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SYSTEM FOR COVID-19 THAT USES VISION TO DETECT CRITICAL DENSITIES AND SOCIAL DISTANCE

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ABSTRACT

An efficient method of halting the transmission of the contagious Coronavirus Disease is social distance (SD). 2019 The COVID-19 pandemic has unquestionably stopped all global activity. We inhabited a totally different world a few months ago than we do now. A novel virus has led to a global epidemic and significant casualties. According to information released by the World Health Organization (WHO) in late December 2019, this coronavirus originated in Wuhan, China. In light of this, we suggest an active surveillance system to inform people in an area of interest in order to stop the spread of COVID-19. We have two main contributions to make. We first present a vision-based real-time system that makes use of state-of-the-art deep learning models to detect SD violations and deliver subtle aural and visual feedback. Our second contribution is the development of an unique critical social density value, which we use to show that SD violations may be prevented or reduced to a negligible level provided pedestrian densities are maintained below a certain threshold.

KEYWORDS: convolutional neural network; social distancing; pedestrian detection, linear regression

INTRODUCTION

Social distancing (SD) has become a successful defense against the new Coronavirus Disease 2019 (COVID-19) outbreak. To stop or delay the virus's spread, it is essential to maintain social distance in public places like train stations, malls, and college campuses. It's possible that social distance (SD) will persist in the coming years until the virus has fully stopped spreading. However, because communities are not used to maintaining the necessary 2-meter bubble surrounding each person, social distance is likely to be breached unintentionally. In this study, an autonomous warning system based on vision is proposed. It can recognize social distance statuses and determine a crucial pedestrian density threshold to control the amount of people entering congested locations. In addition to functioning as an automated monitoring and warning system, the proposed framework may be utilised as a device to uncover crucial elements and data for regional and global viral control. Automatic vision-based detection and control technologies may help restrict the spread of COVID-19 in public places. Despite the apparent ease of the notion, developing and deploying such systems raises serious ethical considerations and calls for meticulous system design.

Social isolation is a successful defense against the new pandemic of Coronavirus Disease 2019 (COVID-19). The average people, however, is not accustomed to maintaining a protective bubble around oneself. An automatic warning system can support and improve a person's perceptive talents. Such an active surveillance system deployment necessitates careful system design and ethical deliberation. Privacy poses the first difficulty. The privacy of persons may be infringed accidently or intentionally if data is recorded and retained. As a result, the system must be real-time and incapable of retaining data. Second, the detector cannot make any distinctions. The most secure method to accomplish this is to create an AI-based detection system. It may not be enough to just remove the human element of detection; the detector itself may need to be unconstrained by any particular set of parameters. Domain-specific systems using bespoke feature extractors pose the danger of creating malicious architectures. Except with one caveat: the training data must be fairly distributed. With no feature space to bias the results, a connectionist machine learning system like a deep neural network is far more fair in this scenario. Being non-intrusive is another important consideration. The warning system shouldn't specifically target any particular person. To do this, an audible or visual indication that isn't meant to cause panic might be sent in the vicinity of the social distance violation.

An extremely serious global health crisis brought on by the COVID-19 Pandemic Disease has had a profound effect on humanity, how we view the world, and how we conduct our daily lives. The Ministry of Health has declared a global pandemic after the first case of COVID-19 was detected in Wuhan, China, in December 2019. (WHO). Services for Health and Humans. According to the Centers for Disease Control and Prevention (CDC), avoiding close contact with many other individuals is the greatest approach to prevent the transmission of Covid-19 (CDC). In order to further stop the spread of the sickness, people are once more recommended to practice cleanliness precautions like routinely washing their hands, wearing masks, and avoiding close contact with contagious people. Instead of risking getting COVID-19 and hoping for the best, it's preferable to be vaccinated against it. The COVID- 19 vaccine aids in protection by stimulating an immunological response in the absence of sickness, even possibly severe illness.

