Grenze International Journal of Engineering and Technology, Jul Issue

Real Time Social Distancing and Mask Detection using Convolutional Neural Networks

M.P.Rajakumar[1], M.K.Kirubakaran[2], N. Manikandan[3] and M. Sameena Fathima[4]
[1, 3, 4]Department of Computer Science and Engineering, St. Joseph's College of Engineering, Chennai 600 119, Tamilnadu, India.
Email: rajranjhu@gmail.com
[2]Department of Information Technology, St. Joseph's Institute of Technology, Chennai 600 119

***Abstract*—The coronavirus disease officially named as COVID-19 pandemic has brought global crisis with its deadly spread to more than 180 countries. Though vaccines are introduced, it is essential for everyone to follow certain precautionary measures. This paper presents the methodology for social distancing and mask detection using computer vision and machine learning technique to reduce the spread of coronavirus pandemic. Real time inputs are provided to the system through computer webcam. Image processing steps such as video to frame conversion, preprocessing and feature extraction are performed. The model for mask detection is trained on a dataset that consists of images of people with and without masks collected from various sources using MobileNetV2 which is very efficient for object detection and segmentation. Faces are detected using Caffe model and trained model is used to detect the presence of mask along with its probability. The Euclidean distance between the faces is calculated and an alert is generated if the distance is below the threshold value. It is hoped that our study would be useful to mitigate the impact of this communicable disease for many countries in the world.**

***Index Terms*— Convolutional neural networks, Deep learning, Mask detection, OpenCV, Social distancing.**

I. INTRODUCTION

The novel coronavirus (nCoV) is a new pandemic which was not prevailing previously. When the pandemic emerged, the spread of the virus has left the public with anxiety. Coronaviruses (CoV) is a wide group of viruses which cause illness that range from cold to deadly infections like Middle East Respiratory Syndrome (MERS) and Severe Acute Respiratory Syndrome (SARS) [1].

To minimize the spread of Covid 19, many countries implemented lockdown where the citizens were enforced to stay at home during the critical situation. The public health bodies such as the Centers for Disease Control and Prevention (CDC) had to make it clear that the most effective way to slow down the spread of Covid-19 is by avoiding close contact with other people [2]. To prevent the spread of Covid 19, many precautionary measures are being taken. Among them are cleaning hands, maintaining social distance, covering the nose, eyes and mouth when you sneeze and wearing mask are important.

To flatten the curve on the Covid-19 pandemic, everyone should practice and maintain physical distancing and wearing mask . But unfortunately, people are not following the rules properly which is speeding the spread of the

Grenze ID: 01.GIJET.7.2.502_1

virus. Detecting the people who are not following the rules and informing them to the corresponding authorities can be the solution to bring down the spread of coronavirus. In Malaysia, the Ministry of Health Malaysia (MOHM) has recommended several disease prevention measures for workplaces, individuals, and families at home, schools, childcare centres, and senior living facilities [3]. These measures include implementing social distancing and decreasing social contacts in the workplace. One of the solutions to find out whether the person is wearing mask or not is to use a regionally automated face mask recognition to differentiate between people who wear masks and those who do not [4]

A smart city [5] means an urban area that consists of many IoT sensors to collect data. These collected data are then used to perform different operations across the city like monitoring traffic, utilities and many more. The growth of COVID-19 can be reduced by detecting the facial mask in a smart city network.

This paper aims at designing the system to find out whether a person is maintaining social distance, using a mask or not and informing the corresponding authority in a smart city network. From the video footage of CCTV, facial images are extracted and features from the images are learned by multiple hidden layers for mask detection and Euclidean distance is calculated to detect social distance between people.

II. RELATEDWORKS

This section deals with the work related to human detection and face mask detection using deep learning. For visual recognition, techniques using deep convolutional neural network (CNN) have been shown to achieve superior performance on many image recognition benchmarks [6]. A study on using facemask to restrict the growth of COVID-19 is introduced in [7]. The study specifies that the mask which perfectly fits can interrupt the spread of droplets while coughing or sneezing. Adapting the idea from the work [8], we present a computer vision technique for detecting people via a camera installed at the roadside or workspace. The camera field-of view covers the people walking in a specified area. The number of people in an image and video with bounding boxes can be detected via the CNN methods. The Euclidean distance between people is calculated and checked whether enough social distance is maintained by people in the video.

The study inspects whether people in a public place maintain social distancing [9]. The drone inspects whether people are maintaining social distance and sends the alert to nearby police station if there is any violation. A noticeable contribution of a smart city in controlling the spread of coronavirus in South Korea is explained by Won Sonn and Lee [10]. A time-space cartographer accelerated the contact tracking in the city including movement of patients, purchase history and cell phone usage. Real-time monitoring has been implemented on CCTV cameras in the hallways of residential buildings. [11] proposed a way to minimize the risk during COVID-19. The proposed model used the position of technology to track the infected people. Drones were used as medical personnel in order to provide sufficient services to the infected people.

