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FACE MASK DETECTION USING DEEP LEARNING

P.Prashanth, Professor, Department Of Data Science, SICET, Hyderabad
N.Harini, G L Venkata Shivasai Manvitha, G.Tarun Reddy, P.Mohan Vamshi, S.Shashank
UG Student, Department Of Data Science, SICET, Hyderabad

ABSTRACT:

Useful tips to help you get started must be followed strictly to prevent the spread of Covid19. In the absence of effective vaccines and limited medical resources, WHO recommends taking various measures to control the disease and avoid the use of limited medical supplies. Wearing a mask is one of the nonmedical measures that can be used to cut off the main source of SARSCoV2 fluid from patients. Despite controversy over differences between medical sources and masks, all countries have made nose and mouth coverings mandatory for the public. This study aims to develop an effective and fa st device that can detect faceless people in public places and control the mask in order to contribute to public health. The proposed system is a combination of one-
and twostage detectors to achieve low reaction time and high accuracy. We use ResNet50 as a framework and use the c oncept of transfer learning to combine high semantic information across multiple maps. We also highlight dynamic chan ges in the box to improve the performance of the field during face detection. The test is based on our popular basic mode l. ResNet50, AlexNet and MobileNet. We are exploring the possibility of combining this model with design to achieve h igh results in a short time. The proposed method was found to achieve a high accuracy (98.2%) when using ResNet50. I n addition, compared with the current public test model of RetinaFaceMask detector, the proposed model improves the a ccuracy and recall of face detection by 11.07% and 6.44%, respectively. The performance of this model is ideal for vide o devices.

1. Introduction

The 209th report published by the World Health Organization (WHO) on August 16, 2020, states that the new coronavir us (COVID-19) is caused by Severe Acute Respiratory Syndrome (SARS-
CoV2) and has infected more than 6 million people. Worldwide. It causes more than 379,941 deaths worldwide [1]. Acc ording to Carissa F. Etienne, Director of the Pan American Health Organization (PAHO), the key to controlling the spre ad of COVID19 is to stay connected, improve surveillance, and keep sanitation [2]. A recent study by researchers at the University of Edinburgh on measures to prevent the spread of the COVID19 pandemic shows that wearing a mask or oth er covering that covers the nose and mouth can reduce the risk of coronavirus by preventing people from moving forwar d. .Exhaled air is reduced by more than 90% [3]. Stephen et al. A comprehensive study was also conducted in New York and Washington to evaluate the impact of mask use by the general population, some of whom were asymptomatically in fected. The findings show that even if masks are poor (20% effective), close adoption (80%) could prevent 1745% of ex pected deaths in the new job within two months and reduce daily deaths by 3458%. 4,5]. Their findings suggested the us e of masks to prevent the spread of coronavirus. In addition, as the country reopens after the Covid19 quarantine, the go vernment and health agencies have recommended wearing masks as an important precaution for public safety. To contro l mask use, technology needs to be developed that forces people to wear masks before going out to public places.Mask t est means checking whether a person is wearing a mask. Essentially, the problem is reverse engineering of face detectio n, where different machine learning algorithms are used to identify faces.For security, authentication and monitoring pur poses. Face detection is an important part of computer vision and pattern recognition. Many studies have been done in th e past on the complexity of face detection algorithms. The first research on facial recognition was conducted in 2001, usi

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ng manual feature design and application of machine learning algorithms to train good operators in detection and experie nce [6,7]. Problems encountered with this method include the complexity of the design and lack of accuracy. In recent y ears, face detection methods based on deep convolutional neural networks (CNN) have been widely developed to impro ve detection [811].Although many researchers are dedicated to creating a good face and know the process, there is a sign ificant ifference between "finding a face wearing a face" and "finding a face wearing a face". Based on the existing litera ture, few studies have attempted to examine facial expressions. Therefore, the aim of our work is to develop a technolog y that can identify facial expressions in public areas (e.g. airports, train stations, shopping mall products, bus stops, etc.) to reduce the spread of coronavirus and thus contribute to public health. . . In addition, face detection with/without mask in public places is not easy because the available data for face detection is small, which makes training models difficult t o train. For this reason, the concept of transfer learning is used here to transfer the content learned from learned network s to similar tasks in the face of many information. The document covers many faces in a single image, including masked faces, unmasked faces, faces with and without masks, and mixed images without masks. With a large database of 45,000 images, our technology achieves an accuracy of 98.2

