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AI Driven Social Distancing Detection

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ABSTRACT: A social distancing detection tool based on deep learning is developed to determine the distance between people and hence keep a constant check on the violation of social distancing norms. It was created to warn people to keep a safe distance from one another. Pedestrian detection is done by processing the input video from the camera by employing a pre-trained open-source object identification model based on the Tiny-YOLOv3 technique. The Euclidean distance between the people in the video frame is calculated and any non-compliant pair of individuals are marked with a red frame in the display. A pre-recorded video of people is used to validate the suggested strategy. The findings show that the proposed strategy can aid in the maintenance of social distance between many people.

KEYWORDS:social distancing, pedestrian detection, deep learning, convolutional neural network

I.INTRODUCTION

The novel coronavirus (Covid-19) epidemic has put public health at huge risk. Due to a rise in the number of cases reported around the world, the World Health Organization (WHO) classified the Covid-19 outbreak a pandemic. Many countries have enacted lockdowns to contain the effects of the pandemic, with the government requiring individuals to remain safe and at home. The Center for Disease Control and Prevention (CDC) and other public health organisations have stressed that avoiding close contact with other individuals is the most effective strategy to reduce the transmission of virus. Citizens all throughout the world are physically separating themselves from one another in order to flatten the curve. The globe is yet to fully recover from the pandemic's effects, and a vaccine to fully and effectively prevent Covid-19 is yet to be discovered. To lessen the economic burden of the pandemic, several countries have allowed a restricted number of economic activities to restart whenever the number of new Covid-19 cases falls below a particular threshold. Concerns about worker safety in the postCovid-19 environment have surfaced as these countries gradually recommence their economic activity. People should avoid any person-to-person contact, such as shaking hands, and keep a gap of at least 1 metre between them to limit the risk of infection.

The main components of this technique are summarised in the following points:

A. Deep learning is gaining popularity in the field of object detection, and it may be used to detect humans.
B. Create a technology to identify social distancing and keep people safe from infection by detecting the distance between them.
C. Analysing real-time video feeds to evaluate classification results

II.METHODOLOGY

The block diagram for the proposed strategy is shown in the figure 1. It depicts the detection of pedestrians using the technique of yolo. The pedestrians detected by the algorithm are further processed and the distance between them is determined to detect any violation from the mandated social distancing.

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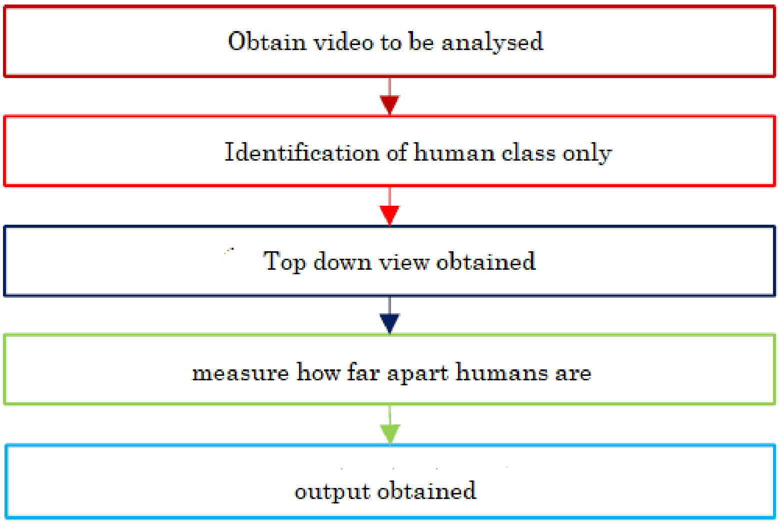

Fig. 1 Block Diagram for the proposed model

For the proposed deep learning model, the Tiny-YOLO algorithm is used. It is a state-of-the-art object detector that has been shown to provide significant speed advantages and is suited for real-time use. The Tiny-YOLO algorithm was viewed as an object recognition method that took a given input image and learned bounding box coordinates (tx, ty, tw, th), object confidence, and related class label probabilities while learning bounding box coordinates (tx, ty, tw, th) (P1, P2, …, Pc). Tiny-YOLO was trained using the COCO dataset, which has 80 labels, including the human class. Only the box coordinates and object confidence of pedestrian object class from the Tiny YOLO model were used in this study.

