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AI Based Real Time Crowd Monitoring and Risk Detection Using Computer Vision

Raghavendra S[1], Gaanashree BN[2], K Jyothi[3], Rachana M[4], Thanisha G[5]

[1]Professor, Department of CS&D, K. S. Institute of Technology, Bengaluru, India
[2,3,4,5]Student, Department of CS&D, K. S. Institute of Technology, Bengaluru, India

Abstract:
Monitoring crowd conditions is a challenge with just CCTV monitors. Whilst the cameras can capture footage this requires monitoring to identify when the platform is getting busy or when people are rushing. An automatic monitoring system has been created that detects people in video footage from CCTV or IP cameras. The model uses YOLOv8 to detect people and ByteTrack to track people between frames. The scene has been split into zones so crowd monitoring can be done to see how many people are in each zone, how many people are coming into and out of the zone and how fast and direction people are moving. A YOLOv8 model has been fine-tuned with the D-Fire dataset to detect fire and smoke. An LSTM Autoencoder has been used to detect movement. The fusion stage will classify each zone as Normal, Caution or Critical. Debouncing has been used to stop multiple alerts being sent. All the information will be displayed on a dashboard created with Flask and all events will be stored in MongoDB.

Keywords: Artificial Intelligence and Computer Vision are important. Crowd Monitoring is vital. Risk Detection is key. YOLO.

1. INTRODUCTION

Crowd monitoring in certain areas can be an issue due to having more visitors than ever before. Areas such as shopping malls, temples and railway stations can have a large amount of people gathering in one place. This can cause issues such as panic and stampeding. Current CCTV camera solutions just record footage, meaning someone has to monitor the footage constantly. It can be difficult to detect anything. This project aims to create an Artificial Intelligence solution for crowd monitoring.

2. PROBLEM STATEMENT

When managing crowds in certain scenario's they can quickly become a hazard. Traditional solutions for monitoring crowd movement require human monitoring of the camera footage. This may mean risks are not detected. Using Artificial Intelligence and Computer Vision can solve this issue. By detecting people within the video footage using YOLOv8 and tracking using ByteTrack, techniques such as CSRNet and Long Short-Term Memory networks can detect how many people are in the crowd. Using both techniques will allow predictions to be made about how the crowd density may change. This can create a system to detect issues and notify the authorities if the crowd density exceeds levels. This project looks at how using an Artificial Intelligence powered Computer Vision solution can help monitor crowd movement in real time to detect hazards.

3. LITERATURE REVIEW

SL NO	YEAR OF PUBLICATION	TITLE	DESCRIPTION
1	2025[1]	CrowdSentry: An AI-Powered Framework for Real Time Crowd Behavior Analysis and Stampede Risk Prediction	CrowdSentry is a technology that uses artificial intelligence and machine learning algorithms to monitor crowds and predict stampedes, which can also be applied at the railway station, among others. For crowdSentry, deep learning techniques, such as YOLOv8 and DeepSORT to detect and track movements using video imagery, respectively, are used. An assessment is made concerning whether the crowd behavior, measured by crowd density, velocity, and directions, is either within normal limits or abnormal through a grid technique. Heat maps and zoning (dividing spaces into safe zones, congested, or high-risk zones) visualization techniques are provided in this technology. Once the pre-set threshold is crossed, an alert will be generated. Some of the key features of crowdSentry include real-time dashboard, data log, high precision, and low latency.
2	2025[2]	A Novel AI-Based Predictive Crowd Monitoring and Stampede Prevention System	In this research work, the utilization of the proposed improved crowd congestion monitoring and prediction AI system would be recommended to prevent the occurrence of stampedes. The detection of people will be done through YOLOv8 based on the CCTV footage or drones' video feed. Thereafter, the area will be sectioned into 5m x 5m squares in order to calculate the population density. Moreover, the LSTM algorithm will predict the future population density based on the previous population density trend, considering the next two minutes. If the population density becomes unsafe, alerts will be issued to prevent stampedes.
3	2025[3]	Vision Crowd: Automated Crowd Monitoring and Analysis Through AI	An AI-based approach will be used in this paper that includes automated detection of helmets as well as crowd monitoring. The use of YOLOv3 will enable the system to detect

