Penerbit Akademia Baru

Journal of Advanced Research Design

Journal homepage:
https://akademiabaru.com/submit/index.php/ard
ISSN: 2289-7984

# Integrating YOLO Algorithms for Dual-Functionality Surveillance

Azim Zaliha Abd Aziz[1,*], Nurul Nadzirah Adnan[1], Nur Farraliza Mansor[2], Nazirah Abd Hamid[1], Ida Nurhaida[3,4], Mohamad Nasucha[2], Nur Uddin[2]

1 Faculty of Informatics and Computing, Universiti Sultan Zainal Abidin, 22200 Besut, Terengganu, Malaysia
2 Collage of Computing, Informatics and Mathematics, Universiti Teknologi MARA, Shah Alam, Selangor, Malaysia
3 Department of Informatics, Universitas Pembangunan Jaya, Tangerang Selatan, Indonesia
4 Center for Urban Studies, Universitas Pembangunan Jaya, Tangerang Selatan, Indonesia

**ARTICLE INFO**

***Article history:***
Received 14 February 2025
Received in revised form 17 March 2025
Accepted 15 July 2025
Available online 28 July 2025

***Keywords:***
Airborne diseases; social distancing monitoring; thermal imaging system; body temperature detection; YOLO algorithms

**ABSTRACT**

Since the outbreak in December 2019, the COVID-19 pandemic has significantly impacted Malaysia, affecting both the nation and its citizens on a substantial scale. Consequently, the government has put forth several recommended standard operating procedures (SOPs) aimed at mitigating the pandemic's impact. These measures include mask-wearing, frequent handwashing, and adhering to social distancing guidelines. Maintaining social distance is crucial in reducing the transmission of this lethal virus from an individual carrying the infection to a person in good health. The method encompasses the utilization of the You Only Look Once (YOLO) object detection algorithm for the widespread application of identifying and overseeing adherence to social distancing practices within monitoring systems. In addition to its effectiveness in object detection, YOLO has gained extensive global utilization in systems for detecting human presence. Thus, this study provides a review of YOLO-based monitoring systems that have been developed previously. From that, this paper introduces a framework integrating thermal imaging for combined social distancing and body temperature monitoring. From the results, only 14% of the total numbers of visitors at the exhibition complied with the social distancing. The other 12.5% were in danger when they broke the rules while 73% of individuals were observed to be in a situation of moderate risk. However, most of the recorded body temperatures were normal.

## 1. Introduction

In recent times, the practice of social distancing has gained prominence as a crucial protective measure to curb the proliferation of infectious diseases such as COVID-19 [1,2]. People can reduce their chances of coming into contact with respiratory droplets [3] and limit the dissemination of infections within society by maintaining a physical distance. Nonetheless, enforcing adherence to social distancing guidelines can be challenging, particularly in densely populated public areas or areas with high foot traffic.

[*] *Corresponding author.*
*E-mail address: azimzaliha@unisza.edu.my*

https://doi.org/10.37934/ard.140.1.121130

The You Only Look Once (YOLO) computer vision algorithms have garnered attention as potential methods for overseeing adherence to social distancing protocols [4]. YOLO serves as a real-time object detection system that can accurately detect and trace individuals within video streams, rendering it well-suited for surveillance-oriented tasks [5-7]. By analyzing video footage, YOLO has the capacity to identify breaches of social distancing norms, like individuals standing in close proximity or surpassing occupancy restrictions within a specific location.

While numerous studies have explored the application of YOLO in tasks related to object detection [8-11], a comprehensive synthesis of its utilization specifically within the realm of social distancing remains absent [9]. Our intention is to fill this void by conducting a systematic review that synthesizes prior research and assesses the effectiveness of YOLO in enhancing compliance with social distancing measures. This systematic review aims to provide policymakers, public health experts, and researchers with a comprehensive understanding of the current knowledge regarding the application of YOLO in promoting social distancing [10,11].

In this study, the You Only Look Once version 5 (YOLOv5) object detection algorithm was employed to monitor social distancing. YOLOv5 was chosen over newer versions because of ease of use and implementation. In addition, YOLOv5 offers an excellent balance between speed and accuracy, making it suitable for real-time applications. A state-of-the-art thermal camera with the YOLOv5 algorithm was calibrated to enable simultaneous measurement of body temperature. The key goal of this work is to introduce a framework that combines monitoring of social distancing and body temperature using a thermal imaging system, and to evaluate its performance by assessing it on a live recording dataset.

