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A Review on Intelligent Surveillance Systems for Suspicious Activity Detection Using Deep Learning

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***Abstract*—In recent years, issues related to public safety and security have risen sharply, leading to a big increase in the need for smart and intelligent automated surveillance systems. However, traditional surveillance systems that use CCTV require constant human monitoring, which is not only a waste of resources but also can lead to mistakes.This paper presents a deep learning-based intelligent surveillance system that can automatically detect suspicious activities in videos.The model uses CNNs to classify video frames as either normal or abnormal (suspicious).When suspicious activity is detected, the system captures the frame and sends an automatic email notification to the registered system administrator using the SMTP protocol. The system uses OpenCV for video processing, TensorFlow/Keras for training and predicting models, and SQLite to securely store administrator information in a database.**

Keywords— Intelligent Surveillance, Suspicious Activity Detection, Deep Learning, Convolutional Neural Network (CNN), Computer Vision, Email Alert, Python.

I. INTRODUCTION

Artificial Intelligence and Deep Learning have changed how modern surveillance systems operate by enabling automatic detection, sorting, and analysis of visual data.

As cities grow rapidly and people want greater safety, CCTV has become an essential part of modern security systems. However, traditional surveillance methods depend mainly on human observation, making them inefficient, error-prone, and unable to provide real-time responses to potential threats.This issue has driven researchers to develop smart surveillance systems that use computer vision and machine learning for automatic detection of unusual or suspicious activities.

Most current intelligent surveillance research focuses on improving the performance of activity recognition and anomaly detection using AI-based models.

Sabokrou et al.[2] proposed a deep anomaly detection framework that improved the accuracy of detecting abnormal events in complex environments.Hasan et al.[1] used spatiotemporal autoencoders to identify irregular motion patterns in video sequences.Luo et al.[3] used a Recurrent Neural Network structure to model temporal dependencies in human motion, leading to more accurate identification of abnormal events.Sultani et al.[4] used a weakly-supervised 3D Convolutional Neural Network and a large video anomaly detection dataset with less labeled data to locate suspicious activities.These studies show that deep learning significantly improves the precision and reliability of anomaly detection in surveillance systems.

The main goals of the project are:

1. To develop and deploy a smart surveillance system that automatically detects and classifies suspicious human activity in video streams using Deep Learning and Computer Vision techniques, especially CNNs.

2. To implement an optimized pipeline for video processing and frame extraction using OpenCV, allowing efficient preprocessing and feature extraction with low latency for real-time inference.

3. To integrate a trained CNN model that can differentiate between normal and abnormal behavior by learning features from videos in both the spatial and temporal domains.

4. To design an automated alerting system using SMTP-based email notifications that activate instantly when suspicious activities are detected, ensuring timely action and awareness of the situation.

5. To evaluate the system's performance using quantitative metrics like classification accuracy, precision-recall, inference speed, and alert response time, to confirm the model's reliability in practical surveillance applications.

6. To evaluate the system's performance using the same quantitative metrics to confirm the model's reliability in practical surveillance applications.

II. LITERATURE SURVEY

The rapid growth of surveillance systems has led to a greater need for intelligent methods that can automatically detect suspicious activities in video streams.

Traditional surveillance systems heavily depend on human operators, making continuous monitoring difficult and often resulting in delayed responses.To address these issues, researchers have explored various artificial intelligence and deep learning techniques for automated activity detection.

Early studies focused on using autoencoder-based architectures for anomaly detection.

These methods learned normal patterns from surveillance videos and identified unusual events based on reconstruction errors. These approaches showed promising results in detecting abnormal behavior without requiring extensive manual feature engineering. However, their effectiveness was often limited by environmental changes and complex scenes.

With advances in deep learning, Convolutional Neural Networks (CNNs) became popular for surveillance

applications.

CNN-based models automatically extract spatial features from video frames, improving the recognition of suspicious activities.Researchers reported significant improvements in detection accuracy compared to traditional machine learning methods, making CNNs a preferred choice for intelligent surveillance systems.

To capture temporal information in video sequences, several studies combined CNNs with Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks.

