Deep Neural Network with Hyperparameter Tuning on Early Detection for Symptom Recognition in Suspected Covid-19

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Abstract **– The Coronavirus outbreak (COVID-19) is still a concern for the world according to WHO. Although this virus has been controlled, prevention efforts are still being carried out. Prevention of the virus can be done by identifying patients with symptoms such as fever, respiratory distress, and sore throat. This research aims to develop an early detection system through the recognition of symptoms of COVID-19 infection using thermal camera sensors combined with the DNN using Hyperparameter Tuning. The result is the DNN algorithm can be proposed as the right algorithm to detect someone suspected of COVID-19.**

Keywords **– Covid 19, thermal imaging, deep neural network, recurrent neural network.**

1. Introduction

Until now, the COVID-19 virus is still a global concern, including Indonesia. Although the government has eased the regulations to prevent the spread of the virus, the emergence of new strain is still a concern.

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One of the government's important efforts in preventing the spread is still implementing a vaccination program that reaches 4 times [1]. Early detection is essential to prevent the spread of this virus. In particular, it is important to identify potential patients who are suspected to be positive for the virus so that identified potential patients can be isolated early. Some places that have the potential to become areas of spread need to be identified early, such as tourist attractions, closed restaurants, education, and shopping centers.

Two important factors used in diagnosing covid-19 symptoms are fever [2] and respiratory disorders [3], [4] such as dyspnea, irregular breathing, and dry cough. These symptoms are detected using non-contact sensors, such as thermal imaging cameras, which is also important for recording fever and respiratory symptoms [5], [6]. To analyze the symptoms detected, AI methods are needed to produce diagnostic conclusions in the process of early detection of suspected COVID-19.

Detection of fever symptoms is done by measuring facial temperature and detection of respiratory disorders is done by measuring respiratory rate. Measurement of temperature and respiratory rate is done using a thermal sensor. This study developed an intelligent system capable of identifying people suspected of being infected with COVID-19 by recognizing symptoms of fever and shortness of breath using the MobileNet V2 algorithm.

The COVID-19 detection process is carried out using CT sensors to obtain lung images which are then extracted to obtain lung condition characteristics. The extraction results are then analyzed with a CNN algorithm to recognize the characteristics of the lung images [7]. CT scans take multiple X-rays of a person's chest to create 3D images of the lungs. These images can be used to look for lung abnormalities to identify infected and uninfected lungs. Infected lungs show inflammation in the tissue, which is visible on a CT scan. COVID-19 activity in the lungs is more apparent when the virus infection reaches its final stages.

In this study, COVID-19 was detected through CT images using the CNN method. Although the CT method is included in the non-contact method, the use of CT in detecting COVID-19 is limited by the flexibility, which requires users to go to a location where CT devices are available, for example, in a hospital.

Another approach that can be used to diagnose COVID-19 is by using X-rays. Through the visual results of these X-rays, lung health and pneumonia diagnosis can be analyzed. Authors Ozturk et al. [8] collected X-ray data from the lungs of patients infected with COVID-19 and then used it to detect COVID-19 patients. However, the use of X-rays is similar to CT scans because it is less portable. Another approach that can be used for non-contact observation is to use camera technology to observe the movement of a person's chest area. The images obtained from this camera can be analyzed for an increase in breathing rate in a person that could indicate symptoms of the COVID-19 virus [9]. However, the accuracy of inferring breathing pattern abnormality in a person by using a camera is still uncertain. This approach is more suitable for monitoring in crowded areas that could potentially spread COVID-19. When a subject is identified as having an abnormal breathing pattern, isolation measures which can than be taken for further diagnosis, for example, using CT scans and X-rays.
Another approach that can be used as a non-contact sensor for the COVID-19 screening process in crowded areas is using thermography. This approach is applied by observing changes in human body temperature in the ROI area using infrared radiation [10]. The appearance of COVID-19 symptoms is indicated by abnormalities in human body temperature which has increased above 37 degrees celsius. Thermography can also be utilized in detecting breathing patterns and detecting abnormalities in breathing patterns in patients using AI methods [11]. The thermography approach is one of the recommended ones to detect COVID-19, especially in crowded areas [12].

