Simulation-Based Stampede Prevention with Machine Learning and Explainable AI

Hariharan M.[1], Asik Ahmed A.[2], Badri Narayana V.[3], Mukilan S.[4], Boobala Muralitharan D.[5]

Department of Computer Science and Engineering, Saranathan College of Engineering, Tiruchirappalli, India.

E-mail: [1]cse251034@saranathan.ac.in, [2]cse251014@saranathan.ac.in, [3]cse251017@saranathan.ac.in, [4]cse251058@saranathan.ac.in, [5]boobala-cse@saranathan.ac.in

Abstract

Large scale events held outdoors present a significant threat to public safety owing to excessive crowd density and insufficient pre-event risk assessment mechanisms. In this study, we propose a simulation-assisted crowd safety framework using pedestrian dynamics modeling, ensemble learning, and Explainable Artificial Intelligence (XAI). We have built digital event venues where pedestrian movement has been simulated considering various arrival rates and other environmental conditions. Features related to crowd dynamics such as density, average velocity, turbulence, and crowd pressure are analyzed from simulations based on around 20,000 scenarios in order to predict risks. XGBoost and LightGBM algorithms are utilized to calculate the continuous score representing the risk of stampedes while SHAP explanations give insightful understanding of the underlying cause of prediction outcomes. Our experiment proves good predictive performance with extremely high R^2 values (>0.998) and negligible prediction errors. The result of the explainability analysis suggests that crowd density and crowd pressure play the most important role in the rising risks. The proposed framework can help authorities to identify hot spots and test out new event venue plans.

Keywords: Crowd Risk Assessment, Pedestrian Simulation, Stampede Prevention, Machine Learning, Explainable AI, Proactive Crowd Management.

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1. Introduction

Massive general meetings like religious meetings, festivals, political events and sporting events are common in India and most of the developing nations. Although these occasions bear cultural and social importance, they also create severe risks to the population safety since the numbers of people present are extremely large, infrastructures and resources are often insufficient, and a human factor is unpredictable. Incidences of stampede that arise during such events usually result in serious injuries and fatalities, mostly due to congestion, rush of crowds, congestion at entry and exit points as well as the lack of effective preventive planning systems [1], [6].

The traditional approaches to crowd management primarily consist of manual layout planning, fixed safety standards, and real-time crowd management with the help of surveillance cameras and ground personnel. Even though these approaches are useful in identifying congestion, they are mostly reactive in nature in that they are only able to identify the risks once the building up of crowds has taken place. Delays in response in high-density cases considerably decrease the possibility of preventing the stampede-like situation and, therefore, proactive risk assessment and planning are indispensable in case of maintaining the safety of people [2].

The current developments in the field of crowd simulation and machine learning provided some future opportunities to study the dynamics of the pedestrian flow and predict the crowd density in different circumstances [3], [9]. Nevertheless, most of the current solutions aim at counting crowds in real-time or analyzing events after the occurrence and do not provide much help with pre-event decision-making [5], [8]. Additionally, the black-box machine learning models are usually not interpretable and this aspect lowers the trust and useability among those in authority whose decision making involves safety [7].

In order to overcome such drawbacks, this paper proposes a stampede prevention system based on simulation and combined with Machine Learning and Explainable Artificial Intelligence (XAI). The system makes the real-life event venues digitalized, in form of entry-gate, pathways, corridors, and bottlenecks, and simulates the movement of pedestrians under varying conditions of crowd arrival [1], [2]. The density, velocity, variation of speed and pressure between people are key parameters of a crowd, which are extracted and analyzed by machine learning models to produce zone-specific stampede risk scores based on simulation [3], [9].

The Explainable AI methods are applied to clarify the perceived risk scores to increase transparency and serve as a good decision-making tool by explaining the most common contributing factors associated to each of the high-risk zones [7]. This helps the officials and organizers of events to know the reason as to why a specific area is not safe, instead of just depending on the numerical forecasts.

The proposed framework adds a data-driven decision-support system comprising of pedestrian simulation, predictive analytics, and explainable reasoning to mitigate the stampede risks in large crowds of people. The system will greatly improve the safety of crowds by being able to plan proactively and make informed interventions, as well as facilitate coordination between the various agencies involved in the process of providing public safety and the organizers of the interacting events.

