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Face Mask Detection and Social Distancing Monitoring

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Abstract: During pandemic COVID-19, the World Health Organization (WHO) reports suggest that the two main routes of transmission of the COVID-19 virus are respiratory droplets and physical contact. Respiratory droplets are generated when an infected person coughs or sneezes.
Any person in close contact (within 1 m) with someone who has respiratory symptoms (coughing, sneezing) is at risk of being exposed to potentially infective respiratory droplets. Droplets may also land on surfaces where the virus could remain viable; thus, the immediate environment of an infected individual can serve as a source of transmission (contact transmission). Wearing a medical mask and social distancing is one of the prevention measures that can limit the spread of certain respiratory viral diseases, including COVID-19.
World Health Organization has made wearing masks and also social distancing compulsory to protect against this deadly virus. This paper is about we developed a generic Deep Neural Network-Based model for mask detection, tracking using cameras and also we developed second application for social distancing monitoring application with the help of Python and Computer Vision.
Keywords: deep learning, computer vision, AI, CNN, MobileNet

I. INTRODUCTION

In the past decade, AI/Deep Learning has shown promising results on a number of daily life problems. Various daily life tasks have been automated with the help of AI. In this project we will go through implementation of how can one use python combined with deep learning and computer vision to monitor social distancing and detect face masks.
Since this pandemic occurred due to COVID-19, it's very important to wear a mask and follow social distancing for prevention purpose. People are asked to limit their interactions with each other, reducing the chances of the virus being spread with physical or close contact.
For this we need face mask detector and social distancing monitor model. Face Mask Detection and Social Distancing is an important way to slow down the spread of infectious diseases. In this project, we are going to implement two applications – 1. Face Mask Detection 2. Social Distancing Monitoring. For face mask detection, we will train face mask detector model with available datasets and will create our deep learning based model and then test the results in a real-time webcam. For social distancing monitoring, we will apply object detection (for person class) to detect all people and then we can apply distancing measures (N pixels). And we will monitor distance between people. We are using python, OpenCV, YOLO (CNN), Deep learning and computer vision for this application.

II. RELATED WORK

Over past some days, many researchers have proposed different face detection techniques and also techniques for social distancing monitoring, motivated by this situation.

A. 'Enabling and Enforcing Social Distancing Measures using Smart City and ITS Infrastructures: A COVID-19 Use Case'

COVID-19 outbreak is unprecedented and has disrupted lives of millions of people across the globe. This pandemic has opened several research challenges and opportunities that our community must address to equip itself for the future. The proposed architecture and AI assisted applications discussed in the article can be used to effectively and timely enforce social distancing community measures, and optimize the use of resources in critical situations. This article offers a conceptual overview and serves as a steppingstone to extensive research and deployment of automated data driven technologies in smart city and intelligent transportation systems. For future, we envision to develop these AI driven applications for wider adoption in the community.

B. 'Monitoring COVID-19 social distancing with person detection and tracking via fine-tuned YOLO v3 and Deepsort techniques'

The article proposes an efficient real-time deep learning based framework to automate the process of monitoring the social distancing via object detection and tracking approaches, where each individual is identified in the real-time with the help of bounding boxes.

The generated bounding boxes aid in identifying the clusters or groups of people satisfying the closeness property computed with the help of pairwise vectorized approach.

The number of violations are confirmed 9 by computing the number of groups formed and violation index term computed as the ratio of the number of people to the number of groups. The extensive trials were conducted with popular state-of-the-art object detection models: Faster RCNN, SSD, and YOLO v3, where YOLO v3 illustrated the efficient performance with balanced FPS and mAP score. Since this approach is highly sensitive to the spatial location of the camera, the same approach can be fine-tuned to better adjust with the corresponding field of view.

C. 'RETINAFACEMASK: A Face Mask Detector'

In this paper, we have proposed a novel face mask detector, namely RetinaFaceMask, which can possibly contribute to public healthcare.

The architecture of RetinaFaceMask consists of ResNet or MobileNet as the backbone, FPN as the neck, and context attention modules as the heads. The strong backbone ResNet and light backbone MobileNet can be used for high and low computation scenarios, respectively.

In order to extract more robust features, we utilize transfer learning to adopt weights from a similar task face detection, which is trained on a very large dataset.

