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# A Real-Time Stampede Detection and Early Warning System

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***Abstract— This document presents an AI-driven real-time surveillance framework aiming at early detection and prevention of stampede in crowded environments. It combines CSRNet, DBSCAN and LSTM models to perform crowd density estimation, anomaly detection and motion trend forecasting respectively. These modules work in sequence to deliver predictive situational awareness, enabling authorities to act before congestion escalates in an alarming situation. The system's adaptive and data-driven design ensures high reliability across diverse event scenarios, reducing dependence on manual monitoring. By providing accurate, real-time insights into crowd dynamics, the system enables timely intervention, ultimately aiming to reduce stampede risks and enhance public safety at mass gatherings.***

***Index Terms— Automated Alerting, Computer Vision, CSRNet, DBSCAN.***

## I. INTRODUCTION

The growing number of accidents and cases of stampede, which are caused by crowds, demonstrate the necessity of intelligent surveillance systems that are able to monitor the situation in real-time and predict risks. Although there has been widespread implementation of CCTV infrastructure, recent tragedies like the 2022 Itaewon crowd crush in South Korea and the 2024 Hathras religious gathering stampede in India show that a traditional human-based monitoring is unable to recognize dangerous crowd environments in time. The rapid increase in density usually leads to stampedes in several seconds, and it is almost impossible to take any action manually.

Conventional surveillance methods are based on human eye or fixed threshold monitoring policies, which cannot be utilized in the analysis of complicated and dynamically developing crowd behaviors. Human operators are fatigued and have a low situational awareness and early computer vision systems that rely on counting and detecting objects are not very well in dense, occluded and challenging visual scenes. Furthermore, majority of the current systems are designed to perform separate tasks, including density estimation or anomaly detection, and do not include time forecasting, thus leading to a slow and reactive response.

This paper will recommend a deep learning-driven real-time crowd analytics system to address these shortcomings by density estimation, detection of abnormal behavior and early prediction of stampede-like scenarios. The suggested framework will combine CSRNet with proper estimation of the crowd density, DBSCAN with the detection of anomalous movement patterns, and LSTM with the modeling of temporal crowd patterns. The system allows proactive crowd safety management due to its use of real-time analytics, predictive modeling, and automated alerts.

### A. Existing Methodologies and Disadvantages

The traditional methods of the crowd are mostly reliant on the use of manual monitoring or a non-portable threshold-based model, which is integrated with CCTV networks. Such techniques are not able to detect finer-scale behavioral dynamics like localized congestion, abnormal clustering and abrupt changes in direction. Manual observation is a subject to error because operators become tired and might not be able to monitor several video streams at the same time.

In situational with high densities, where there is significant occlusion and perspective distortion, earlier vision-based approaches that rely on object detection and simple counting techniques fall short. Camera positioning and changes in lighting also have an impact on their performance. Moreover, the majority of current systems do not combine temporal prediction and spatial analysis, which restricts their ability to issue early warnings. Their usefulness is further limited by the lack of scalable real-time processing pipelines, automated alerts, and unified dashboards.

### B. Proposed System

The proposed Real-Time Stampede Detection and Early Warning System represents a crowd density estimation, anomaly detection, and temporal prediction system that is implemented in one surveillance pipeline. The processing of live video streams of CCTV or drone cameras is based on edge or cloud-based infrastructure to provide low-latency and around-the-clock monitoring.

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CSRNet is also used to compute crowd density in areas of high traffic, and DBSCAN is used to detect unusual cluster and movement patterns. An LSTM mechanism examines the background density and motion data so as to anticipate the trends of congestion in short term along with identifying the initial signs of the stampede risk. The outputs of the system, namely density heatmaps, anomaly alerts, and predicted risk levels are presented on a centralized dashboard and provided by automated multi-channel alert systems to respond in time.

### C. Objectives

- To develop a real-time AI system capable of continuously analyzing crowd density and movement using deep-learning models.
- To detect abnormal behaviors such as sudden density spikes, irregular clustering, or unusual directional shifts through clustering-based anomaly analysis.
- To predict potential stampede risks by modeling temporal patterns in crowd behavior using LSTM-based forecasting.
- To deliver clear visual output, including heatmaps and risk indicators, to support timely decision-making by authorities.
- To enable automated alerts through multiple communication channels for rapid safety intervention.
- To reduce reliance on manual surveillance and improve the reliability and scalability of crowd monitoring.