Several studies using a thermography approach have been carried out to detect COVID-19 infection by identifying symptoms of fever and respiratory problems. The sampling process was carried out in the ROI area of the neck and face using infrared thermal imaging to screen for symptoms of fever and respiratory disorders [13],[14],[15]. Study carried out by Negishi et al. [16], [17] uses a combination of non-box sensors consisting of infrared thermal, RGB cameras, and thermal cameras. The algorithms used include the MUSIC and SVM algorithms to analyze the symptoms of COVID-19, namely blood pulse volume, heart rate, fever, and respiration rate.

Authors Cho et al. [18] uses thermal imaging to observe respiratory infections by tracking temperature changes in the nostrils. The research focuses on developing an accurate respiratory tracking algorithm to detect COVID-19 symptoms.

Several studies have developed a COVID-19 detection system by identifying symptoms of fever and respiratory problems. This research develops an early detection system for suspected COVID-19 by identifying symptoms of fever, respiratory problems, and sore throat using a non-contact sensor in the form of a thermal camera. The detection areas monitored by the thermal camera are the nostrils, neck, and face. The algorithm used for the analysis of COVID-19 detection uses a deep neural network on the MobileNet v2 architecture.

2. Research Methods

This study uses data on symptoms of fever, respiratory problems, and sore throat in the development of a COVID-19 detection system. The symptom data is obtained from the screening process carried out in the nose area, and the face as an ROI area is recorded using a thermal camera [9]. The breathing signal is obtained from the tracking process on the nostril as the ROI area. Several factors affect the respiratory signal tracking process including temperature accuracy calibration, emissivity, camera response, and ambient temperature which have an impact on the SNR value. To maintain the SNR value so that the resulting signal is good, it is necessary to carry out a filtering process to remove noise. The noise filtering method can use an IIR filter.

This respiratory rate value is determined within 1 minute by calculating the number of peaks and valleys of the respiratory signal. Algorithms that can be used to calculate the respiratory rate are the Breath Detection Algorithm (BDA) [11] and the MUSIC algorithm. Furthermore, the classification process using a deep neural network is carried out to detect suspected COVID-19 patients. The stages of the COVID-19 detection process can be shown in Figure 1 below.

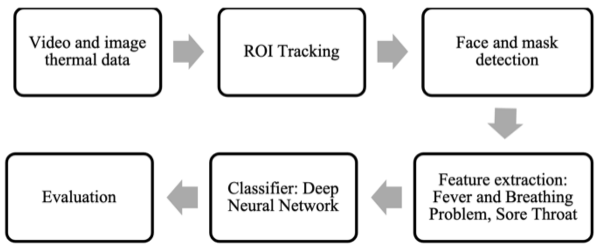


Figure 1. The Stages of The Covid19 Suspect Detection System

To obtain respiratory data, the analysis process is carried out on temperature changes in the area around the nostrils in thermal image data in the form of a sequence of frames as shown in Figure 2. In the facial area using a mask can be a hindering factor causing geometric details and facial textures to be lost and have an impact on face recognition errors. For this reason, determining the ROI area in the mask area needs to be done to obtain a representation of the respiratory features. The following formula (1) can be used to determine the temperature value in each thermal image frame.

$$\bar{s}(t) = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1} s(i,j,t) \quad (1)$$

$$\sigma_s^2(n) = \frac{\sum(\bar{s}(t)-\mu)^2}{T}\ (0 < t < T) \quad (2)$$

$$ROI = \arg\max \sigma_s^2(n) \quad (3)$$

After obtaining the temperature value, then calculate the total variance value using formula (2). The temperature value in the nostril area has a different value which then becomes data or respiratory signals at a certain period. The determination of the ROI area in the nostril is based on the area that has a large variance value indicated by the most heat changes. So that the nostril ROI area can be determined using the following formula (3).

