Issues of COVID 19 Screening with Machine Learning Algorithm and Data Sets Availability

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Abstract. There is a need to wear a mask during the coronavirus outbreak to efficiently deter the transmission of COVID-19 virus. In these instances, traditional facial screening technologies obsolete for monitoring of group entry at Airports, shopping malls, railway stations, etc. It is, therefore, vital to boost the efficiency of screening. This paper addresses the machine learning algorithm for contactless face screening systems in group participation, social interaction, school management, mall entry management, and market resumption scenarios in the case of COVID- 19. A method to screen entry with masks are developed using machine learning, which depends on various face specimens that were discussed here. The second fold discussion in this paper is that previously there are not many freely accessible masked face-databases. To this end, various forms of masked face data sets are identified, namely MFDD, Real MFRD, and Simulated MFRD. Such data sets became widely accessible to businesses and academics, based on which specific apps may be built on masked faces. The mathematical model, with the code was given. The availability and issues of the above data sets were discussed for the benefit of researchers**.**

Keywords: Machine Learning, COVID-19, Face Screening.

1. Introduction

Throughout the COVID-19 coronavirus outbreak, everyone carries a mask. Facial recognition technologies, majority critical means of recognition, have almost collapsed, causing an immense dilemma for authentication applications that depend on facial recognition, including crowd exit and entry, face authentication, face recognition-based entry at public stations, authentication based on face dependent remote payment and facial attendance. In specific, in the case of social safety checks such as train stations, gates focused on standard facial recognition technologies cannot efficiently identify masked faces; however, eliminating masks for passage identification would raise the possibility of virus contamination. Since the COVID-19 virus may be transmitted by touch, opening essentially based on authentication or fingerprints are not secure.

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In order to overcome the above-listed challenges, it is important to enhance current facial recognition methods that rely heavily on all facial attributes, ensuring that identification authentication can be carried out efficiently in the case of inadequately visible faces. Here the data sets for doing research were addressed so that more algorithms can be proposed. The futuristic face detectors were fixed basis of machine learning, which depends on training a large dataset [1]-[5]. Hence, designing masked facial-recognition system includes a considerable of masked facial samples. Under the current, accessible masked face dataset is not available, and this study aims to address such datasets through a number of methods for the benefit of researchers. Face recognition accuracy improves as more facial features become usable as recognition data points. Face occlusions like these are common in real-world use cases, such as when someone is wearing sunglasses, a scarf, a low hat, or when their face isn't turned directly toward the camera. When any part of the face is hidden, a facial recognition algorithm must rely on whatever face landmarks it can see to make an accurate match.

It's a process that takes time to master, but a resilient algorithm can adjust when it sees a partially occluded face and still produce excellent results. Organizations may wish to be alerted when individuals are not wearing a mask, as face masks have become an effective tool in the fight against COVID-19. This kind of logic isn't found in any recognition systems. We can program our facial recognition system to give the workflows when masks are, or are not present.

2.   Identification of Datasets for Future Research

With reference to the latest common face masks, there have been two strongly linked and separate applications, respectively facial mask identification and masked face recognition tasks. The role of detecting a face mask must be to decide if an individual wears a mask as needed. Masked face recognition function requires to recognize the real identification of a masked individual. A growing function has specific data set specifications. The earlier only wants blurred face picture examples, whereas the other includes a dataset including several face images of that same subject with and without a mask. Reasonably, the databases used by the facial recognition function are much more challenging to create. In this respect, this paper identifies two tasks:
First task is to identify datasets for researchers and second one is to identify an algorithm for screening while entering into a mass gathering.
Our First task is to attempt to identify masked face detection and recognition databases; this paper addresses various kinds of masked face databases, comprising Masked Face Detection Dataset (MFDD), Simulated Masked Face Recognition Dataset (SMFRD) and Real-world Masked Face Recognition Dataset (RMFRD) [11]. The description of the MFDD, the RMFRD, and the SMFRD are listed below.
MFDD: The origins of the MFDD primarily consist of two parts: (a) Most of the samples come from similar research [6]; this dataset contains masked faces of 24,771 in count. In particular, to decide if an individual wears a mask since it is unlawful to wear a mask during most of the coronavirus epidemic.
MFRD: A python crawler device is used to search the front-facing photographs of prominent Figures and their accompanying veiled facial pictures from vast Internet infrastructure. Then, we automatically delete the incorrect representation of the face from the wrong communication. The method of filtering photographs requires a lot of manpower. In the same manner, we use semi-automatic label software, such as

LabelImg and LabelMe [7], to construct precise face regions. The collection contains 5,000 pictures of 525 individuals with masks and 90,000 photographs out of which 525 are without mask. To our understanding, this is the largest masked face data collection in the modern world reveals the facial expression pairs.

SMFRD: In the meantime, in order to develop the quantity and variety of masked facial detection databases, additional approaches have been used to place masks on current public large-scale facial databases. In order to show the utility of data processing, we have created a mask with Dliblibrary [8] based tools for automated mask- wearing. LFW [9] and Web face datasets are common face recognition datasets, including In addition, they created a masked face by virtual. In reality, artificial masked face datasets may be used alone. In reality, virtual masked face databases may be used together with unmasked initial equivalents reveals a collection of virtual facial pictures.