Furthermore, we have proposed a novel context attention head module to focus on the face and mask features, and a novel algorithm object removal cross class, i.e. ORCC, to remove objects with lower confidence and higher IoU. The proposed method achieves state-of-the-art results on a public face mask dataset, where we are 2.3% and 1.5% higher than the baseline result in the face and mask detection precision respectively, and 11.0% and 5.9% higher than baseline for recall.

D. 'Detecting Masked Faces in the Wild with LLE-CNNs'

The problem of face detection in the wild have been explored in many existing researches, and the corresponding face detectors have been tested on datasets of normal faces. On these datasets, some face detectors have achieved extremely high performances and it seems to be somehow difficult to further improve them. However, the 'real wild' scenarios are much more challenging than expected for containing faces captured at unexpected resolution, illumination and occlusion. In particular, the detection of masked faces is an important task that needs to be addressed so as to facilitate applications such as video surveillance. In this paper, we introduce the dataset MAFA and LLECNNs for masked face detection. We find that MAFA is very challenging for existing face detectors, while the proposed model achieves the best performance in all settings. This may imply that the data-driven framework may be a feasible solution in finding robust and effective features for masked face detection. We believe this dataset can facilitate the development of face detectors that can effectively detect faces with occlusions. In addition, predicting facial attributes of MAFA like mask type and occlusion degree also has practical meaning in many real-world applications, which will be one of our future research directions.

E. 'Face Detection and Segmentation Based on Improved Mask R-CNN'

In this paper, a G-Mask method was proposed for face detection and segmentation. -e approach can extract features by ResNet-101, generate RoIs by RPN, preserve the precise spatial position by RoIAlign, and generate binary masks through the full convolutional network (FCN). In doing so, the proposed framework is able to detect faces correctly while also precisely segmenting each face in an image. Experimental results with self-built face dataset as well as public available datasets have verified that our proposed G-Mask method achieves promising performance. For the future work, we will consider improving the speed of the proposed method.

III. IMPLEMENTATION

A. Face Mask Detection

1) *Dataset Details:* We took available dataset for this project (Face Mask Detection). In our dataset basically there are two categories "with mask" which contains images of faces with mask and "with_out mask" which contains images of faces without mask.

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2) *Data Preprocessing:* Our first task is we have to train our mask detector model. First we will load dataset by giving path to it. Then we will do data preprocessing, our first task is to convert images into arrays and also we have to do one-hot coding on labels (categories "with mask" and "with_out mask"). Now we are storing this data inside lists but in Deep Learning we have to convert the data into Numpy arrays to do some operations and for manipulation. Now we will do partitioning of our data into training and testing dataset using sklearn "train_test_split" method. We will use 20% of dataset for testing purpose and remaining 80% for training purpose.
3) *Training the model:* Now for data augmentation, we will generate more images using ImageDataGenerator() method from Keras preprocessing methods. Then we will do modeling part. For this we will use Convolution Neural Network (CNN), but here instead of convolution, we will use MobileNet. We will have two models in this project, one is base model and another is head model. Output of the base model will be input of the head model. After doing some modeling operations will place the head fully connected model on the top of the base model then it will become the actual model (output) we will train. Now we will train our mask detector model and will save it on disk and also we will plot and save the graph between epoch (x-axis) and accuracy.

After trained mask detector model, we got following some graphs after changing some parameters again and again –

