AI-Powered Real-Time Crowd Safety and Behaviour Analysis Framework

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ABSTRACT:
Crowded places like transport centers, major events, and public areas in cities are difficult to ensure safety in because of their jocularness and people's unpredictable pattern of conduct plus the emergency response being delayed. Security cameras that are normally used for controlling the crowd situation are mostly non-active and their function depends largely on the manual monitoring hence their effectiveness on preventing crowd-related incidents is limited.

As a solution to these problems, the paper suggests a framework for crowd safety and behavior analysis that is powered by AI and works in real-time. This framework incorporates deep learning and computer vision techniques, which ultimately leads to the enhancement of public safety management that is proactive in nature. The new system is capable of detecting people in the live video streams, estimating the number of people in the crowd, and analyzing the spatial and temporal movement patterns in order to identify the abnormal or possibly dangerous behaviors. A model of object detection that is based on deep learning is utilized for the purpose of performing the accurate detection of people, and at the same time, while the analysis of behavior in time is used to identify changes in motion that are sudden, blending of people that leads to congestion, and movements akin to panic. The alerts generated by the system which incorporates the safety thresholds set beforehand are real-time alerts that support the taking of decisions by the authorities in a timely manner. The experimental evaluations which are based on the publicly accessible crowd datasets provide solid proof that the framework is able to reach a high level of accuracy with very little delay in the processing time. The proposed method brings to the table a solution that is advanced, scalable, economical and also smart which can easily be merged with the current surveillance infrastructure thereby making it operational in such places as smart cities, managing large gatherings, and disaster prevention systems.

Key Words: **Crowd Safety, Crowd Behavior Analysis, Real-Time Video Surveillance, Deep Learning, Computer Vision, Crowd Density Estimation, Abnormal Behavior Detection.**

I. INTRODUCTION

The continuous expansion of city inhabitants and the more frequent conducting of major public events have raised issues about crowd safety and behavior once again. High-traffic areas, like train terminuses, sports arenas, religious gatherings, and city crossroads, usually crowded, hence are exposed to incidents such as stampedes, congestion collapse, panic propagation, and violent behavior. Therefore, the management of the crowds in the first place has turned into an indispensable need for public safety agencies and smart city managers [1]. The standard surveillance systems are in place already, but they do not suffice since they still operate strictly based on human manual observation. At the same time, following several video feeds, the human operator can easily get tired, which will not only lead to some errors but also delayed responses to the changing situations in the crowd. Quite the other way round, any potentially dangerous patterns might remain undetected until they grow into serious incidents, thus revealing the weaknesses of the conventional surveillance tactics [2]. The state-of-the-art in artificial intelligence is one of the major contributors to the hassle-free monitoring of public places; it has in fact revolutionized surveillance since the introduction of deep learning and computer vision the latter primarily depending on the former. One of the most successful deep learning architectures and winning modalities in this field are Convolutional Neural Networks (CNNs) and real-time object detection models, such as YOLO based ones, that have even been proven to work well even with a high number of people and under difficult circumstances [3], [4]. Furthermore, these solutions have turned out to be very quick and accurate, which strangely enough, is the opposite of the case with the traditional handmade methods. Understanding the time-dependent behavior of crowds is crucial for spotting the unsafe situations. The sudden change in the crowd's movement patterns, unusual flow directions, and unexpected quickening are the main signals that alert the authorities.

II. RELATED WORK

Crowd safety and behavior analysis have been widely studied in the domain of intelligent video surveillance. Early approaches utilized handcrafted features and optical flow to model crowd motion; however, these methods performed poorly in dense and dynamic environments. With the adoption of machine learning, regression-based models improved crowd density estimation but showed limited robustness under heavy occlusions. Recent advances in deep learning have significantly enhanced crowd analysis performance. Convolutional neural networks (CNNs) have been widely applied for people detection and density

