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Real-Time Detection of Face Mask Using Convolutional Neural Network

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Abstract

Masks are a simple barrier that can help us prevent transmission and spread of disease from other people who enter the body, avoid exposure to air pollution, and protect the face from the adverse effects of sunlight. However, many people are still ignorant about the importance of wearing masks for health. This study aims to detect whether or not to use masks in real-time by proposing a deep learning model to reduce illness and death caused by air pollution. The convolutional Neural Network (CNN) method was used in this research to detect facial recognition using a mask and not using a mask. The public dataset used in this research consists of 1300 images with 650 data using masks and 650 data without masks. The results of this study show that the proposed CNN method works well in detecting masked and non-masked faces in real time. The proposed method obtains an accuracy value of 97.5% at epoch 50. Previous research on mask detection using the Eigenface method yielded an accuracy of 88.89%, and another study using the Viola-Jones method yielded an accuracy of 95.5%. It can be concluded that this research can increase the accuracy value of previous studies. So, this research is feasible to be applied to the detection of mask use in real time.

Keywords: *mask detection; CNN; face detection; face recognition; pollution*

1. Introduction

Several studies have focused on detecting and analyzing humans using facial features in the last few decades [1], [2], and one of them is face recognition. One of the advanced technologies remembered in the field of computer vision is face recognition. Face recognition is used in several areas, such as attendance systems [2], security detection [3], detection of drowsiness and fatigue [4], crimes from video surveillance [5], robotics [6], biometric security [7], deforestation early detection [8], CT scan images [9], and also SARS-CoV 2 disease [10].

Air pollution is characterized as the presence of unfamiliar materials or substances in the air, which cause changes in the arrangement of the environment from its generally expected state as per the overall setting and is extraordinarily impacted by the climate [11]. Air contamination incorporates environmental (outdoor) and domestic (indoor) pollution. The consumption of non-renewable energy sources is the main source of air contamination. Contaminants delivered into the air from fixed and mobile sources (cars, trucks, ships, etc.), such as coal-fired power plants and steel mills, are significant sources of air pollution [12].

Air contamination is the fourth driving reason for sickness and passing on the planet. Gauges from the World Health Organization (WHO) of 91% of the total populace live where the typical yearly air contamination surpasses the WHO rule of 10 µg per cubic millimeter. A GBD concentrate assessed that air contamination was liable for 6.7 million passings overall in 2019 (95% certainty stretch [CI], 5.9 million to 7.5 million). Of these 1.2 passings, 2.3 million (95% CI, 1.6 to 3.1 million) were inferable from homegrown air contamination, and 4.1 million (95% CI, 3.5 to 4.8 million) were owing to homegrown air contamination. Different appraisals in light of elective openness estimations and late openness reaction capabilities propose that air contamination might add to 9 to 12 million passings yearly [13]–[15].

Convolutional Neural Network (CNN) is a profound learning strategy that can perceive and distinguish objects in computerized pictures. This is mainly due to more powerful computational elements, large datasets, and more profound techniques for training networks [16]. Previous work by Atha, Anefia Mutriara, and others. CNN was used to recognize homegrown plants specialized in skin and hair infections. The image data used up to 1000 images divided into ten categories of

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herbal plants, each containing 100 images, achieving 93% accuracy [17]. According to [18], the CNN method increased accuracy and minimized data loss in cataract salvage procedures. This study uses an epoch of 50 and achieves a high score of 95%. In a subsequent study [19], a neural network was designed to detect drowsiness in various situations using the LSTM-CNN method. The average accuracy of these results is 85.6%.

Moreover, a study [20] successfully detected early breast cancer with CNN, reaching an accuracy of 80%. Samuel et al. conducted a study with CNN on how to detect trees in images of oil palm plantations. This study used the CNN method on ResNet-34 and ResNet-50 architectures. The result is a successful automatic execution of the recognition process with 84% training accuracy and 71% testing accuracy [21].

