REAL-TIME INCORRECT AND TYPE OF FACEMASK DETECTION USING DEEP LEARNING

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***Abstract*— The rising number of COVID-19 tests provides more information about the epidemic's spread, potentially allowing for its containment to prevent further infections. The main problem is that people are not wearing their mask correctly. The aim is to identify whether a person is wearing facemask properly or not and the type of mask worn. As methodology Deep Learning technique was used by real time video along with the libraries such as TensorFlow, Keras and OpenCV-python which consists of dataset of 3835 images in all. We were able to detect the use of mask up to 79.66%, the absence of mask up to 97.08%, the incorrect use of mask up to 98.5% and the type of mask up to 74.05%.**

Keywords*— *COVID-19*, *Deep Learning, TensorFlow, Keras, OpenCV-python

I. Introduction (*Heading 1*)

Since the very first case of covid-19 was reported in Wuhan till present, following a plethora of Covid-19 tests being executed, death-toll had been massively increased by a number of 379,941 people and above 6million infected human beings [1] whereby many countries are already on their knees, not only economically but also socially [2]. Coronavirus was found in 30 and 40% of samples taken from people without face masks, while no virus was found in droplets or aerosols in those who did [3.1]. Recent research show that surgical masks efficiently decrease the release of virus particles but the wrong practicing of wearing mask is still in existence which must definitely be cut off. According to a recent study, wearing masks could possibly prevent the spread of COVID-19 [3]. Although using the mask beneath the nose is one of the most obvious mistakes, there are others, such as using the mask over spectacles, that are more difficult to notice but no less important, or poor mask fitting to the face. The German community is now acknowledging the mask as a common accessory as they are certain that the proper wearing of mask prevents more than 95% of contaminated particles to enter our body while inhaling [9].

Both the author in paper 11 and 12 has analyze the image processing as a solvent procedure. Authors in [11] suggested a novel convolutional neural network (CNN)-based method for detecting COVID-19, with analyzing chest X-ray (CXR) images. This method allows to detect patients with COVID-19 at an accuracy of 91.34%. In [12], the authors introduced a new automatic COVID-19 detection model using CXR images. The model is called "DarkCovidNet." For binary classes (COVID-19 VS no findings), the classification accuracy produced by this model is 98.08%, but, for multiclass cases (COVID-19 VS pneumonia VS no findings), the accuracy is 87.02%. Authors in [19] proposed a hybrid model utilizing deep learning with classical machine learning to detect masked faces. The proposed model consists of two components: the feature extraction applying ResNet-50 and the classification process. The three classifiers used are the decision trees (DTs), support vector machine (SVM), and ensemble algorithm. The Real-World Masked Face Dataset (RMFD), the Simulated Masked Face Dataset (SMFD), and the Labeled Faces in the Wild (LFW) are the three face masked datasets, selected for examination. The SVM classifier is greater than the other classifiers. It reached 99.64%, 99.46%, and 100% of testing accuracy, respectively, in RMFD, SMFD, and LFW.

Several techniques are being carried out to make people aware of different methods regarding incorrect wearing of facemask. Authors such as Chung et al., in [14], have developed an application using AI and CNN solution by detecting patterns in images and processing which is integrated with the mobile phone through the use of images using InceptionV3 CNN, resulting in an accuracy of 81%. Therefore, the aim of this research paper is to provide a solution by using more accurate algorithms and techniques to solve the problem such as to identify the wearing of mask or no mask, incorrect mask and type of mask.

II. Literature Review

"The surgical face mask has become a symbol of our times." - Vanessa Friedman

The condition of mask-wearing habits, as well as the degree to which masks are correctly worn, are unidentified. Mask-wearing is an efficient approach to limit virus transmission among persons who are symptomatic or asymptomatic, but if they are worn inappropriately, they may actually contribute to virus transmission [26]. The correct use of masks necessitates careful attention to general hygiene standards, the most important of which is adequate mouth and nose coverage while avoiding gaps between the face and the mask [27]. Without the proper use of mask, people with severe health issues are proven to be more exposed to this pandemic. Therefore, the aim of this paper is to investigate a technique to detect whether a person is wearing a mask correctly, as well as its right use.

A. Requirement Determination

Facemask-wearing can help reduce the spread of respiratory infections and efficiently interrupts airborne viruses and particles by preventing these infections from entering another person's respiratory system [42-44, 46]. Facemasks effectively prevent the forward movement of particles emitted from a cough or sneeze when properly fitted, reducing disease transmission [45].

