Controlling spread of COVID-19 through Facial Mask Detection using Deep Learning

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Abstract. The corona virus disease continues to spread across the world. The health, humanitarian and socio-Economic policies adopted by countries will determine the speed and strength of the recovery. The coordinated global effort is required to support countries that currently do not have enough finance social policy. Reports indicate that wearing face mask reduces the risk of transmission. This encourages exploring face mask detection technology to monitor people wearing masks in public places. Most recent and advanced face mask detection approaches are designed using deep learning. In this research work, proposed a model to find out people who are not wearing face mask in the public areas that are monitored with cameras. A deep learning-based model called Faster R-CNN is trained on the face-mask-detection and maskedFace-net datasets that consists of people with masks, without masks and improper masks are collected from different sources. The goal of this work is to identify whether the person in a given image is wearing face mask or not wearing face mask. If the person is wearing face mask, this work will also verify the improper face mask. This research work anticipate that the proposed model will achieve high accuracy on differentiating people with mask and without mask and that it will be useful to reduce the spread of this communicative disease.

Keywords: Covid-19, Face mask detection, Faster R-CNN, Deep Learning.

1 Introduction

The COVID-19 pandemic has resulted in a significant loss of human life around the world, and it poses an unprecedented threat to public health, food systems, and the workplace. The pandemic's economic and social effects are devastating 10 million of people are at risk of falling into extreme poverty, and the number of people who are undernourished, which is presently estimated to be around 690 million, might rise to 132 million by the end of the year. The number of those affected fluctuates on a daily basis. Organizations that collect this data, such as the World Health Organization (WHO)[1] and the Centers for Disease Control and Prevention (CDC), are gathering data and learning more about the outbreak on a regular basis. The incubation period is the time between becoming infected and developing symptoms, which can range from 2 to 14 days. The average duration between onset of symptoms is five days. The severity of the symptoms might range from minor to severe. COVID-19 causes fairly minor symptoms in roughly 80% of people. COVID-19 enters the body via the mouth,

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nose, or eyes (directly from the airborne droplets or from transfer of the virus from your hands to your face). It binds to the cells there, multiplies, and spreads into the lung tissue. The virus can then spread to other body tissues. Governments, health organisations, researchers, and healthcare practitioners are all collaborating to devise regulations and procedures to prevent the virus from spreading globally and from person to person. The CDC [2] recommends wearing at least a cloth, covering the face in public, especially in places where it is hard to maintain at least six feet of distance between persons. Face masks protect both the wearer and the people around the wearer. Because we now know that people with COVID-19 might have minor or no symptoms while still distributing the virus to others, cloth face masks are being recommended. To control spread of COVID-19 researchers suggest deep learning algorithms to detect the face mask. Faster R-CNN (Faster Region based Convolutional Neural Network) algorithm is a popular approach to detect the face mask. Faster R-CNN consists of two networks such as Region proposal network (RPN)for generating region proposals anddetect objects. RPN ranks region uses anchors to detect the corresponding location of the images and to estimate the sizes. The main objective of this proposed model is to find out the person who is not wearing face mask and wearing improper face mask as given in Fig.1[8]

