International Journal of Engineering and Computer Science Applications (IJECSA)
Vol. 2, No. 1, March 2023, pp. 1~8
ISSN:2828-5611
DOI: 10.30812/IJECSA.v2i1.2073

COVID-19 Suspects Monitoring System based on Symptom Recognition using Deep Neural Network

Erika Devi Udayanti[1], Etika Kartikadharma[1], Fahri Firdausillah[1], Nur Ikhsan[2]
[1]Universitas Dian Nuswantoro, Semarang, Indonesia
[2]Universitas Negeri Semarang, Semarang, Indonesia

Article Info

Article history:

Received June 29, 2022
Revised September 8, 2022
Accepted November 7, 2022

Keywords:

Convolutional Neural Network
Covid-19
Symptom Recognition
Thermal Imaging

ABSTRACT

The outbreak of the Corona virus or COVID-19 was still a global concern even though it has been declared an endemic in several countries in the world, including Indonesia. However, with the emergence of new variants of this virus, preventive efforts continue to be made to prevent its spread. To prevent the spread of this virus, early detection was important, especially in knowing prospective clients who are positive and reactive to this virus, thus enabling early isolation measures for prospective patients who are taking action. This identification can be carried out in public areas that are the center of community activities. In this study, an intelligent system will be developed that can detect people suspected of COVID-19 through fever and breathing problem symptoms that can provide solutions to prevent the spread of this virus. Identify these symptoms through thermography-based image processing sourced from thermal camera sensors and then look for the possibility of suspected and reactive COVID19. Furthermore, the AI model was used by the early detection system of people suspected of being positive and reactive for COVID-19 using the Deep Neural Network method. This study aims to identify symptoms of fever and respiratory infection through image processing sourced from thermal camera sensors and further diagnose prospective patients who are suspected of being positive and reactive for COVID19 using the CNN method as an intelligent system for early detection of suspected positive and reactive COVID19 patientsIn the process of testing the classification training model, the performance results in the CNN classification process have an accuracy value of more than 88%. Furthermore, a comparison was made between the CNN classification and other classifications, such as SVM, Naive Bayes and Multi-Layer Perceptron (MLP). The results obtained from this comparison have an average percentage of accuracy above 80%. MLP has the lowest accuracy among its classification methods of 83.56%. CNN has the highest accuracy value compared to other methods of 88.68%. Therefore, CNN can be chosen to be the right one for use in the COVID-19 suspect detection system through the recognition of symptoms and respiratory disorders. Based on these performance measurements, the process of detecting COVID19 suspects indicated by health symptoms can be applied to real data.

Corresponding Author:

Nur Ikhsan,
Universitas Negeri Semarang, Semarang, Indonesia.
Email: nur.iksan@mail.unnes.ac.id

1 INTRODUCTION

The outbreak of the CORONA virus or COVID-19 was still a serious concern. Several variants arise with a stronger level of threat to health. In addition to the impact on health, other impacts due to this virus including education, economy and security. Efforts made in controlling this virus include vaccination, using Peduli Lindungi application and health screening. Health screening was important to implement in public areas that aim to identify suspected COVID-19 through symptoms in a person's health. Some of the important symptoms to identify someone suspected of being positive for COVID-19 include symptoms of fever and symptoms of respiratory problems [1], [2], [3]. These symptoms can be identified through a person's temperature data which is detected in the face, nose area using sensors. Detection of fever symptoms using the temperature in the facial area by applying normal and abnormal temperature limits. Furthermore, the detection of respiratory symptoms was carried out using respiration rate data obtained from the temperature signal in the nose area. The use of non-contact sensors needs to be used to avoid direct interaction with someone, such as RGB camera sensors, thermal and infrared cameras [4], [5]. Several other non-contact sensors include computed tomography (CT) scans, X-rays, Camera Technology, Ultrasound Technology, Radar Technology, Radio Frequency (RF) and Terahertz.

