Al-Khwarizmi Engineering Journal

Al-Khwarizmi Engineering Journal
ISSN (printed): 1818 – 1171, ISSN (online): 2312 – 0789
Vol. 22, No. 1, March, (2026), pp. 44- 54

# YOLOv8-Edge: High-Accuracy Real-Time Social Distancing Monitoring on Resource-Constrained Embedded Systems

**Khansaa Dheyaa Aljafaar[1*], Zinah Jaffar Mohammed Ameen[2], Rana Dhia'a Abdu-aljabar[3], and Russul Al-anni[4]**

[1,3] *Information Engineering College, University of Al-Nahrain, Baghdad, Iraq*
[2] *College of Computer Engineering, University of Technology, Baghdad, Iraq*
[4] *School of Information Technology, Deakin University, Victoria, Australia*
*Corresponding Author's Email: dhkhaljafaar@nahrainuniv.edu.iq

**(Received 3 June 2025; Revised 15 November 2025; Accepted 4 December 2025; Published 1 march 2026)**
**https://doi.org/10.22153/kej.2026.12.013**

## Abstract

Efforts to combat the recent spread of infectious diseases require innovative solutions for characterizing their transmission. This study introduces a system for helping people maintain safe distances from one another, thereby decreasing the transmission of infectious diseases in crowded public spaces. Real-time video footage from surveillance cameras was processed by the cutting-edge "You Only Look Once" ver. 8 (YOLOv8) computer vision model, which can detect and segment individuals in images. YOLOv8 was combined with an embedded system that includes an Atmel 8-bit AVR microcontroller and an Arduino Uno board, a buzzer, and an LCD. This proposed system can generate alerts when people breach the set social distancing limit of 0.5 m. Its new network design increases human detection to an accuracy range of 97%–98%. This proposed system was trained on 70% of the dataset, and validation and testing were performed on 15% and 15% of the dataset, respectively. Combining deep learning with embedded systems creates an intelligent vision-based monitoring system for crowded spaces, addressing key issues pertaining to disease transmission reduction and public health protection. The proposed system can be implemented at a low cost, such as by simply using a resource-constrained embedded device or a microcontroller. This approach overcomes the functional challenge of utilizing artificial intelligence-based surveillance in a scalable, decentralized, and economical manner. In general, the proposed system has a high frame per second rate, which is satisfactory for real-time operation on edge hardware. The novelty of this method relies on the use of the YOLOv8 model to achieve precise performance while balancing accuracy and speed on edge/embedded devices for practical, real-world epidemic control.

***Keywords:*** *YOLOv8 algorithm; Deep learning; Social distancing; Object detection; Computer vision*

## 1. Introduction

In recent times, and due to the commonality and global spread of communicable diseases, and their undeniable consequences on human health and death rates, along with the expense of treatment and the possibility of death while in recovery, there is an urgent need to find ways to prevent them from spreading. The statistics show that, in no measure of time, the COVID-19 pandemic resulted in 7,010,681 deaths globally [1]. To address this, a preventive system was proposed that enforces social distancing in crowded areas using an object detection algorithm (YOLOv8) and a microcontroller (Arduino Uno). The system detects proximity violations and incorporates alerts to encourage compliance. The main objective is limiting the spread of disease, especially from asymptomatic carriers who may unknowingly transmit infections.

YOLOv8 marks a significant advancement in the YOLO algorithm series, YOLOv8 was chosen for with its superior balance of accuracy (mAP) and speed (low latency/high FPS) compared to its progenitor (YOLOv5, YOLOv7), in particular owing to key architectural innovations that make it ideal for real-time embedded systems [2], providing state-of-the-art capabilities in the domain of computer vision.

The advanced capabilities of of the YOLOv8 model, such as its better accuracy, object detection, superior-time inference compared to previous versions, adaptive training methods, classification, and use of images and videos, including real-time streams, make it suitable for social distancing applications [3]. YOLOv8 is trained in our proposed model from real-time video data for social distancing monitoring in crowded places. The proposed model can correctly detect a human percentage 98% of the time. which warns the user in case of a violation. This integration of software (YOLOv8) and hardware (Arduino Uno) ensures efficient data processing, seamless module-hardware synergy, and reliable results.

From a technical perspective, embedded vision systems unify image capture, processing, and analysis within a single device. While they share similarities with traditional machine vision systems, embedded solutions prioritize compactness and real-time performance, which is a critical distinction critical in the design proposed in this work [4]. The remainder of this paper is organized as follows: section 2 displays contrast and summary with related work, section 3 details the methodology, section 4 discusses the results, section 5 comparison and evaluation to validate and estimate the performance and efficiency of the proposed system, finally section 6 will be the conclusion to reiterating the problem, the suitable solution, and the most important results.