III. IMPLEMENTATION

The following section will explain the modules involved in the implementation of social distance monitoring and mask detection. Figure 1 depicts the flow of the system to be created. In the initial step, video is captured using webcam. The video input is converted into a sequence of frames. Each frame is read in BGR colour space which involves converting it to RGB for mask detection and grayscale for social distance monitoring. The pre-processed frames are then sent for detection. Here, two types of detections take place-social distancing and mask detection. For mask detection, the dataset consists of images with and without masks for training the model. The model is then trained using MobileNetV2 algorithm and a plot for training loss and accuracy is obtained. The trained model is used to detect the presence of mask along with its probability level. For social distance monitoring, the faces are detected using Haar cascade classifier. Then the distance between the faces is calculated using Euclidean distance and compared with a predefined threshold value. If the distance is less than the given value, it generates an alert.

IV. SOCIAL DISTANCE MONITORING

This section explains the modules involved in monitoring social distance in real time.

A. Image Acquisition

Video is captured through webcam using openCV. It involves selecting four points in the perspective view which is taken as the ROI (Region of Interest) to monitor social distancing as the input frames are monocular (taken from a single camera).

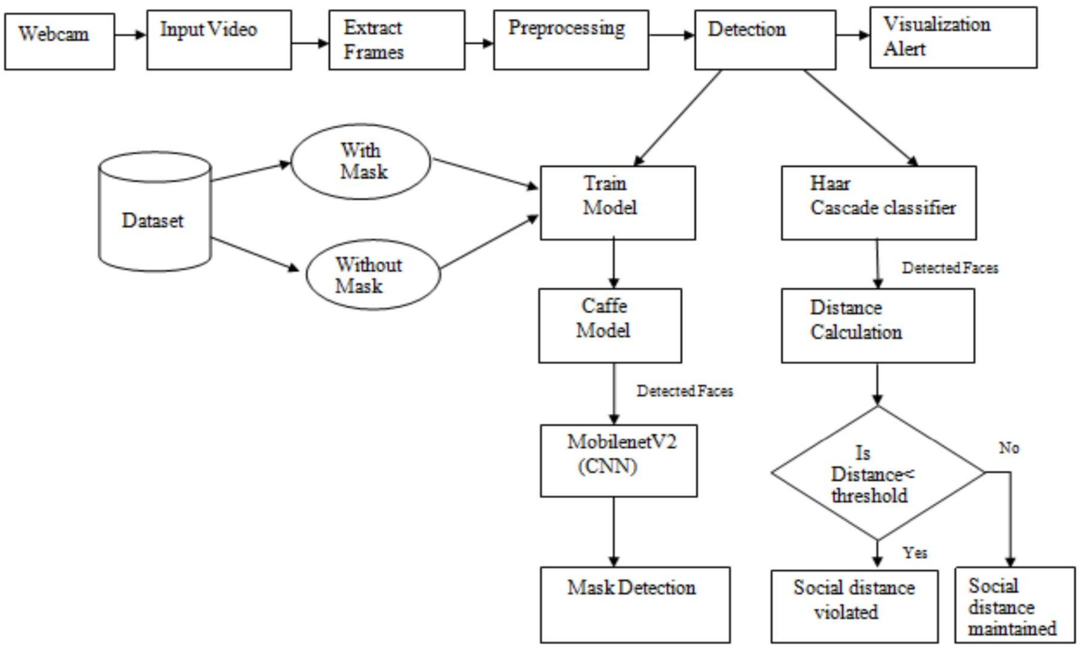

Figure 1. Steps in social distance monitoring

*B. P*reprocessing

The aim of pre-processing is an improvement of the image data in order to suppress unwilling distortions or enhance some important image features for further processing. Once video capturing starts, video to frame conversion happens. Frames are obtained one by one and converted from BGR to RGB color space, resized and sent for detection.

C. Detection Using Caffe Model

The third step is to detect persons and draw a bounding box around each person's face. To clean up the output bounding boxes, minimal post-processing such as non-max suppression (NMS) is applied to minimize the risk of over fitting. For the purpose of detecting faces, Caffe model is used. Initially, the algorithm needs a lot of positive images (images of faces) and negative images (images without faces) to train the classifier. Then we need to extract features from it.

D. Distance Calculation

Now the positions of bounding box for the face of each person in the frame is calculated. To estimate person location in frame, bottom center point of bounding box is taken as person location in frame. Given the position of two persons as (x1,y1) and (x2,y2), distance between them is calculated using the Euclidean distance formula,

$$\sqrt{(x2-x1)^2+(y2-y1)^2} \quad (1)$$

If the distance calculated is below a given threshold value, alert is generated to indicate that social distance is violated.

