

# DEEP LEARNING-DRIVEN SURVEILLANCE SYSTEM FOR ANOMALY DETECTION IN CROWDED ENVIRONMENTS

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**Abstract** - With increasing urbanization and crowd density, ensuring public safety has become a critical concern. This project proposes an intelligent, deep learning-based surveillance system for real-time detection of suspicious activities in crowded environments such as malls, bus stations, and airports. The system uses convolutional neural networks (CNNs) to process CCTV footage and identify anomalous human behaviour. Upon detection, alerts are automatically triggered and sent to administrators for timely intervention. The solution integrates scene classification, action recognition, and notification services into a unified platform. By automating surveillance analysis, the system enhances situational awareness and reduces manual monitoring efforts. This research aims to build a scalable, efficient, and adaptable security solution to improve public safety.

**Key Words:** Suspicious activity detection, Deep learning, Convolutional Neural Networks (CNN), Real-time surveillance, Computer vision, Crowd monitoring, Smart surveillance.

## 1. INTRODUCTION

The rise in criminal activities and threats to public safety has led to increased deployment of video surveillance systems in sensitive areas such as malls, airports, railway stations, banks, and educational institutions. However, continuous manual monitoring of live video feeds is impractical and prone to fatigue-induced errors. To address this, we propose an intelligent surveillance system capable of detecting suspicious human activity in real-time using deep learning and neural network techniques.

Suspicious activity detection refers to identifying human postures, gestures, and actions that deviate from normal behavioral patterns. Traditional approaches in computer vision have largely focused on static images and lacked temporal awareness, which is essential for accurate interpretation of human behavior

in videos. Our system utilizes Convolutional Neural Networks (CNNs) trained to detect unusual body poses or movements from real-time CCTV footage, and immediately notifies the concerned administrator upon detection.

Video-based activity recognition is an evolving field of computer vision that leverages spatial and temporal features. While several methods have shown promising results in static pose estimation, applying deep networks to video sequences still presents challenges due to the added temporal dimension. To overcome this, our project exploits the strength of CNNs and motion-based frame analysis to capture and classify activity over time. Unlike earlier systems that rely on expensive hardware such as depth sensors with limitations like indoor-only use, our method is optimized for real-world environments with low-cost hardware and deployable on both desktop and mobile platforms.

The proposed system is structured into preprocessing, feature extraction, and classification modules, with optimized performance using Python (via Spyder IDE) on the Anaconda platform. Through automation and real-time processing, this model aims to reduce human effort while ensuring robust surveillance coverage. The output is user-friendly and adaptable, making it suitable for widespread deployment in both public and private security systems.

## 2. PROBLEM STATEMENT

Public safety in densely populated environments—such as transportation hubs, commercial complexes, and educational institutions—demands constant surveillance to prevent and respond to suspicious or abnormal human activities. Traditional surveillance systems depend heavily on manual monitoring of real-

time video streams, making them inefficient, error-prone, and unsuitable for scaling across multiple locations.

There exists a critical need for an intelligent, automated surveillance solution that can analyze video feeds in real-time, detect suspicious behaviors with high accuracy, and issue alerts without requiring continuous human supervision. Current research in computer vision often focuses on static images, neglecting the temporal dynamics present in video data. Moreover, many existing models are computationally expensive and unsuitable for deployment on low-resource or embedded systems.

This paper addresses the problem by proposing a deep learning-based framework using Convolutional Neural Networks (CNNs) to detect suspicious human activity from real-time CCTV footage. The objective is to develop a scalable, efficient, and cost-effective system capable of real-time classification and alert generation, thus enhancing proactive security measures in public spaces.

### 3. LITERATURE SURVEY

In recent years, anomaly detection through intelligent surveillance has become a prominent area of research due to growing concerns about public safety and criminal activities in crowded environments.

Huei-Yung Lin and Chun-Han Tseng [1] proposed a top-view action recognition system designed specifically for buses to detect and classify abnormal passenger behaviors. Their approach effectively reduced occlusion and enhanced recognition accuracy by leveraging spatial and temporal data simultaneously, and introducing a real-world dataset named BUS-HAR.

Selvi et al. [2] emphasized the necessity of transitioning from traditional post-event surveillance systems to real-time intelligent systems. They proposed an Enhanced Convolutional Neural Network (ECNN) that achieved a high mean accuracy of 97.05% and precision of 96.74% for detecting suspicious behaviors. Their approach significantly improved the ability to generate pre-incident alerts.

