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Social Distance Assessment and Prevention System Based on Marker

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Abstract

IoT is quickly becoming a leading technology in healthcare. Early detection of health problems and preset protocols after patient recovery are all employed to decrease the chance of COVID-19 spreading to others in the event of COVID-19. Such wireless positioning devices can correctly remind individuals to maintain distance by sensing between people and then warning them if the people are close to each other. Motivated by this notion, in this paper we have proposed and implemented a model of the social distance assessment, monitoring, and marker system for prevention. The goal is to minimize the effects of the coronavirus outbreak while generating the least amount of economic harm possible, as well as to enable or even impose social distance. In the Monitoring System, users can easily access a web-based application integrated with the detection system by following the integration with the Raspberry Pi 4 and Pi Camera, in which they can monitor the detection of safe and unsafe people. Meanwhile, the marker system, which is based on a laser, will guide the user to stand in safer locations with the help of a laser marker module to eliminate violations. The proposed system is implemented using OPEN CV and Mobile NET SSD for object detection, and the Euclidean distance measurement method is used to measure the distance between people. The hardware and software integration is also included in the system with an accuracy level, the system is an effective, low-cost, and user-friendly social spacing tool for preserving distance around people at large gatherings.

Keywords: : Internet of things, Laser, Deep Learning, Social Distancing, Mobile Net SSD, YOLO3

1. Introduction

With the epidemic situation of infectious diseases, organizations, companies, and institutions need to take the necessary measures to sustain the global community while taking care of their employees as well as clients [1]. According to a recent study regarding COVID-19, the infection rate was found to be higher where people are not practicing social distancing, which resulted in the emergence of maximum cases [2-5]. Throughout the COVID-19 pandemic, the World Health Organization

recommended that the community practice social distancing in public places for the prevention of the COVID-19 virus. Despite the current conditions, there is a necessity to practice and monitor social distancing to save time from challenging situations nearby in the future [6].
According to the World Health Organization's guidelines for masks and social isolation, these can only prevent the transmission of the COVID-19 virus. This may be done in the coming years until it is entirely eradicated [7]. The practice may reduce the spread of disease. To avoid the transmission of the disease, people can avoid physical contact as much as possible by keeping a specific distance in public places. According to WHO guidelines, the minimum distance between humans between two people can be 6 ft. [8]. Governments stepped up to help during the outbreak and used a range of social distancing tactics, including travel restrictions, and reminding the public to maintain a space between them. On the other hand, monitoring the extent of virus spread and the effectiveness of the limitations is not easy. People are required to go out regularly to fulfill their needs. As a result, several more technology-based solutions have emerged that play an essential role in facilitating the practice of social distancing [9].

IoT delivers exceptional advancement in the pandemic, and a variety of technological solutions have been proposed, including smart digital technologies based on mobile phone technologies, wearable smart devices, and surveillance systems, ranging from hardware electrical sensors to pedestrian tracking, deep learning, segmentation, and so on, that are being utilized to assist the medical and health communities in dealing with COVID-19 problems and effective social distancing strategies [10-15]. It occurs when a machine learning model becomes too complex and starts to memorize the training data instead of learning the underlying patterns. This leads to poor generalization and low performance on new, unseen data. Deep learning models are especially prone to overfitting due to their large number of parameters and the potential for high variance. To prevent overfitting in this deep learning we have included data augmentation, which generates new training data by applying transformations to the existing data, and batch normalization, which normalizes the inputs to each layer in the network to reduce internal covariate shift. In Conclusion, avoiding overfitting in deep learning requires a combination of these techniques and careful tuning of hyperparameters, such as learning rate and batch size. It is important to regularly monitor the model’s performance on a validation set during training to ensure that overfitting is not occurring.

A data-driven approach can be more appropriate than a model-based approach in social distance monitoring systems because the social distancing guidelines and behaviors can vary across different cultures, regions, and situations. Therefore, it may be difficult to design a model-based approach that can accurately capture all the complex and dynamic factors that affect social distancing, such as crowd density, walking speed, and environmental factors. This approach uses machine learning algorithms to analyze and learn from large datasets of social distance monitoring videos and sensor data and can identify patterns, correlations, and anomalies in the data that may not be easily captured by a model-based approach and it can be more appropriate than a model-based approach in social distance monitoring systems as it can leverage the power of machine learning to analyze large and complex datasets, identify patterns and anomalies, and adapt to the changing conditions and feedback.

Two algorithms are proposed to classify the detected devices; we develop a method to qualify neighborhood social distancing measurement.

