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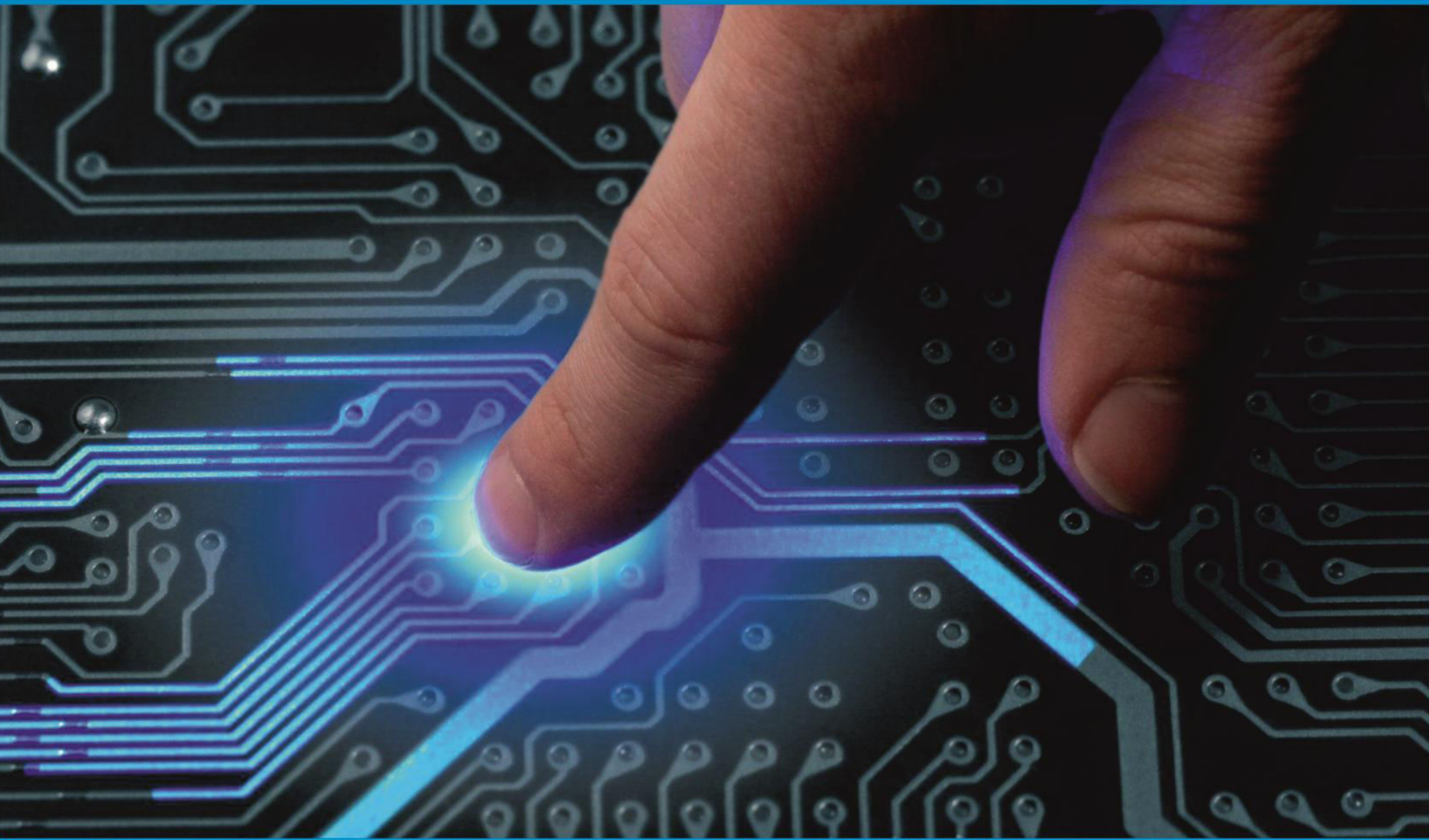

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A Vision-based Social Distancing and Critical Density Detection System for COVID-19