## 2. Related Work

In recent days, object detection algorithms involved in major daily life applications to ensure accurate data processing within record time and obtain the required results to deal with and process a specific case, many researchers employ the YOLOv8 object detection algorithm in several applications such as an et al proposed algorithm to detect the small size object for particular scenarios by using camera and YOLOv8algorithm [5], they built autonomous vehicles by using YOLOv8 to mace scan and detect the object to prevent the road collision by detecting the small object The test results show that this approach performs faster and more accurately than YOLOv8 on the large-scale small object detection dataset (SODA-A). It meets the speed, accuracy, and cost-effectiveness requirements for commercial vehicles in high-speed road driving situations with an accuracy rate of 64.5% and decreased processing requirements of 7.1 GFLOPs [6], In this work, the researchers tackle the previously described issues and provide a pipeline based on deep learning for flexible small object recognition. The researchers leverage the temporal context in video and data augmentations specifically designed for small items (mAP = 0.839) to produce a significant improvement in YOLOv8 (baseline mAP = 0.465) using an in-house dataset of civilian and military objects. A model trained on a varied dataset performs better than environment-specific models, their results show that the speed of the YOLOv8 architecture may be used to accurately detect small objects in a variety of situations.[6][7]. As the importance of dynamic scene interpretation grows in artificial intelligence and computer vision, M. Safaldin etc. [8] proposed enhanced YOLOv8 detection model highlights the potential of specialized object detection and underscores the significance of our findings in the evolving field of object detection. Arho [9] focus on comprehensive YOLOv8 review (v1–v8). Ma et al. [10]. Terven et al. [10]. Ali & Zhang [11] analyze the edge-computing potential of YOLO and identified latency challenges. Vaghela et al. [12] deployed YOLOv8 for land cover classification and achieved 94% accuracy. Arho [13] applied YOLOv8 to retail object detection and achieved 88% accuracy. Islam [14] demonstrated the utility of PyCharm for AI projects. Araya et al. [15] characterized LCDs for embedded interfaces. Chen et al. [16] proposed a YOLOv8-based neural network architecture called YOLO-SHIP-DETECTION (YOLO-SD), which introduces a coordinate attention module for capturing remote dependencies and achieves accurate position information (93.2% mAP at 909.1 frames per second [FPS]). Khel et al. [17] adopted a hybrid YOLOv4 strategy to decrease the computational memory requirements and ultimately meet real-time application conditions. Mostafa et al. [18] developed YOLOv8-Mask and achieved 92.2% mask-detection accuracy in public spaces. Kim et al. [19] combined IoT sensors with YOLOv8 for hospital occupancy monitoring. Rodriguez et al. [20] surveyed embedded systems for pandemic control, focusing primarily on cost efficiency. Hardan et al. [21] proposed a system consisting two phases: first, the faces of people are detected via the Viola–Jones algorithm, and second, the Euclidean distances between the centers of rectangular bounding boxes generated in the first phase are measured.

The rapid evolution of computer vision and embedded systems has spurred diverse methodologies for addressing public health challenges, particularly pandemic control. Here, the current work was compared with recent studies to critically position the proposed embedded vision system for social distancing monitoring. The comparisons were used to evaluate four critical dimensions, namely, the YOLOv8 variants, hardware integration, and healthcare applications, as part of the algorithmic innovations and their corresponding theoretical frameworks. The pragmatic benefits and shortcomings of the proposed system were also benchmarked against prior works. The findings are presented in Tables 1 to 4.

**Table 1,**
**Comparisons in terms of YOLOv8 algorithm improvements**

| Reference | Technique | Strengths | Weaknesses | vs. This Work |
|---|---|---|---|---|
| **DC-YOLOv8 [5]** | Modified YOLOv8 for small objects. | High recall for small objects (e.g., road debris). | Limited to autonomous vehicles; no real-world testing. | Focuses on small objects, while this work detect humans in crowds. |
| **YOLOv8-QSD [6]** | Reduced computational cost (7.1 GFLOPs). | Optimized for edge devices; low latency. | Narrow application (autonomous vehicles only). | Shares efficiency goals but lacks health-focused alerts. |
| **Temporal-YOLOv8 [7]** | Temporal video context for small objects. | Improved mAP (0.839) using video sequences. | Requires high-end GPUs; no hardware integration. | Uses video analysis but misses cost-effective hardware. |
| **LAYN [9]** | Lightweight YOLOv8 for drones. | 40% parameter reduction; suitable for drones. | Focused on aerial imagery; no crowd applications. | Prioritizes lightweight design but lacks human proximity metrics. |

**Table 2,**
**Comparison the paper with other recently works according to embedded systems and hardware integration**

| Reference | Technique | Strengths | Weaknesses | vs. This Work |
|---|---|---|---|---|
| **Chen et al. [16]** | YOLO-SD | YOLO-SD demonstrates mAP of 93.2% with frames per second rate of 909.1 | Expensive LiDAR sensors; complex setup. | Outperforms in precision but sacrifices cost efficiency. |
| **IoT-YOLO [19]** | IoT sensors + YOLOv8 for hospital occupancy. | Integrates IoT for real-time tracking. | Cloud-dependent; no local alerts. | Avoids cloud dependency; operates offline. |