1. To deploy pre-trained MobileNet SSD for people identification and computing the centroid of their bounding box. The Euclidean distance is used to roughly calculate the distance between each pair of centroids of the bounding box observed in order to track the social distance between individuals. A pixel-to-distance calculation is also used to specify a social distance violation threshold.
2. Analyzing pre-trained Mobile NET SSD's performance using an overhead data set. The model's performance is additionally contrasted with that of other deep learning models.
3. The intricate and distinctive element of the study under discussion is the Marker system. The user will be directed by a marker system as to where to stand to keep to the social distance standards once again. The system will add the value into the x and y axis to move the motor to the directed location so the laser may direct the user to move to the right or left of that person nearby so the violation can be removed.
4. Additionally, an announcement has been issued to keep a safe distance from others. Above the viability of the entire [1] [2], is thus something that the regression techniques are bound to follow. This hypothesis makes the supposition that the stock value at the moment may be calculated as a consequence of stock price previous records and reasonable forecasts. Any departure from this premise could make the stock price unexpected.

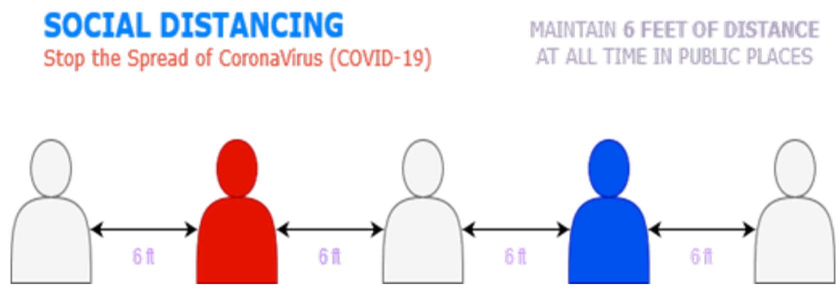

Fig. 1 Standard Social Distancing Protocol

Fig. 1 demonstrates the WHO-assigned standard guidelines for implementing social distancing at large gatherings. People must maintain a minimum distance of 6 feet, or 2 meters, which is a typical protocol for maintaining distance and is also applied in the proposed method, flow chart also shows the system phrases as shown in Fig. 9. Laser systems have transformed medical operations, from LASIK eye surgery to non-invasive therapies for a wide range of illnesses. They enable more precise procedures, lowering recovery periods and boosting results. The development and deployment of laser technologies have fueled growth in the technology industry, resulting in the creation of new goods and services. The adaptability of laser systems has created new markets for medical gadgets, consumer electronics, and industrial equipment. This has resulted in increased competition and innovation in these sectors.

2. Literature Review

The authors employed a pertained repetitive neural model to detect the different models. The human recognition approach employs blob fragmentation. To estimate the distance between such blobs, they are inspected by each other. They had trouble recognizing the desirable body blobs in the outdoors because of their interactions with other things. They discovered that this issue requires more investigation. CNN is used in object detection and complicated classification of objects, including person detection. In comparison to traditional models, CNNs deal with correct and quick detection. The authors addressed the issue of individual distancing. They employed the Mobile Net as a slightly weighted detector to save time and money, although it has lower accuracy than other popular versions [16-18]. Furthermore, this approach focuses solely on public place distance detection and does not give an analysis of viral dissemination. The findings of the distance measurement are not statistically analyzed, as in the previous studies [24]. The authors compared two types of models of DNN, YOLO and Faster CNN. The system's accuracy, on the other hand, has only been approximated using a crude comparison of diverse datasets with non-comparable ground facts. There haven't been many specific studies on the accuracy of people recognition and inter-people distance estimation in crowds since the concept of social distancing has now been upgraded. There were no tests on difficult datasets, standard comparisons on common datasets, analytical studies, or post-processing to investigate the risk of infection spreading beyond the personal identification phase [27].

Authors of [28] include a person's visual vision as well as their capacity to make decisions in a state of uncertainty, errors are inescapable, particularly in surroundings with such limited space, since this system is only a prototype and we are utilizing laser to build the marker system, the only restriction is that it can only work on two individuals at once. However, in the future, to get the best results and for faster processing, GPU and LiDAR can be utilized. The numerous categories of monitoring systems, including smart monitoring systems and traditional monitoring systems, and their respective types, are also represented in Fig. 2. In the solution that we have proposed, we have built remote monitoring that is based on object detection for people. This monitoring identifies individuals based on their distance. We have included some of the most well-known proposed methods that have been used to implement.