			helmets while YOLOv5 will help detect and count people from video footage. This could be done using the DNN function of OpenCV and drawing bounding boxes of those without helmets. No human interference would be needed and this would decrease any kind of error by humans. These kinds of systems would allow for high risk areas where safety guidelines should always be followed, such as during construction activities and similar jobs. There may be some difficulties in implementing such systems in low lit environments and overcrowded places.
4	2025[4]	Anomaly Detection in Crowd Behavior for Public Safety Assurance	The current paper introduces a system that utilizes AI to monitor crowd behavior anomalies with the emphasis on real-time detection of falling individuals for public safety improvement purposes. In particular, the system leverages the potential of YOLOv8 together with the technique of pose estimation for processing live CCTV footage. It implements a two-phase fall detection procedure, which includes verifying that an individual has fallen on multiple frames to minimize false-positive results. Once the system detects a person falling down, alert notifications are immediately delivered via cloud messaging systems such as Firebase or SMS APIs. This non-invasive approach is scalable, does not need any wearables, and provides accurate results (about 91–94%) with minimal delay in crowded conditions.
5	2025[5]	Smart Crowd: AI-Driven Crowd Density Monitoring and Management in Indian Public Hotspots	The Smart Crowd Surveillance is one technology that can be deemed as the future of surveillance systems since they incorporate the use of AI-based algorithms, which help in monitoring individuals within certain locations such as temples, railways, and crowded places in India. The features of the Smart Crowd Surveillance include: - The use of various technological advances for effective performance of the surveillance system. To begin with, there is the application

			of YOLOv5 algorithm, which helps to detect individuals through the surveillance camera videos. Secondly, there is the application of CSRNet algorithm, which aids in detecting crowds in crowded locations. Lastly, the application of LSTM algorithm helps to predict crowd behavior. - The application of various technologies including Wi-Fi, Bluetooth, and visual sensors to overcome visualization issues. Lastly, there is the incorporation of edge computing technology such as NVIDIA Jetson Xavier NX.
6	2025[6]	Proactive Public Safety in 6G: Leveraging AI and Crowdsourcing for Critical Tasks	A proactive public safety framework for 6G network environment is suggested in this research work, which utilizes AI, crowdsourced data, and edge intelligence for efficient real-time decision making. Multiple data sources will be used including mobile devices, IoT devices, vehicles, social media, and digital twins to detect and manage any incident such as accident and congestion in time. This framework will use transformers for detecting incidents and CVAE-based generative AI model to predict future scenarios. Agentic AI combined with reinforcement learning will be implemented for resource management. Blockchain technology will be incorporated for the security of data, and federated learning will enable distributed training without compromising data privacy. This proactive framework is based on SAGIN network, including terrestrial systems, UAVs. The results from the simulation experiments show that the performance is considerably improved regarding accuracy, load balancing and the resilience to malicious data.
7	2025[7]	ShielDir: AI-Powered Real-Time Threat Detection System to Reduce Crime Response Time	ShielDir is an innovative real-time surveillance system that uses AI algorithms for the purpose of ensuring public safety through detecting weapons and aggression in the CCTV cameras' feed. As opposed to current

			state-of-the-art solutions, it offers several significant advantages, such as real-time video analytics, scalability due to a microservices architecture based on Docker and Kafka containers, and immediate notifications. The system uses the YOLOv11 algorithm to detect weapons, while the behavior analysis is performed by OPear, which is a VideoMAE-based deep learning model. Detected events in the system are prioritized into threat levels, including low, moderate, and critical ones, and then immediately reported to the relevant authorities via a cross platform mobile and web app.
8	2025[8]	API-Driven AI Framework for Real-Time Beach Safety and Coastal Hazard Prediction	The SeaAegis is a new system for securing the coast based on artificial intelligence, machine learning and application programming interfaces which are capable of forecasting any hazards that may occur on the beach such as dangerous currents and adverse weather conditions. The system uses geolocation tools and routing optimization and allows for predicting any potential hazards on the beach individually and enables individuals to be safe while using the beach. In addition, it uses environmental factors such as wind velocity and waves, creates predictive models through using ensemble and reinforcement learning methods, and calculates the risk score for that particular beach which reflects the degree of its safety. Moreover, individual notifications are issued and the use of multiple languages is possible, in addition to providing relevant information related to location-based services. Achievements in terms of improvements consist of accurate forecasts (92% vs. 75%), rapid updates and high user satisfaction (4.7/5).
9	2024[1]	Enhancing University Safety through AI-Powered Speed Detection	The current research discusses an automatic speeding detection mechanism based on artificial intelligence techniques that enhance the security of university campus through computer vision-based technology. With the