The proper application of masks involves adherence to general hygiene guidelines, the most important of which is adequate mouth and nose coverage while minimizing gaps between the face and the mask.

Pulling the mask down beneath the nose is a common technique for people who want to escape the hot, sweaty feeling of a mask as well as those who do not want their spectacles to steam up. However, masks provide some protection to the person, and if they are breathing unfiltered air through their nose, the latter will not be protected against airborne viruses. Moreover, the neckbeard design mask provides no protection for the person or their surroundings. Worse, any germs on the exterior of the mask could travel over the face.

B. Incorrect Face Mask Identification

In the following part, the existing related studies were briefly described on classification and tracking of face masks.

The use of YOLO v3-tiny has demonstrated to be adequate for the real-time detection of mask wearing, according to Cheng et al. in [35]. It's also small, quick, and appropriate for both mobile hardware installation and real-time recognition. In [19], Loey et al. proposed a hybrid method for detecting face masks. They chose three data sets to work with. The tagged faces in nature, the replicated masked face data set, and the real-world masked face data set. The image retrieval element of this study 's design is based on Resnet-50 [36]. This method employs an element for the categorization of face masks, which is relied on Support Vector Machines (SVM) and a combined mask classification algorithm. For each of the data sets tested, the system's precision is 99.49 percent, 99.64 percent, and 100 percent respectively. [36]

Using hybrid machine learning techniques, Wang et al. 2021 proposed a two-stage methodology to determine the use of masks in [30]. The user wearing a face mask is identified during the first phase utilizing the Faster RCNN and InceptionV2 [34] structural model. The second phase includes a stage of verification of real face masks using a learning system and a classifier. The accuracy rate for basic scenarios is 97.32 percent, whereas it is 91.13 percent for further difficult scenarios.

Rudraraju et al. [29] designed a two-step application. On the one side, it identified whether or not a facial mask was being worn. After recognizing a mask, it determined whether it was being used correctly or incorrectly. Fog computing is used to do this. The video sequence is processed by two nodes. Two MobileNet models are implemented for each fog node [19]. Haar cascade algorithms are used to recognize faces. Without depending on the Internet, streaming takes place locally for each fog gateway. Only the mask is permitted to access the room in this way, and only if the mask is properly fitted. This method has a 90 percent accuracy rate.

Jauhari et al. sought to recognize facial patterns in order to determine the presence of facial masks in photographs. It was built using the Raspberry Pi Single Board Computer (SBC). To get efficient, quick, and precise results, a face detection system that relies on the Viola Jones method was used. This technique helps the cascade classifier to be adjusted to identify the region of the facial image and this study has a precision of 90.9 %. [24]

In [13], Nagrath et al. used the MobileNetV2 architecture as the classifier's framework, as well as the SSDMNV2 technique, which uses a single-shot multi-box detector as a face detector, to accomplish real-time mask detection. They propose to detect face masks using deep learning techniques such as TensorFlow, Keras, and OpenCV and has a precision of 92.64 percent. Mata in [31] developed a CNN model to distinguish between those who wear masks and those that doesn't. It's based on a deep learning algorithm that uses an image or video stream as input. The proposed method is the simplest, as it requires no segmentation.

In comparison to traditional classification approaches [30], CNN is utilized to decrease empirical training error and generalization error by locating the biggest margin between the separating hyper surfaces. Finally, the deep-learning techniques along with the MobileNetV2, TensorFlow, Keras, and OpenCV algorithms outperform the other four approaches.

C. Algorithm for detecting Face Mask Using Deep Learning

In order to detect the wearing of mask, the following section proposes and describes a deep-learning model and CNN that is developed on a highly tuned customized face mask dataset and its functional (camera, video). There are different steps that has been used before developing the algorithm to detect the wearing of mask in real time. As a result, the SRCNet is proposed to detect facemask use, which has application value, particularly in COVID-19 pandemic prevention.

I. Deep Learning Architecture

For image retrieval and picture processing, deep learning methods is quickly created and used in the form of several deep layers. They eventually demonstrated efficiency in learning numerous layers of facial images that correspond to multiple levels of analysis [37], demonstrating solid invariance to changes in the face, such as lighting, expression, position, or disguise. Deep learning models represents and distinguish continuous face identity with great uniqueness by combining high- and low-level abstraction. The architecture of the learning technique highly depends on CNN. The aspects of deep learning architecture are described below.

