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Realtime Facemask Detection using Deep Learning Framework TensorFlow-Keras

Erwan Eko Prasetiyo *[1], Muhammad Luqman Bukhori [2], Gaguk Marausna [3], Iswanto Suwarno[4], Hendriana Helda Pratama [5]

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Abstract: The spread of the Covid-19 virus can be reduced by implementing health protocols such as using masks properly. But there are still many people who ignore or even are reluctant to use masks when in public places. To increase public awareness and order in using masks, a system for detecting the use of masks is needed using image processing technology. The purpose of this research is to design and build a mask detection system using the deep learning framework TensorFlow. This mask detection system is to help monitor people using masks in implementing health protocols. The existence of this system is expected to help supervise people to comply with health protocols so that the transmission of the Covid-19 virus can be prevented. The proposed system test scenario uses face mask objects of various types of models and different colors. The test is applied to the condition of the object using a mask correctly or incorrectly. The conditions observed during the test included the proximity of the object to the camera, the lighting of the room, the number of people that could be detected, and the results of the decisions made by the mask detection system. The test results show that the mask detection system can function properly. The system developed has an accuracy rate of 93.2% for object detection capabilities with the use of the wrong mask. When detecting objects using masks correctly has an accuracy of 96.25%.

Keywords: *Facemask; TensorFlow; Keras; Detection System; Image Processing*

1. Introduction

Coronavirus disease (COVID-19) is an infectious disease caused by the SARS-CoV-2 virus. This virus is thought to have been spread by bats [1], [2]. Most people who contract COVID-19 will experience mild to moderate symptoms and could recover without special treatment. However, some people will become seriously ill and require medical assistance to the point of death [3]. The number of cases of COVID-19 infection is increasing. Data as of the end of March 2022, cases of COVID-19 transmission in Indonesia had reached more than 6 million cases and gained more than 378 million cases globally [4]. The COVID-19 pandemic has had an impact on several components. The COVID-19 pandemic's effect on the psychomotor elements of chess games for 8–10-year-olds [5]. The effects on overweight persons during the COVID-19 pandemic [6]. The effects on older people's physical and mental health [7].

The spread of the COVID-19 virus is the fastest [8]. The COVID-19 virus can spread from the mouth or nose of an infected person through tiny fluid particles when the person coughs, sneezes, talks, sings, or breathes. The ejected particles can range from larger droplets than the respiratory tract to smaller aerosols. People can catch it when they breathe air that contains the virus if they are close to someone who gets infected with COVID-19. People can also get it if they touch their eyes, nose, or mouth after touching a contaminated surface. Viruses are easier to spread indoors and in crowded places or crowds.

The spread of the COVID-19 virus can be controlled, by implementing health protocols, including maintaining distance, wearing facemasks, washing hands frequently, avoiding crowds, vaccinating, maintaining cleanliness, and using assistive devices with robots [9]. The use of medical facemasks is very effective in preventing the transmission of COVID-19 because they can filter particles up to 95% [10]. However, a founding shows that many people ignore or are reluctant to use facemasks in public areas. An attitude of the community that does not comply with the application of health protocols needs to be a concern. This situation can endanger other people because of the risk of increasing the transmission of the COVID-19 virus.

Several public areas have supported monitoring systems to increase public awareness of implementing health protocols. Efforts have been made by providing handwashing stations, disinfectant spraying system [11], installing thermal cameras to check body temperature, and placing special officers to supervise the use of facemasks and enforcement of health protocols.

The existence of supervisory officers still has limitations to monitor one by one people who are wearing facemasks or not. So this condition still allows people to ignore wearing facemasks in public areas. A real-time facemasks detection system is needed to help supervise the use of facemasks in public spaces. Much research on the facemasks detection system with various issues raised, including the methods, accuracy, detection speed, effectiveness, efficiency, advantages, and disadvantages.