2. Related Works

Crowd safety and stampede prevention studies have been mostly concerned with the behavior of pedestrians and surveillance of crowded conditions. The earliest investigations examined pedestrian dynamics in terms of simulation and behavioral models where high local density and transitioning to panic and interaction forces among individuals can easily transform orderly movement into chaotic crowd flow [1]. The formation of congestions is also affected by the environmental conditions; the small passages, slopes, and other barriers considerably decrease the efficiency of movements, as well as the risk of crowding [2]. Moreover, research on mass gatherings indicates that a lack of organization and spontaneous formation of crowds are significant factors that contribute to stampede cases [6]. Though the causes of disasters related to crowds are explained in these works, they primarily offer analytical information and the general safety principles.

CNN models have been extensively applied to count crowds and densities in surveillance videos [9], and multi-column models enhance the accuracy of estimation by extracting features on multi-scales [3]. Explainable AI design has also been used in categorizing the density levels and enhance monitoring system interpretability [7]. Object detection based real-time surveillance systems are able to estimate the crowd size, speed and direction [8], and anomaly detection systems attempt to estimate abnormal crowd behavior patterns [5]. These systems are however reliant on CCTV feeds and only work out when the crowds are already formed thus making them reactive.

Other researchers come up with smart crowd management systems and artificial intelligence-based coordination of big events like festivals and pilgrimages [10], [4]. However, these solutions primarily aid in monitoring and control of the operations in the event, but not in assessing the safety in advance.

The proposed work rather conducts safety assessment before the event. A simulated model of the venue is built and pedestrian dynamics is modelled to produce crowd behavior data. Machine learning models are then used to predict the risk of stampede in each zone, and explainable AI tells why each risk is caused. The system allows preventive planning instead of post-event response by enabling planners to experiment with alternate layouts and adjust the entry or exit layout before the influx of the crowds.

3. Proposed Work

3.1 System Architecture

The proposed approach involves a simulation-based system to conduct crowd safety assessment using pedestrian dynamics modeling, risk prediction using machine learning algorithms and XAI to prevent stampedes proactively. As depicted in Figure 1 below, the structure of the system has four interconnected layers, including (i) the User Interface Layer, (ii) the Simulation Layer, (iii) the Data Processing Layer, and (iv) the Visualization and Reporting Layer.

Event organizers use the User Interface Layer to set up the layout of the venue, entry/exits, crowd gathering areas, and crowd arrivals. The input data from this layer is transmitted to the Simulation Layer, where crowd dynamics simulations are run based on pedestrian dynamics modeling.

Crowd simulations are then processed through the Data Processing Layer to derive crowd dynamics information like crowd density, crowd velocity, crowd flow rate, turbulence, and crowd pressure. This information will be used by the risk estimation algorithm to determine the stampede risk levels in various zones. The Explainable AI model is then used to explain the basis of high-risk predictions.

Visualization and reporting layer provides crowd heat maps, hot spot locations, risk scoring, and explanations, providing authorities with the ability to assess different scenarios and plan preventive actions prior to the event.

