



# Implementation of smart social distancing for COVID-19 based on deep learning algorithm

Izaz Ul Haq<sup>1</sup> · Xianjun Du<sup>1</sup> · Haseeb Jan<sup>2</sup>

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## Abstract

The first step to reducing the effect of viral disease is to prevent the spread which could be achieved by implementing social distancing (reducing the number of close physical interactions between peoples). Almost every viral disease whose means of communication is air, and enters through mouth or nose, definitely will affect our vocal organs which cause changes in features of our voice and could be traceable using feature analysis of voice using deep learning. The detection of an affected person using deep neural networks and tracking him would help us in the implementation of the social distancing rule in an area where it is needed. The aim of this paper is to study different solutions which help in enabling, encouraging, and even enforcing social distancing. In this paper, we implemented and analyzed scenarios on the basis of COVID-19 patient detection using cough and tracking him using smart cameras, or emerging wireless technologies with deep learning techniques for prediction and preventing the spread of disease. Thus these techniques are easy to be implemented in the initial stage of any pandemic as well and will help us in the implementation of smart social distancing (apply whenever needed).

**Keywords** Deep learning · Covid-19 · Pandemic · Social distancing · Audio signal

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Izaz Ul Haq, Xianjun Du and Haseeb Jan contributed equally to this work.

✉ Xianjun Du  
xdu@lut.edu.cn

Izaz Ul Haq  
izaz.lut@gmail.com

Haseeb Jan  
engrhaseebjan@gmail.com

<sup>1</sup> College of Electrical and Information Engineering, Lanzhou University of Technology, Lanzhou 730050, China

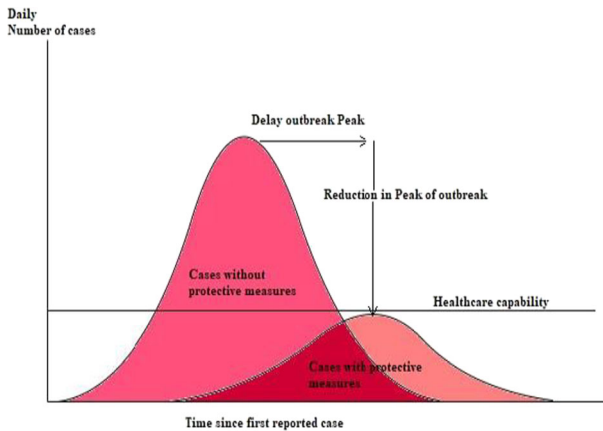
<sup>2</sup> University of Engineering and Technology, Peshawar, Pakistan

## 1 Introduction

With the outbreak of an unknown disease in late 2019 worldwide was one of the biggest challenges of 21st century for today modern world. The disease was initially unknown but the experts identified its symptoms been identical to flu and Corona virus influenza. After the laboratory examination and testing by real time polymerase chain reaction (PCR), this latent infection was named COVID-19 on the recommendation of World Health Organization (WHO). Covid-19 causes desperate consequences in the global health sector. This disease spread quickly across international borders, having a devastating impact on the global population's health, economics, and welfare. At the time of writing this paper according to [worldometer.info](http://worldometer.info) statistics around twenty-seven hundred million infected patients with five million casualties have been recorded. Besides, it is responsible for enormous losses to the local as well as the global economy. The sharp change in the rate of trend in the world's extreme poverty from -9.7% to 25% [7], the global economic fall of around 6% to 8% at the first wave [17], more than a million people lost jobs in Canada [40] and the rate of becoming potentially jobless in the USA is more than 32% [33] are all the effects of a pandemic on the economy. As in recovering from the first wave, the world saw the worse in the second wave and third wave. Currently, as the people start relaxing and expecting recoveries after more than one intensive year of lockdown, causalities, and joblessness, the third wave will be the worst. In such a critical situation, there is a need for a solution that could help in reducing the negative impacts of the pandemic and safe recovery of people [15].

The spread  $R_0$  (which is also known as effective reproductive number) is used for finding the rate of spread of any infection in a population. The values vary from 0 to  $n$ , where 0 represents no spread of disease by any mean, and  $n$  means a numbers of  $n$  people were or will be infected by a single source. As per reported cases, the value of  $R_0$  for Covid-19 is around 6 worldwide which is significantly higher than flu ( $R_0$  of 1.3) [51]. To overcome the effects of the disease the spread value  $R_0$  needs to be reduced to less than 1. Therefore, the intention would be to keep the spread below the threshold to reduce the negative impact. Analyzing the speed of vaccination with respect to the spread rate it turns out that the only compelling and non-pharmaceutical strategy is social distancing [36]. It is the reduction of physical interaction between peoples (having reasonable distance between peoples, avoiding mass gathering, closing public places, shutting educational institutes [46]). As the spread of virus mainly depends on the interaction among people, social distancing can fundamentally reduce the spread of disease and buy us more time to vaccinate all the people and come back to a normal routine. Figure 1 shows the impact of implementation of an appropriate social distancing mechanism on the rate of spread of the disease. Through this technique, people keep the spread always below the threshold of the public healthcare capacity and failing to implement it in early stages may lead to a shortage of pharmaceutical supplies in many regions. More importantly, reducing the rate of spread of the disease means less infection, fewer deaths, and even less adverse effect on other sectors of life [26].

From the above discussion, it is clear that the only non-pharmaceutical compelling solution for reducing the impact of the pandemic is social distancing. However, it is a difficult task even for the authorities to implement such strict rules. By nature, human beings are social animals. Forcing them to stay at home, having some distance, closing public places is far from trivial. There will always be breaches. Figure 1 also shows the effects of failing to implement such rules [26]. Moreover, complete lock-downs and flat social distancing have also negative



**Fig. 1** The Effects of COVID-19 with and without social distancing. As social distancing reduces and delayed the peak

consequences i.e people need to go out for finding food, healthcare, and essential work (to recover from the effects of the first two waves).