Even after receiving the vaccine, it is best to wear a mask, especially in high-risk scenarios, as many people in the country are still not fully protected and the risk of breakthrough cases persists. The coronavirus epidemic of 2019 has had a significant influence on the entire world. Two significant ways that people defend themselves are by dressing up in public and keeping up positive barriers. The use of masks and interpersonal solitude is the only defense against the transmission of COVID-19. The fight against the coronavirus is the aim of this thesis. It has been demonstrated that using a mask and avoiding direct contact with others are both very effective techniques to stop the virus's spread. This study also aims to provide a surveillance system that efficiently uses surveillance tools, cameras, and object recognition to detect people wearing masks and flouting social conventions while keeping tabs on individuals. Face Mask and Social for COVID-19.

Coronavirus Disease can be controlled with the use of social isolation and masks. A virus that affects people is COVID-19. On the other hand, people are not accustomed to keeping a 60 cm distance between themselves and their environment. An active monitoring system that can calculate human migration patterns and warn those at risk of contracting the fatal illness would be an invaluable tool in halting its spread. The chance of social distance violations may also be decreased by calculating the social density in a region of interest (ROI) and then reducing the intake. The human rights of people living in democratic nations will be compromised if information is gathered and people who disobey the law are labelled. We provide an artificial intelligence (AI)-based system for real-time social distance identification and warning that takes into account four main ethical issues: 1. A computer can never save or cache data. 2.Warnings shouldn't be directed at specific people. 3. The detection process shouldn't include any human operators. 4. The source code must be accessible to the general audience. In light of this, We propose measuring social distance using a monocular camera and deep learning-based real-time object detectors. A non-intrusive audio-visual alarm signal is delivered whenever a breach is discovered, but it is not directed towards the individual who compromised the data's social distance measure. If the social density surpasses a certain threshold, the gadget also transmits a control signal to modulate the amount of money into the ROI. Using real-world datasets, we evaluated the performance and generality of the suggested technique. The suggested method is available for usage, and our code is open source.

LITERATURE REVIEW

Yang, Dongfeng et.al (2021) The highly infectious Coronavirus 2019 may be stopped in its tracks by isolating those who have it from the rest of society (COVID-19). However, people aren't used to keeping that kind of distance from their surroundings. An active monitoring system that can detect lapses in touch and send out alerts may help limit the progression of the fatal illness. It's possible that the frequency of social distance breaches might be decreased by evaluating the social density in an area of interest (ROI) and then altering the inflow. On the other hand, in free societies, it is against the law to record data and name those who disobey the rules. Here, We propose an AI-based system for real-time social distance detection and warning, adhering to four key ethical considerations: (1) the system should never record or cache data; (2) the warnings should not specifically target individuals; (3) no human supervisor should be in the detection/warning loop; and (4) the code should be open-source and available to the general public. Thus, we propose gauging interpersonal distance using a single camera and deep learning-based real-time object detectors. If a breach of the social distance is detected, a subtle audio-visual warning signal is sent without single out the offender. If the population density is over a specific threshold, the gadget will also transmit a signal to adjust the amount of food and water entering the ROI. To assess the universality and performance of the suggested strategy, we tested it on real-world datasets. Our code is open-sourced, and the suggested solution is ready for use.

Yassine Himeur et.al (2022) Since the beginning of the COVID-19 pandemic, social distance (SD) has been crucial in halting and reducing the virus's spread in smart cities. Visual SD monitoring (VSDM) offers potential opportunities to assure the observance of SD in public spaces by I monitoring and evaluating the physical distance between pedestrians in real-time, (ii) spotting SD violations amid the crowds, and (iii) tracking and reporting offenders. To the best of the authors' knowledge, this study offers the first thorough analysis of VSDM frameworks, highlights problems with them, and discusses potential solutions in the future. Typically, we assess existing contributions by outlining VSDM's history, outlining evaluation criteria, and talking about SD datasets. After classifying VSDM methods into two broad groups—hand-crafted feature-based and deep-learning-based approaches—they are then closely examined. Convolutional neural networks (CNN)-based techniques are given a lot of attention because most frameworks have either used one-stage, two-stage, or multi-stage CNN models. To determine their benefits and drawbacks, a comparison analysis is also carried out. Then, a critical analysis is carried out to draw attention to the problems and barriers preventing the expansion of VSDM systems. The next step is to derive future directions that will attract major research and development.

