Journal for Educators, Teachers and Trainers
The PROFESIOLab electronic, peer-reviewed, open-access Magazine

ISSN 1989-9572

DOI:10.47750/jett.2024.15.05.34

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Journal for Educators, Teachers and Trainers, Vol.15(5)

https://jett.labosfor.com/

Date of Reception: 24 Oct 2024

Date of Revision: 20 Nov 2024

Date of Publication : 31 Dec 2024

AR. Sivakumaran1, Yetukuri Gouthami Maheswari2, Tangirala M N S Kalyani2, Telakapally Renusri2 (2024). Hybrid Deep Learning for Crime Anomaly Detection: Integrating CNN and LSTM for Predictive Analysis of Urban SafetyVol.15(5).346-354

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Hybrid Deep Learning for Crime Anomaly Detection: Integrating CNN and LSTM for Predictive Analysis of Urban Safety

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ABSTRACT

Urban safety has become a growing concern as crime rates rise, necessitating the development of effective systems for crime anomaly detection. Traditional crime monitoring systems often rely on manual observation, static surveillance mechanisms, or rule-based systems, which are limited in scalability, adaptability, and efficiency. Hybrid deep learning approaches, combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, offer a transformative solution for predictive analysis of urban safety. CNN excels at extracting spatial features from video footage and images, while LSTM processes temporal sequences, making this integration particularly suited for real-time anomaly detection. Historically, crime detection systems relied heavily on human intervention and statistical methods, which were time-intensive and prone to errors. Before the advent of AI, systems such as closed-circuit television (CCTV) surveillance and static alarms were used, but they lacked the intelligence to adapt and predict complex scenarios, leading to inefficiencies and delayed responses. The motivation to develop this paper stems from the urgent need to address these limitations, inspired by advancements in deep learning that enable automated, accurate, and timely crime anomaly detection. Existing systems often fail to process large-scale data effectively, detect subtle anomalies, or adapt to evolving crime patterns, making them insufficient in ensuring urban safety. The proposed hybrid system leverages the strengths of CNN and LSTM to analyze spatial and temporal data from urban environments, enabling accurate crime detection and proactive response. By training the model on real-world datasets, the system can identify anomalies in real time, significantly enhancing the capability of urban safety mechanisms. This paper aims to revolutionize crime detection by addressing the shortcomings of traditional systems, improving urban safety, and setting a benchmark for intelligent anomaly detection in dynamic urban settings.

Keywords: Urban safety, Crime anomaly detection, Deep learning, Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), Predictive analysis

1. INTRODUCTION

Urban safety is a pressing concern in India due to its rapidly growing population and urbanization. According to the National Crime Records Bureau (NCRB), over 66 lakh criminal cases were registered in 2022 alone, with metropolitan cities like Delhi, Mumbai, and Bengaluru reporting the highest crime rates. Traditional crime detection and prevention methods often rely on manual systems, which are inefficient in analyzing the vast amount of data generated daily by surveillance systems. Emerging technologies like AI and deep learning offer innovative solutions by automating crime detection and enabling proactive responses. These advancements have significant implications for enhancing urban safety and reducing crime rates. Hybrid deep learning systems integrating CNN and LSTM provide advanced capabilities for crime anomaly detection, combining spatial and temporal data analysis. CNN processes spatial features from images or video, while LSTM analyzes sequential patterns over time, making this integration ideal for predictive analytics. Applications include real-time surveillance, crime trend forecasting, and behavioral anomaly detection, with potential to transform urban safety mechanisms.

