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SOCIAL DISTANCING MONITORING & ZONE-BASED RISK ASSESSMENT

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Abstract: During the COVID-19 pandemic, governments have tried to implement a variety of social distancing practices, such as restricting travels, controlling borders, closing pubs and bars, and alerting the society to maintain a distance of 1.6 to 2 m from each other. However, monitoring the amount of infection spread and efficiency of the constraints is not an easy task. People require to go out for essential needs such as food, health care and other necessary tasks and jobs. Therefore, many other technology-based solutions have tried to step in to help the health and medical community in copping with COVID-19 challenges and successful social distancing practices. These works vary from GPS-based patient localization and tracking to segmentation, and crowd monitoring. In this research, a generic Deep Neural Network Based model for automated people detection, tracking, and inter-people distances estimation in the crowd, using common CCTV security cameras, is developed. It also performs a live and dynamic risk assessment, by statistical analysis of data from the people movements at the scene. This will enable us to track the moving trajectory of people and their behaviors, to analyze the ratio of the social distancing violations to the total number of people in the scene, and to detect high-risk zones for short- and long-term periods.

Index Terms - **COVID-19, OpenCV, Social distancing, Deep learning, Computer vision, Risk Assessment, CCTV.**

I INTRODUCTION

The tale age of the Covid illness (COVID-19) were accounted for in late December 2019 in Wuhan, China. After a couple of months, the infection was hit by the worldwide flare-up in 2020. On Ma 2020 The World Health Organization (WHO) declared the circumstance as pandemic. The insights by WHO on 25th March 2021 affirms 125 million contaminated individuals in 200+ nations. The death pace of the irresistible infection likewise shows a terrifying number of 2.75 million individuals. With the developing pattern of patients, there is still no viable fix or accessible treatment for the infection. While researchers, medical services associations, and analysts are consistently attempting to create proper meds or antibodies for the dangerous infection, no unmistakable achievement has been accounted for at the hour of this exploration, and there is no sure therapies or proposal to forestall or fix this new illness. Thusly, safeguards are taken by the entire world to restrict the spread of contamination. These brutal conditions have constrained the worldwide networks to search for elective approaches to decrease the spread of the infection. As per the characterized necessities by the WHO, the base separation between people must be at any rate 6 feet (1.8 meters) to notice a satisfactory social distancing among the individuals. Ongoing researches have affirmed that individuals with mellow or no indications may likewise be transporters of the novel Coronavirus disease. Hence, it is significant all people keep up controlled practices and notice social distancing.

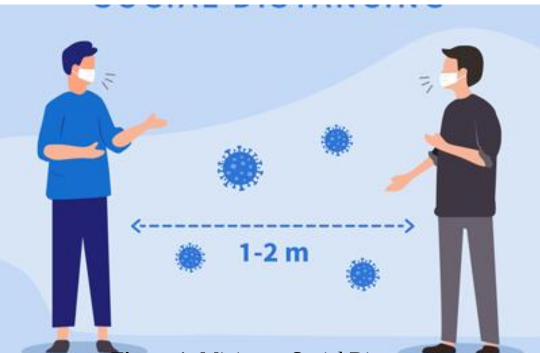

Figure 1: Minimum Social Distance

Many exploration works have demonstrated social distancing as a viable nonpharmacological methodology and a significant inhibitor for restricting the transmission of infectious illnesses, for example, H1N1, SARS, and COVID-19. Figure 2 shows the impact of following suitable social separating rule to diminish the pace of disease transmission among people. A more extensive Gaussian bend with a more limited spike inside the scope of the wellbeing framework administration limit makes it simpler for patients to battle the infection by getting persistent and convenient help from the medical services associations. Any sudden sharp spike and quick disease rate, (for example, the red bend in Figure 2), will prompt the administration disappointment, and thusly, remarkable development in the quantity of fatalities.

Accordingly, social separating now professes to be much more significant than thought previously, and probably the most ideal approaches to stop the spread of the infection notwithstanding wearing facial veils. Practically all nations are currently thinking about it as a required practice.

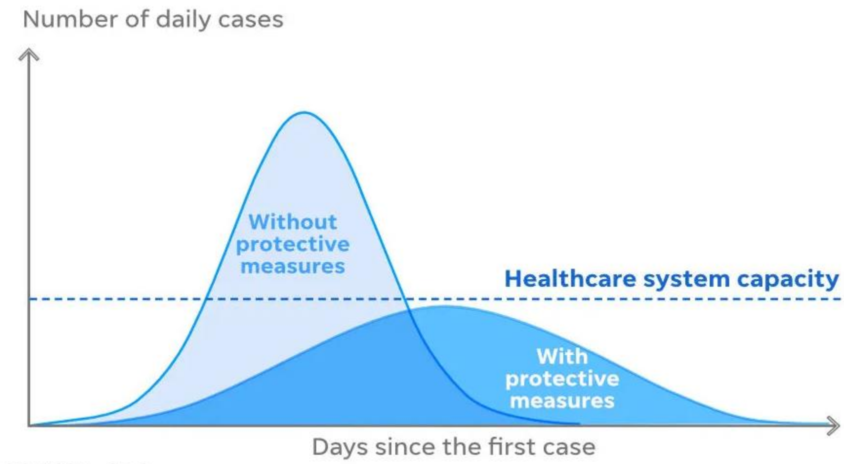

Figure 2: Distribution of virus transmission rate, with and without social distancing.