Considering both extremes, there is a need for a system that would enable to implementation of the so-called smart social distancing. Its essence is to apply the social distancing or lock-down rules whenever and wherever needed. Technology plays a key role in facilitating smart social distancing measures whereas the main component would be deep learning-based artificial intelligence for making complex decisions. These include detection of an infected person, predicting its location, alerting others if the person comes in their vicinity, and informing the authority if there is a violation of social distancing rules. The only reason is its effective performance in highly adoptive complex tasks as well as its evolutionary nature according to the changing environment. By fighting this pandemic, the heroic role of front-line health workers, social and technical organization help a lot to reduce the risk. However, artificial intelligence (AI) and deep learning (DL) also play their vital role to combat this virus in many ways. DL outperform all the conventional models in different fields and got attention of many researchers after defeating the world champion at GO game which is an abstract strategic board game for two players in which the aim is to surround more territory than the opponent, a famous game in China [53], commanding an artificial robotic hand to solve the Rubik cube [41], outperforming in fault detection and diagnosis [66], spread of Covid-19 forecasting, electric load forecasting, and natural language processing (NLP). This study focusses on social distancing framework using deep learning architecture. The proposed framework is being utilized as a preventative measurement tool to decrease close human contact and restrict the transmission of the COVID-19 virus.

If it comes to current publications, in the paper [3], authors analyzed a variety of AI and DL approaches to control pandemics and reduce the effects of COVID-19. The authors did a literature survey of different approaches ranging from natural language processing, computer vision. In natural language processing, they collected techniques for literature mining to find the answer of queries directly from literature's intelligently, misinformation and controversial statement and tweet detection, as well as public sentimental analysis. While in the computer vision the researchers' put techniques for COVID-19 detection, and diagnosis from X-Rays images where the maximum result was achieved by ConVIRT model by the authors of 92.4%

by COVIDx dataset, as well they put the idea of vision-based robotics for disinfection, logistics, and deliveries [68].

As there is work going on every side, there is a need to proceed with that great work with the same potential. Therefore, the main motivation behind this research is to keep the daily life routine unchanged and at the same time reduce the chances of getting infected by implementing social distancing measures effectively. To this end, smart social distancing has been introduced, which will reduce the negative effect of the current pandemic. Smart social distancing is the technique used for the implementation of social distancing measures whenever and wherever it is needed. The reason for such research is the negative impact of any pandemic on our daily routine (which we observed in the past year in the form of COVID-19 and discussed in the first section of the research).

The rest of the paper is organized as follows. Section 2 presents state-of-the-art algorithms and technologies used for person detection, diseased or infected person classification, and distance measuring among peoples through imagery data. Section 3 provides detailed information on how the problem has been studied. Section 4 presents the findings through our experiments. As the research only analyzes a computer vision-based social distancing (small area), Section 5 reviewed other approaches that could be used in combination with infection person detection in monitoring, and preventing spread on different ranges and inapplicable in different scenarios. Finally, the paper is concluded in Section 6.

## 2 Literature review

In the course of the past period, the world saw artificial intelligence (AI) in various fields such as medical to entertainment media [59]. The ability to “learn” useful insight and address helpful findings from data in decision-making and predictions are the most astonishing characteristic of deep learning. These distinctive features of deep learning led us to more intelligent automation, decrease operational costs, and have a great evolving capability.

On the other hand, computer vision an important field of artificial intelligence enable the computer to evaluate visual data. The present progress of AI such as using convolution-based neural networks (CNN) typically in the field of deep learning makes it easy for a computer to analyze digital data, objects identification, or prediction and classify it with a great accuracy [5]. In the field of diagnosis, a hybrid model i-e combination of two or more model to analyze the signal from multiple directions perform well as comparison with simple model like CNN, gcForest, and ANN [66]. Such capabilities of computer vision change simple camera-based devices into intelligent devices. Artificial intelligence and its subset deep learning algorithms also play a significant role in social distancing, mostly in the current pandemic, with abundant practical applications. Computer vision-enabled devices open a door to using such technologies in the implementation of social distancing measures (by detecting, recognizing, and identifying whether people follow such rules or not.)

Specifically in the field of medical deep learning has confirmed itself by providing accurate results in prediction and detection. The developers had published quality work in developing a product for medical tests that will help physicians in analyzing data. Where authors [9] review multiple CNN models used in various fields of testing, diagnosis, and analysis including X-Rays, CT scans, MRI, etc. The accuracy report of almost every model under review was more

than 90%. The present study, [6] illustrate almost all existing techniques for corona detection till the time of publication. Deep learning might be useful in the diagnosis of COVID-19 patients. In the paper, [38] fine-tuned ImageNet model trained using twice transfer learning techniques on NIH ChestX-ray14 dataset as an intermediate set. Accuracy of 100% is obtained by the test dataset. While in [20], researchers obtained an accuracy of 99% with 98% area under the curve by analyzing the Covid-net model.

The top listed model by [37] are shown in Table 1 which listed some of the recent publications of DL based COVID-19 pandemics solutions. The authors used different data sets and different DL models and achieved prominent results for detection and diagnosis of COVID-19 as conventional PCR test method is considered one of the complex, time consuming and costly. The table listed all publication, its purpose, dataset used, AI model used and the accuracy result achieved. The results are promising but the process need a medical devices like CT-scanner or X-Ray scanner and proper deployment.

## 2.1 Disease detection from cough

The work done in testing and finding COVID-19 has been discussed. For every medical analysis or testing, some sort of medical equipment and technique is required such as (X-Rays, CT, MRI, and ECG, etc.). For which the patient has to buy a particular device or wait for such a result which took a lot of time, therefore, for real-time implementation, a faster system could be implemented in every sector.

In a current study for detection purposes cough was used, as authors in the [52] proposed a technique that cough sound could be used for COVID-19 detection using a smart device such as an Android smartphone. On the second side, we have a publicly available dataset named Coswara [12] and Virufy [4]. Using these datasets, authors in [25] got an area under the curve (AUC) of 72%. Which is suitable for research work.

