Waste Classification Model Optimization with Modified MobileNetV3 for Efficient Waste Management

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Abstract: The increase in population and economic activity has a significant impact on the amount of waste. Data in 2023 states that waste in Indonesia still cannot be managed properly. One solution to overcome this problem is through recycling with waste sorting as a crucial stage. This research develops a waste classification model using modified MobileNetV3S. The classification process is performed using Convolutional Neural Network (CNN) method and parameter fine-tuning. This model is able to classify five different categories of waste, namely plastic bottles, leaves, plastic sheets, paper, and metal. These categories were chosen by considering the common practice in waste classification for recycling purposes. The results show that the validation accuracy reaches 96.2% with a loss value of 0.049. These results can significantly contribute to better and sustainable waste management efforts.

Keywords: Waste Management; Classication; MobileNetV3S; Fine-Tuning

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http://dx.doi.org/10.12962/j24604682.v21i2.20876

I. INTRODUCTION

Waste is a solid object that is generated from daily activities and no longer has any benefit to its users. An increase in population has a significant impact on various aspects of a region or city, among which is the surge in the amount of waste in the community. In addition, economic and demographic activities also have an impact on the increase of waste [1]. Based on data submitted by the Coordinating Ministry for Human Development and Culture (KEMENKO PMK), in 2023 there were around 7.2 tons of waste in Indonesia that had not been managed properly. In fact, the World Bank estimates that by 2050, the amount of global waste will reach 3.40 billion tons. This significant amount is expected to cause various environmental and health problems. Therefore, strategic and innovative measures are needed to address it.

One of the solutions to overcome the waste problem is through the recycling process, with waste sorting being a crucial stage for efficiency [2]. In Indonesia, this process is still done manually [3], which presents challenges in waste identification and limits recycling effectiveness. The concept of smart cities, which merges technological solutions with community-focused approaches, addresses these challenges and promotes sustainability [4]. The integration of artificial intelligence (AI) in smart cities enhances data interpretation and decision-making, significantly impacting innovative and efficient waste management [5].

Research on AI-based waste classification has been conducted by many researchers to sort waste efficiently. Various models were developed to obtain accurate recognition of waste types, including the use of Convolutional Neural Network (CNN) to classify images and identify the type of waste material. This study used a dataset of 25.077 self-collected litter images, and the developed model achieved the highest accuracy rate of 84.23%[6]. Another study also used the TrashNet dataset, which was segmented into five categories: cardboard, glass, metal, paper, and plastic. The study achieved a commendable average accuracy of 88.09% [7]. This shows that the number and quality of datasets have a significant influence on the performance of AI models.

Larger datasets tend to provide a better representation of real-life litter variations, including differences in color, texture, and shape. With better representation, the model can learn more complex patterns and improve its generalization ability on new data. Conversely, limited datasets may cause the model to experience overfitting, where the model performs very well on training data but poorly on testing data [8]. Therefore, the use of a wide and varied dataset is an important factor in the successful implementation of AI models for waste classification.

The CNN method can be modified by using various base models. For example, the VGG base model has been used for automatic garbage classification using a smart bin system, where the type of garbage is determined based on machine visual recognition [9]. The ResNet-50 model was also used to classify litter types with a high accuracy of 98.70% on a dataset consisting of 2,751 images [10]. In addition, other basic models such as Xception, InceptionResNetV2, MobileNet, DenseNet121, and EfficientNetV2 have been applied in similar studies [11].

One model that has attracted attention is MobileNetV3-Small, which is specifically designed for high efficiency and performance on devices with limited computing resources. With techniques such as hardware-aware network architecture search (NAS) and NetAdapt algorithm, MobileNetV3-Small