			help of applying YOLOv9c technique alongside real-time video processing, the speed detection can be made possible without any specialized hardware components and accurate tracking of vehicles is obtained. The outcomes obtained from experimental evaluations show excellent accuracy in recognizing the speeding vehicles in comparison to the conventional technique based on radars. The proposed methodology successfully minimizes the risk factors caused by speeding cars. As future improvements, IoTs can be included to boost its accuracy and latency.
10	2024[2]	Crowd Coordination System	The current research is dedicated to the analysis of the newly developed crowd coordination software with YOLOv7 used for crowd identification and counting. With the help of this tool, the video frames will be analyzed, the necessary parameters will be calculated and the alarms will be triggered through the Gmail API in case any pre-specified limits are crossed. In such a way, it will become possible to get in touch with the police services immediately to make crowd management more effective. Having evaluated all results received from the analysis, one can say that the tool works very accurately which can be seen as a basis for evaluating the effectiveness of the solution.
11	2024[3]	Crowd Management using AI & ML	The proposed idea discussed in this paper concerns the use of AI and ML technologies to control crowds in Indian urban areas. This technology is based on using computer vision and analytic to monitor individuals' activities in a crowd, detect any anomalies, and enhance security. Such technologies could be very useful in terms of preventing crimes because such technologies will make it possible to analyze the crowd's activities and identify criminals. Moreover, places of work will become much safer with such technologies since there will be no issues with employees'

			safety. Finally, the use of these technologies would be beneficial for organizers of different events since it allows identifying issues that might arise with the help of monitoring people's activities.
12	2024[4]	Advanced Surveillance System for Public Safety	The present study outlines a sophisticated approach of intelligence supervision that incorporates artificial intelligence supervision tools to ensure the security of cities. The limitations associated with the conventional Cameras approach can be addressed through more effective strategies, such as deploying deep learning algorithms for abnormality detection, crowd behavior analysis, and crowd safety violation monitoring. It entails employing the YOLOv8 algorithm to guarantee precise identification of weaponry, abnormal actions, and violation of people intensity levels. Furthermore, the utilization of object detection approaches, encompassing deep SORT, facial recognition, and internet of things, is necessary for facilitating continuous supervision.
13	2022[1]	Using Computer Vision to enhance Safety in a Post COVID World	The objective of the present paper will be to illustrate how computer vision and deep learning systems may contribute to ensuring safety in the post-pandemic reality. The main focus will be placed on the application of algorithms such as YOLO and Faster R-CNN that will be designed to detect instances when masks should have been worn as well as ensure that there is appropriate social distancing between different people. This system will be based on the analysis of video footage from the camera surveillance cameras used within buildings where gatherings of people take place. The system will not only be capable of detecting safety rule violations, including lack of masks and social distancing, but also tracking individuals' presence using object detection and measuring interpersonal distances.
14	2022[2]	Reducing Viral	This proposed methodology aims to develop

		Transmission through AI-based Crowd Monitoring and Social Distancing Analysis	an AI-driven framework for maximizing public safety by keeping track of crowd behaviors while avoiding any chances of getting infected with the virus. Computer vision algorithms, as well as machine learning models, are applied in order to perform analysis of the Camera feed in real-time mode. Detection of a crowd, body posture analysis, and using face masks are taken into account as the critical factors in evaluating potential threats. On top of that, distance between individuals is calculated to determine whether people tend to stand close together or not. While traditional bounding box methods have already been developed for detecting people, the use of pose estimation can allow one to calculate distances more precisely. Additionally, information about activities performed by crowds, such as walking, standing, or sitting, would also be acquired. Overall risk factor is calculated based on the gathered data.

4. METHODOLOGY

A. Objectives: The system has 5 objectives. Track people in the video/recorded video. Calculate how many people are in each area. Detect changes in movement. Detect fire and smoke. Notify workers appropriately.

B. System Architecture: There are 5 stages in the pipeline. The video can be from a CCTV/IP camera or a recorded file. The frames can be read using OpenCV and prepared for detection. YOLOv8 is used to detect people in each frame.

For a detected person, YOLOv8 produces a bounding box:

$$B_i = (x_1, y_1, x_2, y_2)$$

The centre point is calculated as:

$$C_i = \left(\frac{x_1 + x_2}{2}, \frac{y_1 + y_2}{2} \right)$$

i. Person Bounding Box Centre:

Where:

- Bi*Bi* = Bounding box of detected person.
- Ci*Ci* = Centre co-ordinates of person.

