



# Disaster Monitoring and Intelligent Evacuation Planning System using Edge Computing and Simulation

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**ABSTRACT:** This paper presents an Internet of Things (IoT) and machine learning-based real-time stampede detection and management system aimed at improving safety in crowded public spaces such as religious gatherings, transportation hubs, and large events. Stampede incidents often happen because there is no continuous monitoring or early warning systems in place, leading to serious injuries and loss of life. The system uses vibration sensors to monitor ground vibrations caused by crowd movement. When the detected vibration intensity goes beyond a set limit, the system automatically turns on visual and audible alerts using LED indicators and a buzzer. Additionally, servo motors lift and control access gates to manage crowd entry and exit during critical situations. Real-time vibration data, system status, and alert notifications are sent to users through a cloud-based IoT platform. Sensor data is logged periodically into a cloud-hosted database at regular intervals for centralized storage and further analysis. A Decision Tree machine learning model analyzes the historical data and classifies crowd conditions, allowing for the early identification of potential stampede situations. Experimental results show that the system effectively detects unusual crowd behavior and offers timely alerts, thereby enhancing response time and lowering the risk of stampede incidents. The system is cost-effective, scalable, and suitable for real-world crowd management applications.

**KEYWORDS:** Internet of Things (IoT), Stampede Detection, Crowd Management, Vibration Sensors, Machine Learning, Decision Tree

## I. INTRODUCTION

Stampede incidents are some of the most serious crowd disasters. They often lead to a high number of deaths and severe injuries in a short period. These incidents usually happen in crowded public places, such as religious gatherings, festivals, transit stations, stadiums, and political events. When crowds move uncontrollably, panic can set in, and sudden increases in crowd density can quickly turn into dangerous situations. This leaves authorities with little time to step in and help. Conventional crowd management practices mainly rely on surveillance cameras, manual monitoring, and analysis after events. Although video systems offer visual coverage, they often miss early signs of stampede formation, like unusual ground vibrations caused by sudden crowd pressure and movement. Additionally, these approaches require constant human supervision, which makes them inefficient in large-scale or fast-changing environments. The lack of real-time sensing and automated response mechanisms greatly limits how well traditional systems work.

Recent advancements in the Internet of Things (IoT) have enabled real-time monitoring with low-cost sensors, wireless communication, and cloud-based data processing. Vibration sensors offer an effective way to detect early warning signs of unusual crowd behavior by measuring ground-level disturbances from human movement. With cloud connectivity, these sensors can provide real-time alerts, remote monitoring, and centralized data storage for further analysis. Additionally, machine learning techniques have become important in smart decision-making systems because they can analyze historical data and spot patterns that may not be obvious with just threshold-based methods. Decision Tree algorithms are particularly well-suited for safety-critical applications due to their simplicity, easy understanding, and low computational needs. Inspired by these findings, this paper suggests a real-time stampede detection and management system based on the Internet of Things and machine learning. To improve crowd safety, the system uses vibration sensing, automated alerts, servo motor-based gate control, cloud-based monitoring, and Decision Tree



analysis. The proposed strategy aims to lower the chances of stampede incidents in real situations by providing early detection, quick response, and predictive insights.

## II. PROBLEM IDENTIFICATION

Stampede incidents are a continuing problem in managing large public gatherings. High crowd density, panic situations, and sudden surges can create dangerous conditions quickly. A major issue with current crowd safety methods is the lack of real-time, on-site detection that can spot early signs of stampede formation. Often, warning signs like unusual pressure and vibration buildup go unnoticed until the situation becomes critical. Today's crowd monitoring systems mainly depend on manual surveillance, closed-circuit television (CCTV), or analyzing events after they happen. These methods react to problems after they arise, relying on human intervention that may be slow or ineffective when crowd dynamics change rapidly.

Moreover, visual monitoring is limited by factors like lighting, obstructions, and camera angles, which lowers its reliability in crowded and chaotic settings. Another significant challenge is the lack of automated response systems that can help manage crowds during emergencies. Most current systems can generate alerts, but they cannot physically control crowd movement, such as managing entry or exit points. This limitation makes early warnings less effective since corrective actions still depend heavily on manual crowd management.

Additionally, current safety systems often do not use historical data for predictive analysis. Without smart, data-driven decision-making, authorities cannot spot recurring patterns or potential high-risk situations ahead of time. Without machine learning analysis, systems stay the same and cannot adjust to different crowd behaviors in various environments and events. These drawbacks highlight the need for a solution that provides cloud-based data logging, smart analysis, automated alerts, physical crowd control, and real-time sensing. The proposed IoT and machine learning-based stampede detection and management system discussed in this paper aims to tackle these problems.