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ABSTRACT: The ongoing COVID-19 corona virus outbreak has caused a global disaster with its deadly spreading. Due to the absence of effective remedial agents and the shortage of immunizations against the virus, population vulnerability increases. In the current situation, as there are no vaccines available; therefore, social distancing is thought to be an adequate precaution (norm) against the spread of the pandemic virus. The risks of virus spread can be minimized by avoiding physical contact among people. The purpose of this work is, therefore, to provide a deep learning platform for social distance tracking using an overhead perspective. The framework uses the YOLOv3 object recognition pardigm to identify humans in video sequences. The transfer learning methodology is also implemented to increase the accuracy of the model. In this way, the detection algorithm uses a pre-trained algorithm that is connected to an extra trained layer using an overhead human data set. The detection model identifies peoples using detected bounding box information. Using the Euclidean distance, the detected bounding box centroid's pairwise distances of people are determined. To estimate social distance violations between people, we used an approximation of physical distance to pixel and set a threshold.

KEYWORDS: Social Distancing, Covid-19, Computer Vision, YOLO Object detection, Python, OpenCV, Deep Learning, Social health, Social surveillance, Coronavirus.

I. INTRODUCTION

COVID-19 is a disease caused by a new coronavirus which appeared in China in December 2019. COVID-19 symptoms include mainly fever, cough, chills, and shortness of breath, body aches, loss of taste, and smell. COVID-19 can be severe, and in many cases, it has caused death. The coronavirus can spread from one person to another as diagnosed by researchers in laboratories. This pandemic has spread to over 188 countries around the world . On October 15, 2020, WHO (World Health Organization) declared that there have been 38,394,169 confirmed COVID-19 cases and 1089,047 deaths around the world. The uncertainty, underpinning, and complexity of the coronavirus have made it difficult to predict the duration and spread of this pandemic. As of yet, there is no vaccine available.

Prevention involves wearing masks and washing hands frequently. An infected person should stay at home when people are sick to prevent spreading this pandemic to the others. This situation forces the global community and governments to find the best mitigation plan to stop the spread of coronavirus. Nations stopped their business and closed the border and public places such as schools and workplaces to avoid people’s interactions. It has been reported that all infected countries who applied the lock-down for their communities achieved a reduction of the number of COVID-19 cases and the number of deaths from this pandemic.

Fever or chills are common symptoms of coronavirus. Researchers in China found that 99% of people infected with the coronavirus presented with a high temperature. Thermal cameras and non-contact infrared thermometers, which are non-contact instruments, can be used to measure body temperature. This approach can monitor a person’s surface temperature to limit the spread of coronavirus infections.

Based on the information from the World Health Organization, social distancing is the best practice where individuals can minimize physical contact with possible COVID-19 carriers by maintaining a certain distance between one person and another. The main target is to provide a comprehensive tool and effective technologies that can be utilized to enforce social distancing. Technologies could play an important role to facilitate social distancing practice. In such a context, Artificial Intelligence (AI) and information and communication technology (ICT) can be used in addressing this challenge.

This research aims at mitigating the spread of this virus in communities and saving the lives of people. In

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this work, we propose a deep learning object detection model for people detection in combination with an implemented algorithm for social distancing classification on thermal images. Hereafter, the paper is organized as follows: after the introduction of COVID-19 in Sects. presents the research background and related work. Section shows an overview of object detection. Section presents the proposed methodology to define a measuring system for people detection and social distancing check. Section shows the experimental results and Sect. describes the implementation of the proposed approach on embedded hardware. Conclusions are drawn in Sect.

II LITERATURE SURVEY

Various research work has been carried out on social distancing using different techniques. [1]proposed a system that used raspberry pi4 with a cam-era to automatically track public spaces in real time to prevent the spread of Covid-19. The trained model with the custom data set was installed in the raspberrypi4, and the camera was attached to it. The camera is fed with real-time videos of public places to the model in the raspberry pi4, which continuously and automatically monitors public places and detects whether people keep safe social distances and also checks whether or not those people wear masks.

Their method operates in two stages: first, when a person identified without a mask his photo was taken and sent to a control center at the State Police Headquarters; and second, when the detection of a social distance violation by individuals was detected continuously in threshold time, there rings an alarm that instructs people to maintain social distance and a critical alert is sent to the control center of the State Police Headquarters for further action. They achieved an accuracy of 91 %. Singh Punnet al.[4] proposed a real-time based deep learning to monitor social distancing using object detection and tracking approaches. The number of violations was given by computing the number of groups formed and the violation index term computed as the ratio of the number of people to the number of groups.