Fig. 1 Epoch = 20, initial learning rate = 0.001, batch_size = 32

Fig. 2 Epoch = 25, initial learning rate = 0.01, batch_size = 32

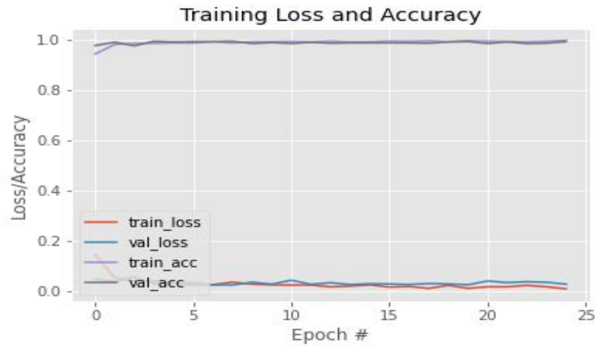

Fig. 3 Epoch = 20, initial learning rate = 0.01, batch_size = 32

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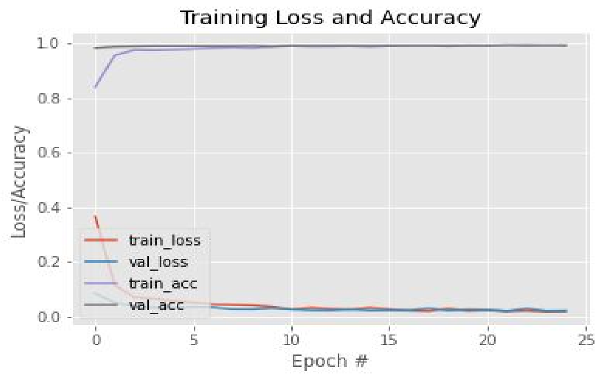

Fig. 4 Epoch = 25, initial learning rate = 0.001, batch_size = 30

4) *Applying Face Mask Detector:* Now our second task is apply Face Mask Detector in real-time. Now we have our trained mask detector model. But we don't have any face detector model here. So for face detection purpose we are adding couple of files used to face detection. Now we will create a function called "detect_and_predict_mask" and will pass three arguments, frame which is our video input, then FaceNet which have our two face detector files, and MaskNet which have our trained face mask detector model. Now we will extract ROI and will bound rectangular box around it. Finally we will do some coding for starting camera and use model in real time camera. We will put text as "with_mask" or "without_mask" and will also show percentage of that. Now our model is completed and it is detecting the faces with mask and without mask. So here our first application Face mask detection is successfully implemented.

B. *Social Distancing Monitoring*

In this application we have three modules (/steps) –

1) *Object detection (Only for person class):* In this application we will take input video/frame or image and will apply object detection (using YOLO) which will filter and detect only people.
2) *Calculating Distance between people:* We will find total people and co-ordinates. Then we will check distance between them (centroids) using distance formula (Euclidean distance formula. Then will check whether they are apart from each other (about 100px) or close to each other (distance < 100px).
3) *Monitoring Social Distancing;* If the people are far away (> 100px) from each other then will categories as "following" and otherwise will categories as "not following". And then we can see final results.