Research on object detection using cameras has been carried out

[1,2,3,5] Aerospace Engineering, Sekolah Tinggi Teknologi Kedirgantaraan Yogyakarta – 55143, INDONESIA
[1] ORCID ID : 0000-0001-9847-9950
[2] ORCID ID : 0000-0003-1724-8785
[3] ORCID ID : 0000-0002-9011-9851
[5] ORCID ID : 0000-0003-0226-9460
[4] Departement of Electrical Engineering, Universitas Muhammadiyah Yogyakarta – 55183, INDONESIA
ORCID ID : 0000-0001-8459-3920
** Corresponding Author Email: erwan.eko@sttkd.ac.id*

and developed in previous studies [12], [13]. The human object detection system establishes robot-human interactions [14], human activity [15] as well as to detect pedestrian objects in real-time [16] and face mask detection [17]–[21] Research on object detection built as a decision-maker in culinary applications in restaurants. In addition, to detecting the type of food menu, the system is also designed to provide information on the food prices [22]. In the era of the COVID-19 pandemic, the researcher develops object detection to detect people wearing facemasks [7], [8], [23], [24].

The application of AI in handling the COVID-19 pandemic has been carried out as early detection and diagnosis of infection, monitoring patient care, tracing patient contacts, projecting cases and deaths, developing drugs and vaccines, reducing the workload of medical personnel, and preventing the spread of the epidemic [25]–[31].

AI technology cannot be separated from the many image recognition systems that can accommodate the need for identifying, monitoring and early warning implementation [32]–[43]. An early warning system using human mobility and website search query data helps the government to establish effective strategies to deal with the COVID-19 outbreak based on the predicted location of the next COVID-19 [44].

Controlling COVID-19 in public areas using AI has lower operational costs compared to human labor as a detector. The technology for detecting the use of facemasks before entering public areas via CCTV can be integrated with AI-based AlexNet [20]. Deep Learning basic models that are widely applied to Computer Vision such as AlexNet, VGGNet, GoogLeNet & Inception, ResNet, DenseNet, MobileNets, EfficientNet, and RegNet. Computer Vision can be used for tasks such as recognition, visual tracking, semantic segmentation, and image restoration [45].

The success of Deep Learning for detecting the use of masks can be increased by sharing images of real masks. Most of the datasets used for training are currently only small, so they do not describe dynamic environmental conditions and various conditions of wearing facemasks [23], [46]–[50].

ResNet50 which has an accuracy rate of 98.2% as a method of detecting the use of facemasks to prevent the spread of COVID-19 when compared to other baseline methods such as AlexNet and MobileNet has been implemented to detect people who are not wearing facemasks correctly and find out their identity when the database of that person has been stored in the data canter [23].

Several types of Neural Networks are ANN, CNN, and RNN. Deep Learning architecture using Python Script, TensorFlow, and CNN as a mask detector can work well as a solution to maintain the implementation of health protocols. Deep Learning has several challenges including the obscurity of Neural Networks, data quality assurance, data security, and AI production classes [24], [51].

This research performs the results and discussion include:

- Training and testing the accuracy of detecting the use of facemasks with several different models and colours of masks.
- Failure to determine conditions or the success of detection of the object during testing of the detection system is carried out with the mouth closed but not covered with a facemask, for example, covered with hands, clothes, books, hats, and testing at a distance and in bright light conditions (need to measure the light intensity).
- The COVID-19 pandemic, its impact, the government's efforts to enforce 5M, one of which is the correct use of masks, the negligence of using facemasks in public places, the need for an automatic mask detection system by intelligent tools/systems to assist surveillance. The purpose/focus of this research is to build a detection system for the use of facemasks using the deep learning framework TensorFlow.

2. METHOD

2.1. Research Steps

In this study, an object detection system is designed to determine whether an object is observed using the facemask correctly, using the facemask incorrectly, or not using the facemask. The research flow can be seen in the following flow chart Fig. 1.