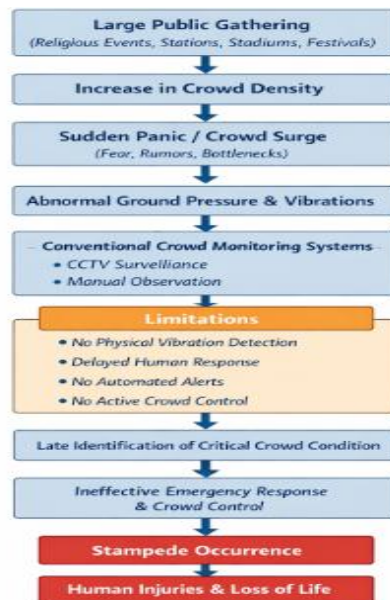


FIG: Problem Identification

## III. LITERATURE SURVEY

Recent advancements in crowd safety and disaster prevention technologies have focused on using sensor-based monitoring systems to detect unusual crowd behavior in public spaces. Early research looked at video surveillance techniques for estimating crowd density and analyzing movement. These systems used image processing algorithms to find congestion and unusual motion patterns. However, their performance was limited by lighting conditions, camera



placement, and high computational demands. This made them unsuitable for real-time stampede detection in crowded environments [1].

Several studies examined pressure and force-based sensing methods to analyze crowd-induced stress on structures. These methods showed that unusual pressure changes could signal potential stampede situations. While they were effective in controlled settings, deploying pressure sensors across large public areas was found to be expensive and hard to scale [2].

With the rise of the Internet of Things (IoT), researchers suggested using distributed sensing architectures for real-time crowd monitoring. IoT-based systems that integrated wireless sensor networks allowed for continuous data collection and remote monitoring. These systems improved response times and scalability, but many depended on static threshold-based decision logic. This limited their ability to adapt to changing crowd conditions [3].

Vibration-based sensing has become a popular method for detecting unusual crowd movement. Studies show that human footsteps and crowd surges create unique vibration patterns that low-cost vibration sensors can capture. These methods allowed for early detection compared to visual systems; however, most implementations only focused on local alerts without connecting to the cloud or using data analysis [4].

Cloud-based crowd management solutions were developed to deal with issues of data access and central monitoring. These systems allowed for real-time data visualization and remote alerts on web and mobile platforms. While cloud integration helped improve situational awareness, many solutions did not include physical response mechanisms to actively manage crowd movement during emergencies [5].

Machine learning techniques have been increasingly used to analyze crowd behavior and address the limitations of rule-based systems. Research on Support Vector Machines, Neural Networks, and clustering algorithms showed better accuracy in identifying unusual crowd behaviors. However, these models often needed large datasets and significant computing power, which made them less suitable for embedded and real-time systems [6].

Decision Tree algorithms were suggested as an alternative due to their ease of understanding and low computational demands. Various studies found that Decision Trees worked effectively in safety-critical situations, providing quick decision-making and easy rule extraction. These features make them a good fit for real-time crowd monitoring systems with limited processing power [7].

Hybrid systems that combine IoT and machine learning have also been studied for use in disaster management. These systems brought together sensors, cloud platforms, and predictive models to detect emergencies like fires, earthquakes, and crowd panic. While promising, many studies concentrated on simulations rather than real-world applications [8].

Research on automated alert systems emphasized the need for multi-channel notification options, such as mobile apps and cloud dashboards. These systems improved communication during emergencies but often did not connect with physical devices for active intervention [9].

The research studies demonstrated how actuator-based control systems with automated gates and barriers performed crowd management functions. The research demonstrated that controlled access systems effectively reduced crowd congestion by activating their systems during specific time windows. The research showed that actuator control systems rarely operated together with smart sensors, which used predictive analytics, according to source [10].

Researchers now study data logging and historical analysis to create better crowd safety plans. The system stored data continuously. This allowed experts to analyze events after they happened while building risk assessment models for upcoming events. However, most systems failed to apply their stored information for immediate predictive decision support during operational activities [11].

To decrease the latency in crowd monitoring systems, the proposals for edge computing methods included processing the data near the source. Even though this reduced the latency significantly, it became a barrier for the implementation of advanced analytics at the edge due to the limited processing resources available [12].

The applications of wearable sensor-based crowd monitoring systems were also looked into as a means of obtaining direct measurements of human movements and physiological parameters. While these types of systems offered precise



data at the individual level, they also had to deal with problems such as user compliance, privacy issues, and large-scale deployment [13].

Multi-sensor fusion methods which integrate vibration, sound, and visual data were implemented to boost detection accuracy. Although these systems proved to be more reliable, they also brought about increased complexity and cost of the system [14].

From the reviewed literature, it is clear that existing systems focus on sensing, alerting, or analysis separately. There is a significant research gap in creating an integrated solution that combines vibration-based sensing, IoT-enabled real-time monitoring, automated gate control, cloud-based data logging, and lightweight machine learning analysis. Filling this gap motivates the proposed IoT and machine learning based stampede detection and management system presented in this paper [15].

## IV. PROPOSED SYSTEM ARCHITECTURE

The proposed system architecture aims to overcome the shortcomings that were pointed out in the problem identification and literature review by combining real-time sensing, automatic response, cloud connectivity, and smart data analysis. The architecture is modular and scalable, which allows dependable stampede detection and management in very crowded public places.

### A. Overall System Overview:

The system is built around an ESP32 microcontroller, which serves as the main processing and communication unit. Two vibration sensors are placed in key locations to constantly monitor ground vibrations caused by crowd movement. These sensors produce analog signals that reflect vibration intensity, which the ESP32 collects and processes in real time. Under normal crowd conditions, the system works in a monitoring mode, where vibration values stay below the set threshold and a green Led shows safe conditions. If it detects abnormal vibration levels that suggest a potential stampede, the system switches to alert mode and a red led indication would be triggered.