Ref	Author (Year)	Technique	Application Focus	Key Contribution	Major Limitation
[1]	Helbing et al. (2018)	Crowd dynamics modeling	Crowd motion analysis	Pedestrian behavior modeling	No real-time AI system
[2]	Velastin et al. (2019)	Traditional video analytics	Crowd density estimation	Vision-based density analysis	Occlusion and lighting sensitivity
[3]	Redmon et al. (2018)	YOLO object detection	People detection	High-speed real-time detection	Lacks behavior analysis
[4]	Wang et al. (2021)	CNN density maps	Crowd counting	Accurate dense crowd estimation	High computational cost
[5]	Sultani et al. (2018)	CNN-based anomaly detection	Abnormal event detection	Real-world anomaly identification	Offline processing
[6]	Zhang et al. (2020)	Spatio-temporal CNN	Crowd behavior analysis	Motion-based abnormal detection	Complex training process
[7]	Zamir et al. (2018)	Temporal learning models	Action recognition	Temporal pattern learning	Not crowd-specific
[8]	Chhapola et al. (2025)	CNN + BiLSTM	Crowd behavior analysis	Temporal behavior modeling	Limited scalability
[9]	Koreddi et al. (2025)	Spatio-temporal deep learning	Public safety monitoring	Crowd analysis for mass events	High resource consumption
[10]	Prakash et al. (2025)	AI-based surveillance	Integrated crowd analysis	Detection and behavior recognition	Limited real-time alerting
[11]	Rehman et al. (2025)	AI + IoT framework	Smart surveillance	Real-time crowd monitoring	Deployment complexity
[12]	DeepCAMS (2025)	Deep learning framework	Suspicious behavior detection	Real-time monitoring	Dataset dependency
[13]	Scientific Reports (2025)	YOLOv8 lightweight model	Crowd monitoring	High efficiency and speed	Counting-oriented

estimation, while real-time object detection models such as YOLO offer high accuracy and speed for live surveillance. To capture temporal crowd dynamics, several studies integrate CNNs with sequence-learning models such as LSTM and temporal convolutional networks for abnormal behavior detection. Despite these advances, most existing works focus on isolated tasks and lack unified real-time frameworks suitable for safety-critical deployment.

Table I provides a comparative overview of existing crowd safety and behavior analysis approaches based on their techniques, application focus, contributions, and limitations. Earlier studies rely on theoretical modeling and traditional video analytics, which lack real-time capability and robustness in dense environments. Recent deep learning–based methods, such as CNN and YOLO models, improve people detection and crowd density estimation but often address isolated tasks. Introduction of spatio-temporal models facilitates the detection of abnormal behavior but still has to deal with computational complexity and scalability issues. The contribution of this research is an integrated, real-time framework that enables the simultaneous monitoring of crowd density and behavior for proactive safety. The preceding discussion clearly indicates that the current literature has largely been concerned with isolated aspects such as the detection of crowds, estimation of their density, or analysis of their behavior. Although the recent deep learning-implemented methods have made accuracy and efficiency better, most of these do not provide a real-time integration and scalability suitable for safety-critical environments. Hence, the limitation give rise to a need for an integrated AI-powered framework that can analyze both crowd density and behavior simultaneously in real time.

III. PROPOSED METHODOLOGY AND SYSTEM MODEL

A. Framework Architecture

The suggested system implements a complete pipeline for the real-time monitoring of crowd safety. Video streams obtained from the surveillance cameras are processed through either the edge or the server-side modules, which consist of a Convolutional Neural Network (CNN) used for both visual feature extraction and people's analysis, and optical flow for motion estimation. As a result of these inputs, three risk components that are interpretable are calculated: density risk (RD), motion instability risk (RM), and behavioral anomaly risk (RA). A fusion based on attention integrates these components, and a temporal predictor provides a continuous output of the Crowd Safety Risk Index (CSRI). In case the CSRI remains above the predetermined thresholds for a certain period, alerts are sent to the operator for intervention.