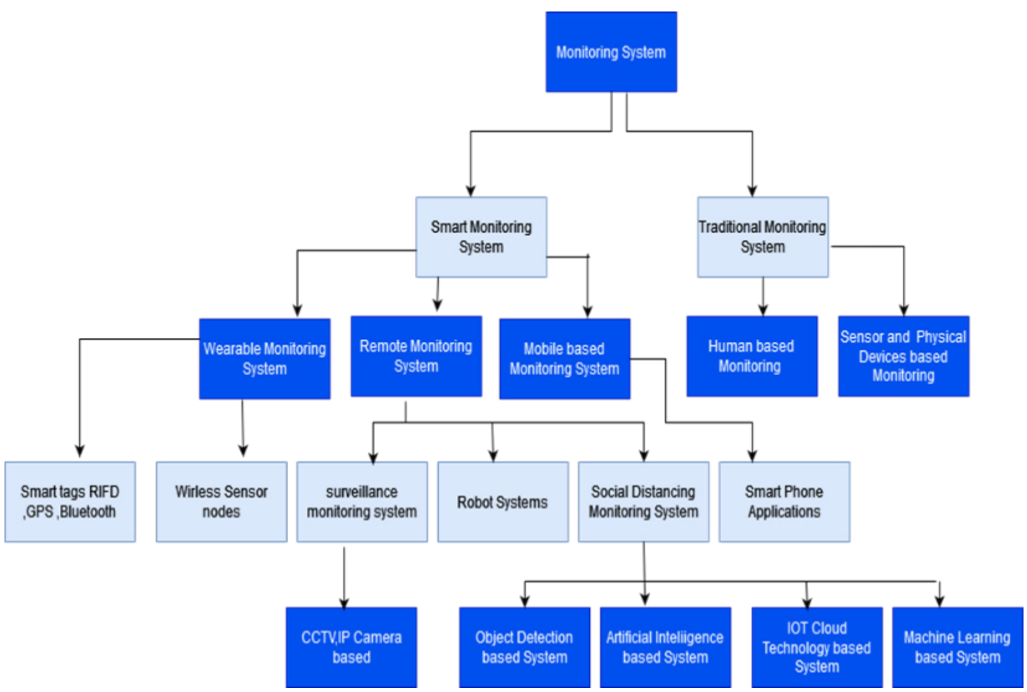

Fig. 2 Taxonomy of Monitoring Systems

Table 1 Comparison of previous approaches to monitoring systems

Reference	System	Technologies	Data Real-time	Thermal image	Facials detect
[19]	Surveillance	IoT	√	X	X
[20]	CT scan	AI sensors	X	X	X
[21]	Facial image	Deep learning framework	√	X	√
[22]	Driver state monitoring	Face detection	X	X	√
[23]	Surveillance	B5G framework	√	√	X
[24]	Thermal, Surveillance	Blockchain	√	√	X
[25]	Thermal body	AI based	√	√	X
[26]	Vision mobile robot	DRL and model based	√	√	X
[27]	Adversarial	DNN	√	X	√
[28]	Facial image pattern	CNN	X	X	√

remote monitoring systems. These methodologies include the system type, the technology that was used for implementation, and a variety of parameters that allow us to determine which method is the most effective out of all of them, as shown in Table 1. At the same time, we have compared the most widely used object detection algorithms and discussed their accuracy rate, actual detection rate, recall, and precision to determine which one is the most accurate in terms of the level of precision, as shown in Table 2.

The literature provides a thorough understanding of the importance of social distancing in mitigating the spread of infectious diseases. It covers various approaches and technologies used in social distance monitoring, which provides a comprehensive overview of the existing solutions, however, it highlights the need for practical solutions for implementing social distancing, which aligns with the aim of our research. Some literature lacks practical solutions for social distancing implementation and focuses more on theoretical aspects, as well as effectiveness of some social distance monitoring approaches mentioned in the literature is questionable, which raises concerns about their practicality.

However, the literature does not consider the potential limitations or drawbacks of certain technologies, such as cost, complexity, and privacy concerns. Furthermore, the literature provides a strong foundation for understanding social distancing and monitoring. This research aims to bridge these gaps by introducing a laser-based marker system that provides a practical solution for maintaining social distancing in public places.