### B. Alert and Crowd Control Mechanism:

When vibration levels go above the threshold, the ESP32 activates several response mechanisms at once. A red LED and a buzzer turn on to provide immediate visual and sound alerts at the site. Additionally, servo motors operate to lift or close access gates, controlling crowd entry and exit to reduce congestion and prevent further issues. It is always dependent on the manual intervention of solidarity responders. It ensures a much faster response when there is a crisis or a catastrophic event.

### C. Cloud Communication and Data Logging:

The ESP32 uses its built-in Wi-Fi to send real-time system status, vibration count values, and alert notifications to a cloud IoT platform. The Blynk platform offers an easy-to-use interface for remote monitoring. This allows authorities to see live crowd conditions and get instant alerts on their mobile devices. At the same time, vibration data and system status information are uploaded to a Google Sheet in the cloud at regular intervals, every 30 seconds. This provides organized data storage for analysis, reporting, and future reference.

### D. Machine Learning-Based Decision Support:

The data stored in the cloud is used for both offline and online analysis with a Decision Tree machine learning model. The model is trained on historical vibration data to classify crowd conditions as normal or abnormal. By looking at patterns in vibration intensity and frequency, the Decision Tree gives predictions about possible stampede situations. The use of machine learning improves system intelligence by allowing flexible decision-making instead of just relying on fixed thresholds.

### E. System Workflow Summary:

The full workflow starts with vibration sensing, then moves to real-time processing on the ESP32, automated alert and gate control, cloud-based visualization, and data-driven analysis with machine learning. This complete system ensures early detection, quick response, and continuous learning, making it effective for managing stampedes in real-life situations. Overall, the proposed system architecture emphasizes reliability, real-time responsiveness, and scalability while maintaining low implementation complexity. By integrating vibration-based sensing with ESP32-based processing, automated gate control, cloud-enabled monitoring, and machine learning-driven analysis, the architecture provides a comprehensive framework for effective stampede detection and management. The modular design allows the system to be easily adapted to different public environments and crowd scales. The detailed hardware configuration and software implementation of the proposed architecture are discussed in the subsequent section.

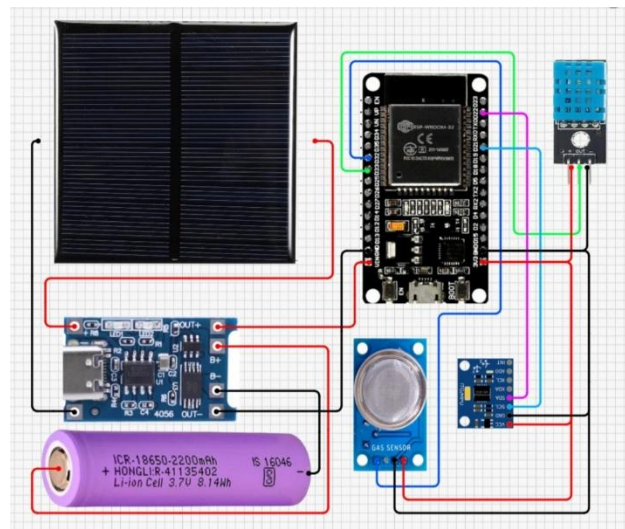


Fig: circuit diagram

## V. HARDWARE AND SOFTWARE REQUIREMENTS

This section details the hardware parts and software tools needed to implement the proposed IoT-based stampede detection and management system. The chosen components and tools are selected to ensure reliability, low cost, and easy deployment.

### A. Hardware Requirements:

Below are the hardware components that were used in the proposed system:

#### I. ESP32 Microcontroller:

The ESP32 microcontroller serves as the main processing and communication unit of the system. It handles sensor data collection, decision-making, actuator control, and Wi-Fi communication for connecting to the cloud.

#### II. Vibration Sensors (Two Units):

Vibration sensors detect ground vibrations caused by crowd movement. These sensors give early warnings of unusual crowd behavior and are essential for detecting stampedes.

#### III. Servo Motors (Two Units):

Servo motors open and close access gates during critical moments. By controlling entry and exit points, the servo motors help manage crowd flow and lessen congestion.

#### IV. LED Indicators (Red and Green):

LED indicators show the system status visually. The green LED signals normal operating conditions, while the red LED points out alert or unusual crowd situations.

#### V. Buzzer:

The buzzer produces an audible alert when it detects high vibration levels. It warns nearby personnel and the crowd during emergencies.

#### VI. Power Supply Unit:

The power supply unit gives a regulated and reliable voltage to the ESP32 microcontroller and additional devices. Correct voltage regulation guarantees the reliable and continuous operation of the system. Here, we are using a 12v Dc adapter with a inbuilt dc-dc converter in expansion board for esp32.



## B. Software Requirements:

The following software tools and platforms are needed for developing, deploying, and analyzing the proposed IoT-based stampede detection and management system:

### I. Arduino Integrated Development Environment (IDE):

The Arduino IDE is for writing, compiling, and uploading the embedded C/C++ program to the ESP32 microcontroller. It provides a straightforward development environment and supports the libraries needed for sensor interfacing, actuator control, and Wi-Fi communication.