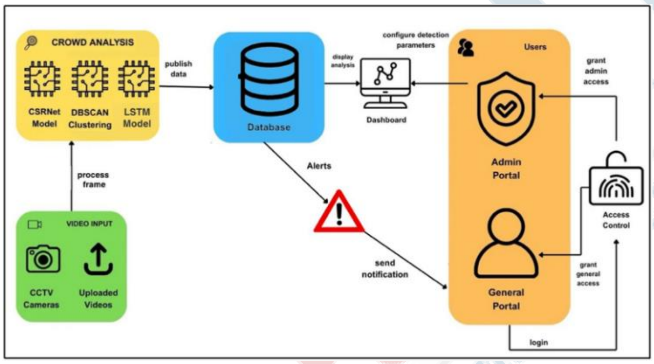


**Figure 1.** Overview of the Proposed Real-Time Stampede Detection System

### D. Thesis organization

- Introduces the motivation, purpose, and background of the work, outlines the limitations of existing crowd monitoring methods, and presents the objectives of the project.
- Provides a detailed literature review covering previous research in crowd density estimation, anomaly detection techniques, predictive modeling approaches, and intelligent surveillance systems.
- Discusses the challenges involved in real-time crowd monitoring, including technical constraints, environmental variations, data complexity, and operational factors.
- Describes the functional and non-functional requirements of the proposed system, along with relevant external interface specifications.
- Outlines the complete methodology, detailing CSRNet-based density estimation, DBSCAN clustering, LSTM prediction, alert mechanisms, and the data streaming pipeline.
- States the process of integration and deployment of multiple components to build the fusion model.
- Concludes the work by summarizing the outcomes and effectiveness of the proposed system.
- Discusses future enhancements, such as edge deployment optimizations, security operational guidance and scaling strategies for large crowd environments with high-risk victims.

## II. LITERATURE SURVEY

Increasing urban density and expanding public events have amplified the necessity for intelligent crowd supervision mechanisms. Contemporary research reflects a transition from manual surveillance toward algorithm-oriented monitoring; nevertheless, integration across methodological paradigms remains limited. Most implementations rely on visual analytics, employing convolutional and transformer-based detection models to approximate crowd concentration levels. Multi-scale feature extraction enhances resilience under occlusion and perspective variation. However, such systems generally respond to congestion after formation rather than anticipating its escalation.

**Table 1.** Structural Classification of Modern Stampede Detection Strategies

| Category [References] | Techniques Used | Core Objective | Primary Limitation |
|---|---|---|---|
| Vision Centric Models [2, 6, 7, 11] | CNN, YOLO, DETR | Crowd density mapping and object detection | Reactive monitoring of crowd behavior |
| Density Clustering [2, 8] | DBSCAN, K-means | Spatial identification of high-risk zones | Dependence on fixed density thresholds |
| Temporal Learning [5] | CNN-LSTM | Sequential motion evolution modeling | Limited validation in large-scale deployments |
| Sensor-Integrated Systems [4, 10, 15] | RFID, vibration sensing, WSN | Monitoring of physical crowd parameters | Hardware and infrastructure complexity |

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| Category [References] | Techniques Used | Core Objective | Primary Limitation |
|---|---|---|---|
| Distributed Architectures [14] | Federated multi-camera learning | Cross-source data fusion and coordination | Synchronization and communication overhead |
| Risk Analysis Frameworks [12, 13] | Velocity, turbulence, pressure modeling | Conceptual hazard assessment | Absence of unified real-time implementation |

Clustering-driven approaches introduce localized structural awareness by isolating concentrated crowd segments. While density grouping algorithms improve interpretability of spatial accumulation, their dependence on predefined density assumptions constrains adaptability to dynamic flow variations. Sequential learning architectures incorporate temporal dependencies to capture motion progression patterns. The fusion of deep convolutional backbones with recurrent units facilitates identification of evolving anomalies.

Despite improved behavioral discrimination, consistent large-scale real-time validation remains sparse. Hardware-augmented infrastructures extend analysis beyond video streams through sensor-based monitoring. RFID modules, vibration sensors, and wireless networks provide additional environmental cues, yet deployment complexity and maintenance cost limit widespread scalability. Analytical studies further argue that density metrics alone cannot sufficiently characterize imminent collapse scenarios. Nonetheless, translation of these theoretical parameters into unified operational pipelines is rarely achieved.