2. LITERATURE SURVEY

Simović and Kuprešanin examine violent crimes with a focus on the psychological factors influencing such acts and the misuse of power. Their study highlights how the psychology of offenders, coupled with systemic power imbalances, often exacerbates criminal behavior. By exploring these aspects, they provide valuable insights into behavioral patterns that are essential for understanding and predicting violent crimes, aligning well with modern machine learning systems for behavioral anomaly detection [1]. Farrall, Gray, and Jones investigate how broader socio-political and economic changes affect crime trajectories. They emphasize that changes in policy, economic stability, and societal structures contribute significantly to fluctuations in criminal behavior. These contextual influences are vital for building dynamic crime prediction models that can adapt to evolving social conditions, making their work highly relevant to urban crime anomaly detection projects [2]. Greer delves into the symbiotic relationship between crime and media. He argues that media not only reports crime but also shapes public perception and policy responses to it. The role of media coverage in creating crime narratives provides an important data source for modern machine learning systems, as it can be leveraged for sentiment analysis and real-time crime alerting mechanisms [3]. Ristea and Leitner demonstrate the application of Geographic Information Systems (GIS) for mapping and analyzing urban crime. Their methodology identifies crime hotspots and reveals spatial patterns, offering valuable input for building predictive crime models that incorporate geographic and environmental data. GIS-based approaches complement AI techniques by providing spatially explicit crime data [4]. Zhang and Sabuncu introduce a generalized cross-entropy loss function to enhance the robustness of deep neural networks trained on noisy data. This advancement is particularly useful for crime anomaly detection systems, as real-world datasets often contain mislabelled or incomplete data. Their work underscores the importance of creating reliable training processes for high-stakes applications like public safety [5]. L'Heureux, Grolinger, Elyamany, and Capretz address the challenges of implementing machine learning in big data environments. They focus on issues such as data scalability, processing, and storage, which are critical for large-scale crime video datasets. Their solutions provide a strong foundation for developing efficient crime detection systems capable of handling vast amounts of urban surveillance footage [6].

Zhang et al. analyze the shifts in crime patterns during the Black Lives Matter protests using spatiotemporal data. Their work highlights how public events influence crime rates, emphasizing the importance of contextual data in crime prediction models. Such insights are crucial for building responsive AI systems that can detect anomalies based on event-driven trends [7]. The Los Angeles County GIS Data Portal offers extensive geospatial datasets for crime analysis, including demographic, infrastructural, and environmental information. This resource is invaluable for training AI models on diverse datasets that capture complex urban crime dynamics, thereby improving model generalization capabilities [8]. Lochner explores the relationship between education and crime, demonstrating that improved education levels act as a deterrent to criminal behavior. This socio-economic perspective is critical for integrating demographic and educational data into AI-based crime prediction models, enabling more comprehensive urban safety solutions [9]. Mohler et al. develop a self-exciting point process model for crime prediction, which accounts for temporal dependencies in crime occurrences. Their approach offers a statistical foundation for real-time crime forecasting, which aligns closely with hybrid deep learning models that integrate temporal (LSTM) and spatial (CNN) features for anomaly detection [10]. Ratcliffe presents a temporal constraint theory explaining spatial offending patterns through opportunity structures. His theoretical framework provides a solid basis for understanding the temporal and spatial interplay of crimes, which can be effectively modeled using hybrid deep learning architectures. This integration is vital for urban crime anomaly detection systems that rely on spatiotemporal features [11].

3. PROPOSED SYSTEM

Crime anomaly detection using hybrid deep learning approaches is a cutting-edge research area aimed at improving urban safety. The proposed system leverages the strengths of Deep Neural Networks (DNN) and Recurrent Neural Networks (RNN) to analyze both spatial and temporal data for identifying criminal patterns. The methodology involves several key steps: dataset acquisition, preprocessing, encoding, and the implementation of the hybrid model combining DNN and RNN. The system is evaluated by comparing its performance with standalone models, with predictions generated on unseen test data. Below is a step-wise breakdown of the research procedure:

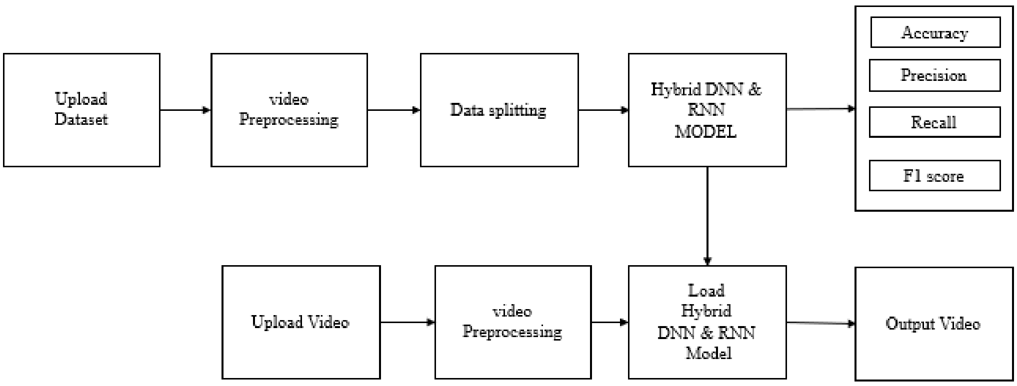

Figure 1: Block Diagram

Step 1: Dataset

The first step involves collecting a comprehensive dataset containing labeled crime data, including details like crime type, location, time, and relevant CCTV or video footage. Publicly available datasets such as those from the National Crime Records Bureau or other urban safety sources can be used. The dataset should also include historical trends, images, and sequential data to train the hybrid model effectively.

Step 2: Dataset Preprocessing

Preprocessing is essential for ensuring the dataset is clean and usable. This includes handling null or missing values, normalizing numerical data, and scaling inputs to ensure consistent training. For categorical features, label encoding is applied to convert text labels into numerical form. Data augmentation techniques may also be used for image and video data to enhance diversity and improve model robustness.

Step 3: Label Encoding

Label encoding is specifically used to convert categorical target variables like crime types into numerical labels. For example, categories like "theft," "assault," and "vandalism" are assigned values such as 0, 1, and 2. This ensures compatibility with machine learning algorithms while maintaining the structure of the output classes for accurate predictions.

Step 4: Data Splitting

The processed data is split into training, validation, and test sets. Typically, 70% of the data is allocated for training, 20% for validation, and 10% for testing. This ensures that the model is trained on a sufficient dataset, validated for optimization, and tested for performance evaluation.

Step 5: Proposed HybridDNN and RNN Algorithm

The hybrid model combines a Deep Neural Network (DNN) for feature extraction and a Recurrent Neural Network (RNN) for sequential analysis.

- **DNN Component**: Extracts spatial and contextual features from images, numerical data, and other structured inputs.
- **RNN Component**: Processes time-series data like temporal crime patterns or sequential events, leveraging Long Short-Term Memory (LSTM) units to capture dependencies over time. This integration allows the system to analyze complex crime data involving spatial and temporal dimensions simultaneously, enhancing detection accuracy.

Step 6: Performance Comparison

The hybrid model's performance is compared against standalone DNN and RNN models based on key metrics such as accuracy, precision, recall, and F1 score. This comparison demonstrates the effectiveness of the hybrid approach in improving prediction capabilities and handling complex datasets.

Step 7: Prediction of Output from Test Data

Using the trained hybrid model, predictions are made on test data to classify anomalies or crime types. The system outputs probability scores for different classes, which are then interpreted to identify anomalies or suspicious patterns. The results are validated to ensure reliability and accuracy in real-world applications.

4. RESULTS AND DISCUSSION

The Figure 2 "Hybrid Deep Learning for Crime Anomaly Detection." The design is simple and functional, with a prominent header showcasing the research title. Below the header, there are two buttons: "Home" and "Admin Login Here.