V. MASK DETECTION

Figure 2 explains the modules involved in mask detection in real time.

A. Data Collection and Pre-processing

The proposed system uses face images with both mask and without mask which are labeled and used for training the model. The data set is divided into training data set and testing data set. The images in the training data collection are classified into two categories: mask and no mask before the custom face mask image dataset is labeled.

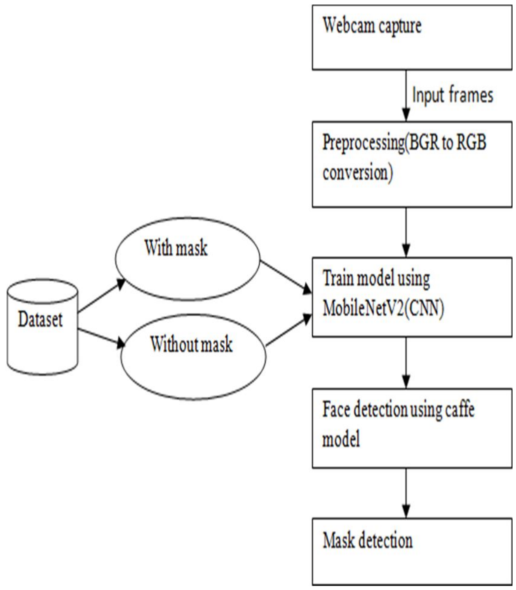

Figure 2. Steps in mask detection

One of the techniques of data preprocessing includes encoding categorical data into numerical type before feeding the data to an algorithm for further processing and yielding better results. In pre-processing steps, the image is converted from BGR to RGB color space, resized, converted to NumPy array format and the corresponding labels are added to the images in the dataset shown in Figure 3. Label Binaries which is a Scikit-learn class accepts the categorical data of with and without masks as input and returns NumPy array.

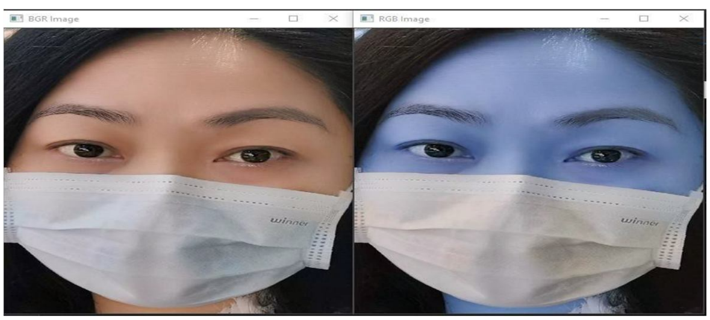

Figure 3. BGR to RGB conversion

B. Training the Model Using MobileNetV2

The custom data set is loaded into the project directory and the algorithm is trained on the basis of the labeled images. The model is then trained using MobileNetV2 (Convolutional Neural Networks) since it is lightweight and faster to train.

The choice of activation function in the hidden layer will control how well the network model learns the training dataset since they are a critical part of the design of a neural network and it has a large impact on the capability and performance of the neural network. Different activation functions may be used in different parts of the model. The activation layers used for training the model are Rectified Linear Unit and Softmax shown in Figure 4.

C. Detection Using Caffe Model and Trained Model

Once the model is trained with the custom data set and the pre-trained weights are given, the accuracy of the model on the test dataset is validated by showing the bounding box with the confidence score and name of the tag at the top of the box. Faces are detected using Caffe model and the trained model is used to detect the presence of mask. If the mask is not detected on the faces, the system generates a warning.

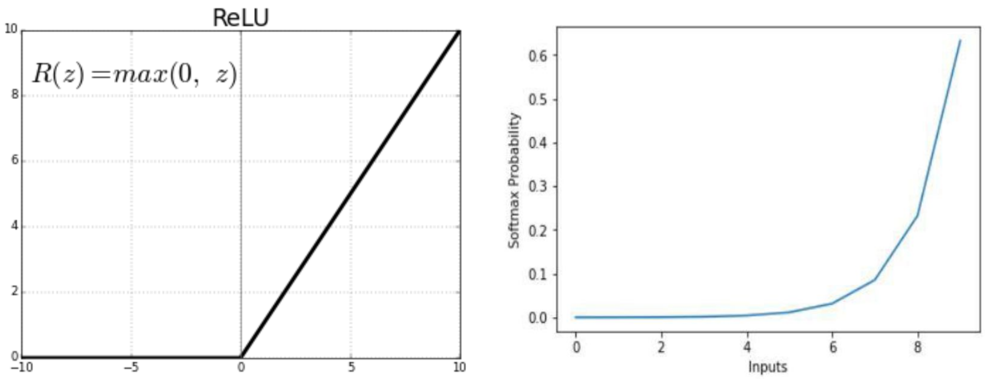

Figure 4. ReLU and Softmax activation function

VI. Web Application Development Using Flask

Once the social distance and mask detection are implemented successfully using openCV and python, they can be converted into a single web application using flask web framework which is a popular python web framework for developing web applications. Flask can be used because it is a lightweight framework and has the ability to scale up to complex applications. Moreover, it can also be easily deployed making it available to the end users.

