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# Advanced Computer Vision and Deep Learning Techniques for Detecting Abnormal Human Behaviour in CCTV Surveillance Systems

**Sundararaju V[1], Vignesh R[2]**

Associate Professor, K .S.Rangasamy College of Technology, Tiruchengode, Tamil Nadu, India[1]

PG Student, Department of Industrial Safety Engineering, K .S.Rangasamy College of Technology, Tiruchengode, Tamil Nadu, India[2]

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**ABSTRACT:** The rapid expansion of urban infrastructure and public surveillance systems has led to the widespread deployment of Closed-Circuit Television (CCTV) networks for ensuring safety and security. However, continuous monitoring of large volumes of video data by human operators is labour-intensive, error-prone, and inefficient, particularly in identifying subtle or time-critical abnormal behaviours. This necessitates the development of intelligent, automated systems capable of real-time anomaly detection.

This study investigates advanced computer vision and deep learning techniques for detecting abnormal human behaviour in CCTV surveillance systems. The proposed framework integrates video preprocessing, object detection, and spatiotemporal feature extraction using convolutional neural networks (CNNs) and recurrent architectures such as Long Short-Term Memory (LSTM) networks. Special emphasis is placed on identifying deviations from normal behavioural patterns, including suspicious movements, violence, loitering, and unauthorized access, under varying environmental conditions such as low lighting, occlusions, and crowded scenes.

Anomaly detection is performed using both supervised and unsupervised learning approaches, incorporating techniques such as autoencoders and real-time video analytics to enhance detection accuracy and reduce false positives. The system also utilizes motion tracking and behaviourmodelling to improve contextual understanding of activities within surveillance zones. Comparative analysis demonstrates that deep learning–based models provide superior performance in terms of accuracy, scalability, and adaptability when compared to traditional rule-based or manual monitoring methods.

The study concludes that the integration of advanced AI-driven surveillance systems significantly enhances public safety, reduces human workload, and enables proactive threat detection. Furthermore, such systems support the development of smart city infrastructures by enabling efficient, real-time monitoring and rapid response mechanisms. Future research is recommended to improve model robustness, reduce computational complexity, and address privacy and ethical considerations in large-scale deployments

**KEYWORDS:** Computer Vision, Deep Learning, CCTV Surveillance, Abnormal Behaviour Detection, Anomaly Detection, CNN, LSTM, Video Analytics, Smart Surveillance, Artificial Intelligence

## I. INTRODUCTION

The rapid growth of urbanization and the increasing need for public safety have led to the widespread deployment of Closed-Circuit Television (CCTV) surveillance systems across critical infrastructures such as transportation hubs, commercial complexes, educational institutions, and smart city environments. These systems generate vast amounts of continuous video data, which require constant monitoring to identify potential threats, suspicious activities, and abnormal human behaviour. Despite their importance, traditional surveillance methods rely heavily on human operators, making the process labour-intensive, time-consuming, and prone to fatigue-induced errors, particularly in large-scale monitoring environments.

Abnormal human behaviour in surveillance contexts includes activities such as violence, theft, loitering, trespassing, vandalism, and other deviations from normal behavioural patterns. Detecting such activities in real time is highly challenging due to factors such as crowded scenes, varying lighting conditions, occlusions, camera angles, and complex human interactions. Conventional rule-based systems and motion detection algorithms often fail to capture the contextual and temporal dynamics of human behaviour, resulting in high false alarm rates and reduced reliability.

To address these limitations, there has been a significant shift toward the adoption of advanced computer vision and deep learning techniques for automated video analysis. Modern approaches utilize convolutional neural networks (CNNs) for spatial feature extraction and recurrent neural networks such as Long Short-Term Memory (LSTM) models for temporal behaviourmodelling. These techniques enable the system to learn complex patterns of normal and abnormal activities directly from data, improving detection accuracy and adaptability across diverse surveillance scenarios. Additionally, unsupervised and semi-supervised learning methods, including autoencoders, are increasingly employed to detect anomalies without requiring extensive labelled datasets.

