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Article

An Automatic Environment Monitoring System Using a MobileNet Transfer Learning

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A B S T R A C T

The universities have an important role to encourage and support the Sustainable Development Goals (SDGs). UIN Alauddin Makassar as one ofthe universities in Indonesia establishes a green campus program to support it. An automatic environment system was built to ensure the cleanliness of the university environment. A comfortable and healthy work environment is expected can improve the productivity and motivation of the academic civities. The system was built using a MobileNet architecture thatusing a transfer learning approach. It can detect the cleanliness level of the environment which consists of three classes: “Clean”, “Less_Clean”, and “Dirty” in real-time. The dataset used to train the model was obtained by capturing images of the environment around the university. The best result of the model was achieved by using an Adam optimizer with applying a dropout in the last layer of the network. The total accuracy of the model is about 83%.

I. INTRODUCTION

Sustainable Cities and Communities is one of 17 Sustainable Development Goals (SDGs) which aims to make cities inclusive, safe, resilient, and sustainable. Sustainable Cities and Communities or Global Goal 11 have many targets including creating green public spaces. Ministries, institutions, universities, and various communities have made action plans to support and realize the SDGs including Universitas Islam Negeri (UIN) Alauddin Makassar.

In recent years, UIN Alauddin Makassar establishes a green campus program to support SDGs and also to create a comfortable and healthy work environment. It aims to improve the productivity and the motivation of the employees.

A healthy workplace environment in Indonesia has been regulated in the regulation of the Minister of Manpower Number 5 of 2018 concerning Occupational Safety and Health in the Work Environment. This regulation is made to create a safe, healthy, and comfortable work environment to prevent work accidents and occupational diseases [1]. The workforces are expected can work more productive and optimal by implementing this regulation.

Based on that regulation, several actions such as providing cleaning facilities, a janitor, and waste managementwas implemented by the government, institutions, or communities to control the work environment. But however, these actions should be managed properly and monitored regularly to ensure the environment is always clean and healthy.

Monitoring of the work environment is usually done manually where the cleaning supervisor will check the environment directly. The manual monitoring has several limitations: the cleaning supervisor is difficult to simultaneously monitor real-time of thousands of observations points, time-consuming, and high mobility.

The use of technology is an alternative that can be applied to address it. The environment monitoring by the system can detect the state of the environment automatically and simultaneously in real-time.

Some studies related to environmental monitoring and waste management have been conducted. An automatic garbage detection system was proposed in [2]. The proposed system uses a deep learning approach to detects and identifies decoration garbage directly and automatically.The proposed model achieved 89.71% of recognition rate.

Autonomous garbage detection was also proposed in [3] for urban environment monitoring. In this research, a Faster R-CNN with a data fusion and augmented strategy is used to build the model. The experiment results show that the proposed method achieved high precision.A challenging object detection related to garbage is also proposed in [4]. In this research, YOLOv4-Tiny and YOLOv5-S architectures are used to detect plastic in marine. The best precision is achieved by YOLOv4-Tiny but the best recall was achieved by YOLOv4-Tiny. The researchers claim that the improvement of the dataset would give a significant impact, but it requires human labor for processing.

Real-time waste management was also proposed in [5]. Convolutional Neural Network (CNN) was used to classify the waste into two categories named digestible and undigestible. The camera module was attached to the microcontroller of the system. The image was captured by the camera will be pre-processed and classified by the microprocessor (Raspberry pi) using a classifier that has been trained. Finally, the microprocessor will send a command to a servo motor to put waste into the corresponding trash box.

A more challenging waste classification was also proposed in [6]. The waste is not only classified into digestible or indigestible, but it is classified into specific class such as glass, metal, paper, or plastic. It aims to address the waste separation that is normally done manually by hand-picking. The proposed model is ResNet-50 that used as a feature extractor and the fully connected layer of this architecture is replaced with Support Vector Machine (SVM) as the end classifier.

The studies that have been conducted only try to detect garbage from an image. It cannot identify the state or the cleanliness level of an environment. However, the cleaning supervisor needs a system that can detect the state or the cleanliness level of the environment. It can help the cleaning supervisor to monitor the environment efficiently and effectively.

