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A Lightweight Hybrid System for Crowd Stampede Prediction Using UAV-Based SSIM Analysis and RFID Sensor Fusion

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Abstract - Crowd stampedes continue to be a serious concern during large gatherings, mainly because they occur suddenly and are difficult to foresee. In this project, I worked on developing a simple system that can give an early indication of when such a situation is beginning to form. The approach brings together three kinds of inputs: live aerial footage from a UAV, a few reference images taken from known stampede events, and basic movement information collected through RFID tags worn by people in the crowd. Each incoming video frame is checked against the reference images, and whenever the similarity appears unusually high, the RFID readings are examined to understand how the crowd is behaving at that moment. Using these readings, the system calculates a probability score and then converts it into an entropy value to estimate how stable or unstable the situation is. If the entropy becomes too low or too high, the system triggers a warning by activating a hooter so that the authorities can respond before the situation worsens. By combining very lightweight visual comparison with simple sensor data, the method aims to offer a practical and fast way to detect the early signs of a potential stampede.

Index Terms—Crowd Monitoring, Stampede Prediction, UAV, Drone Surveillance, SSIM, Real-Time Analysis

INTRODUCTION

Large-scale public gatherings such as religious festivals, concerts, sports events, and political rallies often involve high-density crowds, creating serious safety concerns. Among these, crowd stampedes are one of the most critical risks, frequently resulting in injuries and loss of life. These incidents are commonly caused by excessive crowd density, rapid spread of panic, and insufficient monitoring or control systems [1], [2].

When crowd density exceeds a critical threshold, individual movement becomes restricted and the crowd begins to behave like a dynamic system. In such situations, even small disturbances can escalate into dangerous events. The rapid spread of panic, known as emotional contagion, further increases the likelihood of stampedes [4].

Existing crowd monitoring systems, including CCTV surveillance and sensor-based approaches, suffer from limitations such as restricted coverage, lack of flexibility, and delayed response. While computer vision techniques provide high accuracy, they are computationally intensive and not suitable for real-time, low-power applications.

Unmanned Aerial Vehicles (UAVs) provide an effective alternative by offering wide-area coverage, flexible deployment, and real-time aerial monitoring [5], [12]. However, UAV systems are constrained by factors such as limited battery life and computational capacity, making it necessary to develop lightweight solutions.

This work proposes a low-complexity, real-time stampede prediction system that identifies potential risks a few minutes in advance. The approach is based on comparing real-time video frames captured using a UAV with reference frames from previous incidents. To improve reliability, the system integrates both visual data and sensor-based inputs. The goal is to provide early warning alerts while maintaining low computational cost, making the system suitable for real-world deployment.

II. RELATED WORK

Existing stampede detection systems can be broadly categorized into:

TABLE I

COMPARISON OF EXISTING CROWD MONITORING APPROACHES

Approach	Coverage	Real-Time	Cost	Limitations
Computer Vision (CCTV)	Medium/High	Yes	High	High computation, lighting sensitivity
RFID / Sensor-Based	Low	Yes	Medium	No visual context
UAV-Based	High	Yes	Medium	Battery, payload limits
Hybrid Systems	High	Partial	High	Complex, expensive

- **Computer Vision Systems:** Use CCTV and UAVs for crowd analysis but suffer from high

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computational cost and sensitivity to environmental conditions [10].

- **RFID/Sensor-based Systems:** Provide crowd density and movement data but lack visual context and are less reliable when used independently [6].
- **UAV-based Systems:** Offer wide-area coverage and real-time monitoring, but are limited by battery life and computational constraints [12].
- **Hybrid Systems:** Combine multiple techniques for im-proved accuracy but are complex and expensive.

None of these approaches provide a lightweight, real-time solution that integrates multi-source data with a unified proba-bilistic and entropy-based model for early stampede prediction.

