IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Integrated Crime Detection And Alert System

[1]Akshay M S, [2]Lohith B, [3]Lohit S H, [4]Manoj T V, [5]Devika B

[5]Associate professor,

[1-5]Dept of Electronics and Communication Engineering,

[1-5]K S Institute of Technology, Bengaluru, India

Abstract: In recent years, cctv cameras are used in various locations. The data captured by these cameras can be used for event prediction, real-time monitoring, and goal-oriented analysis, including anomaly and intrusion detection. With advancements in Artificial Intelligence, several methods are applied for anomaly detection, in which convolutional neural networks (CNNs) powered by deep-learning have improved detection accuracy. This article aims to introduce a novel deep learning- based approach for crime detection in video surveillance footage. this method has been tested on the UCSD dataset and has demonstrated improved accuracy in detecting criminal activities.

***Index Terms* - Anomaly detection, Artificial intelligence, CNN, Datasets, Deep learning, Machine learning.**

I. Introduction

The use of unsupervised machine learning for anomaly detection is an evolving area of research in the machine learning community. Since crimes often involve unusual, irregular, and unpredictable events, they stand out from normal patterns. Identifying such anomalies by learning from typical data has significant real-world applications. However, abnormal behaviour detection is influenced by various factors, including the environment, context, and specific circumstances, meaning that anomaly detection methods must be adaptable.Traditional supervised methods, such as CNN-based approaches, require labeled datasets, which are difficult to obtain especially for high-dimensional video data. Video representation and processing add further complexity, making crime detection from surveillance footage.

One effective way to tackle these challenges is through advanced machine learning, particularly deep learning. These techniques excel at handling large, complex datasets because of their ability to automate feature extraction. Deep learning is especially beneficial for processing high-dimensional data, making it well- suited for crime detection.This study introduces a deep-learning based framework for detecting crimes in cctv footage. The proposed method consists of two main phases: a feature extraction network and a detection classifier. The feature extraction phase utilizes five deep structural components to capture relevant information, while the detection phase includes five deep neural network classifiers along with a reconstruction network. Each classifier produces a detection result and a confidence score, which are then combined using an ensemble classifier to determine the final outcome.

The key contribution of this research is the seamless integration of deep learning techniques at every stage of crime detection. Section II provides background on video-based crime detection using deep learning, Section III reviews related work, Section IV details the proposed method, and the final section presents evaluation results showcasing the improvements and advantages over existing approaches.

I. LITERATURE SURVEY

[1]This research presents a deep- learning based real-time crime detection system for video surveillance. This method integrates CNNs to identify suspicious behavior accurately.The model ensures trustworthiness by minimizing false alarms using adaptive learning techniques. The study evaluates performance on large-scale crime datasets, demonstrating high detection rates and computational efficiency. The approach facilitates enhanced security in public areas by enabling early crime intervention. Findings shows that deep learning significantly strengthens automated surveillance systems, making the system more reliable and scalable. Future improvements include refining model generalization and integrating edge computing for real-time processing.

[2]This paper presents a real-time crime monitoring system utilizing deep learning techniques to detect criminal activities in surveillance footage. The model employs a hybrid approach combining CNNs and transformer-based architectures for enhanced accuracy. By leveraging anomaly detection and feature extraction, it effectively distinguishes suspicious behavior from normal activities. The research evaluates performance on diverse datasets, demonstrating significant improvements in crime detection rates. The system integrates with smart city security frameworks, enabling proactive law enforcement. Future research includes optimizing computational efficiency and improving real-time alert mechanisms to further enhance practical deployment in urban safety and crime prevention systems.

[3]This study proposes a intelligent video surveillance system for early armed robbery recognition. The system enhances situational awareness by analyzing human behavior patterns and object interactions. Using datasets containing real-world robbery incidents, the model achieves high detection accuracy. Results demonstrate its effectiveness in reducing crime response times and improving law enforcement capabilities.