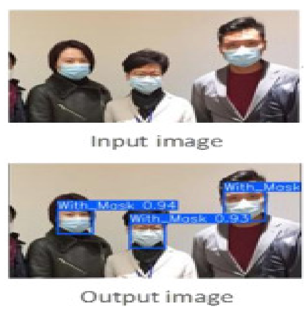

Fig.1.*Face mask Detection, Adopted from[8]*

2.Literature Survey

This section review some of the related works. Several algorithms are there to detect the face mask detection. Paper [4] uses Convolutional Neural Network(CNN) as a primary technique. This study describes a method for a smart city that can help minimise the transmission of coronavirus by alerting authorities when someone is not wearing a COVID-19-required face mask. The dataset used in this paper is Face-mask-detection which includes real-time camera images. The first layer of CNN is input layer which will collect the images. The second layer of CNN is hidden layer which is used for filtering the samples. The filtered samples are given to next layer which is pooling layer that reduces the spatial size and the number of parameters. Next is flatten layer which is used for converting information to vector representation and then it is fed into the dense layer. Finally, dense layer detects the output between the two labels such as with mask and without mask. The accuracy achieved in this paper is 98.7% on the unseen test data. The limitations in this paper is that classifying faces is difficult, needs large number of CCTV cameras to capture the people and could run into network issues while sending messages with images.

In [5] Convolutional Neural Network is used as a primary technique. The dataset used in this paper is PrajnaBhandary which consists of 1376 images divided into two classes such as with mask and without mask. The model is trained and tested using Keras and TensorFlow. In this paper Raspberry Pi camera is installed at the door. Door will be opened only if the person wears the facial mask. The accuracy obtained is 97 %. If a person not wearing mask is detected the rectangular box around the face will be red in colour and if a person is found to be wearing mask, the rectangular box around the face will be green in colour. The limitations are it needs 3 sensors and the implementation cost is high.

In [6] ResNet50, MobileNet and AlexNet are used as primary technique. The dataset used in this paper are Face masked dataset and Masked face detection dataset. The object recognition benchmark problem has three components such as Backbone, Neck and Head. Backbone has a convolutional neural network which converts images into feature maps. Three pre-trained models such as ResNet-50, MobileNet and AlexNet are undergone to achieve best results. Neck component consists of pre-processed tasks that are required for classification. Neck component has different pipelines for training and deployment. Head stands for predicting the identity. By using this algorithm, the detection speed is improved and the system is cost efficient.

In [7] RetinaFace model, Multi-Task Cascaded Convolutional Network (MTCNN), NASNetMobile model is used as a primary technique. The datasets used in this paper are Masked Face Recognition and Face-mask-detection. This paper has two stages. A detector used to recognise the face is added in first stage. This will detect various faces in a single image with different sizes. Intermediate processing block gets the detected face from first stage and it is extracted by ROI extractor. Then resizing and batching of images are also done in intermediate processing block. The detected faces are then given to the second stage for differentiating masked and un-masked. The output from the second stage are post-processed. Finally, the second stage output will be classified as masked and un-masked face. The system's performance is outstanding and it can distinguish face masks in photographs containing several faces from a wide range of angles. It enhances overall stability and video data results. The limitations in this paper islow inference speed, high implementation cost and high latency.

In [8] You Only Look Once (YOLO) V5 is used as a primary technique. The training model and the face mask detection model are separated in the dataset. The face-mask-detection dataset includes 682 images for the training model. The YoloV5 face mask identification algorithm used original photos from the face mask dataset as inputs. An epoch, or a group of passes through the full training dataset, has been proven to alter the model's performance during the training process. The precision and recall were calculated as well. 85 face mask pictures were used to validate each model. For each class precision and recall were determined through the validation process. Among all the training models, the model with 300 epochs produced the best results. An accuracy of 96.5% related to the highest precision and recall is achieved. The limitations in this paper isdetection of incorrect/correct mask is difficult in real time.

In [9] OpenCV is used as a primary technique. The dataset used in this paper is Masked face recognition. This dataset is divided for training phase and testing phase. To obtain faces, a default OpenCV module was utilised. Keras model is used for training to recognise the face mask. Using the database, people's names who ought to wear a face mask will be identified by training the OpenCV model. Using smtplib, the system is made to give a notification through mail to the person who has not been wearing face mask. The data of the company's employees are stored and it is used to identify the information of the person who are not wearing face mask. The limitations in this paper isthat the mail could not be sent if a visitor to that company doesn't wear a mask.