Sergio Saponara et.al (2022) A virus called COVID-19 spreads between people in close proximity via minute droplets created through talking, sneezing, coughing, and most commonly by inhalation. Many people have died as a result of the pandemic's severe respiratory infection, which is still present today. You can reduce your risk of contracting COVID-19 by avoiding physical contact with others. Based on a thermal camera, this study suggests a real-time AI platform for people detection and social distance classification of persons. In this study, YOLOv4-tiny is recommended for object detection. Its straightforward neural network architecture makes it appropriate for embedded devices that are reasonably priced. Comparing the suggested model to other real-time detection methods, it is a better choice. Additionally, an algorithm is used to keep track of social distance from above. The proposed technique is used to movies acquired by thermal cameras in order to recognise individuals, categorise their distance from one another, and measure their skin temperatures all at once. During the training phase, the suggested model is fine-tuned for individual detection using thermal images captured in a variety of indoor and outdoor settings. The final prototype algorithm has been installed on low-cost Nvidia Jetson devices that include a stationary camera. The proposed approach is useful for building a surveillance system in environmentally friendly smart cities, since it can accurately identify individuals, classify their social distance from one another, and track their core temperature. This will make it easier for the government to see how those who are socially isolated are doing while also keeping an eye on their skin temperature.

Rinkal Keniya et.al (2020) The COVID-19 pandemic has unquestionably stopped all of human activity. The world we were living in a few months ago is entirely different from the one we are living in today. The virus is dangerous to humanity and is rapidly spreading. Given the urgent need, one must constantly take some measures, one of which is social estrangement. To ensure a decrease in the growing rate of new cases during COVID-19, maintaining social distance is essential. The major goal of our manuscript is to determine whether or not those around us are keeping social distance. The SocialdistancingNet-19 model we created for identifying a person's frame and presenting labels marks them as safe or unsafe depending on whether the distance is more than a predetermined threshold. People can be watched over using this technique and CCTV video surveillance. Our model had a 92.8% accuracy rate.

Junxiao Li et.al (2021) Based on the COVID-19 epidemic's global expansion, this article constructs a social distance monitoring system in public settings with the goal of reducing the social distance between pedestrians and the virus. In order to identify and label pedestrians, the programmed primarily use the YOLOv4 object recognition method and the Deep SORT multiple objects tracking technique. Affine transformation is then used to calibrate the picture for a more natural bird's-eye view. To prevent the impact of peers on the monitoring results, the author suggests a novel pedestrian grouping technique based on the analysis of pedestrian movement. Finally, three markers are chosen to categories pedestrians in order to analyses and assess the likelihood of virus infection in a specific location. The author infers from this paper's comparison of the yolov4 algorithm with other research's most effective performance that yolov4 is the best approach for social distance monitoring. Additionally, the programmed uses the latest pedestrian clustering technique, which increases the app's viability. In the experiment, it was shown that the average distance between pedestrian clusters and the density of pedestrian clusters were related to the infection index, suggesting that the social distance in the scene could be reliably observed in real time, which could be used to gauge a location's security and stop the spread of viruses.

METHODOLOGY

To detect individuals inside a certain area (ROI) and calculate distances between them in real-time without logging any information, we suggest using a fixed monocular camera. The suggested solution alerts the crowd if any breach of social distance is found by sending a non-intrusive audio-visual cue. Additionally, we create a brand-new crucial social density indicator and advise against participating in the ROI if the density is higher than this number. Figure 1 provides a summary of our strategy, and the formal description follows.