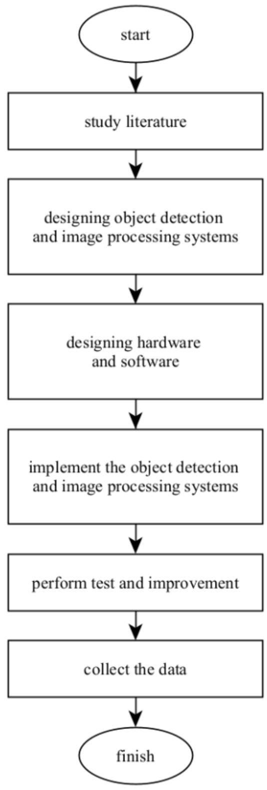


Figure 1. The flowchart of reserach.

The literature study conducts a literature review on various models and image recognition systems. Based on the results of the literature study, this study chose an image recognition system using the TensorFlow Deep Learning Framework. Designing object detection and image processing system are designing a computer vision using the TensorFlow deep learning framework because it is more efficient and lightweight in processing digital image data. Designing hardware and software are using an HD camera to detect objects and a Single Board Computer (SBC) to run artificial intelligence programs. Implement the object detection is trains the device that has been made to recognize objects that use masks correctly or incorrectly. Perform tests and improvements are tests of the performance of the proposed mask detection system to identify objects that have used masks correctly or not. Collecting data is collecting the test data and analyzing it to get a conclusion.

2.2. Device and Specification

The hardware design consists of 3 main components with connectivity as shown in Fig. 2 with the specifications in Table I.

Figure 2. Block diagram of mask detection system.

The camera is a sensor to detect objects in the form of humans. Image object data is sent to Single Board Computer (SBC) or Mini PC for processing. The Mini PC runs an image recognition program using the TensorFlow Deep Learning Framework. The image data is identified and the data on the face is selected. The face data is then re-identified whether using the mask correctly or incorrectly. The result of identifying the correct or incorrect use of the mask is shown on the LED monitors.

Table 1. Devices specifications

No	*Parts*	*Specification*
1	Mini PC	NVIDIA Jetson Nano Developer Kit Full Set
2	Camera	Logitec C920 Pro Stream Webcam
3	LED Monitor	Monitor LED Samsung S24R350 24" IPS 75hz HDMI
4	Power Supply	Corsair CV650 Power Supply 650 Watt

2.3. Developed Design Concept

The learning algorithm uses the MobileNetV2 model. MobileNetV2 is a development of the previous CNN architectural model called MobileNetV1. MobileNet is a CNN architecture designed to address the need for excessive computing resources [52]–[56] The basic difference between the MobileNet architecture and other CNN architectures is the use of a convolution layer with a filter thickness that is almost the same as the input image. MobileNet divides convolution into depth wise convolution and pointwise convolution as shown in Fig. 3.

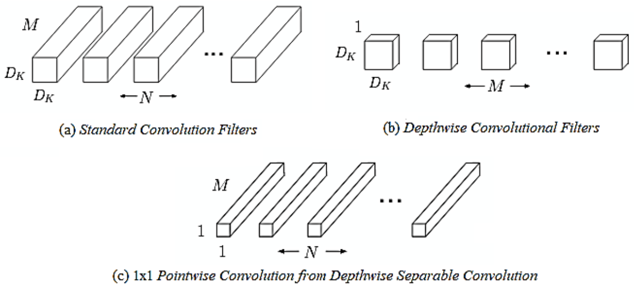


Figure 3. (a) Standard convolution is divided into two layers: (b) depth wise convolution and (c) pointwise convolution to create depth-separated filters.

In MobileNetV2 there are two additional features, namely: 1) linear bottlenecks, and 2) shortcut connections between bottlenecks. The bottleneck contains inputs and outputs between models, while the inner layer encapsulates the model's ability to change inputs from lower-level concepts to higher-level descriptors [57]–[60] As with residual connections on traditional CNNs, bottleneck shortcuts allow for faster training and better accuracy. The basic structure of this architecture can be seen in Fig. 4.