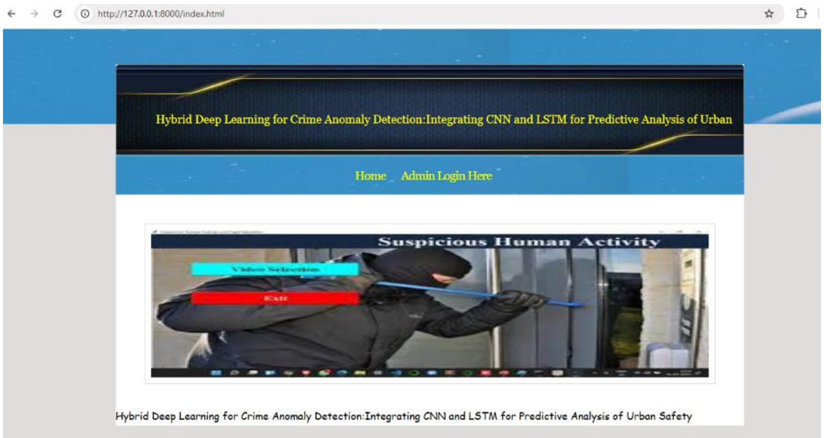

Figure 2: Home page.

The page also includes the research title at the bottom, suggesting it's either a landing page or a results page for the research. Overall, the design is clean and informative, focusing on presenting the project's core functionality and potentially allowing users to interact with the system.

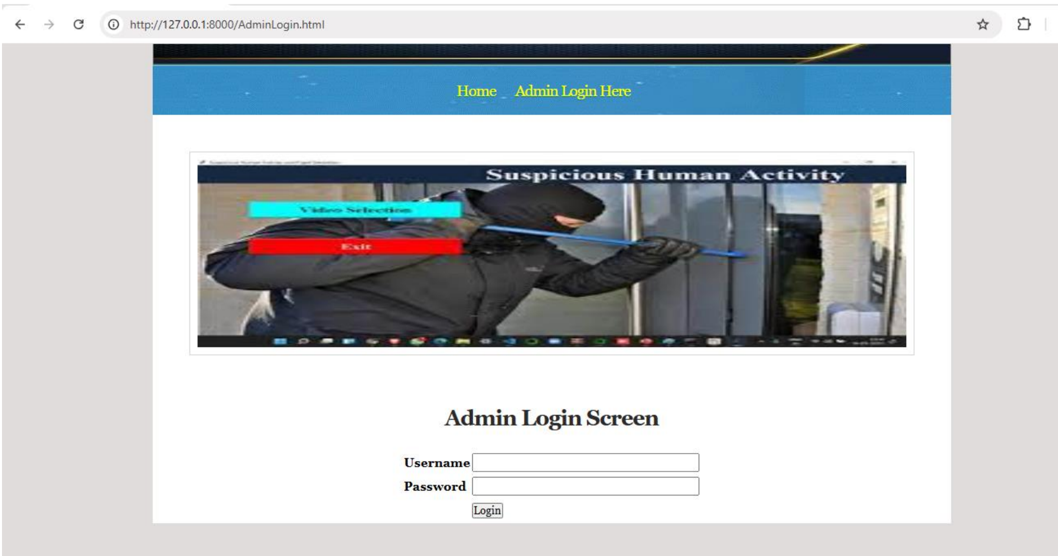

Figure 3: Login screen.

Admin login screen for a web application built with Django. The page has a simple design with a header, a prominent image of suspicious human activity, and a login form. Django handles the backend