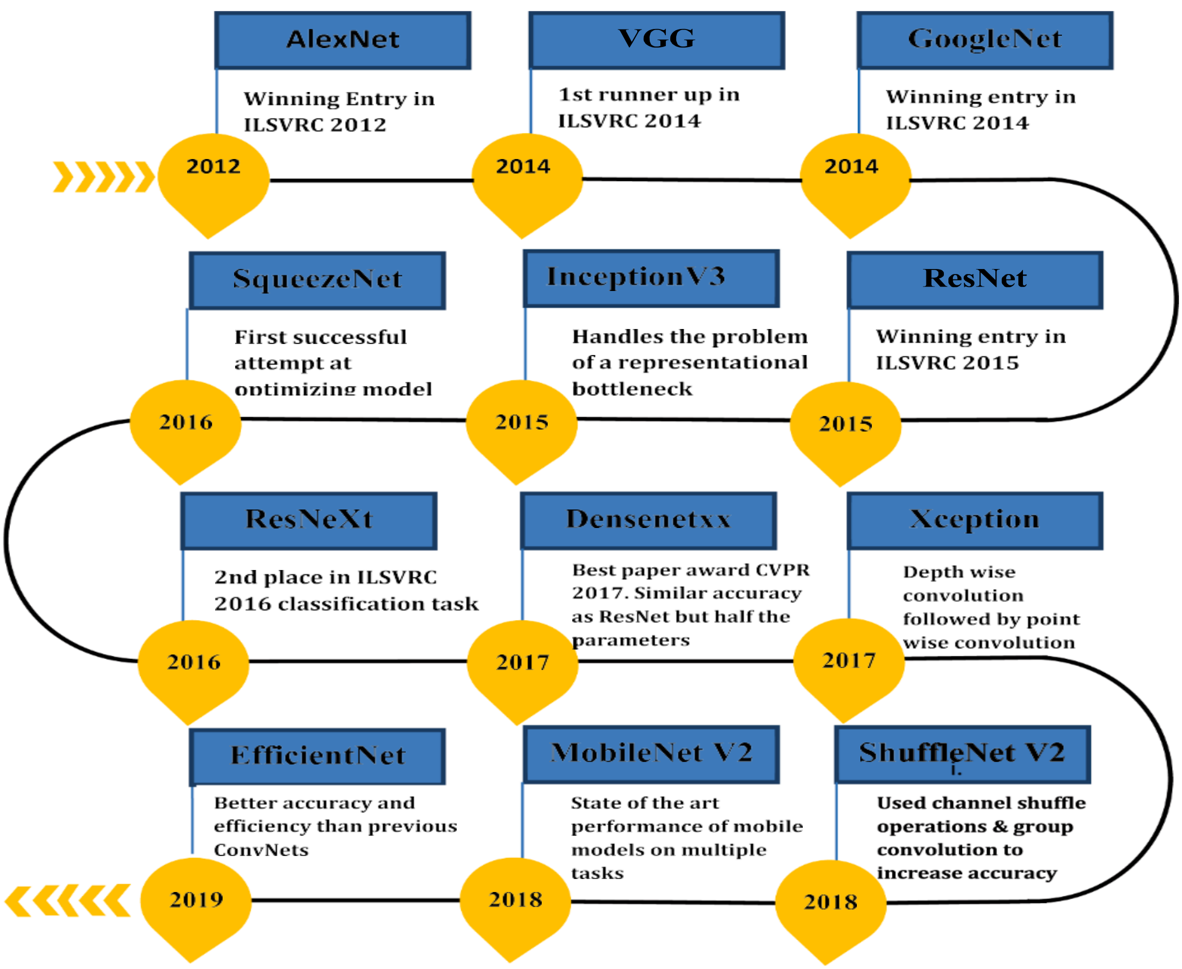

Fig. 1. Various Pre-trained Models based on CNN Architectures.