Several studies on the COVID19 symptom detection system that were carried out previously focused on identifying lung images obtained from CT sensors and feature extraction to obtain their characteristics which were then analyzed to obtain COVID19 predictions using the Convolutional Neural Network [6]. This CT process will produce 3D images of the lungs obtained from several X-Ray images scanned on the human chest. The shape of the image of the human lung can be identified by the presence / absence of abnormalities that will indicate the presence / absence of COVID19 infection. If the CT image results in the lungs of a suspected COVID-19 patient there is inflammation, it will be identified that the lungs have been infected by COVID19. In subsequent infections, inflammation in the lungs will be more prominent due to COVID19 activity. Portability is the biggest challenge of using CT scans for the COVID19 diagnosis process. This is because CT scan machines are only available in certain places, such as hospitals. Although a CT scan is a non-contact device, users are required to come directly to the location of the CT scan machine. In addition, COVID19 detection can use X-rays to analyze the lungs and diagnose pneumonia so that visual indicators of COVID19 can be displayed [7]. The working principle of this X-ray is similar to a CT scan, but this X-ray does not have a problem with the portability factor. The results of the X-ray images of the lungs infected and not infected with COVID-19 are then collected and then used in the process of predicting the presence / absence of COVID-19 infection in patients.

Another technology that can be used to detect COVID19 is cameras. This camera technology is a non-contact device and is used to observe the movement of a person's chest. The chest movement pattern will be represented as respiratory activity and can be used to determine the respiratory rate. This increase in respiratory rate can be indicated as a symptom of COVID19. Several researchers made datasets in the form of recordings from infra-red cameras and RGB cameras that were used for experiments in developing COVID-19 detection methods. Researchers [8] conducted an experiment to identify the breathing pattern of people wearing masks which were then categorized as normal and abnormal breathing. However, the method has not yet been defined to be able to detect COVID-19 through symptoms of irregular breathing patterns. In addition, this method can be used in monitoring systems that exist in public areas that have a high risk of spreading the COVI19 virus. When this monitoring system detects that someone has an irregular breathing pattern, then a warning or notification can be given to the operator to take further action, such as quarantine or isolation measures and a further diagnosis process using a CT scan or X-ray scan can be carried out.

Other non-contact technologies that are used as sensors for mass screening in public areas in the COVID-19 pandemic can use thermography techniques. Thermography technique is used to detect the temperature of the human body, especially in the part determined by infrared radiation [9]. This body temperature will be an indication of a person's symptoms of being infected with COVID-19 when the body temperature shows an abnormal value above 37 degrees Celsius. In addition, thermography technique is also used to monitor a person's breathing and can determine his breathing pattern using the AI method [10], [11], [12]. For this reason, this technique can be used as an alternative for early detection of someone suspected of COVID19 which is implemented in public areas [13]. This study uses an infrared thermography approach that uses thermal and infrared camera devices. The device functions as a non-contact sensor that has the ability to quickly measure variations in body temperature. This study aims to develop an early detection system for suspected COVID-19 by identifying respiratory symptoms and fever symptoms. These symptoms are obtained through recording in the form of infrared thermal images in the nostrils and face area [14]. Furthermore, the recording will be extracted into a feature to determine the symptoms of fever and respiratory disorders. Then proceed with prediction of infected/uninfected with COVID19 using the Deep Neural Networks (DNN) algorithm.

The urgency of this research takes the issue of overcoming the spread of the Corona virus (COVID19) which is currently still the concern of the government and the people of Indonesia. Early identification of people suspected of being positive and reactive for COVID-19 is still limited to temperature measurements carried out through thermo-gun sensors and thermal cameras without being accompanied by an intelligent COVID19 diagnosis system. The development of an intelligent system for early detection of people suspected of being positive and reactive for COVID19 can provide a solution to prevent the spread of this virus. This Smart System provides diagnostic decision support in early detection of suspected positive and reactive COVID19 people. This study aims to identify symptoms of fever and respiratory infection through image processing sourced from thermal camera sensors and further diagnose prospective patients who are suspected of being positive and reactive for COVID19 using the Convolutional Neural Network (CNN) method as an intelligent system for early detection of suspected positive and reactive COVID19 patients.