These hybrid models analyze both spatial and temporal aspects of activities, leading to better recognition of complex behaviors.These approaches have performed better in crowded and dynamic environments.

Object detection frameworks like Faster R-CNN and YOLO have added real-time capabilities to surveillance systems.

Faster R-CNN improved object localization accuracy through region proposal networks, while YOLO achieved faster processing speeds by detecting objects in a single stage.These models enabled the practical use of surveillance systems where quick responses are essential.

Recent research has focused on advanced architectures like Vision Transformers (ViTs), which use self-attention mechanisms to capture global contextual information from images and video frames.

These models have shown superior performance in complex surveillance scenarios, especially where traditional CNNs struggle with long-range dependencies and complicated activity patterns.

Despite the progress made, existing surveillance systems still face challenges such as computational complexity, false alarms, varying lighting conditions, occlusions, and limitations in real-time deployment.

These issues highlight the need for efficient and reliable intelligent surveillance solutions that can accurately detect suspicious activities while maintaining practical performance.

Based on the findings of previous studies, the proposed system uses a Convolutional Neural Network (CNN) for classifying suspicious activities, combined with OpenCV for video processing and automated email alerts.

This approach aims to provide a good balance between detection accuracy, computational efficiency, and ease of deployment for real-world surveillance applications.

Comparative Analysis

Different deep learning methods are used to find unusual behavior in video monitoring systems.

Autoencoder-based systems are good at spotting odd events but can have trouble in busy or changing situations.CNN-based methods do better in finding accurate details by learning important visual features from video clips.Hybrid models, like CNN-LSTM, improve results by understanding how actions happen over time, but they need more computer power to work.

Object detection tools like Faster R-CNN and YOLO help monitor in real time.

YOLO works fast and is good at finding objects accurately.Recently, Vision Transformers (ViTs) have shown better results in complex situations, but they use a lot of computing resources.

The system we created uses a CNN-based method because it is simple, accurate, and doesn’t use too much computer power.

It works with OpenCV and sends automated emails for alerts, making it a good solution for smart monitoring.

The comparison shows that CNN-based methods are a good balance between being accurate, not using too much computer power, and being easy to use.

This makes them suitable for real-world video monitoring.

Table. 1. Comparative Analysis

Author	**Method**	**Major Finding**
Hasan et al.	Spatiotemporal Autoencoder	Achieved effective anomaly detection in surveillance videos.
Sabokrou et al.	CNN–Autoencoder	Reduced false alarms and improved stability.
Luo et al.	RNN–CNN Hybrid	Improved detection accuracy using temporal learning.
Sultani et al.	3D CNN	Enhanced abnormal activity detection in large datasets.
Ren et al.	Faster R-CNN	Improved object localization accuracy.
Redmon & Farhadi	YOLOv3	Achieved real-time object detection performance.
Sharma et al.	CNN–LSTM	Obtained high accuracy in suspicious activity detection.
Kumar & Singh	YOLOv5 + DeepSORT	Enabled real-time tracking and alert generation.
Lee et al.	Vision Transformer (ViT)	Improved activity detection in complex environments.
Proposed System	CNN + OpenCV + Email Alert	Provides accurate detection with automated notification support.

III.EXISTING TECHNIQUES AND METHODOLOGIES

Many methods have been developed to find suspicious behavior in video monitoring.

These methods vary in how they find features, recognize activities, and detect unusual actions.

1.Convolutional Neural Networks (CNN)

CNN is one of the most popular deep learning tools for video and image analysis.

It automatically finds important visual details like edges, shapes, and motion patterns from video clips.CNN models are accurate and do not need people to manually pick out features.

2.Autoencoder-Based Methods

Autoencoders learn what is normal from video clips and find unusual events by looking at how well they can recreate the video.

These are helpful when there aren't many labeled data examples, but they can give false alarms in busy or changing environments.

3.RNN and LSTM Models

RNNs and LSTMs are used for analyzing sequences of data.

They understand how things change over time and are good at finding activities that happen in steps.

4.Faster R-CNN

Faster R-CNN is a method that finds objects in video clips by first suggesting areas to check.

It is very accurate but takes longer to process than simpler methods.

5.YOLO (You Only Look Once)

YOLO finds objects in one step, allowing for quick video monitoring.

