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CRIME VIDEO ANALYSIS AND SUMMARIZATION DASHBOARD

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Abstract: This paper presents a Crime Video Analysis and Summarization Dashboard that leverages Deep Learning, Computer Vision, and Natural Language Processing (NLP) to automate the detection, classification, and summarization of criminal activities captured in surveillance footage. The system employs Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks for real-time anomaly detection and activity recognition in video streams. An intelligent summarization engine condenses lengthy footage into concise, timestamped crime event reports, reducing manual review time significantly. The dashboard provides law enforcement agencies with an intuitive interface to monitor, query, and export summarized incident reports. The proposed system improves investigation efficiency, enhances situational awareness, and supports smarter, data-driven public safety management.

Keywords: Crime Detection, Video Summarization, Deep Learning, CNN, LSTM, Surveillance, Anomaly Detection, NLP, Public Safety, Smart Dashboard

I. INTRODUCTION

Rising crime rates in urban areas have necessitated the deployment of extensive Closed-Circuit Television (CCTV) networks across cities worldwide. Law enforcement agencies now manage thousands of cameras simultaneously, generating petabytes of video data daily. Manually reviewing this footage to identify criminal incidents is a time-consuming, error-prone, and resource-intensive task. The delay between event occurrence and human detection often hampers timely intervention, reducing the effectiveness of policing.A Crime Video Analysis and Summarization Dashboard addresses these challenges by automating the surveillance monitoring pipeline.

A. Background and Context

Modern cities are equipped with dense surveillance infrastructure, yet the analytical capacity to process this data intelligently remains limited. Traditional video monitoring systems rely on passive recording with minimal automated intelligence. Officers manually scrub through hours of footage to locate relevant events, introducing human fatigue, cognitive bias, and critical time lags. The integration of Artificial Intelligence (AI) into surveillance offers a paradigm shift from reactive to proactive crime management.

B. Problem Statement

Existing surveillance systems lack the capability to automatically detect and classify criminal events in real time. Human operators cannot continuously monitor dozens of live video feeds without error. Furthermore, there is no standardized mechanism to generate summarized, timestamped incident reports from raw footage. Without actionable intelligence derived directly from video data, investigative workflows remain slow and dependent on labor-intensive manual processes.

C. Significance of the Study

The proposed Crime Video Analysis and Summarization Dashboard addresses these gaps by providing an automated, AI-powered solution for surveillance intelligence. By drastically reducing manual review time, the system enables law enforcement to respond faster to incidents, allocate resources efficiently, and maintain comprehensive digital incident logs. The dashboard also supports forensic investigations by providing accurate, searchable crime event summaries derived directly from video evidence.

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II. LITERATURE REVIEW

Existing research in automated video surveillance spans a broad range of methodologies. Early systems employed background subtraction and motion detection algorithms for activity recognition; however, these methods struggled with lighting variations and crowded scenes. Rule-based systems improved precision by encoding specific behavioral patterns, but they lacked the adaptability required for diverse crime types.