### II. ESP32 Board Support Package and Libraries:

ESP32-specific board packages and libraries help configure the microcontroller, manage Wi-Fi connectivity, and connect with sensors and actuators. These libraries ensure stable hardware management and communication.

### III. Blynk IoT Platform:

The Blynk IoT platform is for real-time monitoring and alert notifications. It offers a mobile-based dashboard that shows vibration sensor readings, system status, and alert messages received from the ESP32.

### IV. Google Sheets:

Google Sheets serves as a cloud-based data logging platform to store vibration sensor readings and system status updates regularly. It allows easy access to historical data for monitoring and analysis.

### V. Google Colab:

Google Colab is a cloud-based Python environment for machine learning analysis. It is used to implement and train the Decision Tree model using historical vibration data saved in Google Sheets.

### VI. Machine Learning Libraries:

Standard Python machine learning libraries are used in the Google Colab environment to develop and assess the Decision Tree model for classifying crowd conditions.

## VI. HARDWARE IMPLEMENTATION

The hardware setup for the stampede detection and management system aims to provide reliable sensing, quick response, and smooth communication with cloud platforms. The choice of components emphasizes low power use, cost efficiency, and easy deployment in public settings.

### A. ESP32 Microcontroller Unit:

The ESP32 microcontroller acts as the main control and processing unit of the system. It gathers sensor data, makes decisions, controls actuators, and manages wireless communication. The built-in Wi-Fi feature of the ESP32 allows it to connect directly to cloud platforms without needing extra communication modules. Its dual-core design and adequate memory make it suitable for real-time data processing and IoT tasks.

### B. Vibration Sensors:

Two vibration sensors are placed at key locations to detect ground vibrations from crowd movement. These sensors turn mechanical vibrations into electrical signals, which are sent to the analog input pins of the ESP32. Under normal crowd conditions, vibration intensity stays within a safe range. A sudden rise in vibration levels points to unusual crowd behavior and acts as an early warning for potential stampede situations.

### C. Visual and Audible Alert Units:

To provide immediate alerts on-site, LED indicators and a buzzer are included in the system. A green LED shows normal operating conditions, while a red LED indicates an abnormal or critical crowd state. The buzzer sounds at the same time during alert situations to grab attention and warn nearby personnel and the crowd. These alert systems ensure quick local awareness, even without remote monitoring.

### D. Servo Motor-Based Gate Control:

Servo motors serve as actuators to raise or close access gates during critical situations. When vibration levels exceed the set threshold, the ESP32 sends control signals to activate the servo motors. This system allows for automated management of crowd entry and exit points, helping to ease congestion and prevent further crowd pressure increases.

### E. Power Supply Unit:

A regulated power supply unit provides stable voltage to the ESP32, sensors, and other devices. Proper power management ensures the system operates reliably and protects components from voltage changes. The system can be powered with an external adapter or a battery-backed supply to maintain operation during emergencies. The hardware implementation consolidates the four main functions at the same time. The use of vibration sensors for early detection,

ESP32 for real-time processing and communication, and servo motors for active crowd control facilitates the management of stampedes. Software implementation, cloud integration, and data handling .

Mechanisms that allow for real-time monitoring and smart decision-making will be treated in the following section.

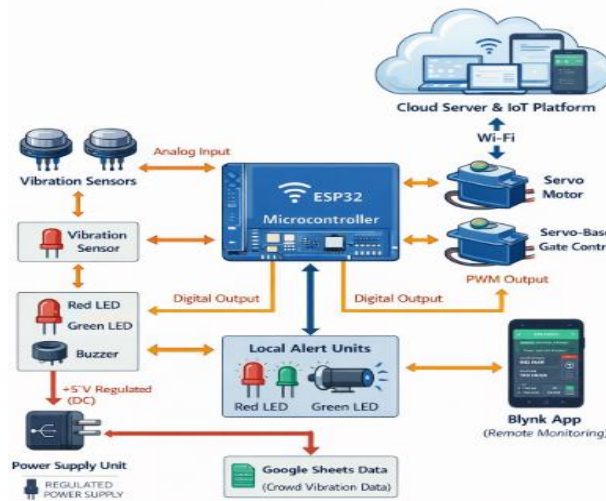


Fig: Block diagram of the overall system connectivity for the proposed IOT Based Stampede Detection System

## VII. SOFTWARE TOOLS AND CLOUD SERVICES

The proposed stampede detection system relies on popular development tools and cloud platforms to ensure simplicity, reliability, and easy implementation. The main software tools and services used in this system include the Arduino development environment, the Blynk IoT platform, Google Sheets for data storage, and a machine learning model for data analysis.

### A. Arduino IDE and ESP32 Programming:

The ESP32 microcontroller is programmed using the Arduino Integrated Development Environment (IDE). The Arduino IDE offers a straightforward platform for writing, compiling, and uploading embedded C/C++ programs to the ESP32. It includes built-in libraries for sensor interfacing, Wi-Fi communication, and peripheral control, making it suitable for quickly developing IoT applications. Using the Arduino compiler, the program continuously reads values from the vibration sensor, compares them with set threshold levels, and performs the required control actions. The simplicity of the Arduino programming model helps achieve fast responses and reliable real-time operation.

