Datasets Training and Testing in Littering Activity Classification

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Abstract. The bad habits of the human who always ignoring their environments could affect some problems, such as diseases, flood, environmental damage, and air pollution. One of the habits is littering. This habit cannot be easily removed due to it has been ingrained in them. Therefore, it is needed a device that can catch their irresponsible action. Using that device, someone will be forced not to do littering. When, it is forced, they will be accustomed to obey the rule. This research presents the training and testing that are conducted in some proposed models of RNN. From the experiments, it can be concluded that the best model is add(Dense(256, 512 and 1024)) with Epoch 25.

Keywords: Littering · Activity classification · Training · Testing · RNN

1 Background

The increasing in garbage production is due to the acceleration in the population growth and urbanization [1]. The lack of public awareness of garbage and the absence of warnings to people who throw it carelessly [2], cause problems, such as flooding [3], unpleasant odors, and various diseases. These problems become worse due to the traditional garbage management technology has low efficiency and accuracy [4].

The problem concerning with the garbage that becomes the focus of this research is the increase of littering. The littering can be described as the body movements or various positions of the limbs in relation to time and gravity [5]. The movement of the human in the littering can be analyzed using artificial intelligence. Nowadays, the research related to the human activity becomes an important, especially in computing. It can be conducted by analyzing human behavior, and human computer interactions [6]. In this research, it is proposed models of RNN that is combined with the pose detection that analyses the movements of one's part of body when he does the littering.

In general, human activities can be identified using sophisticated technology, such as Closed-Circuit Television (CCTV). CCTV has become a fundamental part of the security and surveillance system. This makes it possible to implement real-time supervision that

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focuses on protecting the environment, especially on littering activities [7]. However, this CCTV can only monitor the activity, and cannot catch the doer of littering in real time.

The researchers have a desire to generate a device that can identify human activities in littering using the help of a webcam. It can monitor a real time littering activity using image processing. The images were processed using machine learning with the Reccurent Neural Network (RNN) method. This method is the improvement of the previous reseach [8] that used Convolutional Neural Network (CNN). Thus, to see the characteristics of this method, this research presents the testing and training of the datasets using some models. This is intended to find the best model for the proposed device.

2 Methodology

There are several steps that should be paid attention before conducting the training and testing process, namely:

1. Parameter Settings

At this step, the parameter values for the training experiment should be determined by adopting the proposed RNN model. The parameters include the number of epochs, the number of batches, the number of layers, the size of the convolution layer and the size of the pooling layer.

2. Data Extraction

In the data extraction, the video dataset that has been collected was converted into several images. It is intended to make possible the data to be inputted to the next process.

3. Data Sharing

The next step after extracting the data, all image data of littering and normal (not throwing garbage) activities are divided into 2 data, namely training data and testing data.

4. RNN Classification

In this RNN classification, there is a convolution layer which is an operation of linear algebra that shifts the matrix from the filter in the image to be processed. One of the layers carried out in this classification is usually called the convolution layer process. Convolution layer is the most important main layer used. Another type of layer used is the pooling layer, which is a layer that is used to take the average or maximum value of the pixel layer in an image.

5. Training and Testing

Training and Testing were conducted by entering a testing data image into the RNN classification model. In this testing process, it is expected that the data can classify the testing data into the correct class. This testing is carried out to calculate the accuracy value generated in the classification model that has been made.

3 Result

Several training and testing datasets should be conducted in order to know which model is suitable to be used in this research. In the first experiment, a simple RNN model layer, namely: model.add (Simple.RNN(64,128 and 256)) method was used.