II. Image Pre-Processing

Image pre-processing is used to increase the accuracy of the face recognition and facemask-wearing state identification procedures that occur. SRCNet is a publicfacing categorization system that uses uncontrolled 2D images as input. Since the intensity and exposure of real-life images differ greatly, an image is required to assure the efficiency of facial detection and facemask wearing condition identification. [66] The raw images were changed with the MATLAB image processing toolbox by mapping the input brightness image values to the new value, with 1% of the values saturated at low and high intensities of the input data. Figure 2 shows the image pre-processing diagram and histogram that goes with it.

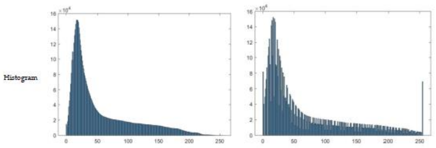


Figure 1

III. *Facial Detection and Cropping*

To improve accuracy, SRCNet needs a face detector to detect faces and crop facial areas because it has to focus on the information from faces rather than the background. Face size, expression, and background are all different in the uncontrolled 2D images. As a result, a reliable and highly accurate face detector is required. For facial detection, a multitask cascaded convolutional neural network was used, which has been proved to perform well in real-world situations [12].

Faces are cropped from the pre-processed image after obtaining the position of the face to serve as the inputs of the SR network or facemask-wearing condition detection network, depending on image sizes. Images with a size of no more than 150 x 150 pixels were first sent into the SR network, and then used to identify whether or not someone was wearing a facemask. Other cropped facial images were sent directly to the condition detection network for facemask users.

IV. *SR-Network*

The cropped facial images have a wide range of sizes, which may compromise SRCNet's ultimate recognition accuracy. As a result, SR is used before classifying. RED [17], which utilizes convolutional layers as an auto-encoder and deconvolutional layers for picture up-sampling, inspired the layout of the SR network. To maintain image features, symmetric skip connections were also used. Figure 4 depicts the SR network's complete architectural information.

There are five convolutional layers and six deconvolutional layers in the SR network. All subsequent convolutional layers are connected to their respective convolutional layers by skip connections, with the exception of the final deconvolutional layer. Information is transferred from convolutional feature maps to equivalent deconvolutional layers and from input to output using skip connections. After that, the network is fitted by solving the problem's residual, which is denoted by

$$Fi(X) = GTi - Ii$$

Where GTi is the ground truth, Ii is the input images, and Fi(X) is the function of the SR network for the ith image.

Normalize all pixels to [0, 1] as the output using the deconvolutional layer and input image. The final deconvolutional layer's phase was set to 1 to allow for information combining without upsampling. The last deconvolutional layer's activation function is Clipped Rectified Linear Unit, which forces output normalization and prevents loss computation errors. The Clipped Rectified Linear Unit is defined as follows:

$$\mathrm{ClippedReLU}(x) = \min(1, \max(0, x))$$

where x is the input value.

The aim of SR network training is to reduce the loss by updating all hidden layers. The mean squared error (MSE) is a common loss function for SR networks [17,27,34,35]. To minimize overfitting, a regularization term (weight decay) for the weights is introduced to the MSE loss. The loss function Loss(w), which is defined as the MES with L2 regularization, was used.

$$Loss(w) = \frac{1}{N}\sum_{i=1}^{N} \|GT_i - O_i\|^2{}_F + \frac{1}{2} \times \lambda \times w^T w$$

GTi is the ground truth, Oi is the output image, and Loss(w) is the loss for collections of given w.

V. *Dataset Collection*

The approach of mask detection has been implemented using a synthetic corpus [33], which involves drawing on a facial image (drawing of a mask). This method has shown to be effective in detecting whether or not a mask is being utilized. The synthetic corpus would not work; hence citizen collaboration is used to solve it. An app is created for mobile phones (see Figure 1) that prompted users to place the mask in various angles and capture selfies. The app is released on Google Play [34], and is used by the media to spread the word, resulting in around 3200 photographs [35].

Figure 2 shows a comparison between mask-wearing and non-mask-wearing faces. These experiments are based on a single original dataset. There are a total of 3835 images in this collection. With a mean height of 283.68 and a mean width of 278.77, this is a balanced dataset with two categories: faces with masks (1919 images) and faces without masks (1916 images). It is divided into two groups. This dataset is utilized not only for training and validation, but also for testing, with the social distance between two individuals being estimated whether or not a participant is wearing a mask [52].

