Intelligent Crime Anomaly Detection in Smart Cities Using Deep Learning

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***Abstract*—With the increasing trend of urbanization, the importance of public safety in the smart city has gained more focus. Conventional systems for video surveillance cannot detect and respond to crime in real time. This paper describes an intelligent crime anomaly detection system based on deep learning techniques for analyzing and understanding large-stacked surveillance data. The proposed approach combines CNNs and RNN networks for the detection of anomalous patterns showing criminal activities. The model is trained using video surveillance datasets to get more accurate detection. Experimental results demonstrate minimal false positives and high precision for the proposed model in the detection of crime anomalies. The research lays the foundation for integrating AI-ready solutions into urban normative infrastructures for future crime-free scenarios due to proactive crime prevention and improved public safety initiatives.**

***Index Terms*—CNN, RNN, HDL, smart surveillance, Neural networks, IoT, Deep Learning, Artificial Intelligence**

I. INTRODUCTION

The lightning increase in urban population has posed significant challenges for law enforcement in effectively monitoring and policing high-crime areas. This lack of control has resulted in heightened insecurity and a surge in criminal activities.[11] Traditional crime detection techniques have relied on auto-regressive models and behavior recognition; however, these approaches present limitations, including high error rates and difficulties in real-time adaptation [2].

To overcome these challenges, we propose an intelligent crime anomaly detection system that integrates deep learning methodologies, specifically the Hybrid Deep Learning (HDL) algorithm [3]. This approach involves extracting frame data from video surveillance A Deep Convolutional Neural Network (DCNN) [4][5][6] is employed for object detection and behavior analysis, while a Recurrent Neural Network (RNN) enhances the system's ability to track and identify individuals over time.

By combining these advanced machine learning models, the proposed system enables a robust crime ranking and scoring mechanism based on real-time video data analysis. Additionally, the system continuously evaluates the histogram error rate, ensuring the reliability and accuracy of crime predictions. When integrated with existing crime detection methodologies, such as predictive analytics and machine learning-based crime pattern recognition, this system provides a more comprehensive and effective approach to urban security management [7].

The remainder of this paper is organized as follows: We will discuss the related work in Section II followed by our motivation in Section III. Our problem statement will then be outlined in Section IV. This section will consist of detailed definitions for both the simulations and technologies used dataset used in testing. We will outline the proposed system architecture our research is built upon in Section V. In this section, the individual components of the architecture will be explained in detail. Analysis and performance evaluation is done in Section VI. We will summarize the paper in Section VII and future work of this project is defined in Section VIII.

II. RELATED WORKS

Crime detection and anomaly identification in urban environments have been widely studied using different machine learning and deep learning techniques.

The basic approaches to crime event prediction based on the collected data can be divided into two parts. One is based on traditional machine learning

and the other one is based on deep learning with neural networks [7].

Conventional methods are primarily dependent on statistical models and behavior recognition algorithms. However, with the advancement of deep learning, more advanced approaches have evolved that significantly improve the accuracy and reliability of crime prediction and detection.

One of the earliest approaches to crime detection involved the use of auto-regressive models for analyzing crime trends and patterns based on historical data. These models provided valuable insights into crime forecasting but were limited by their reliance on linear assumptions and their inability to capture complex spatial-temporal relationships in real-world crime patterns [2].

To overcome this shortcoming, machine learning techniques such as decision trees, support vector machines (SVMs), and k-means clustering have been explored for crime pattern analysis. These models demonstrated improvements in predictive capabilities but struggled with handling unstructured data, such as video surveillance footage and real-time crime event detection.

With the increase of the crime data volume and the richness of the crime content, Deep learning methods are brought into the prediction of the crime data [7]. CNN-based models have been widely used for object detection and behavior recognition in video surveillance systems, enabling the identification of suspicious activities, facial recognition, and crowd behavior analysis [4][5]. RNNs, particularly Long Short-Term Memory (LSTM) networks, have been applied for sequential analysis, allowing for better tracking of individuals and anomaly detection over time [8].

