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ANALYSIS OF THE CONVOLUTIONAL NEURAL NETWORK METHOD WITH MOBILENET ARCHITECTURE IN A COMPUTER VISION-BASED INDUSTRIAL WASTE DETECTION SYSTEM

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Abstract: Industrial waste has had a negative impact on the environment and human health. Industrial waste pollution can occur due to improperly managed waste disposal. Managing industrial waste can be one way to reduce the impact of environmental pollution. Checking industrial waste can be a solution for implementing oversight of waste management, but it will be difficult to implement if done in a large industrial area. Waste classification based on organic and non-organic waste categories. Convolutional Neural Networks (CNNs) and MobileNet can be applied to automatically detect organic and non-organic industrial waste systems. Researchers have conducted a comparative study between the Convolutional Neural Network (CNN) and MobileNet models, which is useful for obtaining the best model. The results of the analysis concluded that MobileNet has better accuracy, precision, and recall compared to the CNN model. The accuracy, precision, and recall generated by MobileNet are 99.5%, 99.4%, and 100%. Therefore, MobileNet is very suitable for implementation in an automatic industrial waste detection system in real-time applications.

Keyword: computer vision; convolutional neural network (CNN); deep learning; industrial waste; mobilenet.

Abstrak: Limbah industri telah mengakibatkan dampak buruk bagi lingkungan dan kesehatan manusia. Pencemaran limbah industri dapat terjadi akibat pembuangan limbah yang tidak terkelola dengan baik. Pengelolaan limbah industri dapat menjadi salah satu cara untuk mengurangi dampak pencemaran lingkungan. Pengecekan limbah industri dapat menjadi solusi untuk menerapkan pengawasan terhadap pengelolaan limbah, namun akan sulit diterapkan jika dilakukan pada area industri yang luas. Klasifikasi limbah berdasarkan kategori limbah organik dan limbah non organik. Convolutional Neural Network (CNN) dan MobileNet dapat diterapkan untuk sistem pendeteksi limbah industri organik dan non organik secara otomatis. Peneliti telah melakukan studi komparatif antara model Convolutional Neural Network (CNN) dan MobileNet yang berguna untuk memperoleh model terbaik. Hasil analisa yang telah dilakukan menyimpulkan bahwasanya MobileNet mempunyai akurasi, precision dan recall yang lebih baik jika dibandingkan dengan model CNN. Akurasi, precision dan recall yang dihasilkan oleh MobileNet sebesar 99,5% 99,4% dan 100%. Oleh karena itu, MobileNet sangat cocok untuk diterapkan pada sistem deteksi limbah industri secara otomatis pada aplikasi real-time.

Kata kunci: computer vision; convolutional neural network (CNN); limbah industri; mobilenet; pembelajaran mendalam.

INTRODUCTION

In recent decades, industrial development has experienced a very rapid increase in various countries. These industrial activities have had a positive impact on economic growth, but they have also caused negative environmental impacts [1]. One of the most significant negative impacts is the increasing amount of industrial waste. Poorly managed industrial waste can pollute the environment and harm human health. The effects of industrial waste pollution can be felt in the water, soil, and air quality around industrial areas [2]. Therefore, industrial waste management has become a serious issue that requires special attention. One of the main causes of environmental pollution is the improper disposal of industrial waste, which does not comply with environmental management standards. The waste can spread and pollute the surrounding environment if not properly controlled [3].

Overcoming the problem of pollution caused by industrial waste, effective waste monitoring and management efforts are needed. One step that can be taken is to monitor industrial waste regularly. This monitoring aims to ensure that industrial waste is managed in accordance with applicable regulations [4]. However, the manual process of monitoring industrial waste is quite a heavy task, especially in large industrial areas with a high volume of waste. The limited number of supervisors and the vast monitoring area are the main obstacles to implementing manual monitoring. Therefore, a system for monitoring industrial waste is needed that can operate automatically and efficiently [5].

Several researchers have proposed various methods for detecting and classifying industrial waste. Computer vision and deep learning approaches are becoming widely used because they can effectively process image data. Several deep learning models have been applied for object detection and image classification with high accuracy levels [6]. However, some models have high complexity, requiring significant computational resources and being less efficient when applied to systems with device limitations. Therefore, selecting the appropriate model is a crucial factor in developing an industrial waste detection system [7]. Convolutional Neural Network (CNN) is one of the deep learning methods widely used in digital image processing. CNN is capable of extracting image features well and achieving high accuracy rates. Additionally, MobileNet is a deep learning model designed for computational efficiency and is well-suited for systems with limited resources. MobileNet has a lightweight architecture but still delivers good performance on various image classification tasks [8]. In previous studies, the evaluation results of the proposed method using the MobileNetV1 model achieved the highest accuracy of 89.93%, followed by the MobileNetV2 model with 89.78%. In this study, the researcher will perform classification using organic and non-organic waste objects combined with the CNN and MobileNet methods.

