SSR Journal of Artificial Intelligence (SSRJAI)

OPEN ACCESS

Volume 1, Issue 1, 2024 Journal homepage: https://ssrpublisher.com/ssrjai/ ISSN: XXXX-XXXX

# Survey of Social Distancing Detection and Effective Crowd Control Using Computer Vision for any Communicable Diseases

K. Govindarajan[1], Dr. S. Sudha[2]

Research Scholar, Department of Computer Applications, Hindustan Institute of Technology and Science, Chennai, India[1]
Professor, Department of Computer Applications Hindustan Institute of Technology and Science, Chennai, India[2]

**Received:** 02.10.2024 | **Accepted:** 11.10.2024 | **Published:** 22.10.2024

***Corresponding author:** K. Govindarajan

**Abstract** **Original Research Article**

Social distancing is still one of the most effective ways to control the spread of infectious diseases. This paper proposes a novel real-time social distancing monitoring and enforcement algorithm in public areas. In the background, we designed a novel algorithm that can automatically examine and quantify compliance to recommended social distancing practices using real-time video streams from cameras deployed on location. It uses sophisticated computer vision to complete a millisecond-by-millisecond spatial analysis of people. Our system accepts both passive monitoring and smart tracking. The solution relies on a tracking mechanism that detects people coming too close to each other against the prescribed distancing norms to identify deviations and immediately alert and guide them (Mobile App Users) into specific "Red Zones" when necessary. The research offers a major advancement in controlling diseases, providing an active real-time solution to enforcing social distancing measures in public places.

**Keywords**: Deep Learning, YOLOv5 / YOLOv6 / YOLOv7 algorithms, person detection, tracking, social distancing surveillance, Public Data Analysis, Computer Vision.

**Abbreviation**: YOLO (You Only Look Once), CNN (Convolutional Neural Network), COCO (Common Objects in Context), Single Shot Multibox Detector (SSD), ResNet (Residual Network), VGG (Visual Geometry Group).

## INTRODUCTION:

In communicable diseases, the practice of social distancing has emerged as a critical and effective non-medical strategy to mitigate the spread of infectious agents within society. According to the guidelines of the World Health Organization (WHO), the spread of any communicable disease like cold, flu or more serious infections like COVID can be reduced by avoiding close contact with sick people. By staying a safe distance away from infected individuals and washing our hands, we can help stop these diseases from spreading and keep ourselves and others healthier.

In the current scenario the fight against any communicable diseases like flu, chicken pox, Coronavirus etc., the computer vision and Deep learning technics has emerged as a formidable ally, particularly in the context of human social distancing compliance monitoring. The rapid advancements in computer vision algorithms, driven by deep learning techniques such as Convolutional Neural Networks (CNNs), have birthed highly efficient object detection models like YOLO (You Only Look Once). These technological actions have transformed our capacity to automate the surveillance of social distancing adherence that is captured using CCTV in a real-time environment, contributing significantly to public health efforts during the outbreak of contagious diseases. This prelude sets the stage for a comprehensive investigation of how computer vision, deep learning, Machine learning, and YOLO-based object detection algorithms are reshaping our approach to monitoring and ensuring social distancing compliance in communicable disease challenges that is captured in the CCTV in real-time.

## RELATED WORK:

Researchers are working worldwide to actively engage in the development of systems and technologies in the field of computer vision for detecting social distance compliance from video feeds. These efforts utilize" or "exploit a variety of techniques, including the Internet of Things (IoT), computer vision, deep learning methodologies, and YOLO. Among the notable object detection approaches employed in this context are YOLO (You Only Look Once), fast R-CNN, RetinaNet, and Single Shot Multibox Detector (SSD).