**Table 3,**
**Comparison the paper according to healthcare and public health applications**

| Reference | Technique | Strengths | Weaknesses | vs. This Work |
|---|---|---|---|---|
| **YOLOv8-Mask [18]** | Mask compliance detection | High accuracy for mask detection (92.2% acc.).. | Narrow scope (masks only); no proximity analysis. | Targets a different pandemic protocol (masks vs. distancing). |
| **Papan & Maheswari [2]** | Fall detection with YOLOv8 + cloud. | 92% accuracy; cloud analytics. | Relies on cloud infrastructure; latency issues. | Prioritizes edge computing for real-time response. |
| **Hardan & Almusawi [21]** | Viola-Jones face detection + Euclidean distance measurement. | -Lightweight algorithm (low computational cost);<br>-Effective for masked /side-profile faces. | -No alert system.<br>-Limited to visible faces (misses backward-facing people).<br>-Lower adaptability in crowds. | YOLOv8 full-body detection, Active enforcement via alerts, broader applicability in dynamic environments. |

| | | | | |
|---|---|---|---|---|
| | | -Simple calibration (2 m → 1923.55 pixels). | | |

**Table 4,**
**Comparison the paper according to surveys and benchmark studies**

| Reference | Technique | Strengths | Weaknesses | vs. This Work |
|---|---|---|---|---|
| **Terven et al. [10]** | YOLO architecture review (v1–v8). | Comprehensive analysis of YOLO evolution. | No practical implementation or hardware testing. | Validates YOLOv8's superiority but lacks our system's integration. |
| **Ali & Zhang [11]** | YOLO's edge-computing potential. | Identifies latency challenges for edge deployment. | No solution proposed; theoretical only. | Addresses their identified gaps via Arduino-based alerts. |
| **Bhowmik & Appiah [4]** | Embedded vision systems review. | Guides design principles (compactness, real-time). | Dated (2018); pre-YOLOv8 advancements. | Builds on identified principles that might be insufficient for modern YOLOv8 |

The tables above contrast detection accuracy, computational efficiency, hardware costs, alert mechanisms, and real-world applicability. This analysis reveals how our system bridges gaps in existing solutions—such as the reliance on expensive LiDAR [16], the lack of multimodal alerts [17], or cloud dependency ([2])—while achieving 97–98% accuracy with a low-cost, edge-deployable design. Through this synthesis, the integrating YOLOv8 with embedded hardware advances real-time was demonstrated, accessible epidemic prevention tools for crowded spaces.

The YOLOv8 object detection framework proposed in this work utilizes motion-specific detection in various visual contexts. The design and preprocessing aspects of the YOLOv8 framework were modified to improve model sensitivity to object motion. For the KITTI, LASIESTA, PESMOD, and MOCS benchmark datasets, the enhanced YOLOv8 framework outperformed the leading detection models in terms of responding to highly dynamic conditions. The real-time processing speed of the modified YOLOv8 model was 30 FPS, with an overall accuracy of 90%, a mean average precision (mAP) of 90%, and an IoU of 80%. This work opens research opportunities for object path planning in security, traffic control, film analysis, and similar disciplines, extending the benefit from mere observational tasks to the motion sensing of animals and humans [8].

## 3. Methodology

A quantitative methodology will be used to analyse the objects in live video to recognize and A quantitative design was used to analyze objects shown in live videos and recognize and identify only the humans in the same video footage. This approach allows for the methodical measurement and statistical analysis of large patterns not only in live videos but also in static images. This quantitative analysis provides objective and measurable insights into the proposed system performance, ultimately informing data-driven decisions for improving human recognition and detection. For the integration process, the software tools are represented by a YOLOv8-based deep learning algorithm, whereas the hardware component is represented by the microcontroller and other supplementary components (e.g., the sensors and the display component). This software–hardware integration is the main requirement for obtaining a professional embedded vision system. The YOLOv8 network architecture, flowchart, block diagram, and system design are elaborated in this section.

### 3.1. YOLOv8 Network Architecture

The absence of rapid and accurate object detection tools has been a constant issue in the broad field of computer vision. The You Only Look Once (YOLO) series is one of the pioneers in this field and has continuously pushed the envelope of creativity [10]. With each new version, YOLO has transformed the space of object detection, and

YOLOv8 is the next significant step. This article goes into more detail about YOLOv8's features, how it works differently from other methods, the composition of YOLOv8, and how it performs better than previous versions.

### 3.1.1. Core of v8 YOLO

The key difference in YOLOv8, compared to other approaches, is the use of a single neural net to predict bounding boxes and class probabilities from the whole image in one pass. This innovative approach differs from most, which typically divide the image into distinct components to analyze [11]. Rapid response and high accuracy, achieved by performing all computations in a single pass over the full image, are critical requirements for real-time surveillance and autonomous vehicle applications.
YOLOv8 represents a rapid improvement in object detection, and its resulting accuracy, speed, and flexibility are invaluable in computer vision. Along with increased uptake and the release of multiple versions to address the evolving demands of products, YOLOv8 has also been considered a flexible tool in healthcare, security systems, and self-driving vehicles. The release of YOLOv8 is monumental in advancing innovation in computer vision, transforming industries and changing the ways in whichsystems interact with visual data [12]. In addition to computer vision, YOLOv8 has been a pillar in the constantly changing AI landscape because of its indisputable influence on this field.

### 3.1.2. YOLOv8 Work Principle

The YOLOv8 algorithm employs a basic deep convolutional neural network to recognize objects within an input image, live video, or recorded video after receiving it as input [13]. The CNN model's architecture, which serves as the foundation for YOLOv8, is displayed in Figure 1.