The ROI area that has been determined can then be analyzed for the respiratory activity that takes place on several frames of thermal cirrus. When there is a change in temperature value in the nostril ROI area, respiratory activity can be identified and will produce respiratory data or signals on several frames as shown in Figure 3. To determine the symptoms of respiratory disorders, the respiratory rate estimation process is carried out using the Multiple Signal Classification (MUSIC) method algorithms [22] with the following formula (4).

$$S_{MUSIC}(f) = \frac{1}{\sum_{k=M+1}^{p}|e^{T}(f)W_k|^2} \times \frac{1}{\delta f} \quad (4)$$

The classification process is used to detect COVID-19 symptoms using the DNN algorithm, namely the MobileNet V2 architecture. The data used for the classification process uses data on symptoms of fever, sore throat, and respiratory problems. MobileNet V2 has a CNN architecture that is effectively used for the classification process. Furthermore, the performance evaluation of the classification process is carried out using the confusion matrix calculation which is observed through the True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) values. The results of this confusion matrix evaluation will produce the accuracy of the classification results. The accuracy results will be compared with other algorithms, namely ResNet 50 and Dense Net 121.

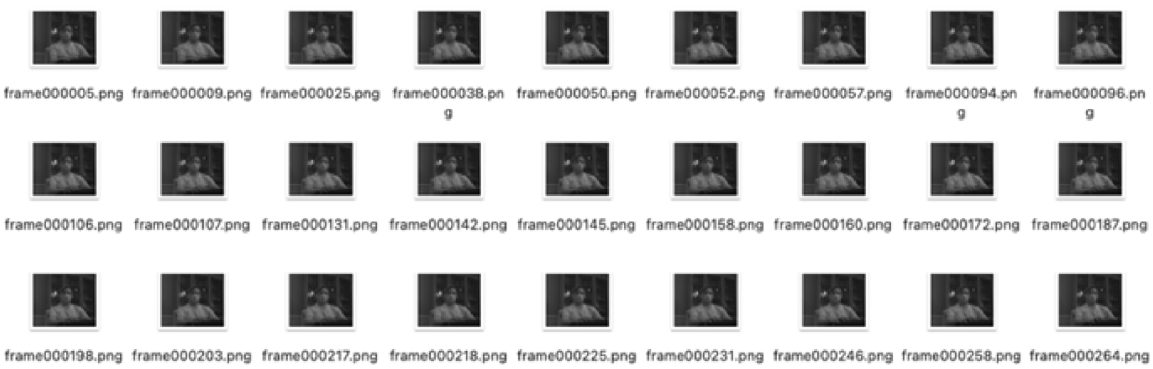


Figure 2. Thermal image data in the form of a sequence of frames

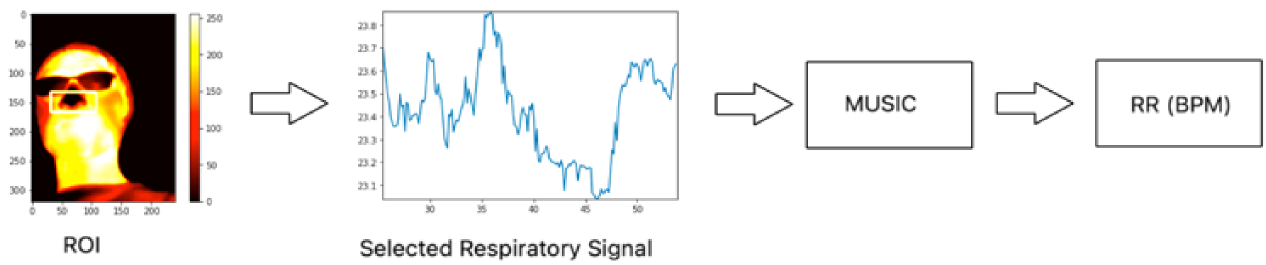


Figure 3. Signal processing for Respiration Rate (RR)