### *1.1 Literature Review*

Since the rise of Covid-19 pandemic, social distancing is the most reliable practice to prevent the contagious virus transmission. An early and immediate practice of social distancing could gradually reduce the peak of the virus attack [12]. Thus, researchers have come up with effective solutions for social distancing measurement using surveillance videos. Figure 1 presents some examples of images used for social distancing monitoring systems. It can be seen from Figure 1 that most of the methods are developed using frontal and overhead view of the camera.

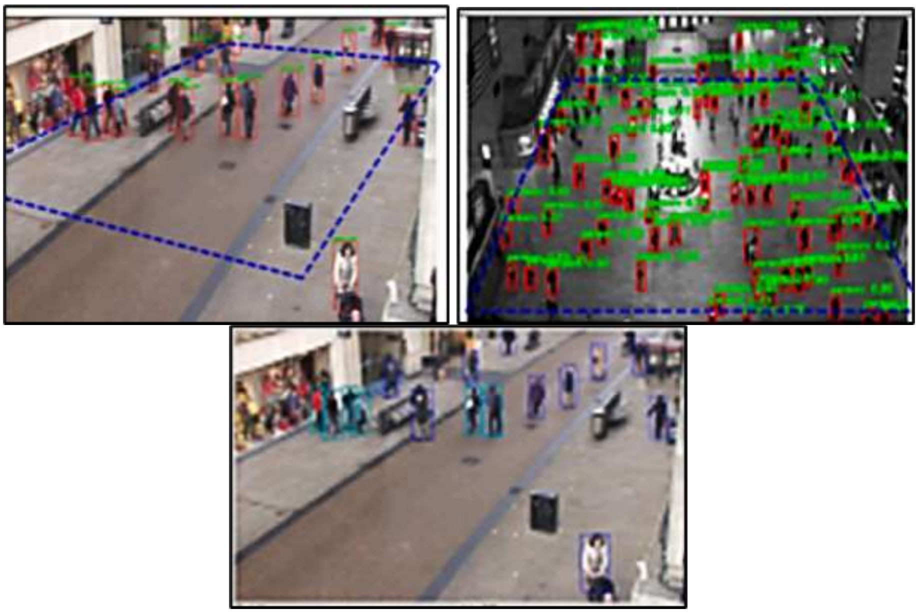

**Fig. 1.** Example of social distance monitoring systems [7]

As in Punn *et al.,* [13], a framework using the YOLOv3 model was proposed to detect humans. The Deepsort approach was then used to track the detected individual using bounding boxes and assigned identity information. In another work, an autonomous drone-based model for social distancing was developed [14]. YOLOv3 model with the custom dataset was trained. The drone camera was also used to identify people in public wearing masks.

In another study, developed a device to measure the distance between individuals for monitoring social distancing using Raspberry Pi [15]. Distances between people detected were measured using the Euclidean distance formula. However, the scope of monitoring spaces could only be applied within small areas. Other than that, YOLOv2-based approach for human detection was proposed by combining a modified YOLOv2, Residual blocks and multiple Spatial Pyramid Pooling blocks [16]. The results show that the proposed model can detect people with higher accuracy on the Microsoft Common Objects in Context (COCO) human dataset. This study should also test on live recording dataset for live system implementation.

In addition to human detection system using YOLO algorithm, a study was carried out to detect humans from a thermal dataset using YOLOv5 [17]. An owned built dataset consists of 30,000 thermal images and 50 thermal videos from different resources was used. Based on the obtained results, it can be concluded that YOLO, one of the leading deep learning algorithms, effectively captures humans in thermal aerial images or videos. One latest study presents a novel approach for real-time monitoring of adherence to physical distancing guidelines in indoor environments [18]. The method employs computer vision and deep learning techniques, leveraging the widely-used YOLO model. To facilitate real-time analysis, the YOLO model is pre-trained on Microsoft COCO dataset, enabling it to accurately detect individuals and estimate their physical distance in real-time.

Convolutional Neural Networks (CNNs) have played a significant role in extracting features and classifying complex objects, including human detection [19]. The advancement of faster CPUs, GPUs, and increased memory capacities has enabled researchers to develop accurate and efficient detectors compared to traditional models. In another study, a deep neural network (DNN)-based detector was employed in combination with the Deep sort algorithm as an object tracker for people detection [20].

