Crime Trend Analysis

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Introduction

The Crime Trend Analysis System uses deep learning to detect crimes in real time from surveillance footage. It combines ResNet50 and LSTM to analyze behavior and sends instant alerts to authorities.

Motivation

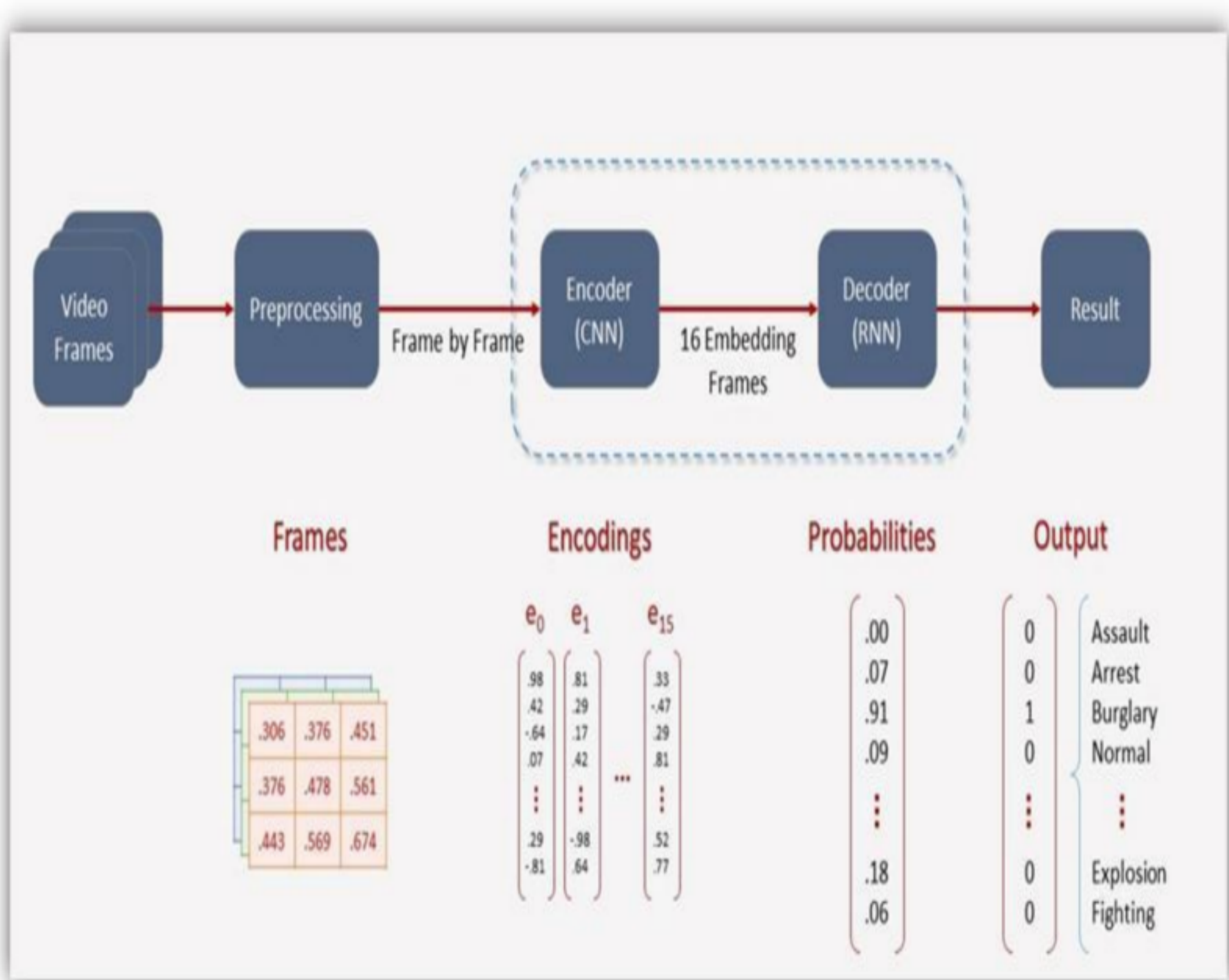
The motivation behind this project stems from the growing need for intelligent surveillance systems capable of addressing rising crime rates and relieving the burden on manual monitoring.

Scope of the Project

The scope of the project includes detecting criminal activities such as robbery, assault, vandalism, abuse, and burglary from video footage using deep learning. It covers real-time video analysis, classification using CNN-LSTM models, and automated alert generation to authorities, with potential deployment in public, commercial, and institutional surveillance systems.