VII. Result Analysis

The model for mask detection has been trained with 4035 images in which 3846 images are with mask and 1930 images are without mask. The dataset collected from sources like Kaggle. 80% of the dataset was used for training and 20% was used for testing for training the model. MobileNetV2 which is a Convolutional Neural Network architecture was used for training the model. The trained model was able to detect the presence and absence of mask along with the probability level of detection shown in Figure 5. For social distancing, distance between the bottom center points of the detected faces were taken as coordinates to calculate Euclidean distance between them. If the distance was found to be lesser than a given threshold value, alert was generated. Finally, a web application was created using flask web framework to create a UI for initiating the process of detection and also to have a good view of the live captured webcam video along with the visualization alerts generated.

```
[INFO] evaluating network...
              precision    recall  f1-score   support

   with_mask       0.99      0.99      0.99       384
without_mask       0.99      0.99      0.99       386

    accuracy                           0.99       770
   macro avg       0.99      0.99      0.99       770
weighted avg       0.99      0.99      0.99       770
```

Figure 5. Classification accuracy

VIII. Conclusion and Future Works

In this paper, we have discussed an approach that uses computer vision and deep learning techniques to prevent the spread of COVID-19 by maintaining a secure environment by ensuring that people wear masks and maintain social distancing. This approach helps in the automatic monitoring of social distancing and mask detection and generating alerts in case of any violation. We have used webcam to analyze face mask and social distancing and tested using python scripts which can be further developed for use in CCTV cameras for monitoring public places like markets, restaurants etc. Further improvement can be done by detecting both presence of mask and social distance maintenance simultaneously and including an additional feature to upload an image or a video to analyze and perform detections in it.

REFERENCES

[1] WHO EMRO | About COVID-19 | COVID-19 | Health topics, [online] Available: http://www.emro.who.int/health-topics/corona- virus/about-covid-19.html.

[2] Implementation of Mitigation Strategies for Communities with Local COVID-19 Transmission, [online] Available: https://www.cdc.gov/coronavirus/2019- ncov/downloads/community-mitigation-strategy.pdf.

[3] Ministry of Health Malaysia (MOHM) Official Portal.COVID-19 (Guidelines), [online] Available: https://www.moh.gov.my/index.php/pages/view/2019-ncov- wuhan-guidelines.

[4] M. S. Ejaz, M. R. Islam, M. Sifatullah and A. Sarker, "Implementation of Principal Component Analysis on Masked and Non-masked Face Recognition", 2019 1st International Conference on Advances in Science Engineering and Robotics Technology (ICASERT), pp. 1-5. M. S. Ejaz, M. R. Islam, M. Sifatullah and A. Sarker,

[5] L. Calavia, C. Baladrón, J. M. Aguiar, B. Carro and A . Sánchez-Esguevillas, "A Semantic Autonomous Video Surveillance System for Dense Camera Networks i n Smart Cities", Sensors, vol. 12, no. 8, pp. 10407-10429, Aug. 2012.

[6] A. Krizhevsky, I. Sutskever and G.E. Hinton, "Imagenet classification with deep convolutional neural networks", Advances in neural Information processing systems, pp. 1097-1105, 2012

[7] L. P. Garcia, "Uso de máscara facial para limitar a transmissão da COVID-19", Epidemiol. e Serv. saude Rev. do Sist. Unico Saude do Bras. vol. 29, no. 2, pp. e2020023, 2020.

[8] Landing AI Creates an AI Tool to Help Customers Monitor Social Distancing in the Workplace, May 2020, [online] Available: https://landing.ai/landing-ai-creates-an-ai-tool-to- help-customers-monitor-social-distancing-in-the-workplace/.

[9] Lalitha Ramadass, Sushanth Arunachalam, Sagayasree," Applying deep learning algorithm to maintain social distance in public place through drone technology", International Journal of Pervasive Computing and Communications, Vol. 16 No. 3, pp. 223-234.

[10] J. Won Sonn and J. K. Lee, "The smart city as time- space cartographer in COVID-19 control: the South Korean strategy and democratic control of surveillance technology", Eurasian Geogr. Econ, pp. 1-11, May. 2020.

[11] R. Jaiswal, A. Agarwal and R. NEGI, "Smart Solution for Reducing the COVID-19 Risk using Smart City Technology", IET Smart Cities, vol. 2, pp. 82-88, 2020.