HOW CAN MACHINE LEARNING HELP THE AUTHORITIES?:
Face Mask Detection in The Era of The COVID-19

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ABSTRACT

Corona Virus Desease (COVID-19) pandemic is causing health crisis in every region in the world, especially in Indonesia. One of the effective methods against the virus is wearing face mask in public place as the regulation made by the authorities. This paper introduces face mask detection that can be used by the authorities to make mitigation, evaluation, prevention, and action planning against COVID-19. On the other hand, this solution can be used as communication tool to evaluate people's habit on wearing face mask. The face mask recognition in this study is developed with machine learning algorithm through the image classification method: MobileNetv2. The proposed model can be integrated with surveillance camera to impede the Covid-19 transmission by allowing the detection of people who are not wearing face mask. After the training, validation, and testing phase, the model can provide the percentage of people using face mask in some cities with high accuracy. The data produced also have a strong correlation to the vigilance index of COVID-19.

Keywords: Face Mask Detection, MobilenetV2, Machine Learning, COVID-19

INTRODUCTION

Since the declaration of the COVID-19 virus as a pandemic by WHO (Lin et al., 2020; Murray et al., 2020), efforts have been made by various parties to reduce the spread of the virus (Fadare & Okoffo, 2020). With no treatment or vaccine available, Indonesia and other countries are relying on the authorities' interventions being implemented, for instance physical distancing and wearing face mask in the public place to impede COVID-19 transmission (Feng et al., 2020; Fund, 2020; Wilder-Smith & Freedman, 2020).

Furthermore, since the New Normal has been implemented, the people are forced by law to wear face mask in the public place and wherever they interact with other people (Setiati & Azwar, 2020). There are some places in Indonesia which has regional law for using face mask in public place such as Bantul Jogjakarta, DKI Jakarta, and Provincial office of Jawa Barat set fines for residents who leave the house without wearing a mask. The second is Lebak Banten, the government punish people who do not use face mask in public place to clean public facilities which have special sign. And the last example is Banjarmasin Kalimantan Selatan, the government punish all the people who do not wear face mask in public place to do some physical punishment, such us doing push-up.

However, the process of monitoring large groups of people by the government or the authorities is becoming more difficult (Loey et al., 2020). The authorities need a solution to be able to validly control the implementation of the law, which begins with the availability of the data quickly and accurately. One of the solutions is to use regionally automated face mask recognition to differentiate between people who wear masks and those who do not (Ejaz et al., 2019; Hussain & Al Balushi, 2020; Qin & Li, 2020).

This paper introduces face mask detection that can be used by the NSO providing the data for the government, so the government can do some preventive action, mitigation, and evaluation of their programs. Moreover, this paper can be early warning for the authorities in capturing the people's habit in their reginal. On the other hand, this solution can be used by the industries to provide the face mask based on the people's habit on wearing face mask; the more people get used to wearing face mask, the more face mask need to be supplied.

The proposed model can be integrated with surveillance camera to impede the Covid-19 transmission by allowing the detection of people who are not wearing face mask. Each camera point is supplied with location data, so the data can be used to determine which locations require more attention from the authorities.

METHODS

The face mask recognition in this study is developed with machine learning algorithm through the image classification method: MobileNetv2. Mobilenetv2 is a method based on Convolutional Neural Network (CNN) that developed by Google with improved performance and enhancement to be more efficient (Sandler et al., 2018).

This study conducted its experiments on two original datasets. The first dataset was taken from the Kaggle dataset and the Real-World Masked Face dataset (RMFD); used for the training, validation, and testing phase so the model can be implemented to the dataset. The model can be produced by following some steps as shown on the Figure 1.

