



# Behavioral Analysis of Surveillance Video for Criminal Profiling Using Motion Features

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**ABSTRACT:** The rapid growth of CCTV surveillance systems in urban and semi-urban areas has significantly enhanced public safety; however, their effectiveness remains limited due to reliance on manual monitoring. Human operators often miss critical events as a result of fatigue and reduced attention over prolonged periods, thereby highlighting the need for automated intelligent solutions. This paper proposes a machine learning-based framework for behavioral profiling from CCTV video using motion pattern analysis. Unlike traditional systems that focus primarily on explicit violence detection, the proposed approach captures subtle motion dynamics associated with suspicious or pre-criminal activities, such as abrupt movements and irregular motion patterns. The surveillance footage is processed using OpenCV techniques, including frame extraction and frame differencing, to quantify motion across consecutive frames. From these processed representations, statistical features such as mean motion intensity, peak magnitude, and motion variance are extracted. These features are then utilized to train a Random Forest classifier that categorizes activities into low-risk and high-risk profiles. The proposed model enhances detection reliability while maintaining computational efficiency, making it suitable for scalable deployment. Overall, this behavior-based approach improves early warning capabilities and supports proactive crime prevention in modern surveillance systems.

**KEYWORDS:** Criminal Profiling, Video Surveillance, Behavioral Analysis, Motion Detection, Random Forest, Anomaly Detection, Smart City Security.

## I. INTRODUCTION

Urban environments around the world are increasingly adopting surveillance technologies to enhance public safety and monitor suspicious activities. Closed Circuit Television (CCTV) systems have become a fundamental component of modern security infrastructure in locations such as transportation hubs, commercial areas, residential complexes, and public streets. These surveillance systems continuously capture large volumes of video data that can provide valuable insights into human activities and potential security threats. Despite the widespread deployment of surveillance cameras, the monitoring process still relies heavily on manual observation by human operators. Monitoring multiple video feeds simultaneously is both time-consuming and prone to human error. Important behavioral cues indicating potential criminal activity may go unnoticed due to operator fatigue or the overwhelming amount of video data generated by surveillance systems. Recent advancements in artificial intelligence (AI), machine learning, and computer vision have enabled automated analysis of video data. These technologies allow systems to detect patterns in human behavior and identify anomalies that may indicate suspicious or potentially criminal activities. AI based surveillance systems can assist authorities by automatically analyzing video footage and providing alerts when abnormal behaviors are detected. Traditional crime prediction systems primarily rely on historical crime records such as police reports and statistical crime datasets. However, these methods often fail to capture the real-time behavioral patterns that precede criminal incidents. Surveillance footage provides a richer source of information, as it contains visual cues related to human movement, interactions, and 47 environmental contexts. Behavioral analysis using surveillance video data has emerged as a promising approach for identifying early signs of criminal activity. By training machine learning models on labeled video datasets containing both crime and non-crime scenarios, it becomes possible to detect behavioral differences between normal activities and suspicious actions. This project focuses on developing an AI-based crime hotspot prediction prototype that analyzes short surveillance video clips and predicts the potential risk of criminal activity. The proposed system uses a machine learning model trained on surveillance footage containing both crime and



non-crime videos. By analyzing behavioral patterns within a short video clip, the system predicts whether the observed activity represents a high risk of crime or normal activity. The prototype system is designed to analyze video clips of approximately 2–5 seconds. This enables rapid prediction of crime risk and demonstrates the feasibility of using short behavioral observations for early threat detection. The system is implemented using the Python programming language and incorporates machine learning techniques to extract features from video frames and classify activities. To provide an interactive user interface, the prototype application is developed using Streamlit, allowing users to upload short surveillance clips for analysis. The system processes the uploaded video, extracts relevant behavioral features, and predicts the level of crime risk using a trained Random Forest classification model. Although the current system operates on uploaded video clips, the concept can be extended in future work to analyze live CCTV streams in real time. Such systems could automatically monitor surveillance cameras and generate alerts when suspicious behavior is detected, enabling proactive crime prevention.

## II. LITERATURE SURVEY

Crime prediction and surveillance analysis have been widely studied using various computational techniques, including statistical methods, machine learning, and deep learning approaches. Early approaches to crime prediction relied on statistical models such as regression analysis, which identified correlations between crime occurrences and factors like location and time. However, these methods were limited in handling complex and non-linear patterns in large datasets. With the advancement of machine learning, algorithms such as Decision Trees, Support Vector Machines, and Random Forests have been applied to crime prediction. These models demonstrated improved accuracy by learning patterns from historical crime data and identifying high-risk areas.