From previous studies and the background above, masks are essential, mainly to prevent the transmission of various diseases related to pollution and breathing. The difference with previous studies on mask detection with CNN is that in this study, optimization of the use of the CNN method is carried out to get accurate results in detecting faces using masks or not. Optimization is done by adding hyperparameters to the CNN architecture. By adding hyperparameters, a higher accuracy value is obtained than those that do not add hyperparameters. Thus, a research entitled Implementation of CNN to increase the accuracy of real-time face detection using the mask is fundamental. It has produced a very high accuracy value of 97.5%, so it is feasible to implement in the broader community.

2. Research Methods

The initial step in this research method is to collect masked and unmasked image datasets, data labeling sessions to sort datasets, create CNN models, process data training, process data testing, Tflite models, and evaluate the work of the models built. accompanying Figure 1 shows the technique completed in this study.

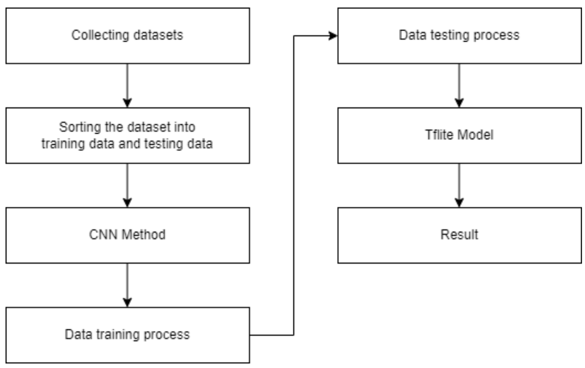

Figure 1. Stages of the Research Method

2.1 Dataset

The dataset utilized in this study is public, uses JPG and JPEG formats, is split into two folders labeled with_mask and without_mask, and split into two types of data, training data, and test data. The training and test data have two folders, a with_mask folder and a without_mask folder, where the with_mask folder contains 650 images and the within_mask folder contains 650 images. Figure 2 shows the information from each class dataset utilized in the study.

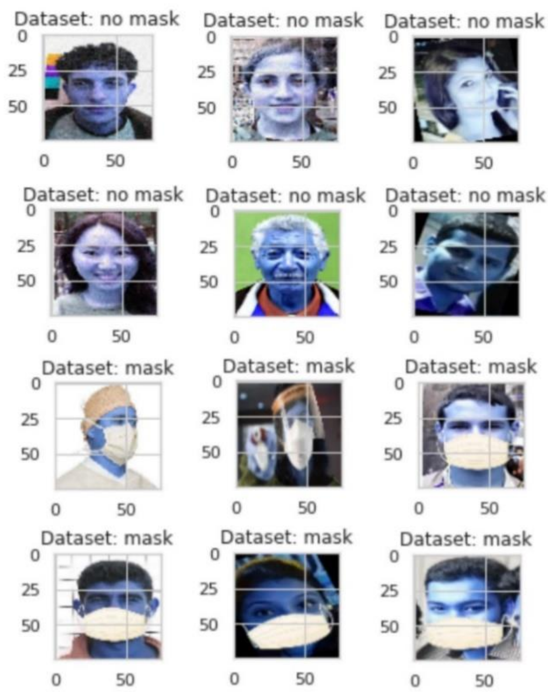

Figure 2. Dataset with Label Mask and No Mask

Each dataset needs to be filtered first and then modified to be consistent with the training data, as we use various recognition techniques, each of which has specific dataset requirements.

