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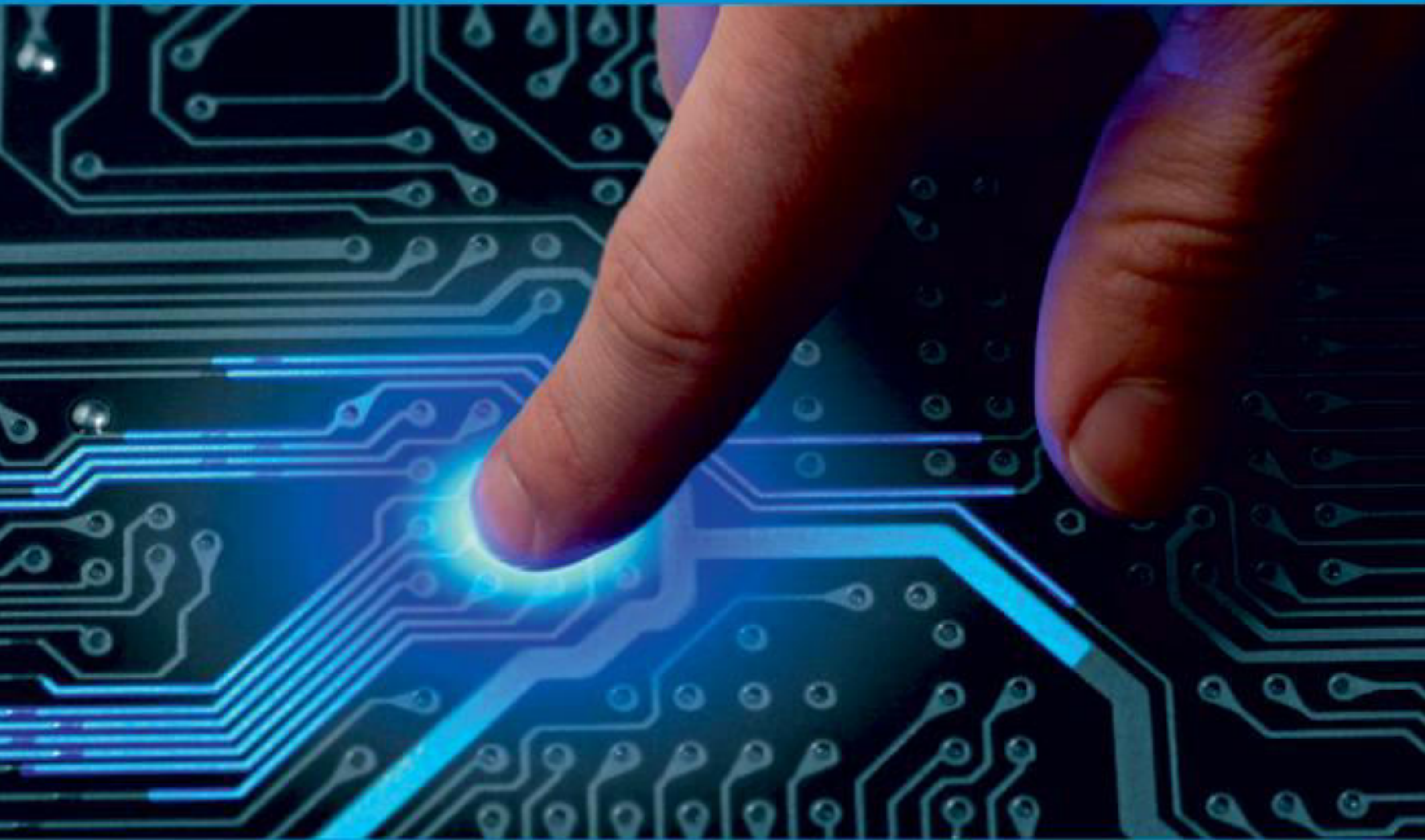

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Deep Learning based Face Mask Detection for User Safety from Covid-19

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ABSTRACT: There is a global health emergency because to the COVID-19 epidemic. Droplets shed by a corona virus-infected person can disseminate this virus to others, making it a danger to others around them. Public settings pose the greatest risk of infection. As recommended by the World Health Organization, wearing a face mask in open areas will help keep you safe from infection (WHO). Using CNN and OpenCV, we present a way to detect face masks on humans. The presence or absence of a mask is indicated by a box drawn around the subject's face. As soon as a face is stored in the database, the system will send an email to the individual who is not wearing a mask, letting them know that they need to take precautions.