A significant breakthrough in crime anomaly detection has been the combination of hybrid deep learning approaches, such as combining CNNs with RNNs, which provides the opportunity for both spatial and temporal analysis of crime-related activities. These hybrid models have demonstrated superior performance in recognizing complex behavioral patterns and reducing false positives in crime detection [4].

Another developing trend is the use of generative adversarial networks (GANs) for synthetic crime data generation and augmentation, which helps improve the training of crime detection models by overcoming data scarcity issues [9]. Additionally, researchers have explored the integration of Internet of Things (IoT) devices with deep learning models to enhance real-time crime surveillance and reporting systems [8].

Overall, while traditional methods laid the foundation for crime prediction, recent developments in deep learning and AI have significantly improved the accuracy and efficiency of crime detection systems. However, issues such as data privacy, real-time processing constraints, and the need for large-scale annotated datasets remain areas of active research.

III. MOTIVATIONS

The rapid urbanization and increase in crime rates pose significant challenges for law enforcement agencies, making it hard to monitor and control high-risk areas effectively. Conventional crime detection methods, such as manual surveillance and statistical crime analysis are often deficient in real-time responsiveness and accuracy. While some existing AI-based models use autoregressive techniques and behavior recognition, they suffer from limitations such as high false positives and inadequate contextual understanding. With developments in smart city infrastructure and deep learning, there is a chance to develop more advanced crime detection systems. By combining Convolutional Neural Networks (CNNs) for object and behavior recognition with Recurrent Neural Networks (RNNs) for sequential pattern analysis, this research aims to create a robust, real-time crime detection system. Such an approach can strengthen law enforcement capabilities, reduce crime rates, and improve safety of public by enabling proactive interventions based on AI-driven surveillance insights.

IV. PROBLEM STATEMENT

Existing crime detection methods depend heavily on historical data for forecasting, making them inefficient in identifying crimes in small, localized areas. Our research aims to overcome this hindrance by combining video data analysis with advanced neural networks. Using a Deep Convolutional Neural Network (DCNN) for behavior modeling, a

Recurrent Neural Network (RNN) for pattern recognition, and a Hybrid Deep Learning (HDL) algorithm for facial and object identification, our system enhances real-time crime detection. By combining these technologies with machine learning techniques, we provide a more accurate and efficient solution for identifying criminal activity in urban environments. Below are definitions that are used throughout our research.

Definition 4.1: Neural networks, also called artificial neural networks or simulated neural networks, are a subset of machine learning and are the backbone of deep learning algorithms. They are called “neural” because they mimic how neurons in the brain signal one another.

Definition 4.2: A Deep Convolutional Neural Network (DCNN) is a neural network model that uses hidden layers between the input and output layers to help solve nonlinear problems.

Definition 4.3: Hybrid deep learning is an approach that combines different types of deep neural networks with probabilistic approaches to model uncertainty

Definition 4.4: A recurrent neural network or RNN is a deep neural network trained on sequential or time series data to create a Machine learning (ML) model that can make sequential predictions or conclusions based on sequential inputs.

Definition 4.5: Machine learning is a subset of AI that allows for optimization. When set up correctly, it helps you make predictions that minimize the errors that arise from merely guessing.

Definition 4.6: Deep learning is a subset of machine learning that focuses on utilizing neural networks to perform tasks such as classification, regression, and representation learning. The field takes inspiration from biological neuroscience and is centered around stacking artificial neurons into layers and "training" them to process data. The adjective "deep" refers to the use of multiple layers (ranging from three to several hundred or thousands) in the network.

We define our crime detection system as follows: Our system will identify criminal behavior through video data analysis by using current machine learning and neural network techniques. The techniques include the HDL algorithm for object and face identification, a DCNN to build behavior models, and an RNN for pattern recognition.