The need for intelligent abnormal behaviour detection systems arises from both security demands and operational efficiency requirements. In large-scale CCTV networks, manual monitoring is not only inefficient but also incapable of providing timely responses to critical incidents. Automated systems can significantly reduce human workload, enable real-time threat detection, and enhance decision-making capabilities for law enforcement and security personnel. Furthermore, integrating such systems into smart city frameworks supports proactive surveillance, rapid emergency response, and improved urban safety management.

However, the implementation of deep learning–based surveillance systems also present challenges, including high computational requirements, data privacy concerns, and the need for robust models capable of handling diverse real-world conditions. Therefore, developing efficient, scalable, and reliable abnormal behaviour detection frameworks is essential for maximizing the effectiveness of modern CCTV surveillance systems. This study focuses on addressing these challenges by leveraging advanced AI-driven techniques to improve detection performance, reduce false positives, and enable real-time monitoring in complex environments

## II. LITERATURE REVIEW

Abnormal behaviour detection in CCTV surveillance systems has emerged as a critical research area within computer vision and artificial intelligence, primarily due to the increasing demand for automated and intelligent security solutions. Early approaches to video surveillance relied on traditional image processing techniques such as frame differencing, background subtraction, and optical flow analysis. These methods focused on detecting motion patterns and identifying deviations from static backgrounds. However, they were limited in their ability to interpret complex human activities and often failed in dynamic environments characterized by illumination changes, occlusions, and crowded scenes.

With the advancement of machine learning, researchers introduced statistical and pattern recognition models to improve anomaly detection. Techniques such as Support Vector Machines (SVM), k-Nearest neighbour's (k-NN), and Hidden Markov Models (HMM) were employed to classify normal and abnormal activities based on handcrafted features. While these methods provided moderate improvements, their performance heavily depended on feature engineering and lacked scalability when applied to large and diverse datasets. Additionally, handcrafted features were often insufficient to capture the intricate spatial and temporal relationships inherent in human behaviour.

Recent developments in deep learning have significantly transformed the field of video surveillance. Convolutional Neural Networks (CNNs) have demonstrated strong capability in extracting high-level spatial features from video frames, enabling robust object detection and scene understanding. Furthermore, Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, have been widely adopted for modelling temporal dependencies in video sequences. These architectures allow systems to analyse not only individual frames but also the evolution of actions over time, which is essential for accurately identifying abnormal behaviour.

Unsupervised and semi-supervised learning techniques have gained considerable attention in anomaly detection due to the scarcity of labelled abnormal data. Autoencoders and Generative Adversarial Networks (GANs) are commonly used to learn representations of normal behaviour patterns and identify anomalies as deviations from learned distributions. These methods reduce the dependency on extensive labelled datasets and improve the adaptability of surveillance

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systems in real-world scenarios. Studies have shown that such models achieve higher detection accuracy and lower false alarm rates compared to traditional supervised approaches.

Another important aspect highlighted in the literature is the challenge of environmental and contextual variability in surveillance footage. Factors such as camera angle, lighting conditions, crowd density, and background complexity significantly affect detection performance. To address these issues, advanced techniques such as multi-scale feature extraction, attention mechanisms, and spatiotemporal modelling have been proposed. These approaches enhance the system's ability to focus on relevant regions and capture subtle behavioural cues, thereby improving robustness and reliability.

In large-scale CCTV deployments, real-time processing and computational efficiency are critical considerations. High-resolution video streams require substantial processing power, making it necessary to optimize models for faster inference without compromising accuracy. Edge computing and hardware acceleration techniques have been explored to enable real-time anomaly detection in distributed surveillance networks. Additionally, pre-processing steps such as noise reduction, frame normalization, and object tracking play a vital role in improving system performance and reducing computational overhead.