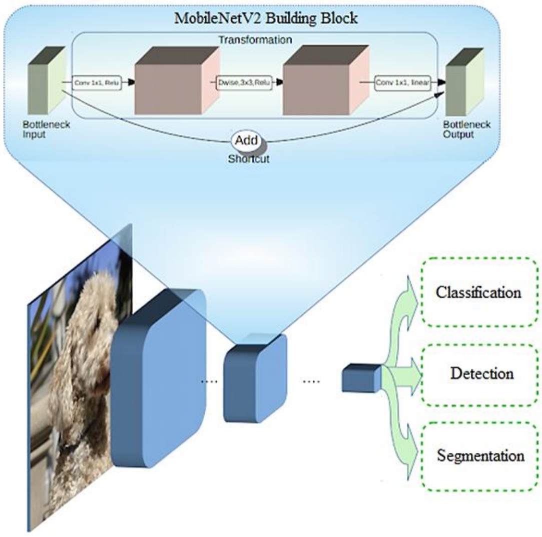


Figure 4. MobileNetV2 Architecture [57].

The proposed research develops a model by loading a dataset for mask detection. Python's deep learning libraries used for data preparation include OpenCV, Keras, and TensorFlow. This library is used to train classification with the MobileNetV2 model. There are two stages in the introduction of the model, namely Training with the TensorFlow library and Testing with the TensorFlow.Keras library [61]. Before the training started, all datasets were extracted based on facial features, namely: face circumference, eyes, nose, and mouth. The trained dataset is then saved as model data with the extension (.model). In the experimental stage, the previously saved model is called the TensorFlow.Keras library. The implementation of the model is applied to the hardware to read the video image in real-time. If the camera captures the image of a person's face wearing a mask correctly, then the result shows "masked". If the camera captures an image of a person's face not wearing a mask or wearing a mask but it is not correct, then the result shows "without a mask". The overall model development can be seen in Fig. 5.

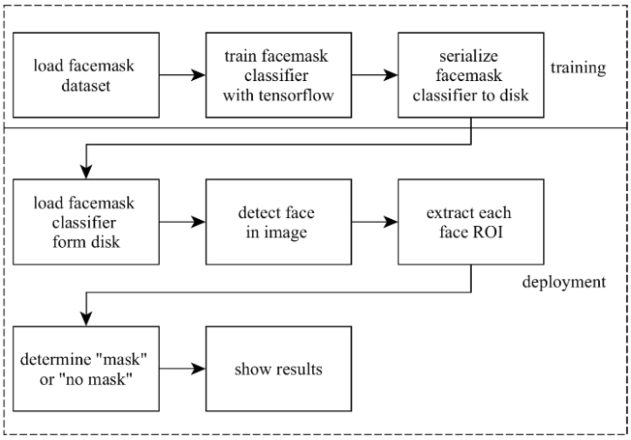


Figure 5. The overall model development

2.4. Model Training

Model training is carried out to obtain one form file (file.model). This file functions as a face detector model to determine the similarity between the image taken from the camera is a masked image or not. Determination of iterations of 50 iterations and batch sample (BS) of 32 data. Evaluation of training results is calculated using (1)-(4) [62], [63].

$$Accuracy = \frac{[TP+TN]}{Total} \quad (1)$$

$$Precision = \frac{[TP]}{[TP + FP]} \quad (2)$$

$$Recall = \frac{[TP]}{[TP + FP]} \quad (3)$$

$$F1\ score = 2\ x\ \frac{[Precision\ x\ Recall]}{[Precision + Recall]} \quad (4)$$

Precision is a metric that shows the number of expected positive values or actual values. The recall statistic was used as a quantity of an algorithm's ability to classify all positive cases, while the accuracy of the F1-score test was quantified. This evaluation step provides the most accurate findings against a balanced dataset. This stage is the verification stage for accurate predictions.