[4]This study introduces an automated crime intention detection system utilizing deep learning to enhance surveillance accuracy. The proposed model processes video footage in real- time, identifying potential criminal activities through pattern recognition. Advanced AI methods, including (CNNs), improve precision by reducing false alarms and enhancing detection reliability. The study evaluates model performance on benchmark datasets, demonstrating superior accuracy compared to traditional methods. The system integrates seamlessly into existing security infrastructures, providing law enforcement with timely alerts. The results suggest that deep learning-based crime detection systems significantly contribute to proactive crime prevention and urban safety enhancement.

[5]This paper explores deep learning-based crime intention detection using object detection techniques. The study develops a framework that leverages CNNs and YOLO (You Only Look Once) models to analyze video streams for suspicious activities. Experimental results on crime datasets confirm its effectiveness, showcasing improved accuracy compared to conventional video surveillance methods. The system minimizes manual monitoring effort while increasing reliability in security applications. Future research may focus on refining model precision and reducing computational complexity for real-world deployment in law enforcement and public safety systems.

[6]This research introduces a real-time crime monitoring system utilizing deep learning to enhance surveillance efficiency. The model applies CNN-based feature extraction to detect criminal activities with high accuracy. By leveraging video analytics and anomaly detection, the system minimizes false alarms while improving recognition precision. The study assesses system performance on various public surveillance datasets, showcasing superior results over traditional monitoring methods. The approach enables proactive crime prevention, assisting security personnel in real-time decision-making. Future enhancements include the integration of federated learning to enhance privacy protection and scalability for widespread deployment in smart city security frameworks.

[7]This study investigates video anomaly detection based on the sparsity and reconstruction error of autoencoders. The model utilizes deep neural networks to detect anomalies by learning normal behavior patterns and identifying deviations. The approach is evaluated on benchmark datasets, demonstrating superior anomaly detection accuracy compared to traditional methods. The outputs suggest that deep learning-based autoencoder models significantly enhance video surveillance effectiveness. Future enhancements include real-time processing optimization and integration with edge computing for scalable deployment in smart surveillance systems, improving overall crime monitoring capabilities in public security applications.

[8]This paper examines video-based abnormal behaviour detection using deep- learning architectures, analyzing challenges and potential improvements. It discusses many deep learning models, consisting CNNs and RNNs, for identifying suspicious activities in video footage. The study highlights the limitations of existing methods, such as high computational costs and generalization issues. Experimental results showcase promising improvements in anomaly detection performance. Future work aims to optimize model efficiency, incorporate explainable AI techniques, and enhance real-time crime detection accuracy through advanced feature learning mechanisms in intelligent surveillance systems.

[9] This review paper explores deep learning-based anomaly detection techniques for video surveillance applications. It evaluates various AI-driven models, analyzing their strengths and weaknesses in crime monitoring. The study highlights the role of feature representation and motion analysis in enhancing detection accuracy. Results suggest that hybrid deep learning approaches significantly improve anomaly detection efficiency. The review provides insights into emerging trends, including transformer-based models and self-supervised learning.

[10] This research explores video anomaly detection using local motion-based joint video representation and OCELM. The proposed system leverages motion trajectory analysis combined with deep learning models to detect irregular activities in surveillance footage. The study highlights the effectiveness of hybrid models in improving anomaly detection accuracy. Performance evaluations on public datasets show significant improvements in precision and recall. The approach reduces false positives while enhancing real-time surveillance capabilities. Future work involves optimizing computational efficiency, expanding dataset diversity, and integrating multi-camera synchronization to enhance large-scale deployment in urban security monitoring.

[11]This study presents an anomaly detection system utilizing deep learning classifiers for surveillance applications. The proposed model employs CNNs and support vector machines (SVMs) to detect unusual behavior patterns in real time. By analyzing video streams, the system distinguishes normal activities from potential threats, enhancing crime detection efficiency. Experimental results demonstrate its robustness in various security scenarios, reducing dependency on manual monitoring. The framework improves security response time and lowers false positive rates. Future research includes optimizing model scalability and integrating edge computing to enhance real-time processing capabilities in large- scale surveillance networks.