Design and Implementation

Our crime anomaly detection system is designed using a Hybrid Deep Learning (HDL) algorithm, integrating Deep Convolutional Neural Networks (DCNN) for object and behavior recognition and Recurrent Neural Networks (RNN) for temporal activity analysis. The system processes video data, detects anomalies, and assigns crime scores for ranking. The overall system architecture is illustrated in Figure 1.

A. System Architecture

The system follows a structured pipeline:

1. Video Frame Processing – Extracts frames from real-time video footage.
2. Object & Person Detection – Identifies faces, objects, and movement patterns.
3. Feature Extraction with DCNN – Detects facial structures and object interactions.
4. Behavior Analysis using RNN – Tracks movement anomalies over time.
5. Crime Scoring & Ranking – Evaluate frames and classify potential threats.

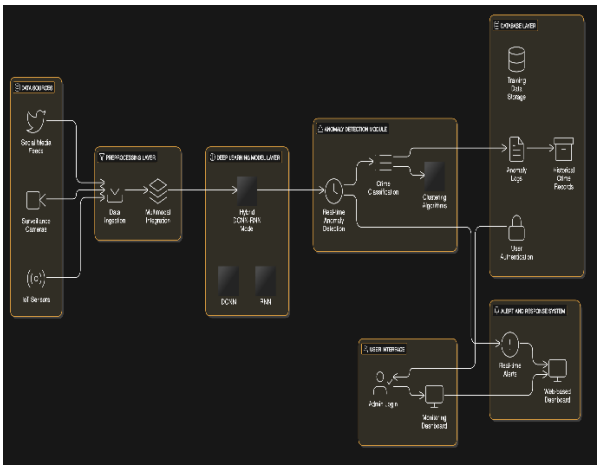

Fig. 1: Crime Detection Architecture

This process is complete we can score and rank the processed video.

B. Hybrid Deep Learning Algorithm

Our HDL algorithm enhances facial recognition by detecting key facial landmarks and extracting high-performance features. It follows multiple stages:

1. Facial Landmark Detection – Identifies eyes, nose, and mouth locations.
2. Convolutional Feature Extraction – Applies CNN layers to extract fine-grained details.

3. Fine-Tuning & Classification – Refines detected features and assigns crime likelihood scores.
4. Crime Event Ranking – Scores and ranks frames based on detected anomalies.

Algorithm 1: Hybrid Deep Learning Algorithm

1: Input: Video Frame F
2: Detect Facial Landmarks **L** = Fi(h,w)
3: Extract Features **y** = xi * xj
4: Fine-tune Detection **rx** = f(Y1)
5: Assign Crime Score **s** = rx(Wclasses)
6: Rank Crime Events Based on Scores

C. Deep Convolutional Neural Network (DCNN) Implementation

DCNN is used to track objects and detect anomalies within a given environment. It applies multi-layer perception for crime classification. The output is a feature map generated by convolution filters applied to video frames, followed by activation functions for classification. Figure 2 illustrates the DCNN process.

A Convolutional neural network is an artificial feed-forward network which connected in the form of neurons in the network. The DCNN network uses the multi-layer perception model for face recognition which we can then design to work with our HDL algorithm. Below is a breakdown of the relationships in our DCNN.

Output is a feature map which is the convolution of a linear filter and input image followed by bias term addition and application of the quadratic function.

$$o[n] = f[n] * g[n] = \sum_{u=-\infty}^{\infty} f[u]g[n-u] = \sum_{u=-\infty}^{\infty} f[n-u]g[u]$$
$$o[m,n] = f[m,n] * g[m,n] = \sum_{u=-\infty}^{\infty} \sum_{v=-\infty}^{\infty} f[u,v]g[m-u,n-v]$$