In [10] You Only Look Once(YOLO) is used as a primary technique. The dataset used in this paper are MFDD, MAFA, MOXA, FMD, RMFRD and SMFRD. This datasets has four labels such as with mask, without mask, annotated and wearing mask incorrectly. Dataset is divided into training, validation and testing. After that, data augmentation is done to enhance the size of images. As data augmentation is used, the dataset with 52635 image samples from 11000 images. These images will be sent to YOLO algorithm which is single-stage object detection algorithm.

The effectiveness of face mask detection is evaluated by implementing eight algorithms which are all variants of YOLO algorithm. The algorithms that are implemented includes YOLO v1, YOLO v2, YOLO v3, YOLO v4, tiny YOLO v1, tiny YOLO v2, tiny YOLO v3, tiny YOLO v4 are shown in Fig.3. Among the above-mentioned algorithms, YOLO v4 has high detection accuracy and it has the highest Mean Average Precision(mAP) value of 71.69%. Among the tiny YOLO variants, tiny YOLO v4 has the highest Mean Average Precision(mAP) value of 57.71% as shown in Fig.2. It is the highest of all tiny YOLO variants. The limitation of this paper is that the accuracy is very less when compared to other models.

YOLO Variant	Precision	Recall	F-1 Score	mAP
YOLO v1	63.2%	54.7 %	61.3 %	52.4 %
YOLO v2	68%	59 %	63 %	55.34 %
YOLO v3	81%	73 %	76 %	65.84 %
YOLO v4	78 %	79 %	78 %	71.69 %
tiny YOLO v1	29%	42 %	34 %	30.75 %
tiny YOLO v2	33%	49 %	39 %	33.78 %
tiny YOLO v3	74%	56 %	63 %	49.03 %
tiny YOLO v4	79 %	65 %	72 %	57.71 %

Fig.2. *Performance of variants of YOLO*

Model Name	Number of layers	Inference	Accuracy
YOLO v1	26	Can process 45 frames/sec	52.4%
YOLO v2	32	Can run at different resolutions	55.34%
YOLO v3	106	Makes detection at 3 different scales	65.84%
YOLO v4	24	AP and FPS are increased by 10% and 12%	71.69%
Tiny YOLO v1	9	Improvements are required for future enhancement purposes	30.75%
Tiny YOLO v2	16	Merging batch normalization layer will reduce hardware resources	33.78%
Tiny YOLO v3	24	It has faster detection speed due to its simple network structure	49.03%
Tiny YOLO v4	29	It has faster inference time	57.71%

Fig.3. Comparison of deep networks for mask detection

In [11] You Only Look Once(YOLO) V3, Haar Cascade Classifier is used as primary technique. A MAFA dataset with 35,806 masked faces is imported. We used 7000 photos from that set, all of which contained frontal images. The MAFA dataset is separated into three sections such as training which includes 5000 rows, validation which includes 1000 rows, and testing which includes 1000 rows. The input image quality is improved using auto white balance and edge improvement utilises the unsharp filter in the pre-processing step. The auto white balance ensures the image's colour uniformity. The unsharp filter is used to improve the image's edges. Detecting the face region is the sixth phase in the face detection process. To detect the facial region, we use the Haar cascade classifier. Finally, the YOLOV3 algorithm is used to determine whether the person in the image is wearing a mask. The accuracy of the algorithm can achieve up to 90% and it can run faster to detect objects at smaller scales. The limitations in this paper is that the pre-processing is difficult and it has less accuracy compared to other models.

In [12] Modified single-shot detector (SSD), Lightweight Backbone Network, Feature Enhancement Module (FEM) are used as techniques to detect the face mask. The COVID-19-Mask dataset is divided into two modules such as training and detection. The dataset is utilised to get a mask detector by training the model. Adaptive Moment Estimation (Adam) is used for optimization function to train the model, with a learning rate of 0.001 at the initial iteration and 0.0001 after 20000 iterations. After 100000 iterations, we end training and utilise the most recent model snapshot to assess item detection performance on the test set. In the detection step, photos from surveillance video are collected in real-time and the trained detector is used to identify whether the shoppers in the photographs are wearing mask. The Mean Average Precision and the run time got by this model is 90% and 0.12s respectively as shown in Fig.4. The limitations are 4 ablation experiments are required so implementation time is more and extra run time calculation is required.