- x1,y1$x1,y1$ = Left Co-ordinates.
- x2,y2$x2,y2$ = Right Co-ordinates.

This is used to allocate the person to a zone.

$$D_z(t) = \frac{N_z(t)}{A_z}$$

ii. Zone-Wise Crowd Density:

Where:

- Dz(t)$Dz(t)$ = Crowd density indicator of zone z.
- Nz(t)$Nz(t)$ = Number of people detected in zone z at time t.
- AzAz = Area of zone.

$$\Delta D_z(t) = D_z(t) - D_z(t-1)$$

iii. Crowd Density Change:

Where:

- ΔDz(t)$\Delta Dz(t)$ = Change in crowd density.
- Dz(t)$Dz(t)$ = Current density.
- Dz(t−1)$Dz(t-1)$ = Previous density.

This helps to detect zones where the crowd is increasing rapidly.

ByteTrack will link detections between frames to give each person a track ID. This will only be used to track movement and will not identify who the person is. Each person will be allocated to a zone using a fixed point on the box such as the centre. The zone counts will be used as an indicator for the density. Using the track positions we can calculate displacement, direction and variation in direction over a time window. As no camera calibration has been done speed will be in pixels per second.

Displacement:

$$S_i = \sqrt{(x_t - x_{t-1})^2 + (y_t - y_{t-1})^2}$$

Velocity:

$$V_i = \frac{S_i}{\Delta t}$$

Direction:

$$\theta_i = \tan^{-1}\left(\frac{y_t - y_{t-1}}{x_t - x_{t-1}}\right)$$

iv. Crowd Movement and Velocity:

Where:

- SiSi = Displacement of tracked person.
- ViVi = Speed of movement (pixels per second).
- θiθi = Direction of movement.

- ΔtΔ*t* = Difference in time between frames.

This helps to detect movement patterns.

The LSTM autoencoder has been trained on movement detection. If there is a high reconstruction error then something may be happening. A second YOLOv8 model has been fine-tuned using the D-Fire dataset to detect fire and smoke.

$$E = \frac{1}{T}\sum_{t=1}^{T}(X_t - \hat{X}_t)^2$$

v. LSTM autoencoder anomaly score:

Where:

- E*E* = Reconstruction error.
- Xt*Xt* = Actual movement feature.
- X^t*X^t* = Reconstructed movement feature.
- T*T* = Number of time steps.

If the reconstruction error exceeds a set threshold then the movement will be flagged as anomalous.

$$C_f \geq \tau_f$$

vi. Smoke detection confidence:

If the confidence score exceeds the threshold then the detection will be seen as valid for risk detection.

The fusion will combine the zone density, density change, movement features, anomaly score and fire/smoke detection. This will classify each zone as normal, caution or critical. The fusion will remember the status of each zone and will only notify when there is a change. The results will be displayed on a dashboard using Flask and Socket.IO. All events will be stored in MongoDB. Email and SMS alerts will be used.

C. Evaluation: The person detection was done using a pre-trained YOLOv8 model. This specifically used the YOLOv8n weights shown in the code of the report. The fire/smoke detection was done using a YOLOv8 model that had been fine-tuned with the D-Fire dataset. The system was tested using recorded crowd clips. Where possible live feeds from IP/CCTV cameras were used. The detection performance will be analysed by calculating the precision, recall and F1 score at a set IoU threshold. The crowd detection results will be compared to the reference using MAE and RMSE. The speed of processing will be given in FPS. The delay will be analysed.

D. Requirements: The system was created using Python. OpenCV, PyTorch (YOLOv8), ByteTrack, NumPy and Pandas were used. The dashboard and event storage was done using Flask, Socket and MongoDB. The system was developed in Visual Studio Code on a Windows machine. It is recommended to have either an Intel Core i5 processor or similar AMD Ryzen processor. The system will require 8GB of RAM. It is better to have 16GB. An SSD will be required. An NVIDIA GPU with CUDA support is not required. The camera can be a CCTV camera or IP camera. It can also be a recorded video file.

