution operations according to certain filters. Each layer creates a model from a different part of the image to simplify the classification process. Development of the ANN (Artificial Neural Network) method [3]

The CNN algorithm has gone through a lot of development and research processes. This study aims to improve the accuracy of the CNN algorithm, reduce resources and reduce errors. This can be done by changing the CNN layer. In that study, several CNN models were designed and calculated to maximize results. [4]

In this paper, the fit model of the Convolutional Neural Network (CNN) algorithm is analyzed to get the best performance in classification. Therefore, the algorithm can be used directly to achieve waste classification automatically using the system. The purpose of this research is to shorten and simplify the process of collecting and segregating waste at the waste recycling stage. Starting from these points, the author explores the application of the convolutional neural network algorithm to classify garbage type images using the Efficient-Net-B0 architecture. The CNN used in this scenario has a more efficient architecture and another deep CNN. [4]

The choice of using the Convolutional Neural Network (CNN) with the EfficientNet-B0 architecture is a crucial part of the solution. EfficientNet-B0 is known for its balance between accuracy and computational efficiency. Convolutional Neural Network (CNN) developed with a focus on computational efficiency and high accuracy. Some of the important roles played by the EfficientNet-B0 architecture in this research include computational efficiency. This architecture is designed to have a lower number of parameters than other architectures with similar performance. This makes it possible to train and deploy models more quickly, even with limited computing resources. EfficientNet-B0 is part of a series of Efficient-Net models that can be scaled in complexity. The models in the Efficient-Net series have variants such as B1, B2, up to B7 with increasing levels of complexity. This allows for adapting the architecture to different datasets and computing needs. EfficientNet-B0 also has convolution layers that are able to extract important features from images with various levels of complexity. This makes it suitable for the identification of organic and non-organic waste, where features such as color, texture and shape can be important indicators.

By utilizing the EfficientNet-B0 architecture, CNN can optimize model training and performance in identifying organic and non-organic waste. This architecture provides efficiency and accuracy benefits, while minimizing the risk of overfitting and speeding up development solutions. It is estimated that this research can contribute to increasing efficiency and accuracy in waste management through innovative technology.

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2. RESEARCH METHOD

a. Dataset

Identification of organic and non-organic waste by computer image recognition using a Convolutional Neural Network with Efficient-Net-B0 Architecture through several processes. These processes include:

The data collection phase is the phase to find a collection of data from various available sources. The dataset for this study consists of 300 Data Training images in .JPG format, with details of 150 organic object files and 150 recyclable non-organic object files.

While the Testing Data for this study consisted of 100 images in .JPG format, with details of 50 organic object files and 50 non-organic object files that can be recycled.

This data set contains images of organic objects and recyclable objects, and can be accessed at the following links: https://www.kaggle.com/datasets/techsash/waste-classification-data.

Some examples of organic and non-organic object dataset images are as follows:

Figure 2.1: Image of Organic Waste Training Data

In the testing phase, the remaining datasets after the formation of the training and validation subsets will be used as the test datasets. This test dataset will be the final reference for measuring the performance of the CNN model that has been trained. The test was carried out by inserting organic and non-organic waste images into the CNN model and obtaining predictions from the identification results. The predicted results are then compared with the actual labels to measure the accuracy and overall performance of the model.

Figure 2.2: Image of Non-Organic Waste Testing Data

b. Method

In this study, the proposed method procedures to be used in this study, such as input data, method design, trial scenarios, and evaluation. The steps taken are shown in Figure 2.3, including importing libraries, defining hyperparameters, collecting data, building the Efficient-Net-B0 architecture, adding the fully connected layer, compiling the model, and evaluating the model.