[12] This paper introduces an energy-based abnormal activity detection framework for video surveillance. This model incorporates deep learning-based motion analysis and pattern recognition to identify abnormal events efficiently. Using energy consumption metrics, the system detects deviations in movement patterns indicative of suspicious activity. The study evaluates performance on real-world datasets, demonstrating improved accuracy in anomaly identification. The proposed approach minimizes computational risks maintaining high detection reliability. Future research focuses on refining model adaptability to different surveillance environments and integrating multi-modal sensor data for enhanced crime prevention and threat analysis capabilities.

[13]This study provides an overview of deep learning- based techniques for unsupervised and semi-supervised anomaly detection in videos. The authors discuss the disadvantages of traditional supervised learning methods, emphasizing that deep-learning models can learn representations from unlabelled data, reducing reliance on extensive labeled datasets. The study highlights the use of autoencoders, generative adversarial networks (GANs), for anomaly detection, comparing their strengths and weaknesses. The research further explores spatiotemporal modeling approaches to analyze abnormal activities in video sequences. The paper underscores the challenges in anomaly detection, such as data imbalance, model generalization, and real-time processing efficiency. It concludes that hybrid models combining multiple deep-learning methods offer good results in improving detection accuracy and efficiency.

[14]This study introduces a novel framework that combines abnormal event detection and recounting by leveraging deep generic knowledge. Unlike conventional models that only classify anomalies, this approach interprets and describes detected events, improving decision-making in real-time surveillance. This model uses a two-stage process: first, it employs a deep-learning to detect unusual activities in video streams; second, it generates explanatory descriptions using (NLP)-based system. The research highlights the need of interpretability in anomaly detection, as security personnel require context to respond effectively. The paper concludes that integrating semantic reasoning with deep learning significantly enhances anomaly detection accuracy while improving situational awareness and real- time security monitoring.

[15]This research examines deep convolutional autoencoders for anomaly detection in videos. The study focuses on the unsupervised learning approach, where the model learns normal activity patterns and identifies deviations. The authors demonstrate that convolutional autoencoders effectively compress and reconstruct frames, capturing structural patterns of normal behaviour. Any deviation in reconstruction error signifies an anomaly, enabling real- time crime detection in surveillance footage. The study also compares autoencoders with recurrent networks and traditional handcrafted feature extraction methods, proving the superiority of deep learning-based techniques in handling complex spatial-temporal dependencies.

[16]This paper presents an abnormal event detection framework based on spatiotemporal autoencoders. The model captures spatial features through convolutional layers and temporal dependencies using recurrent units, allowing it to detect anomalies in surveillance videos effectively. This method is unsupervised, meaning it learns from normal activity patterns and flags unusual behaviors based on reconstruction errors. Unlike conventional techniques, this method requires minimal human intervention, making it highly scalable for large-scale applications. The authors evaluate the framework using benchmark datasets and demonstrate significant improvements in accuracy, robustness, and computational efficiency compared to traditional handcrafted feature-based models. They conclude that integrating attention mechanisms and domain adaptation can further enhance detection performance.

[17]This study explores deep learning-based abnormality detection in video data, focusing on real-time applications. The proposed method employs a hybrid deep network, combining convolutional layers for feature extraction and LSTM units for temporal pattern recognition. The model learns normal behavior patterns and detects deviations, ensuring high accuracy in identifying crime and suspicious activities. The study highlights key challenges such as dataset bias, false alarms, and computational costs, proposing solutions like semi-supervised training and real-time optimization. The research concludes that integrating spatiotemporal attention mechanisms and edge computing architectures can significantly improve system efficiency and scalability for smart surveillance applications.

[18]This paper presents Deep-Anomaly, a fully (CNN) designed for fast abnormal behaviour detection in crowded scenes. The approach focuses on real-time processing by utilizing efficient spatial feature extraction and lightweight model architectures. The proposed framework significantly reduces computation time while maintaining high detection accuracy. The study benchmarks its performance against traditional models, proving its effectiveness in large-scale surveillance environments. Additionally, the authors discuss the potential of integrating real-time anomaly explanation mechanisms to provide more actionable insights. They conclude that further model optimization and transfer learning can enhance adaptability to diverse security applications.