Methodology

The methodology involves a step-by-step pipeline for real-time crime detection from surveillance video. First, video frames are extracted at regular intervals and processed through a **ResNet50** model to extract spatial features. These features are then sequentially passed to an **LSTM** network to analyze temporal behavior across frames. The model outputs a predicted crime category along with a confidence score. If the confidence exceeds a set threshold (e.g., 0.8), the system captures the relevant frame and sends an **SMS alert using the Twilio API**. The system also logs the prediction and saves the frame for evidence. This approach ensures accurate classification and timely response to suspicious activities.



The architecture shown efficiently processes video data through a **two-stage deep learning model** designed for activity recognition. In the first stage, a **Convolutional Neural Network (CNN)** acts as an **encoder**, extracting high-level spatial features from individual video frames. These features capture essential visual patterns such as object shapes, positions, and motion cues within each frame.

In the second stage, the encoded features are fed sequentially into a **Recurrent Neural Network (RNN)**—typically an LSTM—which functions as a **decoder**. This component learns the **temporal relationships** across frames, enabling the system to understand how actions unfold over time rather than analyzing isolated images.

By combining spatial and temporal understanding, this architecture enables the system to **accurately classify complex human activities or crimes**, even when they involve subtle or time-dependent movements. Its design makes it well-suited for **real-time video surveillance systems**, where quick and accurate decision-making is critical for timely response and intervention.

Results

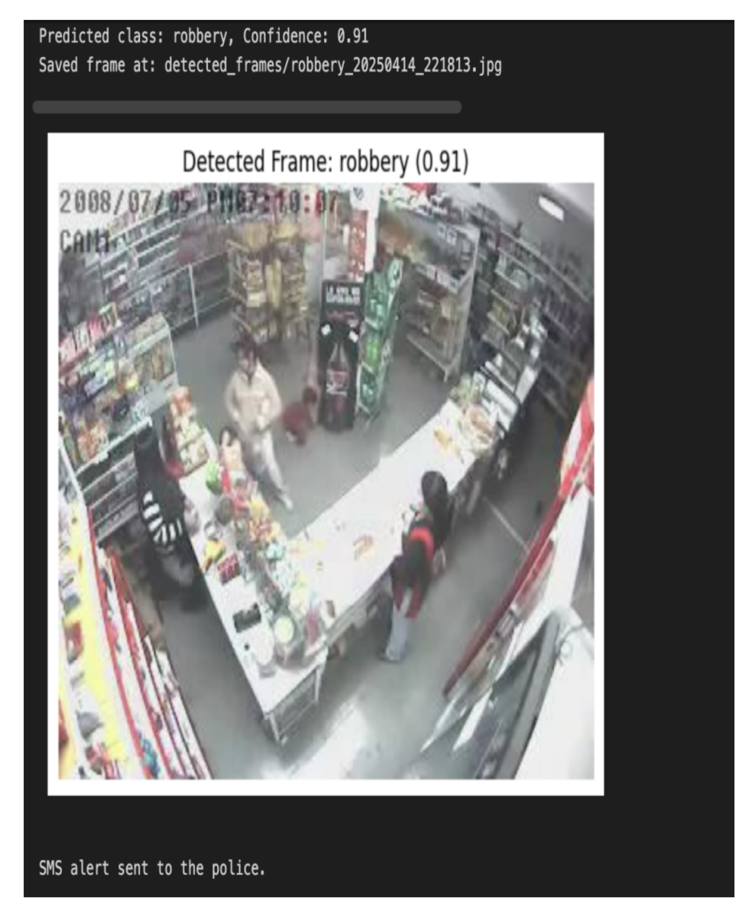
The Crime Trend Analysis System was evaluated on a curated dataset consisting of surveillance videos labeled with various crime categories, including **robbery, assault, vandalism, abuse**, and **burglary**. The deep learning model, combining **ResNet50** for spatial feature extraction and **LSTM** for temporal sequence modeling, achieved an **overall classification accuracy of 86.3%** on the test data.