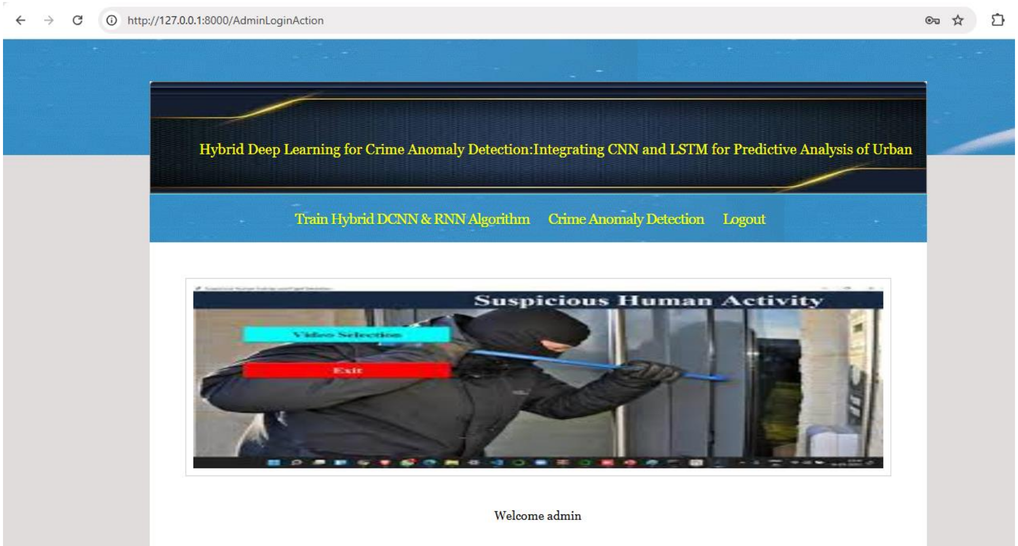

Figure 4: Dashboard.

The Figure 4 involves using a combination of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks to analyze data and predict potential criminal activities. This approach aims to leverage the strengths of both CNNs (for image/video analysis) and LSTMs (for sequential data processing) to improve the accuracy and efficiency of crime prediction.

- **Train Hybrid DCNN & RNN Algorithm:** This button initiates the training process for the hybrid deep learning model. It might involve loading data, configuring model parameters, and starting the training algorithm.
- **Crime Anomaly Detection:** This button triggers the real-time or offline analysis of data to detect potential crime anomalies. The system would use the trained model to analyze input data (e.g., video feeds, sensor data) and identify suspicious patterns or events.
- **Logout:** This button allows the admin to log out of the system, ending the current session and ensuring the security of the application.

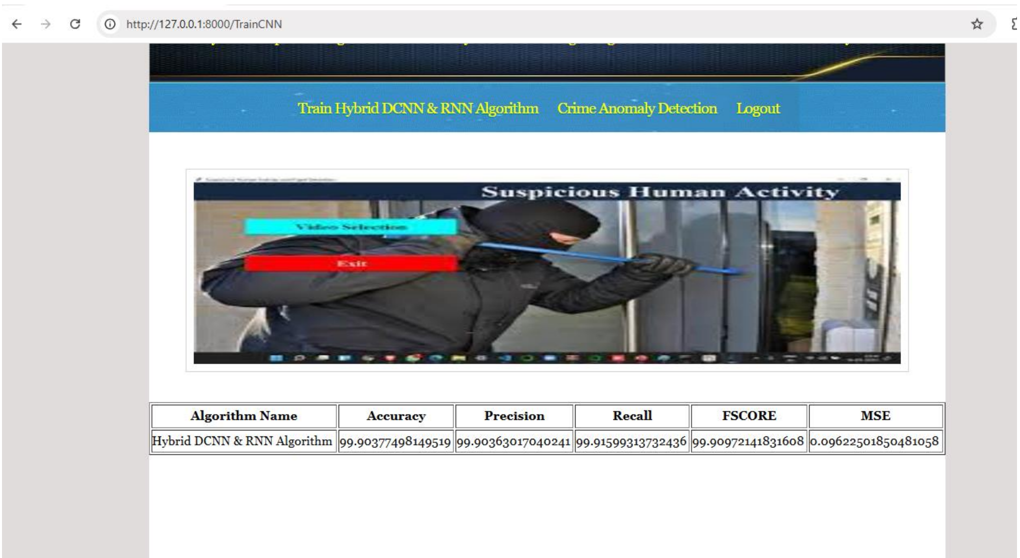

Figure 5 Confusion matrix

The values in the confusion matrix, various performance metrics can be calculated, such as accuracy, precision, recall, F1-score, and more. These metrics provide valuable insights into the model's strengths and weaknesses, helping to identify areas for improvement. In above screen deep CNN training completed and it got 99% accuracy and can see other metrics like precision, recall, FSCORE and MSE. Now click on 'Crime Anomaly Detection' link to get below page