Exp.np.	mAP(%)	Run time(s)
1	72.9	0.20
2	89.3	0.15
3	87.5	0.10
4	90.9	0.12

Fig.4. Run time of Ablation Experiments

In [13] Single shot multibox detector and MobileNetV2(SSDMNV2) is used as a primary technique. The dataset used in this paper are Masked face Recognition and Application dataset. The Masked Face Recognition and Application Dataset had noisy images and the images in this dataset had a lot of repetitions. The data was manually cleaned to remove the faulty photos that were discovered in the dataset. A pre-processing function is built, which accepts the folder as an input to the dataset, the files are loaded and the photos are resized using a model called SSDMNV2 model. The photos are then turned into tensors once the list is sorted alphanumerically. For fast calculation, NumPy array is used. After that, the data augmentation procedure causes the accuracy to be increased. Rotation, zooming, shifting, shearing, and flipping the image are all utilised in this approach to create several variations of the same image. Keras, an advanced-level ANN API is utilised to create a classification model. Finally, it determines whether the person is wearing a mask based on image detection. This model is easy to use in real-time and it can work even on embedded devices. It requires good computational power. The limitation of this paper is data augmentation is mandatory. Till 60 epochs model struggled to learn the features to get accuracy.

In [14] You Only Look Once(YOLO) V2 and ResNet-50 are used as a primary technique. The dataset used in this paper is Medical Mask Dataset(MMD) Face Mask Dataset(FMD). By combining these two datasets new dataset is obtained which is used to train the model. It consists of three components such as anchor boxes, data augmentation and detector. The dataset is divided for training, validation and testing. Data augmentation is done to enhance the size of images. As data augmentation is used the performance of the detector in increased. YOLO v2 with ResNet-50 detector is used for extraction. ResNet-50 consists of 16 residual bottleneck blocks. Feature maps of each block will have different convolutional size. YOLO v2 detector comprises of convolutional layer, transform layer and output layer. The bounding box is converted to target box by the transform layer. The accuracy obtained by YOLO v2 with RasNet-50 is 81% using Adam Optimizer(AP) which can detect the medical masked face. The limitations are that it needs extra metrics i.e. log-average miss rates score and the accuracy reached by this model is less.

In [15] MobileNetV2 model is used as a primary technique. The dataset used in this paper is Face-mask-detection. There are two parts for the preparation of a face mask detector. Face-mask-detection dataset consists of 1376 photos which is divided into two categories such as 690 images with mask and 686 images without mask. Keras and Tensorflow are used to train the classifier for recognising whether an individual is wearing a mask after compiling the facemask dataset. The MobileNetV2 is especially valuable for mobile designs since it aids in the materialisation of large intermediate tensors, reducing the memory footprint required for inference. Finally, the F1-Score is utilised to assess the precision-to-sensitivity ratio. It is detected with the help of Drone, which controlled by smart mobile using Qground control app for autonomy mission. This model is easy to implement and cheaper to apply. The limitation of this paper is that it is dangerous in case of a weak network.