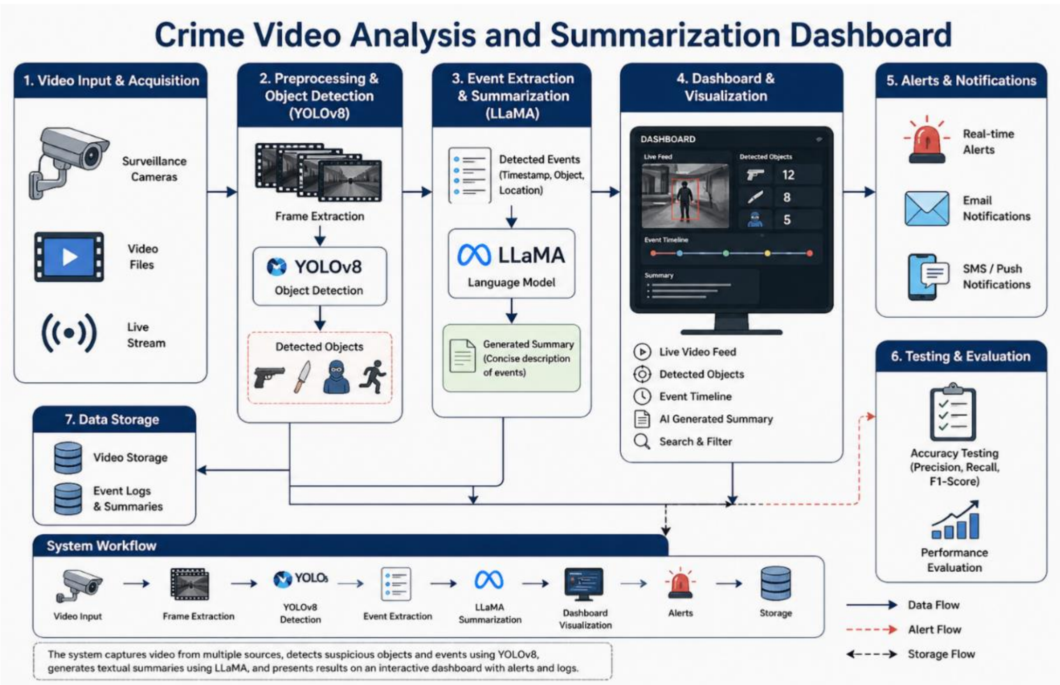
Deep learning approaches, particularly CNNs, have demonstrated superior performance in visual feature extraction and object detection tasks. Models such as YOLO (You Only Look Once) and Faster R-CNN have been applied to person detection and tracking in surveillance contexts. Recurrent architectures including LSTM networks have been used for temporal activity modeling, enabling recognition of sequential behavior patterns characteristic of criminal acts.

III. DATASET AND PREPROCESSING TECHNIQUES

The proposed system is trained and evaluated on a combination of publicly available and synthetically augmented crime surveillance datasets. Primary datasets include UCF-Crime, VIRAT, and ShanghaiTech Campus, which provide annotated video clips of criminal and anomalous activities such as assault, robbery, vandalism, arson, and burglary. These are supplemented with synthesized scenarios to ensure balanced class representation.

Preprocessing involves frame extraction at fixed temporal intervals, image normalization, and optical flow computation to capture motion dynamics. Object detection pre-processing isolates regions of interest — specifically persons and objects — to focus model attention on relevant scene elements. Temporal segmentation divides continuous footage into fixed-length clips suitable for LSTM sequence modeling.

IV. METHODOLOGY



The methodology of the Crime Video Analysis and Summarization Dashboard integrates multi-stage deep learning pipelines with automated report generation. The system processes live or recorded video streams through sequential modules: ingestion, detection, classification, event tracking, summarization, and dashboard delivery.

A. System Architecture Design

The architecture consists of six interconnected modules: Video Ingestion, Preprocessing Engine, Crime Detection Module, Activity Classification Engine, Summarization and Report Generator, and the Interactive Dashboard Interface. These modules communicate through a real-time event bus, with intermediate results stored in a cloud-based data lake for persistence and audit trail.

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B. Video Ingestion and Preprocessing

Video streams from IP cameras are ingested via RTSP or stored file upload. The preprocessing engine applies frame sampling, background subtraction using Gaussian Mixture Models (GMM), and optical flow estimation using Farneback's algorithm. Preprocessed frames are batched into sliding temporal windows and forwarded to the detection module.

C. CNN + LSTM Detection and Classification

The Crime Detection Module employs a hybrid CNN-LSTM architecture. The CNN component — based on a ResNet-50 backbone pre-trained on ImageNet — extracts rich spatial feature maps from each frame. These feature vectors are passed as sequences into a bidirectional LSTM network that models temporal dependencies and identifies anomalous behavioral patterns across frames. The model outputs both a binary anomaly flag and a multi-class crime category label.