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Basic architecture, number of layers, inference speed, memory consumption and search accuracy. The achieve ments of each model, based on current recommended educational standards for public health, are shown in Fig ure 1. people. This pretraining model must be finetuned using test data. Table 1 gives the number of document s with different features for masked and unmasked faces. A general study of facial information shows that ther e are generally two types of information. These are: i) Masked and ii) Unmasked Dataset. The face mask datas et focuses more on images containing faces with different levels of facial expression and space, while the face-centered dataset

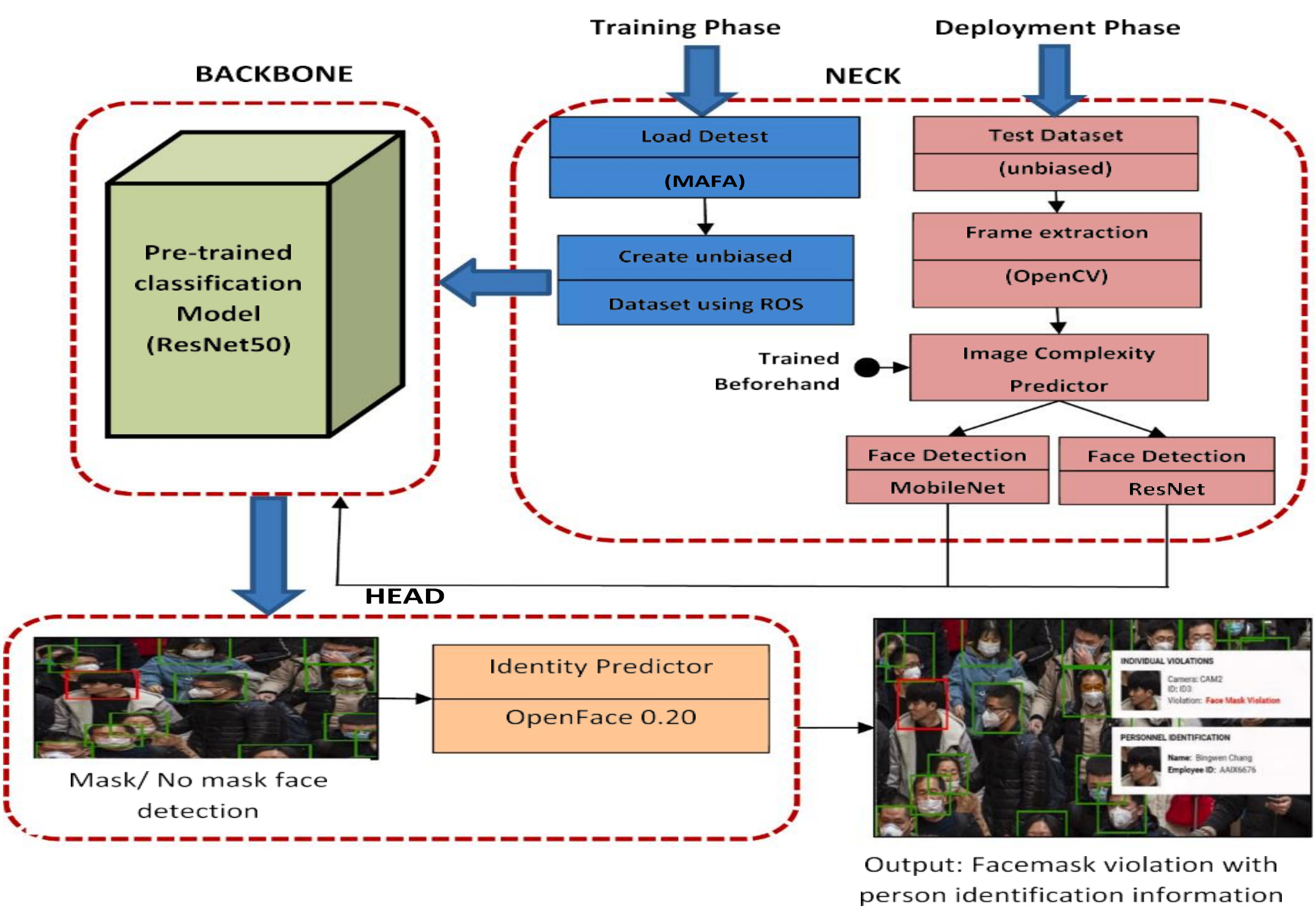

Fig. 2. Proposed Architecture.

Such facial features are often characterized by their congestion and location close to the nose and mouth. Tabl e 1 shows these two popular documents.