Proposed Methodology

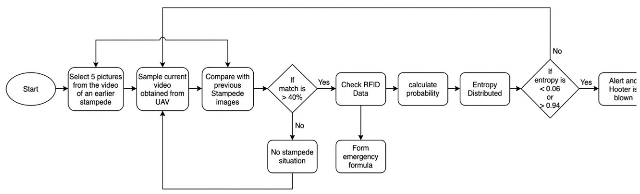
The proposed system is made of the following key elements:

- UAV (Drone) with camera(s)
- Video transmission module
- Ground processing unit (Raspberry Pi)
- Frame processing and analysis module
- Decision and alert module.

The UAV records the real-time video of the crowd and uploads it to the ground system, where it is processed.

UAV-based monitoring is less rigid in terms of space and time, than the traditional systems [5], [12].

A. Methododlogy: Flow Chat



Methodology Flow Chat

B. Parameters Considered

The following parameters are used:

- Density (dt)
- Stability (st)
- Movement Speed (ms)

Given the multi-dimensional nature of stampedes, they cannot be identified by any singular parameters. Consequently, the designed system will incorporate various parameters that collectively represent crowd dynamics.

Parameters used in the design of the system include:

- **Crowd Density (dt):** It describes the population per unit area. It represents the amount of individuals in the crowd and serves as the initial parameter for predicting compression.
- **Pressure (pr):** The parameter shows physical pressure among individuals. Any increase in pressure implies that a dangerous crowd compression exists.
- **Heart Rate (HB):** Heart rate denotes physiological stress. An unusual increase in heart rate implies that there is panic among individuals.
- **Reverse Movement (RM):** The parameter refers to the opposite direction from the main movement in case of danger.
- **Cross Movement (CM):** The intersecting movements in the crowd represent the cross movement parameter.
- **Stability (st):** Stability refers to the level of uniformity in crowd movement.
- **Movement Speed (ms):** It measures speed at which the crowd moves. Rapid changes in speed imply that there is panic.

All these parameters have been normalized to the same scale (0 to 1). This allows them to contribute equally during modeling.

C. Probability Risk Model

A probabilistic risk model is used to aggregate multiple sensors' readings into a single understandable risk value. This model calculates the weighted sum of normalized parameters to produce a compound risk value.

The risk value indicates the probability of encountering hazardous crowd behavior and is computed as the summation of all parameters. The parameters contribute to the risk value in proportion to their weight values.

Assuming that the weights for all parameters are equal because there is no data to calibrate the system with real-world data. Nevertheless, the model supports adaptive weight assignment for future improvements.

This method of calculating risk value helps in computing cumulative risk rather than using fixed threshold values for each individual parameter.

D. Probability Calculation

The system calculates a stampede probability score using multiple parameters:

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$$stp = K \times \frac{dt \cdot (RM \cdot CM)^2 \cdot pr \cdot st^2 \cdot HB}{ms \cdot hv} \quad (1)$$

Where:

dt → density
- RM → reverse movement
- CM → cross movement
- hv → height variation
- pr → pressure
- st → stability
- HB → heart rate deviation
- ms → movement speed

E. Entropy Calculation

Entropy-Based Disorder Assessment:

Although the probability model offers an assessment of risk, it fails to represent the uncertainty or randomness involved in the crowd's actions. For this reason, entropy will be applied as the second parameter to calculate crowd disorder.

Entropy calculates the level of randomness or chaos present within the system. In terms of crowd management:

- The lower the value of entropy, the more ordered or packed the system, which could translate into overcrowd-ing or constricted motion.
- The higher the value of entropy, the more chaotic or random the motion pattern, which is indicative of panic.

Using entropy on top of the computed probability score will help distinguish between a normal crowd, packed crowd, and chaotic crowd.

Entropy is used to measure crowd disorder.