In [16] You Only Look Once (YOLO) V4 is used as a primary technique. It needs digital webcam, PC and speaker to detect. This system runs in real-time application. The YOLO V4 detector used in this study is a two-stage detector. The input, backbone, neck and dense prediction components make up the first-stage detector. In addition, the detector's second stage uses sparse prediction to predict the item based on the bounding boxes and classes on the object. The input image must be processed in real-time at a resolution of roughly 1920x1080 pixels to ensure proper detection of moving objects wearing face masks. The 3x3 convolutional layer is created and the backbone input layer with the most parameters is chosen. As a detector, the Darknet53 has been chosen. The input resolution of the network will be reduced to 512x512 with a receptive field size of 725x725 in this backbone, which has 29 3x3 convolutional layers. Each layer will then be transmitted to the neck detector. To understand the parameter aggregation from distinct backbone level detectors, the PANet is used as the neck detector method. The neck detector's aggregation layer will be passed to the sparse prediction. The dense prediction is where the final detector procedure on stage one takes place. In this step, the YOLO V3 model is utilised to construct a prediction, the outcome of this model will be used as the input prediction for the second-stage predictor. The second-stage predictor uses sparse prediction to predict the output. There are two classes because of this stage such as wearing and not wearing face mask. The system uses camera to detect the user who is wearing and who is not wearing mask. If the user in the image is not wearing mask, the alert will be given by the speaker to wear the mask and the alert will not be stopped till the user wears the mask properly. It detects and distinguishes non-wearing and wearing-mask user properly in every different situation such as lighting, messed up areas and clean areas. The limitations are high hardware cost and the input images needs high resolution to detect.

In [17] Sequential Convolutional Neural Network model is used as a primary technique. This paper uses two datasets for training the model. First dataset used is PrajnaBhandary which consists of 1376 images of two classes namely with mask and without mask and the second dataset used is Face-mask-detection which consists of 853 images of two classes namely with mask and without mask. It consists of 2 process. Data preparation entails converting data from one format to another that is more user-friendly, desirable and relevant. Data visualisation is the process of converting abstract data into meaningful representations using encodings for knowledge exchange and insight finding. Modern descriptor-based image recognition systems work on grayscale images on a regular basis, without commenting on the mechanism for converting from colour to grayscale. During image relegation, the input is a three-dimensional tensor, with each channel containing a salient unique pixel. The Rectified Linear Unit and MaxPooling layers come after the First Convolution layer. Next, a 64-neuron dense layer with a ReLu activation function is introduced. The Softmax activation function is used in the dense layer, which has two outputs for two categories. As a result, the model will only treat a mask that covers the entire face, including the nose and chin, as with mask. The main challenges faced by the method mainly comprises of varying angles and lack of clarity. The method attains accuracy up to 95.77%. The main limitation in this method is that it works even if a person wears a mask in an improper manner.

In [18] Fully Convolutional Network, Semantic Segmentation are used as a primary technique. This paper aims at binary classification. For feature extraction and prediction, the input image of any size is reduced to 224x224x3 and given to the Fully Connected Network. After that, the network's output is subjected to post-processing. The face and background pixel values are first subjected to global thresholding. It is then run through a median filter to reduce noise which has high frequency before being given to an operation to fill in the gaps of the segmented area. Next, draw a bounding box around the split region. The feature extraction and prediction are done with the VGG 16 architecture. The model has 17 convolutional layers and 5 Max pooling layers. The size of the initial image input to the model is 224x224x3. The convolutional layer combines the input image with sliding window whereas max pooling layer reduces the number of parameters by halving the size of the feature vector produced in each layer. The image size is reduced to 28x28x2 after the final max pooling layer. The image is then unsampled again to bring it up to standard size. This paper builds the model in such a way that all the incorrect predictions are ignored when displaying the final discovered faces. In each region, determine the following parameters: Centroid, Major Axis Length and Minor Axis Length as given in Fig.5. These values are shown for all the detected facial regions, including erroneous predictions. For the diameter vector, we compute the mean and standard deviation. Finally, maintain the probable diameters inside the first standard deviation. The designed model uses a distinct label to semantically divide out the facial spatial location. This model achieves great results in detecting non-frontal faces. It can detect the multiple faces in single frame. The model attains the accuracy of 93%. The limitations are that it needs RGB channel images as input and it needs more processing time.