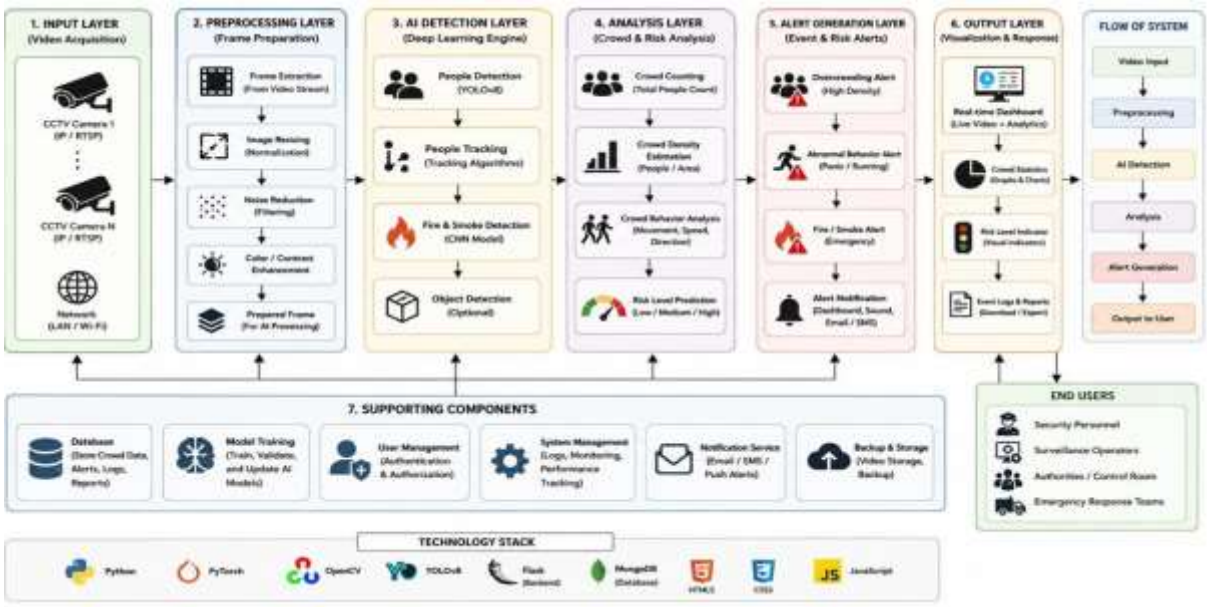


Figure 1: System Architecture.