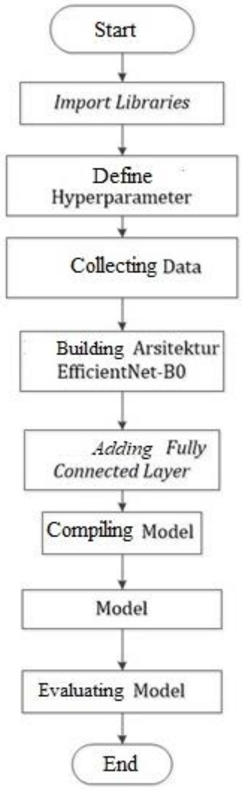


Figure 2.3 Proposed Method

c. Building the CNN Model with the Efficient-Net-B0 Architecture

In this study, the CNN Convolutional Neural Network is one of the deep learning algorithms that is commonly used to solve plant disease identification problems in the last five years. CNN can be developed into a variety of different architectures, which generally consist of 3 main layers or layers, namely the convolution layer, pooling layer, and fully-connected layer.

1. Convolution Layers

This layer is the basic layer whose role is to perform feature extraction of the input data [9]. Feature extraction is carried out through a convolution process involving a collection of two-dimensional filters and certain activation functions to produce a feature map.

2. Pooling Layer

This layer is used to reduce the dimensions of the feature map [9]. Pooling calculations are divided into two, namely max pooling and average pooling. Max pooling takes the maximum value from the feature map, while average pooling takes the average value from the feature map.

3. Fully-connected Layer

This layer performs linear classification with the help of the Softmax activation function which calculates the probability of each input vector value for each possible class. The Softmax activation function can be seen in the equation:

$$e\ xi\ (x) = \Sigma\ k\ e\ xj\ j=1 \qquad (1)$$

Where (x) denotes the value of the Softmax activation function on the i-element vector, x denotes the value of the input vector, and k denotes the number of classes.

The initial stage in the development of this research model is the initialization of the model, namely the Efficient-Net-B0 Architecture is used as the basis for building the CNN model. The CNN model will be initialized with the appropriate parameters and consider the number of classes of organic and non-organic waste identification.

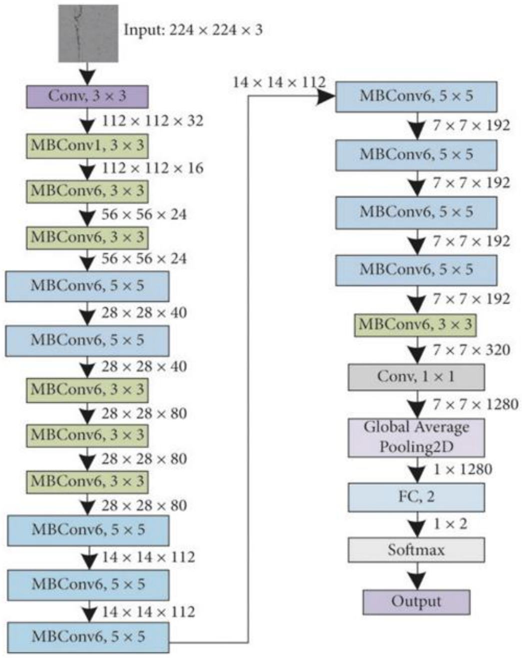


Figure 2.4. Efficient-Net-B0 architecture

3. RESULTS AND DISCUSSION

The results of each experiment were recorded and compared to determine the hyperparameter combination that produced the best performance in identifying organic and non-organic waste. Factors such as accuracy, recall, precision, F1-score are used as a reference in evaluating experimental results. One example of the data training process is as follows:

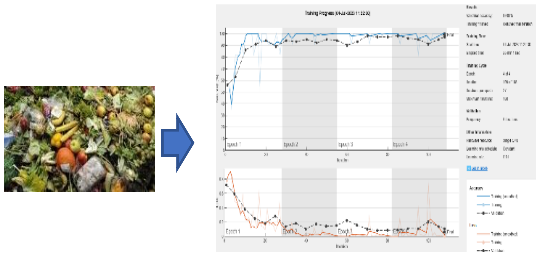


Figure 3.1 Training data for one of the organic waste datasets along with Accuracy, Loss, and Validation results