1. YOLO and its versions is an object detection algorithm that is used in its real-time ability, faster and accuracy. It has been used by researchers to analyse real time CCTV video footage to detect and monitor social distancing violations in crowded public areas.
2. The Fast Region-based Convolutional Network (Fast R-CNN) is another popular object detection method. Researchers have developed systems with which the Fast R-CNN has been integrated to track individuals in videos overtime enabling evaluation of social distance violations.
3. RetinaNet has good recognition capabilities at different scales. In certain scenarios, where there are many objects or people in multiple positions or distances, RetinaNet has been used by researchers to watch advertisements via a video clip in order to calculate physical non-compliance that could put many lives at stake.
4. SSD (Single Shot MultiBox Detector) is a general-purpose object detection framework that is known for its speed, accuracy and robustness. In most of the cases of social distancing violation detection systems, SSD has been used to detect humans and calculate distances between humans, guiding in the detection of violations. Most of the researchers have integrated IoT devices such as CCTV cameras and sensors into their social distancing detection systems. Along with computer vision techniques, data from above mentioned devices has been important in achieving more accuracy, faster and better coverage in monitoring research. In most social distancing detection systems, deep learning models, including CNNs, FCNNs etc., have taken the main stage. These models are trained on huge datasets to identify humans and their positions within captured videos, automatically evaluating their compliance with distancing regulations.
5. Researchers most of the time employ data amplification and preliminary processing techniques to enhance the robustness, accuracy and fastness of the models. This includes techniques like image amplification, background removal, and noise filtering.
6. Most of the studies accentuate real-time monitoring capabilities, ensuring that social distancing violations are identified correctly, allowing for instant interventions and execution of safety measures.
7. Most of the researchers in this field also deal with moral concerns related to privacy. They aim to balance between public safety and individualistic privacy rights; they often implement masking techniques to protect individual personal data.

In short, the venue of social distancing monitoring using CCTV video feeds is dynamism, with the idea of researchers combining the power of IoT, computer vision, deep learning and a variety of object detection algorithms to improve public health efforts during communicable disease epidemics. These multi-disciplinary attempts highlight how technology can safeguard public people's health and safety during pandemic situations.

## LITERATURE REVIEW:

Various researches have been carried out on social distancing using different techniques. Most of the work was done based on VGG-16, VGG-19, ResNet-50, Inception, and a few transfer learning concepts with maximum accuracy limited to 94%. As the deep learning algorithms are gaining popularity, they have been used in most of the models for computer vision, object detection but they have limited accuracy.

In Imran Ahmed et al. proposed a deep learning framework using YOLO V3 and transfer detection for monitoring social distance during the COVID-19 pandemic. The results of this paper show a 92% detection accuracy, which increased to 95% with knowledge transfer. The model also detects a tracking performance of 95%. This research is significant for its real-world application potential and contributes to enhancing public safety during the pandemic. Future work may involve refining accuracy and exploring real-time deployment.[1]

In this study, “Person Detection for Social Distancing and Safety Violation Alert based on Segmented ROI”, employs the MobileNet SSD model and OpenCV for image processing, using the COCO dataset for benchmarking. Hindrances of this research include difficulties in outdoor and distant location detection. The researcher is significant for his practical application in enriching public safety. Future research could explore methods to improve accuracy in challenging outdoor environments and distant location detection. [2]

Sujash Paradkar et al. proposed their novel Social Distance Detector by combining computer vision, OpenCV, and YOLO deep learning with CUDA acceleration, this research demonstrates real-time monitoring of social distancing. This technology has vast potential for applications in hospitals, offices, and public areas like parks, malls, railway stations, etc., Suggestions for improvement include accuracy enhancement and user-friendly interfaces, reinforcing its importance in the pandemic response.[3]

In Marek Vajgl et al. present a new algorithm for improving object detection in automotive applications, specifically for automatic headlamp control in smart cars. Dist-YOLO enhances YOLOv3 by integrating distance estimation, achieving superior object localization accuracy without giving up computational speed. Notably, the generic approach simplifies implementation. The model exhibits a mean absolute distance error of 2.5m and a mean relative error of 11%. Future work should focus on real-world testing, integration into vehicles, and fine-tuning for enhanced accuracy.[4]

Tareq Alhmied at et al. introduce an innovative social distance monitoring system using wearable smart tags for indoor and outdoor environments. The system comprises human detection, distance estimation, broadcasting, and base station processing modules. The SD-tag, equipped with eye detection and range finder sensors, detects humans and estimates their distance to emit warning alerts, ensuring cost-effectiveness, high localization accuracy, and low power consumption. This work offers a valuable contribution to creating effective, affordable social distance solutions.[5]

Paper by Iram Javed et al. introduces a comprehensive system employing deep learning for face mask detection and social distance monitoring. YOLOv3 is optimized, achieving a notable 5.3% accuracy improvement. The study fine-tunes various object detection models and proposes an end-to-end approach, holding promise for real-time surveillance systems. This work contributes significantly to pandemic safety measures. [6]