Figure 2

Three datasets were chosen: RMFD, SMFD, and LFW. There are 5000 masked faces and 90000 unmasked faces in the RMFD dataset. To stabilize the dataset, Loey et al. used just 5000 masked face images and 5000 unmasked face images. There are 785 simulated masked face images and 785 unmasked face images in the SMFD dataset. The LFW dataset includes 13000 masked face images of celebrities from all over the world. It is only used during the testing stage. The RMFD is referred to as DS1 during the training and testing phase, the SMFD is referred to as DS2, a combination of DS1 and DS2 is referred to as DS3, and the LFW is referred to as DS4 during the testing phase. The training and testing datasets are separated into three categories: 70%, 10%, and 20% for training, validation, and testing, respectively. Accuracy, recall, precision, and F1-score are the most common performance measures used to evaluate the performance of the three classifiers [19].

Figure 3 demonstrates the DT classifier's performance in terms of validation accuracy, which is 98 %. When the training is completed over DS3, the DT classifier achieves the best testing accuracy. A competitive accuracy of 99.89 % is obtained on DS4, which is exclusively utilized for testing. The SVM classifier exceeds the DT classifier in terms of validation accuracy for the various datasets [52].

Validation accuracy and testing accuracy of the three classifiers for different datasets.

Classifier	Datasets	Validation accuracy (%)	Testing accuracy (%)
DT	DS1	92 to 94	96.78
	DS2	96	95.64
	DS3	98	96.5
	DS4	—	99.89
SVM	DS1	98	99.64
	DS2	100	99.49
	DS3	99	99.19
	DS4	—	100
Ensemble algorithms	DS1	97	99.28
	DS2	94	99.49
	DS3	100	99.35
	DS4	—	100

Figure 3

III. Methodology

Our aim has been met by using Deep Learning technique to determine whether the mask is properly positioned or not and the type of mask worn. Based on the existing and newly created dataset, the software detects the percentage of accuracy of the proper wearing of facemask.

A. *Requirement Determination*

Mask application requires following general hygiene principles, the most significant of which is ensuring full mouth and nose coverage while reducing gaps between the face and the mask [42]. People who wish to avoid the hot, sweaty feeling of a mask as well as those who don't want their glasses to steam up commonly take the mask down below their nose. Masks give some safety, but if a person is breathing unfiltered air via their nose, they will not be protected against airborne infections.

Facial landmarks help us to deduce the position of facial characteristics such as the eyes, brows, nose, mouth, and jawline automatically [55]. In using facial landmarks, we have to proceed with a picture of a person who is not wearing a mask on their face. The bounding box position of the face in the image is then determined using face detection. We identify the face Region of Interest (ROI) once we know where the face is in the image as shown in figure 4 [55].

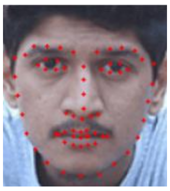


Figure 4

B. *Implementation*

PyCharm was used to implement our software [45]. When the data size is huge, Deep Learning outperforms other techniques since feature engineering is less of a concern. When it comes to complicated issues like image classification, natural language processing, and speech recognition, deep learning really shines [46]. The main objective is to detect if a person is wearing a mask correctly or not and type of mask. For this detection we have used some libraries such as TensorFlow 1.15.2, Keras 2.3.1 and OpenCV-python 4.2.0.

I. *Dataset*

The experiments of this research are conducted on the existing and created dataset. It consists of 3835 images in total. This is a balanced dataset containing five categories, faces with masks (950 images), without masks (686 images), incorrect mask (1936), surgical mask (293) and cloth mask (224). The dataset is used not only for training and validation, but also for testing.

II. *Training*

Training of the facemask-wearing condition identification network comprised five steps as shown in figure 5 below. Each step used a different data set for training. For greater result, a huge classification data set was required, hence the ImageNet dataset was used for network configuration. Non-zero values were assigned to parameters throughout this operation, which improved generalization ability. Furthermore, appropriate initialization enhances training speed and increases the overall face detection model's accuracy [13].

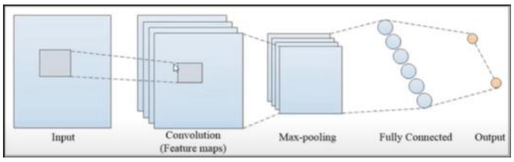


Figure 5

The purpose of Deep Learning network training was to recover face information. Initialization was the first step in facemask-wearing condition detection training phase. The ImageNet dataset was used to train the network, with the training conditions suggested in [53]. The next stage was to create a general model for facial recognition. The output classes have been changed to correspond to the class numbers. The final updated fully connected layer's value and prejudice were initiated using a normal distribution with a mean of 0 and a standard deviation of 0.01. The training dataset was randomly rotated in a limit of 10 (in a normal distribution), shifted vertically and horizontally in a range of 8 pixels, and horizontally flipped in every epoch to train the general facial recognition network. The enhancement was low throughout the fine-tuning stage, with rotation within 6 pixels (in normal distribution), shifting by up to 4 pixels (vertically and horizontally), and a random horizontal flip in every epoch. Every epoch, the training data set was randomized, and the network was trained for 20 epochs. Through a learning phase rate of 10-4, the training number decreases by 0.9 for every 6 epochs to boost training speed, eliminating the problem of the loss remaining stable. To prevent overfitting, the network was trained with Adam as the planner, with 1 = 0.9, 2 = 0.999, = 108, and 10-4 weight decay for L2 regularization [54].