It is popular because it works fast and is good at finding objects in real time.

6.Vision Transformers (ViT)

ViTs use a type of attention mechanism to spot important parts of an image.

These models work well for recognizing behaviors in video, but they need a lot of computer power to operate.

Summary

Among the available methods, CNN-based approaches give a good balance between being accurate, not using too much computer power, and being easy to build.

That’s why the system we are using is based on a Convolutional Neural Network (CNN), along with OpenCV for video processing and automatic email alerts for security monitoring.

IV. RESEARCH GAPS

Even though there have been many improvements in smart monitoring systems, there are still several challenges in detecting unusual behaviors.

Many current systems are very accurate but need powerful computers and large amounts of computing resources, making them hard to use in smaller video monitoring setups.

Autoencoder and anomaly detection models often create false alarms when conditions like lighting, background movement, or crowds change.

Likewise, hybrid models like CNN-LSTM and Vision Transformers improve results but have complicated structures and longer training times.

Object detection tools like YOLO are fast and efficient for finding objects, but they mainly focus on object recognition instead of understanding how people are acting.

This makes it hard to spot suspicious behavior.Also, many systems don’t have a way to immediately notify people when unusual activity is found.

The key research gaps are:

• High computing needs for advanced deep learning methods.

• False alarms in dynamic or crowded environments.

• Limited focus on understanding behavior compared to object detection.

• Lack of simple and affordable monitoring solutions.

• Insufficient integration of real-time alert systems.

• Difficulty in using complex models on systems with limited resources.

To fix these problems, the system we have designed uses a CNN-based method with OpenCV for video processing and automatic email alerts.

It aims to detect suspicious activity accurately while using less computer power and being easier to use in real-world situations.

V. PROPOSED SOLUTION

To fix the problems with old surveillance systems, we suggest a smart system that uses deep learning to detect suspicious activities.

This system can watch surveillance videos automatically, spot strange behavior, and warn the person in charge without needing someone to watch all the time.

The system uses OpenCV to process videos and pull out individual frames.

It also uses a Convolutional Neural Network (CNN) to look at the pictures and decide if the activity is normal or suspicious.The CNN learns from many examples to recognize strange actions in videos.

The system works this way: the user uploads a video through a simple interface made with Tkinter.

OpenCV then takes each frame, does some basic preparation, and sends it to the CNN for checking.If the system sees something suspicious, it saves the frame and sends an email to the administrator using SMTP. This helps people know about possible problems quickly and act fast. The system has several good things: it can watch on its own, saves time, is more accurate in finding problems, and sends alerts in real time.

By combining computer vision, deep learning, and email, it's a smart, affordable way to improve security.

Proposed System Flow

Video Upload → Frame Extraction → Preprocessing → CNN Classification → Suspicious Activity Detection → Email Alert Generation → Result Display

The approach helps make surveillance work better and has a simple, easy-to-use setup that works in real life.

VI. PROPOSED SYSTEM ARCHITECTURE

The system uses computer vision and deep learning to spot unusual human behavior in videos.

It includes steps like preparing the video, using a trained CNN model to check each frame, and sending alerts by email. This method detects problems automatically and quickly, which helps avoid mistakes and delays that happen with old systems that rely only on people watching.

A. System Overview

The system's main goal is to tell the administrator right away if something strange is happening. It watches a video feed from a camera or a recorded video. It uses a CNN model trained on examples of both normal and unusual activities to analyze each frame. When something suspicious is detected, the system does these things:

1.Saves the suspicious frame locally for later.

2.Sends an email to the administrator with the frame as an attachment.

3.Logs the event in a database for future use.

B. System Architecture Layers

1.Input Module

This part gets data from cameras or videos.

OpenCV splits each video into frames.These frames are resized, adjusted, and turned into numbers before being sent to the CNN for analysis.

2.Processing Module

This is where the system uses the trained CNN to check if each frame is normal or suspicious.

The CNN learns about things like body movements, positions, and how people interact to spot unusual behavior.