[19]This research provides an extensive review of video scene analysis techniques, focusing on deep learning algorithms for anomaly detection. The authors discuss various methodologies, including CNN-based feature extraction, RNN-based temporal modeling for abnormal event detection. The study compares different deep-learning designs and highlights challenges such as real-time processing constraints, false alarms, and dataset limitations. The review suggests that integrating attention-based models, self- supervised learning, and multimodal data fusion can improve accuracy and robustness in anomaly detection systems.

[20]This study proposes abnormal behaviour detection in cctv videos using a deep-learning classifier. The model employs a hybrid convolutional- recurrent architecture that learns spatial and temporal features for effective abnormal activity detection. This system outperforms conventional motion- based abnormal activities

detection methods by reducing false positives and improving detection rates. The authors evaluate the model using standard surveillance datasets and demonstrate its adaptability across different environments. The research highlights the need for real-time inference optimization and suggests that edge AI implementation can further enhance deployment efficiency.

[21]This paper introduces energy-based abnormal activities detection for video monitoring. The model applies an energy minimization approach to identify suspicious activities in real-time. By leveraging convolutional features and optical flow analysis, the system effectively detects subtle motion- based anomalies. The study demonstrates that low-energy frames represent normal behavior, while high-energy frames indicate potential threats. The authors validate their approach on various benchmark datasets, proving its effectiveness in detecting anomalies in complex surveillance environments.

[22]This research explores a joint video representation approach for anomaly detection and localization. The proposed model integrates local motion-based features with autoencoder-based reconstruction error analysis. The authors prove that combining spatiotemporal representation learning with anomaly detection significantly enhances accuracy.

[23]This study presents an autoencoder-based approach for video anomaly detection and localization. The model learns compact representations of normal video sequences and detects abnormalities based on reconstruction errors. The research highlights the advantages of unsupervised learning in anomaly detection while addressing challenges like false alarms.

[24]This paper discusses challenges in video-based abnormal activities detection with deep-learning architectures. The study reviews many deep-learning models, like CNNs, RNNs, and hybrid frameworks, highlighting their advantages and limitations. The authors suggest that integrating spatiotemporal attention mechanisms can improve detection accuracy and robustness.

[25]This review paper examines deep-learning based video abnormal activities detection models and their effectiveness in real-world surveillance. The study highlights emerging trends in self-supervised learning, transfer learning, and multimodal data fusion, suggesting that future advancements in AI-driven anomaly detection will lead to more reliable and interpretable security solutions.