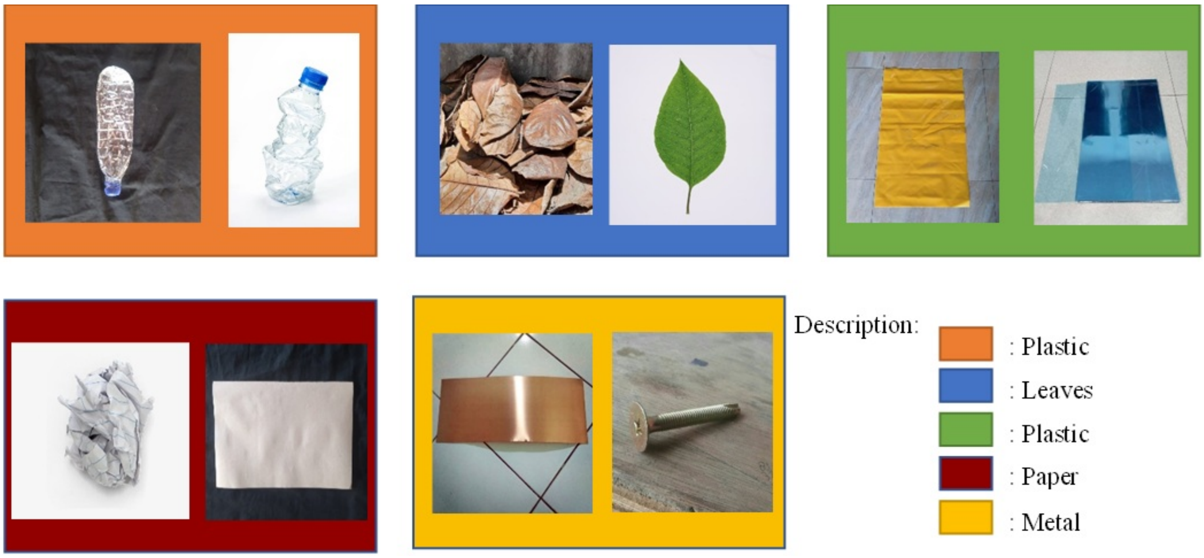

FIG. 1: Example Images of Each Class in the Garbage Dataset.

is able to reduce latency and improve computational efficiency compared to its predecessor, MobileNetV2 [12]. However, in the context of litter classification, this model only achieved 78% accuracy in a previous study [13]. In contrast to previous studies, this study modifies MobileNetV3-Small by adding multiple layers and optimizing hyperparameters through fine-tuning, aiming to improve classification accuracy and computational efficiency in litter sorting tasks. This modification is expected to contribute in creating a more efficient model for waste classification applications.

II. METHOD

This research was conducted in two stages, namely the data collection process and the classification process. image data collection process is done by web scraping and real-time image capture using a webcam [14]. Real-time image data collection using webcam with Full HD specifications is done by taking live images of objects in the surrounding environment. This technique allows for natural variations in lighting, image capture angle, object position, and background [15]. The dataset generated from these two methods consists of 125 images divided into five classes, namely plastic bottles, leaves, plastic sheets, paper, and metal. Each class consists of 25 images with different dimensions, colors, and object characteristics. The dataset was then divided into three groups, 70% for training data, 15% for validation data, and 15% for testing data, in accordance with standard practice in the development of machine learning models [16]. Examples of images from each class are shown in Fig. 1.

The second stage is the image classification process using the MobileNetV3S model architecture. This process is done with two approaches. The first approach uses the pure MobileNetV3S model without the addition of additional layers. The second approach uses MobileNetV3S as the base model

TABLE I: Summary of the model architecture.

Layer (type)	Output Shape	Parameter
Mobilenetv3small (Functional)		
global_average_pooling2d (GlobalAveragePooling2D)	(None, 576)	0
dense (Dense)	(None, 16)	9,232
dense_1 (Dense)	(None, 16)	272
dropout (Dropout)	(None, 16)	0
dense_2 (Dense)	(None, 5)	85
Total params: 948,709 (3.62 MB)		
Trainable params: 9,589 (37.46 KB)		
Non-trainable param: 939,120 (3.58 MB)		

and adds two Dense layers after the Global Average Pooling layer, as well as one Dropout layer to prevent overfitting. The addition of the Dense layer aims to improve the model's ability to capture more complex patterns from the input data [17], while the Dropout layer helps reduce the risk of overfitting by disabling a random number of neurons during training [12].

Then parameter tuning is performed on the classification model for the parameters of the number of nodes, dropout, learning rate, and batch size at 100 epochs. The variations used are the number of nodes 16, 32, 64, 128; dropout 0, 0.1, 0.2; learning rate 0.01, 0.005, 0.001; batch size 32, 64, 128, and Adam optimizer. The selection of these variations refers to the common practice in the optimization of artificial neural network models [18-20].