**Table 1** COVID Diagnosis Results and References

Reference	Aim	Data	Model	Results (Accuracy)
Loey, et al., [30] (Egypt)	Diagnosis (classification)	X-Rays	GoogLeNet	100%
Ko et al., [60] (Korea)	Diagnosis (differentiate)	CT-Images	ResNet-50	99.87%
Ardakani, et al., [68] (Iran)	Detection	CT-Images	GoogLeNet and SqueezeNet	99.51%
Toga, et al., [62] (Turkey)	Diagnosis	X-Rays	SqueezeNet and MobileNet	99.27%
Ucar and Korkmaz, [39] (Turkey)	Classification (diagnosis)	X-Rays	Deep Bayes and SqueezeNet	98.3%
Mart Inez, et al., [8] (columbia)	Detection	X-Rays	NASNet(CNN)	97%
Brunese, et al., [22] (Italy)	Detection and diagnosis	X-Rays	VGG-16	97%
Li, et al., [63] (Greece)	Automatic diagnosis	X-Rays	MobileNetV2	96.78%
Vaid, et al., [47] (Canada)	Detection	X-Rays	VGG-19	96.3%
Rahimzadeh and Attar, [24] (Iran)	Diagnosis	X-Rays	Xception and ResNet50V2	95.5%

In the study [42], the researchers use different machine learning and deep learning models for covid patient detection through cough signals. The Mel-Spectrogram of the signal was used for deep learning models while Mel-Frequency Cepstral Coefficients (MFCCs) along with principal component analysis (PCA) were used for machine learning algorithms. The results which the paper claims on the technique called deep learning-based transfer learning for binary classification were 92.85% of accuracy. In the research [43], the authors claim the maximum accuracy of 93% with Resnet-50 architecture using breathing signal and 87% through cough signal. The technique was similar to that of the previous research that is the extraction of MFCCs features. While in the publication [32], the authors use breath with audio cough signal for classification. They crowd-sourced the data, trained, and tested the model on 355 samples. The technique has segmented the audio into different coughs, and used the MFCCs of each segment to classify it separately, and used SVM to categorize it into two classes (covid and non-covid). On the cross K-fold validation technique the accuracy of the model was 84.6%. In the paper, [35] the authors used three Resnet-50 models (which is computationally expensive) on MFCCs to classify the signal as cough or not and corona or not and got the AUC score of 95%. They didn't mention the overall accuracy but the false positive was 16.8%. as shown in Table 2.

## 2.2 Social distancing

As human is developing in a social environment but in the current pandemic, government recommend social distancing and avoid public gathering while a lot of people still do not properly follow it due to which R0 of disease is not under control [44]. In such conditions, the government needs someone or something to detect rule violations. For such purpose, a popular technology in human detection is computer vision which could help us in real-time detection of crowds through CCTV. An automatic counter (counting the number of people) alerts the authorities to take appropriate action when the number of people on a spot exceeds a certain threshold or the place becomes overcrowded.

In object detection algorithms or models, we have had two main approaches i-e region-based and unified-based algorithms. The region-based technique involves two steps, i) propose a couple of regions in the image and ii) look into that region for human detection [21]. The approach is RCNN which is way slower because it needs to run the process equal to the number of regions proposed by selective region technique [50]. The Fast-RCNN runs the process fast by making it possible to run the model on all-region at once [50], also Faster-RCNN makes it faster by changing the technique from selective search to regional proposal network (RPN) [23].

**Table 2** COVID Diagnosis Results and References

Reference	Aim	Data	Model	Results
[42]	Binary Classification (detection)	cough signal	deep learning based transfer learning	92.85%
[43]	Binary Classification (detection)	breath signal	Resnet-50	93%
[43]	Binary Classification (detection)	cough signal	Resnet-50	87%
[32]	Binary Classification (detection)	breath and cough signal	SVM	84.6%
[35]	Binary Classification (detection)	breath and cough signal	hybrid models	95%

The Faster-RCNN has great precision in detection and recognition [49]. The only problem is the need for high computational cost which is not favorable for devices like cameras and smartphones. In such circumstances, a faster solution in human detection is a unified-based approach which is less complex as well. This approach creates a large number of anchors in the image (mapping of pixels in bounding box grid) and then uses the probability of object in each anchor or box and removes overlapped bounding boxes by using high probability anchors to detect humans or objects in real-time. The specific technique used in a unified approach is You Only Look Once (YOLO) which is used in real-time detection and help in the detection of small objects faster with great accuracy rate [34]. In [1], authors proposed another faster solution known as Single Shot Multibook Detector (SSD). This method first uses a CNN to calculate a feature map from an image further identify or detect objects in the image from that feature map.

As if it comes to social distancing implementation on top of object detection models. Customization in object detection model named Faster-RCNN would be found in research [19]. The researchers customize the models for predictions of social distancing on top of object detection. The work achieves 93% of accuracy. The issue with this technique is that Faster-RCNN is computationally expensive with respect to other detection approaches such as SSD and YOLOv5. The second issue is that each camera needs retraining due to physical variables in environments like camera elevation, heights, and irregularity of floor.

YOLO or SSD methods could be used for human detection by using surveillance cameras installed in public areas. While the automatic counters count the number of people in the real-time image stream. Hence, it enables the possibility of finding the persons who are not following the rules of social distancing. Thus, vulnerable to disease and need extra monitoring.

### 3 Methodology

The proposed methodology is based on analyzing cough audio signals through a model which has been trained using deep learning. Specifically, convolution neural networks have been used because we were interested in the nature of the signal rather than its time-dependent properties. The trained model was embedded in a server application. A mobile application that can record cough audio signals is connected to the server. This application is installed on mobile phones or devices lying at the entrance of an organization or a marketplace.

A social distancing algorithm was implemented as a component of the server application. Therefore, whenever the server detects an infected person from the cough signal, it alerts the public in the vicinity and implements the social distancing rules. Figure 2 shows the high-level flow of the smart social distancing system.

Smart social distancing has been divided into three components. Firstly, we created and trained a cough classifier model. Secondly, we developed a server-side component to implement social distancing rules. Finally, we integrated these two components into a unified system with a mobile application and a server component to analyze surveillance camera streams in real-time.

#### 3.1 Mathematical modeling

As shown in Fig. 2, the model has two parts disease detection through deep learning model as shown in Fig. 3 and social rule violation detection shown in Fig. 5.