Problem Formulation

As a sextuple, S = (I, A0, dc, c1, c2, U0), where I RHW3 signifies an RGB image captured by a stationary monocular camera with dimensions H and W, a scene is described. To calculate the minimal physical distance dc R, we need to know the actual ground plane area of the ROI, denoted by A0 R. Any time the distance between pedestrians falls below dc, a non-intrusive audio-visual cue will be provided in response to the binary control signal c1. To prevent congestion within the ROI, a second binary control signal, c2, is used to manage entry. Our novel critical social density (c) criterion may be used to identify crowding. C makes sure that the likelihood of a social distance violation occurring is less than U_0. To lessen the likelihood of social distance violation, the threshold U0 should be set as low as possible. U0 = 1PCI 2 is one example of a feasible threshold, where PCI is the cumulative probability of a 95% confidence interval for a normal distribution. Depending on the particular needs of social distance monitoring, different U0 alternatives may also be effective.

Detection of People Walking in the Image Domain

A deep CNN model that has been trained on a real-world dataset is used to first detect pedestrians in the picture domain:

$$\{T_i\}_k = f_{\mathrm{cnn}}(\mathbf{I}).$$

f_{cnn} : **I** –[Ti] $_n$ maps an image **I** into n tuples $T_i = (l_i \mathbf{b}_i, s_i), \forall i \in \{1, 2, \cdots, n\}$. n is the number of things that were found. The object class label, li 2 L, is expressed in the fcnn notation for the set L of object labels. The BB for b I is defined as (bi,1, bi,2, bi,3, bi,4). Pixel indices in the picture domain are given by bi,j =. (xi,j, yi,j). The second sub-index j designates the top-left, top-right, bottom-left, and bottom-right corners, in that order. The matching detection score is si. Fcnn implementation information is provided in Section.

We are solely concerned in the situation where l = "person." Using the midpoint of the BB's bottom border, we define pi0 as the person i's pixel poses vector:

$$\mathbf{p}_i' := \frac{(\mathbf{b}_{i,3} + \mathbf{b}_{i,4})}{2}.$$

Real-World Mapping from Images

The next thing to do is get the second mapping function h: p0- p. Using the inverse perspective transformation function h, we may convert the image coordinates p0 to the physical world's reference frame coordinates of 2R2. This is because p is in 2D bird's-eye-view (BEV) coordinates, where the ground plane is assumed to have a z-value of 0. For this objective, we employ the well-known inverse homographs transformation as follows:

$$\mathbf{p}^{\text{bev}} = \mathbf{M}^{-1}\mathbf{p}^{\text{im}},$$

the rotation and translation from are described by the transformation matrix M 2 R3 3. world coordinates to image coordinates. $\mathbf{p}^{\text{im}} = [p'_x, p'_y, 1]$ is the homogeneous the homogeneous representation of the mapped pose vector is denoted by pbev = [pbevx, pbevy, 1] and represents the representation of p0 = [p 0x, p0y] in picture coordinates.

The transformation matrix M may be found by first identifying the geometric connection between a few key locations in the actual world and the image, and then calculating M via holography. Section 5 of this particular study has more information on camera calibration.

The source of the posture vector in the world is $\mathbf{p}^{\text{bev}}$ with $\mathbf{p} = [p^{\text{bev}}{}_x, p^{\text{bev}}{}_y]$.

Detection of Social Distancing

It is simple to retrieve the list of inter-pedestrian distances D after getting P = (p1, p2, pn) in real-world coordinates. Taking the Euclidean distance between the posture vectors of pedestrians I and j yield the distance di, j:

$$d_{i,j} = \|\mathbf{p}_i - \mathbf{p}_j\|.$$

A scene's overall social distancing violations v can be determined by using the formula

where $I(d_{i,j}) = 1$ if $d_{i,j} < d_c$, otherwise 0.

$$v = \sum_{i=1}^{n}\sum_{\substack{j=1\\ j\neq i}}^{n} \mathbb{I}(d_{i,j}),$$

Estimating the Critical Social Density

Finally, we seek a critical social density number (c) that will guarantee that the likelihood of a social distancing violation never exceeds U0. A simple solution of pc = 0 assures v = 0, however this serves no practical use. Instead, we're trying to determine the maximum feasible critical social density (pc).