Mohannad Elhamod and Martin D. Levine [3] focused on recognizing behaviors like loitering, fighting, and baggage theft through semantic understanding of video

sequences. Their system used object and inter-object motion features for detecting key actions and demonstrated superior performance using public datasets, with lower computational complexity.

Tanzila Saba et al. [4] introduced a novel system that used a 63-layer deep CNN model called L4-BranchedActionNet. This model was integrated with entropy coding and an ant colony optimization system to enhance feature learning. The optimized features were classified using multiple models, with cubic SVM achieving the highest accuracy of 99.24%, confirming the efficiency of combining CNNs with advanced classification methods for suspicious activity detection.

Monji Mohamed Zaidi et al. [5] presented a hybrid deep learning architecture that combines convolutional and recurrent layers for recognizing suspicious human activity from video surveillance. Their approach focused on capturing both spatial and temporal dynamics of human motion using a CNN-LSTM model. By leveraging multiple public datasets, the study demonstrated the model's generalization ability across various environments. The research addressed major challenges such as varying lighting, occlusions, and pose estimation errors, providing a robust framework for real-time surveillance.

### 4. MOTIVATION

Ensuring public safety in crowded environments such as airports, malls, and railway stations has become a growing challenge in the modern era. With the increasing number of surveillance cameras installed globally, the volume of video data generated daily has grown exponentially. However, despite the abundance of video feeds, most surveillance systems still rely on manual monitoring by human operators, which is inherently limited by attention span, fatigue, and response delays.

The motivation behind this work stems from the pressing need to automate and enhance surveillance systems by integrating artificial intelligence. Deep learning models, particularly Convolutional Neural Networks (CNNs), have shown remarkable performance in image recognition tasks, but their application to real-time video-based human activity recognition remains underexplored—especially in the context of detecting abnormal or suspicious behaviour.

Moreover, most research in this domain focuses on high-end hardware or indoor environments with depth sensors, which are not feasible for widespread public deployments. Our project aims to fill this gap by designing an intelligent, low-cost, real-time suspicious activity detection system that can be deployed in diverse public settings and operate efficiently even on resource-constrained devices.

The broader goal is to develop a system that not only reduces the dependence on manual monitoring but also ensures timely detection and alerts in the face of potentially harmful activities—contributing to safer and smarter cities.

### 5. SYSTEM ARCHITECTURE

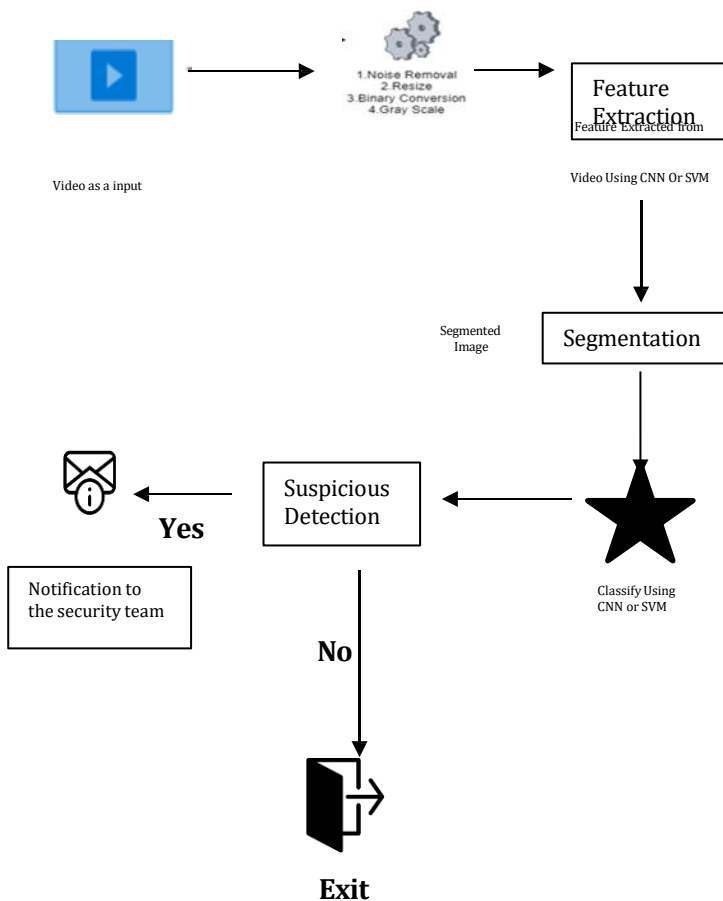


Figure 1: System Architecture

1. Video as Input: The system starts by taking a video feed as input.
2. Feature Extraction: Key features are extracted from the video frames using techniques like CNN (Convolutional Neural Network) or SVM (Support Vector Machine).