Based on the previous research presented, the researcher proposes a study comparing CNN and MobileNet in an industrial waste detection system based on computer vision. CNN was chosen for its ability to achieve high accuracy, while MobileNet was selected for its computational efficiency and good performance. It is hoped that thru this research, the best model can be obtained that can be applied optimally in the industrial waste detection system.

METHOD

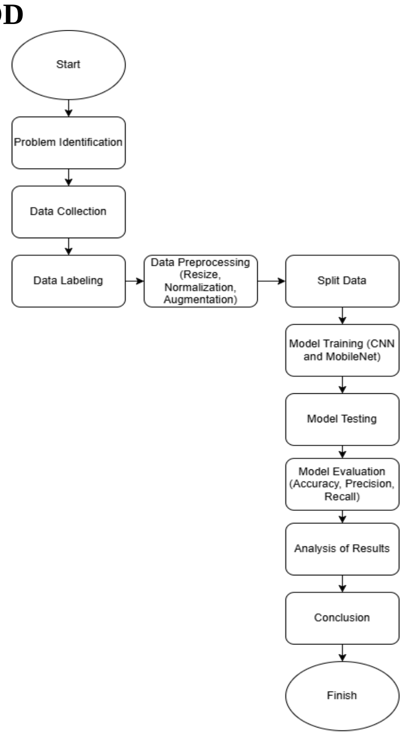

Image 1: Research Flow

Based on the research flow above, it explains that the research begins with data collection and labeling. The data was then preprocessed thru resizing, normalization, and augmentation to increase data variation and model performance. The dataset is divided into training, validation, and test data. Subsequently, the CNN and MobileNet models are trained separately. The trained models are tested using the test data and then evaluated based on the accuracy, precision, recall, and confusion matrix metrics. The evaluation results are used for comparative analysis and drawing conclusions. A Convolutional Neural Network (CNN) is an artificial neural network with a special ability for image recognition. CNNs try to mimic the neural networks [A4.1][A4.2] found in the human brain. It is the visual cortex of the brain that CNN will mimic in recognizing images.

The visual cortex of the brain is an area of the cerebral cortex used to process visual information. When CNN has a deeper neural network, it will be able to recognize images well. CNNs, which have deeper neural networks, can have multiple convolutional layers. The process that occurs in the convolutional layer will produce feature maps. Feature maps contain unique features from the original image. The number of feature maps depends on the number of filters applied to the convolutional layer [9]. Image 2 shows the process that occurs in the convolutional layer. To reduce the number of parameters in CNN and increase computational speed, a pooling layer can be added. The process that occurs in the pooling layer is the merging of neighboring pixels into a single pixel. This process reduces the number of image dimensions and causes the number of parameters in the CNN architecture to decrease. The pooling operations that can occur can be mean pooling or max pooling [10].

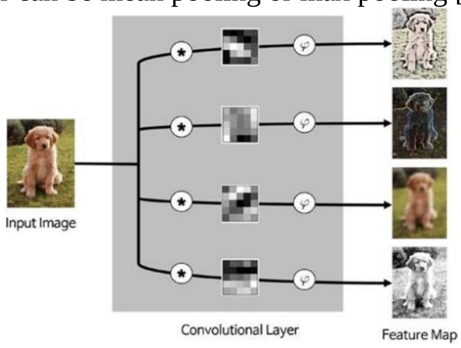

Image 2: Process in the Convolution Layer

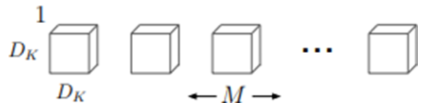

Image 3: Depthwise Convolution

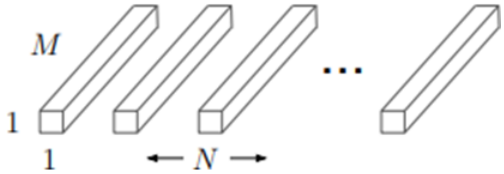

Image 4: Pointwise Convolution

MobileNet is one of the architectures included in the development of CNNs. MobileNet is designed to address the issue of large model size. The MobileNet model is able to reduce model size, thereby increasing the speed of computational processes. In previous research, the results showed that the model achieved an accuracy of 96% before optimization and increased by 2% to 98% after optimization. The difference in this study is the object of waste classification; this study uses organic and non-organic waste classification [11].