IV. RELATED DIAGRAMS

A. *Face Mask Detection*

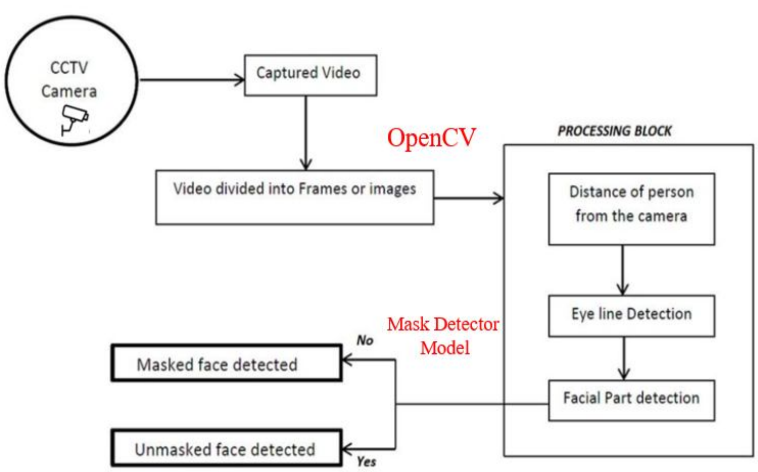

Fig. 5

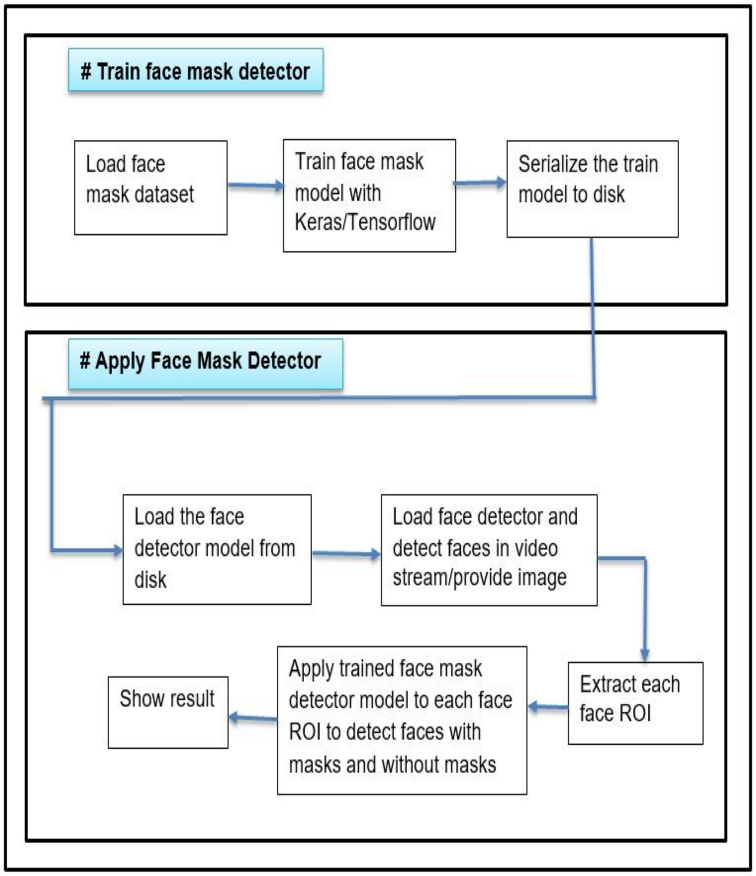

Fig. 6

B. Social Distancing Monitoring

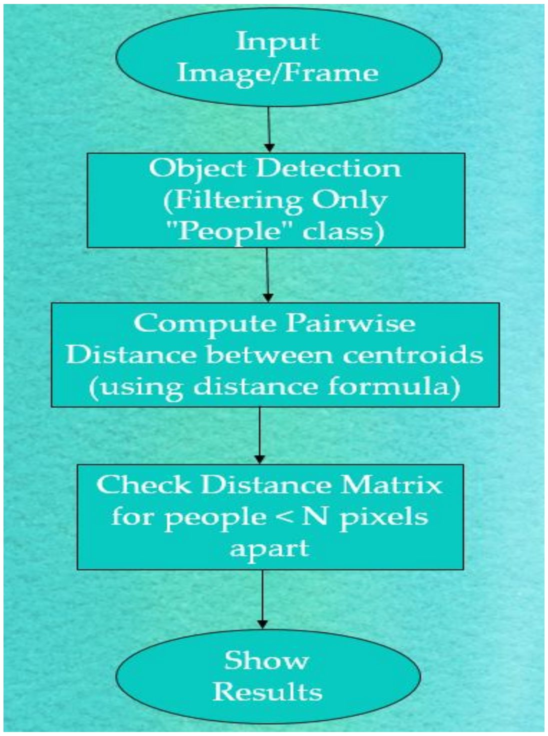

Fig. 7

V. CONCLUSION

The problem of face mask detection within side the wild had been explored in lots of present researches, and the corresponding face detectors had been examined on datasets of normal faces. On the available datasets, some face detectors have achieved extremely high performances and it seems to be somehow difficult to further improve them. However, the 'real wild' scenarios are much more challenging than expected for containing faces captured at unexpected resolution, illumination and occlusion. In particular, the detection of masked faces is a critical undertaking. In this developed a deep learning model for face mask detector, we have implemented mask detection using Python, Keras, and OpenCV. We have trained the model. Training the model was the first part of this project and testing using webcam was the second part. We proposed a Deep Neural Network-Based social distance detector model to detect and track static and dynamic people in public places in order to monitor social distancing metrics in COVID-19 era and beyond. In this system each individual is identified with the help of bounding boxes. The generated bounding boxes aid in identifying groups of people satisfying the closeness property computed with the help of pairwise approach. The number of violations are getting confirmed. The YOLO technology was evaluated using large and comprehensive datasets and proved a major development in terms of accuracy and speed compared to three state-of-the-art techniques. The extensive trials were conducted with popular object detection model YOLO v3, where YOLO v3 illustrated the efficient performance. This applications can be used to analyze for mask detection and social distancing in a public area and perform important moves to higher address the pandemic. Automating the task will lead in effective moves taken in short time hence equipping us better to address the situation. Applications are applicable in various environments using CCTV surveillance cameras. This two applications are very useful in many areas like Hot-spot areas, in offices, colleges, hospitals, airports, railway stations, public places like banks, ATM, Government offices, etc.