KEYWORDS: COVID-19, CNN, OpenCV, Detect Face Mask.

I. INTRODUCTION

COVID-19 had a devastating effect on the lives of many people. As a result of the epidemic, millions were killed and the lives of billions were affected. Almost every commercial establishment, Educational institution, economic system, religious institution, transportation, tourism, employment, entertainment, food safety, and every industry was adversely affected by it. Approximately 55.6 million individuals have been infected with Coronavirus and 1.34 million people have died as of November 2020, according to the WHO (World Health Organization). This is comparable to the Black Death of the 14th century, which claimed the lives of up to 60% of Europe's population. Once infected, the virus takes around fourteen days to grow in the host's body and begin affecting them, and it spreads to nearly everyone who comes into touch with the infected individual. The spread of COVID-19 is therefore extremely difficult to monitor.

COVID-19 primarily spreads through coughing or sneezing droplets produced by infected individuals. This spreads the virus to anyone who comes into touch with the infected individual at a close proximity (within one metre of the infected person). Consequently, the virus is spreading swiftly among the general population. The virus has become considerably more difficult to track and manage after the nationwide lockdowns were removed. Viruses can be prevented by wearing face masks. Wearing face masks has been found to be 96 percent efficient in preventing the spread of the infection. People around the world are now required to wear face masks whenever they leave their homes. However, some people may choose not to wear masks, making it difficult to verify whether or not everyone is covered. Computer vision will come in handy in these situations.

II. LITERATURE SURVEY

[1] C. Szegedy, S. Ioffe, V. Vanhoucke, and A. A. Alemi, "Inception-v4, inception-resnet and the impact of residual connections on learning," in Thirty-first AAAI conference on artificial intelligence, 2017.

The most significant improvements in image identification performance in recent years have been made possible thanks to the use of extremely deep convolutional networks. It has been demonstrated that the Inception design achieves excellent performance at a reasonable computational price. Recent research has shown that the use of residual connections in conjunction with a more traditional architecture has resulted in performance comparable to that of the newest generation of Inception-v3 networks in the 2015 ILSVRC competition. Are there any benefits to using

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Inception architectures and residual connections together? In this paper, we provide empirical evidence that training Inception networks with residual connections speeds up the process significantly. Remaining Inception networks appear to outperform similarly priced Inception networks without residual connections by a little percentage as well, according to the research. As an added bonus, we show various new, more efficient architectures for Inception networks, both residual and non-residual. Improves single-frame recognition greatly on the ILSVRC 2012 classification task. Activation scaling is also shown to stabilise the training of very large residual Inception networks, which we go on to demonstrate. We achieved a top-five error rate of 3.08 percent on the test set of the ImageNet classification (CLS) challenge using an ensemble of three residual and one Inception-v4 networks.

[2] Images categorization with deep convolutional neural networks," in Advances in neural information processing systems (ed. A. Krizhevsky, I. Sutskever, and G. E. Hinton), 2012, pp. 1097–1105 (in Russian).
Our convolutional neural network was trained to categorise the 1.2 million high quality photos in the ImageNet LSVRC-2010 contest into the 1000 different classes. This is a significant improvement over the prior state-of-the-art, as seen by our top-1 and top-5 error rates of 37.5% and 17.0%, respectively. Five convolutional layers, some of which are followed by max-pooling layers, and three fully-connected layers with a final 1000-way softmax make up the neural network with 60 million parameters and 650,000 neurons. We used non-saturating neurons and a GPU implementation of the convolution function to speed up training. We used a recently invented regularisation method termed "dropout" to reduce overrides in the fully-connected layers, and it was extremely effective. A variation of this model was entered into the ILSVRC-2012 competition and earned a winning top-5 test error rate of 15.3%, compared to the second-best entry's 26.2%.