2.2 Convolutional Neural Network

In this research, the method used is the Convolutional Neural Network (CNN). One type of Neural Network with high classification accuracy is CNN [22], [23]. CNN isolates its work into a few layers can be seen in Figure 3. Among them are the convolutional layer, pooling layer, and fully connected layer. To extract data features used for training using convolutional layers. Then the pooling layer makes new channels in view of the ideal standards. The last entirely related layer is an MLP (Multilayer Perceptron) part of an artificial neural network, a movement of neurons. Connect connection weight [23]. The structure of this organization is composed of multiple transforming layers, which include a unit layer or an intermediate and a fully connected layer. Medical applications using CNN tissue models include breast cancer classification [24],

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cardiovascular disease [25], brain tumor detection [26], skin disease [27], and detection of covid-19 [28]. It can also detect the identification of waste types [29].

A CNN is a variety of multi-facet perceptron roused by human neural networks in light of the discoveries of Hubel and Wiesel, who are concentrating on the visual cortex of feline vision. This study is very much inspired by this study since the consequences of the study showed that the visual cortex of creatures was extremely strong in the visual handling framework that has at any point existed.

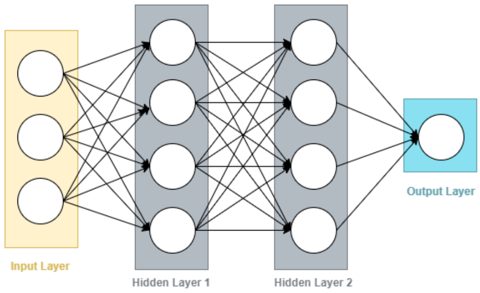

Figure 3. CNN Method Layer

Convolutional Neural Networks are deep artificial neural networks [30]. We can utilize it to characterize pictures (for example, give the name of what they see), group them based on similarities (photo search), and introduce objects in view. This can be utilized to distinguish people, faces, growths, street signs, platypus, and numerous different parts of the visual information.

2.3. Model Architecture

The CNN model used in this mask detection study uses Max Pooling. Max pooling parts of the info picture into a bunch of non-covering square shapes and deciding the greatest incentive for each sub-district. In this model, there are his 12-step shifts that pass through the summer, as shown in Figure 4

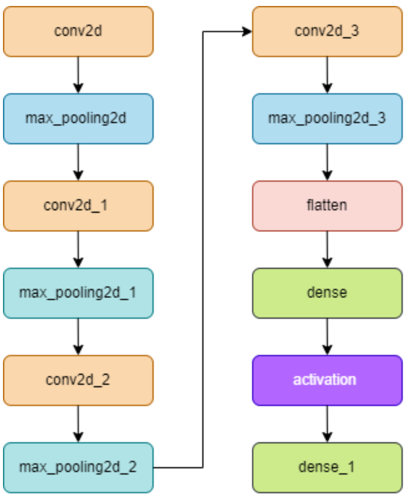

Figure 4. CNN Model Architecture

The result of this summary will get the results of total params, trainable params, and non-trainable params.

This part depicts a portion of the outcomes got from our exploratory outcomes. In this work, we classify images for mask detection. This dataset is split based on 1300 images of 650 masked and 650 unmasked data, 80% as training data and 20% as test data. The research results are as follows

The first thing to do in the training process is to process the image into the first convolutional layer using a 32 kernel filter to obtain the results of the 27776 parameters using the calculation (17 x 17 x 3 + 1) 32 = 27776. The training process aims to train the Convolutional Neural Network (CNN) to produce a high accuracy value. Next, the second layer uses a 64 kernel filter with a size of 17 x 17 x 64 and will get the results of the 18496 parameters using the calculation (17 x 17 x 1) x 64 = 18496. Continued to the third convolutional layer using a 96 filter with a size of 17 x 17 x 96 and will obtain a parameter result of 55329 by calculating (17 x 17 x 2 - 1) x 96 = 55329. In the third layer, if you have obtained the results, it will proceed to the fourth convolutional layer using a 96 kernel filter with a size of 17 x 17 x 96 using the same size results but having a parameter result of 93040 with the calculation (17 x 17 x 3 - 2) x 96 = 83040.