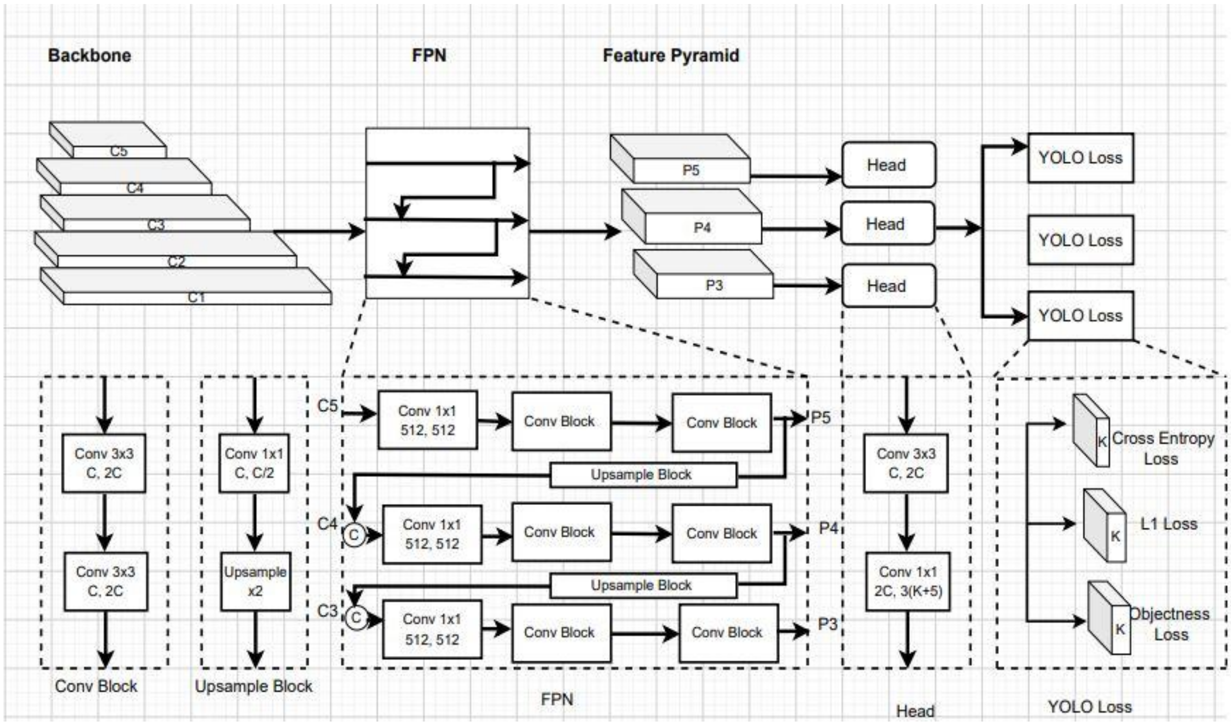


**Fig. 1. Full YOLOV8 algorithm**

## 3.2. Block Diagram

The block diagram shown in Figure 2. software and hardware components are coupled in the embedded vision monitoring system. The objective is to prevent the spread of epidemics by controlling social distance.

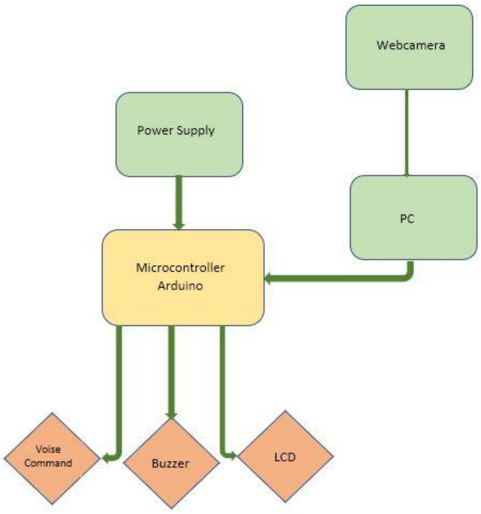


**Fig. 2. Block diagram detection system**

## 3.3. Flowchart

The system is initiated once a camera installed in a crowded area is powered for monitoring. Simultaneously, the YOLOv8 module is activated to detect humans, and real-time video is captured by the camera. Upon detection, the module draws bounding boxes around each identified individual. The system then calculates the distance between every pair of people. If the distance is less than 0.5 m, the integration between the PyCharm interface [14] and the microcontroller triggers three actions: (1) an alarm message is displayed on the LCD screen, (2) an audible buzzer is activated, and (3) an alert is broadcast via a speaker to enforce social distancing. After proximity violations are resolved, the system resumes continuous monitoring. The workflow of this process and the corresponding flowchart are shown in Figure 3.