Table 2 Comparison of Algorithms Accuracy

Model	True detection rate	False detection rate	Precision	Recall	Accuracy
Fast-RCNN (pre-trained)	90%	0.7%	80%	66%	90%
Faster-RCNN (pre-trained)	92%	0.6%	80%	70%	92%
Mask-RCNN (pre-Trained)	92%	0.5%	82%	70%	92%
YOLOv3 (pre-trained)	92%	0.4%	84%	78%	92%
YOLOv3 trained overhead	95%	0.3%	86%	83%	95%

The accuracy and inference speed may vary depending on the dataset and hardware used for evaluation. These approaches are suitable for mobile and embedded devices. However, for desktop and cloud-based applications where higher accuracy is required, approaches like Faster R-CNN, RetinaNet, and EfficientDet may be preferred. This article's work is novel because it explores the implementation of a laser-based marker system that guides individuals to a safe distance for social distancing. Unlike other research papers that focus on social distance monitoring through various approaches and algorithms, our paper addresses the practical implementation of social distancing using a laser marker system. While many papers discuss the importance of social distancing, they often fail to provide practical solutions for its implementation. We introduced a laser marker system that can guide individuals to maintain a safe distance in public spaces. By using laser technology, our system can provide a visual reference point for individuals to follow, making it easier for them to maintain social distance. Our research not only addresses the implementation of social distancing but also highlights the importance of using technology to facilitate public health measures. In summary, our research paper presents a novel solution for implementing social distancing in public spaces through the use of laser-based marker systems. Our findings have significant implications for public health and can help in the development of practical solutions for maintaining social distance in a post-pandemic world. The authors present a unique smart social distance system employing a compact and affordable wearable gadget that allows users to maintain safe distances, reducing COVID-19 exposure and decreasing its local and national spread.

3. Methodolgy

The proposed methodology is based on two major fragments: the social distance detection assessment and the prevention system based on the laser marker system, it will detect the distance violations in the monitoring system and classify them in a web application through a Python flask server. On the other hand, the marker system will guide the violator where to stand through a laser marker system. Marker systems are hard to achieve in real-time scenarios as image processing uses a lot of GPU power and storage time. But for now, in this paper, a prototype is discussed that can be further enhanced to be effective in an era of pandemics and other critical scenarios as well.

The methodology is based on two systems, i.e. assessment and prevention as mentioned.

For the monitoring system, we have used a Pi camera for a live video feed to monitor violations of social distancing. This takes a video input and processes a Python script on it that has social distancing formulae from Euclidian distance, and it uses MobileNet SSD for detecting objects, i.e., only humans. After the detection of objects, it will check the distance between them, which has social distancing formulae from Euclidian distance, and it uses MobileNet SSD for detecting objects, i.e., only humans. After the detection of objects, it will check the distance between them, which means there is no violation in the frame, the frame will then appear green. After that process, an output video will have at least 1 meter between the detected users in a frame if the distance is less than 1m the frame will appear in red, and if it is more than 1 meter, there is no violation in the frame, the frame will appear green. After that process, an output video will be generated by combining all the frames. Meanwhile detecting the distance violations, a counter will show the number of total violations appearing in the frames, Additionally, the distance that elapses between individual frames is measured, which is beneficial to the marker system.

The marker system is a complex and unique entity in the paper discussed. The marker system will guide the user to where to stand to stop violating the social distancing rules. As discussed in the monitoring system, it has already detected the distance between the frames that are violating the social distance protocol by using that calculation to make that distance 1 m, which means subtracting the distance previously obtained from the monitoring system by 1 m. using that value to give a remote signal to the motor, which will be connected to our Raspberry Pi 4, to move to the position by determining the x and y axes of the person violating SOP. After that, the system will move the motor to the guided position by adding the value to the x and y axes so the laser can guide the user to move to the right or left of that person near them so the violation can be eliminated. An announcement to maintain social distance has also been made. The prototype of object detection for individuals is shown in Fig. 3. When we identify people using Mobile NET SSD class 15, we compare the detected object with the class, and if it matches the object, it is declared to be a person in the frame since it already has pre-trained patterns. Fig. 4 represents the calculation of the coordinates of the people in the frame to identify the midpoint, which aids in measuring the distance between individuals, and the formula for determining the distance measurement between two people using the Euclidean distance formula after finding their x and y coordinates, shown in Fig. 5. Fig. 6 represents the proposed system marking through Laser. A person within a frame is deemed unsafe. A laser-attached motor will move to a predetermined distance in the code represented by a mark, and an arrow will direct the person to move towards the mark. Furthermore, an announcement will be played when a violation occurs.