### B. Blynk IoT Platform:

The Blynk IoT platform is used for remote monitoring and alert notifications. It provides a mobile app interface that allows users to see live vibration values, system status, and alert messages. The ESP32 connects to the Blynk cloud server via Wi-Fi, allowing real-time data visualization and notifications on smartphones. Blynk makes it easy to create IoT dashboards without needing complicated web development, which is effective for monitoring crowd conditions from a distance.

### C. Google Sheets for Cloud Data Logging:

Google Sheets serves as a cloud-based data storage platform to log vibration sensor readings and system status information. The ESP32 uploads data to Google Sheets every 30 seconds using HTTP requests. This method offers a simple and low-cost way to keep historical records. The stored data can be accessed from any location and is helpful for analyzing crowd behavior patterns and system performance over time.

### D. Machine Learning for Crowd Condition Analysis:

The historical vibration data recorded in Google Sheets is used for machine learning analysis. A Decision Tree algorithm classifies crowd conditions as normal or abnormal based on vibration intensity patterns. The Decision Tree



model is chosen for its simplicity, low computational needs, and ease of interpretation. This machine learning analysis aids in understanding crowd behavior trends and supports better decision-making for preventing stampedes.

## VIII. MACHINE LEARNING-BASED STAMPEDE PREDICTION USING GOOGLE SHEETS DATA

The proposed IoT-based stampede management system uses a Machine Learning (ML) model trained with real-time sensor data logged in Google Sheets. The collected dataset includes timestamped vibration sensor readings that show how intense crowd movement is at monitored locations.

### A. Dataset Description:

The dataset comes from vibration sensors set up at entry and exit points. Each record includes the following attributes: -

Timestamp: Date and time of data collection

Vibration-Count: Total vibration events detected within a sampling interval.

Delta-Count: Difference between consecutive vibration counts.

Status: System-detected crowd condition (SAFE or STAMPEDE).

Label: Binary class label (0 - SAFE, 1 - STAMPEDE)

The Google Sheets platform serves as a cloud repository to store and organize the sensor data in real time.

### B. Data Preprocessing:

Before training the ML model, we preprocess the dataset to ensure it is reliable. We remove missing values. We also normalize numerical features like vibration count and delta count. The Status column is changed into a binary label to allow for supervised learning.

### C. Machine Learning Model:

A Decision Tree Classifier is chosen for classification because it is simple, executes quickly, and works well in real-time IoT environments. The model is trained with vibration-based features to predict if the crowd condition is SAFE or STAMPEDE.

The dataset is split into training and testing subsets. This helps evaluate how well the model performs.

### D. Performance Evaluation:

The trained ML model shows high classification accuracy when tested on real sensor data collected from Google Sheets.

**Overall Accuracy: 97.56%**

#### 1)SAFE Class (Label 0):

- Precision: 0.97
- Recall: 1.00
- F1-score: 0.99

#### 2) STAMPEDE Class (Label 1):

- Precision: 1.00
- Recall: 0.86
- F1-score: 0.92

The results show that the model correctly identifies safe conditions and performs well in detecting stampede scenarios. The slightly lower recall for the stampede class is acceptable because there are only a few high-risk events in the dataset.

### E. Real-Time Prediction and System Response:

Once trained, the ML model predicts crowd conditions in real time. When a STAMPEDE condition is detected, the system automatically triggers alarms, updates the monitoring dashboard, and starts crowd control actions like gate regulation.

### F. Cloud Analytics Using Google Sheets:

Google Sheets allows:

Real-time data logging from ESP32 nodes.

Visualization of vibration trends. Storage of historical data for ML retraining.



This cloud-based method avoids the need for complicated servers and offers reliable analytics and scalability.

	A	B	C	D	E	F	G	H	I
185	1/6/2026 13:26.2	158	0	STAMPEDE					
186	1/6/2026 11:24.2	97	0	SAFE					
187	1/6/2026 11:24.3	150	53	STAMPEDE					
188	1/6/2026 11:25.0	132	132	SAFE					
189	1/6/2026 11:25.1	174	42	STAMPEDE					
190	1/6/2026 11:25.4	0	0	SAFE					
191	1/6/2026 11:33.5	133	133	SAFE					
192	1/6/2026 11:33.5	165	32	STAMPEDE					
193	1/6/2026 11:34.3	35	35	SAFE					
194	1/6/2026 11:34.5	150	115	STAMPEDE					
195	1/6/2026 11:35.2	49	49	SAFE					
196	1/6/2026 11:35.5	7	-42	SAFE					
197	1/6/2026 11:36.1	150	143	STAMPEDE					
198	1/6/2026 11:47.4	0	0	SAFE					
199	1/6/2026 11:48.1	36	36	SAFE					
200	1/6/2026 11:48.4	137	101	SAFE					
201	1/6/2026 11:48.5	150	13	STAMPEDE					
202	1/6/2026 11:50.0	0	-20	SAFE					
203	1/6/2026 11:50.3	0	0	SAFE					
204	1/6/2026 11:51.0	0	0	SAFE					
205	1/6/2026 11:51.3	0	0	SAFE					
206	1/6/2026 11:51.5	20	20	SAFE					
207	1/6/2026 11:52.0	0	0	SAFE					