The related studies mostly use a deep learning approach to address waste management. The results show that deep learning gives a proper performance

Convolutional Neural Network (CNN) is one of the deep learning algorithms. It has shown excellent performance in many computer vision and machine learning problems [7]. CNN consists of several architectures including: VGG16 [8], Xception, Inception, ResNet[9], MobileNet[10], DenseNet[11], NASNet , AlexNet, and others.

In this study, we propose a deep learning approach that using a MobileNet architecture to detect the state or the cleanliness level of the environment. MobileNet has fewer parameters but can give higher accuracy [12].

The trained model will be used to construct an environment monitoring system which can be integrated into a mobile phone, embedded, and IoT devices.

II. LITERATURES REVIEW

MobileNet is a portable Convolutional Neural Network (CNN) designed for mobile and embedded vision applications that use depthwise separable convolutions. Depthwise separable convolutions consist of two layers, the first is depthwise convolutions which will apply a single filter to each input channel, and the second is pointwise convolutions which will create a linear combination of the output of the depthwise layer [10].

MobileNet proposed new global hyperparameters namely width multiplier and resolution multiplier. Width multiplier is used to reduce computationally while resolution multiplier is used to decrease the resolution of the input image.

All layers except the last layer in MobileNet architecture are followed by a batchnorm and ReLU nonlinearity [13].

III. METHODS

The steps in this research can be seen in Figure 1.

This research consists of three main steps: data collection, model development, and environment monitoring system.

1. Data Collection

The dataset was curated by collecting images of the environment working around the Faculty of Science and Technology, UIN Alauddin Makassar. The images were captured by mobile phone with various angles. Because the input images greatly affect the models, so the image was capture with various weather conditions such as when sunny day, rain, and cloudy.

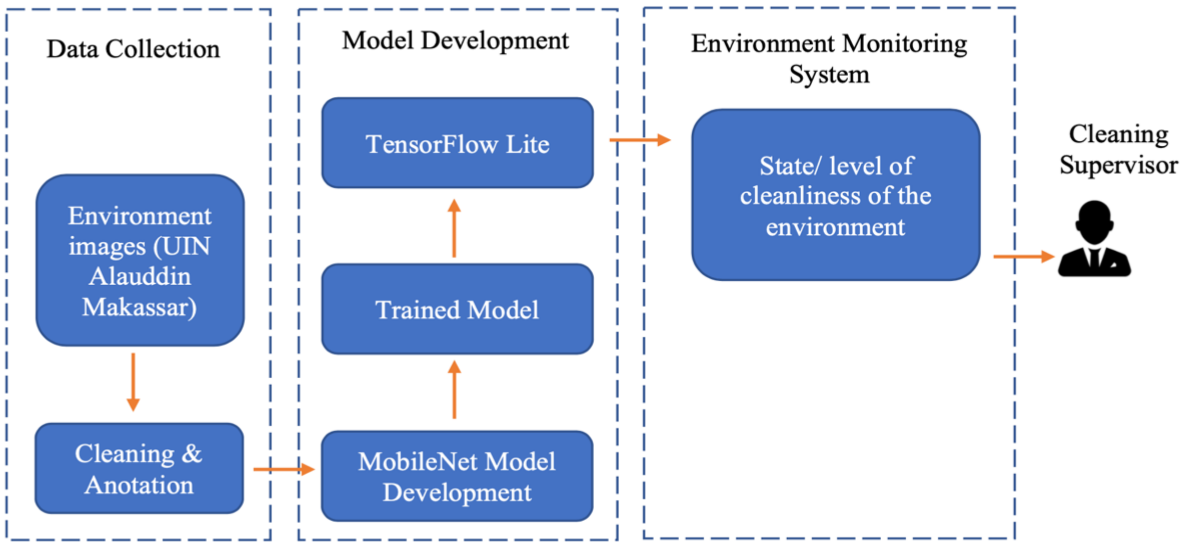

Figure 1:Research Methodology

An improvement of the first version of the MobileNet is proposed in [14], it is known as MobileNetV2. The main changes in the second version are using of inverted residual blocks and linear bottlenecks. In the bottleneck, there are inputs and outputs between the model while the inner layer encapsulates the ability of the model to change the input from lower-level (i.e. pixels) to higher-level descriptors.