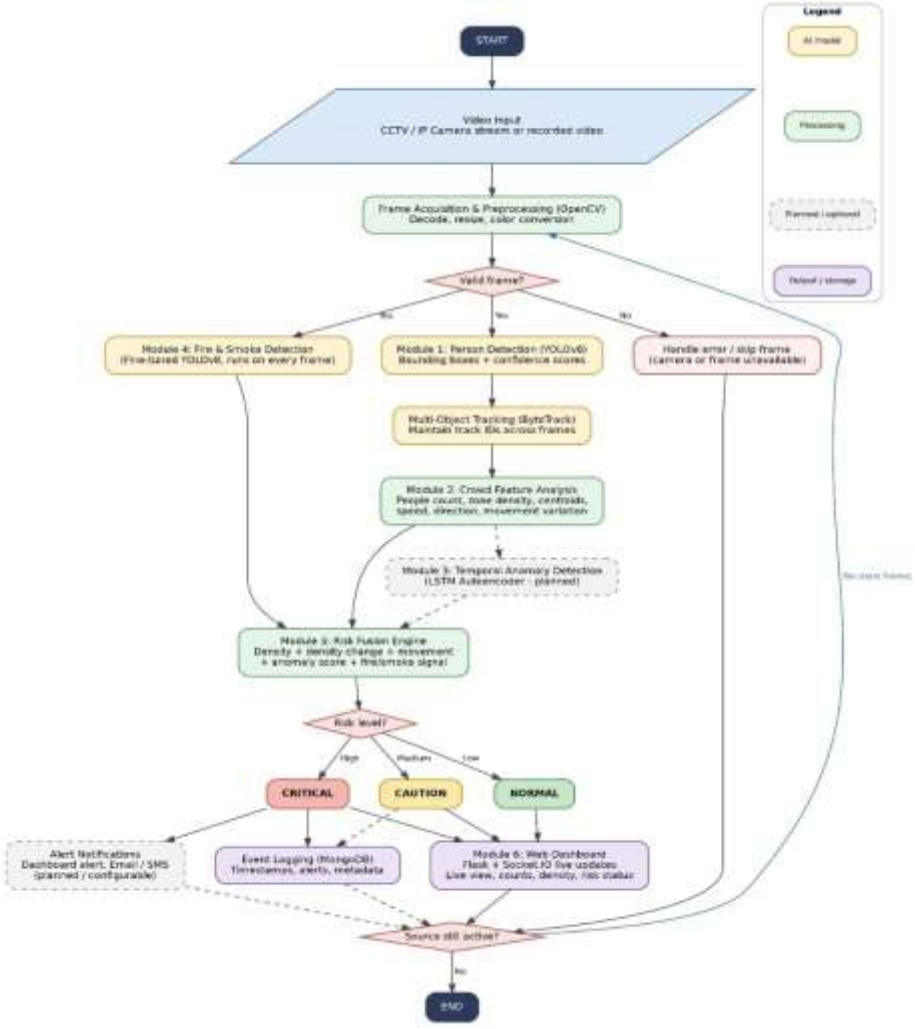


Figure 2: Project Flowchart.

5. MODELING AND ANALYSIS

Imagine a system that has been designed to monitor videos. The design section will focus on creating algorithms using Computer Vision and intelligent learning to detect people in each image of the video and count how many people are present. Analysing how people are moving is key to identifying any actions that could pose a risk. The system will use this to determine risk. In the analysis section all the data that has been collected will be analysed to determine how risky the area may be. The system will estimate a risk level for the area. At the time of detection the algorithms will look for any signs of fire by detecting smoke or flame. Alerts will be sent.

i.Risk Fusion Calculation:

$$R_z = w_1 D'_z + w_2 \Delta D'_z + w_3 M'_z + w_4 A'_z + w_5 F_z$$

Where:

- Rz*Rz* = Overall risk score for zone z.
- Dz′*Dz′* = Normalised crowd density.
- ΔDz′Δ*Dz′* = Normalised density change.
- Mz′*Mz′* = Normalised movement anomaly score.
- Az′*Az′* = Normalised LSTM reconstruction error.
- Fz*Fz* = Fire/smoke detection risk indicator.
- w1,w2,w3,w4,w5*w*1,*w*2,*w*3,*w*4,*w*5 = Assigned weights.

The weights should be positive and add up to 1.

$$Risk(z) = \begin{cases} Normal, & R_z < T_1 \\ Caution, & T_1 \leq R_z < T_2 \\ Critical, & R_z \geq T_2 \end{cases}$$

ii. Risk Classification:

Where:

- T1*T*1 = Threshold for normal/caution.
- T2*T*2 = Threshold for caution/critical.

This will help the system to determine dangerous crowd conditions.

$$Alert_z(t) = \begin{cases} 1, & Risk_z(t) \neq Risk_z(t-1) \\ 0, & Risk_z(t) = Risk_z(t-1) \end{cases}$$

iii. Alert Debouncing:

Where:

- Alertz(t)*Alertz*(*t*) = Alert generation status.
- Riskz(t)*Riskz*(*t*) = Risk status.
- Riskz(t−1)*Riskz*(*t*−1) = Previous risk status.

This will help prevent multiple notifications if the zone remains in the risk category.

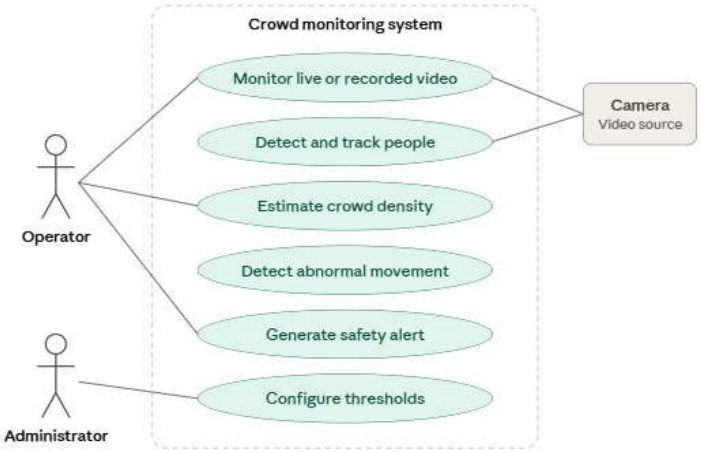


Figure 3: Use Case Diagram.