II. Methodology

A. Block diagram

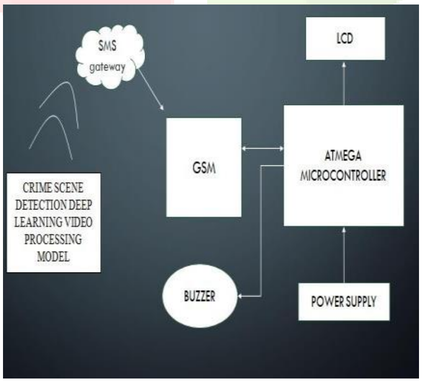
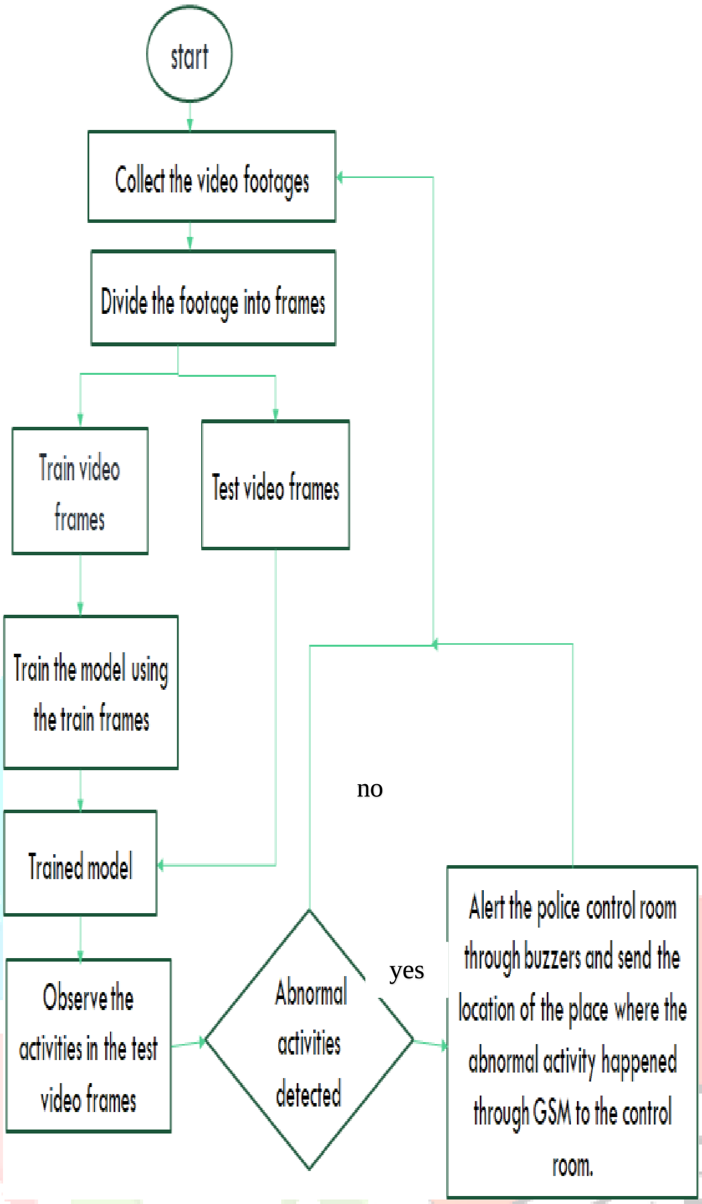


Figure 1 : Block Diagram of Integrated Crime Detection And Alert System

This method is based on deep-learning methods for video anomaly detection. The method has two main components: the first involves feature extraction and learning, while the second focuses on detecting anomalies. Additionally, a pre processing step is included, which deals with background estimation and removal. Like other machine learning methods, this method consists of two primary phases: training and testing. During the training phase, this model is trained using normal frames from the dataset. In the testing phase, the trained model is applied to the remaining dataset, which contains abnormal frames, to detect anomalies.

B. Flowchart of Integrated Crime Detection and Alert System



The flowchart illustrates a system designed to detect abnormal activities using video surveillance and machine learning. The process begins by collecting video footage from surveillance cameras or other sources. Since machine learning models typically analyze static images rather than continuous video streams, the footage is divided into individual frames for detailed examination.

This system operates in two main phases: a one-time training phase and an ongoing testing phase. During the training phase, selected video frames are used to train the machine learning model. The model is provided with labeled examples of both normal and abnormal activities, allowing it to learn and recognize patterns. Once this phase is complete, the trained model is stored and becomes ready for real-time analysis.

After training, the system moves into the testing phase, where it continuously processes new video frames to detect any suspicious activity. The trained model examines each frame in real-time and compares it against the patterns it has learned. If the system determines that an activity is normal, it continues monitoring without interruption. However, if an abnormal activity is detected, the system proceeds to a decision-making step to confirm whether the activity is truly unusual or still within an acceptable range.

When the system detects a confirmed abnormal activity, it immediately triggers an alert mechanism. This includes activating buzzers to notify nearby authorities and sending location details through GSM (Global System for Mobile Communications). Using GSM technology, the system transmits real-time location data to a control room, ensuring that law enforcement agencies can respond quickly to potential threats.