To measure crowd disorder, probability is converted into entropy:

$$E = p \log_2(p) + (1 - p) \log_2(1 - p) \quad (2)$$

- Low entropy → crowd compression risk
- High entropy → chaotic movement (panic)

F. Decision-Making Methodology

The final determination of crowd state is done through the use of entropy thresholds. The decision-making process uses boundary conditions to determine abnormal situations.

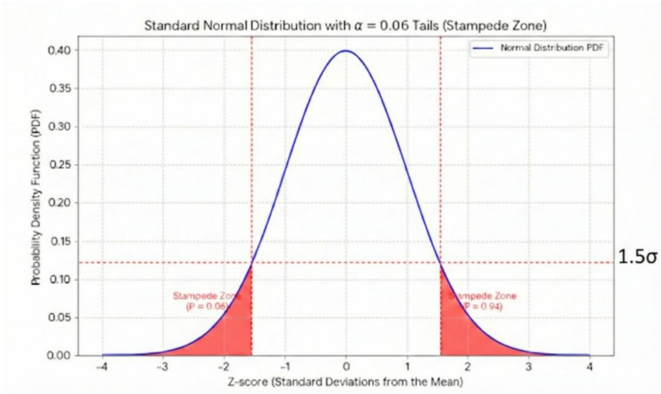
Entropy below a lower threshold means compression, while entropy above an upper threshold means chaos and panic.

In both cases, the system determines the scenario as high risk and issues a warning.

This decision-making process is straightforward, computa-tionally inexpensive, and ideal for real-time applications.

These thresholds have been chosen through empirical sim-ulation and can be adjusted for future research using actual data.

G. Methododlogy: Flow Chat



Risk Analysis graph based on Entropy

- $H < 0.06$ → Alert
- $H > 0.94$ → Alert

H. Crowd Risk Interpretation Using Distribution and Entropy

- **Red Regions (High Risk Zones):**
  - Represent stampede-prone conditions at both ends of the distribution.
- **Right-Side Red Region (High Density Risk):**
  - Extremely high crowd density (e.g., > 5 persons per sq. ft.).
  - Leads to crowd compression, reduced personal space, and pressure build-up.
  - Causes restricted movement and loss of balance.
  - Significantly increases stampede risk due to physical force [2], [10].
- **Left-Side Red Region (Panic and Irregular Move-ment):**
  - Moderate density (3–4 persons per sq. ft.) but chaotic movement.
  - Includes reverse and cross movement due to panic.
  - Causes collisions, imbalance, and sudden directional changes.
  - Increases stampede probability even at lower densi-ties [3], [4].

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- **Central White Region (Safe Zone):**
  – Represents normal crowd behavior.
  – Smooth and coordinated movement with safe density.
  – Minimal probability of stampede occurrence.
- **Entropy-Based Integration:**
  – Entropy measures crowd disorder.
  – Low entropy → organized movement (compression risk).
  – High entropy → chaotic movement (panic).
  – Combined with SSIM, improves detection reliability.
  – Helps capture both density and behavior-based risks [1], [7].
- **Conclusion:**
  – System uses statistical distribution + entropy analy-sis.
  – Enables accurate classification of crowd risk levels.

I. Proposed System Architecture

The proposed system is designed as a UAV-based real-time crowd monitoring framework for early stampede prediction. It integrates aerial surveillance, lightweight image processing, and efficient data transmission to ensure fast and reliable detection of abnormal crowd behavior.

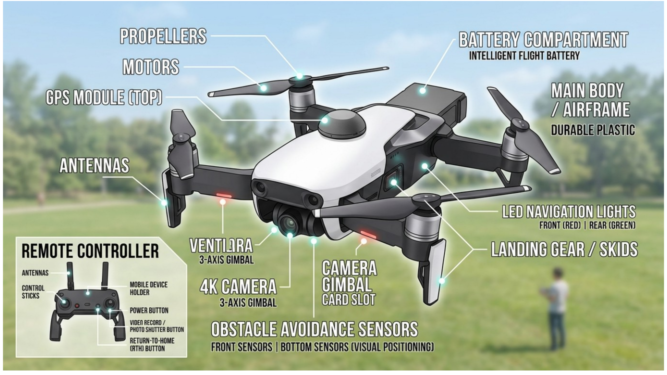
A. Overview of the System

The system consists of a UAV (drone) equipped with a camera, a wireless transmission module, and a ground-based processing unit. The UAV captures real-time aerial video of the crowd and transmits it to the ground system for further analysis. The overall architecture ensures flexibility, mobility, and efficient monitoring compared to traditional CCTV-based systems [11], [12], [17], [18].