Different object deTection models were used like Faster RCNN, SSD, and YOLO v3, where YOLO v3 with balanced performance of FPS and mAP score. An AI monocular camera- based real-time system to monitor social distancing was pro-posed by Yanget al.[5]. The proposed method uses a critical social density to avoid overcrowding by modulating inflow to the region of interest. The method was verified using 3 different pedestrian crowd datasets. But there were some missing detections in the train station dataset, as in some areas the density of pedestrians is very high and occlusion happens. However, after some analysis, they concluded that the maximum pedestrians were captured and the idea of social density is valid. In the proposed method by Seneret al.[2] the motion of the communicating people was extracted from each region of the detected individual.

Then, visual descriptors for two persons are created. As the relative spatial positions of communicating people are likely to complement the visual descriptors, we propose to use embedding of spatial multiple instances, which implicitly integrates the distances between people into the learning process of multiple instances. Experimental findings on two benchmark datasets validate that the use of two-person visual descriptors along with multiple-instance spatial learning provides an efficient way to infer the form of interaction. They achieved an accuracy of 93.3 %. Bieleckiet al.[6] did a study of 508 male soldiers with average age of 21years. They followed the number of soldiers into two groups. For the 354 soldiers affected before social distancing was introduced, COVID-19 caused 30 % to become sick. While no soldier in a population of 154, in which infections occurred after social distancing had been introduced. An innovative localization method was proposed to by Nadikattuet al.[7] to track humans' positions in the surrounding based on sensors.

Social distancing for COVID -19. COVID-19 has caused severe acute respiratory syndromes around the world since December 2019. Recent work showed that social distancing is an effective measure to slow down the spread of COVID-19. Social distancing is defined as keeping a minimum of 2 meters (6 feet) apart from each individual to avoid possible contact. Further analysis [12] also suggests that social distancing has substantial economic benefits. COVID-19 may not be completely eliminated in the short term, but an automated system that can help monitoring and analyzing social distancing measures can greatly benefit our society. Pedestrian detection. Pedestrian detection can be regarded as either a part of a general object detection problem or as a specific task of detecting pedestrians only.

A detailed survey of 2D object detectors, as well as datasets,metrics, and fundamentals, can be found in . Another survey focuses on deep learning approaches for both generic object detection and pedestrian detection. State-of-the-art object detectors use deep learning approaches, which are usually divided into two categories. The first one is called two-stage detectors, mostly based on R-CNN which starts with region proposals and then performs the

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classification and bounding box regression. The second one is called one-stage detectors, of which the famous models are YOLOv1-v4 , SSD ,Retina Net , and Efficient Det. In addition to these anchor-based approaches, there are also some anchor-free detectors: Corner Net , Center Net , FCOS , and RepPoints .

These models were usually evaluated on datasets of Pascal VOC and MS COCO . The accuracy and real-time performance of these approaches are good enough for deploying pretrained models for social distancing detection. Social distancing monitoring. Emerging technologies can assist in the practice of social distancing. A recent work has identified how emerging technologies like wireless, networking, and artificial intelligence (AI) can enable or even enforce social distancing. The work dis-cussed possible basic concepts, measurements, models, and practical scenarios for social distancing. Another work has classified various emerging techniques as either human centric or smart-space categories, along with the SWOT analysis of the discussed techniques. A specific social distancing monitoring approach that utilizes YOLOv3 and Deep sort was proposed to detect and track pedestrians followed by calculating a violation index for non-social-distancing behaviors. The approach is interesting but results do not contain any statistical analysis. Furthermore, there is no implementation or privacy-related discussion other than the violation index. Social distancing monitoring is also defined as a visual social distancing (VSD) problem in the work introduced a skeleton detection based approach for inter-personal distance measuring. It also discussed the effect of social context on people's social distancing and raised the concern of privacy.