Proposed Architecture

The proposed architecture is based on the object recognition parameters given in [38]. Based on these principl es, all activities related to the object recognition problem can be combined according to three elements: bones,

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neck and head, as shown in Figure 2. Here the spine corresponds to the underlying convolutional neural netw ork. extraction of features. Get information from photos and turn it into custom reports. In the proposed archit ecture, the concept of transfer learning is applied to the backbone to use material already learned by powerful prelearned convolutional neural networks to extract new features from the model.One of the best methods in t he system, which includes three popular pretraining models such as ResNet50, MobileNet and AlexNet, is to g et the best results in face detection. ResNet50 was found to be the best choice to form the backbone of the pro posed model (see Section 4.2). The novelty of our study is presented in the neck component. The middle comp onent, Neck, contains all the preliminary work that needs to be done before the image is classified. To ensure our models work well with monitoring tools, Neck uses different pipelines during the training and delivery ph ase. The training process is based on generating unbiased private data and improving ResNet50. The pipeline i ncludes video extraction from video, followed by face detection and removal. To achieve the balance between face detection accuracy and computation time, we propose a blurred image approach (see Section 3.3). Last co mponent, title

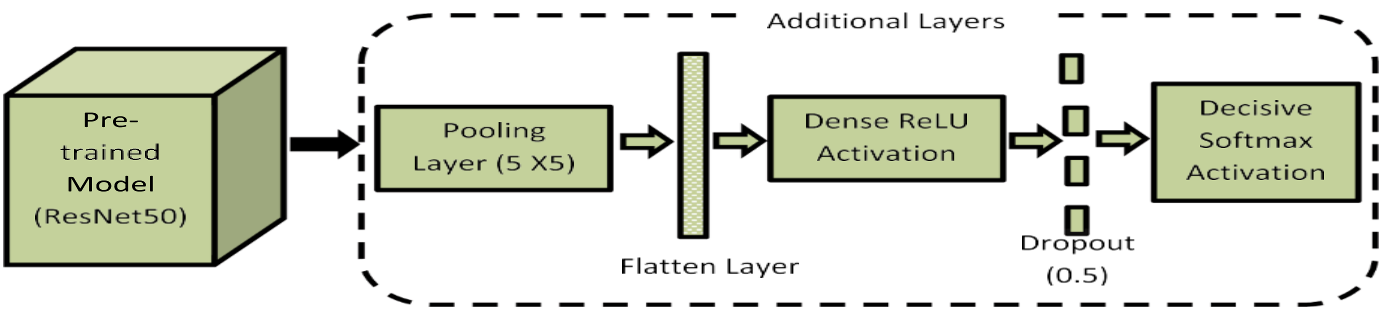

Fig. 3. Fine-tuning of ResNet50.

3.1. Creating an unbiased mask dataset

The mask-
centered dataset, MAFA [35], was initially considered to have a total of 25,876 images divided into two group s: masked and unmasked. The number of images covered in MAFA is 23,858, while the number of disapprove d images is only 2018. It has been observed that MAFA has a class conflict problem that will show bias for m ost classes. Therefore, an ablation study was performed once using the original MAFA (biased) and then the d ataset (unbiased) to verify the performance of the image classifier. 3.1.1

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Fig. 4. Variety of Occlusions Present in Dataset.

Caffe python library [7]. In summary, our CNN model almost matches the performance of Madhura et al. [11], achieving the highest error rate of 1.8% higher in the MAFA validation set. This discrepancy may be due to a simplistic approach to training.

4.2. Model Comparison

As discussed in Section 3.2, we can apply transfer learning to a previous learning model for image classificat ion, but the open question is how to decide which model is good for our job. In this section we compare our p erformance models. ResNet50, AlexNet and MobileNet according to the following standards:

1. Top 1 error: This type of error occurs when the predicted class with the highest confidence differs from the actual class.
2. CPU inference time: The time it takes for the model to predict the category of the input image, that is, start ing from reading the image, performing all intermediate transformations, and finally generating the high conf idence category. The picture belongs.
3. Number of parameters: All topics are included in each layer of the model. These parameters directly affect