In Akansha Potharkar et al. explore the implementation of a COVID-19 monitoring system using machine learning for facemask detection and social distancing measurement. The study utilizes the YOLOv3 algorithm for improved accuracy, achieving up to 94% accuracy using VGG-16, VGG-19, and ResNet-50. Object detection, including YOLO object detection, is employed to calculate distances between individuals, ensuring social distancing compliance. The research leverages recent advancements in machine learning and computer vision, using TensorFlow, Keras, Haarcascade, and MobileNet for mask detection and YOLO for social distancing assessment.[7]

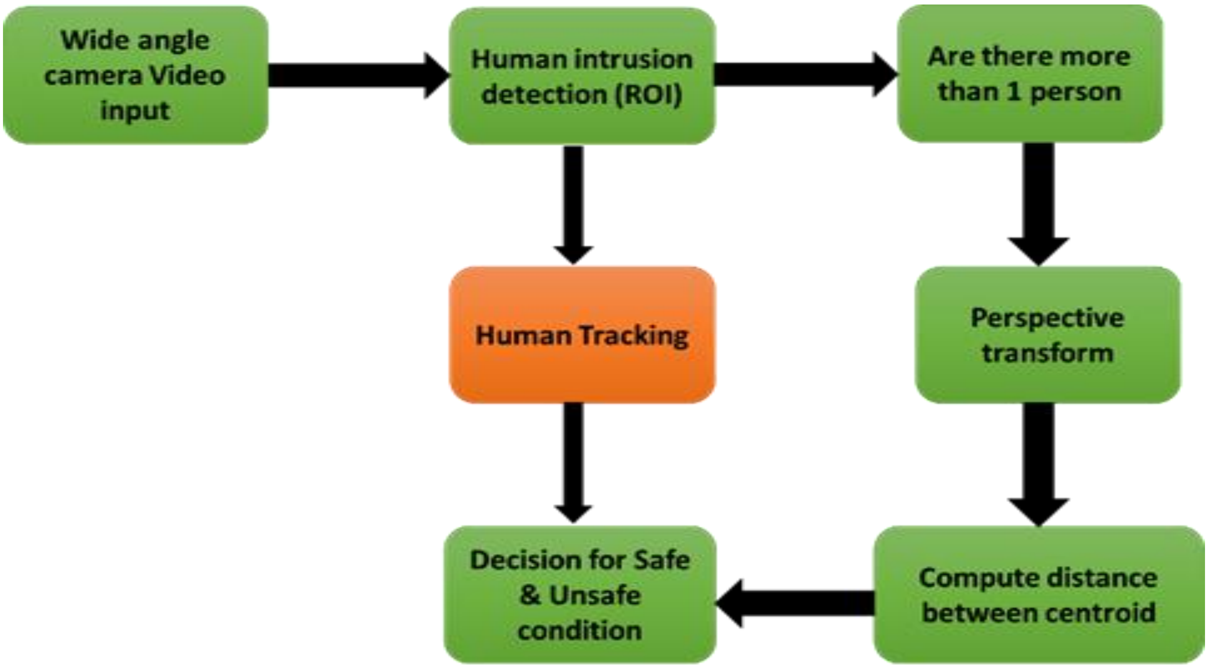
Adlen K Sentini et al. proposed a smartphone app that employs IoT and MEC technologies to monitor and alert users in real-time if they violate social distancing guidelines based on GPS coordinates. The system efficiently detects violations and provides immediate warnings, ensuring compliance with pandemic safety measures. It relies on a scalable MEC-ETSI system for low-latency communication and real-time response, making it a promising tool for COVID-19 mitigation efforts.[8]

Outlines a system for detecting social distancing violations in public spaces. It uses deep learning, particularly YOLOv3, along with Python and CCTV camera streams. The system tracks and calculates distances between objects, highlighting violations with red bounding boxes. Optimization options include advanced YOLO versions and GPU acceleration for faster execution [9].

This paper offers a succinct exploration of the YOLO algorithm and its evolution, presenting a focused overview of development processes, target recognition, and feature selection methods. Notably, it compares YOLO with traditional CNN approaches, highlighting its distinct contributions to object detection. The paper also delves into the application of YOLO in financial and other fields, showcasing its role in targeted picture news and feature extraction. Overall, this concise review provides valuable insights into the nuances of YOLO and its impact on the detection literature [10].