Fig: Google Sheet for Vibrations

```

*** Accuracy: 0.975609756097561
          precision  recall  f1-score  support
0         0.97      1.00    0.99      34
1         1.00      0.86    0.92      7

accuracy          0.98      41
macro avg         0.99      0.93    0.95      41
weighted avg     0.98      0.98    0.97      41
    
```

Fig: Decision Tree based ML output

IX. RESULTS AND DISCUSSION

The IoT-based stampede detection and management system has been suggested, implemented, and tested, to ascertain its effectiveness in detecting the behavior of the crowd that is outside the norm and providing timely responses. Evaluation was done on vibration sensing performance, alert generation, gate control operation, cloud data logging, and machine learning-based analysis. In the case of a common crowd situation, the vibration sensors gave low and stable readings. Under these conditions, the system was in monitoring mode, the green LED was lit indicating normal operation, the buzzer was silent, and access gates were operating without restrictions. There were no false alerts, which indicated that the threshold-based detection logic was reliable under these normal conditions. In the case of abnormal crowd movement simulation, the sensors detected a significant increase in the intensity of the vibration. When the vibration values crossed the specified threshold, the system switched to alert mode instantly.

The red LED and buzzer were turned on, and the servo motors were able to either open or close the access gates. This prompt action shows that the system is capable of detecting very early signs of stampede situations and of taking corrective measures in real time. The Blynk IoT platform displayed live vibration values, system status, and alert notifications. Alerts were received with minimal delay, allowing for effective remote monitoring. Vibration data and system status were logged into Google Sheets every 30 seconds.

This ensured consistent cloud-based data storage without any loss. The stored vibration data was imported into Google Colab for machine learning analysis. A Decision Tree model was trained on the collected dataset to classify crowd conditions as normal or abnormal. The model produced clear and understandable decision rules based on vibration patterns, which is important for safety-critical applications. The machine learning analysis supported the system by confirming threshold-based detection and offering insights into crowd behavior trends.

Overall, the results show that the proposed system effectively combines real-time sensing, automated alerting, gate control, cloud monitoring, and machine learning analysis. The discussion reinforces that the mix of IoT and lightweight machine learning improves response time, situational awareness, and reliability. This makes the system suitable for practical stampede prevention applications.



	A	B	C	D	E	F	G	H	I
185	1/5/2026	13:26:2	158	8	STAMPEDE				
186	1/6/2026	11:24:2	97	97	SAFE				
187	1/6/2026	11:24:2	150	53	STAMPEDE				
188	1/6/2026	11:25:0	132	132	SAFE				
189	1/6/2026	11:25:1	174	42	STAMPEDE				
190	1/6/2026	11:25:4	0	0	SAFE				
191	1/6/2026	11:33:5	133	133	SAFE				
192	1/6/2026	11:33:5	165	32	STAMPEDE				
193	1/6/2026	11:34:3	35	35	SAFE				
194	1/6/2026	11:34:5	150	115	STAMPEDE				
195	1/6/2026	11:35:2	49	49	SAFE				
196	1/6/2026	11:35:5	7	-42	SAFE				
197	1/6/2026	11:36:1	150	143	STAMPEDE				
198	1/6/2026	11:47:4	0	0	SAFE				
199	1/6/2026	11:48:1	36	36	SAFE				
200	1/6/2026	11:48:4	137	101	SAFE				
201	1/6/2026	11:48:5	150	13	STAMPEDE				
202	1/6/2026	11:50:0	0	-20	SAFE				
203	1/6/2026	11:50:3	0	0	SAFE				
204	1/6/2026	11:51:0	0	0	SAFE				
205	1/6/2026	11:51:3	0	0	SAFE				
206	1/6/2026	11:51:5	20	20	SAFE				
207	1/6/2026	11:52:0	0	0	SAFE				

Fig: Google Sheet Tracker for Data



Fig: Stampede Detector at Safe State

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*** Accuracy: 0.975609756097561
      precision    recall  f1-score   support

     0         0.97         1.00         0.99         34
     1         1.00         0.86         0.92          7

 accuracy         0.98         0.98         0.98         41
 macro avg         0.99         0.93         0.95         41
 weighted avg         0.98         0.98         0.97         41
    