TP in (1)-(4) stands for True Positive, TN is True Negative, FP is False Positive, then FN is False Negative [62], [63] A positive value in the equation indicates that the image entered on the label really matches the prediction with the specified label. Likewise, the negative image is actually the image according to the correct category but gets the wrong prediction.

3. Results and Discussion

3.1. Training

In this study, we used the first dataset of 113 populations with facemasks correctly and another 113 populations using facemasks incorrectly or without facemasks. The secondary dataset contains 741 populations with facemasks correctly and 741 populations using facemasks incorrectly or without facemasks. The sample dataset is shown in Fig. 6-7.

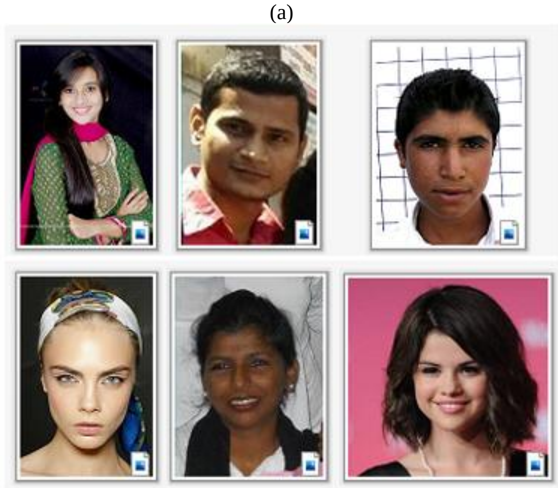
We did three training models shown in Fig. 8. In the first training, the loss and accuracy graph conditions showed near convergence results in Epoch 5. In the second training, the loss and accuracy graph conditions after Epoch 15 showed instability. In the third training, the loss graph conditions are already at the lowest value close to zero and are more stable, while the accuracy graph is already at the highest value close to 100%.

(a)

(b)

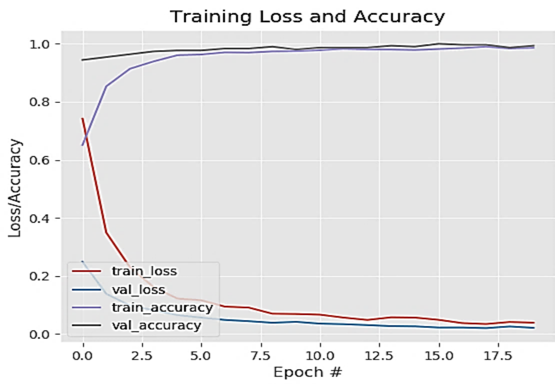
Figure 6. The first dataset using facemask is (a) correctly, (b) incorrectly.

(a)

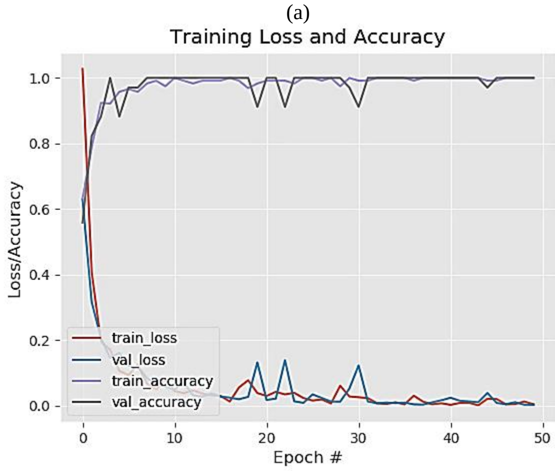


(b)

