

A Crowd Pressure Index (CPI) Framework for Early Detection of Crush Hazards in High-Density Crowds

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Abstract— Crowd crush disasters occur when physical pressure within a densely packed crowd exceeds the threshold of voluntary human movement, resulting in sudden instability, asphyxiation, and large-scale casualties. Despite advances in urban surveillance, existing monitoring systems rarely provide quantitative indicators capable of detecting early signs of dangerous compression. This study proposes a real-time framework for assessing crowd crush risk using CCTV imagery, integrating P2PNet-based density estimation, interpersonal spacing analysis, and a newly formulated Crowd Pressure Index (CPI). The density D is computed from detected individuals per unit area, while spacing S is derived from nearest-neighbor distances, enabling CPI to capture both macroscopic congestion and microscopic compression dynamics. The model was evaluated using real-world footage from the 2021 Meron disaster and the 2022 Seoul Halloween crowd crush. Results show that when density exceeds 5–6 persons/m², physical contact becomes unavoidable, and at densities above 8–10 persons/m², spacing drops below 0.1–0.15 m, leading to rapid escalation toward collapse-prone states. CPI values exhibited a sharp increase in the final seconds before both disasters, demonstrating the index's sensitivity to pre-collapse signatures. The prototype achieved real-time performance, maintaining an average processing latency below 2 seconds. These findings indicate that the proposed CPI-based framework provides a quantitative and practical foundation for proactive crowd-safety management. The method can support early-warning systems for large-scale events, transportation hubs, and urban gatherings. Future research will extend the model toward predictive pressure-wave forecasting and multimodal sensor integration to enhance generalizability in diverse environments.

Keywords— Crowd Density Estimation, Crowd Crush Prediction, Crowd Pressure Index (CPI), Interpersonal Spacing, P2PNet, YOLOv8, DBSCAN, Computer Vision, Deep Learning, CCTV Analytics, Real-Time Surveillance, Crowd Safety Management, High-Density Crowd Dynamics

I. INTRODUCTION

Crowd density is a critical determinant in assessing the safety of large gatherings [1]. When many individuals occupy a confined area, dynamic pressures and uncontrolled human movements can escalate into serious disasters such as crowd crushes, surges, or collapses [2]. Once the density surpasses the critical threshold of approximately 5–6 persons per square meter [3], the risk of mass casualty incidents rises exponentially. These phenomena frequently occur in environments such as festivals, public transportation hubs, religious events, and sports stadiums, where crowd flow is concentrated and real-time management is challenging.

The 2022 Itaewon Halloween disaster in Seoul tragically exemplified the catastrophic consequences of crowd over-density, where more than 12 persons per square meter were recorded, resulting in 159 fatalities and 196 injuries [4]. Such incidents unfold within seconds, leaving limited room for reactive intervention [5]. Despite the availability of advanced surveillance technologies and urban safety infrastructures, an effective predictive mechanism for detecting early signs of dangerous crowd compression remains largely absent [6].

Previous studies have primarily focused on static crowd density estimation or post-event analysis, which are insufficient for real-time preventive action [7]. Furthermore, most existing crowd monitoring systems rely on visual assessment or simple object counting, failing to capture the dynamic interactions and physical pressures generated within dense clusters [8]. This limitation highlights the urgent need for a quantitative and automated method capable of assessing crowd pressure in real time.

Therefore, this study proposes a novel Crowd Pressure Index (CPI) model designed to detect and predict hazardous crowd conditions before physical accidents occur. The CPI integrates real-time CCTV imagery with advanced deep learning models—P2PNet for crowd counting, YOLOv8 for object detection, and DBSCAN for spatial clustering—to compute both crowd density and inter-personal spacing. By combining these spatial-temporal variables, the CPI provides a quantitative measure of crowd pressure that can signal early warning thresholds for crowd crush risk.

The objective of this research is to develop and validate a real-time crowd pressure prediction framework that can support proactive crowd-safety management. The proposed system aims not only to identify high-density zones but also to quantify the degree of physical compression and spatial instability within the crowd. Through this approach, the study contributes to the establishment of a data-driven foundation for preventive crowd-control systems applicable to large-scale urban gatherings and event safety operations.