```

Fig: Decision Tree based ML output

**X. CONCLUSION**

This paper presented an IoT-based stampede management system aimed at improving crowd safety in public areas. The system uses vibration sensors to monitor crowd movement continuously and detect unusual vibration patterns caused by overcrowding or panic. An ESP32 microcontroller processes the sensed vibration data and displays it in real time on an LCD. This allows on-site personnel to see crowd conditions immediately. Along with local monitoring, the system sends vibration sensor data to Google Sheets for cloud storage and analysis. The stored data trains a Decision Tree machine learning model that classifies crowd conditions as SAFE or STAMPEDE. Experimental results show that the ML model reaches an accuracy of 97.56%, proving it can reliably detect dangerous crowd situations. When the system detects a stampede condition, it automatically activates several safety mechanisms. A buzzer sounds to provide an audible warning, a red LED lights up to signal danger, and servo motors open gates for controlled crowd evacuation. During normal crowd conditions, a green LED stays on to show safe operation, and the system continues its regular monitoring without alarms. The combination of vibration sensors, a local LCD display, cloud-based Google Sheets logging, machine learning prediction, and automated control makes the system efficient, low-cost, and practical. It can be effectively used in places like temples, stadiums, railway stations, and public events to reduce the risk of stampede incidents and enhance public safety.



## REFERENCES

1. D. Helbing and A. Johansson, "Pedestrian, Crowd and Evacuation Dynamics," *Encyclopedia of Complexity and Systems Science*, Springer, pp. 6476–6495, 2009.
2. S. Bandini, M. Manzoni, and G. Vizzari, "Crowd Behaviour Modelling: From Individual Agents to Collective Phenomena," *Journal of Artificial Societies and Social Simulation*, vol. 12, no. 1, pp. 1–14, 2009.
3. M. Moussaïd, D. Helbing, and G. Theraulaz, "How Simple Rules Determine Pedestrian Behavior and Crowd Disasters," *Proceedings of the National Academy of Sciences*, vol. 108, no. 17, pp. 6884–6888, 2011.
4. A. Johansson, D. Helbing, and P. K. Shukla, "Specification of the Social Force Pedestrian Model by Evolutionary Adjustment to Video Tracking Data," *Advances in Complex Systems*, vol. 10, no. 02, pp. 271–288, 2007.
6. S. Ali and M. Shah, "A Lagrangian Particle Dynamics Approach for Crowd Flow Segmentation and Stability Analysis," *IEEE Conference on Computer Vision and Pattern Recognition*, pp. 1–6, 2007.
7. V. Raghavan, A. Kumar, and S. Kumar, "IoT Based Smart Crowd Monitoring System," *International Journal of Engineering and Advanced Technology*, vol. 8, no. 5, pp. 1817–1821, 2019.
8. A. Zanella, N. Bui, A. Castellani, L. Vangelista, and M. Zorzi, "Internet of Things for Smart Cities," *IEEE Internet of Things Journal*, vol. 1, no. 1, pp. 22–32, Feb. 2014.
9. J. Wang, G. Yu, and J. Wu, "Crowd Density Estimation Using Vibration Sensors," *Sensors*, vol. 18, no. 5, pp. 1–15, 2018.
10. R. Kumar and M. P. Singh, "Sensor-Based Early Warning System for Crowd Disaster Management," *International Journal of Disaster Risk Reduction*, vol. 27, pp. 239–247, 2018.
11. S. Madakam, R. Ramaswamy, and S. Tripathi, "Internet of Things (IoT): A Literature Review," *Journal of Computer and Communications*, vol. 3, no. 5, pp. 164–173, 2015.
12. T. M. Mitchell, *Machine Learning*, New York, NY, USA: McGraw-Hill, 1997.
13. C. Nagarajan and M. Madheswaran - 'Stability Analysis of Series Parallel Resonant Converter with Fuzzy Logic Controller Using State Space Techniques' - Taylor & Francis, *Electric Power Components and Systems*, Vol.39 (8), pp.780-793, May 2011. DOI: 10.1080/15325008.2010.541746
14. C. Nagarajan and M. Madheswaran - 'Experimental verification and stability state space analysis of CLL-T Series Parallel Resonant Converter' - *Journal of Electrical Engineering*, Vol.63 (6), pp.365-372, Dec.2012. DOI: 10.2478/v10187-012-0054-2
15. C. Nagarajan and M. Madheswaran - 'Performance Analysis of LCL-T Resonant Converter with Fuzzy/PID Using State Space Analysis' - Springer, *Electrical Engineering*, Vol.93 (3), pp.167-178, September 2011. DOI 10.1007/s00202-011-0203-9
16. S. Tamilselvi, R. Prakash, C. Nagarajan, "Solar System Integrated Smart Grid Utilizing Hybrid Coot-Genetic Algorithm Optimized ANN Controller" *Iranian Journal Of Science And Technology-Transactions Of Electrical Engineering*, DOI10.1007/s40998-025-00917-z, 2025
17. S. Tamilselvi, R. Prakash, C. Nagarajan, "Adaptive sliding mode control of multilevel grid-connected inverters using reinforcement learning for enhanced LVRT performance" *Electric Power Systems Research* 253 (2026) 112428, doi.org/10.1016/j.epr.2025.112428
18. S. Thirunavukkarasu, C. Nagarajan, 2024, "Performance Investigation on OCF and SCF study in BLDC machine using FTANN Controller," *Journal of Electrical Engineering And Technology*, Volume 20, pages 2675–2688, (2025), doi.org/10.1007/s42835-024-02126-w