One of the biggest advantages of this AI-driven surveillance system is its ability to automate security monitoring. Unlike traditional surveillance methods, which rely on human operators to manually watch live video feeds, this approach significantly reduces human effort while minimizing the chances of missing critical incidents. Since the model is trained only once but used continuously, it offers long-term reliability. Additionally, the model can be retrained periodically with new data, improving its accuracy over time.

A key benefit of this system is its ability to identify security threats in real-time, allowing for faster responses to incidents like theft, violence, or unauthorized access. By combining machine learning with video surveillance, this technology enhances public safety while reducing the workload of law enforcement agencies. Moreover, the system is highly scalable, making it suitable for various locations, including shopping malls, banks, public transport hubs, and residential areas.

The integration of GSM-based location tracking further improves the system’s effectiveness, ensuring that alerts are sent to the right authorities at the right time. In summary, this AI-powered security surveillance system efficiently collects video footage, processes it into frames, trains a model to distinguish between normal and abnormal activities, and continuously monitors for security threats. If suspicious behavior is detected, the system automatically notifies law enforcement, enhancing surveillance efficiency, reducing manual effort, and improving public safety through real-time alerts and quick responses.

III. Results of Integrated crime detection and alert system .

Figure 2: Web application interface for choosing the video footage

The above figure(Figure 2) represents the web application interface, this interface appears when the code is ran, where the video footage is to be selected, after the video footage is selected the web application processes the video footage by dividing the footage into frames. Then the crime or abnormal activities are detected from the video frames.

Figure 3: Output screen when abnormal activities detected in the footage

After the video footage is processed, the above output screen (Figure 3) is visible if there are any abnormal activities in that footage.

Figure 4: Output screen when no abnormal activities detected in the footage.

The above window (Figure 4) appears when no abnormal activities are detected in the video footage.

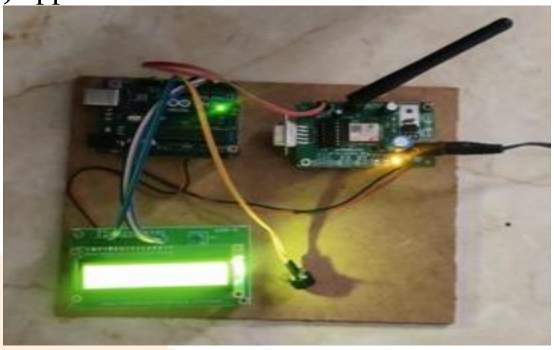


Figure 5: Hardware model of Integrated crime detection and alert system

Figure 6: location of the place where abnormal activities are detected received at the control room through GSM

When abnormal activities are detected in the footage, the location of the place where the abnormal activities took place is sent to the police control room through GSM and SMS gateway.

Figure 7 : LCD output when there is no abnormal activity detected

Figure 8: Risk detected is displayed on the processed video footage.

IV. Applications

The Automated Crime Detection and Alert System using Embedded Deep Learning has diverse applications in improving security and public safety. One of its key uses is in smart surveillance, where it can be integrated with CCTV cameras in locations like airports, railway stations, shopping malls, and banks to detect suspicious activities in real time. Law enforcement agencies can utilize this system to analyze high-crime areas, support forensic investigations, and improve emergency response efficiency.

Additionally, the system enhances public safety monitoring by detecting unusual behaviors in crowded spaces such as stadiums and protests, assisting authorities in preventing potential threats. In residential and commercial security, it helps identify intrusions, unauthorized access, and suspicious movements, sending real-time alerts to homeowners or security personnel.

Transportation hubs, including airports and train stations, can benefit from automated threat detection, identifying abandoned objects, weapons, or suspicious behaviors that may pose security risks. The system is also useful in prisons and correctional facilities, where it can monitor inmate activities and detect violent incidents.

Furthermore, it aids in crime-prone area analysis, allowing proactive law enforcement by predicting potential criminal activities. When integrated with IoT-based emergency response systems, it can automatically detect distress signals, gunshots, or explosions and promptly alert law enforcement, fire departments, or medical services. By utilizing deep learning on embedded systems, this technology provides a cost-effective, real-time, and privacy-conscious approach to crime prevention and public safety.