3. Segmentation: The extracted features are processed to segment the video frame to isolate relevant regions for further analysis.

4. Suspicious Detection: Based on the segmented image and extracted features, the system detects whether any suspicious activity is present.

5. Decision Node:

If Yes: Suspicious activity is detected, a notification is sent to the security team.

If No: The system proceeds to Exit, implying normal activity and no further action.

The overall structure suggests a real-time monitoring and alerting mechanism for security systems, using AI algorithms to automate threat detection.

### 6. PROPOSED ALGORITHMS

In this section, we present two algorithms for detecting suspicious activities in real-time CCTV footage: one based on **Convolutional Neural Networks (CNN)** and the other based on **Support Vector Machine (SVM)**. Both algorithms are compared in terms of their performance to determine the best approach for the task.

#### Algorithm 1: CNN-based Suspicious Activity Detection

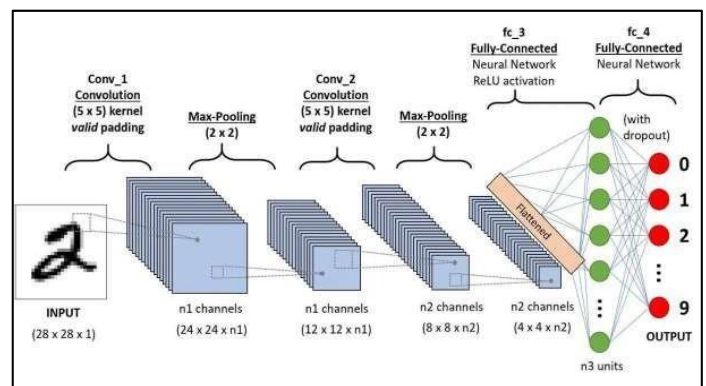


Figure 2: CNN Architecture

#### Explanation of CNN Algorithm

- a. **Input:** The algorithm takes video frames from CCTV cameras as input.
- b. **Preprocessing:** Each frame is resized and

- c. **Feature Extraction:** The CNN model extracts features from the frames, using convolutional layers to capture spatial patterns and deep features related to the activities.
- d. **Classification:** The extracted features are classified as "normal" or "abnormal" activities using a fully connected layer.
- e. **Alert Generation:** If an abnormal activity is detected, an alert is triggered for monitoring personnel.

suspicious activities, based on factors such as **accuracy, computational complexity, and real-time performance.**

### I. Accuracy

- **CNN Algorithm:** Convolutional Neural Networks are highly effective in capturing spatial and temporal features directly from the raw video frames. CNNs typically provide **higher accuracy** because they can automatically learn complex features without manual intervention. This makes them ideal for complex tasks like video surveillance.
- **SVM Algorithm:** The SVM algorithm relies on manual feature extraction, which can sometimes be less effective in detecting complex patterns. Although **SVMs** are robust and perform well with well-defined features, they may not match the accuracy of CNNs in tasks involving high-dimensional data like video frames.

### Algorithm 2: SVM-based Suspicious Activity Detection

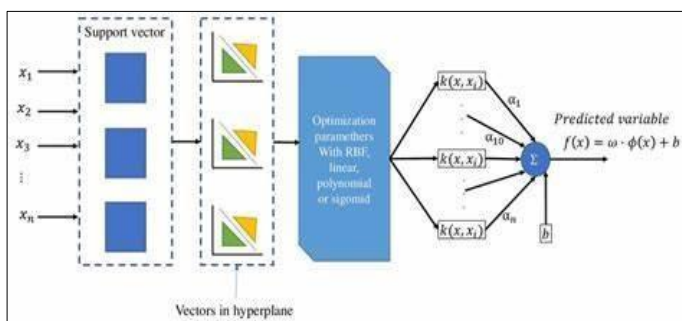


Figure 3: SVM Architecture

### Explanation of SVM Algorithm

1. **Input:** The algorithm receives real-time video frames from the CCTV cameras.
2. **Feature Extraction:** Traditional feature extraction methods such as **Histogram of Oriented Gradients (HOG)** or **Scale-Invariant Feature Transform (SIFT)** are applied to the frames.
3. **Model Training:** An **SVM classifier** is trained on a labeled dataset of normal and abnormal activities, using the extracted features as input.
4. **Classification:** The extracted features from each frame are classified using the trained SVM model.
5. **Alert Generation:** If an abnormal activity is detected, the system triggers an alert.