6. RESULTS & DISCUSSION

A. Evaluation

The system has been analysed using recorded crowd videos and live feeds from IP/CCTV cameras. The testing was done with scenes containing people, moderate crowd and dense crowd. Testing was done with various lighting and camera angles. The person detection has been verified by comparing the people detected using YOLOv8 to a reference count for the selected frames. As some people may be missed and some people may have duplicate boxes this will cancel each other out. The quality of detection can be seen using precision, recall and mean average precision if labelled data is available. The crowd detection has been summarised by looking at the error between the system and reference. The speed of processing has been calculated by seeing how many frames per second the system can process on the test machine.

Sl. No.	Evaluation Metric	Formula	Purpose
1	Precision	$\frac{TP}{TP+FP}$	Measures the correctness of detected persons.
2	Recall	$\frac{TP}{TP+FN}$	Measures how many actual persons are successfully detected.
3	F1-Score	$2 \times \frac{Precision \times Recall}{Precision+Recall}$	Measures the balance between precision and recall.
4	MAE	$\frac{1}{N}\sum_{i-1}^{N}\lvert P_i - G_i\rvert$	Measures the average error in crowd counting.
5	RMSE	$\sqrt{\frac{1}{N}\sum_{i-1}^{N}(P_i - G_i)^2}$	Measures crowd-counting error while penalizing larger errors.
6	FPS	$\frac{\text{Total Frames Processed}}{\text{Total Processing Time}}$	Measures real-time video processing speed.
7	Detection Latency	$T_{output} - T_{input}$	Measures the time taken to produce a detection result.

Table 1: Performance Evaluation Metrics.

B. Expected behaviour of the system

The detection stage will draw a box around each person visible and create a score indicating how confident the system is. ByteTrack will assign a short term ID to each person between frames. This will allow the system to track how each person is moving. The ID's will be used for matching. The system will not reveal who the people are. The system will have an idea of how crowded each area is by

counting how many people are in each area. If there are more people in an area than the set limit then the system will notice that the area is changing from Normal to Caution and then to Critical. Information has been added by looking at how people are moving and how fast they are moving. If a group are moving in one direction they will behave differently to a group moving in another direction. The speed has been measured in pixels per second as to convert to metres we would need to know how the camera is set up.

The fire/smoke model has been trained on the D-Fire dataset. This will detect flames or smoke and send a warning. The LSTM Autoencoder has learnt what normal movement looks like. If the system cannot reconstruct the movement then it will know something is different. This will indicate something is not normal. This does not mean an emergency is happening. The risk fusion has combined all of these warnings. Debouncing will stop the warning from being sent

C. Discussion

The main strength of the design is that it combines signals that depend on how many people there are. A large crowd that isn't changing much will be treated differently to a crowd that is increasing rapidly or moving in a certain way. The modular design means each section can be tested and improved individually.

There are several factors that can affect the accuracy of the system. Poor lighting, long distances and low quality footage will make it harder to detect people. In areas where people are very close together people may be missed or track ID's may be confused. The camera angle is also important. If the camera is high or far away then people will appear smaller and the areas on the screen will not match the actual floor space. Fire/smoke detection can be misleading if there are lights, reflections, fog or steam. The risk levels may not be suitable for all areas so the system must adapt to each location.



Figure 4: Home Page

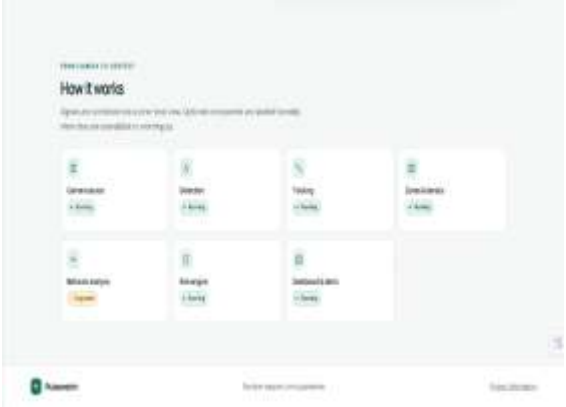


Figure 5: System Workflow.

