CROWDLENS: AI-BASED REAL-TIME CROWD BEHAVIOUR ANALYSER

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Introduction:

1. In today's fast-paced world, managing and analysing crowd behaviour is essential for ensuring public safety and effective event management. Large gatherings such as concerts, sports events, and political rallies often exhibit unpredictable human behaviour that may lead to accidents or stampedes. Traditional surveillance systems rely heavily on manual monitoring, which is time-consuming and prone to human error. Advancements in Artificial Intelligence and computer vision have enabled the development of automated systems capable of analysing crowd movements in real time. These systems can detect unusual patterns and provide alerts to authorities.
2. This project proposes an AI-based real-time crowd behaviour analyser that leverages deep learning techniques to process live video feeds. It identifies anomalies such as congestion, sudden dispersal, or aggressive movements.
3. The system aims to enhance public safety by improving response time and reducing dependency on manual monitoring. This makes it highly relevant for urban environments, event management, and security operations.

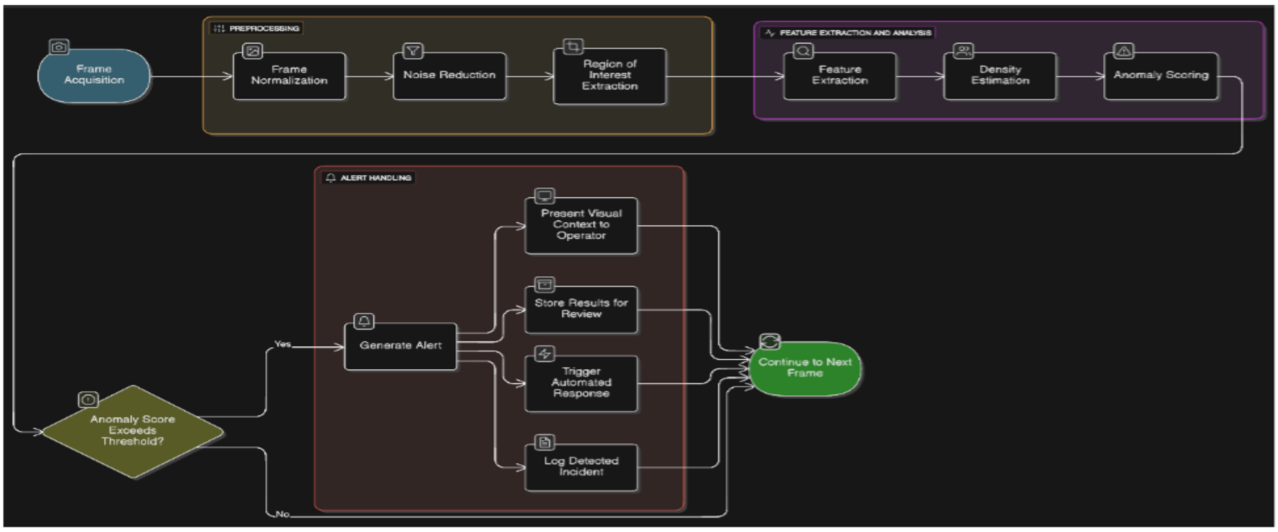

Figure 1: Overall architecture of CrowdLens

Objectives:

1. To develop an AI-powered system for real-time crowd behaviour analysis
2. To detect abnormal crowd patterns using machine learning algorithms
3. To provide instant alerts to authorities during suspicious activities
4. To reduce dependency on manual surveillance systems
5. To improve public safety and crowd management efficiency

Methodology:

1. The project uses a combination of computer vision and deep learning techniques to analyze crowd behaviour. Convolutional Neural Networks (CNNs) are used for feature extraction from video frames, while Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models capture temporal patterns in crowd movement.
2. The system is trained using datasets such as UCF-CROWD, ShanghaiTech, and Mall datasets, along with simulated and real-world surveillance data. Preprocessing steps include background subtraction, normalization, and data augmentation to improve model performance.
3. Anomaly detection is performed using Autoencoders and Generative Adversarial Networks (GANs), which identify deviations from normal behaviour patterns. The model assigns confidence scores to detected activities and triggers alerts when abnormal behaviour is identified.
4. The system is integrated into a real-time monitoring framework that processes live video feeds. Performance is evaluated using metrics such as precision, recall, and F1-score.
5. Additionally, an interactive dashboard is developed for visualization and monitoring by security personnel.

Result and Conclusion:

1. The system is expected to successfully detect crowd anomalies in real time with high accuracy. It can identify behaviors such as overcrowding, panic movement, and sudden dispersal.
2. The developed model demonstrates improved efficiency compared to traditional surveillance methods. It reduces response time by providing instant alerts to authorities.
3. The integration of deep learning techniques ensures adaptability to different environments and crowd densities. The system also improves over time through continuous learning.
4. Overall, the project proves that AI-based crowd monitoring systems can significantly enhance public safety and decision-making in real-world scenarios.

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Future Scope:

The future scope of this project includes:

1. Improving model accuracy using transformer-based architectures. The system can be extended with facial recognition and individual tracking for enhanced surveillance.
2. It can also be deployed on edge devices for faster processing and integrated with IoT systems in smart cities.
3. Expanding datasets for diverse environments, reducing computational complexity, and applying the system in areas such as traffic monitoring and disaster management.