### A. Research Gap

- A prominent limitation across existing solutions is methodological fragmentation. Spatial density estimation, clustering analysis, temporal forecasting, and sensor integration are frequently engineered as isolated modules.
- Consequently, predictive intelligence is often secondary to reactive detection, and structured alert dissemination mechanisms are inconsistently embedded. The absence of an integrated, real-time architecture capable of consolidating spatial analytics, behavioral prediction, and automated response generation underscores a critical research opportunity.
- Developing cohesive multi-layered systems is essential to shift from incident identification toward proactive crowd disaster prevention.
- A further structural weakness lies in limited real-world validation. Many proposed frameworks are evaluated on controlled datasets or simulated environments, which do not fully capture the unpredictability of dense public gatherings. Variations in lighting, camera angles, crowd composition, and environmental noise significantly influence system reliability, yet large-scale deployment evidence remains scarce.
- Another recurring concern is scalability. While several models demonstrate promising accuracy under single-camera configurations, performance often deteriorates when extended to multi-camera or city-scale monitoring scenarios. Computational overhead, synchronization delays, and bandwidth constraints introduce practical limitations that are rarely addressed comprehensively.
- Data dependency also presents a significant challenge. Deep learning models require extensive labelled datasets representing diverse crowd behavior, including rare but critical pre-stampede patterns. However, ethically collecting and annotating such high-risk events is inherently difficult, resulting in models trained on limited or synthetic data.

## III. ISSUES AND CHALLENGES

Developing a real-time AI-powered stampede detection and early warning system involves challenges across technical, operational, and user-centric domains. Although models such as CSRNet for crowd density estimation, DBSCAN for spatial clustering, and LSTM for temporal prediction significantly improve detection and forecasting, real-world environments introduce noise, unpredictability, and infrastructure constraints. Ensuring reliability, ethical compliance, and seamless operational adoption is equally critical.

### A. Technical Challenges

1. Real-Time Processing and Latency:
   - Continuous video streams from drones and CCTV cameras demand high computational power.
   - Processing multiple high-resolution feeds frame-by-frame can increase latency, which directly affects timely alert delivery.
   - Techniques such as edgy inference, model pruning, quantization, and hardware acceleration are often required to meet strict real-time constraints.
2. Data Quality and Environmental Variability:
   - Crowd scenes frequently include occasions, overlapping individuals, unstable cameras, and lighting variations.
   - These factors degrade density estimation and anomaly detection accuracy.
   - While preprocessing techniques help, robust performance typically requires multi-camera or sensor fusion to compensate for single-view limitations.
3. Accuracy and Generalization Limits:
   - Models like CSRNet perform well under controlled conditions but may struggle in extremely dense

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- crowds, unusual camera angles, or low-resolution scenarios.
- Differences in crowd behavior across venues such as transportation hubs, religious gatherings, concerts, or stadiums further challenge generalization.
- Domain adaptation and site-specific fine-tuning is often necessary.

4. Anomaly Detection Reliability:
   - Distinguishing dangerous crowd surges from harmless group activities is complex.
   - False negatives risk public safety, while excessive false positives lead to alert fatigue.
   - Combining spatial clustering, temporal modeling, and contextual rules improves reliability.
5. Scalability and Infrastructure:
   - Large-scale events may involve dozens or hundreds of simultaneous video streams.
   - This requires distributed processing, efficient stream handling, and scalable backend systems.
   - Edge devices also have limited compute and memory, making hybrid edge-cloud architectures essential for backend performance.

### B. Alerting and Response Challenges

1. Severity Classification and Alert Fatigue:
   - The system must prioritize alerts effectively. Poorly tuned thresholds can overwhelm operators with low-risk notifications.
   - Adaptive thresholds and multi-factor risk scoring on the basis of density, clustering intensity, and predicting trends help focus attention on critical situations.
2. Reliable Multi-Channel Communication:
   - Alerts must reach stakeholders through dashboards, SMS, email, sirens, and public-address systems.
   - Robust message queueing, retries, and fallback mechanisms are required especially during network degradation.
3. Human-in-the-Loop Coordination:
   - Despite automation, human decision-making remains central to emergency response.
   - Clear visualizations, actionable recommendations, and predefined protocols are essential to reduce response time and ensure coordinated action among security teams and emergency services.