2 RESEARCH METHOD

The early detection system for COVID-19 symptoms is carried out using non-contact sensors in the form of thermal and infrared sensors. The sensor allows no direct contact with humans as a screening subject so that the potential for spread and transmission can be avoided. This system will detect symptoms including respiratory problems, fever, which are usually found in people who are positive or exposed to the COVID-19 virus. Monitoring of these symptoms is carried out by tracking processes in certain areas of the human body, such as the nostril area as the Region of Interest (ROI to track breathing patterns and the face area to track body temperature. The tracking is done through image processing whose data is sourced from a thermal camera (Figure 1). From the tracking results, a person's breathing pattern will be known so that it can be identified that the breathing pattern is normal or abnormal. An abnormal breathing pattern is identified that a person is experiencing respiratory problems. Furthermore, on the results of tracking facial temperature, if the measured temperature exceeds the normal human temperature limit, which is more than 37C, it can be identified that a person has symptoms of fever. Symptoms of respiratory disorders are identified through breathing patterns with reference to the Respiratory Rate (RR) value. In addition, symptoms of fever are identified if the measured temperature exceeds the normal human temperature threshold. The dataset used was obtained from the public dataset in the form of a thermal image dataset [15]. These two symptoms will be parameters to predict that someone is suspected of having COVID19 using the Deep Neural Network algorithm

Figure 1. Frames of thermal image

The deep learning model developed using the CNN through modification of the Long Short-Term Memory (LSTM) architecture as a Learning model to provide a process for identifying symptoms of people suspected of COVID19. The identification/classification process can be formulated as follows: Respiratory Rate (RR) screening data and Face Temperature (FT) (x1, x2, ..., xn), where n is the number of input parameters. To predict health or infection, the first step is to determine the mapping function between the input and output parameter data from the classification results using formula (1).

$$\hat{y} = f(x_1, x_2, \dots, x_n) \tag{1}$$

The classification of infected and uninfected is represented by n=2 input parameters, as shown in the Figure 2.

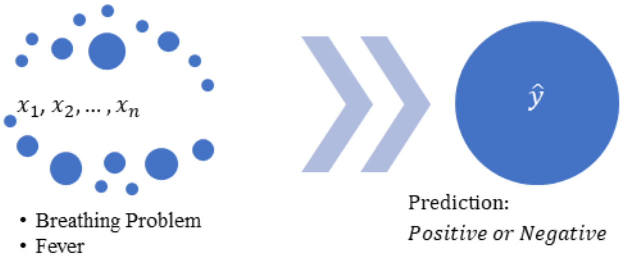

Figure 2. Covid19 prediction models

Based on the covid19 prediction model, a deep neural network model was then developed using the CNN architecture as shown in Figure 3. The architecture used consists of 100 hidden layers with ReLU activation function. Several parameter settings used in this architecture include Learning Rate 1e-3, Epochs 40, Batch Size 256, Optimizer using Adam, and the Loss function using Binary Cross Entropy.