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 75, 75, 32)        27776
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 37, 37, 32)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 37, 37, 64)        18496
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 18, 18, 64)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 18, 18, 96)        55392
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 9, 9, 96)          0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 9, 9, 96)          83040
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 4, 4, 96)          0
_________________________________________________________________
flatten (Flatten)            (None, 1536)              0
_________________________________________________________________
dense (Dense)                (None, 512)               786944
_________________________________________________________________
activation (Activation)      (None, 512)               0
_________________________________________________________________
dense_1 (Dense)              (None, 2)                 1026
=================================================================
Total params: 972,674
Trainable params: 972,674
Non-trainable params: 0
_________________________________________________________________
```

Figure 5. Training Results on Each Layer Using CNN

Figure 5 shows the results of training data from each layer, and it is known that the hidden layer data that has been trained is 972, 674. And this training process uses

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as many as 50 epochs. The results of the data training process are then stored for the following data testing process.

Conv2d performs an elementwise multiplication with the part of the input it is currently on and then sums up the results into a single output pixel. The kernel repeats this process for every location it slides over, converting a 2D matrix of features into yet another 2D matrix of features. Maxpooling2d is used to add a pooling layer. Downsamples the input along its spatial dimensions (height and width) by taking the maximum value over an input window (of size defined by pool size) for each channel of the input. The window is shifted by strides along each dimension. Flatten is the function that converts the pooled feature map to a single column that is passed to the fully connected layer. Dense adds the fully connected layer to the neural network.

3. Results and Discussions

After designing the CNN architecture. The next step is to conduct training on the data obtained to obtain the model. The training process is the process of obtaining a machine-learning model.

3.1 Loss and accuracy training

The training process is the process of obtaining a machine-learning model. When training is set the number of steps per epoch is 50, and the time to complete the epoch is 2-3 seconds. The use of padding and stride is a cause of faster execution time. The results of testing the loss and accuracy of each epoch on the model with hyperparameters are shown in Table 1.

Table 1. Loss and Accuracy Model with Hyperparameters

Epoch	Time	Loss and Accuracy
1/50	3s 45ms/step	loss: 0.1562 - accuracy: 0.9423
2/50	2s 40ms/step	loss: 0.1407 - accuracy: 0.9231
3/50	2s 40ms/step	loss: 0.1089 - accuracy: 0.9577
4/50	2s 40ms/step	loss: 0.1023 - accuracy: 0.9577
5/50	2s 40ms/step	loss: 0.2089 - accuracy: 0.8923
6/50	2s 40ms/step	loss: 0.0835 - accuracy: 0.9615
7/50	2s 40ms/step	loss: 0.0632 - accuracy: 0.9769