B. Problem Formulation and Crowd Safety Risk Index

Let video frames be observed over discrete time steps t∈{1,…,T}. The objective is to estimate a real-valued crowd safety risk signal and forecast its short-term evolution:

$$CSRI(t) \in [0,1], \quad C\hat{S}RI(t+\tau), \tau \in \{1, \dots, \tau_{max}\}$$

Three interpretable risk components are defined: density risk $R_{D(t)}$, motion instability risk $R_M(t)$, and behavioral anomaly risk $R_{A(t)}$. These components are fused into an intermediate raw risk score and mapped to CSRI through a sigmoid function.

C. Mathematical Modeling of Risk Components

1) Density Risk: The monitored area is partitioned into regions Pi. Let $\overline{\boldsymbol{D_\iota}}$ (t) denote the average estimated density in region Pi. A smooth saturating density risk is defined as

$$\boldsymbol{R_D(t) = \sum_i \tanh\left(\beta_D \frac{Area(P_i)}{A_{total}} \left(\frac{\overline{D_\iota}(t)}{\theta_D}\right)^2\right)}$$

Where, $R_{D(t)}$ - Density risk at time t

2) Motion Instability Risk: Let v(x,y,t) denote the optical-flow-based velocity field. Motion instability risk is defined as

$$R_m(t) = \alpha_1 C(t) + \alpha_2 H_M(t)$$

Where $R\_m(t)$ - Motion instability risk at time t, where C(t)=max(0,−∇ .v) aggregated spatially, and HM(t) is the normalized directional entropy.

3) Behavioral Anomaly Risk: Let z_t be a learned embedding of crowd dynamics. A generic anomaly score is expressed as

$$R_{A(t)} = \max_{k \in K} P\,(\,k \mid z_{1:t}\,)$$

where K denotes a set of abnormal or unsafe behavior prototypes and $R_{A(t)}$ denotes Behavioral anomaly risk at time t.

D. Risk Fusion and Prediction :The raw fused risk is computed as

$$R_{raw}(t) = a(t)^{\top}[RD(t), RM(t), RA(t)]$$

where a(t) is an attention vector with non-negative entries summing to one and $R_{raw}(t)$ denotes Raw fused crowd risk score. The final risk index is obtained as

$$CSRI(t) = \sigma(Wh_t + b)$$

where h_t denotes the hidden state of the temporal predictor.

E. Temporal Risk-Weighted Objective: To prioritize early detection, a risk-weighted forecasting loss is defined as

$$\boldsymbol{\mathcal{L} = \sum_t \sum_{\tau=1}^{\tau_{max}} w(t,\tau) l\left(C\hat{S}RI(t+\tau), CSRI(t+\tau)\right)}$$

Algorithm 1 Online Crowd Safety Monitoring
Require: Video stream, regions {Pi}, thresholds θD, θCSRI

1: Initialize temporal state h0, smoothing buffers
2: **for** t=1,2,... **do**
3: Extract features (CNN) and motion field v(·,·,t)
4: Estimate $\overline{\boldsymbol{D_\iota}}\boldsymbol{(t)}$ Average density in region P_i) for each region Pi
5: Compute $R_{D(t)}$ (Density risk at time t) using (2)
6: Compute $R_M(t)$ (Motion instability risk at time t) using (3)
7: Compute $R_{A(t)}$(Behavioral anomaly risk at time t) using (4)
8: Compute $R_{\{raw\}}$ (Raw fused crowd risk score) using (5) and update temporal state h_t
9: Compute CSRI(t)(Crowd safety risk index at time t) using (6) and smooth over a short window
10: **if** CSRI(t) > θ CSRI for k consecutive frames **then**
11: Trigger alert and log (CSRI,R_d,R_m,R_A)
12: **end if**
13: **end for**

Level	Trigger condition	Operator action (example)
Info	CSRI > 0.50 for k frames	Monitor region; verify camera view
Warning	CSRI > 0.60 and (RD or RM high)	Dispatch staff; manage inflow