The main component used in MobileNet is depthwise separable convolution. Depthwise separable convolution can reduce model complexity and size by utilizing filter factorization techniques [12]. Depthwise separable convolution consists of two layers: depthwise convolution and pointwise convolution. Depthwise convolution functions as a filtering layer by applying one filter to each input channel. Pointwise convolution is a convolution process that uses a 1 × 1 kernel [13]. Image 3 shows the mechanism that occurs in the depthwise convolution process, while Image 4 illustrates the mechanism in the pointwise convolution process.

RESULTS AND DISCUSSION

In this research, the researcher analyzed the comparative results of two methods that can be used for automatic industrial waste detection. These two methods are Convolutional Neural Networks with the MobileNet architecture.

1. Dataset

The researcher will use a public dataset available on Kaggle. The dataset used by the researcher consists of 11,792 color-filtered images. Where 5,883 images are organic waste images and the remaining 5,909 images are non-organic waste images [14]. The dataset consisting of 11,792 images will be divided into three parts as follows:

Training Set consisting of 10,000 images divided into two categories: 5,000 organic waste images and the remaining non-organic waste images.

Validation Set consists of 800 images divided into two categories: 400 organic waste images and the remaining non-organic waste images.

Test Set consisting of 992 images divided into two categories: 483 organic waste images and the rest non-organic waste images.

2. Experiment

This experiment was conducted using Jupyter Notebook. Jupyter Notebook uses the Python language. To apply the CNN and MobileNet models to the waste dataset, the researchers used the Keras and Tensorflow libraries.

Data Augmentation in the real world, we will find a diverse variety of images. For example, an image of organic waste with a tilted rotation. To address this issue, the researcher will apply data augmentation, which will process the images into several variations. Rotation, shifting, zooming, vertical flipping, and horizontal flipping were applied to the images during the data augmentation stage for the CNN model. For the MobileNet model, the data augmentation performed was rotating the images and applying horizontal flipping.

Classification stage, CNN and MobileNet will be used. CNN and MobileNet have been trained for 30 epochs. Table I shows a summary of the CNN model, and Table II shows a summary of the MobileNet model built in this experiment.

3. Analysis of Results

To measure the performance of the classification results from the CNN and MobileNet models, the researchers used three performance measurement metrics. These three metrics consist of accuracy, precision, and recall. These metrics can be calculated using the values generated by the confusion matrix. The confusion matrix consists of true positives, true negative, false positive and false negative. Accuracy measures the model's ability to correctly predict all data. Accuracy can be calculated using equation 1. Precision is a metric calculated based on true positive and false positive values. Precision can be calculated using equation 2. Recall is a metric calculated based on true positive and false negative values. Recall can be calculated using equation 3.

$$accuracy = \frac{TP+TN}{TP+FP+FN+TN} \tag{1}$$

$$precision = \frac{TP}{TP+FP} \tag{2}$$

$$recall = \frac{TP}{TP+FN} \tag{3}$$

Table 1. Summary of the Convolutional Neural Network Model

Layer	Output Shape
16 Convolution	96, 96, 16
Max Pooling (2x2)	48, 48, 16
32 Convolution	48, 48, 32
Max Pooling (2x2)	24, 24, 32
64 Convolution	24, 24, 64
Max Pooling (2x2)	12, 12, 64
96 Convolution	12, 12, 96
Max Pooling (2x2)	6, 6, 96
128 Convolution	6, 6, 128
Max Pooling (2x2)	3, 3, 128
Flatten	1152
Dense	1024
Dense	512
Dense	2

Table 2. Summary of the MobileNet Model

Layer	Output Shape
MobileNet	4, 4, 1280

Flatten	20480
Dense	2

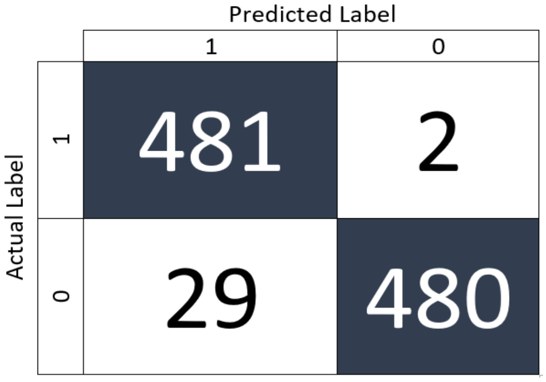

Image 5: Confusion matrix generated by the CNN model (1 is organic waste; 0 is non-organic waste)