[3] "Going deeper with convolutions," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2015, pp. 1–9.
For the ImageNet Large-Scale Visual Recognition Challenge 2014, we present a deep convolutional neural network architecture codenamed Inception that achieves the new state of the art in classification and detection (ILSVRC14). This architecture's most notable feature is its ability to maximise the utilisation of network resources. Through the use of thoughtful planning, we were able to expand the network's breadth and depth while maintaining the same computational budget. Hebbian principles and multi-scale processing intuition guided the architecture selections in order to maximise quality. In our application for ILSVRC14, we employed a 22-layer deep network called GoogLeNet to evaluate the quality of classification and detection.

[4] A. Zisserman and K. Simonyan, "Very deep convolutional networks for large-scale image recognition," arXiv preprint arXiv:1409.1556, 2014.
In the context of large-scale image recognition, we examine how the depth of a convolutional network affects the accuracy of the network. Using an architecture with relatively small (3x3) convolution filters, we evaluated networks of increasing depth and found that raising the depth to 16-19 weight layers yielded considerable improvements over prior-art setups. In the ImageNet Challenge 2014, our team won first and second place in the classification and localization tracks, respectively, based on these findings Aside from this, we demonstrate that our models generalise well to other datasets, resulting in cutting edge findings on those datasets as well. We've made two of our best-performing ConvNet models available to the public so that researchers can continue to explore the use of deep visual representations in computer vision.

III. PROPOSED SYSTEM

SARS-CoV-2 transmission can be prevented by using a deep learning-based, multi-phase face mask detection model. To train and evaluate the model for detecting photos and video streams with and without a face mask, we used two separate datasets of face masks and more than 5,200 images. A 93% accuracy rate was achieved with the validation samples we used in the experiments, while an accuracy rate of nearly 100% was achieved with the validation samples we used.

3.1 Face Mask Detector Training Phase

There are two stages to our proposed strategy for teaching how to use a face mask detector. The first is the classroom section, and the second is the deployment phase, which is unique. Model has been exceptionally knowledgeable during the teaching phase, mostly due to the reachable dataset. Detecting faces with and without masks was the final step after finishing the training portion of the face masks detector. TensorFlow and Keras were used in conjunction with a deep mastering device to categorise face mask carrying scenarios. A fantastically tuned method on the MobileNetV2 [11]

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structure was used to achieve this purpose. The masks detector was trained using a variety of machine/deep learning programmes and photo processing libraries, including OpenCV, scikit-learn,matplotlib, numpy, and many more. The MobilenetV2 architecture was also fine-tuned in three steps to create a baseline model that saves a significant amount of time. For the mask and without mask classification problem, we used binary cross-entropy, the decay agenda of a study rate's studying rate, and Adam's optimizer. Finally, the mannequin was put through its paces and the categorization paperwork was prepared for inspection. In the end, we serialised the mannequin for classifying face masks to disc.

3.2 Face Mask Detector for Webcam/Video Stream

Detecting masks from a webcam or video stream is done in a two-step process. The OpenCV framework provided a pre-trained mannequin that was used to recognise faces on the webcam. Mannequin pre-trained using Single-Shot-Multibox (SSD) detector and ResNet-10 architecture Face mask recognition from video data is depicted in the following Fig. 1 utilising a step-by-step approach.