## PROPOSED METHODOLOGY:

In our proposed system, we concentrate on a balance between computational efficiency and accurate human detection and monitoring. In our work, video input was captured at about 16 fps. Here too, this is by design to keep this frame rate low; this translates to reduced computational intensity while at the same time allowing the system to keep enough detail that this will support dependable analysis. More precisely, the additional frame rates compute more data, and hence the processing power for the same gets consumed for no cause. When the frame rate is kept optimized, the system remains energy-saving, yet provides quality that is sufficient for real monitoring. The capture video feed is streamed into the Human Intrusions Detection (HID) module. This HID module is the center of detection capability for the system. The algorithm in the module is a Human Detection algorithm that is specifically intended to detect and respond to human beings. The module is designed with the ability to reject objects that do not fit its criteria are for the detection of humans. This, in a way, ensures that only meaningful turns of events such as human intrusion trigger an alert or response. It applies a combination of such machine learning techniques as object classification and feature extraction, which help to differentiate humans from other objects in the environment: animals, vehicles, or environmental objects like moving trees or shadows.




***Flow diagram 1**: Human Intrusion detection Tracking and distance calculation*

On detecting the existence of more than one human object inside the predefined surveillance area, the system initiates the tracking module automatically. This tracking module remains in operation to trace the movements of those detected people. The tracking algorithm analyses the position, speed, and trajectory of each detected person and maintains real-time surveillance of their movement. The system is capable of following multiple subjects at a time to ensure that significant activities are tracked properly even in areas that are crowded or complex. This feature could be very critical in applications wherein public safety, access control, and monitoring of large-scale events are involved and where several intrusions/activities may occur concurrently [11].

When the tracking module is on, the perspective transform module is called by the system. This is a very vital module because it is involved in the interpretation of the visual data recorded by the cameras. A perspective transform module is required to translate the 3D representation of the world in 2D images in a way that the video frames can be matched and aligned with the real world. Cameras intrinsically produce 2D images of a 3D world, and the perspective should avoid the ability of the system to accurately estimate the position, distance, and size of objects relative to the camera. This is a mimicking of the process of transformation in the human brain and concerns the visual information, where the system can attain depth and range from the process, and thereby it is compatible with the normal human vision system [12].

Perspective transform, is a module that enhances the accuracy of the monitoring ability of the system. The system can understand situations with active human involvement by carefully assessing the distance between persons and other objects around them in the camera's view. For example, whether a person or people are gradually encroaching into restricted or hazardous areas. It's endowed with the ability to translate 3D space into a 2D image; thus, it provides considerably accurate tracking and monitoring for its application in security surveillance and general safety protocols [13].

Other than detecting human presence and tracking their movements, the system is also designed to raise an alarm in situations where safety is at risk. For instance, if the distance between human entities falls below the instructed gap, such as in cases where social distancing is needed, the system then alerts the concerned personnel through an announcement system. The alarm would be a warning to be thrown up by a display to inform those people who are breaching safety rules and might also be meant as an alert to the security personnel or some other autonomous action instigation. What is more, the function of the tracking module does not stop by only detecting and monitoring the line of the individuals' movement; it predicts the line of movement for those people. Given the detected trajectory and speed of people in a monitored area, the system would therefore predict where these are headed. If someone is approaching a dangerous zone or coming close to an area with restricted human presence, the system should give a prior warning to prevent the occurrence of a hazard at that particular point. This predictive capability enhances the system's effectiveness in such a way that the measures taken are proactive rather than reactive.[14]