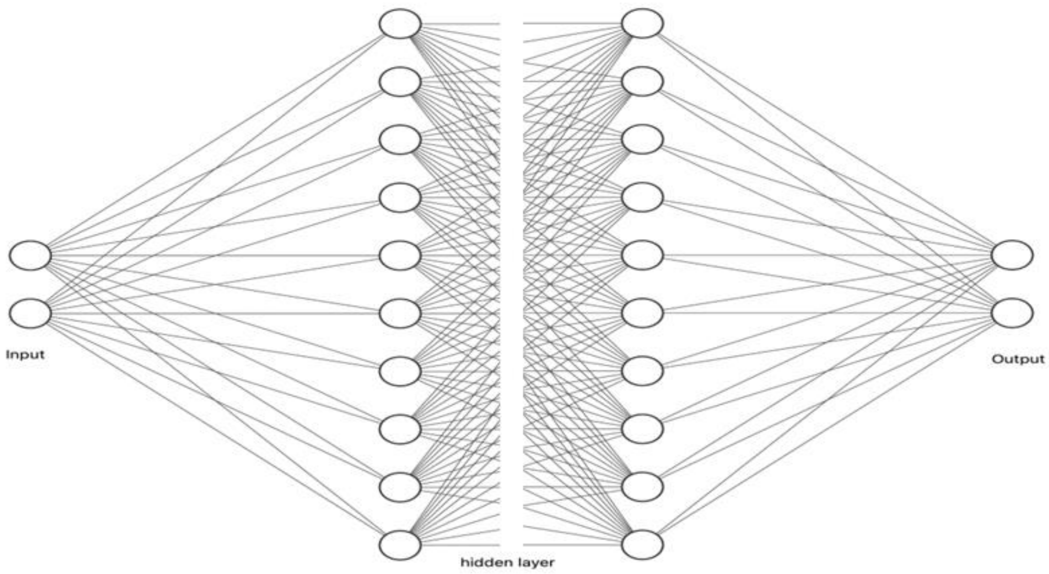

Figure 3. Convolutional Neural Network Architecture

Machine Learning (ML) used in this research is NN with modifications to the LSTM architecture to improve prediction accuracy. The LSTM has the ability to learn what data needs to be read, stored, and deleted from memory by adjusting three different control gates, namely forget gate f (t), input gate x (t), and output gate m(t). This architecture is a standard NN architecture in the form of Multi-Layer Perceptron (MLP) which consists of several layers of fully connected neurons. This architecture was later changed to a DN architecture with LSTM memory which was developed from the basic Recurrent Neural Network (RNN) architecture. Several hidden layers were added to this architecture including the LSTM memory unit. RNN uses temporal information as input data and can make repeated connections between neurons. LSTM has memory cells in its neurons that have the ability to store information. Information that enters and leaves the neuron's memory cell is controlled by three gates, namely the input gate, the output gate, and the forget gate. Each of these gates gets the same input from the input neuron and also has an activation function. The activation function used in this forecasting process can be in the form of the tanh activation function and the Rectified Linear Unit (ReLU) activation function.

The validation method in this study uses a confusion matrix. Each row of the confusion matrix represents the actual class of data, and each column of the matrix represents the predicted class of the data. The confusion matrix consists of four parameters, namely True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). TP stated that there was a lot of data that had an actual positive class for COVID19 and a positive class for COVID19 prediction models. TN stated that there were many data that had a negative class of COVID19 and a negative class of COVID19 in the prediction model. FP stated that the actual amount of data in the class had a negative class of COVID19 but had a positive class of COVID19 in the prediction model. FN stated that the actual number of data classes had a positive class but had a negative COVID19 class in the prediction model. Through these 4 parameters, it can be used to measure the performance of a classification model, i.e., Accuracy. Formula 2 show the performance measurement of the classification model.

$$\text{Accuracy} = \frac{TP + TN}{Total} \tag{2}$$

3 RESULTS AND ANALYSIS

Research begins by first identifying needs, namely determining the components in developing a prototype of an intelligent COVID19 detection system. Furthermore, a model development was carried out starting from the fever detection process using a thermal sensor, namely using a thermal gun, infrared and Thermal imaging camera. Next, develop a Thermal ROI-based COVID19 diagnosis model. This diagnosis process is first carried out in a pre-process stage, namely noise removal and normalization of the Thermal ROI raw data. After the pre-processing is done, it is continued with the feature extraction stage. At this stage, the features that will be used in the COVID19 diagnosis process will be obtained. The next process is to develop a deep neural network method for the COVID19 diagnosis process. In this process, the results of the diagnosis of suspected COVID-19 will be known.

Detection of fever is done by measuring face temperature or facial temperature. This measurement is carried out to determine the condition of a person's temperature that indicates symptoms of fever or no fever. The data used is a thermal image of a person. Furthermore, the Region of Interest (ROI) area is determined on the face to analyze the facial histogram spatial data and converted to a temperature value. Figure 4 shows one of the frames of the thermal image obtained from the thermal camera footage. From the frame, the ROI area is determined which includes the face and then temperature measurements are carried out based on the interpretation of spatial data from the thermal image.