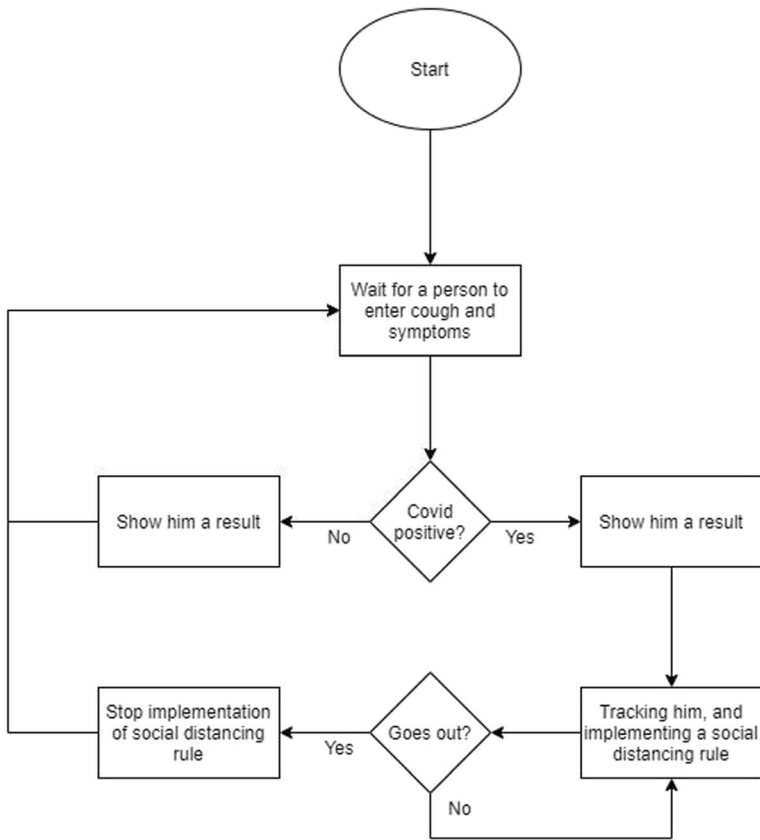


Fig. 2 High-level flow of the smart social distancing system

### 3.2 Data processing

The data is as audio signal, where the feature extraction that is Mel-frequency cepstrum coefficients were done using mechanism discussed in Fig. 4. Where the analog signal was converted into a digital signal using a mobile mic and A/D converter with a frequency of

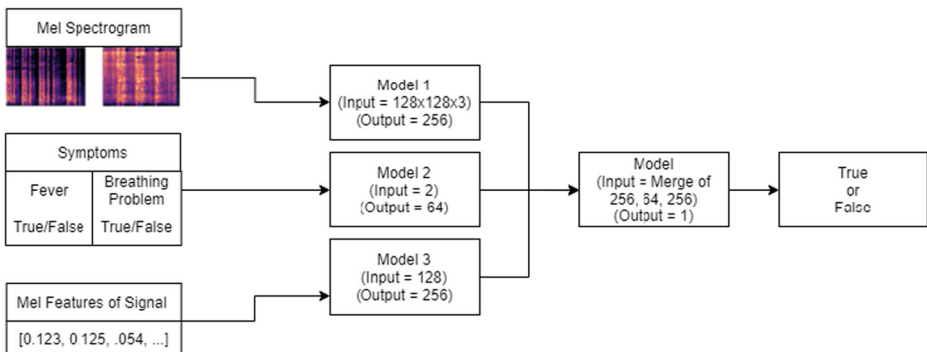


Fig. 3 Model Overview



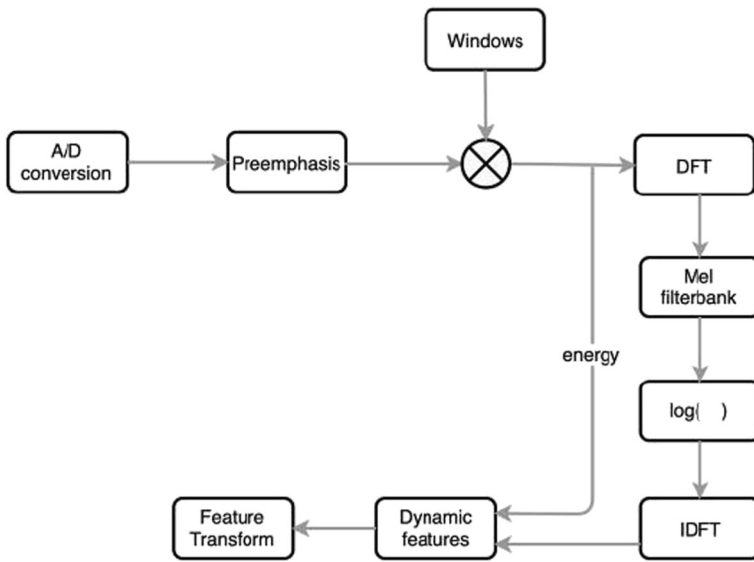


Fig. 4 Algorithm for MFCC

44.1 kHz. Then the first-order high pass filter was used for emphasizing high-frequency elements in a signal. As for vowel sounds, the high-frequency area of a signal has a high effect on a performance of a model. Then windowed the signal by using 25 ms of window size. The reason is that on average person speaks 3 words per second with 4 phones and every phone has 3 states, the average number of states per second is 38. The time taken by a single state is 28 ms approximately to 25 ms. For each window, the 39 features were calculated. Then every window was converted into the frequency domain using DFT (Discrete Fourier Transform) with Eq. (1).

$$X_k = \sum_{n=0}^{N-1} X_n \cdot e^{-\frac{j2\pi}{N}kn} \tag{1}$$

The ear of humans perceives sound differently from a machine. The human ear is more sensitive to low frequencies than higher frequencies. The machine perceiving sound would be converted to human (expert) perceiving by using the sound into log scale is done by the mel-filter bank using Eq. (2). The next step is converting the sound again to the time domain. Which provides the sound in such a format how the human ear reacts to it. It is also known as cepstrum. The inverse DFT is used here as shown in Eq. (3). Take the first selected number of features and discard the rest. The lower frequencies has more effect on performance of model than higher frequencies, it would be found near the origin of the spectrum.

$$mel(f) = 1127 \ln \left( 1 + \frac{f}{700} \right) \tag{2}$$

$$X_n = \frac{1}{N} \sum_{k=0}^{N-1} X_k \cdot cepstrum^{-\frac{j2\pi}{N}kn} \tag{3}$$

The second necessary feature which was extracted from the signal is Mel spectrogram calculation. Which represents the signal in a visual format in such a way that it represents the cepstrum signal, not the one how the machine recorded using the Eq. (4). The short term Fourier transform (STFT) records the phase and magnitude of frequency at a short interval of time by using Eq. (5). The square of STFT represents the energy or power of a signal.

$$\text{spectrogram}(t, w) = |\text{STFT}(t, w)|^2 \quad (4)$$

$$\text{STFT}(t, w) = \sum_{n=-\infty}^{\infty} x(n)w(n-t)e^{-i\omega n} \quad (5)$$

This signal represents the audio cough in such a way that how medical experts use it for diagnosis. Hence, the only reason for extracting these features was to mimic the medical expert (physician).