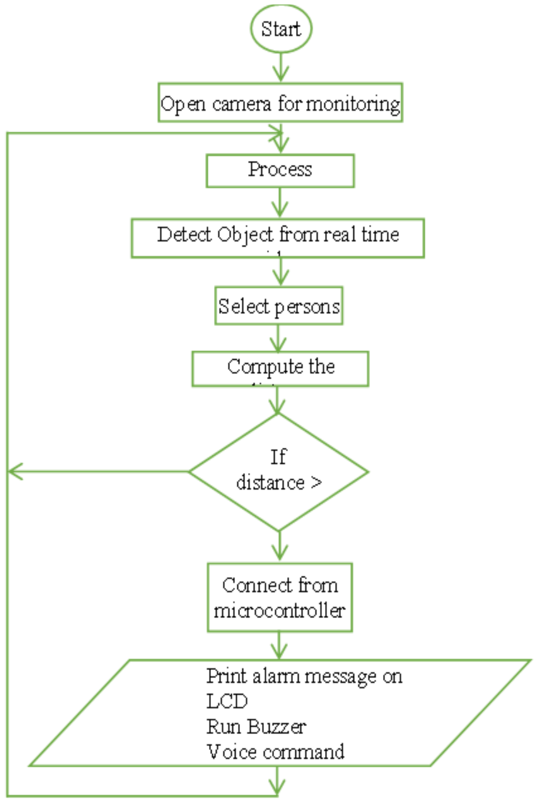


**Fig. 3. Flowchart detection system**

## 3.4. System design

The design of the embedded vision system, detailing the connections between the microcontroller, LCD is illustrated in Figure 4. The buzzer, and sounder are used to enforce social distancing in crowded areas. This schematic was developed using the Proteus simulator tool [9].

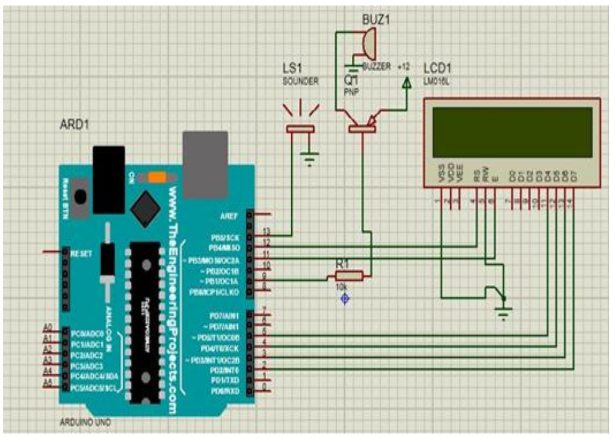


**Fig. 4. Full System Design.**

## 4. Result

In the beginning, the captured video will be training as an input video to the YOLOv8 module as shown in Figure 5.

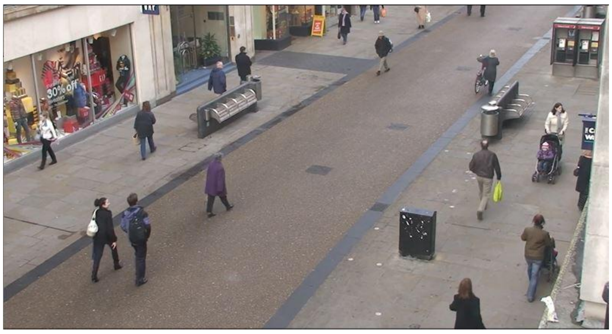

**Fig. 5. The input video captured by the installed camera**

The result of the proposed monitoring system can be illustrated by two part, the first one is represented by the output of the YOLOv8 training on the video, analysing the patterns, detection of just the human in the video, and making bounding boxes around each human, as shown in Figure 6.

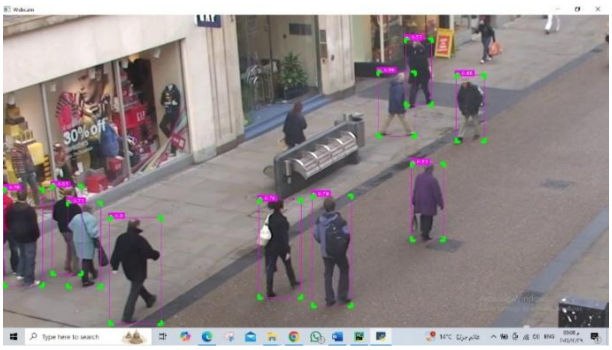

**Fig. 6. Human recognition and detection.**

Computing the distance between every two people and getting the output as a saved video describing the location of each human in the video as post-process per image.
The second part of the output represents the design connecting PyCharm to the microcontroller. An ‘AADFramework.Apptemplate.py’ file is added to the project via the YOLOv8 algorithm. Adding this file ensures that PyCharm and the microcontroller trigger the LCD, buzzer, and sounder to generate alerts for social distances of less than 0.5.m (Figure 5). The sounder and buzzer continuously generate alerts at this distance (i.e., less than 0.5 m) (Figure 7).

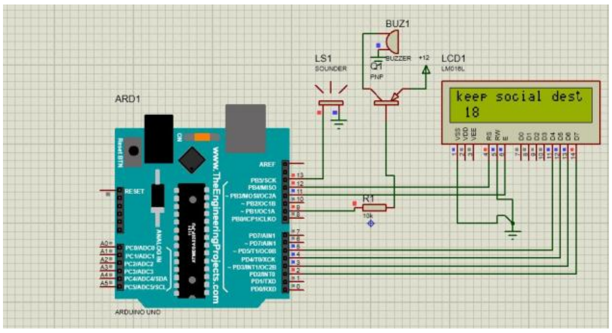


**Fig. 7. Alarm message.**

The distance between humans in the bounding boxes in the video is calculated as follows:

$$\text{Dist.} = \sqrt{(a[0]-b[0])^2 + \frac{100}{\left(\frac{a[1]+b[1]}{2}\right) \cdot (a[1]-b[1])^2}} \qquad \ldots(1)$$