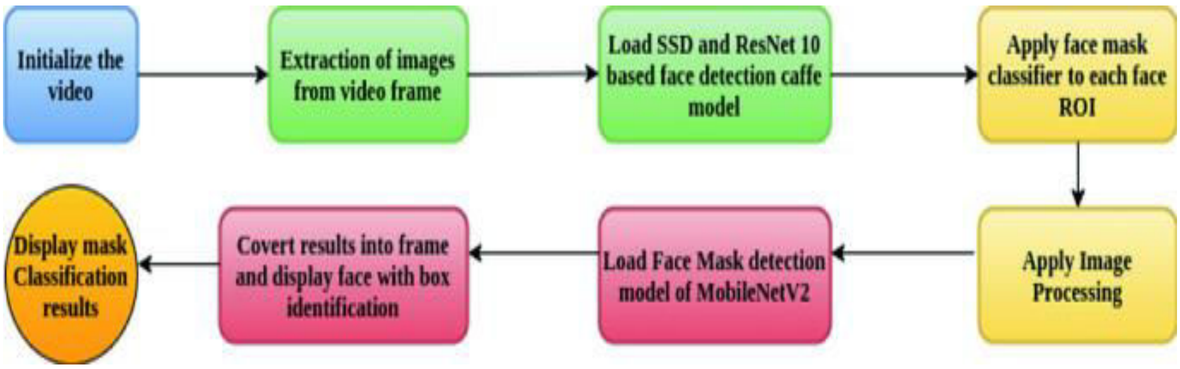

Fig 1: Face Mask Detection Workflow For Webcam Or Video Stream

IV. CNN

Convolutional Neural Networks (CNN) are used in a variety of applications. It is, without a doubt, the most well-known profound study of architecture. Because of the widespread recognition and success of convnets, there has been a recent increase in interest in deep learning. AlexNet launched the pastime in 2012, and it has developed enormously since then. Researchers went from an eight-layer AlexNet to a 152-layer ResNet in just three years.

CNN has become the easy mannequin for any photograph-related issue. They blow opposition out of the water with precise language. It's also useful in recommender systems, herbal text analysis, and other applications. CNN's key benefit over its antecedents is that it detects the key features without requiring human intervention.. For example, given a large number of photographs of cats and puppies, it learns unique facets for each category on its own.

Furthermore, CNN is highly scalable. It accomplishes parameter sharing and uses one-of-a-kind convolution and pooling procedures. CNN styles may now be viewed on any device, making them widely appealing.

Overall, this appears to be truly magical. We're working with a highly effective and environmentally friendly mannequin that uses automatic characteristic enhancement to achieve superhuman accuracy (yes CNN models now do photograph classification higher than humans). Perhaps, this post will assist us in discovering the techniques and procedures of this wonderful technology.