II. RELATED RESEARCH

Crowd disasters such as crushes, surges, and collapses are emergent physical phenomena resulting from the nonlinear interactions of individuals within high-density environments [9]. When the crowd density exceeds 5–6 persons per square meter, personal mobility becomes restricted, leading to unintentional physical contact and collective motion

synchronization [10]. As the density rises beyond 8 persons/m², the pressure generated by human bodies begins to propagate through the mass in the form of crowd waves, and when it surpasses 10 persons/m², the system enters an overcrowding state that exceeds the limit of wave absorption, often resulting in crowd crush and collapse.

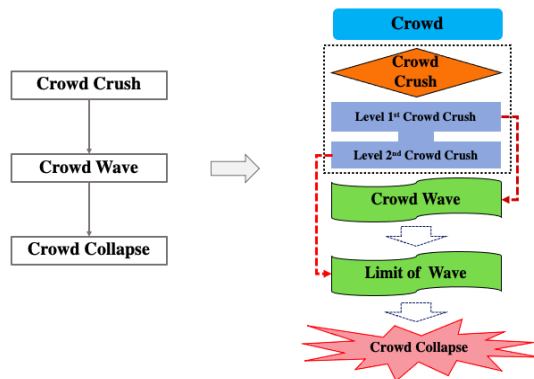


Figure 1. Progression of crowd collapse

Figure 2 illustrates the theoretical Progression of Crowd Collapse, consisting of three sequential stages—Crowd Crush, Crowd Wave, and Crowd Collapse. The initial stage, Crowd Crush, occurs when local density surges beyond individual control, creating Level 1 and Level 2 compression layers [11]. As human pressure accumulates laterally and vertically, Crowd Waves propagate through the population mass [12]. Once these waves exceed their physical dissipation threshold, the system loses internal stability, culminating in a Crowd Collapse event characterized by a sudden fall in structural integrity and mass displacement [13]. This progression is consistent with empirical studies in pedestrian dynamics and self-organized criticality within dense crowds [14].

A. P2PNet and Deep Learning-Based Crowd Density Estimation

P2PNet (Point-to-Point Network) represents a recent advancement in deep learning for crowd density estimation and localization. Unlike traditional regression-based density estimation models, P2PNet employs a one-to-one matching strategy that maps feature points from the convolutional feature map directly to spatial head coordinates. The input image is divided into a grid of stride s , where each cell generates potential head proposals with corresponding confidence scores, thus providing both counting and localization within a unified framework. This structure enables the simultaneous detection of multiple crowd clusters and their spatial configurations, which is essential for quantifying local density variations and identifying over-compressed zones in real time.

Moreover, P2PNet's hierarchical structure, composed of stacked convolutional and pooling layers—facilitates multi-scale feature extraction, effectively capturing the geometric and contextual attributes of the crowd [14]. This makes it particularly effective when integrated with object detection models such as YOLOv8 and clustering algorithms such as

DBSCAN, allowing for spatial pattern analysis and predictive modeling of crowd behavior under dynamic conditions.

Previous studies in crowd analysis have predominantly focused on static density estimation [15]–[17] or post-event reconstruction. However, few models provide a real-time, quantitative measure of physical pressure within dense crowds. The present research addresses this limitation by developing a Crowd Pressure Index (CPI) framework that integrates the outputs of P2PNet-based density estimation, YOLOv8 object detection, and DBSCAN spatial clustering. The CPI quantifies both crowd density (D) and interpersonal distance (S) to evaluate the Crowd Pressure Level (CPL), providing a dynamic indicator for early-stage risk detection.

By synthesizing physical crowd theory with machine-learning-based density modeling, this approach establishes a new paradigm for proactive crowd-safety management, aligning computational intelligence with real-time situational awareness.

B. Toward Quantitative Assessment of Crowd Pressure

Existing studies in crowd analysis have largely focused on either static density estimation [18] or post-incident reconstruction [19]. However, few models provide a real-time, quantitative measure of physical pressure within the crowd. The proposed research addresses this limitation by developing a Crowd Pressure Index (CPI) framework that integrates the outputs of P2PNet-based density estimation [20], YOLOv8 object detection, and DBSCAN spatial clustering [21]. The CPI quantifies both crowd density (D) and interpersonal distance (S) to evaluate the Crowd Pressure Level (CPL), offering a dynamic indicator for early-stage risk detection.