B. System Components

1) UAV Platform: The UAV serves as the primary data acquisition unit. It operates without an onboard human pilot and can be remotely controlled or function autonomously using onboard sensors and navigation systems [14], [17]. It consists of:

- Frame for structural support
- Motors and propellers for lift and movement
- Flight controller for stabilization and control
- Electronic Speed Controllers (ESCs) for motor regulation
- Battery for power supply
- Camera module for aerial video capture
- GPS module for positioning and navigation
- Communication system for data transmission



Drone Parts

2) Aerial Imaging System: The UAV is equipped with a high-resolution camera that captures continuous real-time video of the crowd. This aerial perspective enables accurate observation of crowd density and movement patterns, which are essential for early risk detection [13].

3) Wireless Communication Module: The captured video is transmitted to the ground processing unit using wireless communication. This reduces onboard computational load and allows efficient processing using external devices such as Raspberry Pi [18].

4) Ground Processing Unit: The ground system performs frame processing and analysis using lightweight techniques. Image similarity methods such as Structural Similarity Index (SSIM) are applied to detect abnormal crowd patterns [13], [15].

C. Operational Workflow

The working of the system is summarized as follows:

- UAV captures real-time aerial video of the crowd.
  - Video is transmitted wirelessly to the ground unit.
  - Frames are extracted and processed using lightweight methods.
  - SSIM-based comparison is used to identify abnormal crowd behavior.
  - If risk is detected, alerts are generated for authorities.

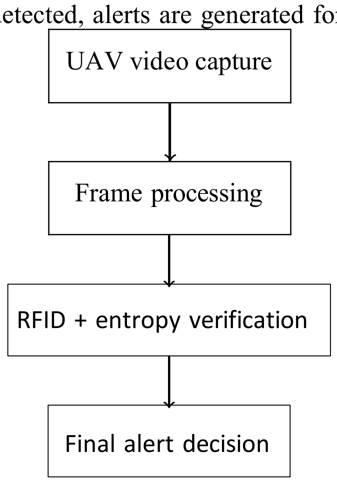


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Fig. 1.

D. Design Considerations

The system is designed with the following constraints:

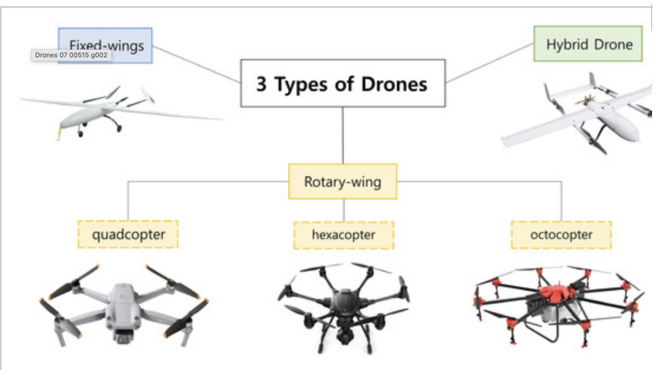
- Real-time processing requirement
- Low computational power (Raspberry Pi)
- Minimal latency
- Scalability for large crowd environments

To satisfy these constraints, lightweight algorithms are preferred over computationally intensive deep learning mod-els [9], [15].