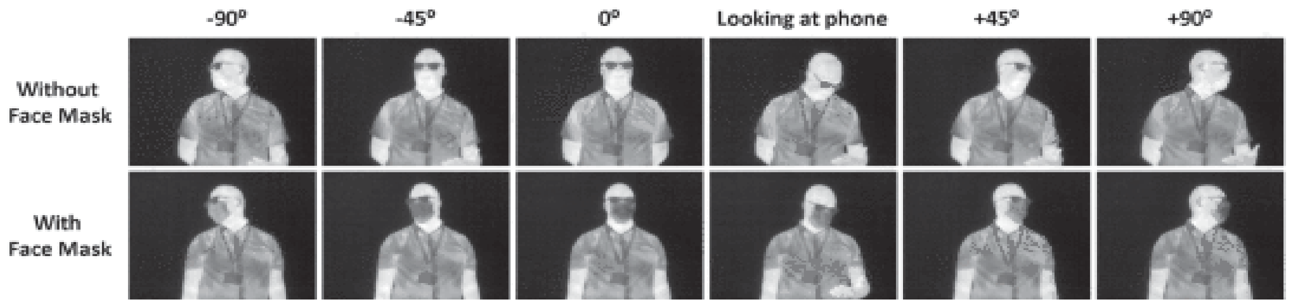


Figure 4. Thermal images dataset for face mask detection process

3. Results and Discussion

This research aims to develop a system for detecting suspected COVID-19 in humans through symptoms that appear in COVID-19 patients. This research uses a dataset consisting of 2 classes, namely the infected class and the uninfected class. The variables used for the feature consist of respiratory problems, sore throat and fever. Normal respiratory symptoms will be identified if the pattern in each period per minute has an irregular breathing rate. Fever symptoms will be identified when the facial temperature shows a value above 37 degrees celsius

The first dataset is a thermal image in the form of a frame of a person wearing a mask which is used to detect the breathing rate and temperature on the face with a mask. The next dataset uses data on the detection results of COVID-19 infected patients and normal patients accompanied by symptom parameters which will then be used for classification using the MobileNet V2 algorithm. To test the face detection method, a dataset consisting of thermal images with a mask cover and without a mask on the face is used. The thermal image is taken with different facial positions as shown in Figure 4.

3.1. Case 1: Mask Detection

In the mask detection process, the method used is almost the same in determining ROI [19] on RGB image data. In this study, the data used is in the form of thermal images with the classification method using the DNN algorithm with the MobileNet V2 architecture. OpenCV DNN is used as a method for detecting faces which produces an ROI area with matrix values in the form of location, width and height of the face. The DNN architecture has several parameter values that have been determined, namely learning rate, optimizer, batch size, loss function, epoch, average pooling layer, flatten layer, hidden layer, activation function in the hidden layer, dropout value, and activation function in the output layer as shown in Figure 5.

Parameter	**MobileNet V2, ResNet 50, Denseet 121**
Learning rate	*1e-4*
Optimizer	*Adam*
Batch size	*32*
Loss function	*Binary Cross Entropy*
Epoch	*50*
Average pooling	*7 x 7*
Activation function (128 Hidden Layer)	*RELU*
Activation function (2 Output Layer)	*SoftMax*
Dropout	*0.5*

Figure 5. Parameter values on DNN architecture

Evaluation of the performance of the classification process for using masks and without masks is carried out by calculating the confusion matrix. Through this matrix, TP, TN, FP, and FN values can be obtained. The following Figure 6. shows the confusion matrix for the three classification models which include MobileNet V2, ResNet 50, and DenseNet 121.