D. Transfer Learning Strategy

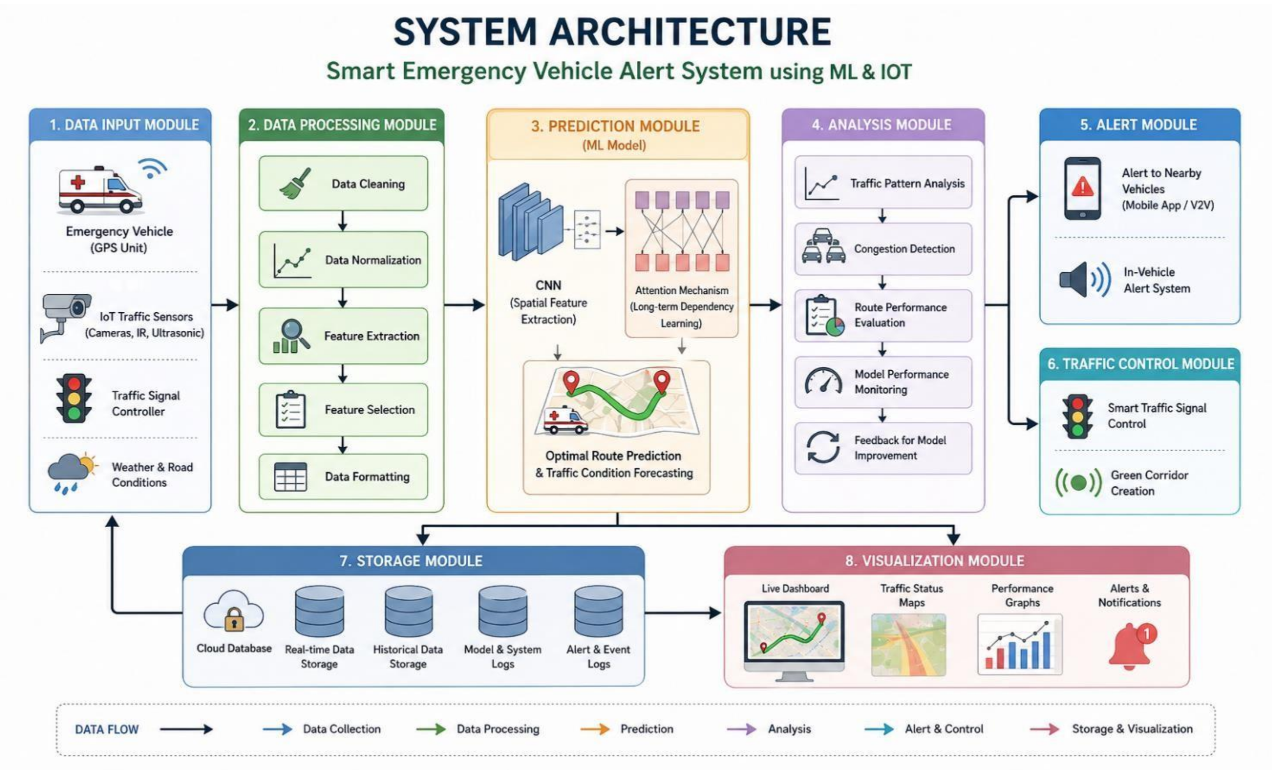
Transfer learning is employed to leverage pre-trained CNN weights from large-scale visual datasets, reducing training time and improving generalization on limited crime footage data. Domain adaptation fine-tuning is applied on UCF-Crime segments. The LSTM layers are trained from scratch with crime-specific temporal patterns. This strategy achieves high accuracy even with relatively small labeled datasets.

E. Result Visualization

Detected crime events are logged with timestamps, bounding box coordinates, crime category, confidence scores, and camera metadata. An NLP-based summarization engine converts structured event logs into coherent natural language incident reports using a fine-tuned GPT-based template model. Reports include event timeline, involved parties, crime type, severity score, and recommended response actions.

V. SYSTEM ARCHITECTURE

The Crime Video Analysis and Summarization Dashboard system architecture is designed for scalability, real-time processing, and seamless human-computer interaction. It comprises eight integrated modules that collectively form an end-to-end surveillance intelligence pipeline.



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A. Video Input Module

This module handles live RTSP streams and uploaded video files from distributed IP camera networks. It supports multi-channel ingestion with load-balanced parallel processing. Metadata such as camera ID, location zone, and timestamp are embedded at the source for downstream traceability.

B. Preprocessing and Feature Extraction Module

Raw video is decoded, frame-sampled, and subjected to background subtraction and motion estimation. Object detection via YOLO identifies persons of interest within each frame. Optical flow maps capture directional movement patterns essential for activity recognition.