### 3.2.1 Deep learning model

The special design of deep learning models was used as shown in Fig. 3. A hybrid CNN and ANN model which have convolution, max-pooling, dropout, flatten, and dense layers. The convolution layer is a special layer in the deep learning model that uses filters for feature extraction from data as shown in Eq. (6). As all the features are not important for the overall results, max-pooling is used for the conception of removing the unnecessary features. The flatten layer was used after CNN to transform the higher-order array into a single-order array. In the end, the dense layer as shown in Eq. (7) was used. The input was multiplied with the weights and added bias to find the sigmoid and forward the results to the next layer. For single-dimensional inputs like symptoms and MFCCs features, the dense layers were used with the dropout layer. Dropout layer is using a probability for activating and deactivating the neurons in different iterations to avoid biasing toward this branch.

$$(f * g)(t) = \sum_{t=-\infty}^{\infty} f(t) g(t-T) \quad (6)$$

$$\begin{aligned} h &= W \times x + b \\ H &= \frac{1}{1 + e^{-h}} \\ y &= w \times h + b \\ Y &= \frac{1}{1 + e^{-y}} \end{aligned} \quad (7)$$

### 3.3 Model training on cough data

As the first part of the proposed methodology for the implementation of smart social distancing is creating, training, and implementing the model for Covid-19 detection through a cough. In the existing literature for Covid-19 patient detection through cough signal, the researchers have used MFCCs, Spectrogram, and Mel-Spectrogram but neither explored a combination of these in a single model. Moreover, in most of the publicly available datasets, namely Coswara [12] and Virufy [4] include the symptoms of the patients, however, no researcher used those. The common insight from those publications was that convolution neural networks (CNNs)

perform well in the detection of Covid-19 disease with respect to other models. Therefore, there was room for using a custom deep learning model which has CNN and artificial neural network (ANN) branches for classifying using the combination of inputs from the list that is Mel-Spectrograms (through CNN branch), MFCCs, and symptoms (through ANN).

The datasets for training, validation, and testing were from Coswara [12] and Virufy [4]. There were 2854 samples in the dataset of which 527 were corona patients. The model creation was based on the important insight that features of the signal are more important than its temporal parameters. In the pre-processing, the frequency-based features were extracted using Mel-Frequency Cepstral Coefficients with a Mel-Spectrogram. The multi-input custom model was created. The three inputs were Mel-spectrogram of cough signal of size 128x128x3, Mel-Frequency Cepstral Coefficients (MFCCs) features of signals of size 120, and a symptom branch of size 2 (fewer/muscle-pain, and respiratory-problem). As shown in Fig. 3, the dropout layers in the models were added to those branches where the input dimension was less than other branches to avoid output biasing toward that branch.

The technique for training the models was twice transfer-learning for training. In this technique, the model was trained on a cough dataset obtained from Kaggle [27] to classify cough and not-cough. The three inputs were the Mel-spectrogram, MFCCs features of an audio signal, and randomly selected binary numbers in symptom-based inputs. For cough-based classifiers the need for symptoms is irrelevant. After training, the model was retrained on the corona cough dataset name Coswara [12] and Virufy [4]. The inputs were fed in the same sequence as to how it was to the cough classifier, however, in this case, there was a need for symptoms and they were also present in the dataset. In general, two different models were created and the same process was repeated. In the first model, the symptoms were there but for evaluation (i-e finding biasing of the model toward it) it was excluded from the second model.

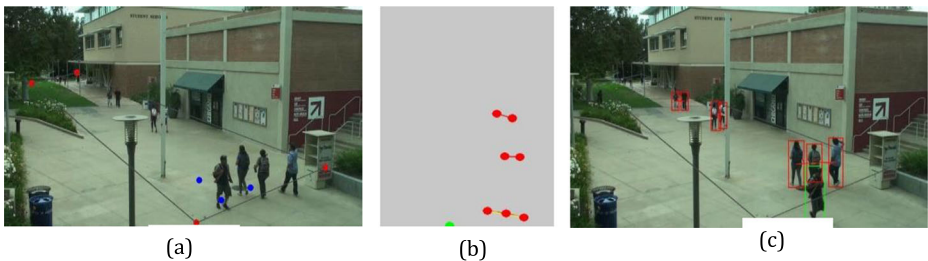
### 3.4 Social distancing through computer vision

For this part, the technique-based computer vision was used to monitor social distancing. More specifically, to check whether individuals are two meters apart from each other. The bird-eye-view transformation algorithm was applied for this purpose. The algorithm needs an area-of-interest which should be a rectangle in reality but could be of any four-sided closed surface in image or video, based on the angle of elevation of cameras. The area-of-interest in an image would be transformed in such a way that the array of pixels per area is similar or equal to as if the camera had been installed above that area. Since every pixel covers the same amount of area, therefore, counting the pixels would allow computing the distance among individuals.

The setup is simple. At the beginning of the server application, the admin needs to configure it. The configuration requires four points for area-of-interest (as mentioned it should be a rectangle in reality), and the 2-m distance horizontal and vertical in that area-of-interest as shown in Fig. 5a. The bird-eye transformation of the same scene was shown in Fig. 5b, whereas Fig. 5c shows the applied social distancing rule in real-time.

### 3.5 Integrating the two components

The final step is to integrate both components into a client-server architecture based real-time distributed application. The system was installed at the entrance of our lab. Every person had to cough and enter the two specified symptoms mentioned in the model training section. This data was sent to the server. The server would analyze the data and send the results back to the



**Fig. 5** Social Distancing (a) Initial Setup, (b) Bird-Eye View, and (c) Real View

client. If the person is corona positive then the server would alert the people through an alarm and start monitoring the social distancing rule. Otherwise, nothing would happen and the server would continue to wait for the incoming request(s).

## 4 Results and discussions

The proposed methodology for the implementation of effective social distancing was based on multiple sub-systems and their collaboration. The results of each sub-system will be discussed separately. First, the performance of the classifier model (custom CNN model and corona detection through it) will be presented. Next, the performance of the social distancing algorithm, detection of a person, and measuring the distances between them, will be discussed.