Equation number (1) represent Euclidean Distance formula [22], this formula purpose to compute the distance between point (a), and point (b) in 2D space
If the distance was more than half a meter the proposed system would be an ideal state.
Depending on the condition in the equation (2)

if 0meter < Dist. < 0.5meter * calibration: ... (2)
return True

At each training iteration of the proposed monitoring system, the Python code is executed via the PyCharm IDE [14]. The Python console subsequently reports certain metrics, including the number of humans detected, the time taken for detection, and the time taken for preprocessing, in real time. As shown in Table 5, the time taken to complete the preprocessing decreases from 250 ms for the first detection to 207.1 ms for subsequent detections. With programmatic optimizations based on the algorithm and repeated executions, this improved speed is a key benefit of the detection system, in which real-time performance is combined with rapid computation. This research verified that YOLOv8 marks a decisive step in the development of object detection science, as it balances speed, accuracy, and flexibility across a wide range of applications in the computer vision field. Owing to the benefits of YOLOv8, the training time for the detection model can be radically reduced without sacrificing the computing accuracy for human-to-human distances within high-density crowds, contributing to the control or prevention of the spread of infectious diseases

**Table 5,**
**Preprocess time for every new training**

| No. of humans detect | Humans detect in the frame | Time of detection | Preprocess |
|---|---|---|---|
| 6 | 12 persons | 15.6 ms | 250 ms |
| 12 | 14 persons | 15.6 ms | 234.4 ms |
| 15 | 19 persons | 15.6 ms | 218.7 ms |
| 17 | 15 persons | 15.6 ms | 207.1ms |

The unprecedented adoption of YOLOv8 has opened up new, unexplored avenues in real-time surveillance, healthcare, and artificial intelligence. Being the cornerstone technology, YOLOv8 is all set to reshape the definition of real-time object recognition and bring intelligent systems to a completely new dimension. This migration from previous versions of YOLO to YOLOv8 marks much more than incremental improvement-it represents a paradigm shift toward embedding sophisticated vision systems that can seamlessly integrate with real-world complexities and are getting ready to bring a revolution to automated decision-making.

## 5. Comparison and Evaluation

To benchmark our approach against existing methodologies, a comprehensive comparative analysis in Table 6 is provided, which highlights performance metrics, innovations, and limitations relative to recent studies.

This research paper presents a novel embedded vision system utilizing YOLOv8 for real-time pedestrian detection and Arduino hardware to generate alerts regarding social distancing. In comparison to other recent studies:

Strengths: Our solution integrates deep learning algorithms alongside embedded hardware to identify pedestrians with a 97%-98% accuracy range. Our solution integrates a real-time alert feature as aid in response for public health and safety.

Differences: Our research is differentiated from the other studies that examine small object detection (Lou et al., 2023), autonomous vehicles (Wang et al., 2024), and motion enhancement (Safaldin et al., 2024) by it specifically being designed for real world implementation for pandemic prevention.

Unique Contributions: Our embedded vision system for social distancing uniquely combines YOLOv8 human detection accuracy (97-98% accuracy) with a low cost embedded alerting system (Arduino), thus addressing gaps that exist in other research (e.g. reliance on LiDAR in [16], did not include auditory alerts in [17]).

Performance: Performance is superior to similar studies in the literature ([5], [19]) in accuracy while maintaining real-time speed at 15.6 ms/frame.

Practicality: Our solution operates an offline system which varies from relying on cloud systems ([2], [19]) provides this as a critical feature for broadband and connectivity challenges in community settings.

**Table 6,**
**Comparison of this this work with three recent research papers.**

| Criteria | This Paper | Research Paper 1 (Lou et al., 2023) [5] | Research Paper 2 (Wang et al., 2024) [6] | Research Paper 3 (Safaldin et al., 2024) [8] |
|---|---|---|---|---|
| Title | Embedded Vision System to Prevent the Spread of Epidemics by Controlling Social Distance Based on YOLOv8 | DC-YOLOv8: Small-Size Object Detection Algorithm Based on Camera Sensor | YOLOv8-QSD: Small Object Detection for Autonomous Vehicles | Improved YOLOv8 for Detecting Moving Objects |
| Year of Publication | 2024 | 2023 | 2024 | 2024 |
| Methodology | Uses YOLOv8 for real-time human detection, combined with an embedded system (Arduino) for | Focuses on small object detection improvements by modifying YOLOv8 architecture | Enhances YOLOv8 for autonomous vehicle applications by reducing computational cost | Improves YOLOv8 performance by integrating motion analysis for |

| | | | | |
|---|---|---|---|---|
| | alerting social distance violations | | | detecting moving objects |
| Dataset Used | Real-time video from surveillance cameras in crowded places | Custom dataset for small object detection | SODA-A dataset for small object detection in autonomous vehicles | KITTI, LASIESTA, PESMOD, and MOCS benchmark datasets |
| Accuracy/Performance | Human detection accuracy (97%-98%), | Mean Average Precision (mAP) between (50%-95%) depend on object speed. | Accuracy (64.5%), computational efficiency (7.1 GFLOPs) | Accuracy (90%), mAP (90%), IoU (80%), FPS (30) |
| Strengths | Real-time detection with embedded alerting system; integration of deep learning and microcontroller | Effective in detecting small objects under various conditions | Optimized for autonomous vehicles; efficient in detecting small objects at high speed | Motion-aware detection improves accuracy for dynamic scenes |