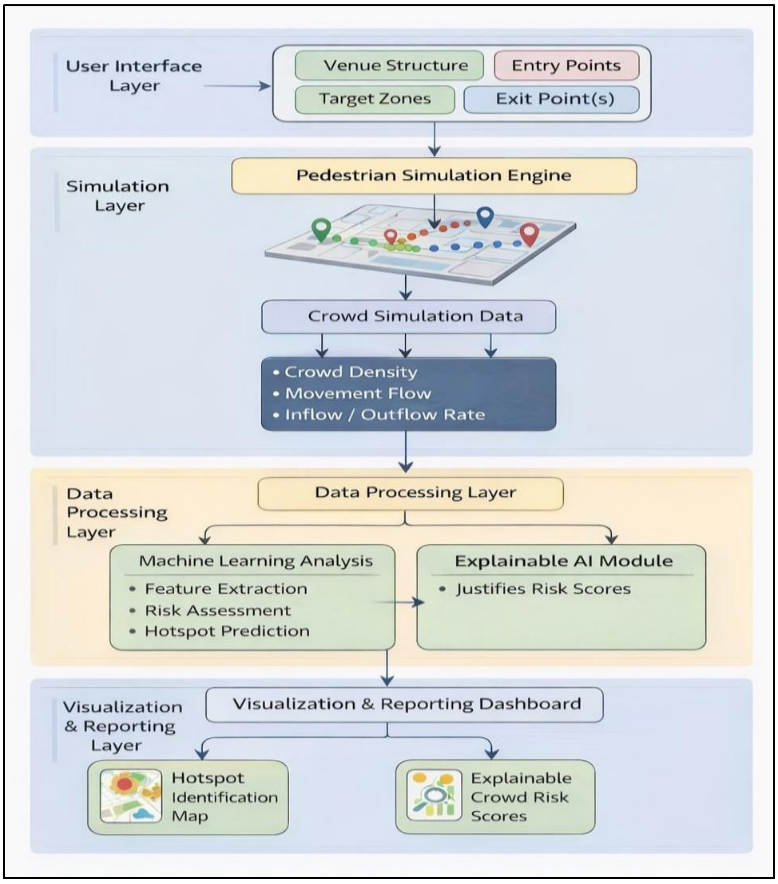

Figure 1. Overall Architecture of the Proposed AI Based Stampede Risk Prediction and Decision Support Framework

3.1.1 Venue Configuration and Crowd Modelling

The first step in the process entails generating a mathematical model of the layout of the event venue. Given that people tend to keep a distance between themselves and any surrounding obstacles, the effective walking width is less than the actual physical width of the passage. As such, the effective width of a passage is calculated using the following equation:

$$W_{eff} = W_{\text{actual}} - 2\delta \tag{1}$$

where W_{eff} is the effective walking width, W_{actual} is the physical corridor width, and δ is the pedestrian clearance distance for pedestrians. In practice, the clearance distance can be assumed to range between 0.3m and 0.5m depending on the situation.

$$A(t) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(t-\mu)^2}{2\sigma^2}\right) \tag{2}$$

where $A(t)$ denotes the pedestrian arrival rate at time t, μ is the mean arrival time, and σ is the standard deviation. The above equation allows for the generation of surge-like arrivals in the simulation rather than a uniform distribution.

3.2 Pedestrian Simulation and Crowd Dynamics

The pedestrian simulation module serves as the backbone for the framework. Individual pedestrians are modeled as autonomous agents that are defined by spatial location, velocity, and information about their destinations. The motion of agents depends on the availability of a path, crowd density, and environment.

The flow capacity of pedestrians in a corridor is modeled according to the pedestrian flow equation:

$$Q = W_{eff} \times q_{\max} \tag{3}$$

where Q represents pedestrian flow rate, W_{eff} is the effective corridor width, and $q_{\max}$ is the maximum pedestrian flow per unit width. Pedestrian planning norms estimate $q_{\max}$ at around 82 persons/m/min in free-flowing situations.

The environment is modeled as a graph (G=(V,E)), with (V) representing traversable places and (E) representing permissible pedestrian paths. Route calculation is carried out using the Open Source Routing Machine (OSRM) to enable agents to traverse via realistic routes as opposed to perfect straight paths.

With an increase in pedestrian density, there is a decrease in the freedom of movement. This effect is incorporated by adjusting the speed of movement of the agents based on density conditions using

$$\rho = \frac{N}{A} \tag{4}$$

where ρ denotes crowd density (persons/ m^2), N is the number of pedestrians, and A is the observation area.

$$\bar{v} = \frac{1}{N}\sum_{i=1}^{N} v_i \tag{5}$$

where $\bar{v}$ is the average pedestrian velocity and v_i is the velocity of the i^{th} pedestrian.

The present model recreates the slowdown in walking speeds that takes place when congestion is high and also simulates bottleneck situations.

$$T = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (v_i - \bar{v})^2} \tag{6}$$

where T represents the turbulence index, v_i is the velocity of the i^{th} pedestrian, and $\bar{v}$ is the average velocity.

The key factor in measuring crowd safety is crowd pressure, which is a combination of crowd density and crowd velocity variations and measures the overall stress in a crowd. Crowd pressure is given by

$$P = \rho T^2 \tag{7}$$

where P denotes crowd pressure, ρ is crowd density, and T^2 represents velocity variance. The higher the value of crowd pressure, the more unstable is crowd movement and thus the occurrence of crowd crush situations and stampedes is expected.

3.3 Synthetic Dataset Generation

As real-time data on stampedes is rare and hard to obtain, a synthetic dataset was produced based on the proposed simulation framework. Around 20,000 simulation cases were run through altering crowds' size, rate of arrival, width of corridor, number of gates, placement of obstacles and severity of bottlenecks. Every simulation produced measurements at a zone level, describing dynamic changes in crowds' behavior during the simulations.