The MobileNet SSD model can identify people and provide bounding box data. Following human detection, the identified bounding box and its centroid information are used to compute the Euclidean distance between each detected pair of centroid pairs. Using pixel to distance assumptions, a predetermined minimum social distance violation threshold is specified. The estimated data is compared with the violation threshold to see if the calculated distance falls under the set of violations or not. Initially initialized as green, the bounding box's color is changed to red if it falls under the violation set.

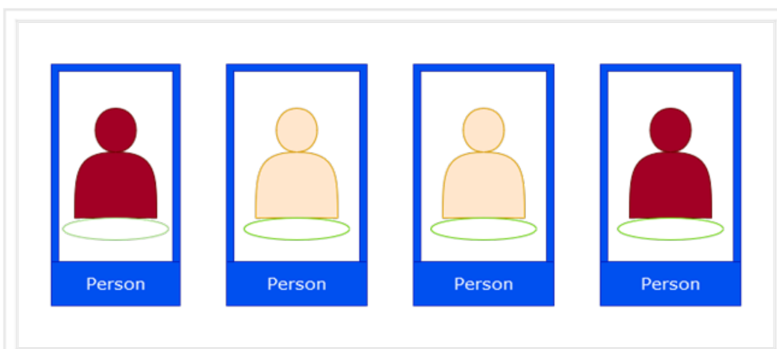

Fig. 3 Object Detection Prototype

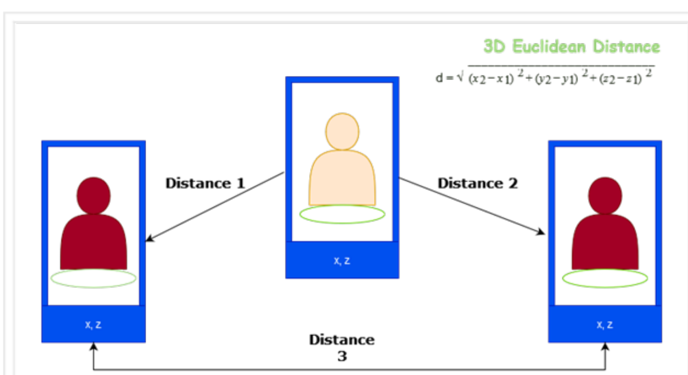

Fig. 4 Calculation of X, Y, Z coordinates

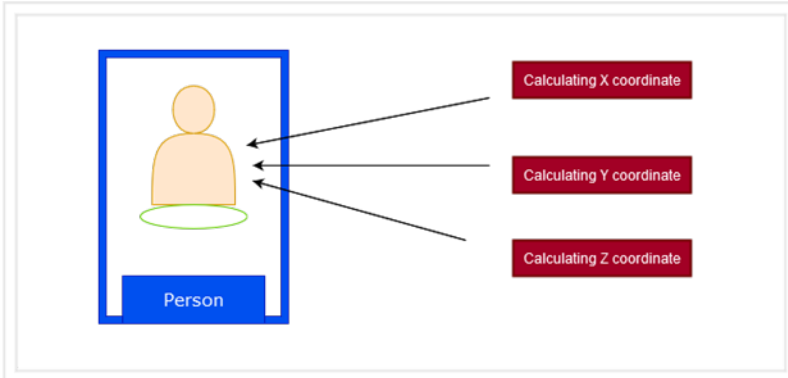

Fig. 5 Distance measurement

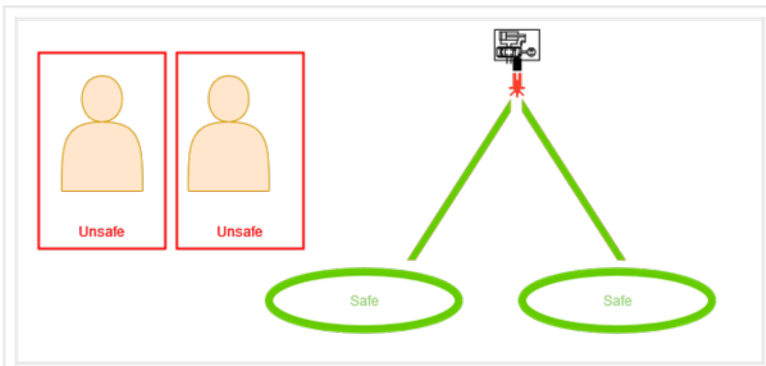

Fig. 6 Marking through laser

3.1 Implementation of Algorithm

It works towards the goal of developing methods that assist computers in "seeing" and comprehending the content of images. It is possible to create these digital images using both traditional photographs and audio recordings. The usefulness of computer vision is essentially determined by the kind of issues it can successfully resolve. CV refers to a type of technology that permits interaction between the digital and physical worlds. In addition to that, it is utilized in applications that deal with face recognition. The phrase "facial recognition" refers to a collection of several technologies that allow computers to match the faces of people with their respective identities. This is accomplished with the use of computer vision algorithms that analyses photos in search of face characteristics and evaluate those qualities in relation to facial identity datasets. Pre-trained MobileNet-SSD models are available online, and they are usually trained on publicly available object detection datasets.