C. Testing

The software detects the improper wearing of mask, the percentage of accuracy and the type of mask worn using video stream as input. For the testing of mask, we have tested a number of times and we have received a good accuracy and also it has indicated the type of mask when mask is worn properly. Moreover, for incorrect face mask testing, we have test face mask under the nose and under the mouth and different accuracy was received.

IV. Result and Discussion

A. Requirement Determination

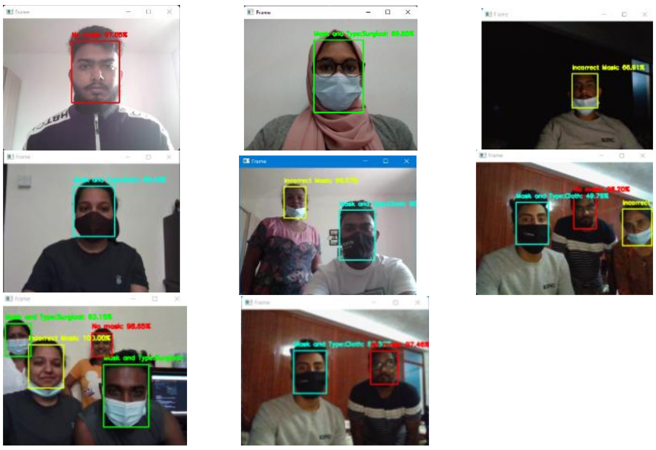
The outcomes of various facemasks' detection are shown in the table below. Surgical and cloth masks are the two common sorts of facemasks. The results reveal that the TensorFlow accurately detects several types of facemask-wearing circumstances.

B. Identification

In all, 22 images were tested in our system. It identified face-masked, type of face-masked and non-face-masked pictures with an average of 98.6% accuracy. Table below shows the results of using the face mask detector on different pictures. The red frame represents no mask, the blue frame represents cloth mask, the green frame represents surgical mask and lastly the yellow frame represents incorrect mask.

C. Testing

The overall accuracy rises to 100 % when we simplify the results to "Mask and Type:" and "No Mask." The outcomes differ based on the type of testing we performed. This demonstrates how real-time video processing knowledge is utilized to precisely determine the correct usage and type of face mask.



V. Discussion

The results obtained from the table above for incorrect facemask detection somehow matches that of what (Adrian R., 2020) have done [55]. However, to our knowledge, there has not been any study on detecting incorrect face mask wearing condition together with its type of mask identification using deep learning. In the case of our research, a system was developed that can detect not only the presence or absence of the mask, but also type of mask worn that existing system cannot identify, such as surgical and cloth masks, as well as incorrect mask position due to the use of glasses, and that the nasal bridge of the mask isn't properly adjusted, resulting in gaps where the virus can easily enter.

The implementation of a facemask-wearing state detection system, on the other hand, it is difficult for a variety of reasons. One of the difficult problems is the lack of datasets. In comparison to conventional facial recognition datasets, facemask-wearing condition datasets are typically small. Furthermore, the difficulty of identifying those who use facemasks wrongly increases significantly. Therefore, to overcome this challenges, Deep Learning algorithm have been utilized to achieve this. We have placed the most effective approaches to the test. The outcomes differ based on the network that was employed and the best results come from the Deep Learning model.

VI. Conclusion

Mask-wearing condition dataset is typically limited and simply detect the existence of masks. To our awareness, no deep learning projects have been completed on the identification of incorrect and type of facemask. Our solution is able to recognize additional types of difficulties that occur regularly when wearing facemask. Many people are not even aware that they are wearing the mask wrong. The results show a high accuracy in detecting people that are not wearing facemask and are wearing facemask incorrectly. The model was able to reach a performance accuracy of 100%, which is a great achievement. Furthermore, by encouraging everyone to wear a facemask, the study is a helpful weapon in combating the spread of the COVID-19 disease.

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