During the COVID-19 pandemic, governments have attempted to actualize an assortment of social distancing rehearses, for example, limiting voyages, controlling fringes, shutting bars a lot, and making the general public aware of keep up a separation of 1.6 to 2 meters from each other10. Be that as it may, observing the measure of disease spread and effectiveness of the limitations isn't a simple assignment. Individuals need to go out for fundamental requirements, for example, food, medical care and other essential errands and occupations. In such circumstances, Artificial Intelligence can assume a significant function in encouraging social removing checking. To monitor social distancing at public places, this paper provides a pinpointing solution. In this pandemic period using CCTV and drones we can keep a track on human activities at public places and henceforth we can compute and summarize distances between people and monitor the social distancing violations across the city. This proposed survey will also there and then restrict people from coming together and prevent social gatherings. People who gather in massive amounts at religious places can make conditions worse. Recently all countries in the world were and mostly are in the lock down period and this has imposed the citizens to be at home but as time passes people will tend to visit more and more public places, religious places and tourist destinations, so in those circumstances this system of monitoring social distancing will be beneficial all around the world. With the help of computer vision and deep learning and the installed CCTV we can keep a track on humans and compute the distance between them in pixels by using computer distance algorithms and set the standard maintained distance to be followed and get an overview of people violating the law and concerned authorities can take the actions accordingly.

II METHODOLOGY

It is a 3-stage model including individuals recognition, tracking, inter-distance estimation as an absolute answer for social distance monitoringand a zone-based infection risk analysis. The framework can be coordinated and applied on a wide range of CCTV observation cameras with any resolution from VGA to Full-HD, with continuous execution.

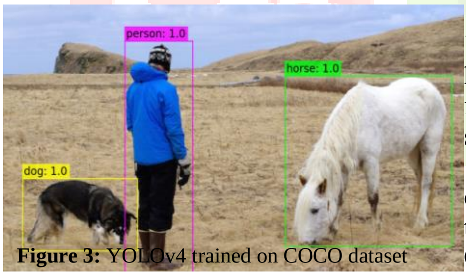

Figure 3: YOLOv4 trained on COCO dataset

2.1 Object Detection

YOLO (You Only Look Once) is a method to do object detection. It is the algorithm behind how the code is going to detect objects in the image. Earlier detection frameworks, looked at different parts of the image multiple times at different scales and repurposed image classification technique to detect objects. This approach is slow and inefficient. YOLO takes entirely different approach. It looks at the entire image only once and goes through the network once and detects objects. Hence the name. It is very fast. That's the reason it has got so popular. We'll be using YOLOv4 trained on the COCO dataset.

2.2 People Tracking

Here we use SORT(Simple Online and Real-time) tracking technique. It will act as a framework for the Kalman filter and Hungarian optimisation technique. Kalman filter predicts the position of the human at time t+1 based on the current measurement at time t and the mathematical modeling of the human movement. This is an effective way to keep localising the human. The Hungarian algorithm is a combinatorial optimisation algorithm that helps to assign a unique ID number to identify a given object in a set of image frames, by examining whether a person in the current frame is the same detected person in the previous frames or not.

Figure 4: People detection, ID assignment, tracking and moving trajectory representation.

From figure 4, we can see if an identified person is observed at new location, the respective bounding box will be updated. This is calculated based on velocity and acceleration components which are given by the Kalman framework.

After the detection and tracking process, for every input frame $I_{w\times h}$ at time t, we define the matrix D_t that includes the location of n detected human in the image carrier grid:

$$D_t = \{P^t_{(x_n,y_n)} | x_n \in w, y_n \in h\}$$

2.3 Inter-Distance Estimation

In this research we aim for an efficient solution that can be integrated with only a basic CCTV camera in public places. Th e problem with the single camera is that the projection of a 3D world into a 2D perspective image plane leads to to unreali stic pixel-
distances between the objects. This is called perspective effect, in which we can not perceive uniform distribution of distan ces in the entire image.

In a 3-
dimensional plane, every point has three parameters (x,y,z), while in camera, the image is reduced to (x,y) only and the (z) parameter is not known. Therefore to apply our algorithm we first need to set camera calibration as z = 0 to eliminate the perspective effect. We must also gather other data such as camera location, height and view angle.

By applying the IMP, the 2D pixel points (u,v) will be mapped to the corresponding world coordinate points (X_w,Y_w,Z_w):

$$[uv1]^T = KRT[X_w Y_w Z_w 1]^T$$

where R is the rotation matrix:

$$R = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & cos\theta & -sin\theta & 0 \\ 0 & sin\theta & cos\theta & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix},$$

T is the translation matrix:

$$T = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & \frac{-h}{sin\theta} \\ 0 & 0 & 0 & 1 \end{bmatrix},$$

and K, the intrinsic parameters of the camera are shown by the following matrix:

$$K = \begin{bmatrix} f*ku & s & c_x & 0 \\ 0 & f*kv & c_y & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

where h is the camera height, f is focal length, and ku and kv are the measured calibration coefficient values in horizontal and vertical pixel units, respectively. (cx,cy) is the principal point shifts that corrects the optical axis of the image plane.