8/50	2s 41ms/step	loss: 0.0735 - accuracy: 0.9692
9/50	2s 41ms/step	loss: 0.1194 - accuracy: 0.9538
10/50	2s 41ms/step	loss: 0.0662 - accuracy: 0.9808
11/50	2s 40ms/step	loss: 0.0622 - accuracy: 0.9769
12/50	2s 42ms/step	loss: 0.0567 - accuracy: 0.9769
13/50	2s 40ms/step	loss: 0.0490 - accuracy: 0.9846
14/50	3s 49ms/step	loss: 0.1139 - accuracy: 0.9385
15/50	2s 41ms/step	loss: 0.0568 - accuracy: 0.9846
16/50	2s 40ms/step	loss: 0.0587 - accuracy: 0.9808
17/50	2s 40ms/step	loss: 0.0375 - accuracy: 0.9808
18/50	2s 40ms/step	loss: 0.0528 - accuracy: 0.9769
19/50	2s 40ms/step	loss: 0.1259 - accuracy: 0.9577
20/50	2s 40ms/step	loss: 0.0649 - accuracy: 0.9692
21/50	2s 39ms/step	loss: 0.0361 - accuracy: 0.9808
22/50	2s 42ms/step	loss: 0.0672 - accuracy: 0.9731
23/50	2s 40ms/step	loss: 0.0331 - accuracy: 0.9808
24/50	2s 40ms/step	loss: 0.0688 - accuracy: 0.9846
25/50	2s 40ms/step	loss: 0.0613 - accuracy: 0.9769
26/50	2s 40ms/step	loss: 0.0731 - accuracy: 0.9769
27/50	2s 42ms/step	loss: 0.0502 - accuracy: 0.9808
28/50	2s 44ms/step	loss: 0.0321 - accuracy: 0.9808
29/50	2s 42ms/step	loss: 0.0477 - accuracy: 0.9846
30/50	2s 40ms/step	loss: 0.0956 - accuracy: 0.9654
31/50	2s 40ms/step	loss: 0.0824 - accuracy: 0.9808
32/50	2s 42ms/step	loss: 0.0647 - accuracy: 0.9731
33/50	2s 40ms/step	loss: 0.0326 - accuracy: 0.9885
34/50	2s 40ms/step	loss: 0.0293 - accuracy: 0.9846
35/50	2s 40ms/step	loss: 0.1043 - accuracy: 0.9615
36/50	2s 40ms/step	loss: 0.0417 - accuracy: 0.9846
37/50	2s 44ms/step	loss: 0.0449 - accuracy: 0.9846
38/50	2s 40ms/step	loss: 0.0655 - accuracy: 0.9731
39/50	2s 40ms/step	loss: 0.0330 - accuracy: 0.9846
40/50	2s 41ms/step	loss: 0.0732 - accuracy: 0.9808
41/50	2s 40ms/step	loss: 0.0545 - accuracy: 0.9885
42/50	2s 42ms/step	loss: 0.0314 - accuracy: 0.9846
43/50	3s 51ms/step	loss: 0.0403 - accuracy: 0.9846
44/50	2s 40ms/step	loss: 0.0581 - accuracy: 0.9769
45/50	2s 39ms/step	loss: 0.0429 - accuracy: 0.9846
46/50	2s 41ms/step	loss: 0.0525 - accuracy: 0.9808
47/50	2s 42ms/step	loss: 0.1318 - accuracy: 0.9577
48/50	2s 40ms/step	loss: 0.0821 - accuracy: 0.9692
49/50	2s 40ms/step	loss: 0.0473 - accuracy: 0.9808
50/50	2s 40ms/step	loss: 0.0457 - accuracy: 0.9846

The graphical visualization of each loss value and accuracy can be seen in Figure 6 and Figure 7.

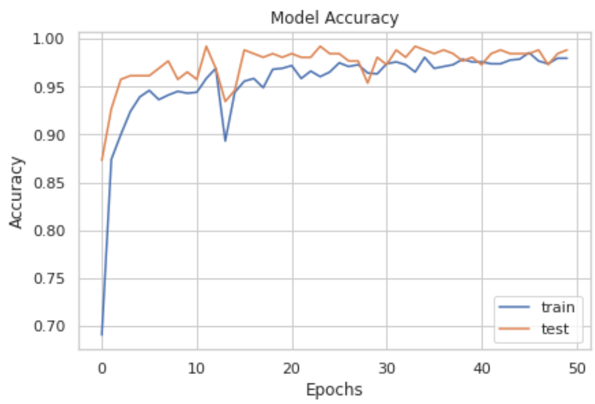

Figure 6. Model Accuracy Graph

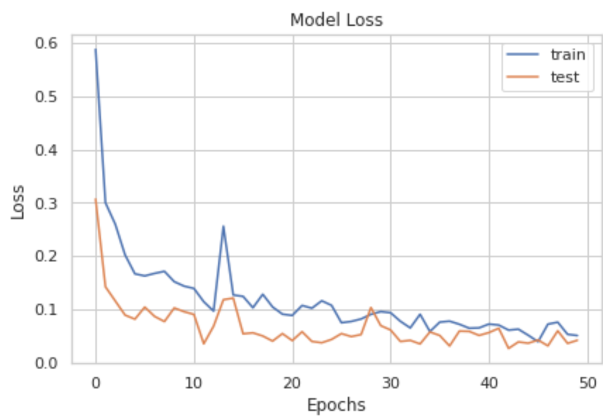

Figure 7. Model Loss Graph

Figure 7 shows the results of 2 different graphs but with the same model. The two graphs have the same number of layers and filters and use the same epoch of 50 epochs, but the content displayed is different. The high level of accuracy of the data owned by the training data

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and testing data is addressed by the accuracy graph, while the loss graph displays a minor error during the data learning process owned by the training data and testing data. The accuracy and loss graphs have different waves caused by the overfitting of the model and the excessive number of batches.

Then, this study also gets confusion matrix results or predictions on each detection data that has been prepared can be seen in Figure 8 and Table 2.

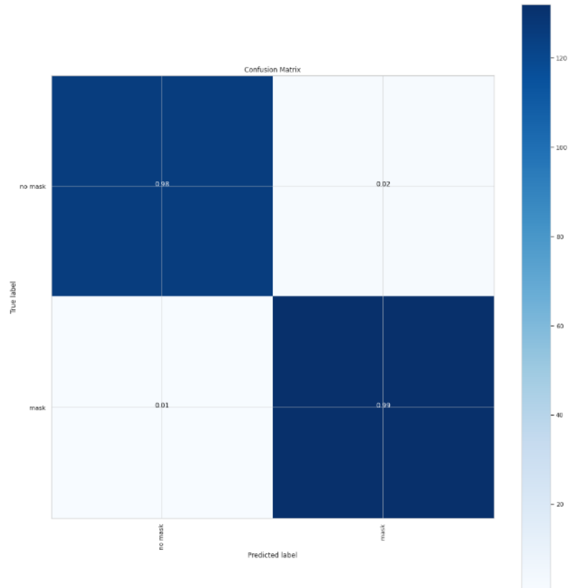

Figure 8. Confusion Matrix Results

Figure 8 shows the display of confusion matrix results containing the data classification process with high accuracy.

Table 2. Accuracy Table Based on Confusion Matrix

Original Label	Predicted Label	Accuracy
Mask	Mask	0.99
No Mask	No Mask	0.01
Mask	Mask	0.02