## 2. Methodology

The method used in this study had three main parts: calibrating the thermal image system, putting the YOLOv5 algorithm into action, and creating a way to measure both social distance and body temperatures at the same time. Each step was carefully planned out to make sure it would work correctly and reliably in the real world.

### *2.1 Thermal Camera System*

A Hikvision Network Bullet camera (Figure 2) with a thermal channel was used to measure body temperature. Calibration involves comparing thermal readings to a standardised temperature source under controlled environmental conditions, assuring an accuracy of ±0.5°C across a temperature range of 30°C to 45°C. To provide best coverage and precision, the camera was positioned 1.5 meters above ground level on a tripod. Regular calibration checks were undertaken to achieve consistent results in a variety of indoor environments.


**Fig. 2.** Hikvision Network Bullet camera with night vision with 8 MP 1/2.8” CMOS sensor

*2.2 YOLOv5 Algorithm Implementation*

In this study, YOLOv5 was selected as the human detection algorithm based on the detection speed which allows it to process images in real time [6]. YOLOv5 was chosen due to its optimal balance of speed and accuracy, which is essential for real-time applications. The training datasets comprised the Microsoft COCO dataset, along with a custom thermal imaging dataset that included 30,000 thermal images and 50 videos. Data augmentation methods, including rotation, scaling, and brightness adjustment, were employed to replicate real-world conditions. Model training was performed using a learning rate of 0.01, 50 epochs, and a batch size of 16. During live monitoring, the algorithm identified individuals and categorised social distancing conditions into three classifications:

i. Green: a safe distance has been maintained.
ii. Yellow: a moderate level of risk.
iii. Red: breach of distancing protocols.

*2.3 Body Temperature Measurement*

To measure body temperature of each individual recorded in the scene, the same thermal imaging camera as in Figure 2 is used. The camera measures body temperature between 30ºC to 45ºC with 0.5ºC accuracy and with 160 x 120 resolution in the thermal channel. The camera was installed 1.5 meter high using a tripod in an indoor environment. The distance between the target and the camera was set to 1.5 meter. Figure 3 presents the experimental setup of the screening scheme. From Figure 3, it can be seen that the thermal camera was connected to this proposed dual-functionality monitoring system *via* WIFI connection. In this experiment, a threshold of 37.2°C was established to define a normal body temperature. Any individual found to have a body temperature exceeding 37.2°C will be labelled as non-healthy.

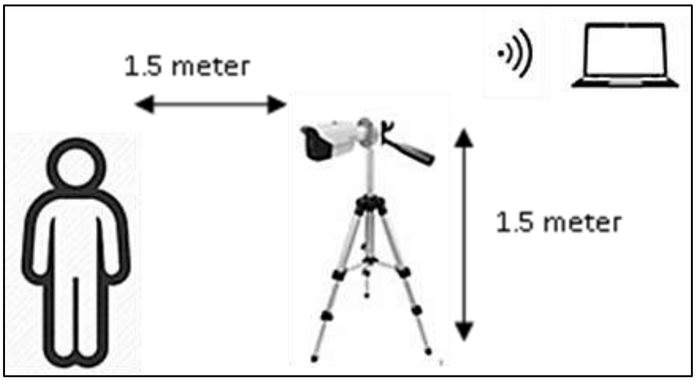


**Fig. 3.** Experimental setup of the proposed system

*2.4 Social Distance Measurement*

The Euclidean distance formula was utilised to evaluate social distancing by calculating the spatial separation between individuals within the camera's field of view. Ensuring compliance with social distancing regulations, particularly in densely populated and enclosed spaces, poses a significant challenge. Therefore, there is a pressing requirement to develop an automated system capable of identifying individuals who do not adhere to these distancing directives. The distance between individuals within the camera's field of view was calculated using the geometric distance formula as in Eq. (1) to assess social distancing:

$$E = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \tag{1}$$

Where, *x* and *y* represent the coordinates of two individual. When the calculated distance between two individuals' dips beneath a pre-established threshold, it signals a breach of the social distancing standard. Consequently, the threshold for the present frame is established by deducting the shoulder width from the height value, as follows in Eq. (2):

$$\text{Threshold (T)} = \text{height (h)} - \text{width (w)} \tag{2}$$

Once the threshold value for the frame has been calculated, the next step involves determining the distances between the detected individuals in pairs. To accomplish this, it is necessary to utilize the YOLO models and detect at least two individuals enclosed within bounding boxes in the video frame. To compute the pixel distance between the center points of these paired individuals, the Euclidean formula outlined in Eq. (1) was employed. Figure 4 illustrates the center points of two bounding boxes of detected persons that were used to compute the distance between two individuals.