### C. User Experience and Ethical Considerations

1. Clear Visualization and Interpretability:
   - Operators need intuitive dashboards with heatmaps, risk-level indicators, and concise recommendations instead of complex analytics.
   - A streamlined incident review workflow reduces cognitive load and improves reaction time.
2. Privacy and Ethical Surveillance:
   - Continuous video monitoring raises privacy concerns. Systems must incorporate encryption, strict access controls, transparent retention policies, and privacy-preserving approaches e.g., anonymized heatmaps.
   - Legal compliance and stakeholder communication are crucial for acceptance.
3. Integration and Adoption:
   - Real-world deployment requires compatibility with existing CCTV networks, SOPs (Standard Operating Procedures), and communication systems. Training drills, and well-documented response protocols build trust in automated alerts.

## IV. SOFTWARE REQUIREMENT ANALYSIS

This chapter defines the system's functional, non-functional, and external interface requirements. It outlines what the real-time AI-based stampede detection systems must do, how it should perform, and how it integrates with external components to ensure clarity and alignment with project objectives.

### A. Functional Requirements

1. User Management & Access Control:
   - Secure login-based authentication.
   - Role-based access (Admin: configuration + full monitoring; Security: alerts, dashboard, reports)
2. Real-Time Monitoring:
   - Continuous analysis of live CCTV feeds or uploaded videos.
   - Dashboard displays real-time person counts, density heatmaps, and risk levels.
3. Automated Detection & Prediction:
   - CSRNet estimates crowd density per frame.
   - DBSCAN detects abnormal clustering or sudden surges.
   - LSTM predicts potential crowd escalation trends.
   - Frame-wise real-time risk classification.
4. Alert & Notification System:
   - Automatic alerts for high/critical risk events.
   - Multi-channel notifications (SMS, email, field alerts).
   - Alerts include timestamp, camera ID, and severity level.
5. Data Streaming & Integration:
   - Real-time data handling via Redis.
   - Processed metrics published for dashboards and external consumers.
   - Supports cloud storage integration.
6. Incident Logging & Review:
   - Automatic logging of detected incidents with metadata.
   - Storage of video snippets/images for further review and analysis.

### B. Non-Functional Requirements

1. Performance:
   - Low-latency real-time processing across multiple video feeds.
   - Immediate alert generation upon threat detection.
2. Reliability:
   - Continuous monitoring with automatic recovery from stream/network interruptions.
3. Usability:
   - Intuitive dashboard with clear visualizations and adjustable configuration settings.
4. Scalability:
   - Expandable to additional cameras, sensors, and large-scale environments.
5. Security:
   - Encrypted user authentication and alert transmission.
   - Role-based access control and protected data storage.

### C. External Interface Requirements

1. User Interface:
   - Web-based dashboard (browser-compatible, optionally mobile responsive).
2. Hardware Interface:
   - Compatible with IP/CCTV cameras and GPU-enabled systems.
3. Software Interface:
   - Integration with Redis for streaming.
   - Integration with third-party alert APIs (e.g., SMTP, Twilio, SMS services).

## V. METHODOLOGY

This section explains the three-stage real-time detection pipeline used in our system: crowd density estimation (CSRNet), spatial anomaly detection (DBSCAN), and temporal risk prediction (LSTM).

### A. Crowd Density Estimation (CSRNet)

We use CSRNet, a deep convolutional neural network designed for dense crowd counting. It combines a VGG-16 feature extractor with dilated convolutions to preserve spatial resolution while capturing large crowd patterns. For each video frame:

- The image is resized and normalized.
- The model generates a density map where each pixel estimates crowd concentration.
- The density map is unsampled and visualized as a heatmap overlay for real-time monitoring.

The pretrained model (trained on ShanghaiTech Part A dataset) enables accurate estimation even in highly congested environments. Before inference, frames are resized with a maximum dimension of 512, changed to RGB and normalized. GPU-based PyTorch inference ensures real-time performance.

### B. Spatial Anomaly Detection (DBSCAN)

To detect abnormal crowd formations, we apply DBSCAN clustering on high-density regions extracted from the density map.

Key steps:

- The density map is resized to fit the original frame and then split into and 8 x 8 grid.
- Pixels above a defined density threshold are selected, each grid cell adding up to local density creating a compact spatial representation.
- DBSCAN groups nearby dense points into clusters without requiring predefined cluster counts.
- Clusters exceeding size and density limits are flagged as potential anomalies.