The dataset contains 2854 samples of which 527 samples were of corona-positive subjects. This dataset was divided equally into 70%, 15%, and 15% of training, validation, and testing, respectively. The model exhibited an accuracy of 97.28% on test data while 97.58% on validation data. The classification scores on the test dataset which were not used in the training step are shown in Table 3. It shows more than 95% scores in all categories i-e precision, recall, and F score. The confusion matrix of the test data shows that the accuracy of true value detection is higher than that of false detection (with having less than 10% of false values and more than 90% of true values as shown in Fig. 6a). The AUC is shown in Fig. 6b and according to the graph, the classification is almost perfect. The overall accuracy is higher than that of the previously published results mention in the literature review i-e 92.8% in the publication [42], 93% in another research [43], 84.6% claimed by authors using the dataset of 355 samples [32], and the false positive is also in the range of 10% which is less than 15.8% claimed by [35].

The sub-system for social distancing involves two components, namely human detection and calculating the distance among them. For human detection, the retrained YOLOv5-nano was used and got results of intersection over union (IoU) of 0.3, with class confidence of 0.99. For distance calculation, the bird-eye view technique was used. It converts a non-rectangular area into the rectangular region (seen like the camera is mounted exactly above the area of interest). The accuracy deeply depended on the angle of elevation and the region that comes beneath the camera. The greater the angle of elevation the better the results would be. Moreover, training of a person detection model on the data obtained on that elevation is a crucial factor. The resulting snapshot is shown in Fig. 5 which shows that configured snapshot for a social distancing system in which the four red points would be for transformation while the three blue points show the minimum allowed distance in social distancing (i-e 2meter) as shown in Fig. 5a, on that configuration the predicted objects would be seen in bird-eye view as

**Table 3** Classification Matrix

	Precision	Recall	F1-score	support
Covid Negative	0.98	0.99	0.99	309
Covid Positive	0.97	0.91	0.94	75
Accuracy			0.98	384
Macro Average	0.97	0.95	0.96	384
Weighted Average	0.98	0.98	0.98	384

green and red dots mean following and not following social distancing rules as shown in Fig. 5b, and the real view on the basis that results are shown in Fig. 5c which have green and red colors bounding boxes obtained from the bird-eye-view stream of the video.

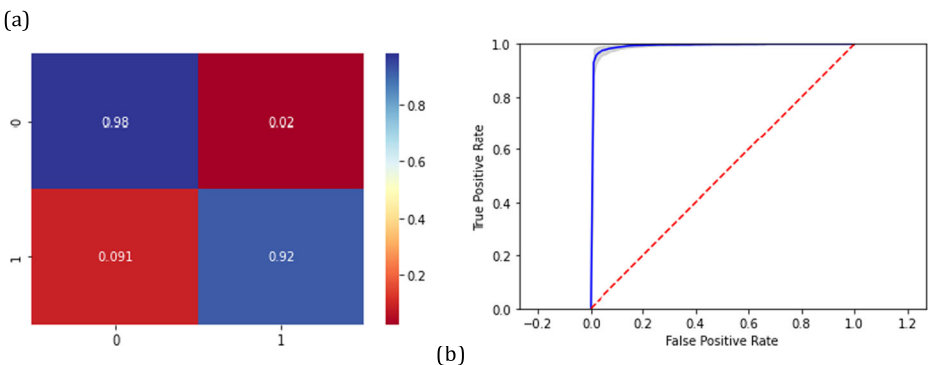
As for the diagnosis from the cough signal the accuracy is around 97% means that implementing the mode of three-time check will never miss the infected person. The data also could be used for real time location monitoring and statistical analysis of infected person flows. As well the test is instantaneous could be used for pre medical testing for suggestions and recommendations for what to analyze.

The nano version of YOLOv5 is light weighted (i-e 3.4 MB of weight size) and way intelligent that it could detect a person with good accuracy. Due to being a light-weighted social distancing detector, the algorithm was implemented on NanoJetson which gave 40FPS of video processing speed. Therefore, the idea could be easily implementable using edge devices with cameras and mobile. As the server and social distancing rule, both could be implementable on a single edge device.

The limitation lies in the object detection algorithm. As every object detection algorithm has the issue of occlusion. Besides occlusion, the angle of elevation performs a major role in bird-eye-view transformation. The higher the angle of elevation the better the results would be. The size area of interest is inversely proportional to the accuracy of the transformation.

## 5 Other technologies in combination

In this section, we are going to present some other solutions or scenarios which could be used besides our Covid detection solution in the corresponding or beside social distancing using computer vision. The main idea is to find the infected person by using the system (developed

**Fig. 6** a confusion matrix and b Area under the curve (AUC) for the test dataset

in Section 3) and implement the following solutions independently or combinly with each other to obtain the best scenario for reducing, monitoring, and avoiding the spread of disease.

### 5.1 Distance to/from infected and contact tracing

As the distance between the individual using computer vision was already implemented and analyzed. The challenging part was that it would be implemented on short areas and ranges. The fact is that it is depended on cameras and provides the present situation. There are some other techniques which could be used in long-range as well as provides the future positions of individuals. In [2], authors took a friend's location dataset, train a Temporal-Spatial Bayesian model on it, and analyze the accuracy of a user's location prediction. In [65], authors employed a deep learning model for prediction of the next position of users for coordinated beamforming in high mobility in the millimeter-wave system. Where in [14], researchers used long term user location prediction through deep learning models i-e LSTM-PPM (long short-term model with period pattern mining).

The authorized service provider can easily predict the current exact position of the mobile user using the temporal-spatial Bayesian Model and with a deep learning model like LSTM-PPM for the prediction of the next position. This allows the authorized department to alert the users when they are near another person (in avoiding social distancing rules) and can be used to alert others if the infected one is present in their vicinity as shown in Fig. 7. This method can also be helpful in contact tracing purposes by giving status (not-infected, infected, etc. by using our mentioned solution) to the users and tracing them when their status is infected.

### 5.2 Infected movement prediction

The COVID-19 disease can be spread by moving of infected one, making physical contact with infected one or also with goods which he contaminated by any means (touch, cough, and sneezing, etc.). The geographic movement of the disease can be predicted by knowing two variables that is the current location and destination of the infected person.