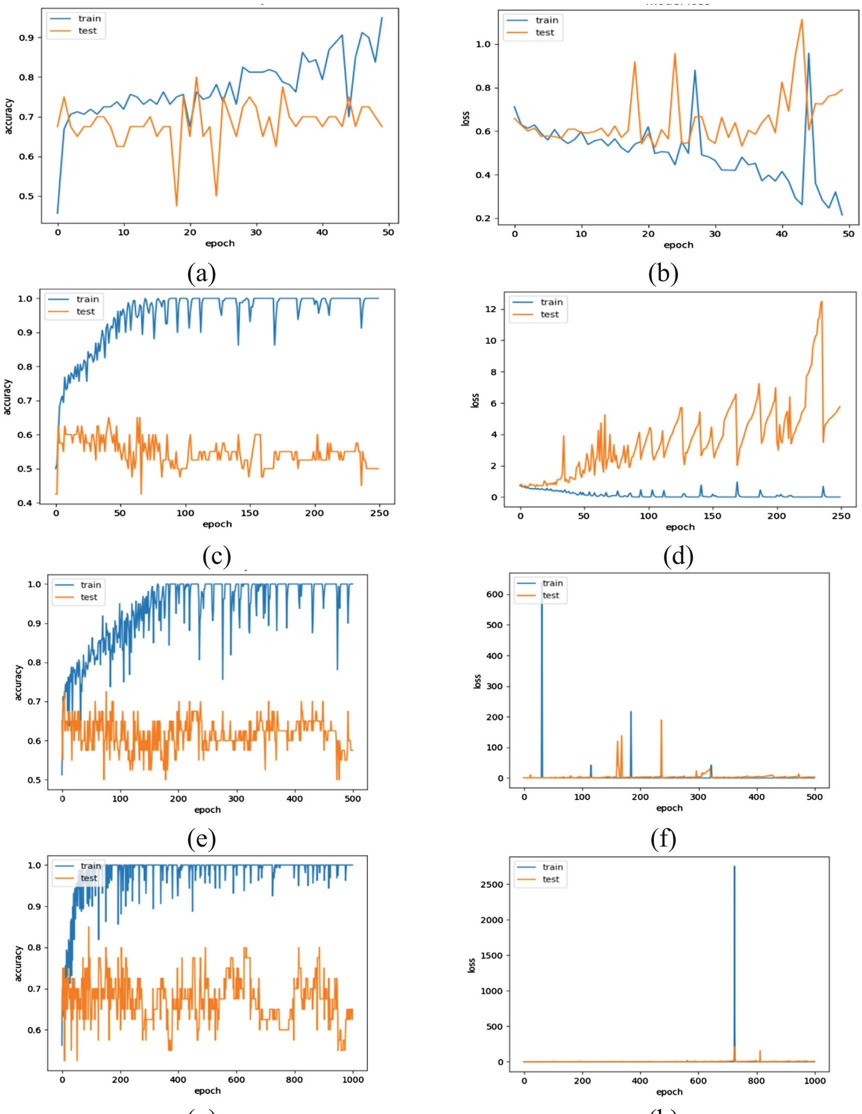


Fig. 1. Accuracy and Loss using model.add.dense (Dense(128, 256 and 512)). (a)-(b) Epoch 50, (c)-(d) Epoch 250, (e)-(f) Epoch 500, (g)-(h) Epoch 1000