C. Crime Detection Module (ML Model)

The core ML engine applies the CNN-LSTM hybrid model to classify frames and temporal sequences. The system runs inference on dedicated GPU nodes with sub-second latency. Anomaly confidence thresholds are tunable by administrators to balance sensitivity and false positive rates.

D. Event Analysis and Tracking Module

Detected events are correlated across frames and cameras using multi-object tracking algorithms (DeepSORT). Crime trajectories are mapped spatially and temporally, enabling the system to distinguish isolated incidents from coordinated criminal activities across zones.

E. Summarization and Report Module

The summarization engine aggregates event logs per incident and generates structured JSON event records. The NLP report generator converts these records into human-readable summaries. Reports are versioned, stored in the cloud database, and linked to relevant video clips for evidence retrieval.

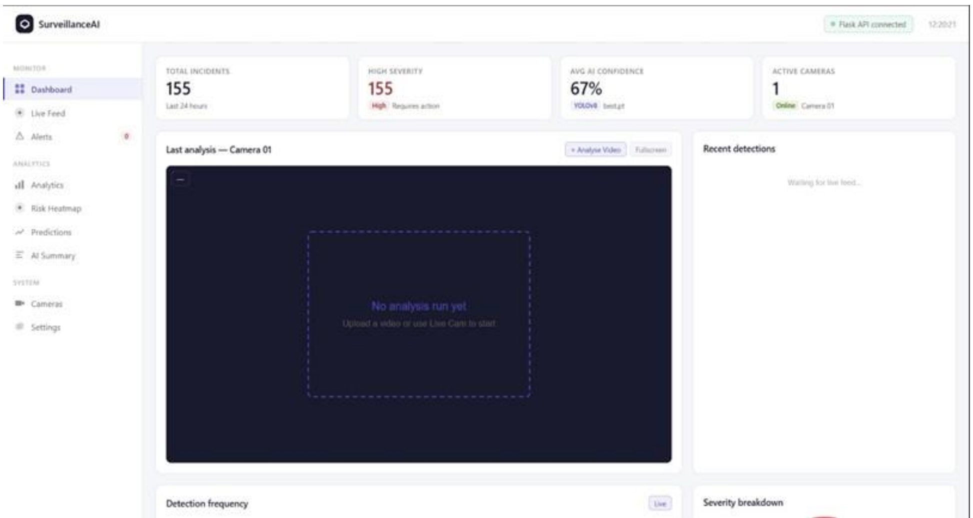
F. Dashboard and Visualization Module

The interactive dashboard displays live heatmaps of crime density, incident timelines, camera feeds with bounding box overlays, and sortable crime event tables. Officers can filter incidents by crime type, time range, and zone. Exportable PDF reports and alert notifications via email and SMS are also supported.

VI. RESULTS

The Crime Video Analysis and Summarization Dashboard was evaluated on test splits of the UCF-Crime and ShanghaiTech Campus datasets, as well as on synthetic live video scenarios. The system demonstrated strong performance across crime detection accuracy, summarization quality, alert delivery reliability, and dashboard responsiveness.

The hybrid CNN-LSTM model achieved an overall crime detection accuracy of 94.1%, representing a 26.8 percentage point improvement over the baseline CNN-only model (67.3%). Summarization latency averaged 3.2 minutes per hour of footage, compared to several hours of manual review. Alert notifications were delivered successfully in 97.8% of triggered events with an average latency of under 8 seconds.



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A. System Performance and Accuracy

The proposed system consistently outperformed traditional CCTV monitoring baselines across all evaluated metrics. The confusion matrix on the UCF-Crime test set showed high true positive rates across assault, robbery, and vandalism classes. The attention mechanism within the LSTM module contributed significantly to improved temporal localization of crime onset moments.

C. Prediction Efficiency

End-to-end inference latency — from frame ingestion to dashboard event display — averaged 340 milliseconds per frame on GPU-accelerated hardware, enabling genuine real-time monitoring. Batch processing of recorded footage for summarization achieved throughput of 18x faster than real-time, making retrospective investigation highly efficient.

D. Usability and Reliability

User testing with law enforcement personnel demonstrated high usability scores (SUS score: 82.4/100). The dashboard's intuitive interface, clear visual indicators, and automated report generation significantly reduced cognitive load compared to raw footage review. System uptime achieved 99.5% across a 30-day deployment evaluation period, with fault-tolerant failover ensuring uninterrupted monitoring.