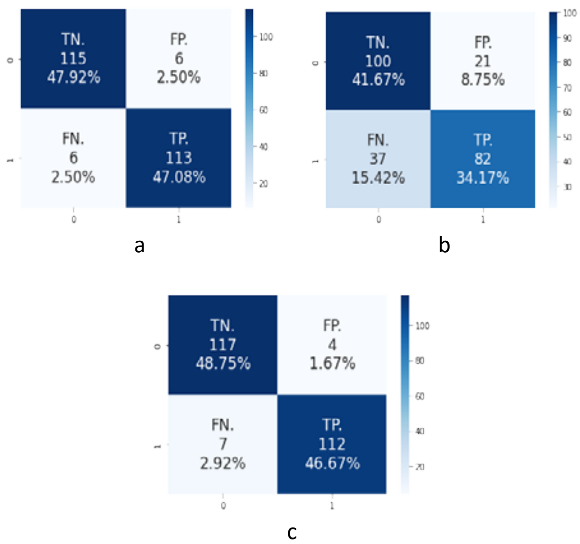
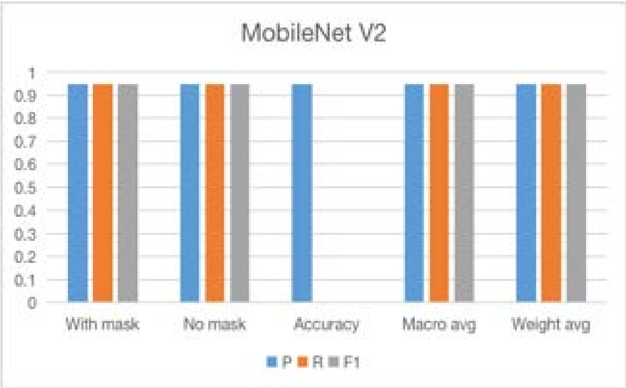


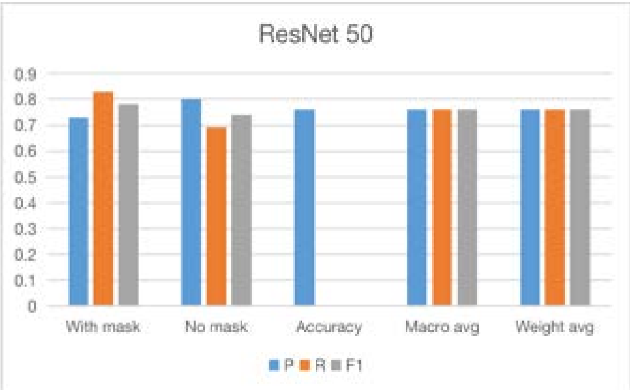
Figure 6. Confusion matrix for the three classification models which include MobileNet V2 (a), ResNet 50 (b), and DenseNet 121(c)

Furthermore, the confusion matrix to determine the values of Precision (P), Recall (R), F-Measure (F1), macro avg, and avg weight.

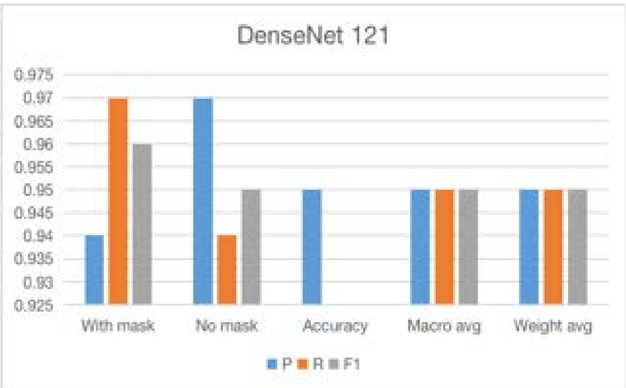
The measurement of performance results is applied to three classification methods, including MobileNet V2, ResNet 50, and DenseNet 121 as shown in Figure 7 and 8. The MobileNet V2 and Dense Net 121 methods have the same performance in accuracy values while in the ResNet 50 model the performance results tend to have accuracy values lower.