The discussions are inspirational but again it does not generate solid results for social distancing monitoring and leaves the question open. Very recently, several prototypes utilizing machine learning and sensing technologies have been developed to help social distancing monitoring. Landing AI has pro-posed a social distancing detector using a surveillance camera to highlight people whose physical distance is below the recommended value. A similar system was deployed to monitor worker activity and send real-time voice alerts in a manufacturing plant. In addition to surveillance cameras, LiDAR based and stereo camera based systems were also proposed, which demonstrated that different types of sensors besides surveillance cameras can also help. The above systems are interesting, but recording data and sending intrusive alerts might be unacceptable by some people. On the contrary, we propose a non-intrusive warning system with softer omni directional audio-visual cues. In addition, our system evaluates critical social density and modulates inflow into a region-of-interest.

III. PROPOSED WORK

We propose to use a fixed monocular camera to detect individuals in a region of interest (ROI) and measure the inter-personal distances in real time without data recording. The proposed system sends a non-intrusive audio-visual cue to warn the crowd if any social distancing breach is detected. Further more, we define a novel critical social density metric and propose to advise not entering into the ROI if the density is higher than this value. The overview of our approach is given in Figure 1, and the formal description starts below.

Problem formulation:-

We define a scene at time t as a 6-tuple $S=(I,A0,dc,c1,c2,U0)$, where $I\in RH\times W\times 3$is an RGB image captured from a fixed monocular camera with height Hand widthW.$A0\in R$ is the area of the ROI on the ground plane in real world and $dc\in R$ is the required minimum physical distance.c1is a binary control signal for sending a non-intrusive audio-visual cue if any inter-pedestrian distance is less thandc.c2is another binary control signal for controlling the entrance to the ROI to prevent overcrowding. Overcrowding is detected with our novel definition of critical social density ρc. Pc ensures social distancing violation occurrence probability stays lower thanU0.U0is an empirically decided threshold such as 0.05.Problem 1.Given S, we are interested in finding a list of pedestrian pose vectors $P= (p1,p2,\cdots,p\ n),p\in R2$, in real-world coordinates on the ground plane and a corresponding list of inter-pedestrian distances $D=(d1,2,\cdots,d1,n,d2,3,\cdots,d2,n,\cdots,dn-1,n),d\in R+$.n is the number of pedestrians in the ROI. Also, we are inter-ested in finding a critical social density value ρc.ρc should ensure the probability $p(d > dc|\rho < \rho c)$stays over$1-U0$,where we define social density as $\rho:=n/A0$.Once Problem 1 is solved, the following control algorithm can be used to warn/advise the population in the ROI. Algorithm 1.If $d\leq dc$, then a non-intrusive audio-visual cue is activated with setting the control signal$c1= 1$,otherwise$c1= 0$. In addition, If $\rho > \rho c$,then entering the area is not advised with setting$c2= 1$, otherwise$c2= 0$.Our solution to Problem 1 starts below.

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Pedestrian detection

In the image domain First, pedestrians are detected in the image domain with a deep CNN model trained on a real-world data set:{Ti}k=fcnn (I).(1)fcnn :I→ {Ti}n maps an image I in ton tuples Ti=(libi,si),∀i∈ {1,2,⋯,n}.n is the number of detected objects. li∈L is the object class label, where L, the set of object labels, is defined in fcnn .bi=(bi,1,bi,2,bi,3,bi,4)is the associated bounding box (BB) with four corners .bi,j= (xi,j,yi,j)gives pixel indices in the image domain. The second sub-index j indicates the corners at top-left, top-right, bottom-left, and bottom-right respectively .s i is the corresponding detection score. Implementation details of fcnn is given in Section 5.1.We are only interested in the case of l=‘person’. We define p'i, the pixel pose vector of person i, with using the middle point of the bottom edge of the BB: p′i:=(bi,3+bi,4)2.(2)

Image to real-world mapping

The next step is obtaining the second mapping function h:p′→p. his an inverse perspective transformation3