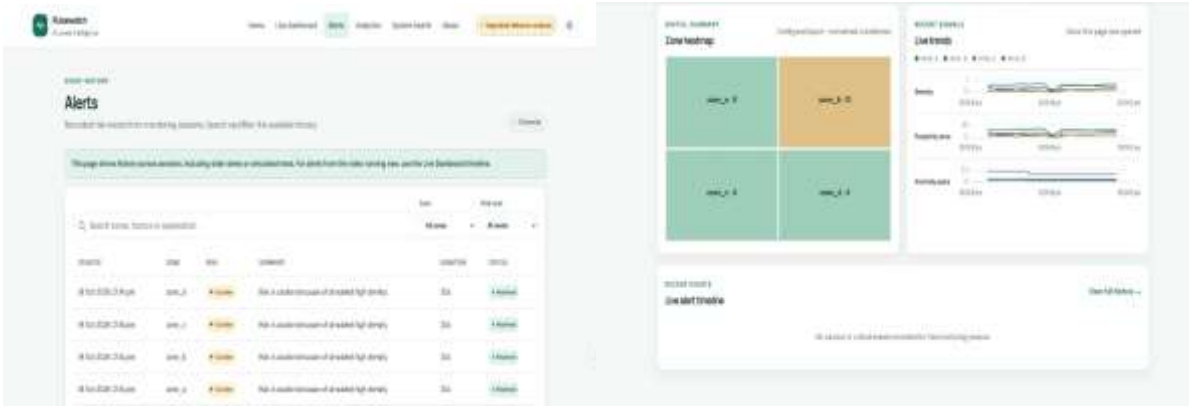


Figure 6: Video Upload & Real-Time Analysis.

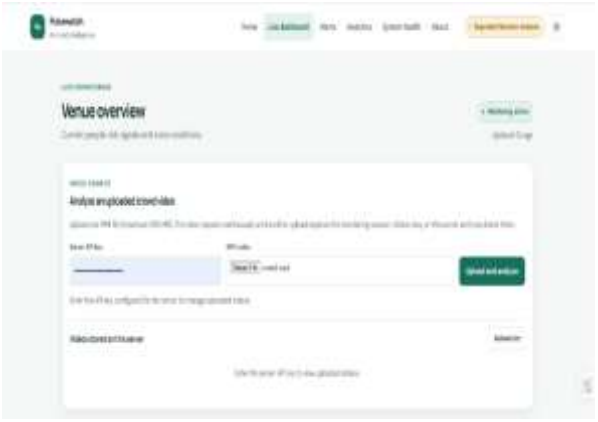


Figure 7: Time & Zone Dashboard

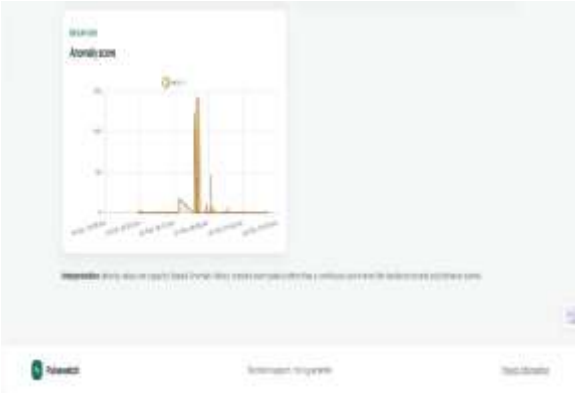


Figure 8: Zone-wise Crowd Density Heatmap & Live



Figure 9: Alert History Dashboard.

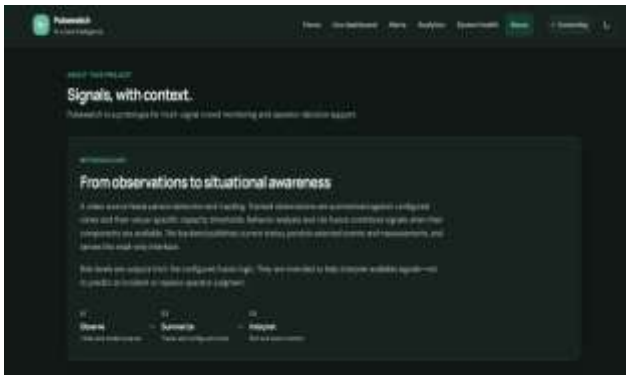


Figure 10: Crowd Density & People Count Analysis.



Figure 11: Anomoly Score Analysis.



Figure 12: About Page.

7. CONCLUSION

This paper details a crowd monitoring technology. The system has been designed to detect and track people and see how crowded each area is. The system will also monitor for fire, smoke and risk conditions. The system can be used as a decision support tool meaning a person must make the final decision. Future work will include testing the planned modules. The system uses cameras to create heatmaps using edge computing systems and send alerts to devices.

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