VI. ACKNOWLEDGMENT

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By doing this project we have received a lot of knowledge which can assist us in the near future and additionally this entire project helped us in doing a variety of Research and we came to know about so many new things we are really grateful for them.

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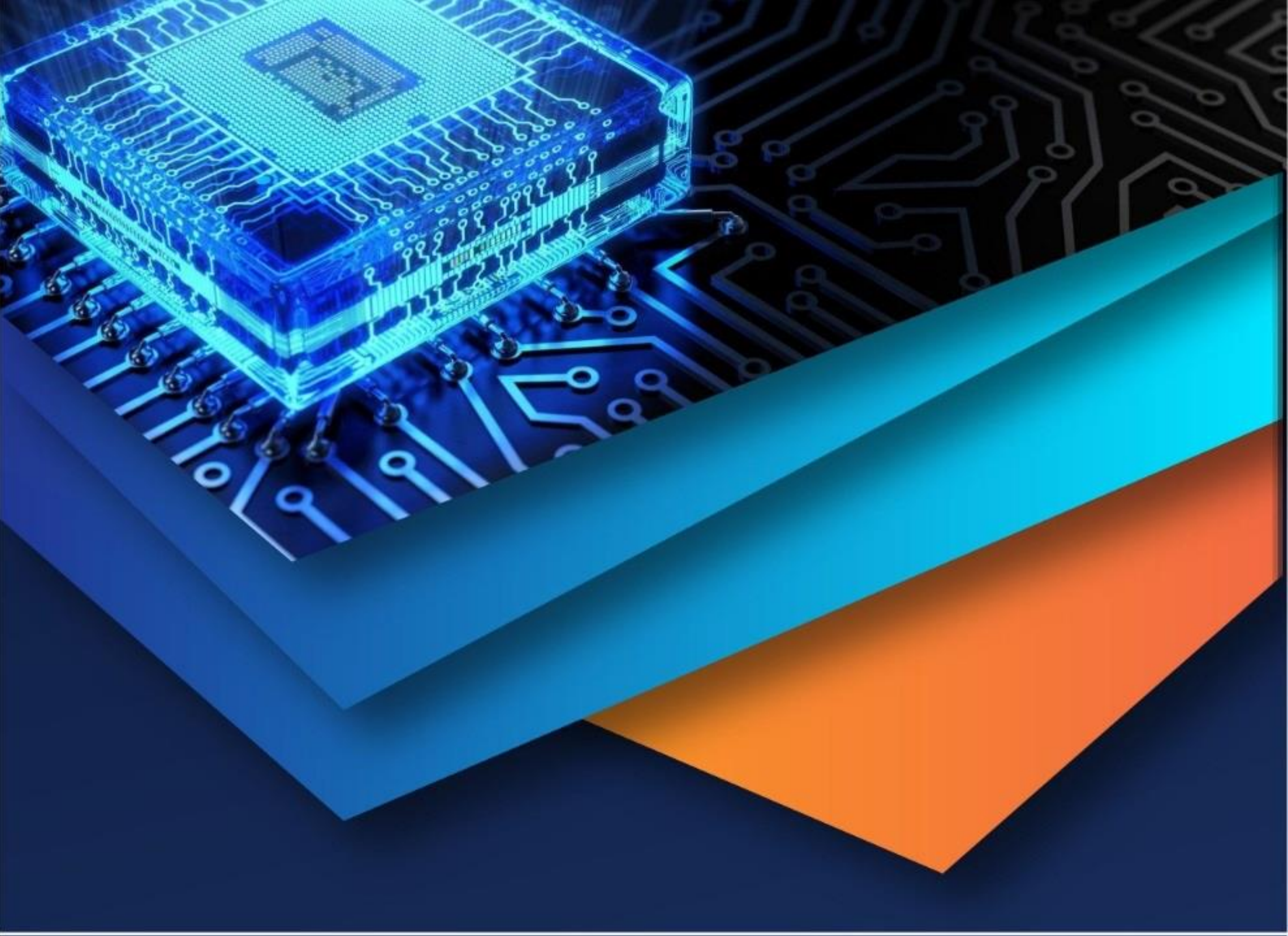

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