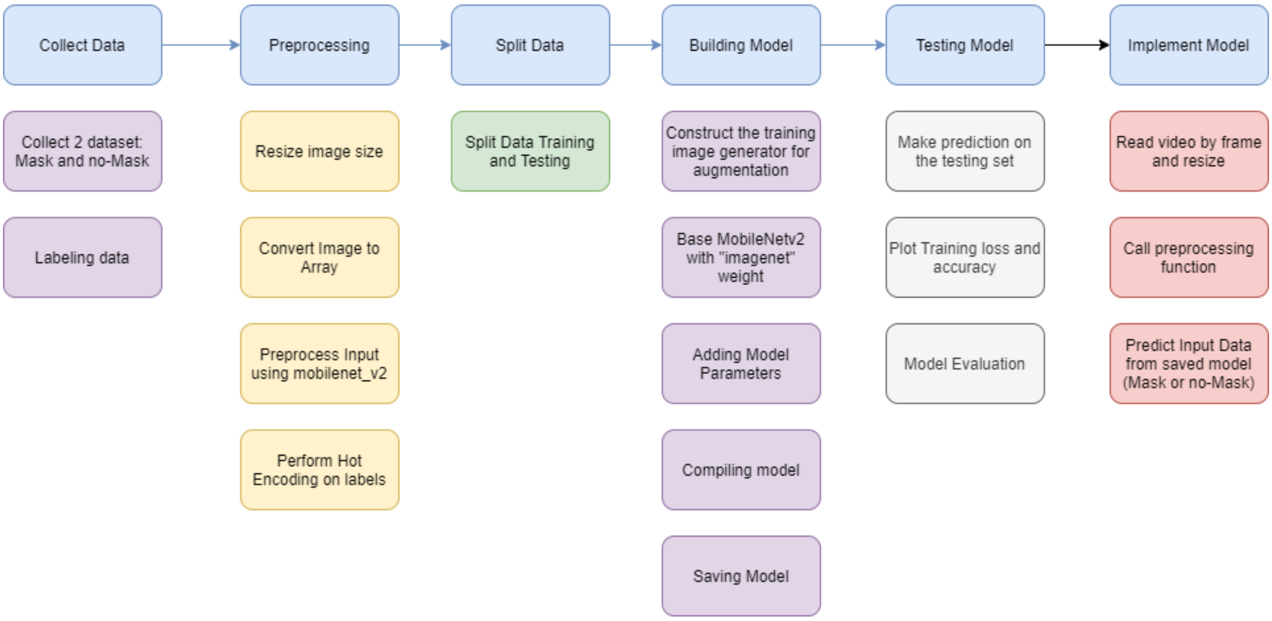


Figure 1. The Step in Developing the Model

The second dataset is used to apply the model to the dataset from 25 cities in Indonesia. Some cities were chosen based on data availability. The dataset was taken from some sources, for instance, public place CCTV, shop, and traffic lamp camera. Considering the quota sampling, the images were chosen based on the population proportional size of the cities, while the duration of capturing the image is equal for every city.

RESULT AND DISCUSSION

A. BUILDING THE FACE DETECTION MODEL

1. Data Collecting

The development of the Face Mask Recognition model begins with collecting the data. The dataset train data on people who use masks and who do not. The model will differentiate between people wearing masks and not. This study uses 1.916 data with mask and 1.930 data without mask. At this step, the image is cropped until the only visible object is the face of the object. After the data has been collected, the data is labelled and grouped into two part; with mask and without mask.

2. Pre-processing

The pre-processing phase is a phase before the training and testing the data. There are four steps in the pre-processing which are resizing image size, converting image to array, pre-processing input using mobilenet v2, and the last is performing hot encoding on labels. The resizing image is a critical pre-processing step in computer vision due to effectiveness of training models. The smaller size of the image, the better the model will run. In this study, resizing image is making the image into 224 x 224 pixels.

The next step is to process all the images in the dataset into array. The image is converted into the array for calling them by the loop function. After that, the image will be used to pre-process input using mobilenet v2. And the last step in this phase is performing hot encoding on labels because many machine learning algorithms can not operate on data labelling directly. They require all input variables and output variables to be numeric, including this algorithm. The labelled data will be transformed into numerical label, so the algorithm can understand and process the data.

3. Split the data

After the pre-processing phase, the data is splitted into two batches, which are training data namely 75 percent, and the rest is testing data. Each batch is containing both of with-mask and without-mask images.