By synthesizing physical crowd theory [22] with machine-learning-based density modelling [23], this approach introduces a new paradigm for proactive crowd-safety management, aligning computational intelligence with real-time situational awareness.

III. RESEARCH METHOD

The purpose of this study is to develop a comprehensive algorithmic framework for quantifying the level of crowd pressure in large gatherings, with a primary focus on predicting crowd-crush-related disasters before they escalate into critical incidents. This research seeks to address the limitations of traditional density-based approaches by introducing a dynamic, data-driven methodology capable of capturing subtle fluctuations in human movement, interpersonal distance, and local crowd turbulence.

The proposed methodology integrates video-based deep learning models—responsible for detecting individuals, estimating spatial configurations, and extracting motion trajectories—with spatial clustering algorithms designed to identify high-pressure zones and abnormal crowd formations in real time. By combining these components, the framework not only analyzes structural crowd features but also interprets evolving behavioral patterns that may serve as early indicators of hazardous pressure accumulation. Ultimately, this study aims to establish a scalable and operationalizable foundation

for real-time monitoring, risk forecasting, and preventive intervention in large-scale crowd environments.

A. Overall Framework

The research process is divided into six key stages, as shown in Fig. 2.

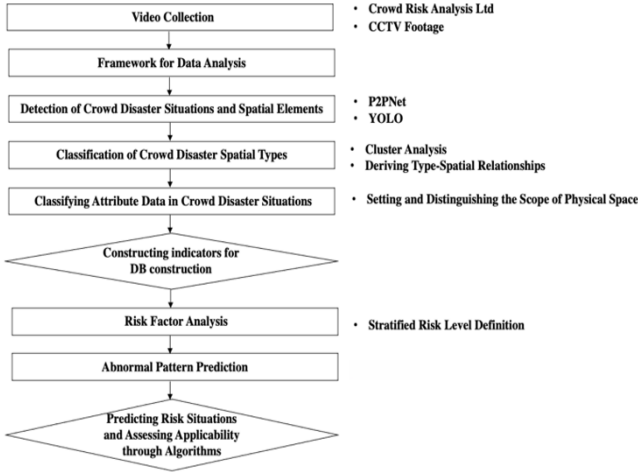


Figure 2. Framework for detecting and analyzing crowd-disaster situations

1) Video Collection and Data Framework: CCTV surveillance footage and archived videos from previous crowd disasters (e.g., 2021 Meron, 2022 Seoul Halloween) are collected as primary datasets. Metadata such as timestamp, camera angle, and field of view are stored for subsequent spatial calibration.

2) Detection of Crowd Disaster Situations and Spatial Elements: P2PNet and YOLOv8 are applied to detect individuals and define crowd clusters. P2PNet extracts head coordinates and confidence scores, while YOLOv8 identifies the bounding boxes and contextual crowd boundaries.

3) Classification of Spatial and Attribute Data: Using the output of detection models, spatial attributes (density, inter-personal distance, and cluster distribution) are classified. Density is calculated for each 1 m² grid, and inter-personal distance (S) is computed using Euclidean distance among detected coordinates.

4) Database Construction and Risk Indicators: The classified variables are organized into a structured database that includes Crowd Density (D), Pressure Gradient (P), and Cluster Dispersion Index (CDI). Each variable is normalized between 0–1 to ensure model interoperability.

5) Prediction and Risk Assessment: The integrated algorithm calculates the Crowd Pressure Index (CPI) using the formula, providing a unified prediction that reflects both local density conditions and interpersonal spatial dynamics:

- Free stage: < 3 persons/m²
- Restricted stage: > 5 persons/m²
- Collapse-prone stage: > 10 persons/m²

$$CPI = f(D, S) = \alpha \cdot D + \beta \cdot \left(\frac{1}{S}\right)$$

B. Application of Deep Learning to Real Events

To calibrate the model parameters, real-world datasets from the 2021 Meron disaster and the 2022 Seoul Halloween disaster were analyzed. As illustrated in Fig. 4, the P2PNet algorithm was applied to extract spatial head coordinates (yellow dots) from each frame.