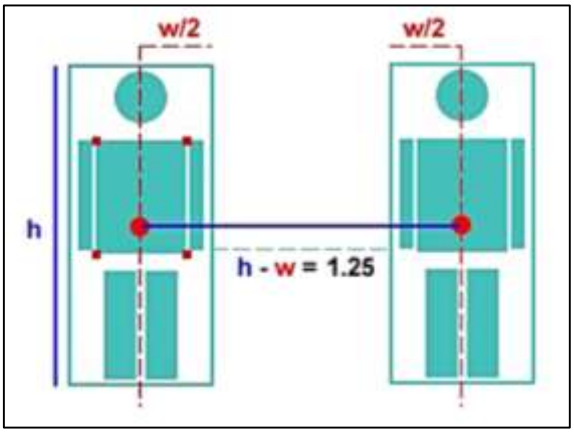


**Fig. 4.** Center points of the bounding boxes [21]

According to Yurttas [21], the average height of men and women in Malaysia is 1.68 m and 1.57 m, accordingly. Meanwhile, the average shoulder width of a Malaysian is 0.4 m [22]. These values were then applied to Eq. (2), values of 1.28 m and 1.17 m were obtained respectively for men and women. However, gender is not a distinctive factor in this study. Hence, one could consider that the threshold values determined in pixels within video frames effectively represent a distance of 1.28 meters. The rationale behind utilizing the threshold value of 1.28 meters in this context is to ensure a minimum social distance of one meter between individuals. When the estimated distance between two individuals falls below the threshold value, a violation of social distancing is detected. In such cases, the colour of the bounding box of the individuals automatically changes to red to indicate the situation.

There are three distinct colours assigned to the bounding boxes of individuals, each colour indicates a specific meaning or condition. Firstly, green colour indicates safe social distancing between individuals. Secondly, yellow bounding box illustrates medium risk. Finally, red colour is used to indicate that social distancing is violated.

### *2.5 Data Collection*

The proposed system was tested during an indoor show at TATI University College in Malaysia. A total of seven movies were taken, capturing 651 people at various crowd densities. YOLOv5 achieved an average detection speed of 30 frames per second, indicating real-time capability appropriate for surveillance purposes. Figure 5 shows several recorded scenes during the exhibition. In Figure 4, YOLOv5 algorithms detected visitors and indicated their presence by creating bounding boxes around them. This detection occurred in real-time during the recording process.

**Fig. 5.** Human were detected using YOLOv5 in live scene

The study looked at social distancing compliance and found that just 14% of people kept safe distances (green), 73% were categorised as intermediate risk (yellow), and 12.5% were in violation (red). These findings highlight a considerable gap in adherence to public health guidelines. Body temperature monitoring found constant values in the usual range of 36°C to 37.2°C, with no individuals identified as febrile. The dual-functionality system recognised and classified both characteristics simultaneously, demonstrating its operational capabilities. Figures 5 depicting the distribution of bounding box colours and the relationship between crowd density and distance compliance demonstrate these findings. Interestingly, higher crowd densities were related with more red boundary boxes, indicating a corresponding increase in social distance breaches.

**Table 1**
Properties of the recorded videos

| Test data | Number of frames | Duration (second) | Resolution |
|---|---|---|---|
| Video-1 | 325 | 13.7 | 800 x 600–1024 x 768 |
| Video-2 | 341 | 13.8 | 800 x 600–1024 x 768 |
| Video-3 | 325 | 13.7 | 800 x 600–1024 x 768 |
| Video-4 | 333 | 14 | 800 x 600–1024 x 768 |
| Video-5 | 375 | 15 | 800 x 600–1024 x 768 |
| Video-6 | 359 | 14.4 | 800 x 600–1024 x 768 |

## 3. Results

All bounding boxes were documented and depicted in Figure 6. In the figure, three distinct colours of bounding boxes were utilized: red denoted instances of social distancing violations, yellow indicated a medium risk distance, and green represented a safe distance maintained between individuals. As can be seen in Figure 6, the results show that the dual-functionality system works well for monitoring social distance and body temperature in real time, but there are still some areas that need more research. The low rate of compliance (14% green) shows that action is needed right away. For example, real-time feedback systems (like audible or visual alerts) could be used to encourage proper behaviour. The system's fast detection speed (30 FPS) also shows that it can be used in the real world. However, it is still hard to make it work in bigger places with bigger surveillance areas.