The camera creates an image with a projection of three-
dimensional points in the world coordinate that falls on a retina plane. Using homogeneous coordinates, the relationship bet ween three-dimensional points and the resulting image points of projection can be shown as follows:

$$\begin{bmatrix} u \\ (v) \\ 1 \end{bmatrix} = \begin{bmatrix} m_{11} & m_{12} & m_{13} & m_{14} \\ m_{21} & m_{22} & m_{23} & m_{24} \\ m_{31} & m_{32} & m_{33} & m_{34} \end{bmatrix} \begin{bmatrix} X_w \\ \begin{bmatrix} Y_w \\ Z_w \end{bmatrix} \\ 1 \end{bmatrix}$$

where $M \in R^{3\times4}$ is the transformation matrix with m_{ij} elements, that maps the world coordinate points into the image points based on the camera location and the reference frame, provided by the Camera Intrinsic Matrix K, Rotation Matrix R and t he Translation Matrix T.

Considering the camera image plane perpendicular to the Z access in the world coordinate system (i.e., z=0) the dimension s of the above equation can be reduced to the following form:

$$\begin{bmatrix} u \\ (v) \\ 1 \end{bmatrix} = \begin{bmatrix} m_{11} & m_{12} & m_{13} \\ m_{21} & m_{22} & m_{23} \\ m_{31} & m_{32} & m_{33} \end{bmatrix} \begin{bmatrix} X_w \\ (Y_w) \\ 1 \end{bmatrix}$$

and finally transferring from the perspective space to inverse perspective space (BEV) can also be expressed in the followi ng scalar form:

$$(u, v) = (\frac{m_{11} \times x_w + m_{12} \times y_w + m_{13}}{m_{31} \times x_w + m_{32} \times y_{+m_{33}}},$$
$$\frac{m_{21} \times x_w + m_{22} \times y_w + m_{23}}{m_{31} \times x_w + m_{32} \times y_w + m_{33}})$$

III ZONE-BASED INFECTION RISK ASSESSMENT

We tested the effectiveness of our model in assessing the long-term behaviour of the people. This can be valuable for health sector policymakers and governors to make timely decisions to sa ve lives and reduce the consequent costs. Our experiments provided very interesting results that can be crucial to control the inf ection rates before it raises uncontrolled and unexpectedly.

In addition to people inter-distance measurement, we considered a long-term spatio-temporal zone-based statistical analysis by tracking and logging the movement trajectory of people, density of each zone, the total number of p eople who violated the social-distancing measures, the total time of the violations for each person and as the whole, identifying high-risk zones and ultimately, creating an informative risk heat-map.

In order to perform the analysis, a 2-D grid matrix G_t(initially filled by zero) was created to keep the latest location of individuals using the input image sequences. G_t represents the status of the matrix at time t and w and h are the width and height of the input image I, respectively. The grid matrix G will be updated for every new frame and accumulates the latest information of the detected people.

Figure 5: Accumulated tracking maps after 500 frames. Blue: low-risk, Red: high-risk

In addition to people raw movement and tracking data, it would be more beneficial to analyse the density and the location o f the people who particularly violated the social distancing measures.

After representation of a long term heat-map of the detections, movements, and total social-distancing violations, we can identify the risk zones and apply the restrictions or redesign the layout of the place to make it saf e.

Applying the social distancing violation criteria, we identified each individual in one of the following categories:

- **Safe:** All people who observed the social distancing (green circles).
- **High-risk:** All people who violated the social distancing (red circles).
- **Potentially risky:** Those people who moved together (yellow circles) and were identified as coupled. Any two people in a coupled group were considered as one identity as long as they did not breach the social distancing measures with t heir neighbouring people.

Figure 6: A single frame 2D crowd map VS Long term crowd map

IV CONCLUSIONS

As we envision the world post COVID-19 pandemic the need of self-responsibility emerges irrefutably. The scenario would mostly focus on accepting and obeying the precautions and rules that W HO has imposed more precisely as responsibility of one will totally embark on themselves and not government. Social Distanci ng would undoubtedly be the most important factor as COVID 19 spreads through close contact with infected ones. In order to supervise large mobs, an effective solution is important and this research focuses on that. Using installed CCTV and drones, aut horities can keep a track of human activities and control large crowd to come together and prevent violating the law. As control ling large mob is not an easy task, using this survey, conditions can be managed before situation goes out of control. Thus, imp lementing this idea can reduce the on ground efforts of the police and based on the zone-based risk assessment, they can entirely focus on supervising conditions exclusively on those areas where conditions are unfavo rable and thus, they can utilize time wisely and save energy for equitable situations.

Also this algorithm is a view-point independent algorithm, hence can be effective regardless of camera perspective. It can be applicable in various other indus trial applications like driver assistance system, surveillance systems, public places crowd management, sports action recognition, etc.

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