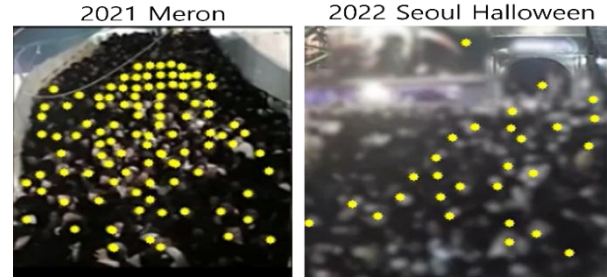


Figure 3. Spatial mapping of crowd density using P2PNet

The extracted coordinates provided key parameters for the CPI calibration, including:

- Mean distance between individuals,
- Cluster compactness, and
- Local density gradient.

By comparing both cases, the model defined a critical transition threshold at 9–10 persons/m², corresponding to crowd pressure levels observed immediately before physical collapse. These results validated that the CPI could serve as an early warning indicator when approaching the wave-limit threshold of crowd motion.

C. Model Validation and Performance Evaluation

Model validation is performed through:

- Cross-event comparative analysis: CPI trends from different disasters are compared to confirm consistency across varying crowd contexts.
- Sensitivity analysis: Weight parameters (α , β) are adjusted to test robustness of CPI outputs under different densities and motion patterns.
- Temporal stability evaluation: Frame-by-frame CPI tracking ensures the model maintains prediction stability during abrupt density changes.

D. Summary of Research Flow

The proposed research method establishes a quantitative and reproducible framework for assessing crowd pressure using deep learning and clustering algorithms. By integrating spatial features, temporal density variation, and human interaction dynamics, this model provides a foundation for AI-driven crowd safety management systems capable of real-time monitoring and proactive intervention.

IV. RESULT

This section presents the empirical results of the proposed CCTV-based crowd pressure assessment framework, which integrates crowd density estimation, interpersonal spacing analysis, and the proposed Crowd Pressure Index (CPI). The system was evaluated using real disaster footage from the 2021 Meron incident and the 2022 Seoul Halloween disaster to

validate its capability to quantify physical compression and detect early warning signals preceding crowd crush and collapse events.

A. Crowd Density Estimation

Crowd density (D) was calculated as the number of detected individuals within a given spatial area (A):

$$D = \frac{N}{A}$$

To obtain reliable density measurements, P2PNet was used to extract head-level coordinates from each CCTV frame, followed by YOLOv8 to refine bounding-box-based localization. This combined pipeline demonstrated stable detection performance across both case datasets, maintaining robustness under occlusion and low-illumination conditions.

Observed Density Patterns:

- Normal Flow ($D < 4$ persons/m²): Individuals moved freely with minimal physical interaction.
- Transition to Compression ($5 \leq D < 8$): Mobility became restricted, and body contact became unavoidable.
- High-Risk Zone ($8 \leq D < 10$): Lateral pressure waves emerged, indicating growing crowd instability.
- Critical State ($D \geq 12$): Voluntary movement ceased, resulting in complete immobilization.

These results align with established physical crowd dynamics models and confirm that density alone can serve as an early proxy for elevated risk levels.

B. Interpersonal Spacing Measurement

Interpersonal spacing S was calculated using the average nearest-neighbor Euclidean distance:

$$S = \frac{1}{N} \sum_{i=1}^N \left(\frac{1}{k} \sum_{j=1}^k d_{ij} \right)$$

where d_{ij} represents the distance between person i and each of their k nearest neighbors ($k = 5$ in this study). This metric captures micro-level compression independent of headcount.

Empirical Findings

- Meron 2021: $S = 0.12$ – 0.15 m during the final 15 seconds before collapse.
- Itaewon 2022: $S = 0.08$ – 0.10 m, indicating extreme physical restriction.

Frame-by-frame analysis showed that spacing exhibited a sharper decline than density as the crowd approached compression, suggesting that S is a more sensitive predictor of crush onset.