S. No.	Centroid	Major Axis Length	Minor Axis Length
1.	9.414	11.62	7.2
2.	18.00	22.65	13.36
3.	13.18	14.84	11.51
4.	22.81	32.09	13.52
5.	18.07	27.35	8.8
6.	20.67	30.55	10.7

Fig.5. Parameter values

In [19] ResNet-50 model is used as a primary technique. This paper consists of three datasets such as Real-World Masked Face Dataset (RMFD), Simulated Masked Face Dataset (SMFD) and Labeled Faces in the Wild (LFW). The model consists of two components such as ResNet-50 as feature extractor and machine learning models like decision tree, support vector machine and ensemble classifier. The dataset is divided into training , validation and testing phase. This is done by using formula of machine learning algorithms as shown in Fig.6,7 and 8. Among the above-mentioned algorithms, the support vector machine classifier achieves the higher accuracy for all the three datasets. As it is a machine learning algorithm, its performance is decreased in case of large dataset. Further it can be implemented using deep learning algorithms and neutrosophic domain can be used as it is effective in classification and detection problems.

$$loss = \frac{1}{n}\sum_{i=1}^{n} \max\left(0, h_i\right)$$

Fig..6. Support Vector Machine

$$I = E(D) - \sum_{v \in D} p(v)E(v)$$

Fig..7. Decision Tree

$$\overline{z} = \sum_{i=1}^{M} \alpha_i z_i$$

Fig.8. Ensemble Method

In [20] Optimistic Convolution Network is used as a primary technique. The dataset has 3918 images of two classes such as with mask and without mask images. In this dataset the face without mask has different skin colours and different angles and the face with mask has hand and other objects that covers the face. The collected dataset is pre-processed using MobileNet and OpenCV. MobileNet acts as a backbone and the model is trained using TensorFlow. The webcam is used to detect the face mask and this works in an automated manner. The output will be in the form of bounding box around the face, where red bounding box indicates not wearing face mask and the green bounding box indicates wearing face mask. The confidence score will be displayed on the top of the bounding box. Finally, the face of the person who are not wearing face mask will be notified and their image will be sent to higher authorities.

In [21] Convolutional Neural Network is used as a primary technique. The annotated images are collected and used as a dataset. This high-quality images with and without mask faces using digital camera, cell phones or scanners are collected and given Pre-processing. These images are split by segmentation process and it is used in extraction of face mask from the background. In convolutional layers featured images are obtained from resized images. After this process max and average pooling is done to reduce the spatial size of the images. Finally, the images are classified using deep learning model. This paper uses open-source implementation such as TensorFlow using python, OpenCV and VGG-16 CNN model. To measure the performance of the model Accuracy, training time and learning errors are used as a metrics. An accuracy obtained by this model is 96%. The results will obtain by distinguishing person wearing mask and person not wearing mask.

According to the study on various papers, it is found that there were many limitations. One of the main limitations is not detecting the improper face mask. This limitation can be overcome by using an efficient deep learning algorithm called Faster R-CNN(Faster Region based Convolutional Neural Network). Hoped this model will attain a reasonable level of accuracy using basic deep learning tools and simplified techniques. It can be used for a wide range of purposes. In this Covid-19 situation, wearing a mask may become mandatory in future. The model will make a significant contribution to the public health care system by reducing the spread of communicative disease.

3.Conclusion

Masks are a simple way to prevent the spread of COVID-19. Several studies have found that asymptomatic people can spread the virus to others. For controlling the spread of infection, Face mask detection system plays a vital role. This research paper provides detailed overview of face mask detection system using different algorithms. The Faster R-CNN model learns how to generate high-quality region proposals because of the end-to-end training, allowing it to stay accurate in mask recognition with a smaller number of region proposals learned from data. As a result, it can be inferred that a model detecting the different classes of images such as masked face, un-masked face and improper mask would be very useful in encouraging safe practices to avoid the spread of COVID-19.

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