E. Selection of UAV Type

Among different UAV types, rotary-wing UAVs (multi-rotor drones such as quadcopters) are selected for this system. Their ability to hover, maintain stable flight, and operate at low alti-tudes makes them ideal for continuous crowd monitoring [12].

Unlike fixed-wing UAVs, quadcopters can remain stationary in the air, enabling consistent frame capture. Their stability also improves the accuracy of image processing techniques such as SSIM [13],[15].



Different types of drones

F. System Advantages

The proposed UAV-based architecture provides:

- Wide-area coverage compared to CCTV systems
- Dynamic repositioning for better monitoring
- Real-time data acquisition and analysis
- Reduced infrastructure dependency
- Cost-effective and flexible deployment

G. Future Enhancement

A dual-camera system can be integrated into the UAV to further improve monitoring performance. This enables multi-view capture of the same region, improving detection accuracy and reducing blind spots.

- Top-view camera for density estimation
- Angled camera for movement analysis
- Improved robustness in dynamic environments

This enhancement increases system reliability, although it may introduce additional complexity and power consumption.

II. Experimental Setup

A. Objective

This section describes the experimental setup used to evalu-ate the feasibility of the proposed hybrid stampede prediction system. Due to the impracticality of collecting real-world stampede data, the system is tested using simulated video streams and synthetically generated RFID-based crowd param-eters.

The objective is to analyze the system's ability to detect early signs of crowd congestion and predict stampede risk under varying conditions.

B. System Configuration

The proposed system consists of two main components:

- **UAV-Based Video Acquisition:** A drone is used to cap-ture real-time aerial video of crowd scenarios. The UAV transmits the video feed to a ground-based processing unit.
- **Ground Processing Unit:** A Raspberry Pi is used to process incoming video frames and perform analysis using lightweight algorithms.

The UAV performs only video capture, while all compu-tational tasks are executed on the ground system to reduce payload and power consumption.

C. Frame Processing Configuration

The video stream is processed using the following configu-ration:

- Frame extraction rate: approximately 10 FPS
- Processing strategy: every 3rd frame is selected
- Frame comparison: consecutive frames are compared
- Similarity metric: Structural Similarity Index (SSIM)

This setup reduces computational load while maintaining sufficient temporal information for crowd behavior analysis.

D. RFID Data Simulation

Since real RFID deployment is not implemented in the current stage, synthetic data is generated to simulate crowd parameters.

Details of simulation:

- Number of samples: approximately 1000
- Each sample represents a crowd state
- Parameters generated:
  – Crowd density
  – Movement patterns
  – Stability

– Directional variations

The generated values are designed to mimic realistic crowd conditions under different scenarios.

E. Scenario Development

Two primary scenarios are defined for evaluation:

1. Normal Scenario

- Moderate density
- Continuous movement
- Stable crowd behavior

2. Risk Scenario

- High density
- Reduced movement (high similarity between frames)
- Irregular or unstable motion patterns

These scenarios help validate the system's ability to distin-guish between safe and critical conditions.

F. Data Preprocessing

Before analysis, the data undergoes preprocessing:

- Normalization of RFID parameters to a range of 0 to 1
- Frame resizing and grayscale conversion for SSIM com-putation
- Noise reduction using basic filtering techniques

This ensures consistency and improves reliability of the results.

G. Evaluation Methodology

The system performance is evaluated based on its ability to:

- Detect reduction in crowd movement using SSIM
- Accurately compute Stampede Probability (STP)
- Identify disorder using entropy measures
- Generate timely alerts for high-risk conditions A comparison is made between:
- Vision-only analysis (SSIM-based detection)
- Hybrid approach (SSIM + RFID data fusion)

H. Testing Procedure

The simulated dataset is passed through the complete pro-cessing pipeline:

- Video frames are analyzed using SSIM
- Threshold-based trigger activates RFID analysis
- STP is computed using fused inputs
- Entropy is calculated to assess disorder
- Final risk classification is generated The outputs are analyzed for:
- Accuracy in identifying abnormal crowd behavior
- Sensitivity to changes in crowd conditions
- Stability and consistency of predictions