No Mask	No Mask	0.98

The data testing process is carried out using 260 images taken from 20% of the training data used, then divided into 2 folders, namely the mask and no mask folders.

	precision	recall	f1-score	support
no mask	0.99	0.98	0.99	127
mask	0.99	0.99	0.99	133
accuracy			0.99	260
macro avg	0.99	0.99	0.99	260
weighted avg	0.99	0.99	0.99	260

Figure 9. Results of the Testing Process

Figure 9 displays the testing process results with a high accuracy value of 0.99 out of 260 images used.

3.2 Testing image

After the detection system is completed, the next step is the testing stage which is done to acquire the accuracy percentage. System testing is performed in real-time to distinguish the utilization of masks with different positions and shooting distances using an android smartphone. At this testing stage, the detection system uses 80 sample test images with and without masks.

Figure 10. Test Image 1

The first digital test results were conducted with the first few people, as shown in Figure 10. This test was conducted with a few people, and the standard camera was positioned parallel to the human with little light. The distance between the camera and the object was 3 to 4 meters. The success rate in the first test for mask use detection using CNN was up to 100%. From this success rate, CNN can accurately detect whether a mask is worn or not, as well as the standard camera position. From the image, the two people are not wearing masks detected by the system by showing a red indicator.

Figure 11. Test Image 2

The second test was conducted in the house shown in Figure 11, with 3 people. The standard camera was positioned parallel to the average human view and with different face direction positions. The accuracy of human detection in this second test with an average

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camera-to-object is 1 meter. Then the mask detection accuracy reached 100% because, in Figure 11, we can see 3 people who are not wearing masks.

Figure 12. Test Image 3

The third test was conducted in the market, shown in Figure 12, with several people. The standard camera was positioned parallel to the average human view and with different face direction positions. The accuracy of human detection in this third test with an average camera-to-object is 4 meters. The mask detection accuracy reached 100% because in Figure 12 we can see 3 people who are not wearing masks. In the image above, the detection position does not match the face because of the moving object.

Figure 13. Test Image 4

The fourth test was conducted in a public place shown in Figure 13, with many people. The standard camera was positioned parallel to the average human view and with different face direction positions. The human detection accuracy in this fourth test with the average camera-to-object is 3 meters. The mask detection accuracy reached 100%. There are some people who do not use masks that are detected by the system by showing a red indicator, and those who use masks are detected by showing a green indicator.

Figure 14. Test Image 5

The fifth test was conducted in an open field as shown in Figure 14, with many people. The standard camera was positioned parallel to the average human view and with different face direction positions. Human detection accuracy in this fifth test with an average camera-to-object reached 5 meters. The mask detection accuracy reached 100%. Two people are detected not wearing masks and detected by the system by showing a red indicator, and then there are 2 people wearing masks who are detected by showing a green indicator. Some are not detected because the distance of the object is too far and looks small in the camera, as well as the lack of lighting on the object's face, so CNN cannot detect the object.