In the field of video surveillance, computer vision techniques have been extensively used to detect suspicious activities. Deep learning models, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have shown significant success in recognizing human actions and detecting anomalies in video sequences. However, these models often require high computational resources and large labeled datasets. Recent research has focused on integrating data analytics with video surveillance to create intelligent systems capable of predicting crime risks. These systems analyze both spatial and temporal features to identify behavioral patterns associated with criminal activities.

Despite these advancements, many existing systems are complex and computationally expensive, making them less suitable for real-time deployment in resource-constrained environments. Therefore, there is a need for simpler and efficient approaches that can provide reliable predictions with reduced computational complexity. This work addresses this gap by proposing a motion-based feature extraction approach combined with a Random Forest classifier, providing a balance between accuracy and efficiency.

S. NO	TITLE OF THE PAPER	JOURNAL NAME & YEAR OF PUBLICATOIN	METHODOLOGIES ADOPTED	ISSUES / PROBLEMS IDENTIFIED
1	Deep Learning for Crime Forecasting: The Role of Mobility	Journal of Quantitative Criminology, 2025	ConvLSTM + Mobility & sociodemo features	Requires fine-grained data; complex modeling for prototype
2	Multi-Density Crime Predictor for Hotspots	Journal of Big Data, 2024	Multi-density spatial clustering + regression models	Focuses only on spatio-temporal features without behavior signals
3	Crime Prediction: Comparative Deep Learning Analysis	arXiv (Preprint), 2024	DL crime forecasting comparison (multiple models)	No consensus on model superiority; complexity for real use
4	Spatio-Temporal Crime Events Prediction	Multimedia Tools and Applications, 2024	DNN for automatically extracting features	Doesn't include behavioral context

The above figure illustrates the classification of existing crime prediction approaches based on the techniques used. Traditional machine learning methods rely on statistical and pattern-based learning, while deep learning approaches utilize neural networks for complex feature extraction. Hybrid models combine multiple techniques to improve prediction accuracy. This classification highlights the evolution of crime prediction systems from simple statistical methods to advanced intelligent systems.