To calculate pc, we propose a standard linear regression using population concentration (r) as the dependent variable and total violations (v) as the independent variable.

$$\rho = \beta_0 + \beta_1 v + \epsilon,$$

where $\boldsymbol{\beta} = [\beta_0, \beta_1]$ the regression criterion the error term, e, is a vector and is thought to be normal. The conventional least squares method is used to fit the regression model. This model needs training data to fit. Data are necessary before learning the model, but not after. The surveillance system doesn't start recording data until after it is deployed.

When no social distance violation is taking place (v = 0), the projected social density pjv=0 may be obtained once the model has been fitted. We suggest calculating the critical social density as instead of pjv=0 to significantly decrease the likelihood of social distancing violation occurring:

$$\rho_{\mathrm{c}} = \rho_{\mathrm{lb}}^{\mathrm{pred}},$$

where $\rho_{\mathrm{lb}}^{\mathrm{pred}}$ is the lower bound of the 95% prediction interval $(\rho_{\mathrm{lb}}^{\mathrm{pred}}, \rho_{\mathrm{ub}}^{\mathrm{pred}})$ at v = 0, as

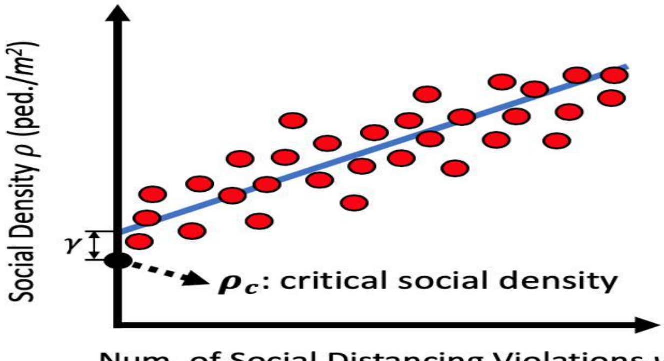

Figure 1. Keeping *r* under *p_c* will drive the number of social distancing violations v towards zero with the linear regression assumption.

If we keep the social density (r) of a scene below the bottom limit (plb) of the 95% prediction interval (pi) of the social density when v = 0, the likelihood of social distance violations happening is almost eliminated.

Considering that under the linear cumulative probability, the regression premise $P(\rho < \rho_{\mathrm{lb}}^{\mathrm{pred}})$ = 0.05, This is extremely tiny.

Extension of Application

To make use of the critical social density pc1 that was collected further the spread of COVID-19 must be stopped by further actions. The post-processing mechanisms can be divided into two categories.

To start, social distance can be tracked and managed online. Non-alarming audio-visual signals are sent in areas where the social density r is higher than the crucial value pc. When people do this, they are acutely aware that they are violating the unspoken "social distance rule." Signals for inflow modulation can also be sent by the system. These signals can be used by site administrators to maintain a low population density. Overcrowding is avoided in this manner.

Second, offline analysis is possible using both the statistics and the critical density computer. Regulators can use analyzed offline data to better plan large events and determine mean population densities in specific public locations or trends in population densities during public events.

When necessary, wider preventive steps can be implemented as soon as feasible by combining the offline and online information the suggested system provides. Figure 1 depicts the aforementioned procedures.

Experiments

To evaluate the suggested strategy, we ran three case studies. A distinct dataset of pedestrian crowds is used in each example. They are the Train Station Dataset, the Mall Dataset, and the Oxford Town Center Dataset. Table 1 displays information on the aforementioned data sets. We evaluated the suggested method's ability to detect social distance violations using the Oxford Town Center Dataset.

Table 1. Information of each pedestrian dataset.

	FPS	Resolution		Duration
Oxford Town Ctr.	25	1920	1080	5 mins
Mall	1	640	480	33 mins
Train Station	25	720	480	33 mins

Implementation

Finding the perspective transformation matrix M for each dataset's scene was the initial step. We immediately used the transformation matrix found on the Oxford Town Center Dataset's official website. We must manually locate the transformation matrices because the other two datasets do not supply them. The first step was to calculate the physical distances between four landmarks in the scene and their associated picture coordinates. This four-point data set was then used to calculate the perspective transformation matrix M. We located the Grand Central Terminal floor plan in New York City and determined the precise separations between the important locations for the Train Station Dataset. For the Mall Dataset, we compared the width of observed pedestrians to the size of a reference object in the image to estimate its size before using the reference object's key points.