Figure 15. Test Image 6

Furthermore, the sixth study was conducted at a considerable distance, and the camera position was below the average face of the object to obtain such a perspective, as shown in Figure 15. At this considerable distance, human detection using CNN received an accuracy rate of up to 100%. This time, the system for human detection decreased because the human object was too far away, with the camera distance to the farthest object being 10 meters, so the object appeared small on the camera and could not be detected by CNN.

So, it can be concluded that the maximum limit for a human detection system if it wants to achieve a high level of accuracy is a maximum of 8 meters with a qualified lighting level. This detection is reduced because someone is not wearing a mask, but the human object is not detected because it is too far away and too close to other people. Other humans cover human objects so the camera does not capture them nor are they detected by the system.

After conducting the test process on objects taken in real-time, the detection results of each image obtained on the use of face masks are to calculate the accuracy or accuracy value carried out by formula 1.

$$Accuracy = \frac{a}{b} \times 100\% \quad (1)$$

Where a is number of detected images and b is total of number of data.

$$Accuracy = \frac{78}{80} \times 100\%$$

$$Accuracy = 97.5\%$$

Based on the calculation of the accuracy value above, the accuracy result obtained is 97.5%, with 80 data of the entire image successfully detected, as many as 78 samples, and two undetected models. The system can detect masks with a distance of ± 8 meters and with different body angles and lighting positions.

His study shows that the method proposed by the researcher can beat a few past examinations in execution assessment, with a precision worth 97.5%. Compared to research [31], sing the Eigenface method for face detection only achieved 88.89% accuracy, and the study [32] used the Viola-Jones model and achieved 95.5% accuracy.

4. Conclusion

Based on this research, real-time detection of mask using convolutional neural network, consisting of data collection, labeling session, and network structure development. However, it is difficult to detect if the object is too far from the camera and the lighting is minimal, where the system uses the CNN method. After testing using the camera distance to the object from 1 to 10 meters, the accuracy of this system can be calculated, namely the accuracy of object detection using CNN. object detection using CNN obtained an accuracy result of 97.5%. This shows that the CNN model can be used to detect masks in real time and works well. From the analysis results in the study, the factor affecting the accuracy of this system is the distance from the camera to the object. If the space is too far so that the human face object looks small, it cannot be detected by CNN. In the distance test conducted, the accuracy of the detection object will decrease when the object's distance from the camera reaches 10 meters and above. Another factor is that objects cannot be detected if other objects block them, so the system cannot detect them.

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