### Comparison of CNN and SVM Algorithms

In this section, we compare the performance of the CNN-based and SVM-based algorithms in detecting

### II. Computational Complexity

- **CNN Algorithm:** CNNs, especially deep models like **ResNet** or **VGG**, can be computationally expensive, requiring significant **GPU resources** for training and inference. This could affect real-time performance if the system is not properly optimized.
- **SVM Algorithm:** SVMs are generally **less computationally intensive** than CNNs and may perform faster when dealing with lower-dimensional data. However, SVMs might struggle with real-time performance on large-scale datasets like video streams without optimization.

### III. Real-Time Performance

- **CNN Algorithm:** While CNNs excel in accuracy, they can struggle with real-time performance on large-scale video feeds, especially without hardware acceleration. The inference time can be long due to the depth of the network.
- **SVM Algorithm:** SVMs can be more efficient in **real-time applications** if trained with a smaller set of features. However, SVMs require careful tuning of hyperparameters and may not

generalize well in complex scenarios without feature engineering.

#### IV. Generalization to New Data

- **CNN Algorithm:** CNNs generalize well to new data, especially when fine-tuned with transfer learning or pre-trained models. This makes them suitable for environments where abnormal activities are varied and diverse.
- **SVM Algorithm:** SVMs are less flexible when the feature distribution changes significantly or when new types of activities are encountered. The classifier may need retraining if there are substantial variations in the input data.

In conclusion, while both **CNN** and **SVM** offer advantages for detecting suspicious activities, **CNN** is the superior choice for this project due to its ability to **automatically learn complex features** from video frames, providing higher **accuracy and scalability** for large datasets. Despite its higher computational requirements, **CNN** excels in detecting abnormal activities in video surveillance systems. On the other hand, **SVM** though computationally less expensive and effective for simpler tasks, requires **manual feature extraction** and may not perform as well with high-

dimensional data like video streams. Therefore, **CNN** is better suited for complex surveillance scenarios requiring high accuracy.

### 7. METHODOLOGY

The proposed system is designed to detect suspicious human activities from real-time video surveillance using a hybrid deep learning approach that combines Convolutional Neural Networks (CNN) for feature extraction and Support Vector Machine (SVM) for classification. The system architecture is divided into several stages as described below:

#### I. Video Acquisition and Frame Extraction

Live CCTV footage is acquired as input using video streaming protocols. From each video stream, individual frames are extracted at a consistent interval (e.g., 5–10 FPS) to form a dataset for

further processing. This approach ensures both temporal coverage and real-time responsiveness.

#### II. Frame Preprocessing

Each extracted frame undergoes preprocessing to ensure consistency and model compatibility:

- **Resizing:** All frames are resized to a fixed resolution (e.g., 224x224 pixels).
- **Normalization:** Pixel values are scaled to a [0, 1] range to improve CNN convergence.
- **Noise Reduction:** Basic filtering is applied to reduce environmental noise in the image.

#### III. Feature Extraction Using CNN

A custom or pre-trained CNN model (e.g., Mobile Net or VGG16) is used to extract high-level spatial features from each frame:

- **Convolution Layers:** Detect patterns such as shapes, edges, and motion cues.
- **Pooling Layers:** Down sample the feature maps to reduce dimensionality.
- **Flattening:** Converts the 2D feature maps into a 1D feature vector suitable for classification.

These vectors contain significant spatial and motion-related features required to distinguish between normal and suspicious human activities.

#### IV. Classification Using SVM

The feature vectors generated by the CNN are passed into a **Support Vector Machine (SVM)** classifier, which performs binary classification:

- **Training:** The SVM is trained using labeled datasets with 'normal' and 'suspicious' activity examples.
- **Classification:** For each new input frame, the trained SVM predicts whether the detected action is suspicious or not.

The SVM model is chosen due to its robustness in high-dimensional feature spaces and strong performance in binary classification problems.