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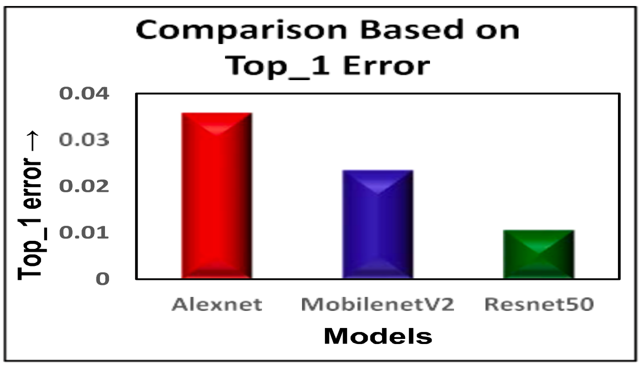
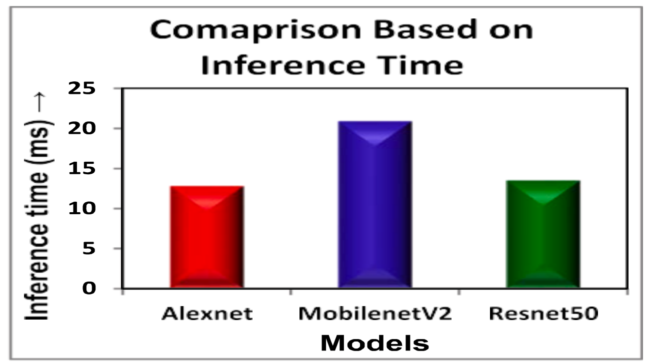
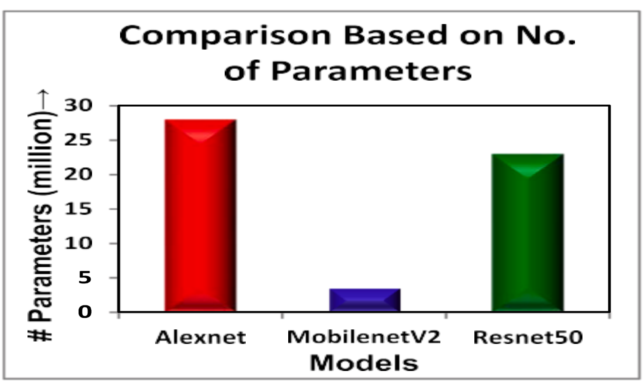
predictive power, model complexity, and memory usage [45]. This information is useful for understanding t he minimum amount of memory required for each model. Also he



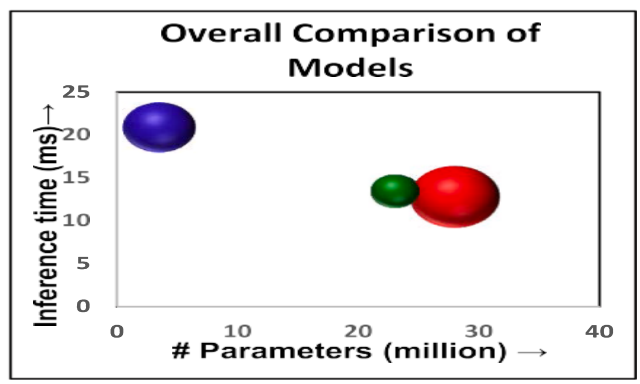
(a) Top_1 error



(b) Inference Time (CPU)



(c) Model Size



(d) Overall Comparison

Fig. 7. Comparison of Various Models on Different Performance Criteria.

Correlation between ground truth visual difficulty

score and predicted image complexity score

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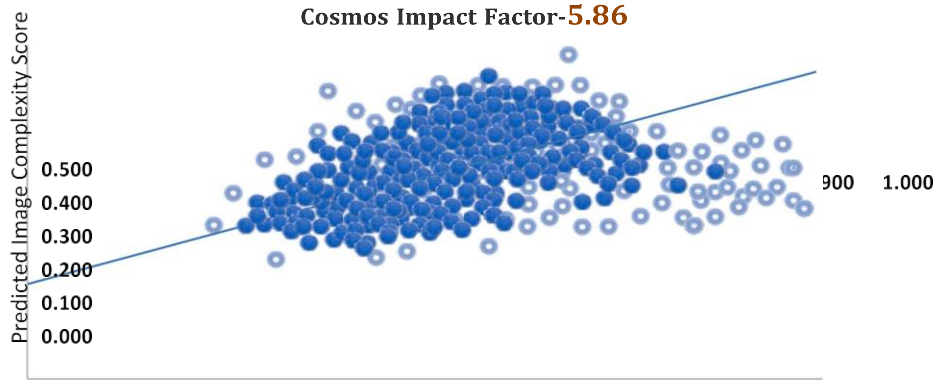

Fig. 8. Correlation between Ground Truth Visual Difficulty Score and Predicted Image Complexity Score.