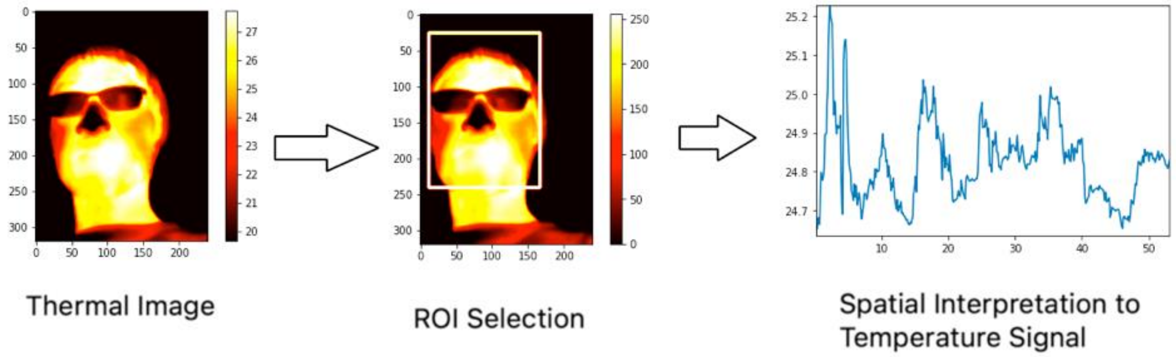

Figure 4. Face Area Spatial Interpretation of Thermal Image to Temperature Signal

Detection of respiratory disorders is done by measuring nostril temperature. This measurement is carried out to determine the condition of temperature changes in a person's nose area that shows respiratory activity. To detect the presence of respiratory disorders, the respiration rate (RR) is determined in units of breath per minute (bpm). Furthermore, ROI is determined in the nose area to analyze the spatial histogram data which is then converted into nasal temperature signal data as shown in Figure 5.

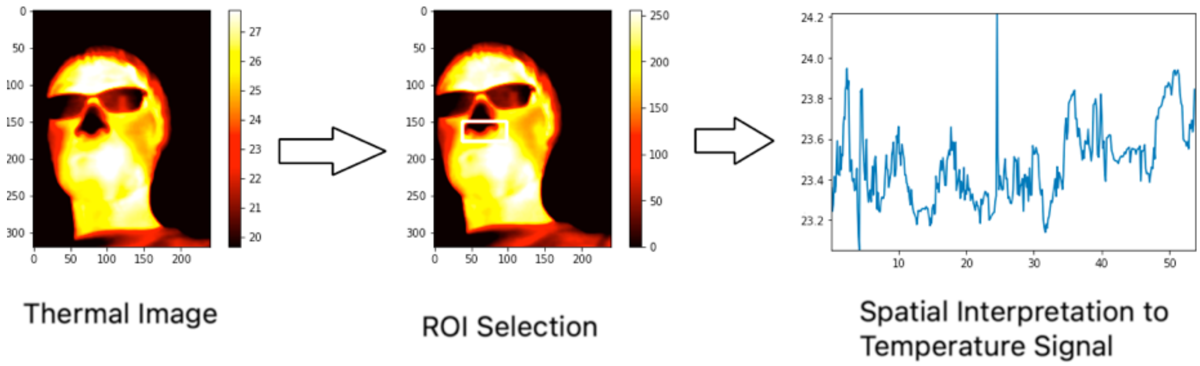

Figure 5. Nostril Area Spatial Interpretation of Thermal Image to Temperature Signal

The process of detecting suspected COVID-19 uses secondary data with features that refer to data on COVID-19 symptoms including fever, respiratory problems. The amount of data used is 5434 data, each of which is 4386 with symptoms of COVID-19 and 1084 data without symptoms of COVID-19. The following Figure 6 and 7 is the distribution of data showing the symptoms of COVID-19. The distribution of data in the dataset used has a percentage of 80.7% positive with COVID-19 symptoms and 19.3% negative with COVID-19 symptoms.