Table 1. Sample Records from the Synthetic Crowd Dynamics Dataset

Scenario ID	Density (persons/m²)	Avg. Velocity (m/s)	Turbulence Index	Crowd Pressure	Risk Score
S001	0.85	1.32	0.08	0.005	0.12
S002	1.45	1.18	0.15	0.033	0.25
S003	2.1	0.97	0.24	0.121	0.43
S004	2.95	0.82	0.37	0.404	0.61
S005	3.78	0.64	0.49	0.908	0.78
S006	4.52	0.51	0.63	1.794	0.91
S007	5.1	0.43	0.71	2.572	0.97

Four main aspects of crowd dynamics were identified for each zone (see Table 1): local density, average speed, turbulence, and crowd pressure. Local density is the number of pedestrians in a square meter. Average speed, in turn, describes the speed of movement of a whole crowd. Turbulence describes variability of pedestrian motion. It is a measure used to capture chaotic nature of movement usually associated with the crowd under stress. Crowd pressure is a combination of density and speed variations in the crowd and can be regarded as an indicator of physical pressure experienced by pedestrians. The risk levels were assigned based on Fruin's Level of Service (LOS) guidelines. Simulation results in terms of density were mapped to corresponding safety levels and then were normalized into risk score between zero and one.

3.4 Machine Learning-Based Risk Assessment

The extracted crowd dynamics features constitute the input to the machine learning layer. Let the feature vector associated with a particular zone be represented as

$$F = [\rho, \bar{v}, T, P] \tag{8}$$

where F represents the feature vector used for risk prediction.

The objective of the learning model is to estimate a continuous risk score (R) using the mapping

$$R = f(F) \tag{9}$$

where R is the predicted stampede risk score and $f(\cdot)$ represents the trained machine learning model.

In order to enhance the accuracy of prediction, two algorithms based on the gradient-boosting approach are used. XGBoost algorithm is considered the main algorithm for prediction due to its capability to analyze complicated non-linear relationships between parameters of the crowd. LightGBM is considered the secondary one as well as an efficient computational approach for large-scale simulations.

The final value of stampede risk is determined through averaging of the two model outputs:

Ensemble Risk Score

$$R_{\text{final}} = w_1 R_{XGB} + w_2 R_{LGBM} \tag{10}$$

subject to

$$w_1 + w_2 = 1 \tag{11}$$

where R_{XGB} and R_{LGBM} are predictions from XGBoost and LightGBM, respectively, and w_1 and w_2 are their corresponding weights. This ensemble strategy improves robustness and reduces the influence of individual model bias.

3.5 Explainable AI and Decision Support

While gradient boosting models deliver accurate predictions, their decision-making algorithm is hard to interpret. As an improvement in this respect, the proposed methodology utilizes SHAP Explainable Artificial Intelligence for better explainability.

Risk Score Prediction can be attributed to its contributing factors via the formula:

$$R = \phi_0 + \sum_{i=1}^{n} \phi_i \tag{12}$$

where ϕ_0 represents the baseline prediction and ϕ_i denotes the contribution of the i^{th} feature toward the final risk score. This formulation enables the system to quantify the influence of density, velocity, turbulence, and pressure on every prediction.

These predictions are then included into the visualization tool so that the authorities could locate regions with heightened risk levels and analyze the reasons why there is a higher probability of a dangerous situation. Thus, planners are able to consider different layouts, expand the capacity of corridors, open more exits, and control the inflow of people well before the onset of crowd crisis.

4. Results and Discussion

4.1 Risk Visualization and Crowd Behavior Analysis

The proposed system presents a visual representation of a crowd risk supported by a heatmap view of space (see Figure 2). In the case of all exits open and normal operating conditions, the risk levels are predicted to be low and evenly distributed throughout the venue.