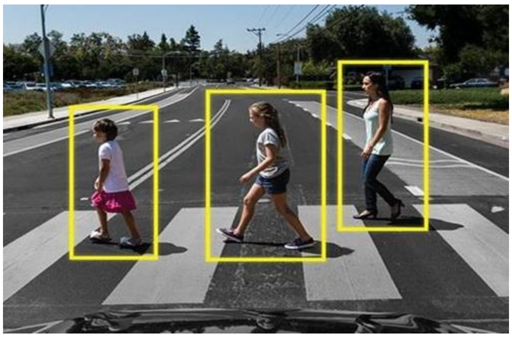
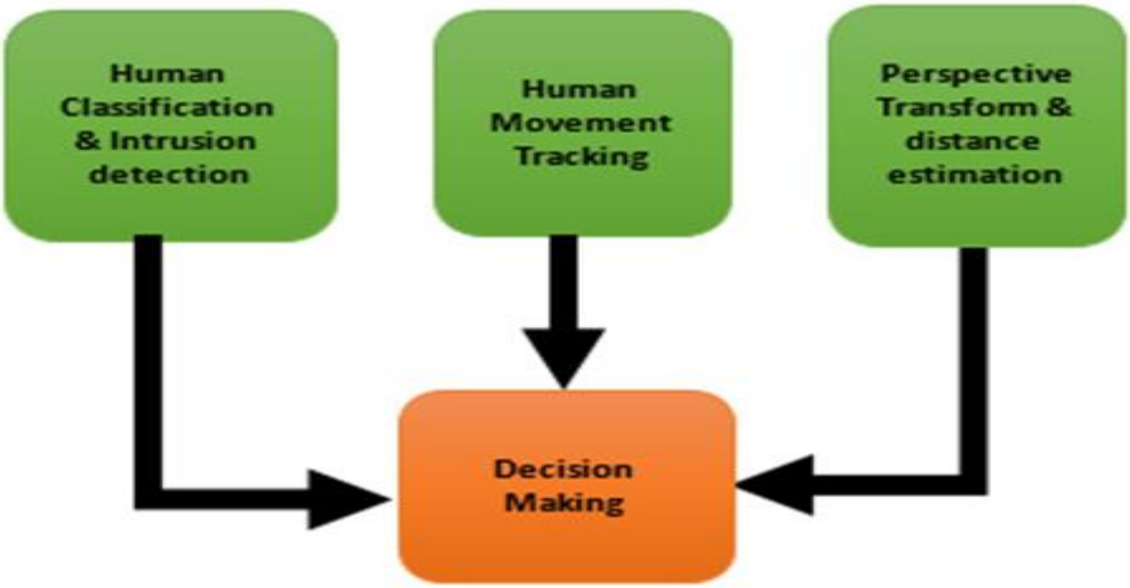


***Fig.1:*** *Human Movement Tracking*

***Fig 2 :*** *Human Movement Tracking*

The major advantages of the system proposed lie in the fact that it can operate in real-time [15]. The entire application of the algorithm, from human detection to even tracking and perspective change, was complete without a noticeable delay. This real-time operation successfully ensures that monitoring and subsequent countermeasures are taken in a timely and effective manner. In security applications, a serious incident may happen if alerts or responses are delayed, but real-time monitoring enables immediate intervention. It ensures that possible human intrusions and other safety concerns are alerted immediately, so it is applicable for security monitoring, automated surveillance, and public safety, among many more [16].

In this way, the system has the capacity, perspective transformation, and real-time performance for large-scale monitoring with efficient safety measures supported by a high level of integration of human detection and tracking. The capability of this system does not limit it to the detection and tracking of human intrusion but has also ensured accurate and reliable results in the prediction and prevention of dangers presented to humans [17].




***Flow diagram 2*** *: Final Integration*

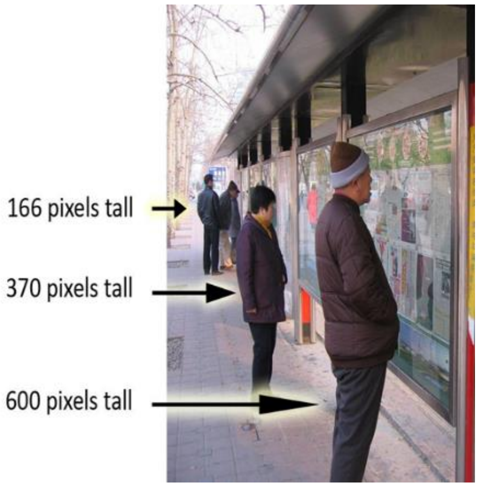



***Fig. 3** Distance Estimation*

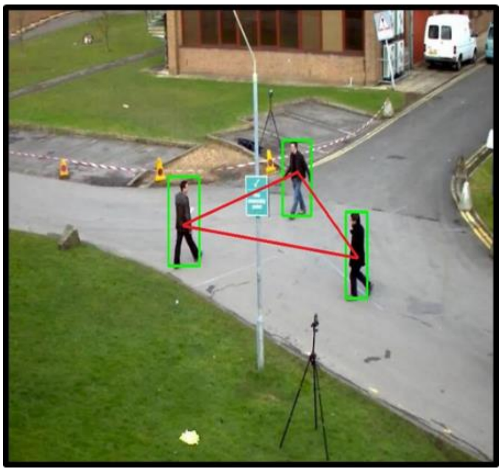


***Fig 4 :** Expected Outcome*

## RESULT AND DISCUSSIONS:

The video input with a low, 16 FPS frame rate, combined with an HID module, serves as the basic structure of a proposed methodology that is strong in computing efficiency in optimization for human intrusion detection. We chose a reduced frame rate very carefully to find a balance between computational load and accurate intrusion detection. The reduced frame rate will decrease the per-second data that needs to be processed, reducing the processing power required for efficiency in real-time applications. With a lower frame rate, the used advanced algorithms keep the ability for still promising human detection accurate in environments where computational resources are low but reliable detection is important.