The accuracy of detection was affected by things in the environment, such as lighting and the moving of people. For example, in pictures with a lot of people, overlapping bounding boxes sometimes caused wrong classifications. To solve this problem, you might need to use more advanced tracking methods, such as DeepSORT, to make things more accurate. Also, the fact that the system didn't pick up on any cases of elevated body temperature says that it can be used for more than just responding to pandemics. It can be used to keep an eye on public health in general, like finding people in busy places who are likely to get sick from the heat.

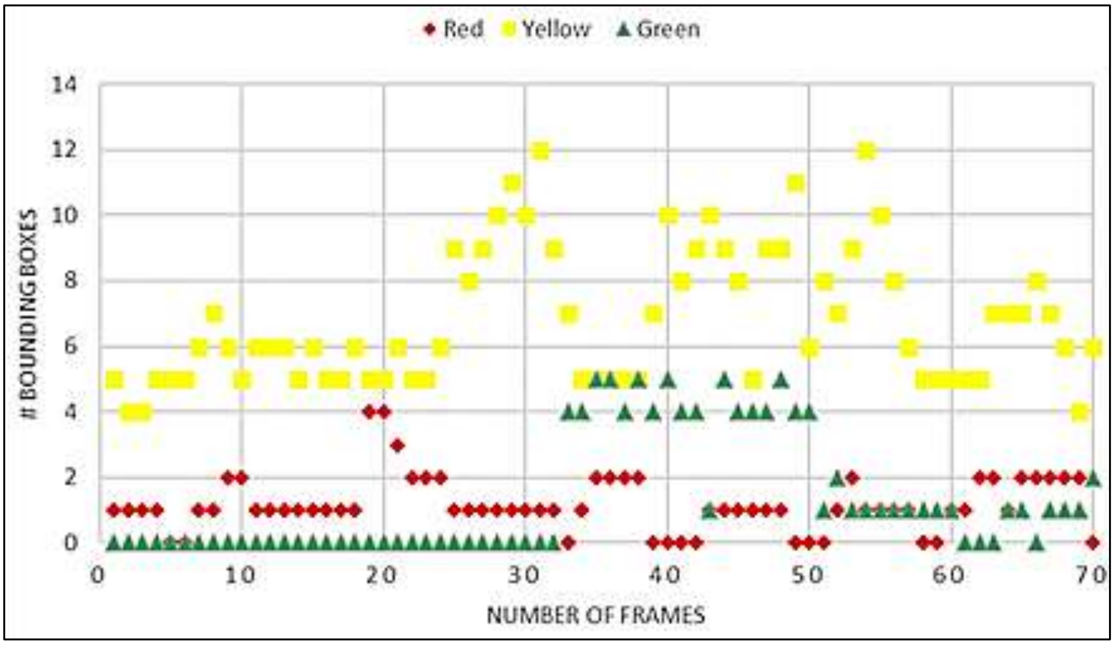


**Fig. 6.** Number of bounding boxes per individual

Ethics are still the most important thing. Data security laws must be followed when collecting personally identifiable information about people. To build trust among the public, future versions of the system should include methods for making data anonymous and safe ways to handle data. Findings would be more useful if they could be applied to a wider range of situations by including more locations in the dataset, like outdoor areas and busy public places. Comparative studies with other detection models, like Faster R-CNN, could also help put the system's performance benefits in context. Adding AI-powered behavioural analytics to predict how crowds will move and look at long-term compliance trends would make the system even better.

The dual-functionality system has a lot of promise as a public health tool, but it needs to be improved all the time and be supervised in an ethical way to make it work best and be accepted by everyone. In Figure 7, the body temperature of an individual is visibly presented at the top of each corresponding bounding box. As shown, the body temperature of the depicted persons read as 36.5$^{o}$ C and 36.1$^{o}$C. This functionality enables the system to effectively measure two critical factors potentially associated with the transmission of the COVID-19 virus, or any other airborne diseases. By simultaneously monitoring social distancing compliance and recording body temperatures, this system facilitates a comprehensive approach to mitigating the spread of the virus.