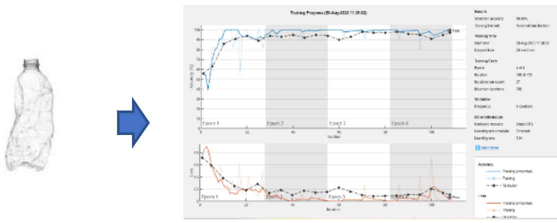


Figure 3.2 Training data for one of the non-organic waste datasets along with a graph of the validation results

Model accuracy improves as the iteration increases. In the 10th epoch, the accuracy seemed stagnant or fluctuated, at 42% to 93%, while the validation value fluctuated at 53% to

91%. In the 20th epoch, the accuracy seemed stagnant or fluctuated, at 89% to 93%, while the validation value fluctuated at 86% to 92%. In the 30th epoch, the accuracy seemed stagnant or fluctuated, at 88% to 95%, while the validation value fluctuated at 87% to 93%. In the 40th epoch it can be seen that the validation accuracy line is getting closer to or even crossing the optimal accuracy line, with a range of 95% to 98%, and reaching a stable point at 98%, and the validation value is 92% to 97%. , this indicates that the model has experienced a good increase in performance, as illustrated in the graph of the results of the training data for all datasets along with the following graph of the validation results:

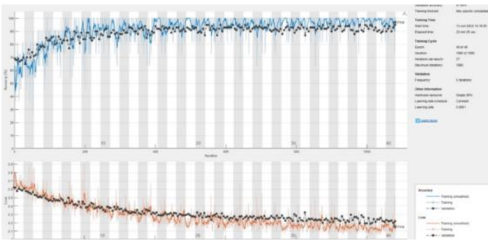
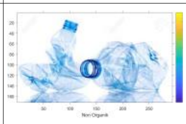


Figure 3.3 Training data for all datasets along with their validation results graphs

In the trial process, samples from a dataset were used which contained photos or images of waste, taken at random, both organic and non-organic waste, both those whose shape was still clearly visible and whose shape was not clearly visible or had decayed.

Table 3.1. An example of the results of identifying organic and non-organic waste using the CNN method with the Efficient-Net-B0 Architecture

No	Hasil Prediksi	Keterangan
1		The image shows the prediction results that the image is identified as organic waste
2		The image shows the prediction results that the image is identified as non-organic waste
3		The image shows the prediction results that the image is identified as organic waste
4		The image shows the prediction results that the image is identified as organic waste
5		The image shows the prediction results that the image is identified as non-organic waste

Convolutional Neural Networks (CNNs) are a class of deep learning models that have been widely used for image and video recognition tasks. They consist of multiple layers, including convolutional layers, pooling layers, and fully connected layers. The architecture of CNNs can be optimized using techniques like Optuna for hyperparameter optimization.

Optimizing CNN Architecture with Optuna used for hyperparameter optimization, including those related to the architecture of CNNs, it can be appied to CNN architecture:

1. *Hyperparameter Search: With Optuna, a search space for hyperparameters related to the CNN architecture can be defined, such as the number of convolutional layers, filter sizes, kernel sizes, dropout rates, learning rates, and batch sizes.*
2. *Objective Function: Objective function that takes hyperparameters as inputs, constructs a CNN model with the specified architecture, trains the model, and returns a performance metric. In this article, the accuracy of 98%, a precision of 96%, a recall of 96.1538%, and an F1 score of 0.960034.*

Optimization Process: Optuna then runs a series of trials, adjusting the hyperparameters in each trial to find the best combination that optimizes the objective function. This process continues until a stopping.