Each detected cluster is assigned a risk score (0-100) based on:

- Density intensity
- Spatial Size
- Growth trend over recent frames

This stage helps distinguish localized surges from normal crowd distribution.

### C. Temporal Risk Prediction (LSTM)

To capture evolving crowd behavior, we use an LSTM network that analyzes patterns over time. An A4D feature vector is made for each frame formed with the following attributes:

- Total crowd count
- Number of anomaly clusters
- Maximum cluster intensity
- Density variation and motion trends (CSRNet score)

The LSTM takes in a sliding window of 10 frames. The model outputs probabilities across three risk states: Safe, Warning, and Critical. Based on computed risk scores, the system classifies situations into SAFE, WARNING, ALERT, or CRITICAL levels. It runs all the time with a buffer, so it need not be reset manually between video segments.

## VI. IMPLEMENTATION

The stampede detection system prominently has four phases: handling media input, computer vision analysis, fusion model aggregation and risk assessment analytics. A lightweight Flask-based web service connects these parts so that they can be monitored and alerted in real time.

### A. Backend Architecture

Flask is used by the system to handle video streams and images to process workflows. The sources of input is a huge range from capturing images to live CCTV footage and HTTP streams. The system is built in such a way that it recognizes the kind of input source and applies the necessary changes in the system.

The system also enables an option where the administrator can set an estimated count for the usual density of crowd expected for any event and the anomalies can be tracked accordingly instead of marking the scenario critical-like or vice versa.

*MJPEG (Motion Joint Photographic Experts Group) over HTTP* is used to stream processed frames to frontend. This enables the frames to be displays in the real-time monitoring dashboard. The system additionally checks the health of the stream by validating the connection status and logs errors. It is capable of sending updates to Redis for use with other systems if required.

### B. Fusion Model Aggregation

A Fusion model is aggregated consisting of CSRNet, DBSCAN and LSTM models to support an efficient prediction and assessment of the subject and the aggregated model has been trained accordingly focusing on each model at once. CSRNet is fine-tuned on labeled crowd images and synthetic event sequences are generated from these labels on which the LSTM model is trained. During runtime, trained models are saved and loaded.

Flask, OpenCV, NumPy, PyTorch, Scikit-learn help integrate the entire web application. Redis supports storage of the data with an in-built mechanism to send alerts and notifications when the interface calls for it. Environment variables control configuration, allow the adjustment of thresholds, alert settings and notification window.

### C. Computer Vision Analysis

The backend helps process the media in individual frames, on each of which the system performs preprocessing and normalization, CSRNet inference creating a density map and scores, spatial analysis forming grids and performs clustering, feature extraction and LSTM prediction.

It also takes into consideration from database, the recently occurred incidents and analyses further in case of similar patterns where the aggregated model learns from improvising the model's efficiency and accuracy. On a CPU, the system processes ~8 FPS, making it suitable for real-time applications with modest hardware.

### D. Risk Assessment and Analytics

Final risk estimation combines several signals in a weighted manner that comprises of 10% baseline rules, 25% cluster-based score, 30% LSTM and 35% CSRNet score. The system may assess the risk accordingly in 4 labels – NORMAL, MODERATE, HIGH and CRITICAL. To keep things consistent and avoid underestimating, each label level has a minimum probability "risk floor".

The system maintains a JSONL log file of all events, which include the frame index, crowd metrics, risk level and timestamps of occurrence of the event.

- Frames pertaining to high risk (stampede probability ≥ 0.80) are saved for further analysis and reporting.
- When any set limits are crossed, Redis helps push notifications and SMS alerts. There is a cooldown period to keep people from receiving excessive alerts as well.

## VII. RESULTS

The proposed system was evaluated across different crowd conditions to examine its performance under varying density levels. The analysis included various levels of severity labelled as normal, moderate and high-density crowd situations in order to verify the system's ability to correctly differentiate between safe and critical situations.

The display monitor additionally follows Red/Amber/Green border for further caution while visualizing the interface if security personnel or other users were to monitor it.