4. Building the model

The next phase is building the model. There are six steps in buling the model which are cunstructing the training image generator for augmentation, base model with mobilenetv2, adding model parameters, compiling the model, training the model, and the last is saving the model for the future prediction process.

5. Testing the model

To make sure the model can predict well, there are steps in testing the model. The first step is make prediction on the testing set. The result for 20 iteration in the checking the loss and accuracy when training the model is shown on the Table 1.

Table 1. Iteration of checking the loss and accuracy

Epoch	Loss	Accuracy	Val_loss	Val_acc
1/20	0.5163	0.7434	0.4009	0.8260
2/20	0.2881	0.8876	0.3050	0.8675
3/20	0.2423	0.9129	0.3091	0.8649
4/20	0.2225	0.9047	0.1917	0.9195
5/20	0.1772	0.9343	0.2394	0.8922
6/20	0.1651	0.9382	0.1720	0.9247
7/20	0.1550	0.9419	0.2695	0.8922
8/20	0.1296	0.9541	0.2764	0.8922
9/20	0.1510	0.9456	0.3226	0.8779
10/20	0.1363	0.9497	0.2606	0.8974
11/20	0.1180	0.9583	0.2140	0.9065
12/20	0.1204	0.9596	0.3547	0.8766
13/20	0.1065	0.9632	0.1792	0.9195
14/20	0.1189	0.9560	0.3814	0.8727
15/20	0.1286	0.9524	0.3104	0.8831
16/20	0.1081	0.9622	0.2735	0.8948
17/20	0.1074	0.9570	0.2102	0.9143
18/20	0.1084	0.9576	0.2578	0.8974
19/20	0.1068	0.9593	0.2178	0.9117
20/20	0.0915	0.9685	0.2502	0.9052

From the Table 1, we can see that the accuracy is increasing start on second epoch, and loss is decreasing after it. So then, next step is making the model evaluation as shown on the Table 2.

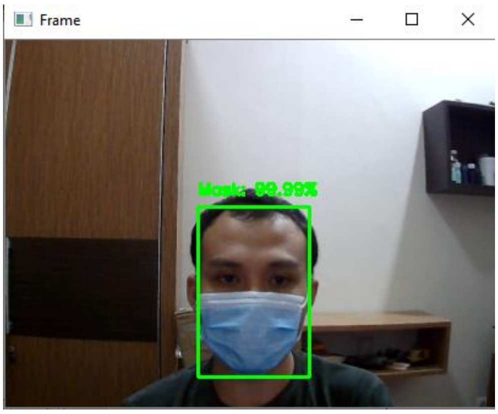
Table 2. Model Evaluation

	Precision	Recall	F1-Score	Support
With mask	0.98	0.83	0.90	384
Without mask	0.85	0.98	0.91	386
Accuracy			0.91	770
Macro avg	0.92	0.90	0.90	770
Weighted avg	0.92	0.91	0.90	770

6. Implementing the model

The model implemented to the video. The video read from frame to frame, then the face detection algorithm works. If a face is detected, it proceed to the next process. From detected frames containing faces, reprocessing will be carried out including resizing the image size, converting to the array, pre-processing input using mobilenetv2.

The next step is predicting input data from the saved model. Predict the input image that has been processed using a previously built model. Besides, the video frame will also be labelled that the person is wearing a mask or not along with the predictive percentage. Figure 2 is the example of implementing the model.



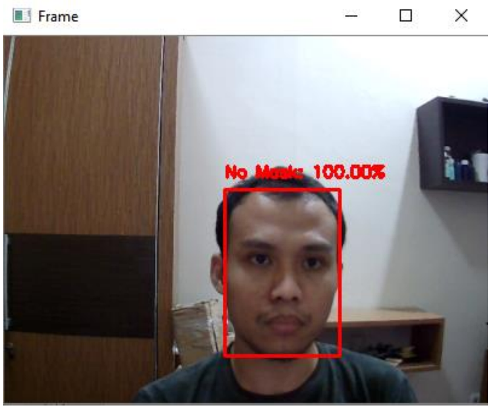


Image 3 – with mask Image 4 – without mask

Figure 2. The result example of predicting input data

B. FACE MASK DETECTION REGIONAL RESULT

The model applied to the image which obtained from various sources in 25 cities in Indonesia. The cities were chosen based on the data availability. After applying the face recognition model to the dataset, the percentage of people not using a face mask in public place was revealed. The percentage of the people in the cities with top five highest and lowest percentage is shown on the Table 3 and 4.

