

AI-DRIVEN METHODS FOR REAL-TIME MONITORING OF CROWD CONGESTION AND ABNORMAL ACTIVITIES IN PUBLIC SPACES

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Abstract:

The rapid growth of urban populations and the increasing use of public spaces have intensified the need for effective crowd monitoring and security management systems. This study investigates artificial intelligence (AI)–driven methods for real-time monitoring of crowd congestion and detection of abnormal activities in public spaces. The proposed approach integrates computer vision, deep learning, and behavioral analysis techniques to process video surveillance data and extract meaningful spatiotemporal patterns. Crowd density estimation and flow analysis are employed to identify congestion zones, while anomaly detection models are used to recognize unusual movement patterns and suspicious behaviors. Experimental evaluations demonstrate that AI-based methods significantly improve detection accuracy, responsiveness, and scalability compared to traditional surveillance systems. The findings highlight the potential of AI-driven solutions to enhance public safety, support proactive decision-making, and optimize crowd management in complex urban environments.

Keywords: artificial intelligence, crowd congestion, abnormal activity detection, real-time monitoring, computer vision, deep learning, public safety

Introduction

Rapid urbanization and population growth have led to increased congestion in public spaces such as transportation hubs, shopping centers, stadiums, and city squares. High crowd density and uncontrolled movement can result in safety risks, including stampedes, accidents, and the spread of panic during emergencies. In parallel, the presence of abnormal or suspicious activities in crowded environments poses serious challenges for public security authorities. Traditional surveillance systems, which rely heavily on manual monitoring, are often inefficient, error-prone,

and incapable of providing timely responses in complex and dynamic crowd scenarios.

Recent advances in artificial intelligence (AI), particularly in computer vision and deep learning, have opened new opportunities for intelligent crowd monitoring. AI-driven systems can automatically analyze large volumes of video data in real time, enabling the detection of crowd congestion, abnormal behavior, and potential threats with higher accuracy and speed. These systems aim to shift surveillance from passive observation to proactive risk prevention.

Crowd analysis involves several interrelated tasks, including crowd density estimation, flow analysis, object tracking, and behavior recognition. Detecting abnormal activities requires understanding typical movement patterns and identifying deviations that may indicate unsafe or suspicious behavior. However, challenges such as occlusion, varying illumination, complex backgrounds, and real-time processing constraints continue to limit system performance.

This study focuses on AI-driven methods for real-time monitoring of crowd congestion and abnormal activities in public spaces. By integrating deep learning–based visual perception with behavioral and spatiotemporal analysis, the proposed approach aims to improve detection accuracy, scalability, and responsiveness. The research contributes to the development of intelligent surveillance systems that enhance public safety and support decision-making in smart city environments.

Materials and Methods

Data Collection and Preprocessing

The study utilizes video data captured from fixed surveillance cameras installed in public spaces, including transport terminals and open urban areas. The video streams are recorded at standard frame rates and resolutions suitable for real-time analysis. Preprocessing steps include frame normalization, background subtraction, noise reduction, and resizing to ensure computational efficiency.

Crowd Density Estimation

Crowd congestion is analyzed using convolutional neural networks (CNNs) trained for density estimation. The models generate density maps that represent the spatial distribution of individuals within each frame. These maps are used to identify high-density zones and monitor temporal changes in crowd concentration.

Object Detection and Tracking

Real-time object detection is performed using deep learning-based detectors such as YOLO or similar single-shot architectures. Detected individuals are tracked across frames using multi-object tracking algorithms, allowing the extraction of trajectories and movement patterns. Tracking data provide essential input for flow analysis and behavior modeling.

Abnormal Activity Detection

Abnormal behavior detection is implemented through a combination of trajectory analysis and anomaly detection models. Normal crowd behavior is learned from historical data using unsupervised or semi-supervised learning techniques. Deviations from learned patterns—such as sudden direction changes, unusual speed, or erratic motion—are classified as anomalies.

System Evaluation

The performance of the proposed system is evaluated using metrics such as detection accuracy, precision, recall, and processing speed (frames per second). Comparative experiments are conducted against conventional rule-based surveillance methods to assess improvements in efficiency and reliability.

Results and Discussion

The experimental results demonstrate that AI-driven methods significantly enhance real-time crowd monitoring capabilities. Crowd density estimation models accurately identified congestion zones, enabling early detection of potentially hazardous conditions. Compared to traditional counting-based approaches, the deep learning models showed higher robustness in densely populated and partially occluded scenes.

Object tracking results indicate stable trajectory extraction even in moderately crowded environments. The integration of trajectory data with anomaly detection models allowed effective identification of abnormal activities, including sudden crowd dispersion, unusual movement patterns, and isolated suspicious behaviors.

Quantitative evaluation shows notable improvements in detection accuracy and response time. The system maintained real-time performance, processing video streams at acceptable frame rates for practical deployment. These results confirm that AI-driven surveillance systems can outperform manual and rule-based approaches, particularly in complex and dynamic public spaces.

Despite the promising outcomes, challenges remain. High-density crowds with severe occlusion can reduce tracking accuracy, and ethical concerns related to privacy and data protection must be addressed. Future improvements may involve multi-camera fusion, edge computing, and privacy-preserving AI techniques.

Conclusion

This study presented AI-driven methods for real-time monitoring of crowd congestion and abnormal activities in public spaces. By combining deep learning-based computer vision, object tracking, and behavioral analysis, the proposed approach effectively addresses key limitations of traditional surveillance systems. Experimental results confirm that AI-based solutions improve detection accuracy, scalability, and responsiveness, contributing to enhanced public safety and proactive crowd management.

The findings highlight the potential of artificial intelligence as a core component of intelligent surveillance and smart city infrastructures. Future research will focus on improving robustness in highly congested environments, integrating multi-modal data sources, and ensuring ethical and privacy-compliant deployment. Overall, AI-driven crowd monitoring systems represent a critical step toward safer and more resilient urban environments.

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