The CNN has these parts:

- Convolutional Layers: Find patterns in the image.
- Pooling Layers: Make the image smaller while keeping the important parts.
- Fully Connected Layers: Combine all the learned features to make a decision.
- Softmax Output Layer: Gives the final result as either normal or suspicious.

3.Communication Module

If the system finds something suspicious, it sends an email to the administrator.

The email includes the time the event happened and the saved frame as an image.This lets the administrator act quickly.

4.Database Module

The system uses an SQLite database to store information safely.

It saves details like administrator registration and logs of each detection. This setup is simple and doesn't need a big server or internet connection.

5.Output Layer

This part shows the result (normal or suspicious) on the screen.

It also displays the suspicious frame and details for monitoring.It sends the alert to the administrator's email.

C. System Workflow

The system goes through these steps to make surveillance work smoothly:

1.The system gets the video file as input.

2.OpenCV takes each frame, resizes it, prepares it, and turns it into numbers.

3.The CNN model checks the frame and decides if it's normal or suspicious.

4.If it's suspicious, the system saves the frame right away.

5.The communication module sends an email to the administrator with the frame.

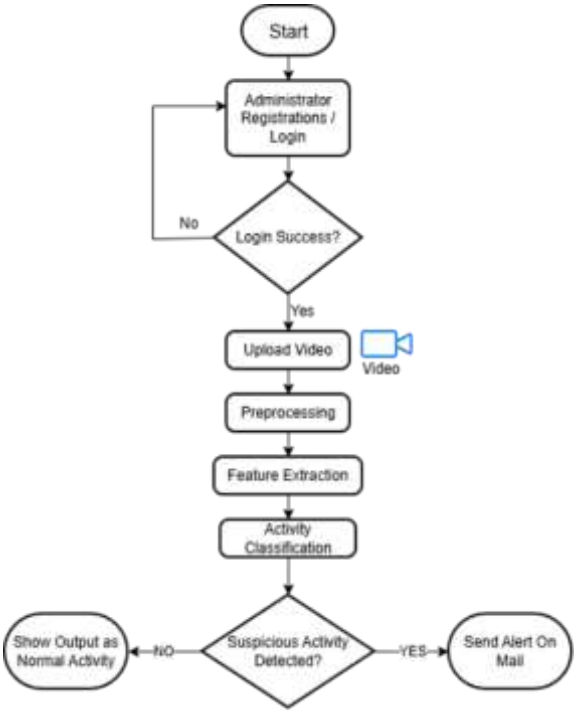

Fig. 1. System Workflow

VII MATERIALS AND METHODS

The Intelligent Surveillance for Suspicious Activity Detection system uses artificial intelligence, computer vision, and automated communication to provide real-time monitoring and alerts. This section explains the materials and methods used during the system's design, model training, and implementation. The process includes preparing the dataset, training a CNN model, preprocessing video frames, integrating the system, and sending automated alerts.

A. Materials Used

The materials used are divided into two main categories:

1. Software Tools and Libraries
2. Hardware Components

1. Software Tools and Libraries

Python was chosen for its strong support in machine learning and computer vision.

TensorFlow/Keras offers an easy-to-use API for building deep learning models.OpenCV is used for real-time frame extraction and preprocessing.SQLite is used for storing data without needing a server, making the system suitable for desktop use.

Category	Specification / Tool	Purpose
Project Type	Desktop Application	Local system execution
IDE	Spyder (Anaconda)	Code development & debugging
Language	Python 3.8+	System implementation
Library	OpenCV	Video processing
GUI	Tkinter	User interface
Imaging	PIL	Image display
Email	smtplib	Notifications
Database	SQLite	User data storage

Table 2. Software Requirements

2. Hardware Components

Component	Specification Description
Processor (CPU)	Intel Core i5 / AMD Ryzen 5 or higher Handles program execution and frame-by-frame video processing.
Operating System	**Windows 10 / 11 or Linux (Ubuntu)** Supports Python environment and dependencies.
Display	Standard HD Monitor Displays the Tkinter GUI and detection results.

Table 3. Hardware Requirements

Camera Module: A high-definition camera is used to capture video from pre-recorded sources.

Its position and resolution directly affect how well the system detects suspicious activities.