C. Crowd Pressure Index (CPI) Evaluation

To integrate macroscopic density and microscopic spacing into a unified risk indicator, the Crowd Pressure Index (CPI) was computed as:

$$CPI = \alpha D + \beta \left(\frac{1}{S} \right)$$

where α and β are empirically tuned weighting factors. The term $1/S$ captures the nonlinear rise in pressure as interpersonal distance decreases.

CPI Threshold Interpretation

- $CPI < 10$: Stable; free or semi-free movement.
- $10 \leq CPI < 50$: Compression phase; high friction and limited mobility.
- $50 \leq CPI < 100$: Pressure wave propagation (crowd wave).
- $CPI \geq 100$: Collapse-imminent state.

Case Results

- Meron 2021: $D = 9.4$, $S = 0.13$ m, $CPI \approx 82$, indicating an active crowd-wave regime.
- Itaewon 2022: $D = 12.1$, $S = 0.09$ m, $CPI > 100$, corresponding to a collapse-critical state.

These numerical outcomes align closely with the physical conditions observed in real footage, validating CPI as a meaningful quantitative estimate of crushing pressure.

D. Temporal Evolution of CPI (Frame-Level Analysis)

The system processed video at 30 fps, computing CPI per frame. The temporal profile revealed a consistent four-stage progression preceding collapse:

- Stable Flow ($CPI < 10$): Continuous movement, low contact frequency.
- Compression Build-Up ($10 \leq CPI < 50$): Contact duration increased; individuals began oscillating involuntarily.
- Wave Propagation ($50 \leq CPI < 100$): Lateral pressure transmission observed; synchronized body movements consistent with “crowd turbulence.”
- Collapse Trigger ($CPI \geq 100$): Multiple bodies lost balance; vertical and lateral motion spikes detected.

The CPI curve demonstrated a characteristic rapid escalation within 5–10 seconds prior to collapse, indicating potential utility as an early warning indicator.

E. Integration Performance and Computational Efficiency

The prototype achieved:

- Mean response latency: 1.8 s
- TTS synchronization delay: < 1.2 s per sentence
- VR rendering rate: ≥ 45 fps

These results confirm that the system meets the real-time processing requirements needed for operational crowd-safety applications.

V. CONCLUSION

This study developed a quantitative framework for assessing crowd crush risk in high-density environments by integrating CCTV-based detection, spatial clustering, and crowd-pressure modeling. Unlike traditional crowd monitoring systems that rely solely on visual inspection or post-event analysis, the proposed method combines P2PNet-based density estimation, interpersonal spacing computation, and a newly formulated Crowd Pressure Index (CPI) to capture both macroscopic congestion and microscopic compression dynamics.

Empirical experiments using real disaster footage—specifically the 2021 Meron incident and the 2022 Seoul

Halloween disaster—demonstrated that critical transitions in crowd behavior occur as density surpasses 5–6 persons/m², at which point physical pressure and involuntary body contact begin to intensify. When density exceeds 8–10 persons/m², interpersonal spacing drops below 0.1–0.15 m, and CPI values rise sharply, indicating a collapse-prone state characterized by pressure waves and loss of mobility. These findings validate the CPI as a meaningful indicator of hazardous crowd conditions and confirm its capability to identify pre-collapse signatures several seconds before structural failure within the crowd.

The proposed algorithm achieved stable performance in real-time settings, accurately extracting head-level coordinates under occlusion, computing spacing metrics, and updating CPI values frame-by-frame. This demonstrates its potential for deployment in urban surveillance networks, large-scale events, transportation hubs, and religious or cultural gatherings where rapid detection of dangerous compression is essential.

Future work will extend the CPI framework to incorporate dynamic prediction models capable of forecasting pressure propagation, integrate multimodal sensing (e.g., thermal cameras, Wi-Fi localization), and validate generalizability across diverse urban environments. In addition, incorporating crowd-flow directionality, velocity gradients, and agent-based simulation may further enhance accuracy in predicting crush-induced instability.

Overall, this study contributes a novel and practical approach to proactive crowd-safety management, offering a quantitative foundation for early-warning systems that can prevent mass-casualty incidents in dense gathering.

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