There is some gap researches based on the comparison between the performance of this approach and other researches:
1. Limited Application to Waste Identification: Prior research may have focused on general image recognition or waste classification but not specifically on identifying organic and non-organic waste. Therefore, there may be a research gap in terms of developing a dedicated model for this specific purpose.
2. Lack of EfficientNet-B0 in Waste Identification: The use of the EfficientNet-B0 architecture in the context of waste identification could represent a research gap if previous studies predominantly used other CNN architectures for similar tasks.

Summarize your contributions either in bullet points or using numbered lists.

This research may offer several valuable contributions to the field of waste management and computer image recognition. These contributions can be summarized as follows:
1. Advanced Technology for Waste Identification: The research likely contributes by introducing and demonstrating the use of advanced technology, such as the Convolutional Neural Network (CNN) with the EfficientNet-B0 architecture, for the specific task of identifying organic and non-organic waste in images. This technology represents a novel and efficient approach to waste management.
2. Increased Efficiency: The use of the EfficientNet-B0 architecture can contribute to more efficient and faster waste identification. This can lead to improved waste sorting and recycling processes, reducing the environmental impact of waste disposal.
3. Improved Accuracy: The research likely demonstrates enhanced accuracy in distinguishing between organic and non-organic waste, potentially outperforming earlier techniques. Improved accuracy can minimize errors in waste sorting and recycling.
4. Interpretability and Explainability: If the research addresses the interpretability and explainability of the CNN model's predictions, it contributes to a better understanding of how the model makes decisions. This is valuable in making AI systems more transparent and accountable.
5. Application in Real-World Settings: The research might demonstrate the practical application of the waste identification system in real-world settings such as waste sorting facilities, recycling centers, or waste management systems. This can have a tangible impact on improving waste management practices.
6. Environmental and Economic Benefits: The accurate identification of waste types can lead to more effective recycling and waste disposal, reducing the environmental impact and costs associated with waste management.
7. Future Research Directions: The research may suggest future research directions and potential improvements in waste identification, thereby guiding the research community towards areas that need further exploration and development.

Overall, the research contributes to the field by advancing the state of the art in waste identification, offering practical solutions, and addressing critical challenges associated with waste management and computer image recognition. These contributions can lead to more efficient, accurate, and ethical waste management practices, benefiting both the environment and society.

4. CONCLUSION

Based on the results of research on Identification of Organic and Non-Organic Waste with Computer Image Recognition Using Convolutional Neural Networks with Efficient-Net-B0 Architecture, several conclusions can be drawn as follows:

1. The research "Identification of Organic and Non-Organic Waste with Computer Image Recognition Using Convolutional Neural Networks with Efficient-Net-B0 Architecture" makes a significant contribution to the identification of organic and non-organic waste using computer image recognition methods. With an accuracy of 98%, a precision of 96%, a recall of 96.1538%, and an F1 score of 0.960034, this study provides excellent results in classifying waste using the Convolutional Neural Network (CNN) model and the Efficient-Net-B0 architecture.
2. Based on the research results, the computer image recognition method using a Convolutional Neural Network with the Efficient-Net-B0 architecture can be used for more efficient waste management. This method can be applied to waste recycling management on a small scale, namely in the community environment, as well as in urban waste management. It is hoped that the implementation of waste recycling using an intelligent system can have a positive impact on the environment and improve the country's economy. Recycling waste can create jobs for many people, create a cleaner environment and improve people's health.

In this study there are several suggestions that are expected to be carried out for improvement and development and application of the method, as follows:

1. In this study there are still deficiencies and limited use of datasets. It is hoped that in further research the quantity and quality of the dataset can be increased, and it would be very good if private datasets were used, so that they could contribute and be considered in waste sorting by identifying organic and non-organic waste with computer image recognition using a Convolutional Neural Network with an Efficient architecture -Net-B0.
2. In future research, it is hoped that the application of the CNN Method with the Efficient-Net-B0 architecture can classify data and create a design such as an automatic waste sorting machine using an intelligent system, which can sort waste using Artificial Intelligence technology with a deep learning approach.

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