The Tensor Flow Model Zoo contains a pre-trained MobileNet-SSD model trained on the COCO dataset that can be used for object detection tasks. It is available for download on the TensorFlow website. Open CV is a framework for computer vision, machine learning, and image analysis that is offered under an open-source license. It is also known as the "Open-Source Vision-based Library." Real-time processing relies on it, making it a vital component of today's computer systems. We look at photos and video feeds using Open CV in order to detect things like faces, objects, and now even handwriting on the page. The input may consist of things like surveillance footage, the views of numerous cameras, and complicated data. Choosing MobileNet SSD (Single Shot Multibox Detector) over alternative object detection models requires careful consideration, especially when balancing speed and efficiency for individual applications. Here are some of the rationales for considering MobileNet SSD.

MobileNet SSD is meant to be fast and efficient. MobileNet, as a lightweight architecture, is best suited for mobile and embedded devices. The SSD foundation enables it to recognize objects in real-time, making it ideal for applications that require speedy reactions, such as mobile apps or real-time video analytics.

Faster R-CNN, while very accurate, is computationally demanding and slower than MobileNet SSD. MobileNet SSD is a feasible solution for cases when accuracy is significantly compromised in favor of speed and efficiency. In essence, MobileNet SSD is chosen for its efficient mix of speed, accuracy, and resource utilization, making it an ideal solution for mobile and embedded systems with limited computational capability. Its selection over more resource-intensive object identification models is primarily motivated by its real-time performance, low latency, and resource efficiency.

Mobile net SSD is an image classification model that uses an input image to determine the classification model and type of an object. This Single Shot Detector concept, which is based on a mobile network, may enable mobile platforms to detect objects rapidly. Mobile net SSD creates 1, 300, 4 compartments and 1, 321, 21 scores from a 3,300,300-pixel image. Fig. 7 depicts the SSD's entire architecture for object detection, from image input to extraction by each layer, including classification and regression. The following illustration demonstrates that the first few layers, denoted by white boxes, comprise the backbone, while the last few layers, denoted by blue boxes, constitute the SSD head.