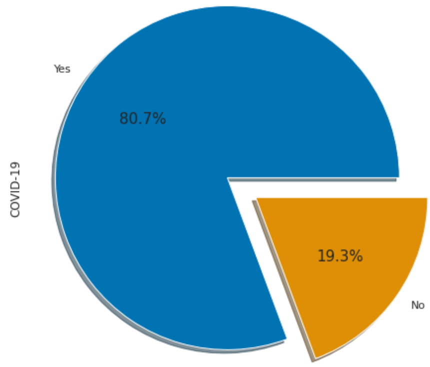

Figure 6. The distribution of data showing the positive and negative COVID-19

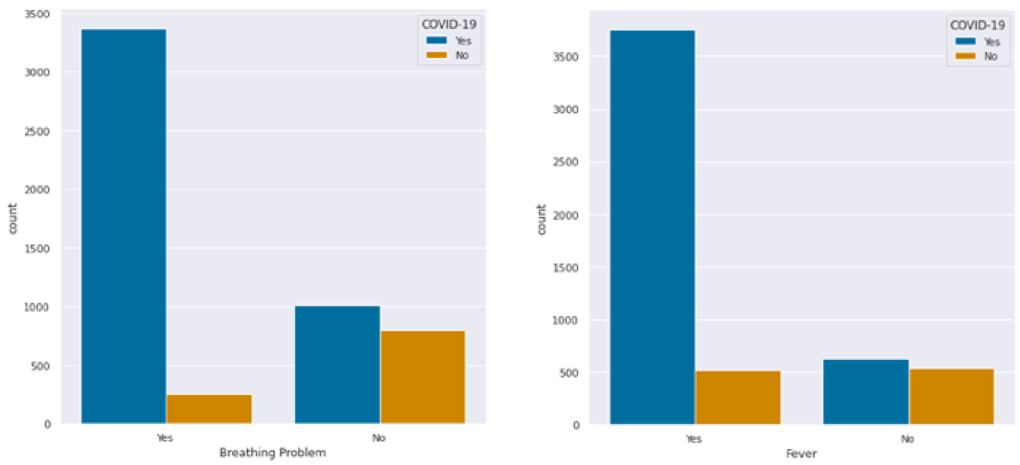

Figure 7. The Distribution of Data Showing The Symptoms of COVID-19

The preprocessing stage was done by removing the missing value and transforming the data. The missing value is determined by looking for row data that has a null value and then deleting the row data that has null value. Data transformation was done by converting categorical data into numerical data so that it can be used in the training and classification process. In this paper, the data transformation process uses the LabelEncoder() function which is part of the SciKit-learn library. The correlation between the variables using correlation analysis so that the degree of relationship between these variables is obtained. The variables used in this study included respiratory problems, fever and Covid19. Correlation analysis was carried out using the Pearson, Spearman and KendallTau approach with the coefficient values shown in Table 1. Furthermore, the results of the correlation analysis can be seen in Table 2.

Table 1. Correlation coefficient value

Stats	Pearson	Spearman	KendallTau
Highest Positive Correlation	0.444	0.444	0.444
Highest Negative Correlation	0.0	0.0	0.0
Lowest Correlation	0.09	0.09	0.09
Mean Correlation	0.197	0.197	0.197

Table 2. Result of Correlation Between Feature

	Breathing Problem	Fever	Covid-19
Breathing Problem	1.000000	0.089903	0.443764
Fever	0.089903	1.000000	0.352891
Covid-19	0.443764	0.352891	1.000000

The CNN algorithm as a method of DNN is used in the training and testing process to predict someone exposed to COVID19 through symptoms of respiratory disorders and fever. CNN architecture uses 100 hidden layers. In addition, some of the parameters used in the CNN architecture can be seen in Table 3.

Table 3. Configuration of CNN Model

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

In the process of testing the classification training model, 20% of the data is used as test data and the remaining 80% is used to train the model. Figure 8 shows a graph of the performance results in the CNN classification process. In the 5th epoch convergence occurs with an accuracy value of 88%. Based on the results of these performance measurements, the process of detecting suspected COVID19 indicated by health symptoms can be applied to real data.