The pedestrian detector was applied to each dataset in the second stage. Tests were conducted on a regular desktop computer outfitted with a 64-bit Ubuntu 16.04 LTS OS, an Intel Core i7-4790 CPU, 32GB of RAM, and an Nvidia GeForce GTX 1070Ti graphics processing unit. Pedestrians' whereabouts were calculated by converting picture coordinates to their physical world counterparts.

The final phase involved measuring social distance and determining the critical density pc. Only pedestrians within the ROI were taken into account. Statistics on the number of violations v, the inter-pedestrian distances di, and the social density r were tracked over time.

DATA ANALYSIS

Detection of Pedestrians in Real-Time Faster R-CNN and YOLOv4 are two different deep-CNN-based object detectors that we tested. The qualitative outcomes of Faster R-CNN-based pedestrian recognition in the image are shown in Figure 2, along with the appropriate social distance in world coordinates. Some false positives were found in the qualitative data. As far as I can tell, there are two potential origins. At the outset, occlusions may prevent detections from being made. This is shown in the Mall Dataset, where the presence of a shopping cart may confound the detection. Second, missing detections may also occur if the pedestrian size is too tiny. The Train Station Dataset has information on this. Since the system's top objective is to identify social distance violations, a small number of missed detections have little impact on the violation's severity. For our purpose, if we can get a reasonably close estimate for both the number of violations and the critical social density, then it will enough.

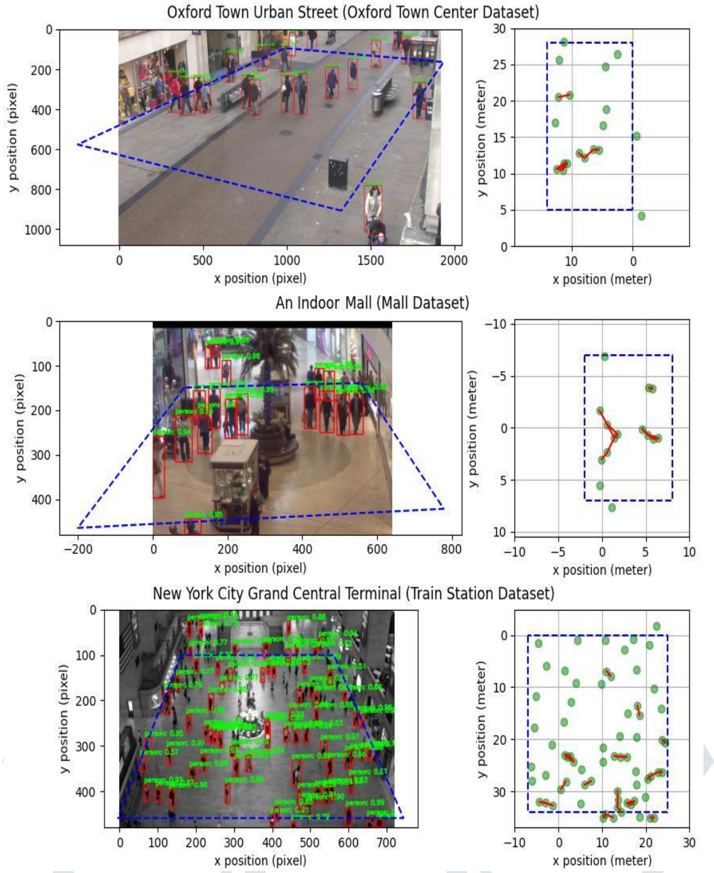

Figure 2. Illustration of pedestrian detection using Faster R-CNN and the corresponding social distancing.

Table 2 lists the detector performances. Both detectors reached an inference time of around 0.1 seconds per frame, as shown in the Table. This is sufficient to detect social distance in real-time. We provide the results of the original works MS COCO dataset for detection accuracy.

Table 2. Real-time performance of pedestrian detectors.