a

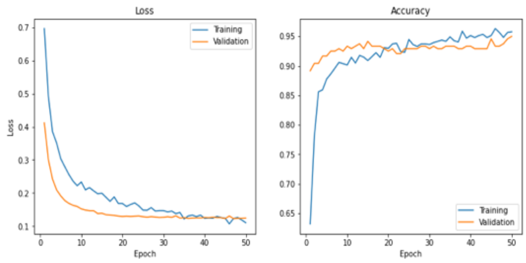


b

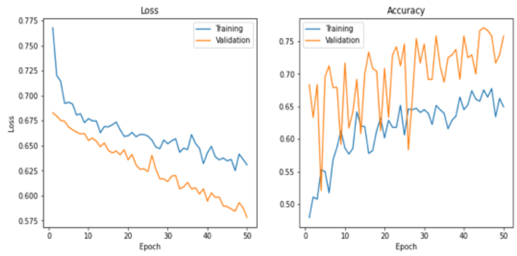


c

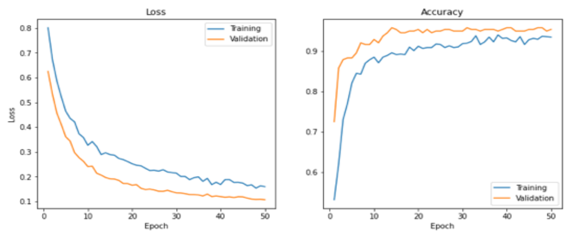
Figure 7. The values of Precision (P), Recall (R), and F-Measure (F1), for the three classification models which include MobileNet V2 (a), ResNet 50 (b), and DenseNet 121(c)



a. MobileNet V2



b. ResNet 50



c. DenseNet 121

Figure 8. Training loss and accuracy validation

The next performance evaluation of the mask detection process is by observing the CPU processing execution time for each algorithm. Figure 9 shows a comparison of the CPU execution time for the MobileNet V2, DenseNet 121, and ResNet 50 algorithms. The results of the execution process show that the MobileNet V2 algorithm has the fastest execution time among other algorithms.

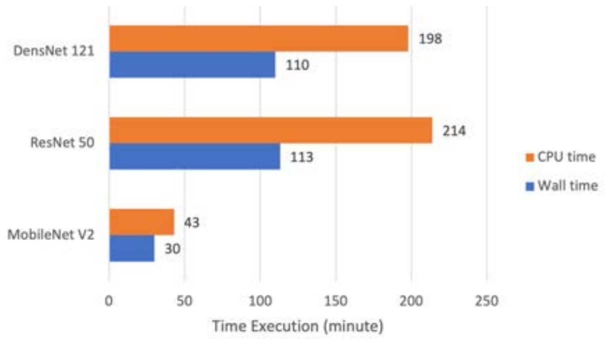


Figure 9. Comparison of the CPU execution time for the MobileNet V2, DenseNet 121, and ResNet 50 algorithms

3.1. Case 2: Detection of Suspected Covid-19

The process of detecting suspected COVID-19 is carried out by first observing the symptoms present in persons affected by COVID-19 which will later become parameters in the classification process. To get the parameters of respiratory symptoms, the RR calculation process is carried out. This RR value will determine a person's breathing pattern, including normal or experiencing respiratory problems. Furthermore, the symptoms of sore throat and fever are observed through changes in temperature in the face and throat area. The dataset used is in the form of video recorded using a thermal camera which is then processed into several frames for observation.

The observation process was carried out by first determining the ROI areas, namely the face area, the nostril area, and the throat area.

Each of these ROI areas will take data on temperature changes as indicated by the histogram image. When there is respiratory activity in the ROI area of the nostrils and mouth, changes will be seen in the histogram which is then extracted into a respiratory signal as shown in Figure 10. The breathing signal is then processed using the MUSIC algorithm to obtain the RR value in bits per minute (BPM).