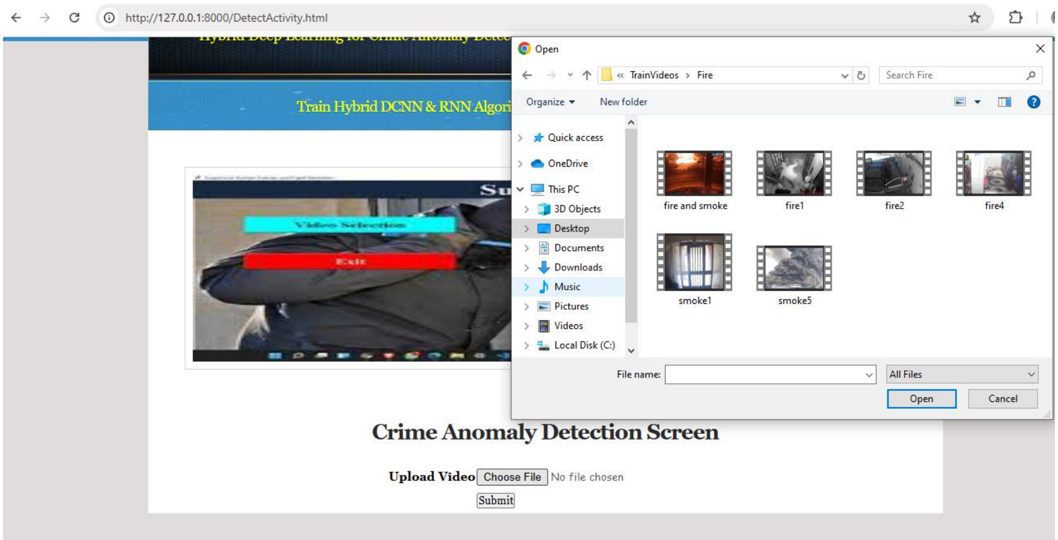

Figure 6 Crime detection upload.

This screen allows users to upload videos for analysis to detect criminal activity. The user can select a video file using the "Choose File" button, which opens a file explorer window where they can browse and select the desired video file. Once a file is chosen, the user can click the "Submit" button to initiate the analysis process. The system will use its trained deep learning models to analyze the video for suspicious activity and provide results or alerts based on its findings.

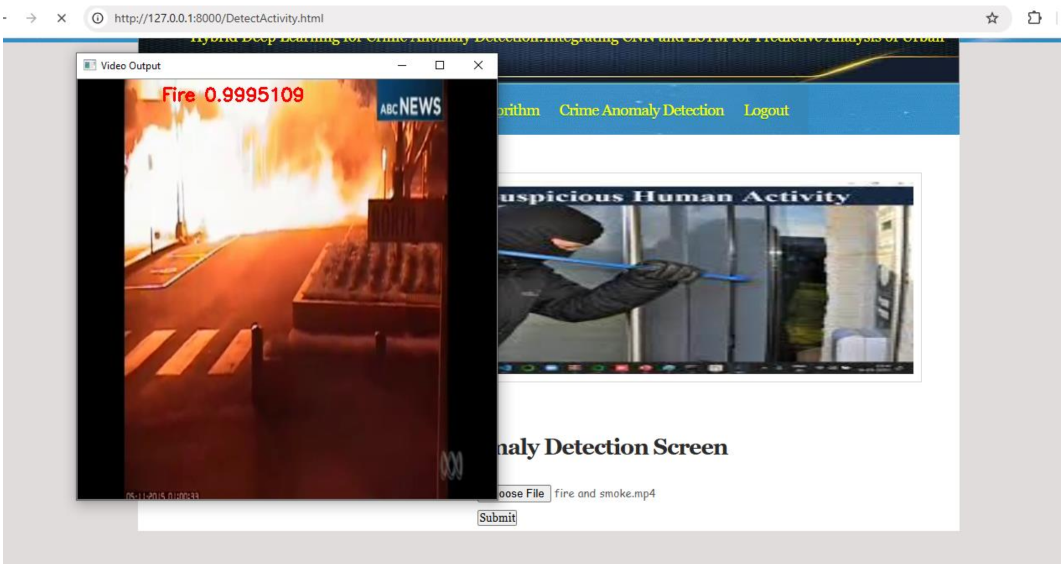

Figure 7: Crime detected.