Among the core strengths of this methodology is the activation of the Human Intrusion Detection (HID) module at that specific time, when a human is detected, and the system can be set to reject any object that is not human. This selective activation enhances the overall system efficiency and also ensures that the switching on of resources is relevant only to the relevant data, avoiding unnecessary processing of irrelevant objects whether they might be animals, vehicles, or environmental movements such as swaying trees. The HID module is designed so that it can differentiate between a human and a non-human entity by the application of advanced machine learning-based algorithms and computer vision techniques to increase the ability of the system to focus on real threats.

The methodology is initiated with a tracking module that has the capability to track several subjects located in the field of view of the camera along with the HID module. This is very important when more than one potential intruder and human subject are in motion at the same time. Sophisticated algorithms enable the module of the tracking feature, allowing it to monitor each detected person's movement, leaving and re-entering the camera's field of view, effectively and continuously. Proper multi-subject tracking is required in environments such as industrial plants, construction sites, or public facilities because human intrusion could lead to hazardous situations, and effective security critically requires continuous observation.

Another relevant module of the perspective transform methodology is enhancing system accuracy so that erroneous distance estimations can be corrected per human vision principles. In the real-world setup, images from cameras typically include many viewing angles and elevations, which could change the impression of the distance between contraptions. This means that the input of the camera is compensated mathematically through the module in order for the distortions brought about by perspective to be considered. In safety-critical applications, like perimeter protection, where the presence of an intruder within a critical area could be the difference between a small incident and a big accident, much more accurate distance measurements can be obtained.

The simple formula to calculate the social distance between two humans in an image, based on their pixel coordinates, is

$$D_{pixel} = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

Where $D_{pixel}$ – is the pixel distance between the two humans.

(x1,y1) are the coordinates of the first human in the image,

(x2,y2) are the coordinates of the second human in the image.

This formula calculates the Euclidean distance between the two points (representing the two humans) in pixel space [18].

In the case of real-time operation, the system offers high potential by raising alerts to security personnel or initiating an automated response upon possible human intrusion detection. The alerts are designed to trigger in cases where the HID module has confirmed the presence of a human intruder; hence, measures can be issued immediately in such dangerous cases. Proactive security should always translate into faster response to probable breaches and accidents, hence minimizing the chances of causing harm to personnel or damage to property. The level of overall security would be enhanced by integrating such real-time alerts with other security protocols, including automated barriers, alarms, or even surveillance systems.

It is indeed very useful that the proposed methodology is very accurate, but it faces yet a number of challenges when in varied environmental conditions. Varied lighting, weather conditions, and background noises may affect the actual different accuracy while detecting humans and existence from this distance. For instance, poor lighting conditions may led to poor detection accuracy, or extreme weather could distort the camera feed in a manner that the HID and perspective transform modules themselves cannot operate at optimal levels. In such environments, the ability of the system to discriminate human objects from things that are not human is also possibly compromised since human distinguishing features may be obscured or confused with other objects [19].

A considerable amount of empirical testing will therefore be required to solve these issues and to fine-tune the algorithm in a variety of real-world environments. Tests of such nature should be designed to pinpoint scenarios where system accuracy will be degraded and apply countermeasures that will reduce the said effects [20]. For example, robustness against changes in lighting may be achieved in a system by using infrared cameras, increasing robustness by deep learning models trained over very vast and diverse data sets, and data sets with environmental conditions changing drastically. Moreover, this module could be more robust in allowing uninterrupted and consistent monitoring if occlusions, such as part of the human subject, were hidden from the camera view[21].

This is another factor in which the practical deployment can confirm this methodology for whatever results it yields. The running of the system throughout industrial sites, warehouses, or even public areas helps to give a good idea of the overall performance of the system under real working executing conditions [22]. Such trials will help to point out limitations that are inbuilt into the design of the system and therefore inform necessary adjustments for attaining better efficacy and reliability in its performance. Moreover, feedback from operators and stakeholders that are using the application in the actual environment will be crucial before refining the usability and actualizing the interactive systems within the different environment settings [23-24].