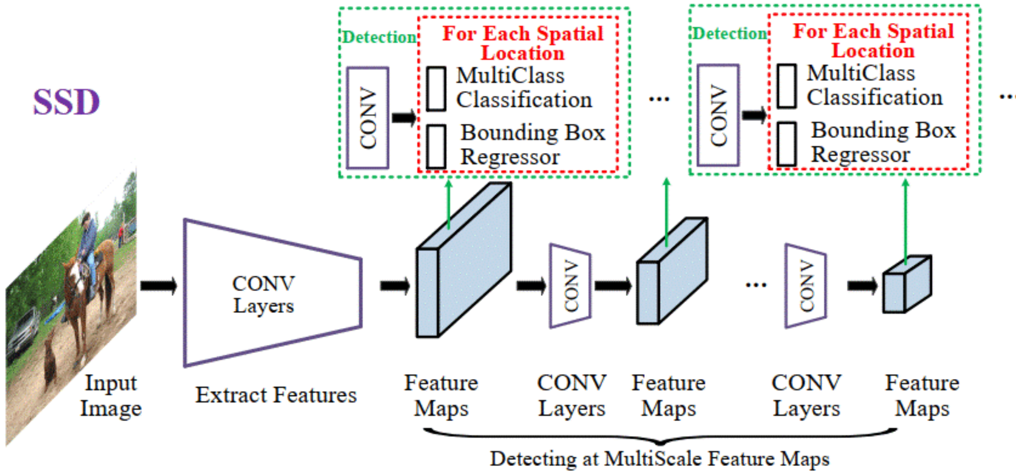

Fig. 7 Object Detection Framework using SSD

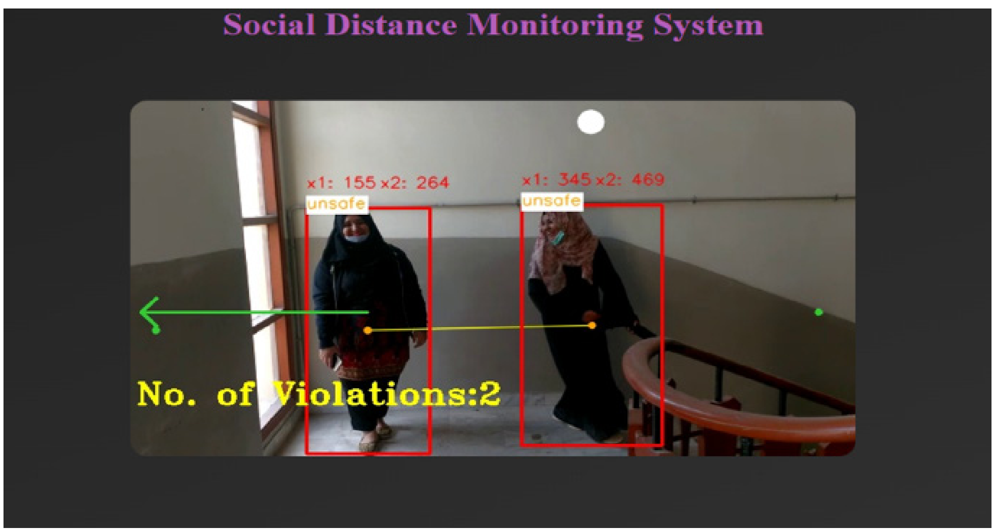

Fig. 8 Final output on web interface

Fig. 8 shows the final output that the flask server generated. This output is generated by the flask server and displayed on an HTML page. Because Flask is easier to work with Django, we were able to effectively display our video by using Flask instead. The video depicts the individuals who have been observed, the total number of violations, their computed coordinates, and the location where they must be relocated to eliminate the violations. Previous research has shown risk perception as a leading indicator of protective behavior when determining the elements that influence social distancing. However, no study has been conducted to determine if individuals' varying risk perceptions influence their interpretation of social distancing regulations in the same way.