To obtain top-down view of the given input video feed, in OpenCV four points in the perspective view are selected and mapped to the corners of a rectangle in the 2D image view. Here the assumption created is that every person is standing on the same level flat plane. The number of pixels in the 2D top-down view determines the real distance between pedestrians.If the positions of two pedestrians in the input image are (x1, y1) and (x2, y2) respectively, then the distance between them is given by$d= \text{sqrt}[(x2-x1)^2 + (y2-y1)^2]$. If d is below the minimum acceptable distance, the pair is marked red, else in green.The people are then alerted employing a buzzer to maintain a safe distance between each other. The buzzer beeps until the violations are none. The buzzer will beep at an interval corresponding to the reciprocal of the number of violations detected i.e if the number of violations detected is 1 then the buzzer will start beeping in intervals of one second until the detected violations become zero. Hence the social distancing norms can be implemented successfully and the impact of the pandemic reduced.

III.SOFTWARE

The tiny yolo is trained using the MS COCO dataset (Microsoft Common Objects in Context) which is a large-scale dataset for object detection, segmentation, key-point identification, and captioning. It is intended to reflect a wide range of objects that we come across daily. It's one of the most widely used open-source object recognition datasets for deep learning. The ability to learn from a big and well-documented dataset is arguably the most crucial aspect of supervised machine learning. COCO is a Microsoft-sponsored project that categorises and tags photos, as well as giving machine-readable context captions and tags. This collection contains hundreds of thousands of photos with millions of already labelled objects, which can be used to train supervised computer vision models that can recognise the dataset's common objects.

The standard YOLOv3 method is a more accurate and faster variant of the original YOLO method. It uses the Darknet-53 architecture as its backbone, as well as three different detection scales known as "output layers" or "heads." When trained on standardised datasets like Common Objects in Context (COCO), it outperforms approaches like SSD, YOLO, YOLOv2, and Faster RCNN in terms of performance. Tiny-YOLOv3 has fewer convolution layers and is faster but less accurate. Tiny YOLOV3 is hence a lightweight target identification technique based on YOLOv3 that can be

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used on embedded platforms. The model size compression is implemented, despite the detection accuracy being lower than YOLOv3. Tiny YOLOV3 used a 13*13, 26*26 two-scale prediction network to anticipate the target, reducing the YOLOv3 feature detection network darknet-53 to a 7-layer classic convolution and a 6-layer Max Pooling layer.

IV. IMPLEMENTATION

The Raspberry Pi 4 Model B was set up and updated as the first stage in implementing the detecting tool. All of the required packages and libraries, as well as OpenCV and TensorFlow, were then installed. The YOLOv3 algorithm was loaded from the GitHub repository. The Raspberry Pi's USB port is connected to a Logitech C270 HD camera, which provides video feed of people who are being monitored for transgressions. The Raspberry Pi is connected to the display (TV monitor) via HDMI cable, which displays the number of detected violations and the frames per second that are processed. The buzzer is connected to the Raspberry Pi's 26th GPIO pin and helps to alert people, ensuring that the mandated minimum safety distance is maintained at all times.

V. VALIDATION

A pre-recorded video was analysed to test the AI model developed using the yolo algorithm. When there are violations between people in the video frame, the people are shown surrounded in red bounding boxes, and the buzzer starts beeping until the number of social distancing violations is decreased to zero, according to the output results. When there are no violations between the people in the video frame, they are presented enclosed in green bounding boxes as shown in figure 2 and figure 3.

Fig. 2 Without violation

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Fig. 3 With violation

As shown in figures 2 and figure 3, the output video frame also shows the number of detected violations and the frames per second processed. The confidence scores of the humans enclosed in bounding box is also denoted on top of the respective bounding boxes. The model developed was also validated using the real time video feed from theLogitech C270 HD camera and hence it is understood that the model proposed can be used for real time application in various spaces such as office room, restaurants, classrooms etc.

VI. CONCLUSION

Using deep learning and computer vision, the social distancing detection tool assesses the distance between people, and those determined to be violating social distancing norms are recognised and signalled with a red frame. A pre-recorded video of people was used to validate the model. The visualisation results revealed that the suggested system is capable of determining social distancing measures between people, and that it might be further developed for real-time use in different settings such as offices, restaurants, and schools. Furthermore, by enhancing the pedestrian detection algorithm, integrating other detection methods such as mask detection and human body temperature detection, increasing the computing capacity of the hardware, and calibrating the camera perspective view, this work can be improved even further

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