This was confirmed by Simone Bianco and others. get. We need a large number of training parameters to ensure the balance between model accuracy and memory usage [45].
A model with the least errors in the top-1, less CPU inference time and the number of defects will be considered a good model for our study.
Confusion matrices of different models during the testing process are shown in figure 6. The actual comparison of various models with respect to Top1 error is shown in figure 6. 7(a). As can be seen from the figure, AlexNet has more errors, while ResNet50 has the lowest error. We then compare the models in terms of inference time. Test images are fed into each model and the inference time across all iterations is averaged. It can be seen from the picture. As can be seen from Figure 7(b), MobileNet requires more time to extract images, while ResNet and AlexNet spend almost the same time for image extraction. Additionally, the memory usage of the base model is compared by calculating the number of failed subjects. These parameters can be obtained by creating a content model for each model in Google colab. Figure 7(c) shows that the number of parameters in AlexNet for our particular dataset is approximately 28 million. Additionally, the number of non-MobileNet and ResNet 50 is around 3.5 million and 25 million respectively.After analyzing the performance of each model against various models,We will condense all these points into an empty bubble form. X coordinate is the parameter and Y coordinate is the inference time. The large bubble represents the Top-1 error (the smaller the bubble, the better). The overall comparison of each model is shown in the bubble diagram in Figure 7(d).It can be seen from Figure 7(d). 7. Smaller bubbles are better for accuracy, while bubbles closer to the origin are better for memory and thinking speed. Now the answer to RQ1 can be given as follows:AlexNet has a high error rate. MobileNet is slow to make decisions.
ResNet50 is the best choice in terms of accuracy, speed and memory usage when detecting masks using transformation learning.

4.3. Evaluating the effectiveness of complex image Predictor

We use Kendall coefficient α (tau) to evaluate the effectiveness of complex image. We calculated the Kendall rank correlation coefficient α between the estimated visual difficulty score and the actual perceived difficulty on the ground. The Kendall rank correlation coefficientis suitable for our analysis as it does not differ between different types of competition. Based on the characteristics of the image, each annotator assigns a difficulty score to the image based on the image's difficulty score range. Kendall rank correlation coefficients were calculated using the kendalltau()SciPy function in Python. This function takes two scores as parameters and re

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turns the correlation coefficient. Our experts obtained the Kendall correlation coefficient α as 0.741; This me ans that it is not easy to predict the performance of the image. It can be seen from the picture. As can be seen from Figure 8, there is a very good correlation between the ground truth and the estimated difficulty scores.F urther in Figure 8, it can be seen that the cloud points form a skewed Gaussian distribution and their main poi nts follow the diagonal line, confirming the relationship between the two points.

Particularly, the proposed model generates 11.75% and 11.07% higher precision in the face and mask detection respectively when compared with Retina FaceMask. The recall is improved by 3.05% and

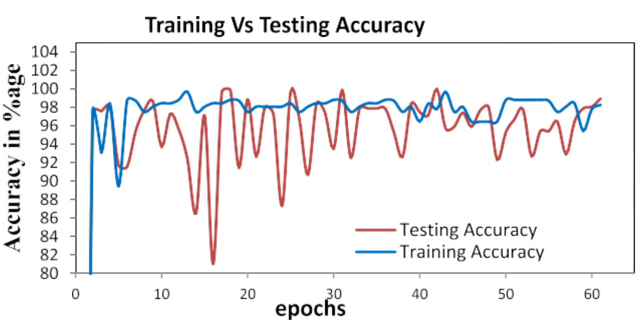

Fig. 10. Training and Testing Accuracy over 60 Epochs.

6.44% in the face and mask detection respectively. We had observed that improved results are possible due to optimized face detector discussed in Section 3.3 for dealing with complex images.

5. Conclusions

This study proposes a deep learning method to detect facial expressions in public places to prevent the spread of coronavirus in society. The proposed system effectively achieves occlusion in severe conditions by using a group of single-
and twolevel detectors at the preprocessing level. The combination method not only helps in achieving high a ccuracy but also makes it very fast. Additionally, adaptive learning is applied to pre-
trained models and multiple experiments are performed on conflicting data, resulting in high efficiency and lo w cost. Facial recognition further violates the masking law and turns the body into a public presence.
Finally, this study opens up interesting directions for future researchers.First of all, the technology can be inte grated into a highdefinition video surveillance device, including but not limited to face detection. Secondly, th e model can be extended to include to be, to be, to be, to be cut to be cut to be cut to be cut
Credit Author Guideto be done to be cut by Shilpa Sethi: Design, Process, Author -
Original . Mamta Kathuria: Data curation, Conceptualization, Writing –
first draft. Trilok Kaushik: Career.Declaration of Competing InterestsThe authors declare that they are not aw are of any competing financial interests that might appear to have influenced the work published in this article Interests or personal relationships.

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