The data was collected then annotated by the researchers into three classes: clean, less-clean, and dirty. The total number of the dataset was collected is 120 images where each class contains 40 images.

The example of images from each class can be seen in Figure 2, Figure 3, and Figure 4.

Figure 2: Example of clean environment

Figure 3: Example of less-clean environment

Figure 4: Example of dirty environment

2. Model Development

The model was constructed using MobileNetV2 architecture. The detail of the model building process can be seen in Figure 5. The dataset is split into 80% for training and 20% for testing. In this research, a pre-trained MobileNet was used to construct a new model. It is known as transfer learning approach. This approach uses a model that was trained (pre-trained model) on a dataset and it is reused on a new different dataset.It works by transferring knowledge gained from an existing model to a new model designed for a similar task [15]. Transfer learning usually transfers general knowledge which makes up the main processes for completing a task. This could be the process behind how images are being classified. To perform a new task, we need to add layers for getting more specific knowledge from a new dataset. This approach can give satisfying results on a small dataset [16].

In this research, several parameters tuning was tested to obtain the best model. We have also added a dropout layer in the last layer to prevent overfitting [17]. The model was evaluated by using accuracy, precision, and recall metric. It was built by using Keras and TensorFlow library.

3. Environment Monitoring System

The environment monitoring system was constructed by using a model that had been trained.

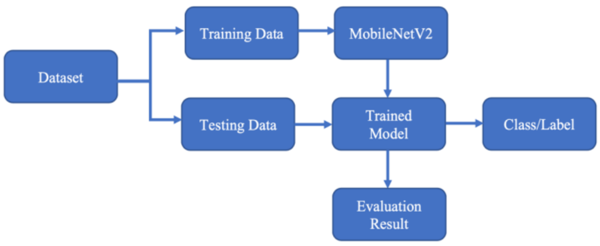

Figure 5: Development model process

We have used TensorFlow Lite to test the model in real-time. TensorFlow Lite is open-source software designed for running the pre-existing model on mobile, embedded, and IoT devices [18].

TensorFlow Lite supports Android and IOS. Currently, it is in the review of development, so it may not support TensorFlow operates in all models. The TensorFlow Lite is not designed for training model, so to get a robust model we need to train the model that is supported by a powerful system and hardware and then convert it to a TensorFlow Lite format.

IV. RESULT

In this research, a pre-trained MobileNet on ImageNet dataset which contains 1000 classes such as animals, cars, airplanes, trash, garbage, and otherswas used to construct a new model.

In general, the earlier layers of the Convolutional Neural Network will learn to recognize objects, the middle layers learn the shape of the objects, and the last layer learns some task-specific feature. In transfer learning approach, the early and middle layers of the pre-trained model are used while the latter layers will be retrained to get specific feature of the new dataset so it will learn what separates the new object from other objects.

Adapting the pre-trained model to construct a new model will extract some different features. Thus, we need to tune the parameters before transferring the knowledge. In this research, we add 64 dense layers in the last layer of the MobileNet, and the pre-trained model was used as the starting point.

The fixed parameters were used are: learning rate set is 0.001, the batch size is 32, the number of the epoch is 25, and the dropout is 0.7.

We have also compared two popular optimizers on the deep learning models to get the best model which can be seen in Table 1.

Table 1. Comparison of Accuracy Value

Optimizer	Dropout	Accuracy (%)
SGD	Without Dropout	0.38
	With Dropout	0.75
Adam	Without Dropout	0.71
	With Dropout	**0.83**

Table 1 shows that using a dropout can improve the accuracy rate both of SGD (Stochastic Gradient Descent) and Adam optimizer. The best accuracy is achieved by using an Adam optimizer and dropout in the last layer.

The precision and recall value of the best model can be seen in Table 2.