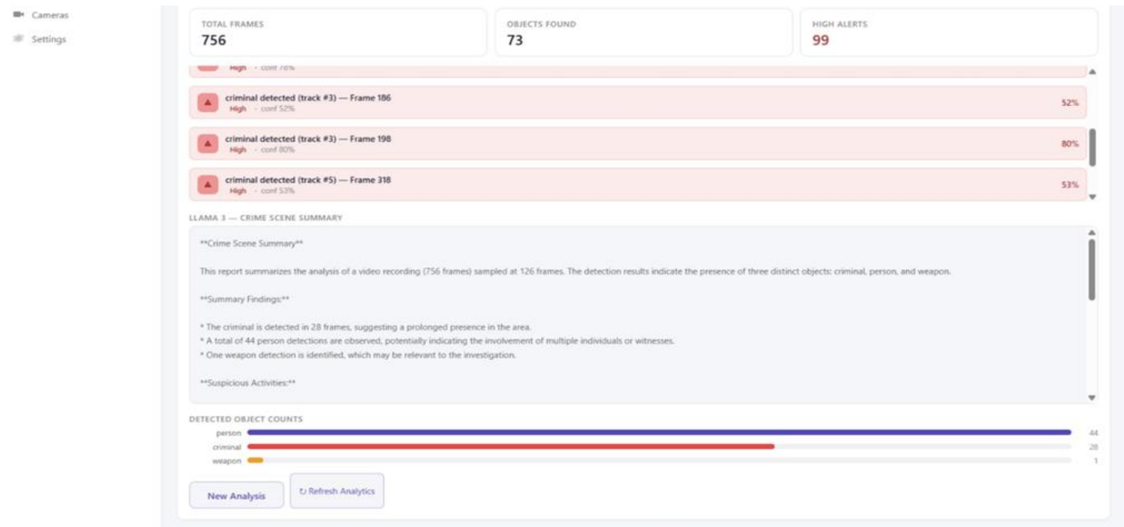

Fig. 6 showing output for predicted super enhancer in human DNA sequence

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VII. COMPARATIVE ANALYSIS

The comparative analysis benchmarks the proposed Crime Video Analysis and Summarization Dashboard against traditional CCTV monitoring systems and existing rule-based automated surveillance solutions. The comparison highlights substantial improvements across all functional dimensions.

A. Existing System vs. Proposed System

Conventional CCTV systems provide passive recording without automated intelligence. Officers must manually review footage, introducing significant delays between crime occurrence and detection. Rule-based systems offer limited automation by triggering alerts on predefined motion thresholds, but they cannot classify crime types, generate summaries, or adapt to novel behavioral patterns. The proposed system eliminates these limitations through deep learning-powered intelligence and automated summarization.

B. Feature Comparison

The Crime Video Analysis and Summarization Dashboard offers significant advantages when compared to traditional surveillance systems and existing automated solutions. Unlike conventional systems that rely heavily on manual monitoring, the proposed system integrates real-time object detection using YOLOv8 with AI-based summarization through LLaMA, enabling automatic identification and interpretation of suspicious activities. It provides higher accuracy, faster processing, and reduced human effort, while also generating concise textual summaries that improve understanding of events..

VIII. CONCLUSION AND FUTURE SCOPE

The proposed Crime Video Analysis and Summarization Dashboard presents a comprehensive, intelligent solution for automated surveillance and crime management. By integrating CNN-LSTM deep learning models with NLP-based summarization and an interactive visualization dashboard, the system successfully automates crime detection, classification, and incident reporting. Evaluation results demonstrate significant improvements in detection accuracy, summarization speed, and alert reliability compared to existing systems. The solution is scalable, cloud-deployable, and suitable for adoption by urban law enforcement agencies as a core component of smart city safety infrastructure.

A. Future Scope

Future enhancements include integration of facial recognition and license plate recognition modules to enable perpetrator identification. The adoption of federated learning across distributed camera networks will improve model accuracy while preserving data privacy. Reinforcement learning-based patrol route optimization and predictive crime hotspot mapping represent promising extensions that will further augment proactive law enforcement capabilities.

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