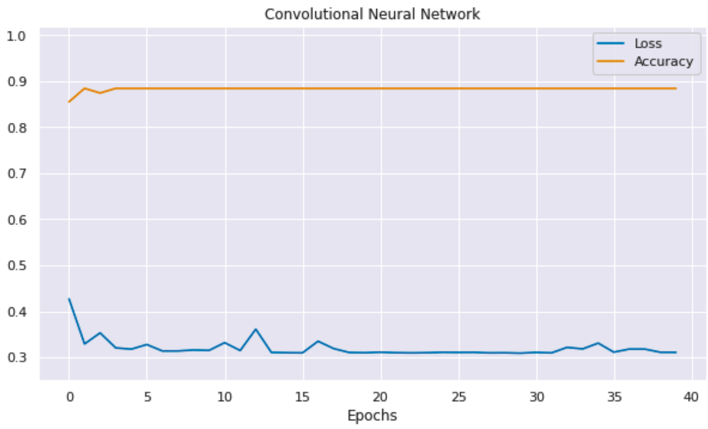

Figure 8. Accuracy And Loss Performance of CNN Classification

Furthermore, a comparison was made between the CNN classification method and other classification methods, such as SVM, Naive Bayes and Multi-Layer Perceptron (MLP). The results obtained from this comparison have an average percentage of accuracy above 80%. MLP has the lowest accuracy among its classification methods of 83.56%. CNN has the highest yield compared to other methods of 88.68% (Figure 9). Therefore, CNN can be chosen to be the right method for use in the COVID-19 suspect detection system through the recognition of symptoms of fever and respiratory problems.

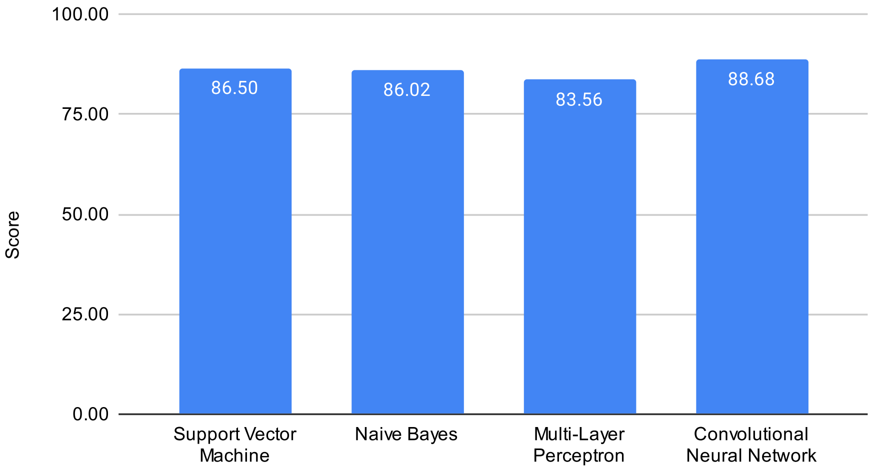

Figure 9. Comparison of Accuracy Score on Several Classification Models

4 CONCLUSION

This study aims to identify symptoms of fever and respiratory infection through image processing sourced from thermal camera sensors and further diagnose prospective patients who are suspected of being positive and reactive for COVID19 using the CNN method as an intelligent system for early detection of suspected positive and reactive COVID19 patients. This system detects symptoms including respiratory problems dan fever by tracking in the nostril and face area as the Region of Interest (ROI) to track breathing patterns and body temperature. So that it can be identified that the breathing pattern is normal or abnormal and a person has symptoms of fever. These two symptoms be parameters to predict that someone is suspected of having COVID19 using the CNN algorithm. In the process of testing the classification training model, the performance results in the CNN classification process have an accuracy value of more than 88%. Furthermore, the results comparison with other algorithm has an average percentage of accuracy above 80%. MLP has the lowest accuracy among its classification methods of 83.56%. CNN has the highest accuracy value compared to other methods of 88.68%. Therefore, CNN can be chosen to be the right one for use in the COVID-19 suspect detection system through the recognition of symptoms and respiratory disorders. However, this detection process needs to be tested in real conditions so suggestions for the improvement of this research are implementation and testing in real conditions.

5 ACKNOWLEDGEMENTS

We would like to thank Dian Nuswantoro University for their assistance in facility.

REFERENCES

[1] C. Huang *et al.*, "Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China," *The Lancet*, vol. 395, no. 10223, pp. 497–506, 2020, doi: 10.1016/S0140-6736(20)30183-5.