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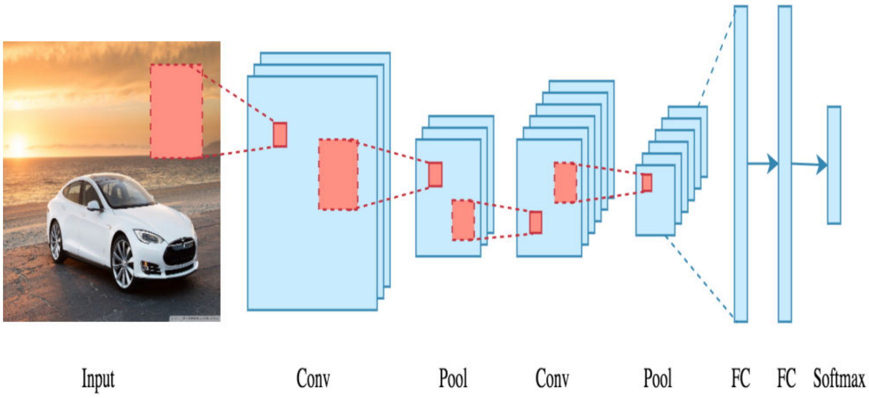
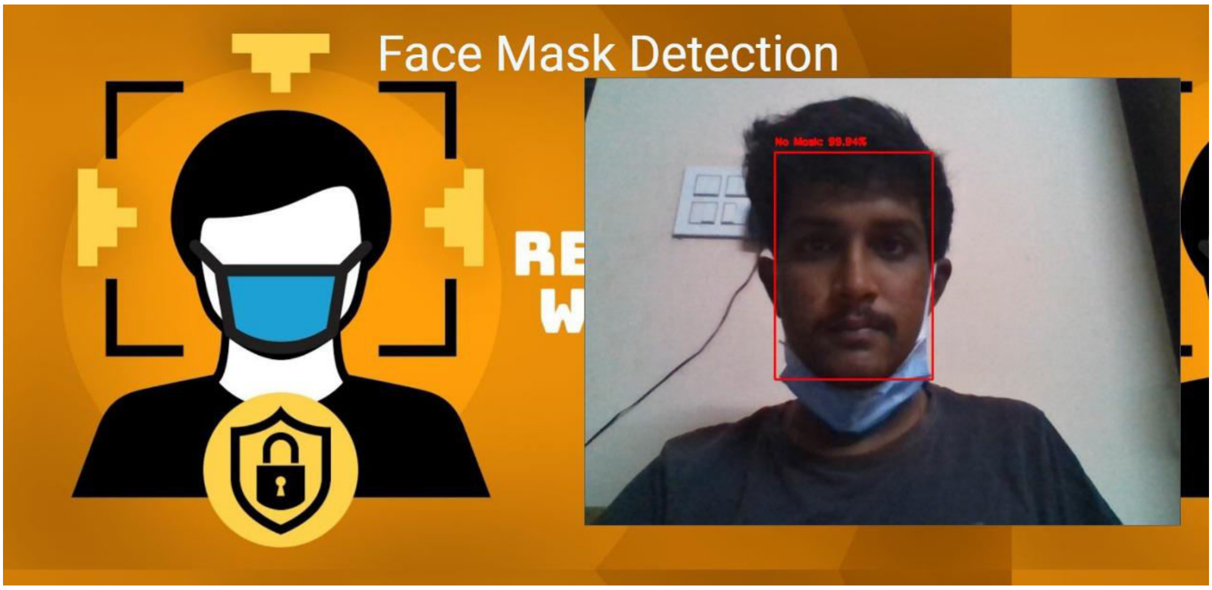
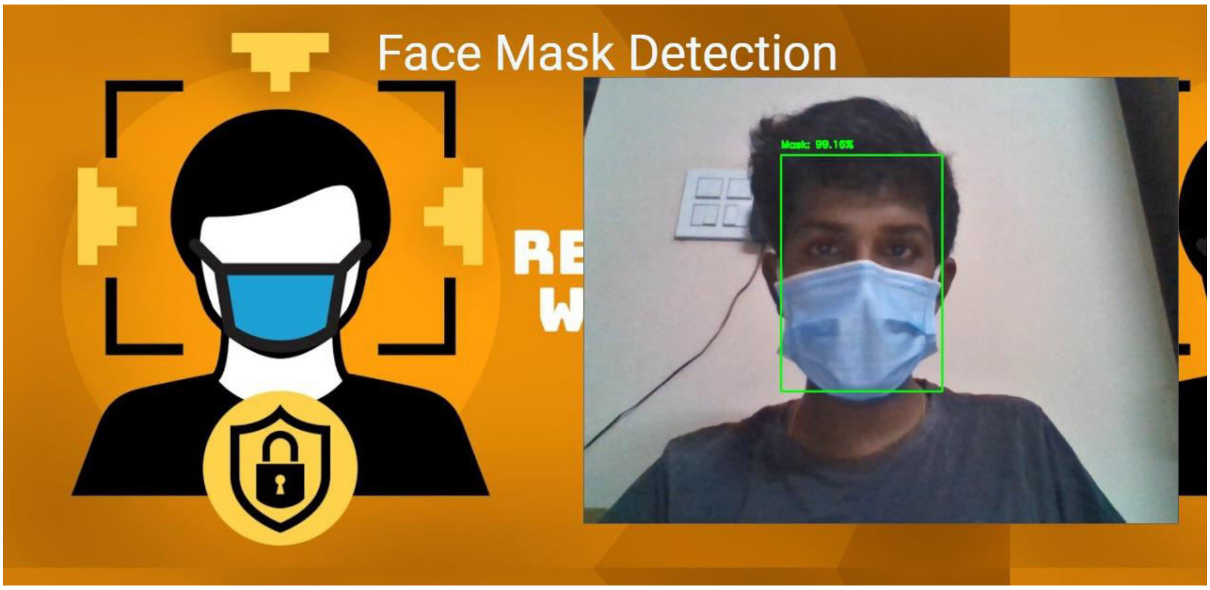