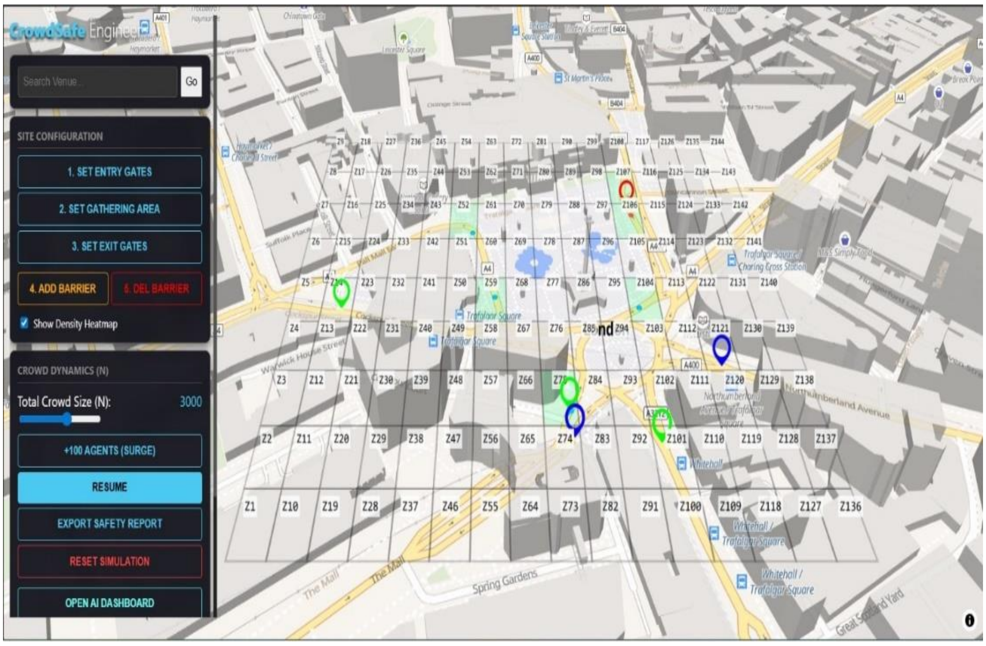

Figure 2. Free flow of the Crowd Without Congestion Under Normal Conditions

Congestion would occur around bottleneck areas when the number of people who are passing by is high, or the exit capacity is very low. The system can mark these areas as high-risk zones and assign more risk scores to them (see Figure 3).

Figure 3. Stampede Occurring in a Particular Zone due to Congestion

4.2 Performance Evaluation

The proposed crowd safety framework offers robust performance in risk prediction and also replicates real-world behavior of pedestrian flows and hazardous crowd conditions.

Table 2. Performance Metrics of Proposed Models

Metric	XGBoost	LightGBM
Mean Squared Error (MSE)	0.000144	0.00014
Root Mean Squared Error (RMSE)	0.012013	0.011851
Mean Absolute Error (MAE)	0.001684	0.002053
R2 Score	0.998854	0.998885

The performance of the proposed crowd risk prediction framework was evaluated using two ensemble learning models, namely XGBoost and LightGBM. Table 2 summarizes the prediction accuracy obtained on the simulated crowd dynamics dataset. Both models achieved extremely low prediction errors, with Mean Squared Error (MSE) values below (1.5×10^{-4}) and Root Mean Squared Error (RMSE) values close to 0.012. Furthermore, the coefficient of determination (R^2) exceeded 0.998 for both models, indicating that the extracted crowd dynamics features effectively explain the variation in crowd risk levels.

As a measure to verify the prediction ability of the developed framework, Figure 4 shows the correlation between the actual risk value and the estimated risk value using our proposed method. Most data points are clustered around the 45-degree reference line, showing the high level of correspondence between estimated risk values and true risk values. A few points deviate from the perfect line, especially when there is a high risk of congestion. Such a phenomenon is anticipated because crowd behaviors tend to become nonlinear under high levels of crowd density.

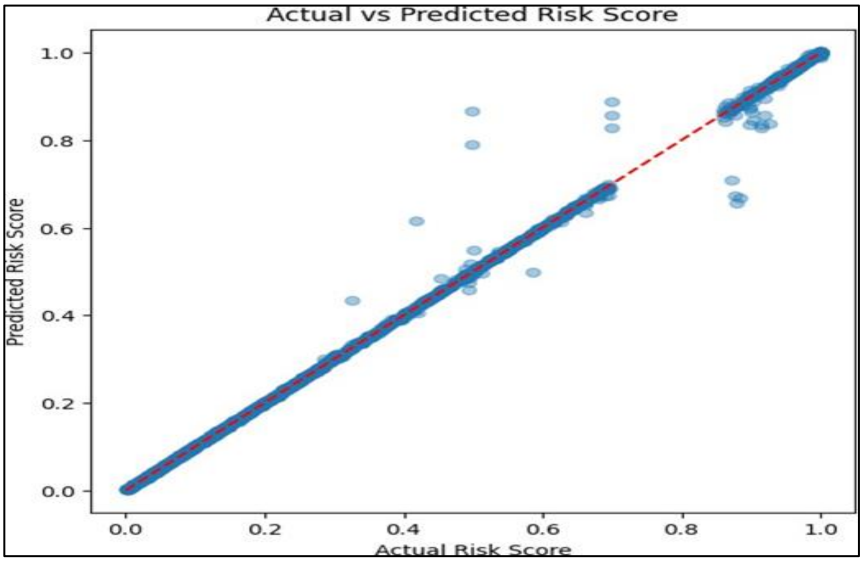

Figure 4. Actual vs Prediction Risk Score

The proximity of the data points to the line implies that the training algorithm is able to capture the dependencies between crowd density, crowd speed, turbulence, and crowd pressure. Based on this finding, it can be concluded that the suggested ML solution allows one to make consistent risk estimates for various scenarios of crowd behavior and is useful for predicting stampedes.