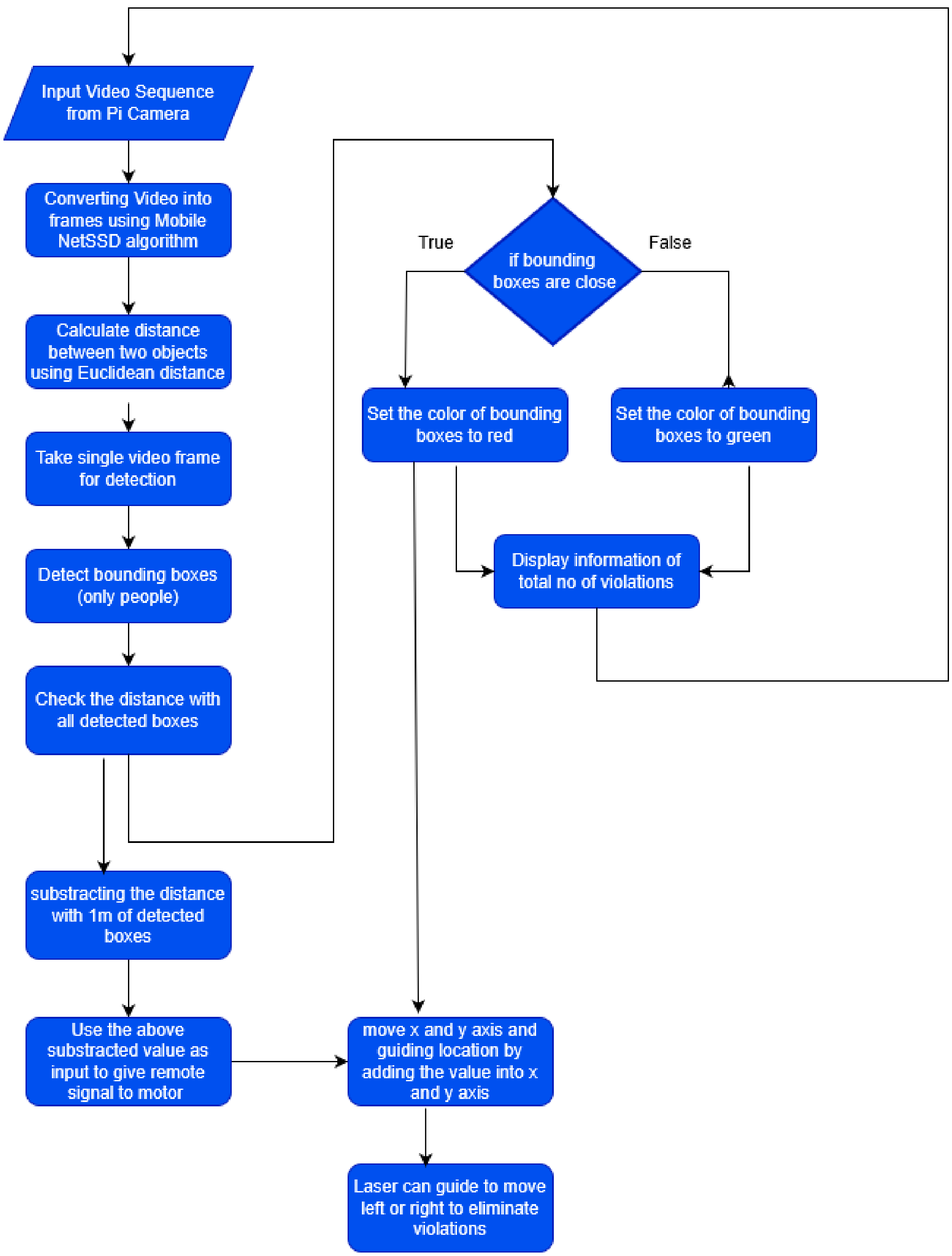

Fig. 9 Flowchart of the proposed system

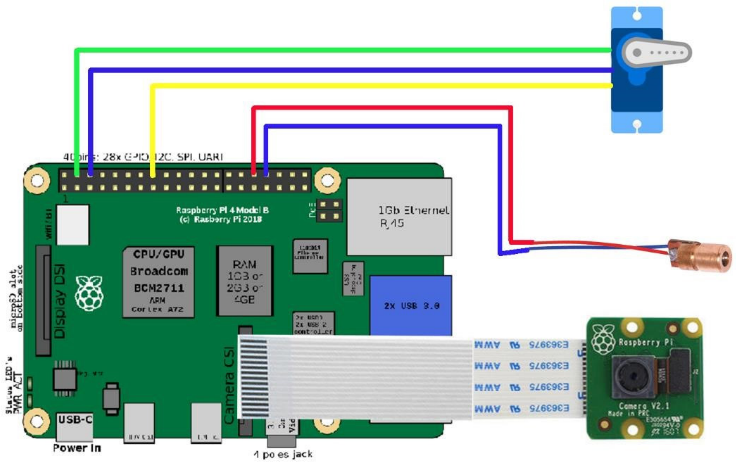

Fig. 10 Implemented Circuit Diagram

4. Results and Discussion

The most effective way to prevent the spread of the disease is to maintain a social barrier between infected individuals. Due to the implementation of the automatic monitoring system, numerous shortcomings in data collection have been ameliorated. This study suggests integrating an effective autonomous monitoring system with a marker prevention system. This system aids in the localization of each individual, monitors them for the social distance parameter, and identifies precise standing locations. This can be utilized both inside and outside the building for surveillance purposes. It can be used in any public location, including airports, train stations, department stores, grocery stores, and supermarkets, as well as superstores. In comparison to other object detectors, the proposed method demonstrated superior performance in real-time. The proposed solution can be implemented in a video surveillance system with cameras located in numerous different locations, the hardware integration is shown in Fig. 10. It is a viable option for authorities to monitor individuals while maintaining social distance. The prototype uses pre-trained models, eliminating the need for any training time. Our laser-based marker system relies solely on the calculation of individuals' X-axis and Y-axis coordinates. The pre-built model has been utilized only to identify humans in the video and nothing beyond that.

5. Conclusion

A social distance monitoring and marker system is proposed in this paper. This system is a social distance monitoring and marking solution that can be employed both indoors and outdoors to reduce transmission in public gatherings. The proposed system can detect the presence of people in the area of interest and estimate the user's distance from the object of interest. Furthermore, the proposed system can assist the user in maintaining social distance protocols by standing in various locations. Using the Mobile Net SSD algorithm, a prototype has been developed to realize SD in real-time. Integration encompasses both hardware and software between individuals in public spaces, with an average accuracy of 80%. The only limitation of this system is that the marker system can distinguish between two people simultaneously; however, this can be overcome in future work, and GPU and LiDAR can be used for future work to obtain maximum results. In the future we can Integrate several data sources (e.g., environmental, genetic, and mobility data) to improve accuracy and early warning systems, as well as create and test mobile apps and digital platforms for monitoring health status, controlling COVID-19 symptoms, and encouraging adherence to public health policies.

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