V. RESULTS





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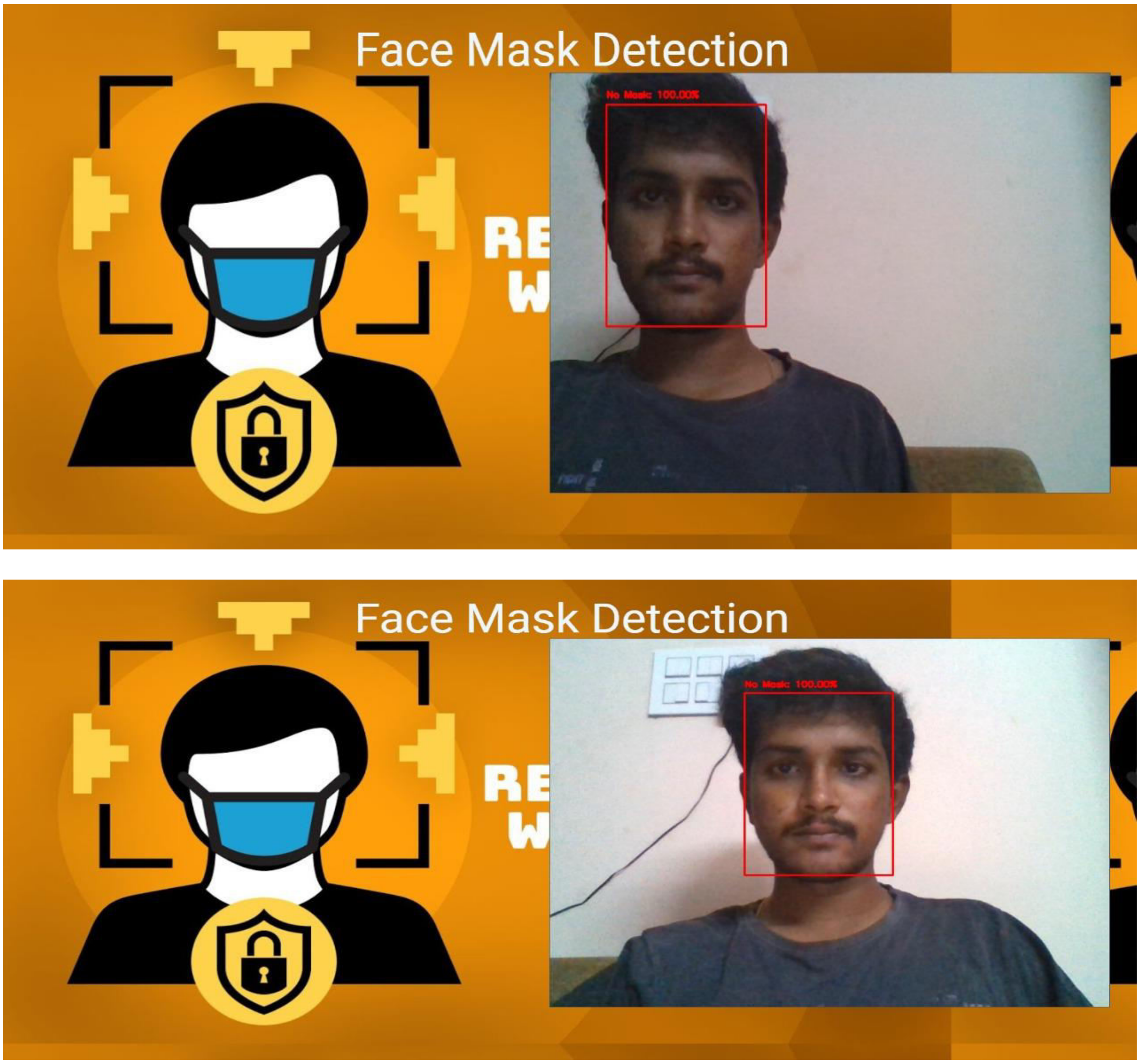