19. C. Nagarajan, M. Madheswaran and D. Ramasubramanian- 'Development of DSP based Robust Control Method for General Resonant Converter Topologies using Transfer Function Model' - *Acta Electrotechnica et Informatica Journal*, Vol.13 (2), pp.18-31, April-June.2013, DOI: 10.2478/aei-2013-0025.
20. C. Nagarajan and M. Madheswaran - 'DSP Based Fuzzy Controller for Series Parallel Resonant converter' - Springer, *Frontiers of Electrical and Electronic Engineering*, Vol. 7(4), pp. 438-446, Dec.12. DOI 10.1007/s11460-012-0212-0.
21. C. Nagarajan and M. Madheswaran - 'Experimental Study and steady state stability analysis of CLL-T Series Parallel Resonant Converter with Fuzzy controller using State Space Analysis' - *Iranian Journal of Electrical & Electronic Engineering*, Vol.8 (3), pp.259-267, September 2012.
22. C. Nagarajan and M. Madheswaran, "Analysis and Simulation of LCL Series Resonant Full Bridge Converter Using PWM Technique with Load Independent Operation" has been presented in ICTES'08, a IEEE / IET International Conference organized by M.G.R. University, Chennai. Vol.no.1, pp.190-195, Dec.2007
23. Suganthi Mullainathan, Ramesh Natarajan, "An SPSS and CNN modelling based quality assessment using ceramic materials and membrane filtration techniques", *Revista Materia (Rio J.)* Vol. 30, 2025, DOI: <https://doi.org/10.1590/1517-7076-RMAT-2024-0721>



24. M Suganthi, N Ramesh, "Treatment of water using natural zeolite as membrane filter", Journal of Environmental Protection and Ecology, Volume 23, Issue 2, pp: 520-530,2022
25. J. Quinlan, "Induction of Decision Trees," Machine Learning, vol. 1, no. 1, pp. 81–106, 1986.
26. F. Provost and T. Fawcett, "Data Science and Its Relationship to Big Data and Data-Driven Decision Making," Big Data, vol. 1, no. 1, pp. 51–59, 2013.
27. A. Al-Fuqaha et al., "Internet of Things: A Survey on Enabling Technologies, Protocols, and Applications," IEEE Communications Surveys & Tutorials, vol. 17, no. 4, pp. 2347–2376, 2015.
28. P. S. Rao and K. R. Rao, "IoT-Based Crowd Monitoring and Stampede Avoidance System," IEEE International Conference on Smart Technologies and Management for Computing, Communication, Controls, Energy and Materials (ICSTM), pp. 214–219, 2017.
29. Vimal, V. R., & Banerjee, J. S. (2025). Integrating PSO, GA, and ACO for Optimized ECG Feature Selection and Classification of Cardiac Disorders. *SGS-Engineering & Sciences*, 1(5).
30. Gopinathan, V. R. (2023). Cloud-First AI Security Architecture for Protecting Enterprise Digital Ecosystems and Financial Networks. *International Journal of Research and Applied Innovations*, 6(6), 10031-10039.
31. Mathew, A. A Secure, Trustworthy, and Regulated Framework for AI Agents in Distributed Networks.
32. Anbazhagan, K. (2025). Secure AI Enabled Enterprise Ecosystems for Fraud Prevention Compliance Automation and Real Time Analytics. *International Journal of Multidisciplinary Research in Science, Engineering, Technology & Management*, 1(4), 6-13.
33. Soundappan, S. J. (2026). Building Trustworthy AI: Explainability and Security in Modern Cloud-Native Data-Driven Ecosystem Platforms. *International Journal of Engineering & Extended Technologies Research (IJEETR)*, 8(2), 570-579.
34. Sugumar, R. (2025). Cyber-Secure Cloud Architecture Integrating Network and API Controls for Risk-Aware SAP Healthcare Data Platforms. *International Journal of Humanities and Information Technology*, 7(4), 53-60.
35. Vimal, V. R., & Banerjee, J. S. (2025). Integrating PSO, GA, and ACO for Optimized ECG Feature Selection and Classification of Cardiac Disorders. *SGS-Engineering & Sciences*, 1(5).
36. Gopinathan, V. R. (2025). AI-Powered Kubernetes Orchestration for Complex Cloud-Native Workloads. *International Journal of Research Publications in Engineering, Technology and Management (IJRPETM)*, 8(6), 13215-13225.
37. Mathew, A. From Conversation to Command Execution: A Comparative Threat Modeling and Risk Analysis of OpenClaw and ChatGPT. *Risk*, 100(1).
38. Inbavalli, M., & Arasu, T. (2015). Efficient Analysis of Frequent Item Set Association Rule Mining Methods. *International Journal of Scientific & Engineering Research*, 6(4).
39. Sugumar, R. (2025). Secure and Explainable AI Systems in Cloud-Based Applications: Bridging Trust and Performance. *International Journal of Engineering & Extended Technologies Research (IJEETR)*, 7(4), 10328-10335.
40. Rajasekar, M. (2025). Risk-Aware Generative AI and Machine Learning Frameworks for Privacy-Preserving Banking and Trade Analytics over Cloud and 5G Networks. *International Journal of Computer Technology and Electronics Communication*, 8(4), 11078-11086.
41. Gopalakrishnan, S., Dhinakaran, D., Raja, S. E., Raghavan, P., & Girija, M. S. (2026). Fusion-Driven Medical Image Encryption Framework with Entropy-Calibrated Control and Integrity Assurance. *KSII Transactions on Internet & Information Systems*, 20(2).
42. G. Vimal Raja, K. K. Sharma (2014). Analysis and Processing of Climatic data using data mining techniques. *Envirogeochimica Acta 1 (8):460-467*.