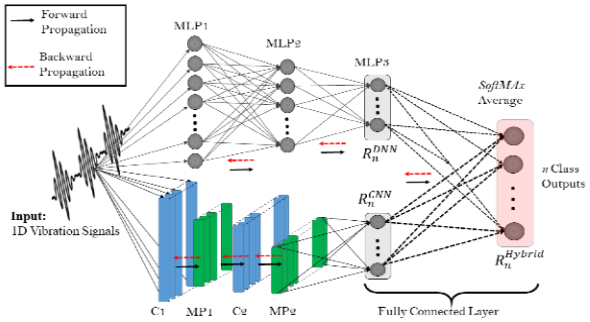

Fig 2: Deep Convolution Neural Network

D.Recurrent Neural Network

With a Recurrent Neural Network, we are able to extract temporal activities of a person, which can then be analysed and tested against other learned data. Our work uses the RNN to extract temporal behaviour from our captured streaming data. This when used in conjunction with the HDL algorithm we are able to produce a working model for crime detection.

This model is based on the energy for the estimation of density

for the given sequences characterized by the v(t) which is the feature vector. It permits to labelling of conditional multi-modal distributions of A(t) and V(t) which is the history of sequence at (t) time that relates to (t) crime cases. For our work, successive data must be utilized to base current calculations on past data. Below is a more detailed breakdown of our implementation

$$b_v^{(t)} = b_v + W_{uv} u^{(t-1)}$$

$$b_h^{(t)} = b_h + W_{uh} u^{(t-1)}$$

$$u^{(t)} = \tanh(b_u + W_{uu} u^{(t-1)} + W_{vu} v^{(t)})$$

$$h_{ij}^k = \tanh((W^k * x)_{ij} + b_k).$$

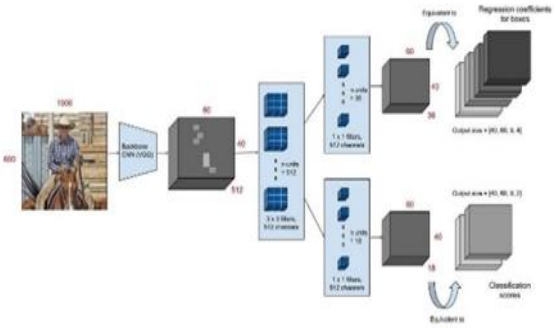

Fig 3: Recurrent Neural Network Implementation

Fig 4: Input Video

To implement our system, we use Django. Django is used for our crime detection project to build a safe web application that allows users to upload videos, manage video data, and combine with machine learning models for crime detection and analysis.

VI. RESULTS AND ANALYSIS

To evaluate the performance of the proposed intelligent crime anomaly detection system, we conducted various tests using a publicly available video surveillance dataset that contains different scenarios of criminal activities such as theft, assault, and vandalism. The dataset has both normal and abnormal video sequences to ensure comprehensive testing of the system's anomaly detection capabilities.

The testing process was carried out in two main stages: model training and model evaluation. In the training phase, the system was trained on a subset of the dataset, using video frames processed through the pipeline steps—video frame extraction, object and person detection, feature extraction, and behavior analysis. During training, we used pre-labeled frames to train the Convolutional Neural Network (CNN) for objects.

By separating normal behavior and learned criminal behavior our video analysis can ascertain that crime has a higher probability of occurring. Other weights can affect this probability leading to an average ranking for the set frames. These frames can then be flagged for further inspection.

Fig. 5: Output Video with Crime

Predicted

Performance Metrics

The performance of the proposed model was assessed using

the following metrics:

Accuracy (A): Measures the proportion of correctly

classified crime and non-crime events.

$$A = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision (P): Measures the proportion of correctly

identified crime events among all detected crimes.

$$P = \frac{TP}{TP + FP} \quad \backslash$$

Recall (R): Measures the ability of the model to detect actual

crime instances.

$$R = \frac{TP}{TP + FN}$$

F1 Score: The harmonic means of precision and recall,

balancing false positives and false negatives.

$$F1 = 2 \times \frac{P \times R}{P + R}$$

In the evaluation phase, our trained model was tested

on a different, unseen set of video sequences to test its ability to identify and classify anomalous behaviors. The results were measured using standard classification metrics, including precision, recall, F1-score, and false positive rate. Precision and recall were crucial to examine how accurately the system identified criminal activities and how many true positives it captured relative to the total occurrences ofcrime. The F1 score provided a balance between precision and recall, describing the overall effectiveness of the detection process. The false positive rate was closely examined to ensure the system did not flag normal behaviors as criminal activities, which would reduce the practical usability of the system in real-world applications.