Fig 2:Screenshots with & without mask

VI. CONCLUSION

As COVID instances rise worldwide, the necessity for a system to replace humans in the process of checking people's masks has never been greater. To meet that demand, we've developed this system. Public venues like train stations and malls can benefit from this technology. It will be extremely useful in large corporations and other places where there are a lot of employees. They'll benefit much from this method, as it's a cinch to gather and store personnel information, as well as to identify those who aren't wearing masks.

REFERENCES

[1] W. H. Organization et al., “Coronavirus disease 2019 (covid-19): situation report, 96,” 2020.
[2] P. A. Rota, M. S. Oberste, S. S. Monroe, W. A. Nix, R. Campagnoli, J. P. Icenogle, S. Penaranda, B. Bankamp, K. Maher, M.-h. Chen et al., “Characterization of a novel coronavirus associated with severe acute respiratory syndrome,” science, vol. 300, no. 5624, pp. 1394–1399, 2003.
[3] Z. A. Memish, A. I. Zumla, R. F. Al-Hakeem, A. A. Al-Rabeeah, and G. M. Stephens, “Family cluster of middle east respiratory syndrome coronavirus infections,” New England Journal of Medicine, vol. 368, no. 26, pp. 2487–2494, 2013.

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| DOI: 10.15680/IJIRCCE.2022.1005212|

[4] Y. Liu, A. A. Gayle, A. Wilder-Smith, and J. Rocklöv, "The reproductive number of covid-19 is higher compared to sars coronavirus," Journal of travel medicine, 2020. [5] Y. Fang, Y. Nie, and M. Penny, "Transmission dynamics of the covid-19 outbreak and effectiveness of government interventions: A data-driven analysis," Journal of medical virology, vol. 92, no. 6, pp. 645–659, 2020.

[6] N. H. Leung, D. K. Chu, E. Y. Shiu, K.-H.Chan, J. J. McDevitt, B. J. Hau, H.-L. Yen, Y. Li, D. KM, J. Ip et al., "Respiratory virus shedding in exhaled breath and efficacy of face masks."

[7] S. Feng, C. Shen, N. Xia, W. Song, M. Fan, and B. J. Cowling, "Rational use of face masks in the covid-19 pandemic," The Lancet Respiratory Medicine, 2020.

[8] D. Chiang., "Detect faces and determine whether people are wearing mask," https://github.com/AIZOOTech/FaceMaskDetection, 2020.

[9] Z. Wang, G. Wang, B. Huang, Z. Xiong, Q. Hong, H. Wu, P. Yi, K. Jiang, N. Wang, Y. Pei et al., "Masked face recognition dataset and application," arXiv preprint arXiv:2003.09093, 2020.

[10] Z.-Q. Zhao, P. Zheng, S.-t. Xu, and X. Wu, "Object detection with deep learning: A review," IEEE transactions on neural networks and learning systems, vol. 30, no. 11, pp. 3212–3232, 2019.

[11] A. Kumar, A. Kaur, and M. Kumar, "Face detection techniques: a review," Artificial Intelligence Review, vol. 52, no. 2, pp. 927–948, 2019.

[12] D.-H. Lee, K.-L.Chen, K.-H.Liou, C.-L.Liu, and J.-L. Liu, "Deep learning and control algorithms of direct perception for autonomous driving," arXiv preprint arXiv:1910.12031, 2019.

[13] K. Savita, N. A. Hasbullah, S. M. Taib, A. I. Z. Abidin, and M. Muniandy, "How's the turnout to the class? a face detection system for universities," in 2018 IEEE Conference on e-Learning, e-Management and e-Services (IC3e). IEEE, 2018, pp. 179–184.