## CONCLUSION AND FUTURE SCOPE:

In Conclusion, the proposed algorithm greatly provides a very practical and effective step to deal with the deadly need for social distancing in environments where people clutter together, like malls, schools, colleges, workspaces, and so on. Basically, the algorithm works on a single-camera input, which is an important starting point in the technology development. With a single camera, the system can monitor movements and the positions of various people within a given area and alert in case predefined social distancing guidelines are breached. This is a basic approach for a reliable and easy way to support crowd control and the necessity to ensure proper distance in public However, this basic single-camera approach also includes a lot of scopes for future progress. An interesting add-on that can be developed is the incorporation of multiple cameras to increase the scope and effectiveness of a system. By allowing the placement of a network of cameras in areas that have many crowds for the use of panoramic or 360-degree view algorithms, would allow for a larger area to generate an environment. This is going to require that areas of interest that contain crowds are effectively monitored, as a person is monitored across several angles and locations. The creation of a panoramic view could be particularly useful in large venues such as shopping malls, stadiums, or public transport hubs, where the number of people is large and dense, and thus enforcement of social distancing might be harder. The algorithm, having a wider field of view, would have belonged to a better detection of social distancing rule breakers and real-time alerts to individuals and officers on duty regarding a possible threat to spreading communicable diseases over a wider area.

Future research efforts will likely focus on several critical challenges as the system expands to handle multiple camera inputs. One of the most central concerns is the refinement of the accuracy of the algorithm. Such factors as changes in lighting, occlusions, and unpredictable human behavior in crowded public places can affect the system's ability to detect and track a person accurately. Detection and tracking algorithms accuracy needs to be improved for such challenged conditions in order to ensure the system's working capability when deployed in the greatest variety of environments. Another area of future research would be to develop optimal real-time processing capabilities. Public spaces are intrinsically replete with motion and changing conditions most of the time, and for its application, the algorithm has to respond to data quickly and effectively in real-time, otherwise with delays or errors, it will not be of much service to the real world. This optimization will become necessary so that the system issues timely alerts and responds to situations that change at a fast rate in public places.

Machine-learning techniques could be employed to further enhance the adaptiveness and robustness of the algorithm, whereby the system would use machine learning to learn from the data it captures in an ongoing manner to enhance its performance over time. For instance, machine learning can enable the algorithm to understand patterns in the behavior of crowds, learn to adapt to variability in environmental conditions, and understand new evolving guidelines in social-distance enforcement. This will make the system much more flexible and able to cope with what may be going on in real-life public spaces. More importantly, machine learning can show a better offer of sophistication to a false alarm filtering system, and this should sharply decrease its inflow of errors to the equation, therefore increasing the reliability of the alerts it churns out. Indeed, dynamic environments surely would enjoy this benefit most of all since a crowd's density or the characteristics of individual behaviors can change dramatically over a very short period.

This would definitely involve an effort from other stakeholders such as health authorities, urban planners, and local government in general. For example, the health authorities can weigh in with the proper measures of social distancing and then inform the types of public health problems that need focus. The urban planners and local governments could, on their part, help to infuse this very essence into their public infrastructure, public transport systems, parks, and commercial areas. The process of the implementation of the algorithm could be smooth, particularly with these stakeholders, to further ensure that the technology is aligned with these broader public health and safety objectives. Such collaboration could also connect the system itself with other smart city technologies and so multiply the potential impact on public health and urban management.

The algorithm envisioned through this work will meet the urgent and critical need it aimed to do: create a pioneering solution for enforcing social distancing in public spaces. What offers promise is that it uses current technologies and sets the pace for upcoming innovations, limiting the spread of communicable diseases. Being dynamic will enable the system to add more cameras, machine learning, and collaborative abilities with stakeholders; thus, it will bring great potential into the already set public health and urban management areas. In the future, the algorithm will work toward a safe and healthy public space as the creation keeps evolving.

## REFERENCES


[1] Ahmed, I., Ahmad, M., Rodrigues, J. J., Jeon, G., & Din, S. (2021). A deep learning-based social distance monitoring framework for COVID-19. *Sustainable cities and society*, *65*, 102571.

[2] Ahamad, A. H., Zaini, N., & Latip, M. F. A. (2020, August). Person detection for social distancing and safety violation alert based on segmented ROI. In *2020 10th IEEE international conference on control system, computing and engineering (ICCSCE)* (pp. 113-118). IEEE.

[3] Sujash Paradkar, Shreya Tekade, Komal Ganatra, Saloni Sarwade, Rahul Bhole, “Social Distance Detector using Computer Vision, Open CV, and YOLO Deep Learning Algorithm”, International Research Journal of Engineering and Technology (IRJET), 03 March 2022, Volume: 09 issues

[4] Vajgl, M., Hurtik, P., & Nejezchleba, T. (2022). Dist-yolo: Fast object detection with distance estimation. *Applied sciences*, *12*(3), 1354.