Table 2. Precision and Recall Values of the Best Model

Class	Precision (%)	Recall
Less_Clean	0.75	0.75
Clean	0.88	0.88
Dirty	0.88	0.88

Table 2. shows that the "Less_Clean" class obtain lower precision and recall than other classes. It is caused by some of the input images of this class look similar with "Clean" and "Dirty" class, so the model still difficult to identify it correctly. And addition, the number of the dataset is relatively small.

The trained model has been implemented on an Android mobile phone for testing in real-time. It was tested to detect the cleanliness level of the environment at the Faculty of Science and Technology, UIN Alauddin Makassar. The results can be seen in Figure 6 and Figure 7.

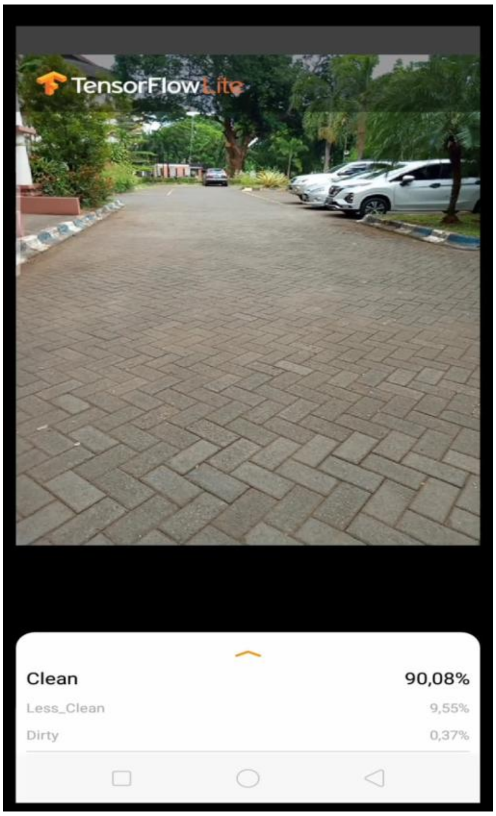

Figure 6. The result test of the system

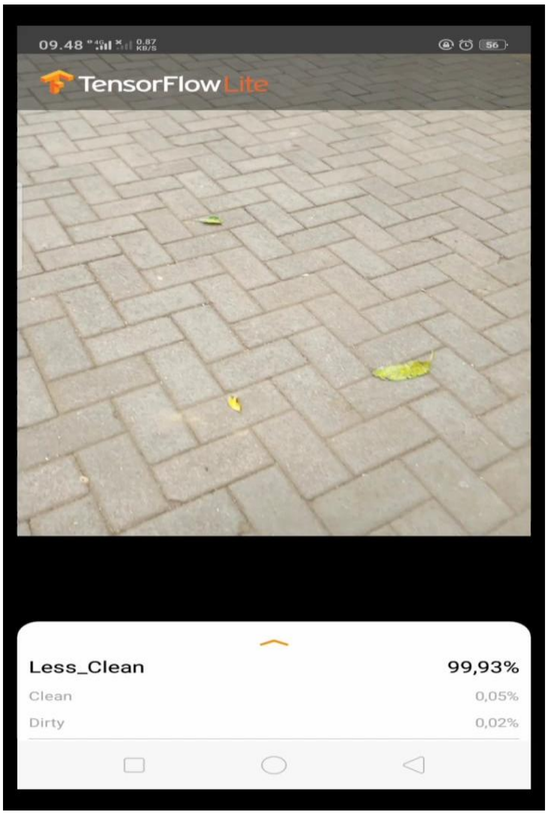

Figure 7. The result test of the system

Based on Figure 6 and Figure 7, the result test of the system shows that the system can detect the cleanliness level of the environment.

V. CONCLUSION

In this research, MobileNet as a powerful deep learning architecture was applied to build a model. The trained model was used to construct an automatic environment monitoring system and it was tested directly at the Faculty of Science and Technology, UIN Alauddin Makassar. The model can be integrated into embedded or IoT devices. It can be used to monitor all areas of the universities in real-time.

Overall, the test results show that the system can detect the cleanliness level of the environment accurately. However, the increase of the number and variation of the sample images are needed to get a more robust model.

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BIOGRAPHY

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