The infected one and its starting position could be stored on the first prediction of COVID-19 using the app. He would be tracked using work done in this domain as, in [16], authors analyze the smartphone-based system for location recognition and prediction. They used Decision Tree learning and K-Nearest Neighbor algorithms for location recognition, while Hidden-Markov Model for destination prediction. Thus, the geographical movement of the disease can be predicted by giving the movement history of infected peoples to the system. And even it is possible by this system to predict the spread of disease before the infected people know that they carry the disease and advised other people using smartphone notification to stay away from the infected locations as illustrated in Fig. 8.

As above we discuss the infection movement prediction using machine/deep learning. To increase the confidence of prediction and track the exact path which the infected one takes, the better approach will be fusing that technique with computer vision. Thus, we can get the exact path which the disease takes to reach this place or that path has a high probability of spreading the disease. In [67], the authors proposed a method on which he gets the trajectory of movement and the location with 2 m of accuracy. The combining of human detection from computer vision with digital map information gave an accuracy of between 2 m [45]. The

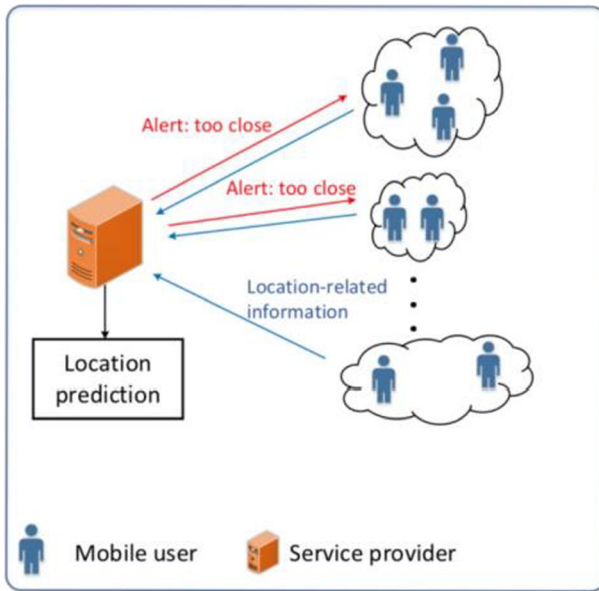


Fig. 7 Distance to/from the crowd

approach applied in [48] where authors use a smartphone camera with an inertial sensor-based system to accurately predict the location and trajectory within 7 cm of accuracy. For compensating the error in inertial sensors and enhancing accuracy this technique uses the combination of two approaches that are key points and squared planer markers.

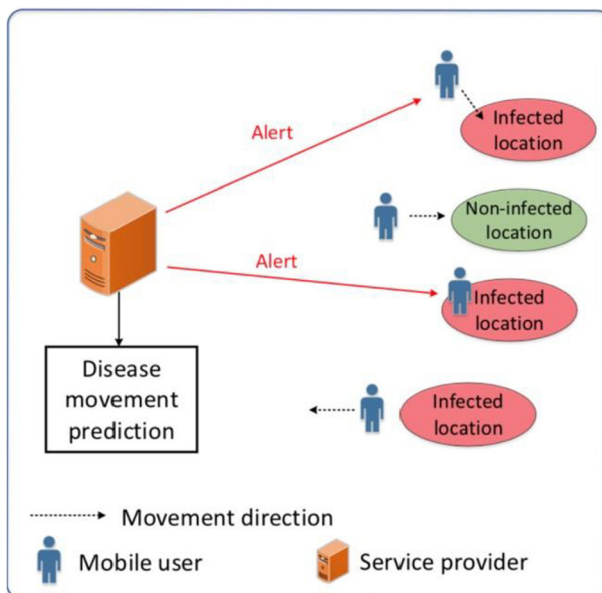


Fig. 8 Infected movement prediction

### 5.3 Sickness trend prediction

The most important features of deep learning are predicting trends from data and extrapolating it in making strategies and taking decisions for the future as shown in Fig. 9. If we know the trend of disease in a specific area, we can easily take precautionary steps to avoid the spread of diseases like isolating the area from outside and giving extra importance to people in such areas with keeping the safety of ours and others including the peoples in that area in mind.

### 5.4 Detecting and monitoring quarantined people

The challenge with that monitoring quarantine and at-risk peoples (infected or vulnerable) is that tracking their smartphones very precisely is an easy task, but having smartphones with them is not necessary that they have anywhere. Therefore, the other solution which will help with the previous one will be tracking them directly. In this case, computer vision has the capability of face recognition, which identifies quarantined people from surveillance cameras installed on public spots. It alerts the authorities if they found such a person who needs to be in self-isolation on a public spot. And even help those countries that have a lack of isolation facilities in implementing home isolation measures.

The dataset for object detection contains objects with labels, while in the face recognition dataset we need the full-face images of the isolated people. Then train the recognition system on the dataset (contain faces of infected ones) and use it on surveillance cameras in the vicinity where the person is isolated for identifying their appearance in public places as shown in Fig. 10b1. DeepFace is a framework built on deep neural network (DNN) that gave an accuracy of 97.35% on Label Face in the Wild dataset (LFW) while 91.4% on YouTube Faces Dataset (YTF). To improve the network for

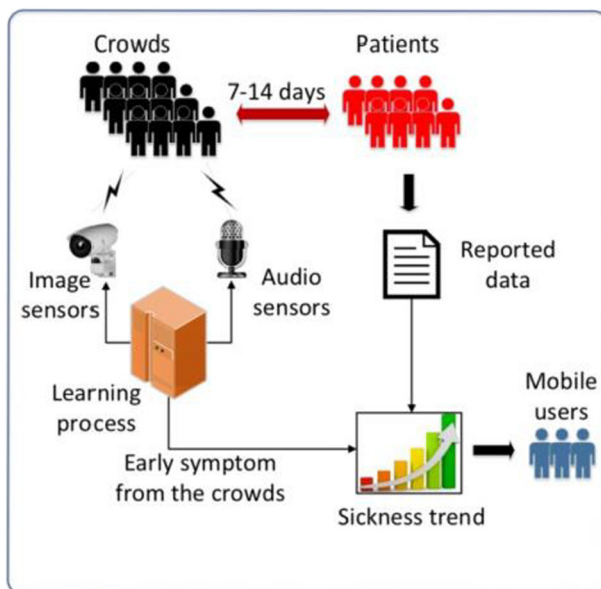


Fig. 9 Sickness Trends Prediction



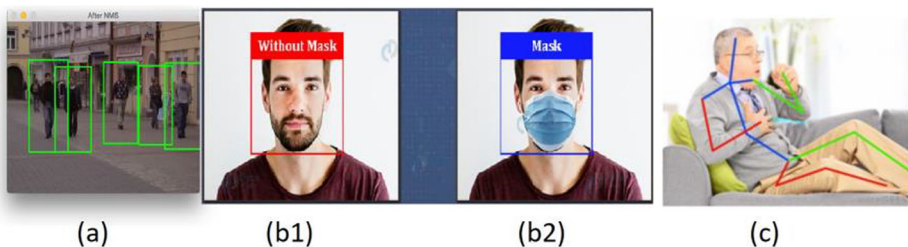
practical use, the research [56] which try to solve the issue of makeup (as makeup changes the features of faces), while other advanced technique can also be used with DeepFace such as [55, 57, 58].