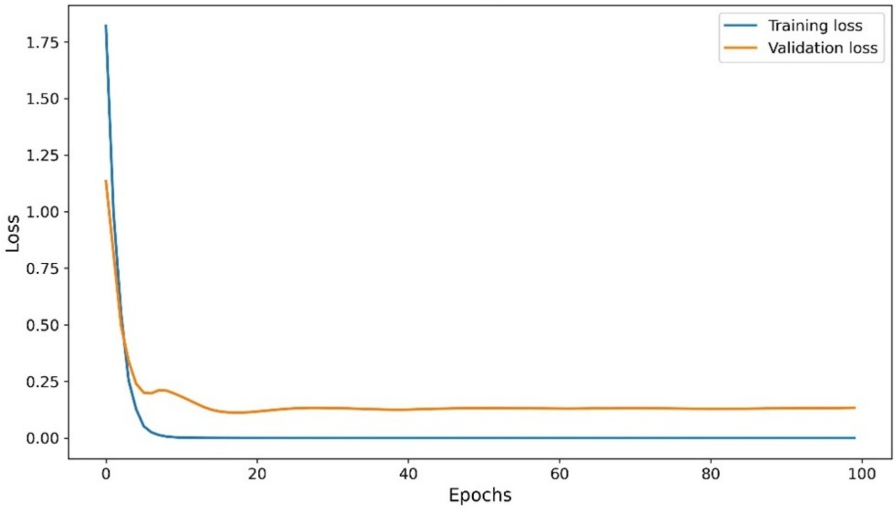

FIG. 2: Graph of training and validation data loss values.

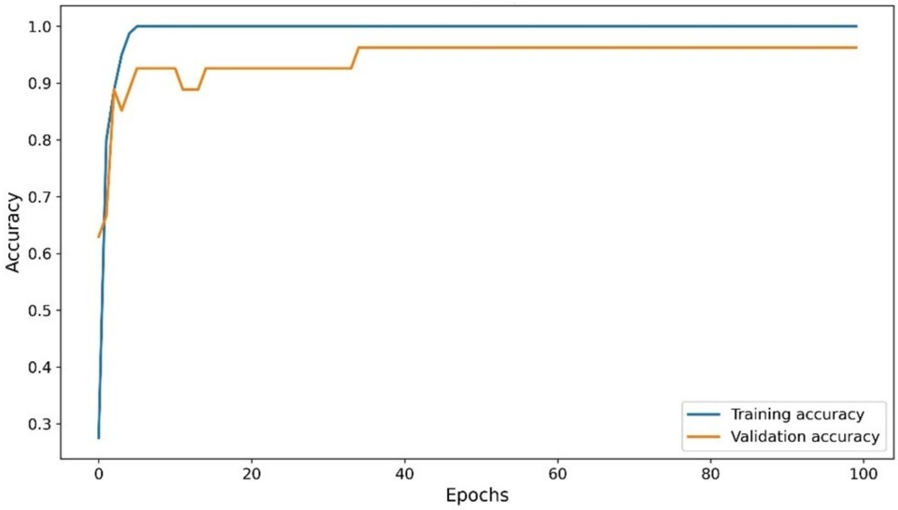

FIG. 3: Graph of accuracy value of training and validation data.

III. RESULT AND DISCUSSION

Training the MobileNetV3S model without additional layers resulted in an validation accuracy of 48% and a validation loss value of 1.318. Meanwhile, the fine tuning results on the modified MobileNetV3S model with the architecture as shown in Table I showed significant performance improvement. The results of the fine tuning performed to achieve this performance are shown in Table II.

Table II shows that the best results are obtained by using 64 nodes, no dropouts, a learning rate of 0.005, and a batch size of 64. This configuration produces the highest validation accuracy of 96.2% and the lowest loss value of 0.086. This shows that a learning rate of 0.005 is very effective in increasing accuracy while reducing loss. In addition, batch sizes 32 and 64 consistently provide good results in terms of accuracy and loss, while batch size 128 tends to produce lower performance.

TABLE II: Parameter Fine-Tuning Results for the Modified MobileNetV3S Model.