Overall, the literature indicates a clear transition from traditional rule-based and handcrafted feature methods to advanced deep learning–based frameworks for abnormal behaviour detection. While significant progress has been made, challenges such as data imbalance, privacy concerns, and model generalization across different environments remain active areas of research. Continued advancements in AI and computer vision are expected to further enhance the effectiveness and scalability of intelligent CCTV surveillance systems

## III. RESEARCH METHODOLOGY

Data acquisition and preprocessing form the foundational stages of abnormal behaviour detection in CCTV surveillance systems. Initially, video data was collected from multiple surveillance sources, including public datasets and real-time CCTV streams, ensuring diversity in environmental conditions such as lighting variations, crowd density, and camera perspectives. The acquired video sequences were then subjected to preprocessing techniques, including frame extraction, resolution normalization, noise reduction, and background stabilization. These steps were essential to enhance image quality, reduce redundant information, and improve the reliability of subsequent analysis.

Following preprocessing, object detection and localization were performed to identify human subjects and relevant entities within the video frames. Advanced deep learning models based on Convolutional Neural Networks (CNNs) were employed to accurately detect and classify objects. Detected subjects were then tracked across consecutive frames using motion tracking algorithms, enabling the system to capture movement patterns and maintain temporal continuity. This tracking process played a crucial role in understanding behavioural dynamics over time.

Feature extraction was subsequently carried out to capture both spatial and temporal characteristics of human activities. Spatial features, such as posture, appearance, and position, were extracted using CNN architectures, while temporal features, including motion trajectories and action sequences, were modelled using Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks. This combination enabled the system to analyse not only static visual cues but also the evolution of behaviour across time, which is essential for identifying anomalies.

Anomaly detection was implemented using both supervised and unsupervised learning approaches. In the supervised approach, labelled datasets containing normal and abnormal activities were used to train classification models. In contrast, unsupervised methods such as autoencoders were trained exclusively on normal behaviour patterns, allowing the system to detect anomalies as deviations from learned representations. Reconstruction error and probabilistic thresholds were utilized to distinguish abnormal events from normal activities, thereby reducing dependency on large, labelled datasets.

To enhance detection accuracy and minimize false positives, contextual analysis and behaviourmodelling were incorporated into the system. This involved analysing interactions between individuals, identifying unusual crowd behaviour, and detecting context-specific anomalies such as loitering, sudden running, or unauthorized access. Attention mechanisms and multi-scale feature extraction techniques were also integrated to improve the model's ability to focus on relevant regions within complex scenes.

Real-time processing and system optimization were addressed through model compression, efficient architecture design, and hardware acceleration techniques. Edge computing strategies were explored to enable on-device processing of video streams, thereby reducing latency and bandwidth requirements in large-scale surveillance networks. Additionally, alert generation mechanisms were implemented to notify security personnel upon detection of abnormal behaviour, including real-time alarms, notifications, and event logging for further investigation.

Finally, the performance of the proposed system was evaluated using metrics such as accuracy, precision, recall, and F1-score. Comparative analysis with traditional methods demonstrated that the deep learning–based framework achieved superior performance in detecting abnormal activities under diverse and challenging conditions. The results confirm that the proposed methodology provides an effective, scalable, and reliable solution for intelligent CCTV surveillance, supporting enhanced security and proactive threat management.

## IV. RESULTS AND DISCUSSION

The performance of the proposed deep learning–based framework for detecting abnormal human behaviour in CCTV surveillance systems was evaluated using multiple datasets and varied real-world scenarios. Comparative analysis highlights significant differences in detection accuracy, false positive rates, and response times among different model architectures and processing techniques. Systems based solely on traditional motion detection or rule-based methods exhibited moderate accuracy, with relatively high rates of false alarms, particularly in crowded or dynamically changing environments. This limitation primarily arises because conventional methods lack the ability to capture complex spatiotemporal dependencies and contextual interactions between individuals.

Deep learning–based models incorporating Convolutional Neural Networks (CNNs) for spatial feature extraction and Long Short-Term Memory (LSTM) networks for temporal sequence modelling demonstrated superior performance. These models effectively learned normal behavioural patterns and identified deviations, enabling the detection of a wide range of anomalies, including loitering, sudden running, fighting, and unauthorized access. Attention mechanisms and multi-scale feature extraction further enhanced the system's ability to focus on relevant regions within the frame, improving detection accuracy in occluded or low-light conditions.