[5] Alhmiedat, T., & Aborokbah, M. (2021). Social distance monitoring approach using wearable smart tags. *Electronics*, *10*(19), 2435.

[6] Javed, I., Butt, M. A., Khalid, S., Shehryar, T., Amin, R., Syed, A. M., & Sadiq, M. (2023). Face mask detection and social distance monitoring system for COVID-19 pandemic. *Multimedia Tools and Applications*, *82*(9), 14135-14152.

[7] Potharkar, A., Songire, A., Late, S., Mulani, S., & Malpani, M. R. (1869). A Survey on Face Mask Detection and Social Distancing Measurement Using Machine Learning.

[8] Ksentini, A., & Brik, B. (2020). An edge-based social distancing detection service to mitigate covid-19 propagation. *IEEE Internet of Things Magazine*, *3*(3), 35-39.

[9] Manthri Sriharsha, Lalith Sai Allani, Akhila Gandla, Sowjanya Jindam, “Social Distancing Detection using Deep Learning”, International Journal of Recent Technology and Engineering(IJRTE).

[10] Jiang, P., Ergu, D., Liu, F., Cai, Y., & Ma, B. (2022). A Review of Yolo algorithm developments. Procedia computer science, 199, 1066-1073.

[11] Faisal Dharma Adhinata, diovianto Putra Rakhmadani, Alon Jala Tirta Segara, “YOLO Algorithm for detecting people in social distancing system”, Transformitika, Vol 19, No.1, July 2021.

[12] Karaman, O., Alhudhaif, A., & Polat, K. (2021). Development of smart camera systems based on artificial intelligence network for social distance detection to fight against COVID-19. Applied Soft Computing, 110, 107610.

[13] Narayan, H., Pawar, A., Kumar, A., Narayan, A., & Waware, P. Social Distancing Detection Using Computer Vision.

[14] Kumavat, M. K. S., Sao, A. K., Khedekar, H., Panpaliya, C., & Korde, S. Social Distancing Detector using YOLO v3 Image Processing Algorithm.
[15] Sumathi S, Rathnambika, Sanjay S, Surya K, " Covid-19 Indoor Safety Monitoring System Using IoT", Journal of Emerging Technologies and Innovative Research (JETIR), May 2022, Volume 9, Issue 5.
[16] Hermina, J., Karpagam, N. S., Deepika, P., Jeslet, D. S., & Komarasamy, D. (2022). A Novel Approach to Detect Social Distancing Among People in College Campus. International Journal of Intelligent Systems and Applications in Engineering, 10(2), 153-158.
[17] Ksentini, A., & Brik, B. (2020). An edge-based social distancing detection service to mitigate covid-19 propagation. IEEE Internet of Things Magazine, 3(3), 35-39.
[18] Weng, W., & Zhu, X. (2021). INet: convolutional networks for biomedical image segmentation. Ieee Access, 9, 16591-16603.
[19] Manthri Sriharsha, Lalith Sai Allani, Akhila Gandla, Sowjanya Jindam, "Social Distancing Detection using Deep Learning", International Journal of Recent Technology and Engineering(IJRTE).
[20] Shah, J., Chandaliya, M., Bhuta, H., & Kanani, P. (2021, April). Social distancing detection using computer vision. In 2021 5th International conference on computing methodologies and communication (ICCMC) (pp. 1359-1365). IEEE.
[21] Al Amin, I. H., & Arby, F. H. (2022). Implementation of yolo-v5 for a real time social distancing detection. Journal of Applied Informatics and Computing, 6(1), 01-06.
[22] Özbek, M. M., Syed, M., & Öksüz, I. (2021). Subjective analysis of social distance monitoring using YOLO v3 architecture andcrowd tracking system. Turkish Journal of Electrical Engineering and Computer Sciences, 29(2), 1157-1170.
[23] Ansari, M. A., & Singh, D. K. (2021). Monitoring social distancing through human detection for preventing/reducing COVID spread. International Journal of Information Technology, 13(3), 1255-1264.
[24] Hou, Y. C., Baharuddin, M. Z., Yussof, S., & Dzulkifly, S. (2020, August). Social distancing detection with deep learning model. In 2020 8th International conference on information technology and multimedia (ICIMU) (pp. 334-338). IEEE.