Num Nodes	Dropout	Learning Rate	Batch Size	Vallidation Loss	Vallidation Accuracy
16	0.1	0.001	128	0.392	0.839
16	0	0.005	32	0.291	0.920
16	0.2	0.001	64	0.295	0.920
32	0	0.001	64	0.316	0.879
64	0	0.005	64	0.049	0.962
64	0.1	0.001	64	0.380	0.879
128	0.2	0.001	64	0.323	0.879

Experiments with a smaller number of nodes, namely 16, also produced quite good results. The model with 16 nodes and a learning rate of 0.005 as well as a batch size of 32 or a dropout of 0.2 and a batch size of 64, resulted in validation accuracy reaching 92% with relatively low loss values (0.291 and 0.295). In contrast, models with a larger number of nodes, such as 32 or 128, did not always show significant performance improvements. This shows that increasing the number of nodes is not always directly proportional to the performance improvement. This is influenced by the size of the dataset used. On small datasets, increasing the number of nodes can actually cause overfitting. Some studies have shown that models with fewer nodes tend to perform better on small datasets due to lower complexity, thus reducing the risk of overfitting [21,22].

The best configuration with the results of the validation accuracy value and the loss value is visualized in the Fig. 2 and Fig. 3.

In the Fig. 1, it can be seen that the loss values for the training and validation data decrease rapidly during the first few epochs. After that, the loss values stabilize close to zero, indicating that the model is successfully learning and minimizing the prediction error. This indicates that the model converges well, which is a sign of efficient model performance in the training process [23]. In addition to the loss value, the model's training and validation accuracy values are also plotted to illustrate the model's performance.

Fig. 3 above shows a significant increase in accuracy over the first few epochs, with training and validation accuracy approaching 100% after about 20 epochs. The stability of accuracy after several epochs indicates that the model does not suffer from overfitting, which is a condition where the model learns too specifically on the training data and is less able to generalize to new data. This consistency also reflects the effectiveness of the model in handling previously unseen data [24]. Compared to previous studies, such as those reported in [6] which used a much larger dataset and achieved an accuracy of 84.23%, and [7] which also used a fairly large dataset and obtained an accuracy of 88.09%, our model shows higher accuracy despite using only 125 samples. This shows that despite the smaller number of samples in our study, the modifications made, such as adding layers and fine-tuning hyperparameters, contributed to the improved performance of the model. This comparison indicates that proper training techniques can optimize performance even with a limited number of samples.

Overall, the performance of the classification model is shown in the confusion matrix in Fig. 4. The confusion matrix above demonstrates the performance of the classification model on the test data. The model successfully predicted all samples from classes 0, 1, 3, and 4 correctly, as indicated by the bright boxes on the main diagonal. Although there are challenges in predicting class 2, where only 2 out of 6 samples were correctly predicted while 4 samples were incorrectly predicted as class 1 or 3, the model overall shows a strong ability to classify the majority of the classes with high accuracy.

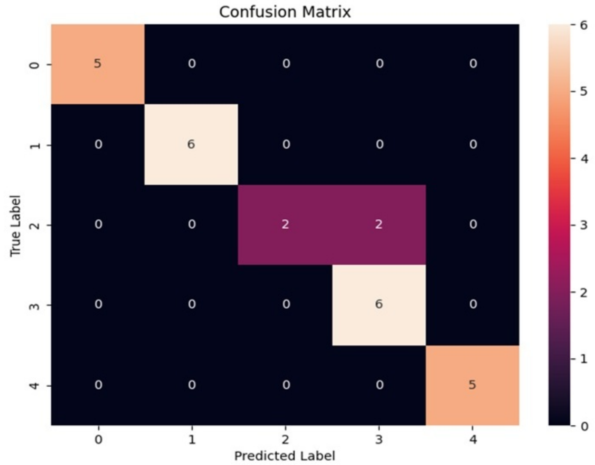

FIG. 4: Performance evaluation chart.

IV. CONCLUSION

In this study, a waste classification model was created into 5 classes, namely plastic bottles, leaves, paper, plastic sheets and metal. This study modifies the MobileNetV3S model by adding layers and performing fine tuning. The results show that fine-tuning parameters such as the number of nodes, dropout, learning rate, and batch size is very important to achieve optimal performance. The fine-tuned model was able to classify waste with a validation accuracy of 96.2% and a loss value of 0.049. Based on these classification results, it is expected to contribute significantly to better and more sustainable waste management efforts in the future.

Acknowledgments

This research was funded by DIPA BLU University of Mataram with Contract Number 1428/UN18.L1/PP/2024.

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