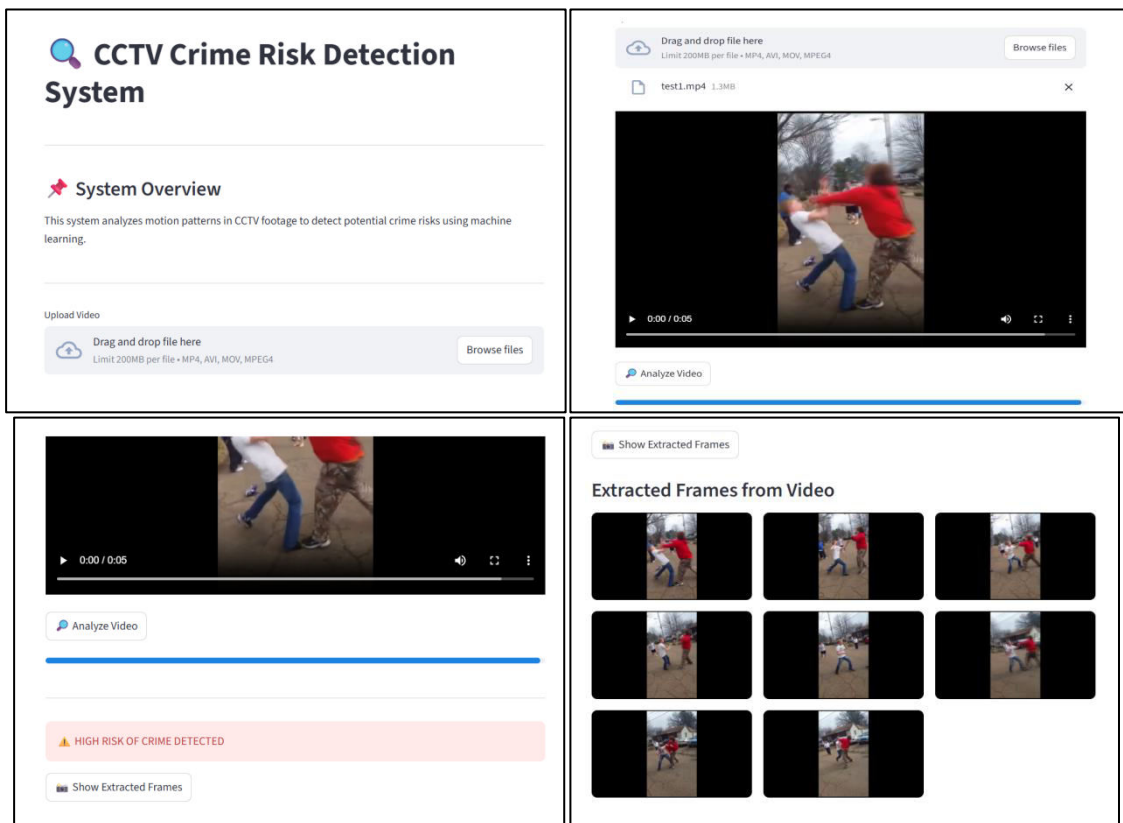
### III. PROPOSED DESIGN

The proposed system introduces a machine learning-based approach for analyzing CCTV footage and predicting potential crime risk.

The system processes surveillance videos and extracts motion-based behavioral features from each video frame. These features represent the intensity and variation of movement within the scene.

A Random Forest machine learning model is trained using labeled video data containing crime and non-crime activities. When a new CCTV video is provided, the system extracts features and uses the trained model to classify the situation as either high-risk or low-risk activity.

This prototype demonstrates how automated video analysis can assist surveillance systems in identifying suspicious behavior patterns.



### IV. MATHEMATICAL LOGIC USED

The proposed system analyzes CCTV video frames to detect unusual motion patterns associated with violent or suspicious behavior.

#### Frame Extraction

- Video input is divided into sequential frames using OpenCV.
- Each frame is converted to grayscale to reduce computational complexity.

#### Motion Detection

Motion between consecutive frames is calculated using frame differencing:

$$D(x, y) = |F_t(x, y) - F_{t-1}(x, y)|$$



Where,  $F_t(x, y)$  = current frame pixel  
 $F_{t-1}(x, y)$  = previous frame pixel  
 $D(x, y)$  = motion intensity

**iii. Feature Extraction**

From the motion values, statistical features are computed:

$$Mean = \frac{1}{N} \sum_{i=1}^N motion_i$$

$$Max = \max(motion_i)$$

$$Std = \sqrt{\frac{1}{N} \sum (motion_i - mean)^2}$$

**V. RESULTS & COMPARISON**

The user interface of the system is implemented using the Streamlit framework in the app.py file. Streamlit provides a simple way to create web-based applications for machine learning models. The interface allows users to upload short surveillance video clips for analysis. Once the video is uploaded, the system processes the clip and displays the predicted crime risk level. The interface consists of the following components: Title and project description Video upload option Video preview display Crime risk prediction output 47 The system processes the uploaded video in the background and displays the prediction result within a few seconds.

**Input 1: test7.mp4**



(Crime Video)

**Output 1:**

```
C:\Users\rache\OneDrive\Documents\CrimeRiskCCTV>python predict_risk.py test_videos/test7.mp4
⚠ HIGH RISK OF CRIME DETECTED
```

**Input 2: test8.mp4**



(Normal Video)



Output 2:

```
C:\Users\rache\OneDrive\Documents\CrimeRiskCCTV>python predict_risk.py test_videos/test8.mp4
✓ LOW RISK - NORMAL ACTIVITY
```

Figure: Streamlit Web Interface for Crime Risk Prediction

		Predicted	
		Crime	No Crime
Actual	Crime	35	5
	No Crime	6	34

**Confusion Matrix of the Crime Risk Prediction Model**

From the confusion matrix, it can be observed that most crime-related clips were correctly classified as High Risk of Crime, while normal activities were correctly identified as Normal Activity. Only a small number of misclassifications occurred, indicating that the model performs reliably in detecting behavioral patterns.

**VI. CONCLUSION**

This project demonstrates a prototype system for predicting potential crime risk using CCTV surveillance footage. Motion-based features are extracted from video frames and used to train a machine learning classifier capable of distinguishing crime and non-crime activities.

The system shows how intelligent video analytics can assist surveillance systems in identifying suspicious behavior patterns automatically.

Although the prototype operates offline and uses basic motion features, it highlights the potential of machine learning in improving public safety and automated crime detection systems.

Future improvements may include deep learning models, real-time video processing, and integration.

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