**Fig. 7.** The body temperatures of two individuals have been recorded. Both individuals exhibit normal body temperatures, as indicated by the presence of green bounding boxes around them

## 4. Conclusions

A study shows that YOLOv5 object identification and thermal imaging can track social distance and body temperature simultaneously. However, certain limitations must be noted to contextualise the findings. The method is less successful in vast or dynamic areas due to fixed camera positioning. Crowded places may overlap bounding boxes, reducing social distancing accuracy. Camera height and angle affect detection accuracy, especially for people at the frame's margins. Since training and testing took place indoors, YOLOv5 may function poorly in low-light or outdoor scenarios. Reflections, external heat sources, and barriers can cause thermal imaging noise. Training datasets lack age, clothing, height, and body type variation, which may restrict generalisability to different groups. Extreme temperatures and unusual human positions were not effectively represented, which may impair detection accuracy.

The study also calculates social separation using a typical anthropometric threshold based on average height and shoulder breadth. Individual or regional body dimensions may impact these estimations' accuracy. The single threshold of 37.2°C for healthy and ill people does not account for natural body temperature changes induced by exercise or ambient circumstances. Due of high-resolution cameras and computationally costly algorithms, scalability is another issue. Real-time processing speed depends on GPU performance and network connectivity, which may limit scaling to larger installations or multi-location implementations. Finally, ethical and privacy issues must be addressed. Privacy difficulties arise with surveillance technologies, especially in public. The system anonymises data, although misuse or unauthorised access is possible. Clear data usage communication and user permission are essential for GDPR compliance.

**Acknowledgement**
Universiti Sultan Zainal Abidin through Special Research Grant Scheme - International Collaboration (SRGS-IC-R0291).

**References**

[1] Freitas, Fernanda da Fonseca, Anna Cecília Queiroz de Medeiros, and Fívia de Araújo Lopes. "Effects of social distancing during the COVID-19 pandemic on anxiety and eating behavior—a longitudinal study." *Frontiers in Psychology* 12 (2021): 645754. https://doi.org/10.3389/fpsyg.2021.645754
[2] Arya, S., L. Patil, and A. Wadeganokar. "Study of various measure to monitor social distancing using computer vision: a review." *International Journal of Engineering Research & Technology (IJERT)* 10, no. 5 (2021): 329-326. https://doi.org/10.22214/ijraset.2022.43501
[3] McAleer, Michael. "Is one diagnostic test for COVID-19 enough?" *Journal of Risk and Financial Management* 13, no. 4 (2020): 77. https://doi.org/10.3390/jrfm13040077
[4] Redmon, J. "You only look once: Unified, real-time object detection." In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2016. https://doi.org/10.1109/CVPR.2016.91
[5] Liu, Chengji, Yufan Tao, Jiawei Liang, Kai Li, and Yihang Chen. "Object detection based on YOLO network." In *2018 IEEE 4th Information Technology and Mechatronics Engineering Conference (ITOEC)*, p. 799-803. IEEE, 2018. https://doi.org/10.1109/ITOEC.2018.8740604
[6] Li, Shasha, Yongjun Li, Yao Li, Mengjun Li, and Xiaorong Xu. "Yolo-firi: Improved yolov5 for infrared image object detection." *IEEE Access* 9 (2021): 141861-141875. https://doi.org/10.1109/ACCESS.2021.3120870
[7] DSR, G., and V. JA. "Social distance detection using deep learning and risk management system." arXiv (2023). http://arxiv.org/abs/2304.10259
[8] Farhadi, Ali, and Joseph Redmon. "Yolov3: An incremental improvement." In *Computer vision and pattern recognition*, vol. 1804, p. 1-6. Berlin/Heidelberg, Germany: Springer, 2018. https://doi.org/10.48550/arXiv.1804.02767
[9] Shalini, G. V., M. Kavitha Margret, MJ Sufiya Niraimathi, and S. Subashree. "Social distancing analyzer using computer vision and deep learning." In *Journal of Physics: Conference Series*, vol. 1916, no. 1, p. 012039. IOP Publishing, 2021. https://doi.org/10.1088/1742-6596/1916/1/012039
[10] Li, Xin, Cheng Wang, Haijuan Ju, and Zhuoyue Li. "Surface defect detection model for aero-engine components based on improved YOLOv5." *Applied Sciences* 12, no. 14 (2022): 7235. https://doi.org/10.3390/app12147235
[11] Adarsh, Pranav, Pratibha Rathi, and Manoj Kumar. "YOLO v3-Tiny: Object Detection and Recognition using one stage improved model." In *2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS)*, pp. 687-694. IEEE, 2020. https://doi.org/10.1109/ICACCS48705.2020.9074315
[12] Kucharski, Adam J., Petra Klepac, Andrew JK Conlan, Stephen M. Kissler, Maria L. Tang, Hannah Fry, Julia R. Gog, and W John Edmunds. "Effectiveness of isolation, testing, contact tracing, and physical distancing on reducing transmission of SARS-CoV-2 in different settings: A mathematical modelling study." *The Lancet Infectious Diseases* 20, no. 10 (2020): 1151-1160. https://doi.org/10.1016/S1473-3099(20)30457-6
[13] Punn, Narinder Singh, Sanjay Kumar Sonbhadra, Sonali Agarwal, and Gaurav Rai. "Monitoring COVID-19 social distancing with person detection and tracking via fine-tuned YOLO v3 and Deepsort Techniques." *arXiv Preprint arXiv:2005.01385* (2020). https://doi.org/10.48550/arXiv.2005.01385
[14] Ramadass, Lalitha, and Sushanth Arunachalam. "Applying deep learning algorithm to maintain social distance in public place through drone technology." *International Journal of Pervasive Computing and Communications* 16, no. 3 (2020): 223-234. https://doi.org/10.1108/IJPCC-05-2020-0046
[15] De Guzman, Sophia Riziel C., Lauren Castro Tan, and Jocelyn Flores Villaverde. "Social distancing violation monitoring using YOLO for human detection." In *2021 IEEE 7th International Conference on Control Science and Systems Engineering (ICCSSE)*, p. 216-222. IEEE, 2021. https://doi.org/10.1109/ICCSSE52761.2021.9545098