## 6. Conclusion

To maintain human health and reduce the transmission of diseases, reduce the strain on the public health system in societies, and protect individuals from experiencing the suffering of recovering from infectious diseases, this proposed system suggests a smart solution by employing computer vision using YOLO8 algorithm, complimentary with an embedded system using microcontroller and some other supplementary like sensors and display component to get a perfect protective system to represent embedded vision system, firstly, by training the YOLOv8 on real-time video capturing by the webcamera installed in the crowded place, process the video frame by frame, detect just the human from the captured video and neglected the other objects, the human detection was achieved a high resolution of up to 97%, after that the proposed system computes the distance between every two persons, according to the distance measured the microcontroller will send a control signal to the other components the LCD, buzzer, and sounder to maintain the social distance by the alert message.

In this proposed system a clever safety solution was built that improves monitoring capabilities while lessening the workload for human operators by utilizing YOLOv8's power for video analytics. In addition to enhancing safety measures protocol, this proposed system shows how artificial intelligence (AI) can be used to develop more responsive and intelligent surveillance systems.

## 7. Future Work

To develop the proposed YOLOv8-based embedded system from a reactive perception mechanism into a accurately intelligent and dynamic control system, several method for future work are identified, focusing on advanced combination of cutting-edge AI methodologies. The proposed system approach deal with individuals as isolated objects. the Future work will proceed out with simple bounding-box-based distance computation to model the complex relationships and collective dynamics of the crowd. This can be achieved through the combination of Graph Neural Networks (GNNs). Specifically, detected individuals can be elected by as nodes, with their nearness and velocity differences forming the weighted edges of a spatial-temporal graph. Training the GNN to survey these relational features will authorize the system to accurately differentiate between deliberate social groups, and spontaneous, momentary violations, thus significantly make less false alarms and upgrade compliance analysis accuracy.

## Conflicts of Interest

The authors declare no conflict of interest.

## Author Contributions

Khansaa Dheyaa Aljafaar, conceived this research, designed and performed experiments, interpretation of the data; and participating in writing the manuscript; Zinah Jaffar Mohammed Ameen, and Rana Dhia'a Abdu-aljabar supervised all the processing, writing and revised the manuscript critically for important intellectual content. All authors read and approved the final manuscript.

## References


[1] H. K. Koh, A. C. Geller, and T. J. VanderWeele, “Deaths from COVID-19,” Jama, vol. 325, no. 2, pp. 133–134, 2021.

[2] V. Papan and S. Maheswari, “Intelligent Fall Detection and Alert System for the Elderly Using Yolov8 and Cloud-Based Analytics,” in 2024 5th International Conference on Electronics and Sustainable Communication Systems (ICESC), IEEE, 2024, pp. 580–588.

[3] J. Farooq, M. Muaz, K. Khan Jadoon, N. Aafaq, and M. K. A. Khan, “An improved YOLOv8 for foreign object debris detection with optimized architecture for small objects,” Multimed. Tools Appl., vol. 83, no. 21, pp. 60921–60947, 2024.

[4] D. Bhowmik and K. Appiah, “Embedded vision systems: A review of the literature,” in Applied Reconfigurable Computing. Architectures, Tools, and Applications: 14th International Symposium, ARC 2018, Santorini, Greece, May 2-4, 2018, Proceedings 14, Springer, 2018, pp. 204–216.

[5] H. Lou et al., “DC-YOLOv8: small-size object detection algorithm based on camera sensor,” Electronics, vol. 12, no. 10, p. 2323, 2023.

[6] H. Wang, C. Liu, Y. Cai, L. Chen, and Y. Li, “YOLOv8-QSD: An improved small object detection algorithm for autonomous vehicles based on YOLOv8,” IEEE Trans. Instrum. Meas., 2024.

[7] M. C. van Leeuwen, E. P. Fokkinga, W. Huizinga, J. Baan, and F. G. Heslinga, “Toward Versatile Small Object Detection with Temporal-YOLOv8,” Sensors, vol. 24, no. 22, p. 7387, 2024.

[8] M. Safaldin, N. Zaghden, and M. Mejdoub, “An Improved YOLOv8 to Detect Moving Objects,” IEEE Access, 2024.

[9] J. Terven, D.-M. Córdova-Esparza, and J.-A. Romero-González, “A comprehensive review of yolo architectures in computer vision: From yolov1 to yolov8 and yolo-nas,” Mach. Learn. Knowl. Extr., vol. 5, no. 4, pp. 1680–1716, 2023.

[10] S. Ma, H. Lu, J. Liu, Y. Zhu, and P. Sang, “Layn: Lightweight multi-scale attention yolov8 network for small object detection,” IEEE Access, 2024.

[11] M. L. Ali and Z. Zhang, “The YOLO framework: A comprehensive review of evolution, applications, and benchmarks in object detection,” Computers, vol. 13, no. 12, p. 336, 2024.