Table 3. Five cities with the highest percentage of people using face mask

No	City	Province	Percentage
1	Jambi	Jambi	82,76
2	Tangerang Selatan	Jawa Barat	80,53
3	Pangkalpinang	Kepulauan Bangka Belitung	79,37
4	Sabang	Aceh	79,20
5	Jakarta Barat	DKI Jakarta	78,92

Table 4. Five cities with the lowest percentage of people using face mask

No	City	Province	Percentage
1	Surabaya	Jawa Timur	64,14
2	Lubuk Linggau	Sumatera Selatan	65,42
3	Jakarta Pusat	DKI Jakarta	66,91
4	Kupang	Nusa Tenggara Timur	67,78
5	Malang	Jawa Timur	67,95

From the Table 4, as we can see there are two cities in Jawa Timur which has categorized into the five lowest percentage of people using face mask. While Jawa Timur, these days has known as the province in Indonesia which have high case of COVID-19. Furthermore, to assess the validity of the measurement which is the percentage of people wearing a face mask in public place by the cities, it can be correlated with another valid measurement or index (OECD, 2008). This study correlates the percentage with the vigilance index of COVID-19 published by kawalcovid19 team. This step needs to be done because the study only covers and captures the image from particular places, so there will be a probability of response burden on specific population segmentation.

Table 5. Bivariate Correlation of The Percentage to the Vigilance Index

	Vigilance Index of COVID-19	
The percentage of People Wearing Face Mask in the Cities	Peason Correlation Sig. (2 tailed)	-0,62* 0,000

*Correlation is significant at the 0,01 level (2-tailed)

Based on the bivariate correlation as shown on the Table 5, the percentage from the face recognition model and the vigilance index of Covid-19 have strong enough, positive, and significant correlation. The pattern of the percentage has a negative correlation which means the lower percentage, the more people in the city need to be vigilant or cautious of COVID-19 transmission.

Actually, the main reason why people do not wear face mask in the public place is not just because of their caution to the COVID-19, but also the economic condition of people and the face mask supply in the community (Cheng and Lam, 2020). This reason can be the next concern for the authorities to mitigate further intervention in the community.

For the authorities who concern to the face mask supply, if the medical face mask is limited in some places, cloth face mask can be the solution to be mass produced as recommended by the CDC (US CDC, 2020). Cloth face mask can be easily manufactured or made at home and reused after washing. Furthermore, the authorities can control the safety and minimum requirements of the face mask through public education.

Moreover, the data indicates that percentage of people using face mask in the cities varies among the provinces. There is city in DKI Jakarta which has the five highest percentage but also there is city which categorized into the five lowest percentage. It means that the distribution of the people wearing facemask is uneven between the cities. When the resources is limited, the model in this study can be used to prioritize which city has the low percentage, especially for the province or district which has a regulation to wear face mask in the public place, such as DKI Jakarta which has Pergub Nomor 2 Tahun 2020 (Pemprov DKI, 2020).

The model which can produce percentage of people using face mask also can be good for an evaluation (Fekete, 2011). It can motivate people to take action and evaluate their awareness to impede the spread of the virus in their community.

CONCLUSION

In conclusion, this study presents a model using machine learning for face mask detection. After the training, validation, and testing phase, the model can provide the percentage of people using face mask in some cities with high accuracy. In the name of the statistical organization that needs to move quickly to adopt and take advantage of machine learning and new digital data resources, this study can be an easy move for authorities to use more unstructured data resources for more data-based mitigation, evaluation, prevention, and action planning against COVID-19.

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