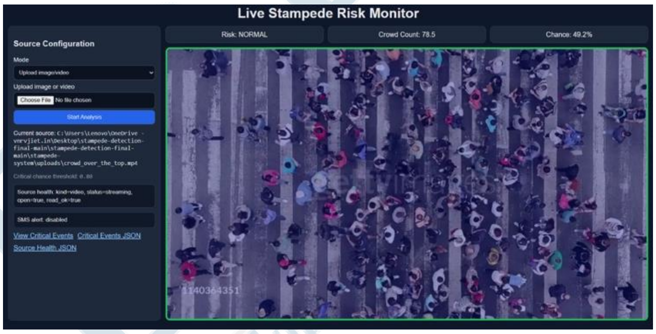


**Figure 2.** Monitoring dashboard showing NORMAL risk classification with moderate crowd density – Crowd Count ≈ 78.5, Stampede Chance ≈ 49.2%

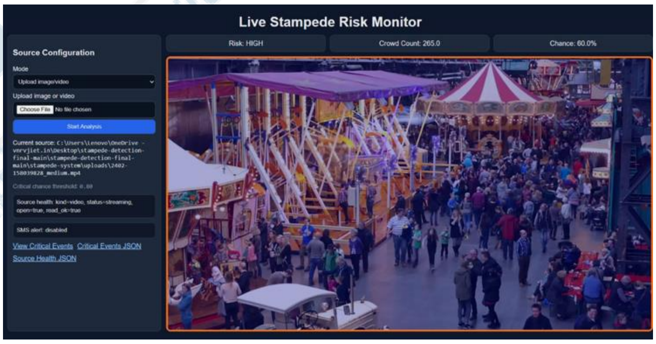


**Figure 3.** Monitoring dashboard showing HIGH risk classification with moderate crowd density – Crowd Count ≈ 265.0, Stampede Chance ≈ 60.0%

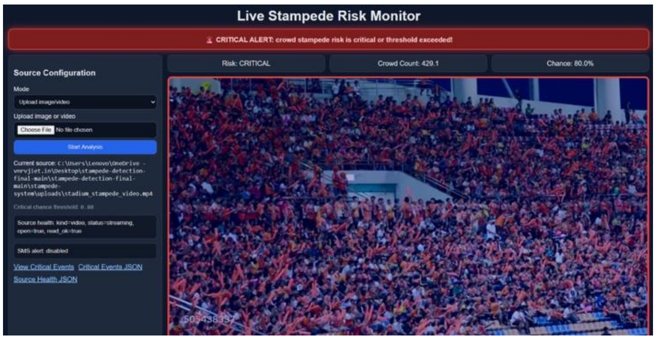


**Figure 4.** Monitoring dashboard showing CRITICAL risk classification with moderate crowd density – Crowd Count ≈ 429.1, Stampede Chance ≈ 80.0%

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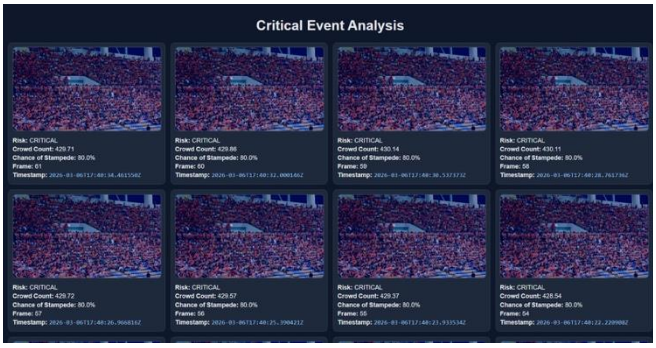


**Figure 5.** Monitoring dashboard showing CRITICAL event analysis displaying consecutive frames with crowd metrics for advanced analytics.

The moderate crowd conditions as illustrated in Figure 3. was estimated to be approximately 78.5 individuals and produced a stampede probability of 49.2%. Based on these values, the situation was categorized as NORMAL. The visual output shows a relatively uniform distribution of people without any noticeable congestion zones. The clustering module detected only minor group formations, and the temporal model did not indicate any upward trend in risk. This confirms that the system can reliably recognize stable and non-critical crowd behavior without triggering unnecessary alerts.

In contrast, as shown in Figure 5. the system was evaluated on a highly dense crowd scenario, such as a stadium environment. In this case, the estimated crowd count increased to approximately 429.1 individuals, and the stampede probability reached 80.0%, resulting in a CRITICAL risk classification. The density estimation output highlighted multiple regions with high concentration, indicating severe crowd accumulation. The clustering algorithm identified several dense clusters, pointing to localized congestion areas.