2.1. Machine Learning Algorithms:

Our second task is to identify a machine learning algorithm to screen or identify the persons who are with masks protection and who are not following the rules. So that while in mob gathering like shopping malls, airport entry, cine complex entry screening, we can identify with the system and warn them to leave from the entry and have the protection of masks and enter again.

3. Inception v3 model for identifying masked faces

In this method, we use the Inception v3 model to identify the pictures as masked and unmasked. Inception v3 is a machine learning image recognition algorithm which has demonstrated better than 78.1 percent precision in the ImageNet dataset. This has 42 layers and less constraints than other similar models, including AlexNet, VGG, and Inception v1. The concept is the result of several theories generated through the ages by several researchers. It's was built by Szegedy, et. al. This method can be adopted for identifying the people with masks and without masks so that the model can screen them at starting point and avoid the non-mask persons, to address the downside in Inception v2, which was that the auxiliary classifiers did not make a substantial impact until the end of the training cycle, when the precision was approaching saturation they often act as regularizes, particularly if they have Batch Norm or Dropout operations. The model is trained with MAFA dataset. The Figure. 1 shows brief glimpse of the Dataset and Figure. 2 show the Input to the Inception algorithm.

The layout itself comprises of symmetrical and including convolutions, asymmetrical building blocks, max pooling, concats, average pooling, dropouts, and completely linked layers. BatchNorm is commonly utilized in the software, and it is used to trigger inputs. Loss is being calculated through Softmax. The maximizing RMSProp is used together with the decay $\alpha= 0.9$, the intensity $\beta= 0.9$, and the $\epsilon= 1.0$. The following is the input and output using this method to screen the people while COVID 19 disaster. The output Figure. 3 shows the non- mask lady with "N," and its prediction took over 0.052 seconds.

```
# compilngthe classifier
classifier.compile(loss='binary_crossentropy',metrics=['accuracy'],
optimizer='RMSProp')
```

3.1. Results of screening test Conducted

Figure 1. Glimpse of Input Data Set

EXPLORING THE DATA

```
#EXPLORING THE DATA
sample_img_path = os.path.join(DIR_IMG_TRAIN,'M_1.jpg')
sample_img = plt.imread(sample_img_path)
plt.imshow(sample_img)
print ('Image have shape: {}'.format(sample_img.shape))
```

```
Image have shape: (91, 91, 3)
```
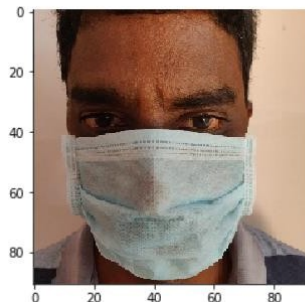

Figure 2. Input to Inception V3

```
img_path = DIR_IMG_TEST+'N_776.jpg'
display_img = image.load_img(img_path)
start = time.time()
score = predictFromPath (img_path)
end = time.time()
print("Prediction took {:.3f} seconds".format (end - start))
print("It's a {}! (with a score of {}) 0 -> Non Mask / 1 -> M
e))
plt.imshow(display_img)
```

```
Prediction took 0.052 seconds
It's a N! (with a score of 0.07839389145374298) 0 -> Non Mask
<matplotlib.image.AxesImage at 0x7f1bee9e10b8>
```
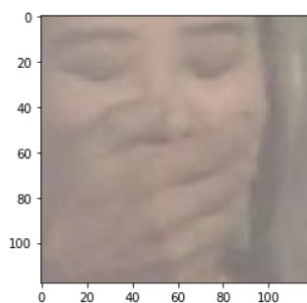

Figure 3. Inception V3 output 1

4. Identification of Issues

Face-based recognition can be loosely split into two design scenarios: unregulated and managed design conditions. The previous applies primarily to public video monitoring cases where the angle between the cameraand the image, the posture, the occlusion, and the illumination are all unknown. For such situations, the quality of facial recognition is fairly poor. For a fact, the precision of using a face mask would be greatly decreased. Though, there are still a wide range of monitored implementation situations, such as compliance tests at job places, health screening at rail stations and facial recognition fees, etc.

Therefore, big-quality frontal facial photographs are quickly obtained, such that the job of masked facial identification is no longer such challenging. Of example, the idea is to eliminate mask intrusion and to assign greater emphasis to the valuable features of the uncovered face. The above issues should be consider while doing further research.

5. Application Status and accuracy

Perhaps owing to the abrupt outbreak of the COVID-19 virus, there are currently limited organizations that, implement facial recognition technologies to individuals wearing masks. Based on this study, the authors in registered 85 percent accuracy while individual's nose is exposed to 50 percent. Approximately 85 percent reliability of masked facial recognition is given by Hanvon Technology. The best result recorded over 90% is from MINI VISION Technology.

6. Conclusion

In the scenario of the COVID 19 disaster outbreak, we have identified an algorithm for screening people to enter into the mass gathering with masks and refuse the non-mask persons using deep learning inception v3 model. We have also addressed the available data sets for facial recognition so that more algorithms can be proposed for identifying or recognizing people even they wear masks for easy passage into shopping malls, airports, railway stations, cine complex, etc. According to the World Health Organization, two-thirds of COVID-19 patients have a dry cough rather than the usual wet cough associated with the common cold or allergies. Cough sounds have also been used to diagnose whooping cough, asthma, and pneumonia. As a future work we can extend this work to new diagnostic tests using machine learning algorithms "to determine what kind of frequencies the cough is made up of".

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