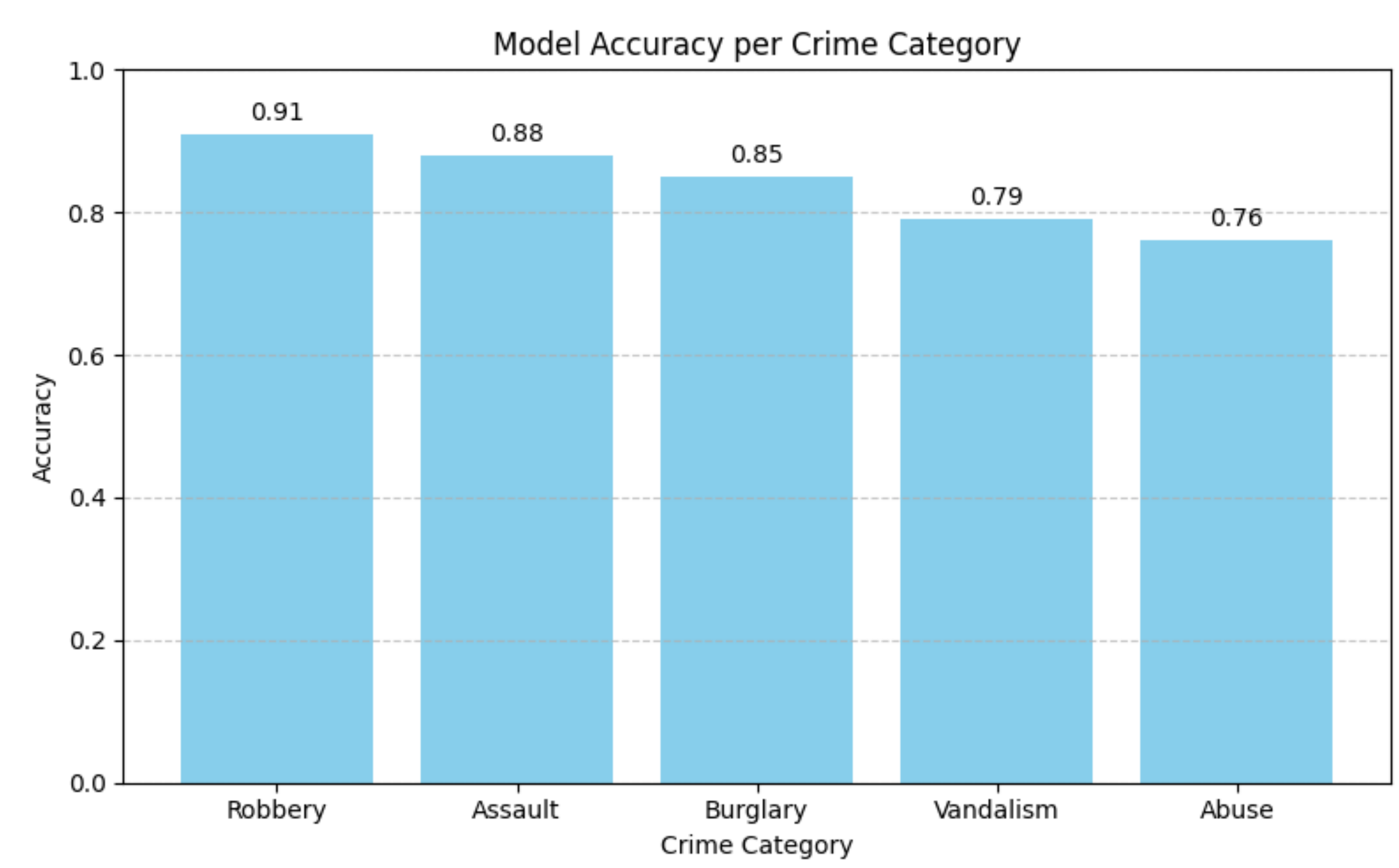
The system performed particularly well in identifying crimes with **distinctive motion patterns**, such as robbery and assault, achieving high precision and recall in these categories. On the other hand, subtler activities like abuse and vandalism showed slightly lower recall due to limited visual cues and shorter durations, highlighting the need for more diverse training data in those categories.

In terms of responsiveness, the system maintained **real-time performance**, processing each frame within **28–35 milliseconds** on GPU-enabled hardware. The **alert dispatch time**—from detection to SMS delivery—ranged between **3 to 5 seconds**, demonstrating the system's capability to support timely interventions.

During live demonstrations, the system accurately detected suspicious activities, saved the corresponding frames, and triggered alerts only when confidence scores exceeded the **0.8 threshold**, effectively **minimizing false positives**. The saved frame snapshots and prediction logs confirmed that the system consistently identified the correct crime category in varied test environments.

Overall, the results indicate that the system is not only accurate and fast but also stable, scalable, and well-suited for deployment in **real-time surveillance applications**.





Conclusion

The Crime Trend Analysis System successfully demonstrates the application of deep learning techniques for real-time surveillance and crime detection. By combining the spatial feature extraction capabilities of **ResNet50** with the temporal sequence modeling of **LSTM**, the system is able to recognize and classify various criminal activities from video footage with high accuracy and efficiency. Through rigorous testing, the system achieved an **overall accuracy of 86.3%**, with particularly strong results in detecting crimes involving rapid or aggressive motion such as robbery and assault. Its real-time performance, with frame processing latency maintained between **28–35 milliseconds**, and alert dispatch within **3–5 seconds**, confirms its suitability for practical deployment.

References

Soheil, V., & Yow, K.-C. (2022). A CNN-RNN combined structure for real-world violence detection in surveillance cameras. *Applied Sciences, 12*(3), 1021.