The visual output clearly shows multiple high-density regions represented by intensified areas in the density map. These regions correspond to tightly packed groups of individuals, which are identified as significant clusters by the DBSCAN algorithm. The presence of overlapping and closely spaced clusters increases the overall congestion level, leading to a higher computed risk score. The system successfully captures these spatial characteristics and reflects them in the elevated stampede probability. The clear visual distinction between low-density and high-density zones demonstrates the effectiveness of the model in identifying critical crowd formations.

Another key observation is the consistency of the system's predictions over time. As presented in Figure 6., during critical conditions, the system produced stable outputs across multiple frames, with the crowd count remaining approximately within 429 ± 1 and the stampede probability consistently at 80.0%. The risk level remained CRITICAL throughout these frames. This behavior indicates that the system responds to persistent crowd conditions rather than temporary fluctuations, thereby improving the reliability of predictions.

The system also demonstrated efficient event detection and logging functionality. Whenever the stampede probability exceeded the threshold value of 0.80, the system automatically recorded the event along with relevant details such as frame index, timestamp, crowd count, and risk level. The presence of multiple consecutive critical entries confirms that alerts are generated only for sustained high-risk situations, reducing the likelihood of false positives.

Overall, the obtained results show that the proposed system effectively combines density estimation, spatial clustering, and temporal modeling to assess crowd risk in real time. It accurately distinguishes between normal and critical conditions, maintains consistent predictions across frames, and provides reliable outputs suitable for practical deployment in crowd monitoring and safety management systems. In addition to detection accuracy, the system demonstrates stability under continuous input streams, indicating its capability to handle real-time surveillance scenarios. The integration of multiple analytical components also enhances decision reliability by reducing dependency on a single factor, thereby improving robustness in diverse crowd environments. These observations suggest that the system can serve as a dependable tool for early warning and proactive crowd control, supporting timely intervention and improved public safety outcomes.

## VIII. FUTURE SCOPE

Enhancements to the existing proposed system can be incorporated to enhance adaptability, safety coverage, and intelligent decision-making for all users. The system can be developed into a more comprehensive crowd safety solution by implementing other sensing modalities, advanced behavioral analysis, and proactive response capabilities.

- *Advanced Behavioral Modeling:* Adoption of transformer-based spatiotemporal learning and graph neural networks can accurately understand movement patterns collectively which can enable a better and earlier detection of stampedes.
- *Women and Vulnerable Group Safety:* Expansion of the system to recognize distress indicators, irregular proximity patterns or unsafe movement in crowds, enabling rapid assistance to women and other groups at risk.
- *Infant and High-risk Priority Alerts:* Automated detection of children, infants or elderly individuals at risk during crowd turbulence, enabling high-severity alerts and faster response escalation.
- *Intelligent Navigation and Operational Guidance:* Providing real-time routing suggestions, identification of safe-zones and decision support for security personnel such as opening additional lanes, placing barricades or redirecting crowd flow.

- *Adaptive Alert Mechanisms:* Dynamic alert sensitivity based on expected density, event category, and predicted behavioral trends to reduce false triggers.
- *Broader Public Safety Applications:* Potential extension to scenarios such as identifying abnormal coordinated movement patterns and high-risk clustering in public spaces such as transport hubs, and supporting traffic congestion control, emergency pathway clearance during critical situations.
- *Artificial General Intelligence Support:* Integrating AGI-based reasoning for autonomous decision support, scenario simulation, and continuous learning from operational data to enhance emergency response strategy.

## IX. CONCLUSION

Maintaining public safety during mass gathering has become tediously difficult due to the increasing population, which leads to dense crowds at public locations, making it challenging for conventional crowd monitoring techniques to identify potential risks in time to avoid disasters. The proposed real-time stampede warning system combines computer vision and predictive analytics to identify and avoid any dangerous or alarming situation that might occur. The system will use crowd density estimation, anomaly detection, and alerting to move from a reactive mode to a proactive mode in managing crowd safety.

- *AI-Enabled Awareness*: Deep learning models and insights from artificial intelligence improve detection accuracy and help prevent further escalation of stampede by learning on the motion trends.
- *Integrated Response Mechanism*: Real-time alerts and decision support enable coordinated reaction among security personnel and emergency responders.
- *Proactive and Scalable*: Modular architecture supports expansion with multi-sensor fusion, edge deployment, and real-world validation.

This research establishes the foundation for an AI-powered crowd safety monitor reducing human risk and improving emergency preparedness.

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