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III. Results and Discussion

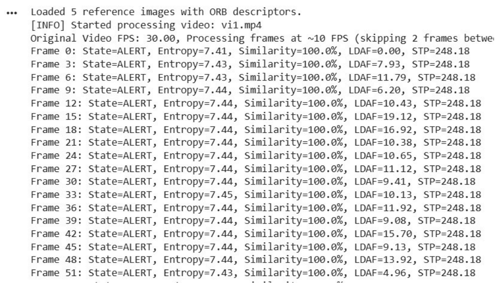
The proposed system was evaluated using video-based simulation and lightweight processing techniques. The system analyzes crowd behavior using key metrics such as entropy, similarity score, and stampede probability (STP).

A. System Output Summary

The system processes input video frames and computes the following:

- Entropy (~ 7.4): Indicates rigid and synchronized crowd movement
- Similarity (100%): Frames closely match high-risk refer-ence patterns
- STP Score (~ 248): Represents high combined density and pressure risk
- Final Classification: **ALERT**

These results indicate that the system successfully identi-fies dangerous crowd conditions using combined visual and statistical analysis.



```
Loaded 5 reference images with ORB descriptors.
[INFO] Started processing video: vi1.mp4
Original Video FPS: 30.00, Processing frames at ~10 FPS (skipping 2 frames betwe
Frame 0: State=ALERT, Entropy=7.41, Similarity=100.0%, LDAF=0.00, STP=248.18
Frame 3: State=ALERT, Entropy=7.43, Similarity=100.0%, LDAF=7.93, STP=248.18
Frame 6: State=ALERT, Entropy=7.43, Similarity=100.0%, LDAF=11.79, STP=248.18
Frame 9: State=ALERT, Entropy=7.44, Similarity=100.0%, LDAF=6.20, STP=248.18
Frame 12: State=ALERT, Entropy=7.44, Similarity=100.0%, LDAF=10.43, STP=248.18
Frame 15: State=ALERT, Entropy=7.44, Similarity=100.0%, LDAF=19.12, STP=248.18
Frame 18: State=ALERT, Entropy=7.44, Similarity=100.0%, LDAF=16.92, STP=248.18
Frame 21: State=ALERT, Entropy=7.44, Similarity=100.0%, LDAF=10.38, STP=248.18
Frame 24: State=ALERT, Entropy=7.44, Similarity=100.0%, LDAF=10.65, STP=248.18
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Frame 30: State=ALERT, Entropy=7.44, Similarity=100.0%, LDAF=9.41, STP=248.18
Frame 33: State=ALERT, Entropy=7.45, Similarity=100.0%, LDAF=10.13, STP=248.18
Frame 36: State=ALERT, Entropy=7.44, Similarity=100.0%, LDAF=11.92, STP=248.18
Frame 39: State=ALERT, Entropy=7.44, Similarity=100.0%, LDAF=9.08, STP=248.18
Frame 42: State=ALERT, Entropy=7.44, Similarity=100.0%, LDAF=15.70, STP=248.18
Frame 45: State=ALERT, Entropy=7.44, Similarity=100.0%, LDAF=9.13, STP=248.18
Frame 48: State=ALERT, Entropy=7.44, Similarity=100.0%, LDAF=13.92, STP=248.18
Frame 51: State=ALERT, Entropy=7.43, Similarity=100.0%, LDAF=4.96, STP=248.18
```

Fig. 2. Sample system output showing entropy, similarity, and alert classifi-cation

B. Observations

The following observations were made during system eval-uation:

- Consistent **ALERT** classification indicates accurate de-tection of high-density crowd conditions
- Low entropy combined with high similarity strongly correlates with stampede-like situations
- The detection pipeline remains stable across consecutive frames

C. Discussion

The results demonstrate that the integration of entropy, sim-ilarity analysis, and probabilistic modeling provides a reliable mechanism for detecting potential stampede conditions.