Method	mAP (%)	Inference Time (s)
Faster R-CNN	42.1–42.7	0.145/0.116/0.108
YOLOv4	41.2–43.5	0.048/0.050/0.050

The mean average precision, or mAP, is displayed. The inference time reports, respectively, statistically significant differences in the mean inference times for the Oxford Town Center, Train Station, and Mall datasets.

Detection of Social Distancing Violations

The number of violations v and the change in pedestrian density r over time are depicted in Figure 3. The outcome shows that r and v have a clear positive association. For instance, when r is low, In the Oxford Town Center Dataset, t = 41 s, the Mall Dataset, and the Train Station Dataset, t = 84 s, and t = 6 s, respectively, are all times when v is typically low. 2D histograms of this association are shown in Figure 4. It supports the found favourable association even further. The ensuing linear regression approach to determine the crucial social density is suggested as a result of this correlation.

To verify our proposed approach, we tested it on the Oxford Town Center dataset, which has reliable ground truth pedestrian detection. As of this count, there are 4501 annotated frames. During the training phase, 2500 frames were utilised, whereas during the validation phase, 2001 frames were used. The dataset was segmented such that the proposed method could be compared against a fully-convolutional neural network (CNN) model trained on the dataset's training frames for the identification of social distance violations. All assessment results were mapped into the validation frameworks.

Min(di,j) = I 2 f1, 2, and ng is the closest real distance for a particular pedestrian I. The mean absolute error (MAE) of the social distance violation ratio was also calculated as pv = v/n, where n is the total number of pedestrians inside the ROI. These results were compared to those obtained by using a variant of our approach described in Section 4.2, in which the location of the pedestrian is used as the centre of the detected BB rather than the centre of the bottom edge.

The mean absolute errors (MAE) for davg and pv are shown in Table 3. It provides a numerical estimate of the inaccuracy in identifying breaches of both physical and social distance. Comparatively low MAEs distinguish the proposed BB-bottom approach from its BB-center counterpart.

Table 3. Social distancing detection performance.

Method	MAE of davg (m)	MAE of pv (Count)
BB-center	1.416	0.196
BB-bottom	0.587	0.143

Additionally, The detection of social distancing violations was evaluated for its precision, recall, and accuracy in comparison to the actual violation. In addition to contrasting our original technique with the one using the BB centre, we also tried our hand at an end-to-end CNN model. To determine whether or not a social distance violation has occurred, the CNN model explicitly inputs the visual frame and returns an output. Based on ResNet50, this new model adds layers specifically for identifying breaches in social distance. The cost is defined in terms of a weighted binary cross entropy. The first 2500 pictures were used to teach the model. Model performance was evaluated using the remaining 2001 frames, providing a fair comparison to the other two methods.

The confusion matrix for the BB-bottom approach of detecting social distancing violations is displayed in Table 4. Due to the prevalence of social distance violation in the Oxford Town Center Dataset, true positives dominate the confusion matrix. Table 5 reports the precision, recall, and accuracy of the violation detection in the End-to-End CNN, BB-center, and BB-bottom techniques for your perusal and comparison. Results show that across all three measures, the BB-bottom approach is superior. The precision and recall metrics cannot be balanced by the other two approaches. Although the precision of end-to-end CNN is inadequate, the recall is comparatively high. BB-center has a low recall yet a relatively high precision. This further demonstrates the usefulness of deploying trained pedestrian detectors in the image domain by translating the centre point of the BB bottom edge to the pedestrian location into world coordinates.