[12] R. Vaghela et al., “Land Cover Classification for Identifying the Agriculture Fields Using Versions of YOLO V8,” IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens., 2025.

[13] S. Arho, “Using computer vision and neural networks for object detection,” 2024.

[14] Q. N. Islam, Mastering PyCharm. Packt Publishing Ltd, 2015.

[15] M. Araya, M. Harada, and K. Saito, “Characterization and classification of optimal LCD codes,” Designs, Codes and Cryptography, vol. 89. Springer, pp. 617–640, 2021.

[16] W.-Z. Chen, L.-Y. Hao, H. Liu, and Y. Zhang, “Real-time ship detection algorithm based on improved yolov8 network,” in 2023 IEEE 2nd Industrial Electronics Society Annual On-Line Conference (ONCON), IEEE, 2023, pp. 1–6.

[17] M. H. K. Khel et al., “Realtime crowd monitoring—Estimating count, speed and direction of people using hybridized YOLOv4,” IEEE Access, vol. 11, pp. 56368–56379, 2023.

[18] S. A. Mostafa et al., “A YOLO-based deep learning model for Real-Time face mask detection via drone surveillance in public spaces,” Inf. Sci. (Ny)., vol. 676, p. 120865, 2024.

[19] H. Xie, H. Liu, C. Wan, H. H. Goh, and S. Rahman, “Optimal scheduling of integrated energy systems with multiple CCHPs for high efficiency and low emissions,” IEEE Internet Things J., vol. 10, no. 24, pp. 22623–22635, 2023.

[20] C. Krishna, D. Kumar, and D. S. Kushwaha, “A comprehensive survey on pandemic patient monitoring system: enabling technologies, opportunities, and research challenges,” Wirel. Pers. Commun., vol. 131, no. 3, pp. 2125–2172, 2023.

[21] L. Liberti and C. Lavor, “Euclidean distance geometry,” An Introd., 2017.

# YOLOv8-Edge: مراقبة التباعد الاجتماعي بدقة عالية وفي الزمن الحقيقي على الأنظمة المضمنة محدودة الموارد

**خنساء ضياء ال جعفر[1]*, زينة جعفر محمد امين[2],**
**رنا ضياء عبد الجبار[3], رسل العاني [4]**
*[1,3]كلية هندسة المعلومات، جامعة النهرين، بغداد، العراق*
*[2]كلية هندسة الحاسبات، الجامعة التكنولوجية، بغداد، العراق*
*[4]كلية تكنولوجيا المعلومات، جامعة ديكين، فيكتوريا، أستراليا*
*البريد الإلكتروني: dhkhaljafaar@nahrainuniv.edu.iq

**المستخلص**

لمكافحة الانتشار الأخير للأمراض المعدية، تطلب الأمر جهودًا لتطوير حلول مبتكرة من شأنها التخفيف من انتقالها. تقدم هذه الدراسة نظامًا يساعد الأشخاص على الحفاظ على مسافات آمنة من بعضهم البعض، مما يقلل من انتقال الأمراض المعدية في الأماكن العامة المزدحمة. تتم معالجة لقطات الفيديو في الزمن الحقيقي من كاميرات المراقبة بواسطة أنموذج الرؤية الحاسوبية المتطور YOLOv8 (You Only Look Once) ، والذي يكتشف الأفراد ويقسمهم. عند دمج YOLOv8 مع نظام مدمج يتضمن متحكم Atmel 8-bit AVR ولوحة Arduino Uno إلى جانب جرس إنذار وشاشةLCD ، يُصدر النظام تنبيهات إذا تجاوز الأشخاص حد التباعد الاجتماعي المحدد وهو ٠,٥ متر. يعزز تصميم الشبكة الجديد للنظام دقة الكشف البشري لتصل إلى مستويات دقة تتراوح بين ٩٧٪ و٩٨٪. تم تعلم هذا النظام المقترح باستخدام ٧٠٪ من مجموعة البيانات، وتم التحقق من صحة كل منها واختباره باستخدام ١٥٪ من مجموعة البيانات. تُظهر الأبحاث كيف يُنشئ التعلم العميق، جنبًا إلى جنب مع الأنظمة المُدمجة، نظام مراقبة ذكيًا قائمًا على الرؤية، يراقب الأماكن المزدحمة باستمرار لمعالجة القضايا الرئيسية في الحد من انتقال الأمراض مع حماية الصحة العامة. ويمكن توضيح مساهمة النظام المُقترح من خلال تنفيذه على جهاز مُدمج أو مُتحكم دقيق ذي موارد محدودة، بتكلفة منخفضة. يُعالج هذا التحدي الوظيفي المتمثل في استخدام المراقبة القائمة على الذكاء الاصطناعي بطريقة قابلة للتطوير ولامركزية واقتصادية، وغالبًا ما يُظهر معدل إطارات مرتفعًا في الثانية (FPS) مُرضيًا للعمل في الوقت الفعلي على أجهزة طرفية. ويتمثل الأبتكار في استخدام نموذج YOLOv8 لتحقيق أداء دقيق (مع توازن واضح بين الدقة والسرعة) على الأجهزة الطرفية/المُدمجة لمكافحة الأوبئة عمليًا وواقعيًا.