[2] R. Boulding, R. Stacey, R. Niven, and S. J. Fowler, "Dysfunctional breathing: A review of the literature and proposal for classification," *European Respiratory Review*, vol. 25, no. 141, pp. 287–294, 2016, doi: 10.1183/16000617.0088-2015.

[3] Z. Xu *et al.*, "Pathological findings of COVID-19 associated with acute respiratory distress syndrome," *The Lancet Respiratory Medicine*, vol. 8, no. 4, pp. 420–422, 2020, doi: 10.1016/S2213-2600(20)30076-X.

[4] W. Taylor *et al.*, "A review of the state of the art in non-contact sensing for covid-19," *Sensors (Switzerland)*, vol. 20, no. 19, pp. 1–19, 2020, doi: 10.3390/s20195665.

[5] M. Hu, Y. Fan, and X. Chen, "Synergetic use of thermal and visible imaging techniques for contactless and unobtrusive breathing measurement," *Journal of Biomedical Optics*, vol. 22, no. 3, pp. 1–11, 2022, doi: 10.1117/1.JBO.22.3.036006.

[6] L. Li *et al.*, "Using Artificial Intelligence to Detect COVID-19 and Community-acquired Pneumonia Based on Pulmonary CT: Evaluation of the Diagnostic Accuracy," *Radiology*, vol. 296, no. 2, pp. E65–E71, 2020, doi: 10.1148/radiol.2020200905.

[7] T. Ozturk, M. Talo, E. A. Yildirim, U. B. Baloglu, O. Yildirim, and U. Rajendra Acharya, "Automated detection of COVID-19 cases using deep neural networks with X-ray images," *Computers in Biology and Medicine*, vol. 121, no. April, pp. 1–11, 2020, doi: 10.1016/j.compbiomed.2020.103792.

[8] Z. Jiang *et al.*, "Combining Visible Light and Infrared Imaging for Efficient Detection of Respiratory Infections such as COVID-19 on Portable Device," no. 19, 2020, [Online]. Available: http://arxiv.org/abs/2004.06912.

[9] T. A. E. da Silva, L. F. da Silva, D. C. Muchaluat-Saade, and A. Conci, "A computational method to assist the diagnosis of breast disease using dynamic thermography," *Sensors*, vol. 20, no. 14, pp. 1–21, 2020, doi: 10.3390/s20143866.

[10] L. Wang, Z. Q. Lin, and A. Wong, "COVID-Net: a tailored deep convolutional neural network design for detection of COVID-19 cases from chest X-ray images," *Scientific Reports*, vol. 10, no. 1, pp. 1–12, 2020, doi: 10.1038/s41598-020-76550-z.

[11] P. Jagadev and L. I. Giri, "Non-contact monitoring of human respiration using infrared thermography and machine learning," *Infrared Physics & Technology*, vol. 104, no. January, p. 103117, 2020, doi: https://doi.org/10.1016/j.infrared.2019.103117.

[12] M. Farooq and A. Hafeez, "COVID-ResNet: A Deep Learning Framework for Screening of COVID19 from Radiographs," *arXiv*, pp. 1–5, 2020, [Online]. Available: http://arxiv.org/abs/2003.14395.

[13] A. Ulhaq, A. Khan, D. Gomes, and M. Paul, "Computer Vision For COVID-19 Control: A Survey," *arXiv*, pp. 1–24, 2020, [Online]. Available: http://arxiv.org/abs/2004.09420.

[14] A. V. Nguyen *et al.*, "Comparison of 3 infrared thermal detection systems and self-report for mass fever screening," *Emerging Infectious Diseases*, vol. 16, no. 11, pp. 1710–1717, 2010, doi: 10.3201/eid1611.100703.

[15] Y. Cho, S. Julier, N. Marquardt, and N. Bianchi-berthouze, "Robust tracking of respiratory rate in high-dynamic range scenes using mobile thermal imaging Robust tracking of respiratory rate in high- - dynamic range scenes using mobile thermal imaging," *Biomedical Optics Express*, vol. 8, no. 10, pp. 4480–4503, 2017, doi: 10.1364/BOE.8.004480.