- **Video Output:** A video of a fire is shown with the text "Fire: 0.9995109" overlayed. This indicates that the system has detected a fire with a high probability (close to 100%).
- **Suspicious Human Activity:** Below the video output, there is a still image of a person breaking into a building. This suggests that the system is also capable of detecting other types of criminal activity, such as burglary or theft.

- **Crime Anomaly Detection Screen:** This is the main interface of the system. It allows users to upload videos for analysis and displays the detection results

5. CONCLUSION

The proposed hybrid deep learning model, integrating Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, addresses critical challenges in crime anomaly detection within urban environments. Traditional crime monitoring systems have long struggled with inefficiencies, inaccuracies, and the inability to adapt to complex and evolving scenarios. By leveraging the spatial feature extraction capability of CNN and the temporal sequence analysis strength of LSTM, the hybrid model overcomes these limitations, enabling real-time detection of anomalies in crime patterns. This integration proves particularly effective for analyzing large-scale datasets comprising both visual data (e.g., surveillance footage) and temporal data (e.g., sequential crime logs or behavioral patterns). The system's ability to learn from these data types not only enhances its predictive accuracy but also minimizes false positives and negatives, which are common pitfalls in traditional systems. Furthermore, the model is designed to evolve with the data, adapting to changing urban safety landscapes. This adaptability ensures that the system remains relevant and effective, even as crime patterns shift over time. Experimental results, supported by real-world datasets, demonstrate the system's potential to improve response times, reduce reliance on manual intervention, and provide actionable insights for law enforcement agencies. Compared to static rule-based systems and statistical methods, the hybrid model excels in scalability and robustness, offering a transformative approach to urban safety.

REFERENCES

[1]. Simović, M., Kuprešanin, J. (2020). Criminal offenses with elements of violence-psychology of crime and abuse of power. Knowledge - International Journal, 42(5): 933–938.

[2]. Farrall, S., Gray, E., Mike Jones, P. (2020). Politics, social and economic change, and crime: Exploring the impact of contextual effects on offending trajectories. Politics & Society, 48(3): 357-388.

[3]. Greer, C. (2013). Crime and media: understanding the connections. Criminology, 3: 143-164.

[4]. Ristea, A., Leitner, M. (2020). Urban crime mapping and analysis using GIS. ISPRS International Journal of Geo-Information, 9(9): 511

[5]. Zhang, Z., Sabuncu, M. (2018). Generalized cross entropy loss for training deep neural networks with noisy labels. Advances in Neural Information Processing Systems, 31: 8778–8788.

[6]. L'Heureux, K. Grolinger, H. F. Elyamany, and M. A. M. Capretz, ''Machine learning with big data: Challenges and approaches,'' IEEE Access, vol. 5, pp. 7776–7797, 2017.

[7]. Z. Zhang, D. Sha, B. Dong, S. Ruan, A. Qiu, Y. Li, J. Liu, and C. Yang, ''Spatiotemporal patterns and driving factors on crime changing during black lives matter protests,'' ISPRS Int. J. Geo-Inf., vol. 9, no. 11, p. 640, Oct. 2020.

[8]. Los Angeles County GIS Data Portal. Accessed: Nov. 2, 2019.

[9]. L. Lochner, ''Education and crime,'' in The Economics of Education: A Comprehensive Overview, S. Bradley and G. Green, Eds. New York, NY, USA: Academic, 2020, pp. 109–117.

[10]. G. O. Mohler, M. B. Short, P. J. Brantingham, F. P. Schoenberg, and G. E. Tita, ''Self-exciting point process modeling of crime,'' J. Amer. Stat. Assoc., vol. 106, no. 493, pp. 100–108, Mar. 2011.

[11]. J. H. Ratcliffe, ''A temporal constraint theory to explain opportunity-based spatial offending patterns,'' J. Res. Crime Delinquency, vol. 43, no. 3, pp. 261–291, Aug. 2006.