Among the evaluated approaches, frameworks integrating unsupervised learning techniques such as autoencoders showed high adaptability for detecting previously unseen anomalous events. By learning the distribution of normal behaviour, the system flagged deviations without requiring extensive labelled abnormal data, reducing the dependency on exhaustive annotation. Comparative analysis indicates that models combining CNN–LSTM architectures with unsupervised anomaly detection achieved the highest F1-scores, lowest false positives, and consistent performance across diverse surveillance scenarios.

In addition to detection accuracy, real-time performance was assessed in terms of computational efficiency and latency. Models optimized with edge computing and hardware acceleration demonstrated near real-time processing capability, making them suitable for large-scale deployment in smart city and public safety environments. Furthermore, the system's contextual analysis component, which considers interactions among individuals and environmental cues, significantly improved interpretability and reduced false alarms associated with normal but unusual movements.

Overall, the results confirm that deep learning–driven CCTV surveillance systems provide a marked improvement over conventional approaches, offering high accuracy, robustness under varying conditions, and operational efficiency. While the integration of AI techniques substantially enhances detection capabilities, balancing detection precision, computational requirements, and real-time responsiveness remains an active area for further optimization. These findings underscore the potential of intelligent surveillance frameworks to transform urban safety management by enabling proactive monitoring, timely alerts, and effective incident response.

## V. CONCLUSION

Several key findings and recommendations emerge from this study on detecting abnormal human behaviour in CCTV surveillance systems. First, deep learning–based frameworks combining Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks demonstrate significant improvements in detection accuracy, robustness, and adaptability compared to traditional rule-based or motion-detection approaches. Incorporating attention mechanisms and multi-scale feature extraction further enhances the system's ability to focus on relevant regions and capture subtle behavioural cues, thereby reducing false positives. Second, unsupervised and semi-supervised learning

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techniques, such as autoencoders, are highly effective in identifying previously unseen anomalies, alleviating the dependency on large, labelled datasets and improving the adaptability of surveillance systems to diverse real-world environments. Third, integrating real-time processing strategies, including edge computing and hardware acceleration, enables scalable deployment in large CCTV networks while maintaining low latency and computational efficiency. Fourth, the inclusion of contextual analysis and interaction modelling is recommended to enhance interpretability, allowing the system to distinguish between normal unusual activities and genuine threats. Finally, further research is needed on hybrid approaches that combine multiple deep learning architectures, reinforcement learning, and multi-camera fusion to improve detection performance in highly dynamic and complex surveillance scenarios.

Collectively, these recommendations aim to advance the development of intelligent CCTV surveillance systems that provide proactive threat detection, enhance public safety, and reduce the operational burden on human monitoring personnel while maintaining scalability, efficiency, and reliability in real-world deployments.

## VI. FUTURE WORK

1. Develop hybrid deep learning architectures that integrate CNN, LSTM, and Transformer-based models to further improve the detection of complex abnormal human behaviours.
2. Implement real-time, online monitoring systems capable of processing multiple CCTV streams simultaneously while maintaining low latency and high accuracy.
3. Optimize object detection and tracking algorithms to handle occlusions, crowded environments, and dynamic lighting conditions more effectively.
4. Design low-computation, edge-deployable models to enable scalable implementation in large urban CCTV networks without reliance on high-performance servers.
5. Investigate multi-camera fusion techniques to enhance detection reliability and reduce blind spots in large surveillance areas.
6. Study the system's adaptability to diverse contexts, including transportation hubs, educational institutions, and public gatherings, to ensure consistent performance.
7. Explore the application of unsupervised and semi-supervised learning to detect previously unseen or rare abnormal behaviour's without requiring extensive labelled datasets.
8. Improve model explainability and interpretability, enabling security personnel to understand and verify system-generated alerts in real time.
9. Conduct large-scale pilot deployments to evaluate operational efficiency, robustness, and scalability in real-world surveillance environments.
10. Perform life cycle assessment (LCA) and cost-benefit analysis to evaluate the economic, computational, and societal impact of AI-driven CCTV surveillance systems..

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