In the above paragraph, the discussion was on tracing infected ones. But to prevent the public from being infected they have to follow safety measures as well. If someone wants to be safe from infection then they need to wear masks when going outside. The example in Fig. 10b2 illustrates the computer vision method of mask detection in which authors [10] uses YOLOv3 to demonstrate who is not wearing masks.

## 5.5 Symptoms detection and monitoring

The infected person shows some symptoms (coughing and sneezing) at the start of being infected. So, it could be used with infection detection through cough for better results. The detection of infected ones allows us to reduce the spread by isolating the person and sending him/her for further screening and testing. For detection of symptoms of cough and sneezing, the thermal camera can be used with a computer vision technique named Pose Estimation to detect the specific poses of sneezing and coughing of humans and inform the authorities to take a certain action. Pose Estimation is a technique that detects different parts of a person (like legs, hands, head, etc. As demonstrated in Fig. 10c and detection of human behavior by studying the movement of parts and their correlation. For example, the impulsive movement of the head shows the behavior of sneezing or coughing and even if hands are near to mouth confirms it as illustrated in Fig. 10c.

Human behavior recognition from a 2D video stream like obtain from a surveillance camera is a challenging task. The same movement corresponds to different implications. It depends on their relationship with the other movements (like jumping also shows us the impulsive movement of the head) and context [61]. So, authors [31] propose another CNN [64] model with the pose estimation model in detecting the behavior of humans. In [13], the authors introduce several different methods to detect body parts (pose estimation) in 2D images of multiple people. And authors in [18] propose a method of 3D pose estimation from matching pose estimation in 2D images with the 3D pose library. This work can be used in the development of techniques through which it will help in detecting symptoms of an infected person from their poses. And thus combine these techniques with thermal imaging cameras to obtain good results. In the paper, [28], authors proposed a whole system for temperature detection and tracking the person.



**Fig. 10** Computer vision technologies for social distancing (a) human detection to identify the number of people in the public place, (b) face recognition to identify (b1) the full face of isolated person, (b2) person with mask or person behind the mask and (c) pose estimation to detect one with coughing symptom

## 5.6 Social distancing on individual level

The main theme of social distancing is keeping a safe distance according to social distancing rules define by authorities. The main idea is to reduce the spread of disease. In [29], writers proposed a technique in which they leverage radar sensors with a smartphone camera. When radar sensors detect movement in near surroundings, it opens the cameras and uses a computer vision algorithm in the detection of humans. In [54] the technique of distance detection between vehicles can be utilized here and implemented in surveillance cameras in detection distance between peoples. The work of [11] could be used in the prediction of social distancing violation before the event happened by detecting the speeds of people and mapping it on the computer.

The other effective application in this section would be the use of such computer vision techniques in vehicular communication. Where the guiding of the drivers in rerouting to alternate paths in such a way that they avoid violation of social distancing parameters like high traffic and crowded areas. For such cases, authors [11] introduces a UAV-based intelligent system for transportation. Where UAV will be used as a roadside unit. And they create clusters that communicate the status of traffic on roads using wireless carriers. UAV uses cameras and seniors with convolution neural networks and recurrent networks for the prediction of the number of vehicles on road in the desired area. Thus, the people in the vehicle be guided using cellular or WI-FI networks accordingly as shown in Fig. 11.

## 6 Conclusion

Social distancing is one of the imperative measures for reducing and preventing the spread of contagious diseases. On the other hand, it is a hard and expensive solution to implement. In this research, an integrated technique was introduced and analyzed for the successful

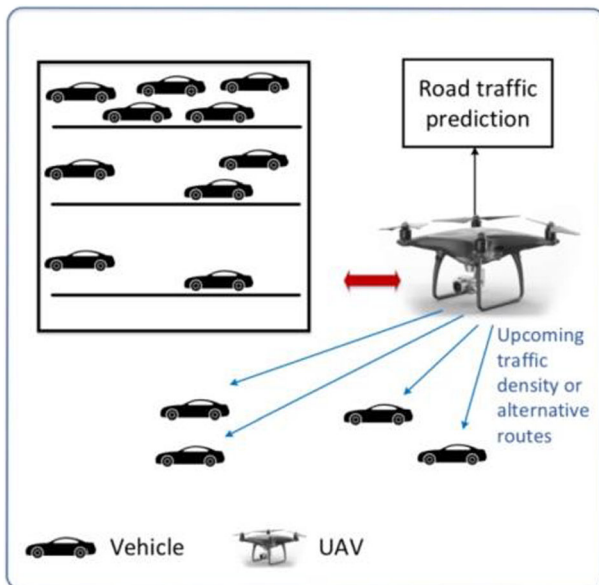


Fig. 11 UAV based traffic monitoring

implementation of effective social distancing by using deep learning models specially convolution neural networks. The detection accuracy of an infected person is up to 97%. Moreover, the model with techniques for monitoring the social distancing measures, as tested in a realistic real-time environment, is reliable and sufficiently fast. Therefore, this technique could be used for the detection of patients and contagious places. It will help in the prevention of future airborne pandemics which attack our vocal organs (as for corona). At last, this technique could be used with other techniques like disease tracing, spread analysis, and future trends prediction.

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**Data availability** The data is publicly available on the repositories named Coswara-Data, and Virufy by iicleap, and Virufy (URLs are <https://github.com/iicleap/Coswara-Data>, and [https://zenodo.org/record/4048312/files/public\\_dataset.zip](https://zenodo.org/record/4048312/files/public_dataset.zip)) respectively.

## Declarations

**Conflict of interest** The authors declare that they have no conflict of interest.

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