4.3 Explainable AI Interpretation

Despite the effectiveness of the developed machine learning approaches in terms of high risk prediction accuracy, it is important to investigate which variables are responsible for predictions since it is crucial when using ML algorithms for solving practical problems related to public safety. For this reason, an XAI module based on SHAP was introduced to measure how much each crowd dynamics variable contributes to prediction risk.

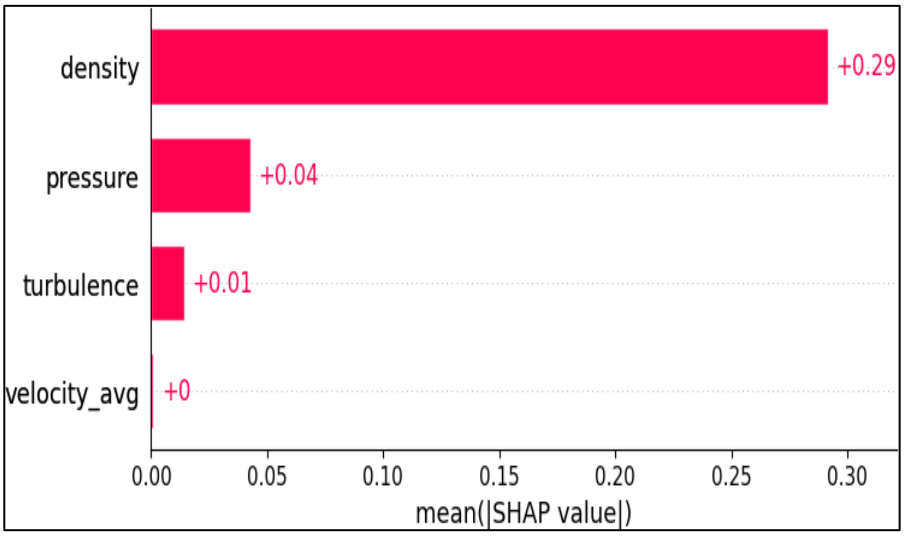

Figure 5. SHAP Feature Importance Plot

The SHAP values of crowd dynamics variables are shown in Figure 5. As seen, the variable that exerts the greatest influence on the prediction of the risk of a stampede is the crowd density variable, which has the highest mean absolute SHAP value compared to all other variables considered. This statement corresponds to real-life examples of crowd disasters, according to which high crowd density is usually the main factor leading to crowd crushes and stampedes.

Crowd pressure takes second place regarding its effect on prediction since the relationship between crowd density and fluctuation of velocity plays a significant role in ensuring crowd safety. The contribution of turbulence is medium as it indicates that unpredictable and unstable movements of pedestrians lead to risky crowd behaviors. In turn, average pedestrian velocity has the minimal contribution.

The SHAP analysis demonstrates that the proposed framework not only predicts the occurrence of high-risk situations but also provides interpretable explanations for those predictions. Such transparency enables event planners and public safety authorities to understand the underlying causes of risk escalation and implement targeted mitigation measures, such as increasing corridor capacity, opening additional exits, or regulating crowd inflow rates.

5. Conclusion

The current study proposed a crowd safety evaluation approach based on simulations using models of pedestrian dynamics, ensemble machine learning algorithms, and Explainable Artificial Intelligence techniques to ensure the prevention of stampedes. The simulation system generates a model of an event venue and produces simulations of pedestrian movements under various configurations of crowd and infrastructure conditions to obtain realistic crowd behaviour data. Crowd dynamics characteristics such as density, average speed, turbulence, and crowd pressure are extracted and employed in predicting risks in zones within venues. Experimental evaluation results showed that the proposed method had great potential since it produced predictions with high accuracy levels as the R^2 of both XGBoost and LightGBM exceeded 0.998. The predicted and actual values comparison further proved the success of the method by showing that there was a significant agreement between predictions made using the method and actual risk levels in a venue. In addition, SHAP analysis indicated crowd density and crowd pressure as two factors having a notable influence on hazardous situations.

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