Critical	CSRI > 0.75 with persistence	Open exits; redirect flow; pause entry

TABLE II. Illustrative Alert Policy (Configurable

A. Probability Calibration of Risk Outputs : Let the model output a logit s(t)∈R. Temperature scaling applies a scalar T > 0:

$$\boldsymbol{CSRI_{cal}(t) = \sigma\left(\frac{s(t)}{T}\right)}$$

B. Uncertainty-Aware Risk for Early Warning

Suppose the predictor yields mean and variance μ^(t+τ) and σ^2(t+τ). A conservative score is:

$$\boldsymbol{CSRI^{+}(t+\tau) = \mathrm{clip}_{[0,1]}\left(\hat{\mu}(t+\tau) + \lambda\hat{\sigma}(t+\tau)\right)}$$

An equivalent probabilistic alert can be stated as:

$$\boldsymbol{\Pr(CSRI(t+\tau) > \theta_{CSRI}) \geq}$$

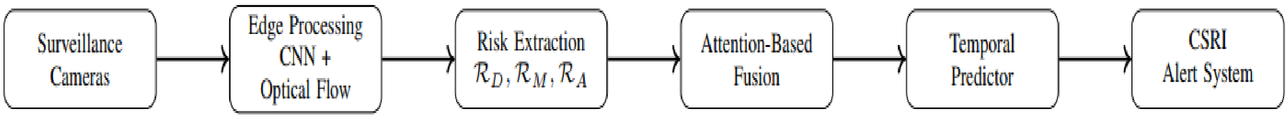

Fig. 1. End-to-end architecture of the proposed AI-powered crowd safety framework

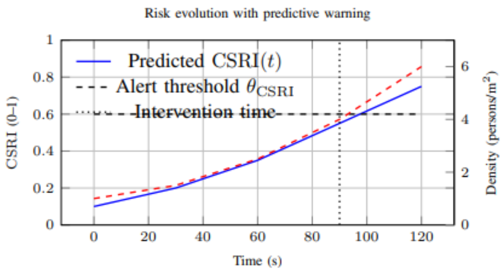

Fig. 2. Predictive CSRI(t) rises before density alone becomes critical (illustrative values).

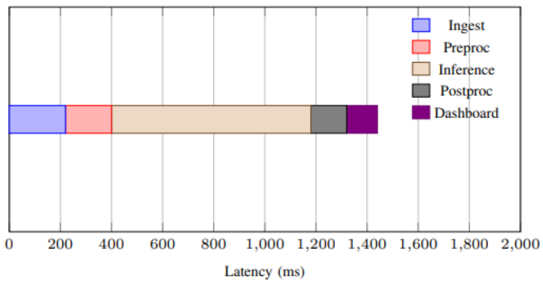

Fig. 5. Illustrative end-to-end latency decomposition

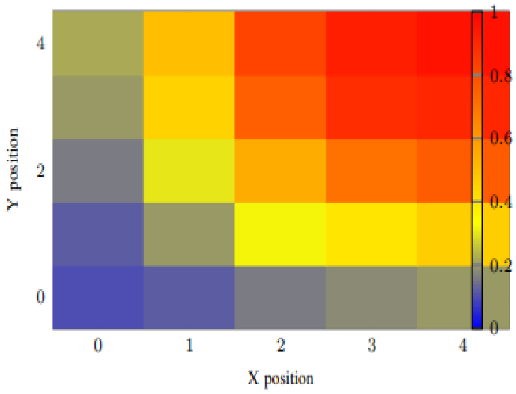

Fig. 3. Spatial heatmap of normalized risk (illustrative values)

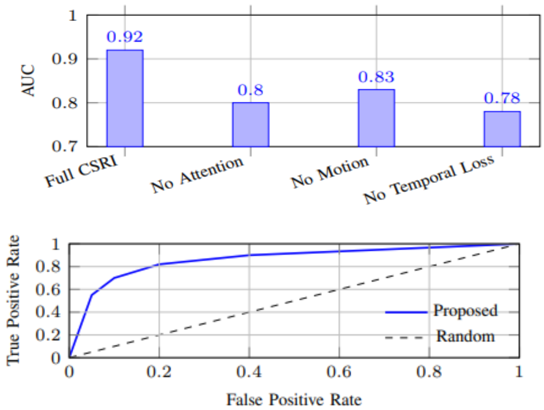

Fig. 6. ROC curve template for anomaly/event detection.