The process of detecting suspected COVID-19 is carried out using the Deep Neural Network algorithm. The dataset used is in the form of secondary data which has a total of 5434 data. The parameters consist of values for respiratory conditions, sore throat, and fever. The distribution of data for each parameter in the detection of COVID-19 is shown in Figure 11.

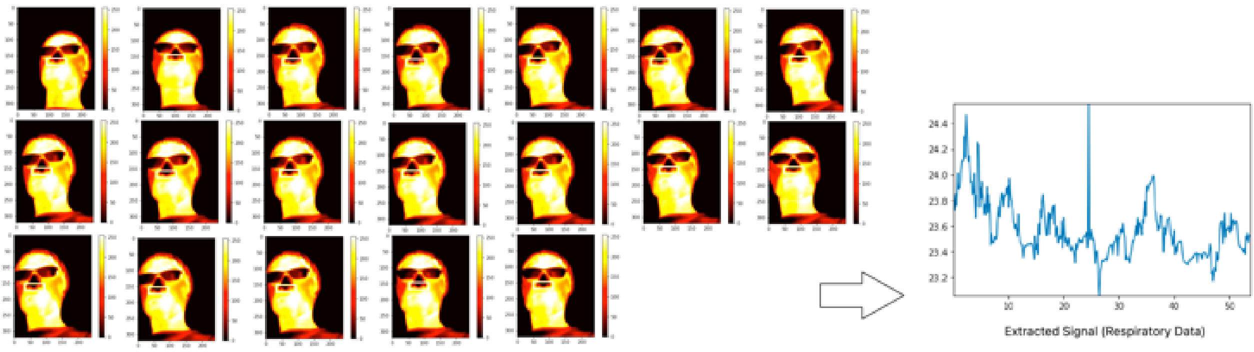


Figure 10. Respiratory activity in the ROI area of the nostrils and mouth will be seen in the histogram

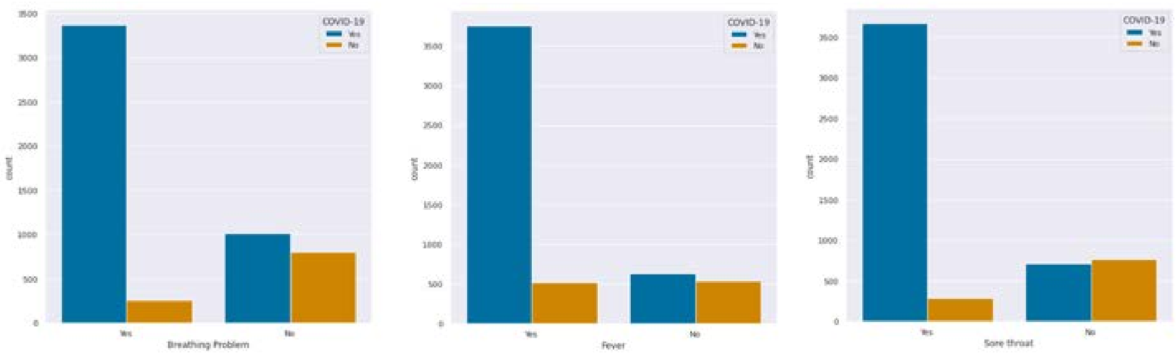


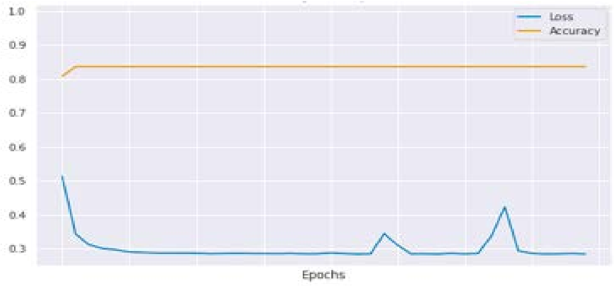
Figure 11. The distribution of data for each parameter in the detection of COVID-19

The process of detecting suspected COVID-19 begins with conducting a training process using the DNN algorithm with the RNN architecture. Several parameters in the architecture have been determined including the number of hidden layers, activation function, learning rate, epoch, batch size, optimizer, and loss function. Figure 12. below shows the parameter configuration of the RNN architecture.