[16] Nguyen, Huy Hoang, Thi Nhung Ta, Ngoc Cuong Nguyen, Hung Manh Pham, and Duc Minh Nguyen. "Yolo based real-time human detection for smart video surveillance at the edge." In *2020 IEEE Eighth International Conference on Communications and Electronics (ICCE)*, p. 439-444. IEEE, 2021. https://doi.org/10.1109/ICCE48956.2021.9352144

[17] Kannadaguli, Prashanth. "YOLO v4 based human detection system using aerial thermal imaging for UAV based surveillance applications." In *2020 International Conference on Decision Aid Sciences and Application (DASA)*, p. 1213-1219. IEEE, 2020. https://doi.org/10.1109/DASA51403.2020.9317198

[18] Gündüz, Mehmet Şirin, and Gültekin Işık. "A new YOLO-based method for social distancing from real-time videos." *Neural Computing and Applications* 35, no. 21 (2023): 15261-15271. https://doi.org/10.1007/s00521-023-08556-3

[19] Maity, Madhusri, Sriparna Banerjee, and Sheli Sinha Chaudhuri. "Faster r-cnn and yolo based vehicle detection: A survey." In *2021 5th International Conference on Computing Methodologies and Communication (ICCMC)*, p. 1442-1447. IEEE, 2021. https://doi.org/10.1109/ICCMC51019.2021.9418274

[20] Rahim, Adina, Ayesha Maqbool, and Tauseef Rana. "Monitoring social distancing under various low light conditions with deep learning and a single motionless time of flight camera." *Plos One* 16, no. 2 (2021): e0247440. https://doi.org/10.1371/journal.pone.0247440

[21] Yurttas, Dr. Yuksel. *The average height of men and women worldwide*. Advanced Limb Lengthening Solutions.

[22] Ahmad Habibillah, Nadia Hanani, and Fairuz Izzuddin Romli. "Anthropometric measurements of Malaysian population for passenger cabin design of transport aircraft." *Journal of Mechanical Engineering (JMechE)* 19, no. 1 (2022): 99-112. https://doi.org/10.24191/jmeche.v19i1.19689