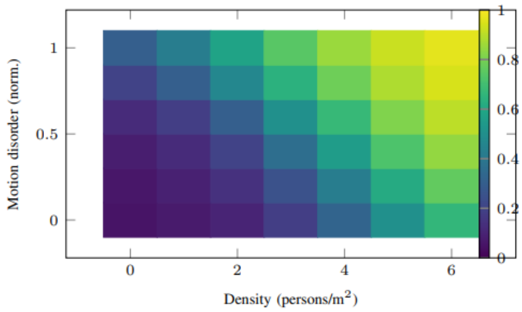

Fig. 4. Ablation study template (illustrative AUC values).

C. Sequential Change Detection for Stable Alerts

Let x_t= CSRIcal(t) and μ0 be the baseline mean risk. A one-sided CUSUM statistic is:

$$g_t = \max\{0, g_{t-1} + (x_t - \mu_0) - \nu\}, \quad g_0 = 0$$

Where,

x_t **-** Calibrated Crowd Safety Risk Index at time t

g_t **-** CUSUM test statistic at time t

g_0 **-** Initial CUSUM value (set to zero)

μ_0 **–** Baseline mean risk under normal (safe) conditions

ν - Drift parameter controlling sensitivity

D. Threshold Selection Under a False-Alarm Budget Let A(θ) denote the expected false-alarm rate and M(θ) denote miss cost. A practical selection objective is:

$$\theta^{\star} = \arg\min_{\theta} M(\theta) \quad \text{s.t.} \quad A(\theta) \le A_{max}$$

Where,

θ⋆ - Optimal Threshold

θ – Alert threshold

$M(\theta)$ **–** Miss detection cost

A(θ) – Expected false-alarm rate

A_{max} **–** Maximum allowed false-alarm rate

arg min – Argument minimizing the objective

IV. RESEARCH GAP AND FUTURE DIRECTION

Despite significant progress in crowd safety and behavior analysis, existing research largely focuses on isolated tasks such as people detection, crowd density estimation, or abnormal behavior recognition. Many approaches operate in offline or near-real-time settings and lack unified frameworks capable of jointly analyzing spatial and temporal crowd characteristics. Moreover, the problems of scalability, interpretability, and actual deployment in the world are still very far from being solved completely, thus the use of existing systems in safety-critical areas is hindered. The suggested framework fills these gaps by merging real-time crowd detection, density estimation, and behavior analysis into one system. On the other hand, there are still many areas for new research to be done. The next experiments will include the use of multiple data sources such as sensor and mobility data to boost robustness, adaptive learning methods that can cope with changing crowd patterns, and lightweight edge-based deployment for large-scale smart city applications. Continued testing on different real-world datasets and additional abnormal behavior categories may also prove to be the reasons for greater reliability and generalization of the system.

Fig. 7. Compact risk map (illustrative values

.V. CONCLUSION

The paper illustrated a framework that uses AI to analyze in real-time the behavior of the crowd and the associated safety in a high-density public environment. The approach that proposed by the inarguable system combines people detection, crowd density estimation and spatio-temporal behavior analysis cutting out the major limitations of the existing crowd monitoring solutions the whole system. It demonstrates the suitability for real-time and the situation awareness for public safety applications it has even increased. In addition, the system is a sort of solution that can be integrated with the present surveillance infrastructure giving the smart city authorities the capability to make timely and informed decisions on large gatherings or emergencies. The framework that automates the detection of abnormal crowd behavior cuts the number of manual monitors thereby decreasing response times and assisting in the prevention of hazards such as stampedes or congestion. To conclude, the suggested framework is a major milestone towards the establishment of intelligent and complete crowd safety management while its use is possible in the case of public transportation hubs, stadiums, and mass events. The future extensions can be leaning toward integration of multimodal data, adaptive learning, and edge devices deployment to further enhance robustness and efficiency in various real-world scenarios.

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