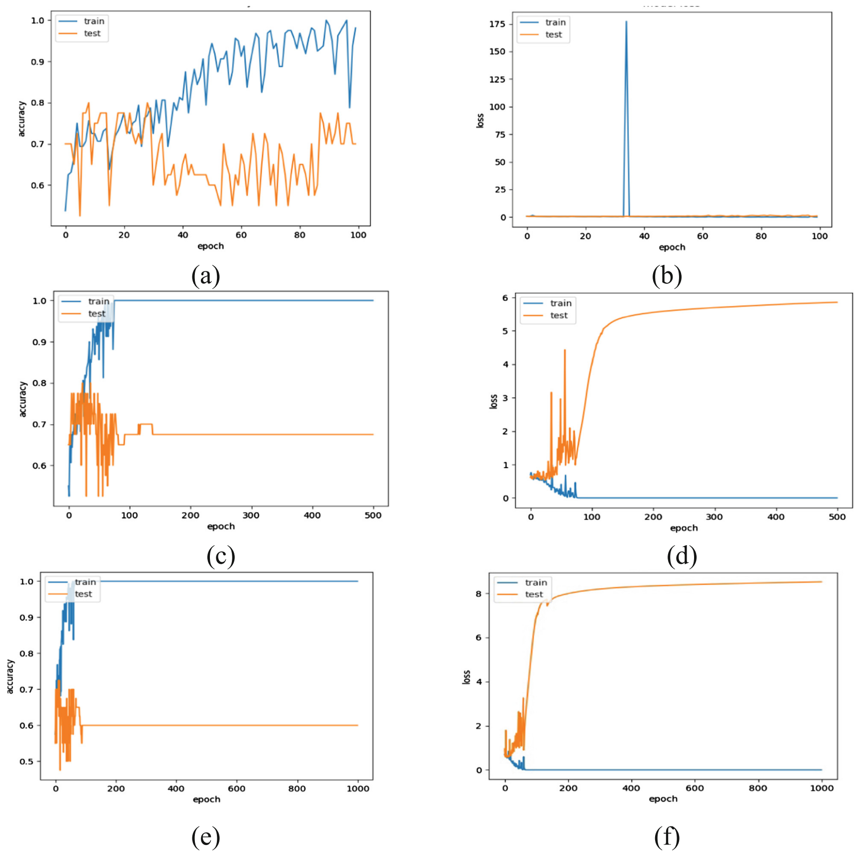


Fig. 2. Accuracy and Loss using model.add (simpleRNN (64,128,128 dan 256)), (a)-(b) Epoch 100, (c)-(d) Epoch 500, (e)-(f) Epoch 1000

It was then followed by model.add.dense (Dense(128, 256 and 512)) with activation 'ReLU'. By monitoring the loss and the accuracy of each epoch, then the best model could be chosen. It should be the model that has the lowest loss value and the highest accuracy. The results of the training process in this project are shown in the form of a comparison graph between the loss value and accuracy as shown in Fig. 1

By using the model above with variation of epochs, starting from 50, 250, 500 and 1000, it can be seen that none of them shows good results. Therefore, the training and testing was then continued by adding one more layer, i.e., model.add (simpleRNN (64,128,128 dan 256). The model was tested using various epoch as shown in Fig. 2

Although in this experiment it was already added 1-layer to the previous model, however, the results still showed unsability. Thus, it was then continued with the third experiment, i.e., by changing the model into model.add (Dense (256, 512 and 1080)). The results are shown in Fig. 3

In this third experiment, the changing in the dense gave effects to the results. The graphs obtained in these experiments were smoother than before, however, they were

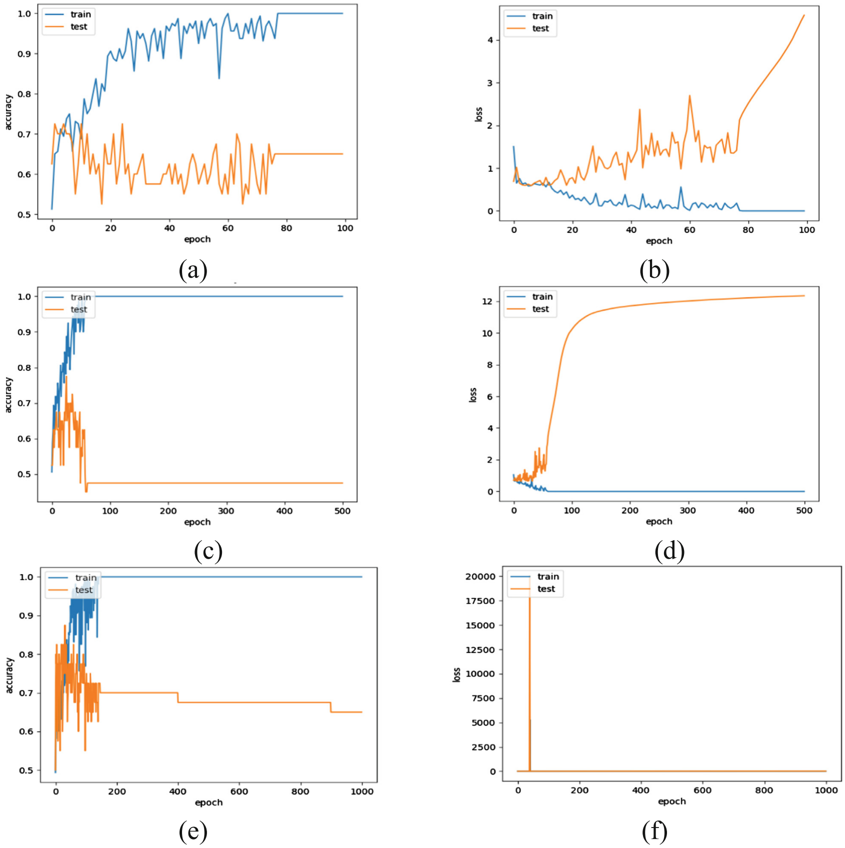
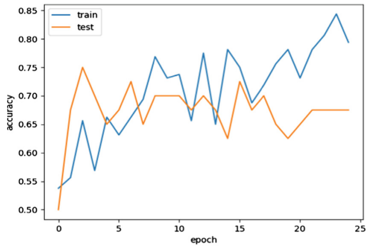