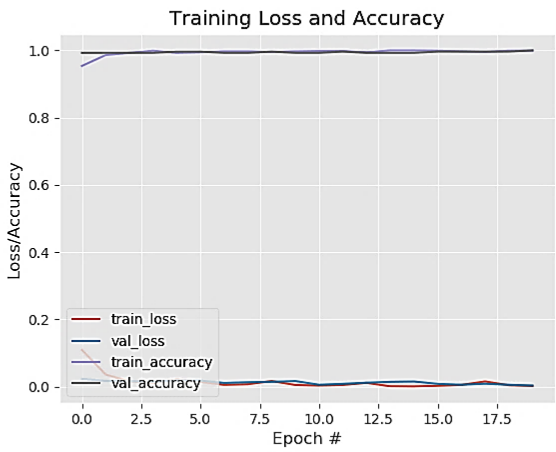
Figure 7. The secondary dataset using facemask is (a) correctly, (b) incorrectly.



(a)



(b)



(c)

Figure 8. Training graph.

3.2. Failure to Determine Conditions

As the object distance from the camera increases, there is a decrease in light intensity, which makes it fail to detect all facial conditions at a distance of more than 2 m. Errors in determining the condition of the facemask can also appear if the detected object experiences movement and instability in the light intensity received by the camera. This is shown in Fig. 9.

Detection errors can occur in conditions without a facemask, when using a facemask correctly or when using a facemask incorrectly. Factors that can affect it include the movement of objects. Moving objects can cause detection failure because the captured image is not very clear in recognizing patterns in the nose and mouth area. This is also supported by the low light intensity received by the camera when it detects objects. The solution that can be done to make the right decision is to do object tracing and perform several detections and determine whether the observed object matches one of the three criteria for using masks based on several detection samples for the same object.

(a)

(b)

(c)

Figure 9. Error detected object, (a) without a facemask, (b) using facemask correctly, (c) using facemask incorrectly.

3.3. The Success of Detecting the Object

Detection of objects with three criteria, namely without a facemask, using the facemask correctly, and using the facemask incorrectly is shown in Table II-IV and Fig. 10. Detection displays precise detection results if the object tends to move slightly or is stationary. This is because a stationary object makes the camera able to capture the image correctly and the light intensity is more stable.

The accuracy of detecting an object has a correlation with the distance between the camera and the object. Increasing the distance between the camera and the object increases the accuracy. Average accuracy at a distance of 1 m = 87.8%, a distance of 1.5 m = 88.8%, and a distance of 2 m = 93.2%. A different trend is shown in the use of the facemask incorrectly, with the trend of accuracy increasing and then decreasing as the distance between the camera and object increases. The best object detection performance with 100% accuracy occurs in face detection without a mask in various object distance variations.

Table 2. The accuracy object detection performance

Condition	*Object distance (m)*	*Accuracy (%)*
Without facemask	1	100
	1.5	100
	2	100
Using facemask correctly	1	87.8
	1.5	88.8
	2	93.20
Using facemask not correctly	1	95.25
	1.5	96.25
	2	94.75

(a)

(b)

(c)

Figure 10. Detected object, (a) without a facemask, (b) using facemask correctly, (c) using facemask incorrect.

4. Conclusion

The factor that affects the failure of object detection is distance, where in this study the maximum detection distance is 2 m. The object movement factor affects the stability of the light intensity and the quality of the images captured by the camera. The movement of a lot of objects and unstable light intensity cause failure. It takes object tracking and sampling detection several times before deciding whether an object meets one of the criteria for wearing a facemask. The designed system can detect objects without a facemask with 100% accuracy. The designed system can detect objects with the correct facemask with 93.2% accuracy. The system is designed to detect objects with the facemask incorrectly with 96.25% accuracy. So that the developed mask detection system can help detect people who use masks correctly or incorrectly.

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Author contributions

Erwan Eko Prasetiyo: Conceptualization, Field study **Muhammad Luqman Bukhori:** Methodology, Software, Data curation **Gaguk Marausna:** Writing-Original draft preparation **Iswanto Suwarno:** Validation, Writing-Reviewing and Editing **Hendriana Helda Pratama:** Data collection.

Conflicts of interest

The authors had no conflict of interest with any parties while researching and writing this paper.

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