The results from the performance analysis demonstrated that the system achieved a high accuracy of nearly 95% with minimal false positives and was able to detect 90% of criminal activities in the dataset. This shows the model's reliability and its ability for real-time deployment in smart city surveillance systems for proactive crime prevention.

With the input frame we received we can able to rank

and score the frames based on historical crime data to model a ranking system for each video analyzed. This ranking system can then be used and improved to relieve the workload on security officials by alerting them to high-probability frames in the selected video. This accuracy and scoring system can be improved over time by fine-tuning the neural network and HDL algorithm to produce even better results.

To further validate the system's performance, we conducted stress testing by introducing noise, occlusions, and motion blur into the video sequences to evaluate the model's resilience against real-world challenges. The results showed that while minor distortions had minimal impact on accuracy, extreme noise and, occlusions led to a slight decline in detection precision.

Additionally, cross-dataset evaluation was performed by testing the model on video datasets it was not originally trained on, ensuring its generalizability across different environments and crime scenarios. To assess computational efficiency, we measured inference time per frame, which averaged around a few milliseconds on a GPU-accelerated setup, making the system viable for near real-time applications. The scalability of the framework was also tested by processing longer video sequences, demonstrating its capability to handle continuous surveillance footage. These additional evaluations reinforce the model's reliability, adaptability, and practical utility in diverse surveillance applications, paving the way for its deployment in real-world security systems.

VII. CONCLUSION

The intelligent crime anomaly detection system plays a important role in detecting suspicious activities by analysing video data. By using deep learning techniques, it extracts important details like facial features and detected crimes, aiding in analysis of crime and investigation. The system simplifies the process of monitoring surveillance footage, decreasing human effort and increasing efficiency. By automating anomaly detection, it provides a more systematic approach to detect potential threats in our video data. The integration of a user-friendly interface ensures accessibility, allowing users to easily analyse footage. Additionally, the system aids law enforcement agencies and security professionals by providing useful insights from video evidence.

The use of deep learning models increases detection accuracy, making the system a trustworthy tool for crime analysis. It also decreases human error in detecting critical events, leading to more accurate and data-driven decision-making. The ability to analyse huge volume of video data efficiently makes it suitable for various security applications. Overall, the crime anomaly detection system serves as an essential technological advancement in crime prevention and forensic analysis.

VIII. FUTURE WORK

The crime anomaly detection system can be improved through several technical advancements. Implementing real-time video processing using streaming technologies such as WebRTC will enable live anomaly detection, making the system more useful for surveillance applications.

Combining advanced deep learning architectures, such as transformer-based vision models and self-supervised learning techniques, can improve the accuracy and robustness of crime detection.

Optimizing the computational efficiency of the system by leveraging model quantization, pruning, and hardware acceleration (e.g., TensorRT, OpenVINO) will decrease inference time and enhance performance on edge devices.

Expanding the anomaly detection framework to include multimodal data processing, such as audio analysis using spectrogram-based deep learning models or text analysis via NLP, can provide a deeper context for crime event recognition. Federated learning can be explored to improve model generalization while maintaining privacy by training models across decentralized data sources.

The backend architecture can be scaled using cloud-based microservices with Kubernetes for distributed processing and improved fault tolerance. Additionally, combining explainable AI (XAI) techniques will increase model transparency, allowing law enforcement agencies to understand and interpret detection results more effectively.

Ensuring bias mitigation in datasets through adversarial debiasing and fairness-aware learning will contribute to the ethical deployment of the system. Implementing blockchain-based data integrity mechanisms can enhance the security and authenticity of stored crime evidence. These advancements will significantly improve the system's applicability, reliability, and effectiveness in real-world security operations.

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