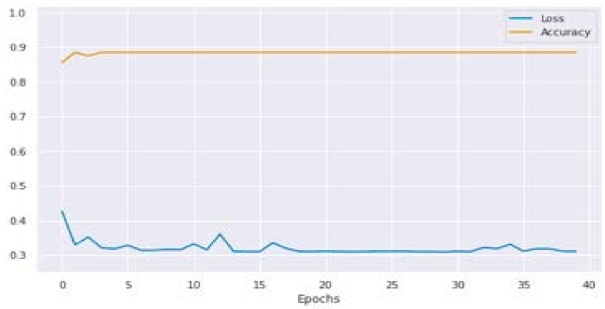
Parameter	***RNN***
Learning rate	*1e-3*
Optimizer	*Adam*
Batch size	*256*
Loss function	*Binary Cross Entropy*
Epoch	*40*
Activation function (100 Hidden Layer)	*RELU*

Figure 12. Parameter configuration of the RNN architecture

In the classification training process, the data used consists of training data and test data with a ratio of 80% and 20% of the total dataset used. For the initial stage, the classification training process is carried out by comparing the RNN algorithm with the Multi-Layer Perceptron Neural Network (MLP) algorithm. The results of the training classification process show that the RNN algorithm has a higher accuracy value as shown in Figure 13.



a. MLP Neural Network



b. RNN

Figure 13. The results of the training classification process

Furthermore, the performance evaluation of the RNN algorithm will be compared with other classification algorithms. The results of the performance evaluation show that the RNN algorithm has the highest accuracy value, as shown in Figure 14.

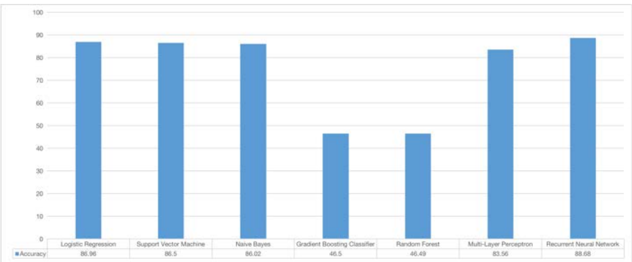


Figure 14. The results of the performance evaluation show that the RNN algorithm

4. Conclusion

This research develops a suspected COVID-19 detection system using thermal image data and the DNN algorithm.

The experimental scenario begins by first detecting the use of masks on the face using the DNN algorithm with the MobileNet V2 architecture. Performance evaluation is carried out by using the confusion matrix and comparing the results with other algorithms, namely ResNet 50 and Dense Net 121. The evaluation results show that the MobileNet V2 and DenseNet 121 algorithms have the same good performance value of 0.95 on accuracy, precision, and recall values, and f-mesure. Besides using the confusion matrix, performance evaluation is also carried out by calculating the loss value and accuracy value. The experimental results show that the MobileNet V2 and DenseNet 121 algorithms have the same high-performance values, namely accuracy performance in the training and validation process with a value of 0.94 and loss performance in the training and validation process with a value of 0.15. The next performance evaluation uses the measurement of execution time on the CPU. The test results show that the MobileNet V2 algorithm has the fastest execution time, which is 43 minutes. The next experimental scenario detects suspected COVID-19 using the RNN algorithm. This detection process uses the parameters of respiratory symptoms, sore throat and fever whose values are obtained from thermal image processing. From the results of the performance evaluation, the RNN algorithm has the highest accuracy value compared to other algorithms, namely 88.68%. From the results of these two experimental scenarios, the RNN Algorithm can be proposed as the right algorithm to detect someone suspected of COVID-19.

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