V. Conclusion and Future scope

A key advantage of this method is the integration of deep learning at every stage of the process, from training to detection. Traditional crime detection methods often rely on manual monitoring or rule-based approaches, which can be inefficient and prone to human error. In contrast, deep learning automates the process by analyzing vast amounts of video data, identifying suspicious activities, and alerting authorities in real time. The model is trained using a large dataset of surveillance footage, annotated with various criminal and non criminal activities. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are utilized for feature extraction and pattern recognition. The detection phase involves video processing, where frames are analyzed, and the system classifies actions as normal or suspicious. If a potential crime is detected, the system can trigger alerts, send notifications, or even provide tracking of suspects. By fully integrating deep learning into crime detection, this system significantly improves accuracy, reduces response time, and minimizes reliance on human monitoring. The use of AI-driven techniques ensures that even subtle or previously unseen criminal activities can be detected, making video surveillance more effective and intelligent in preventing crime.

To enhance the efficiency and reliability of deep learning-based crime detection in video surveillance, additional components can be integrated to improve interpretability and localization. Two key enhancements include adding descriptions to detection classifiers and incorporating a localization mechanism in the detection phase.

One of the biggest challenges in AI-powered crime detection is that it often lacks clarity in its decision-making. While these systems can recognize suspicious activities, they don't always explain why something is flagged as a potential threat. Security teams might get alerts with vague labels like "fight detected" or "theft occurring," but without additional context, it's hard to determine the severity of the situation or how to respond effectively. To bridge this gap, AI systems can be enhanced with a description generation component that provides a clearer picture of what's happening. This upgrade would involve combining Convolutional Neural Networks (CNNs) with language models like Recurrent Neural Networks (RNNs) or Vision-Language Models (VLMs). CNNs analyze video footage to detect key visual details, while the language models generate descriptive text based on those findings.

AI-powered crime detection systems have come a long way in identifying criminal activities, but a key challenge remains—their inability to accurately pinpoint where exactly an incident is happening within a surveillance frame. While many AI models can classify events, they often struggle with providing precise location details, which makes it harder for security teams to respond effectively. To bridge this gap, integrating crime localization techniques using object detection models like YOLO (You Only Look Once) or Faster R CNN can significantly enhance these systems.

REFERENCES

[1]M. A. Khan, M. Sharif, and M. Y. Javed, "Finding Real-Time Crime Detections During Video Surveillance by Trustworthy Deep Learning Models," in Proc. 2024 ACM Conf. Multimedia, 2024

[2]M. M. Mukto, M. Hasan, M. M. A. Mahmud, I. Haque, M. A. Ahmed, T. Jabid, M. S. Ali, M. R. A. Rashid, M. M. Islam, and M. Islam, "Design of a real-time crime monitoring system using deep learning techniques," Intell. Syst. Appl., vol. 21, no. 200311, 2024.

[3]A. K. Paul, "Distributed Intelligent Video Surveillance for Early Armed Robbery Recognition," arXiv preprint arXiv:2410.09731, 2024.

[4]M. Anas, A. Sami, M. Shinde, and V. Sowmya, "Automated Crime Intention Detection Using Deep Learning," Int. Res. J. Modernization Eng. Technol. Sci., vol. 5, no. 5, pp. 6658–6660, May 2023.

[5] O. Hashi, A. A. Abdirahman, M. A. Elmi, and O. E. R. Rodriguez, "Deep Learning Models for Crime Intention Detection Using Object Detection," Int. J. Adv. Comput. Sci. Appl., vol. 14, no. 4, pp. 300–302, 2023.

[6]Bhalla and R. K. Singh, "Design of a Real-Time Crime Monitoring System Using Deep Learning Techniques," in Proc. 2023 Int. Conf. Innovations Cyber Phys. Syst., 2023, pp. 297–304, 2023.