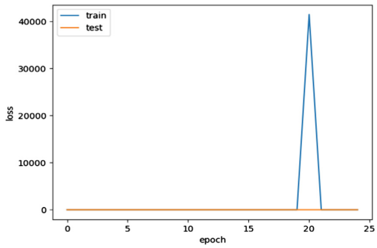
Fig. 3. Accuracy and Loss using model.add (Dense (256, 512 and 1080)), (a)-(b) Epoch 100, (c)-(d) Epoch 500, (e)-(f) Epoch 1000

still not stable and good enough. The model was then changed to the fourth experiment using model.add (Dense(256, 512 dan 1024)). The results are shown in Fig. 4

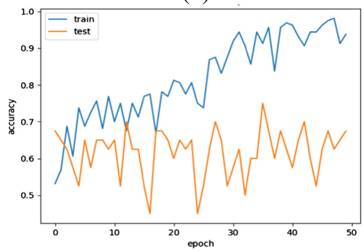
From this fourth experiment, changes in dense 1024 greatly affected the graph displayed, especially on the graph using epoch 25 which shows a balanced and stable accuracy model graph between the training and testing graphs, as well as the loss model in epoch 25. The graph was obtained with a small loss even though there was an increasing in epoch 20, however, after that, it fell and stabilized again and produced a graph with a very small loss. As for the 50 and 100 epochs in these experiments, it produced almost the same graph in the previous experiment. The graphs were unstable and also had a large gap. Based on the above experiments, in this study the selected model is the Accuracy and Loss using Epoch 25 model. Add(Dense(256, 512 and 1024)).



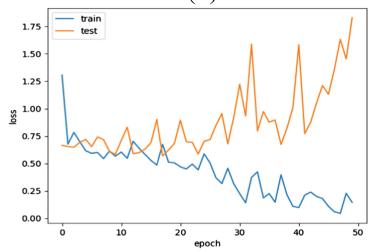
(a)



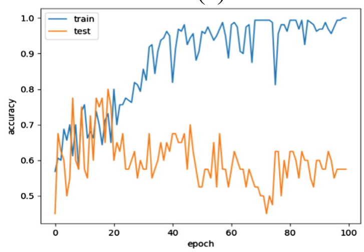
(b)



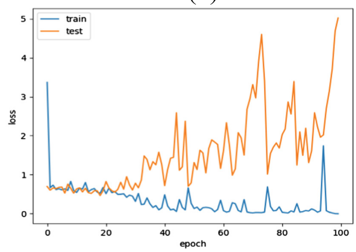
(c)



(d)



(e)



(f)

Fig. 4. Accuracy and Loss using model.add (Dense(256, 512 and 1024)), (a)-(b) Epoch 25, (c)-(d) Epoch 50, (e)-(f) Epoch 100

4 Conclusion

From the experiments conducted in this research, it can be seen that the best model in this research is the model. Add(Dense(256, 512 and 1024)) with Epoch 25.

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