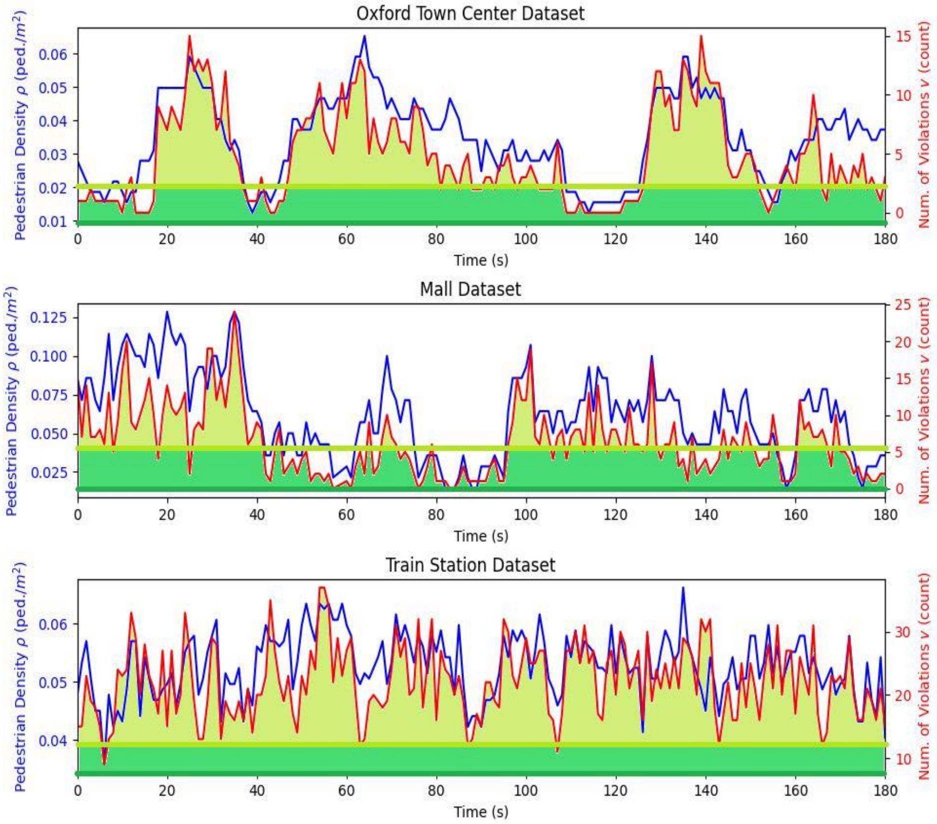

Figure 3 shows the evolution of pedestrian density (r) and infractions (v) over time. It demonstrates a clear inverse relationship between r and v. The linear relationship between r and v in Figures 4 and 6 further demonstrates the favorable association. The intercept density (b0) is shown by the lighter green line, while the critical pedestrian density (pc) is shown by the darker green horizontal line. They were acquired using the crucial social density estimation technique that was suggested in Section 4.5. If the pedestrian density is higher than b0, there will be more violations, as indicated by the lighter tinted green region. The darker shaded area of green indicates that if pedestrian density is further reduced below PC—our critical social density—more infractions will be resolved.

Table 4. Confusion matrix of social distancing violation detection.

		Ground Truth		
		Violation	No Violation	Total
Detected	Violation	1584	77	1661
	No Violation	67	273	340
	Total	1651	350	2001

The table reports the results of the BB-bottom method.

Table 5. Social distancing violation detection accuracy.

Method	Precision (%)	Recall (%)	Accuracy (%)
End-to-end CNN	83.27	94.37	79.71
BB-center	94.60	79.59	79.41
BB-bottom	95.36	95.94	92.80

CONCLUSIONS

This study proposes a real-time method to identify and track social distance based on AI and monocular cameras. In order to automatically measure social distance, the study proposes a real-time deep learning-based system that employs object identification and tracking techniques. Each person is identified in real time using bounding boxes. The sign language dataset was developed using the YOLOv3, YOLOv4, and YOLOv5 algorithms. Due to some regions' exceptionally high pedestrian density and occlusions, several missed detections in the mall dataset and train station dataset occurred. However, the majority of pedestrians were successfully captured after our qualitative and quantitative study, and the missed detections only slightly affect the suggested strategy. Testing and verifying the suggested method using other datasets of various scene types could be one future project. Lastly, we did not take into account in this work that a group of people can be related to one family or have another link that does not call for social distance. This issue's comprehension and resolution could be the subject of further research. However, one can contend that even those with close relationships ought to make an effort to maintain social distance in public.

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