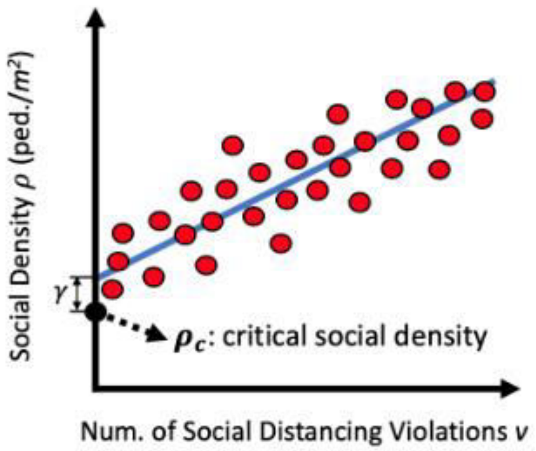

Figure. Obtaining critical social density ρc. Keeping ρ under ρc will drive the number of social distancing violations v towards zero with the linear regression assumption. function that maps p′in image coordinates top∈R2inreal-world coordinates. pis in 2D bird’s-eye-view (BEV)coordinates by assuming the ground planez= 0. We use the following well-known inverse homography transformation [38] for this task:p bev=M−1pim,(3) where M∈R3×3is a transformation matrix describing the rotation and translation from world coordinates to image coordinates .pim= [p′x ,p′y,1]is the homogeneous representation of p′= [p′x,p′y]in image coordinates, and pbev= [pbevx,pbevy,1]is the homogeneous representation of the mapped pose vector. The world pose vector pis derived from p bev withp=[pbevx,pbevy].

Social distancing detection

After getting P= (p1,p2,⋯,pn)in real-world coordinates, obtaining the corresponding list of I inter-pedestrian distances Dis straightforward. The distance di,j for pedestrians I and j is obtained by taking the Euclidean distance between their pose vectors:di,j=‖pi−pj‖.(4)And the total number of social distancing violations v in a scene can be calculated by:v=n∑i=1n∑j=1j6=iI(di,j),(5)where I(di,j) = 1ifdi,j< dc, otherwise0.

Critical social density estimation

Finally, we want to find a critical social density value ρc that can ensure the social distancing violation occurrence probability stays belowU0. It should be noted that a trivial solution of ρc= 0 will ensure v= 0, but it has no practical use. Instead, we want to find the maximum critical social density ρc that can still be considered safe.To find ρc, we propose to conduct a simple linear regression using social density ρ as the independent variable and the total number of violations v as the dependent variable:v=β0+β1ρ+,(6)where β= [β0,β1]is the regression parameter vector and/span>is the error term which is assumed to be normal. The regression model is fitted with the ordinary least squares method. Fitting this model requires training data. However,once the model is learned, data is not required anymore .After

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deployment, the surveillance system operates without recording data. Once the model is fitted, critical social density is identified as:ρc=ρ pred lb,(7)where ρ pred lb is the lower bound of the95%prediction inter-val(ρpred lb,ρ predub)at v= 0, as illustrated in Figure 2.Keeping ρ under ρc will keep the probability of social distancing violation occurrence near zero with the linear regression assumption

IV. FUTURE SCOPE

This publishing is focusing on surveillance of public places and detecting whether the people are maintaining social distancing or not. Social Distancing is the only best option for us to protect ourselves from diseases, not limited to COVID-19, where no medicinal antidote has been prepared, and that may be transmitted through human contact. The paper explains the development of a technology through use of AI based procedures to detect whether the social distancing norm is followed or not, in any public video stream. The software embedded can distinguish between a person maintaining social distance (marke dgreen) and a person who is not (marked red). We will also keep a count of incidents where social distancing was not followed.

A. Objective

To develop technology that may trace whether the social distancing rules are obeyed or not.To control any outspread of any future contagious disease.To develop a Privacy-friendly software; no PII is used or stored. To Preserve the work continuity while also keeping the people safe. To Increase confidence in people moving in public places.

B. Future scope of the system

With advanced technical updates, the system may be capable to trace and detect the violations from an aerial view.

V. CONCLUSION

Based on the results obtained, we can see that social distancing detector is correctly marking people who violate social distancing rules. Whileall the people who are following the norm are enclosed in green rectangular boxes, people violating the social distancing norm are enclosed in a red rectangular box. Nowadays, social distancing along with other basic sanitary measures are very important to keepthe spread of the pandemic (Covid-19) as slow as possible. Along with the color representation, the count, that is the number of the times the norm is violated is also displayed based on the video stream. The algorithm is used to analyze social distancing in a public area and carry out necessary actions to better deal with the pandemic. The project has beencompletedusing the implementation of computer language technology onto a video stream to develop an application working as a social distancing detector, also capable of keeping count of norm violation. This also included the testing of the application, cross-checking of the data until a satisfactory, required, correct and good result was obtained

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