[7] M. Sabokrou, M. Fathy, M. Hoseini., "Video anomaly detection and localisation based on the sparsity and reconstruction error of autoencoder", ELECTRONICS LETTERS, IEEE, 2022.

[8] Yong Shean Chong, Yong Haur Tay, "Modeling Video-based Anomaly Detection using Deep Architectures: Challenges and Possibilities", Control Conference (ASCC), IEEE, 2022

[9] Shean Chong, Yong Haur Tay, Yong, "Modeling Representation of Videos for Anomaly Detection using Deep Learning: A Review", arXiv:1505.00523v1, 2022.

[10] Siqi Wanga, E.Z., Jianping Yin, "Video anomaly detection and localization by local motion based joint video representation and OCELM", Neurocomputing, 2021

[11] Revathi, A. R., Kumar, Dhananjay "An efficient system for anomaly detection using deep learning classifier", Signal, Image and Video Processing, Springer, 2020

[12] Hung Vu, Tu Dinh Nguyen, Anthony Travers, Svetha Venkatesh And Dinh Phung, "Anthony Travers, Energy-Based Localized Anomaly Detection in Video Surveillance", Springer International Publishing AG, 2020

[13] B Ravi Kiran, Dilip Mathew Thomas, Ranjith Parakkal, "An overview of deep learning based methods for unsupervised and semisupervised anomaly detection in videos", MDPI Journal of Imaging,arXiv:1801.03149v1, 2018

[14] Ryota Hinami, Tao Mei, and Shin'ichi Satoh, "Joint Detection and Recounting of Abnormal Events by Learning Deep Generic Knowledge", arXiv:1709.09121v1, 2017

[15] M. Ribeiro, A.E.L., and H. S. Lopes, "A study of deep convolutional auto-encoders for anomaly detection in videos", Pattern Recognition Letters, ELSEVIER, 2017
[16] Yong Shean Chong, Yong Haur Tay, "Abnormal Event Detection in Videos Using Spatiotemporal Autoencoder", International Symposium on Neural Networks, Springer International Publishing AG, 2017
[17] Hung Vu, "Deep Abnormality Detection in Video Data", Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence, 2017
[18] M. Sabokroua, M.F., M. Fathyc, Z. Moayedd and R. Kletted, "Deep- Anomaly: Fully Convolutional Neural Network for Fast Anomaly Detection in Crowded Scenes", Journal of Computer Vision and Image Understanding, 2017
[19] Qaisar Abbas, Mostafa E. A. Ibrahim, M. Arfan Jaffar1, "Video scene analysis: an overview and challenges on deep learning algorithms", Multimedia Tools and Applications, Springer, 2017 [20] Revathi, A. R., Kumar, Dhananjay "An efficient system for anomaly detection using deep learning classifier", Signal, Image and Video Processing, Springer, 2016
[21] Hung Vu, Tu Dinh Nguyen, Anthony Travers, Svetha Venkatesh And Dinh Phung, "Anthony Travers, Energy-Based Localized Anomaly Detection in Video Surveillance", Springer International Publishing AG, 2017
[22] Siqi Wanga, E.Z., Jianping Yin, "Video anomaly detection and localization by local motion based joint video representation and OCELM", Neurocomputing, 2017
[23] M. Sabokrou, M. Fathy, M. Hoseini., "Video anomaly detection and localisation based on the sparsity and reconstruction error of autoencoder", ELECTRONICS LETTERS, IEEE, 2016.
[24] Yong Shean Chong, Yong Haur Tay, "Modeling Video-based Anomaly Detection using Deep Architectures: Challenges and Possibilities", Control Conference (ASCC), IEEE, 2015
[25] Shean Chong, Yong Haur Tay, Yong, "Modeling Representation of Videos for Anomaly Detection using Deep Learning: A Review", arXiv:1505.00523v1, 2015.
[26] B Devika ,PN Sudha "Power Optimization in MANET using Topology Management" published in Engineering Science and Technology, an International Journal, ISSN 22150986, ELSEVIER BV, July 2020.