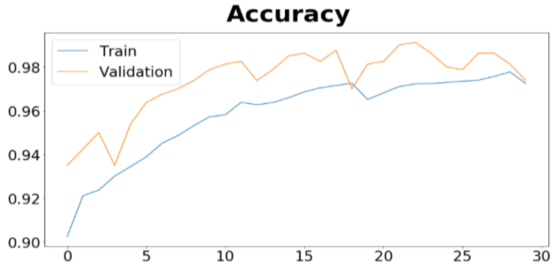

Image 6. Accuracy of the Convolutional Neural Network Model

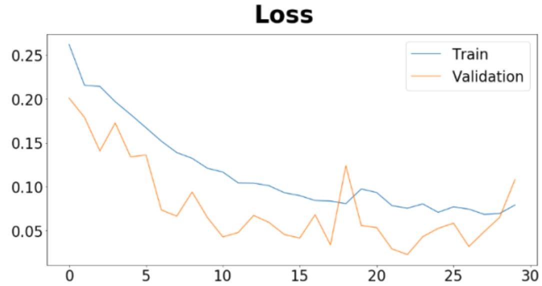

Image 7. Loss Convolutional Neural Network Model

Based on the experiments conducted, the CNN model showed good performance. The resulting accuracy was 96.88% and the lLoss was 15.17%. The precision value was 94.31% and the recall value was 99.58%. Image 5 visualizes the accuracy of the CNN model on training and validation data. Image 6 visualizes the loss of the CNN model on training and validation data. The experiments on the MobileNet model showed good results. The resulting accuracy was 99.5% and the loss was 0.324. The precision value was 99.3% and the recall value was 100%. Image 7 visualizes the accuracy of the MobileNet model on training and validation data. Image 8 visualizes the loss of the MobileNet model on training and validation data.

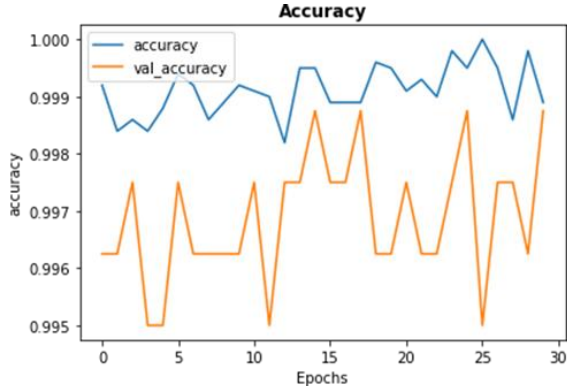

Image 8: Accuracy of the MobileNet

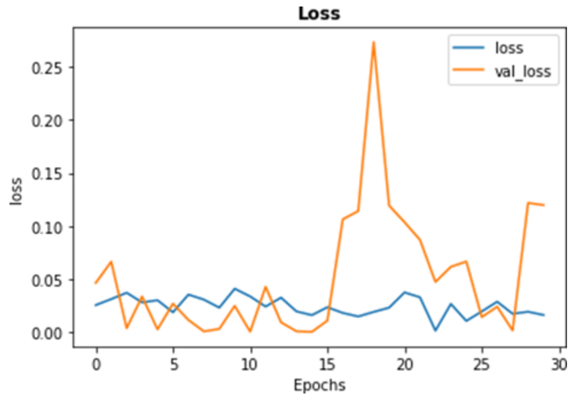

Image 9: Loss MobileNet model

The graphs in Images 8 and 9, the pattern is fluctuating or noisy, indicating that the model training process is not yet fully stable. One of the main causes of this condition is an excessively high learning rate, which makes the model's weight updates too aggressive, causing the loss value and evaluation metrics to fluctuate sharply with each iteration. When the learning rate is not optimal, the model struggles to reach a stable convergence point.

Table 3. Performance Comparison

Model	Accuracy	Precision	recall
CNN	96,88	94,31	99,58
MobileNet	99,50	99,30	100,00

Based on the data in Table III, it shows a comparison of performance between CNN and

MobileNet. MobileNet successfully outperformed CNN models in terms of accuracy, precision, and recall.

4. Discussion

The proposed MobileNet model has achieved good performance, yielding an accuracy of 99.50%. The training process using the MobileNet model takes a long time. MobileNet has a computational speed that is faster than CNN models. The computational process depends on the complexity of the network built. Network simplification in the model can increase the speed of computational processes.

CONCLUSION

This research discusses the comparative analysis of CNN and MobileNet methods for industrial waste detection. Experiments have been conducted on a dataset of 11,792 entries. The data to be processed at the classification stage has already undergone data augmentation. The data augmentation stage involves image processing techniques such as rotating images, horizontal flipping, vertical flipping, and others. The data will then be processed at the classification stage. At the classification stage, CNN and MobileNet will be tested for their performance in terms of prediction accuracy for industrial waste detection. The research results show that the best performance is achieved by MobileNet. MobileNet successfully achieved higher accuracy than CNN. The resulting accuracy is 99.5%. Therefore, MobileNet can be selected for application in an industrial waste detection system in a real-world application. For future research, the researcher suggests conducting experiments by building a simpler network architecture that is still accurate in classification or prediction. Thus, a method can be produced that has high computational speed while remaining accurate in performing classification.

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