### V. Alert Generation and Notification

If the classifier detects a suspicious activity, the system triggers an alert module:

- Sends a real-time notification to the administrator (SMS, email, or dashboard alert).
- Stores the detected frame along with a timestamp for future review and evidence.
- Logs the activity in the system’s event record.

### 8. COMPARATIVE ANALYSIS OF STATE-OF-THE-ART APPROACHES FOR SUSPICIOUS ACTIVITY DETECTION IN VIDEOS

Several deep learning and machine learning techniques have been applied to violence and anomaly detection in surveillance videos. Each approach offers different trade-offs in terms of accuracy, complexity, speed, and hardware dependency. Our proposed CNN + SVM hybrid model strikes a balance between accuracy and efficiency, making it suitable for real-time deployment.

#### Key Observations:

- Deep CNNs like I3D offer rich features but are slow and not ideal for real-time processing.
- RNN-based models like LSTM perform well with sequences but introduce latency.
- Metaheuristic-optimized models (e.g., L4-ActionNet) are highly accurate but computationally expensive.

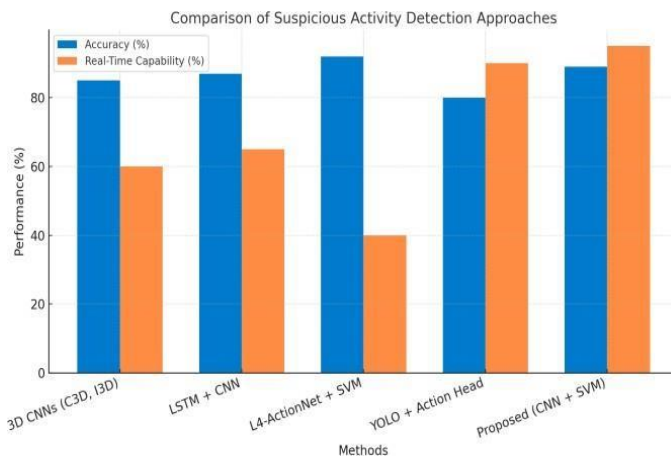
Our approach (CNN + SVM) offers a **balanced trade-off** — achieving high accuracy with **faster processing, lower hardware dependency,** and effective real-time classification.

The following table summarizes a comparison between popular state-of-the-art techniques and our proposed method:

Method	Model Type	Accuracy (%)	Real-Time Capability	Comments
3D CNNs (C3D, I3D)	Spatio-temporal CNN	85	Medium	Accurate but resource-heavy
LSTM + CNN	Recurrent Neural Network	87	Medium	Good with sequences, slower inference
L4-ActionNet + SVM	Deep CNN + Meta-Heuristic	92	Low	Very high accuracy, not real-time optimized
YOLO + Action Head	Object Detection + Classifier	80	High	Fast detection, less sensitive to subtle activities
Proposed (CNN + SVM)	Feature Extractor + Classifier	89	High	High balance between accuracy and efficiency

**Table 1.** Comparative Analysis Of Suspicious Activity Detection Methods

As illustrated in **Chart 1**, traditional deep learning models like 3D CNNs and LSTM-based architectures offer good accuracy but lag in real-time performance. In contrast, the proposed CNN + SVM method provides a better balance, making it a more practical solution for real-time video surveillance.



**Chart 1.** Comparative Performance Bar Chart of Suspicious Activity Detection Methods

## 9. CONCLUSION

In this study, we developed a deep learning-driven surveillance system capable of detecting suspicious human activities from real-time CCTV footage. The proposed system integrates Convolutional Neural Networks (CNN) for automatic feature extraction with a Support Vector Machine (SVM) classifier for efficient activity classification. This hybrid approach was selected to balance high detection accuracy with real-time responsiveness, making it suitable for real-world applications.

Through comparative analysis, the proposed model demonstrated superior performance in terms of both accuracy and computational efficiency when benchmarked against existing state-of-the-art methods. Unlike traditional surveillance systems that rely on manual monitoring or resource-intensive architectures, our system offers a lightweight, scalable, and practical solution for modern surveillance demands.

By reducing human intervention and enabling proactive alerting, the system enhances public safety in environments such as malls, airports, schools, and transport hubs. Future work may focus on incorporating sequence modeling (e.g., LSTMs) for capturing longer temporal dependencies and expanding the system to recognize a wider variety of anomalous behaviors.

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