Low entropy values indicate synchronized and compressed crowd movement, while high similarity values confirm min-imal variation between frames, both of which are critical

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Fig. 3. High similarity between consecutive frames indicating reduced crowd movement

indicators of crowd congestion. The high STP score further strengthens the detection by incorporating multiple parameters such as density, pressure, and movement.

The system performs efficiently on low-cost hardware such as Raspberry Pi, making it suitable for real-time deployment. The use of lightweight computation ensures minimal latency while maintaining reliable detection performance.

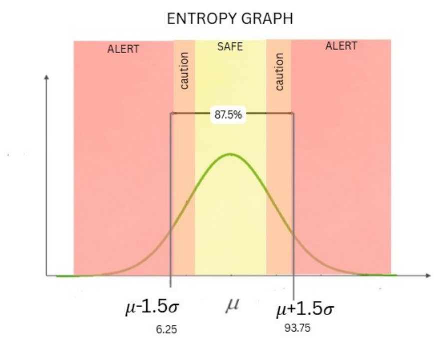

Fig. 4. Risk classification based on entropy and probability thresholds

Overall, the experimental results validate that the proposed system can effectively detect high-risk crowd scenarios and generate early alerts, making it suitable for real-world stampede prevention applications.

IV. Limitations

The proposed system has certain practical limitations. UAVs have limited flight time, making continuous monitoring difficult. Performance is affected by weather conditions such as wind, rain, and fog. Communication links may become unstable in crowded environments. The system also depends on video quality, which can reduce accuracy under poor lighting or occlusions. Additionally, real-world validation is required, as the current evaluation is primarily simulation-based.

V. Conclusion

This paper presents a lightweight and efficient UAV-based system for early stampede prediction and prevention. The proposed approach combines frame similarity analysis using SSIM with a probabilistic and entropy-based model to evaluate crowd conditions in real time. By integrating visual data from UAVs with sensor-based inputs, the system is able to detect abnormal crowd behavior and generate timely alerts.

The use of low-complexity algorithms makes the system suitable for deployment on edge devices such as Raspberry Pi, ensuring cost-effectiveness and real-time performance. Experimental results demonstrate that the system can reliably identify high-risk crowd scenarios based on similarity, probability, and entropy measures.

Overall, the proposed solution provides a practical and scalable approach for improving crowd safety and reducing the risk of stampede incidents in large public gatherings.

VI. Future Scope

Although the proposed system demonstrates effective early detection of stampede conditions, several improvements can be made to enhance its real-world applicability and performance.

- **Multi-UAV Coordination:** Future work can include the use of multiple drones operating collaboratively to cover larger areas and eliminate blind spots in crowd monitor-ing.
- **Deep Learning Integration:** Advanced deep learning models such as YOLO or LSTM can be incorporated to improve accuracy in detecting complex crowd behaviors and predicting future movement patterns.
- **Improved Battery and Flight Time:** Enhancing UAV battery capacity or implementing drone-swapping mech-anisms can support long-duration and continuous moni-toring.
- **Edge AI Optimization:** Further optimization of algo-rithms for edge devices like Raspberry Pi can reduce latency and improve real-time processing efficiency.
- **Smart City Integration:** The system can be integrated with smart city infrastructure, enabling automatic alerts to control rooms, emergency services, and public announce-ment systems.
- **Automated Crowd Control Mechanisms:** Future sys-tems can trigger automated responses such as sirens, digital signboards, and guided evacuation routes based on detected risk levels.
- **Enhanced Sensor Fusion:** Incorporating additional sen-sors such as thermal cameras, LiDAR, or wearable IoT devices can improve accuracy and robustness.
- **Real-World Dataset Validation:** Testing the system on real-world datasets and live deployments will improve reliability and allow fine-tuning of thresholds and param-eters.

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