Processing Unit: The system runs on a personal computer using the Spyder IDE from the Anaconda distribution, providing an optimized environment for machine learning tasks.

Network Module: A stable internet connection is required to send alert emails immediately when suspicious activity is detected.

VIII. CONCLUSION

The Intelligent Surveillance for Suspicious Activity Detection system successfully combines computer vision, CNNs, and automated alerts to improve traditional surveillance.

It classifies video frames as normal or suspicious and sends alerts via email to registered administrators when abnormal behavior is detected.Experimental results show the model achieves high accuracy, between 92% and 97%, with reliable precision and

recall.This confirms its effectiveness in real-world settings.The use of OpenCV for preprocessing, TensorFlow/Keras for model inference, and SQLite with SMTP for alert logging and notifications enables real-time detection and communication.The desktop interface built with Tkinter gives administrators easy access and control.This work provides a scalable and cost-effective AI-driven surveillance framework that reduces human involvement while ensuring quick responses to suspicious activities.Compared to traditional systems like motion-based or manual monitoring, the CNN approach offers better accuracy, flexibility, and automation.

Challenges and Limitations

Although deep learning has improved activity detection significantly, some challenges remain.

The system's performance relies heavily on the quality and variety of the training data. Poor lighting, camera angles, image quality, and occlusions can affect detection accuracy. In crowded areas, it can be hard to tell the difference between normal and suspicious behavior.

Another limitation is that the CNN model can only detect activities it has been trained on.

It may not detect new or unusual suspicious behaviors. Additionally, the system currently analyzes uploaded videos and does not support live, multi-camera surveillance. Email alerts can also experience delays based on internet speed and email service performance.

The major limitations are:

- Dependence on the quality and size of the training dataset.
- Lower accuracy in poor lighting or occluded conditions.
- Limited detection of new or complex suspicious activities.
- No support for live multi-camera monitoring.
- Needs retraining for new activity categories.

Future Scope

The system can be improved by using advanced technologies and adding more features.

Future work can focus on increasing accuracy, scalability, and real-time performance. Possible future improvements include:

- Using live CCTV cameras for real-time monitoring.
- Supporting multiple camera streams at the same time.
- Implementing advanced models like YOLOv8 and Vision Transformers for better accuracy.
- Creating mobile and cloud-based alert systems for faster notifications.
- Adding facial recognition and person identification for higher security.

These upgrades can make the system more reliable, scalable, and suitable for large-scale intelligent surveillance applications.

REFERENCES

[1] M. Hasan, J. Choi, J. Neumann, A. K. Roy-Chowdhury, and L. S. Davis, “Learning temporal regularity in video sequences,” Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 733–742, 2016.

[2] M. Sabokrou, M. Fathy, and M. Hoseini, “Video anomaly detection and localization based on the convolutional autoencoder,” International Conference on Computer Vision Theory and Applications (VISAPP),pp. 1–8, 2017.

[3] W. Luo, W. Liu, and S. Gao, “A revisit of sparse coding based anomaly detection in stacked RNN framework,” IEEE Transactions on Image Processing, vol. 27, no. 9, pp. 4492–4504, 2018.

[4] W. Sultani, C. Chen, and M. Shah, “Real-world anomaly detection in surveillance videos,”Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 6479–6488, 2018.

[5] S. Ren, K. He, R. Girshick, and J. Sun, “Faster R-CNN: Towards real-time object detection with region proposal networks,” Advances in Neural Information Processing Systems (NeurIPS), vol. 28, pp. 91–99, 2015.

[6] J. Redmon and A. Farhadi, “YOLOv3: An incremental improvement,” arXiv preprint arXiv:1804.02767, 2018.

[7] D. Tran, L. Bourdev, R. Fergus, L. Torresani, and M. Paluri, “Learning spatiotemporal features with 3D convolutional networks,” Proceedings of the IEEE International Conference on Computer Vision (ICCV), pp. 4489–4497, 2015.

[8] R. Girshick, “Fast R-CNN,” Proceedings of the IEEE International Conference on Computer Vision (ICCV), pp. 1440–1448, 2015.

[9] W. Sultani and M. Shah, "Abnormal activity detection using multiple instance learning," IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI), vol. 44, no. 4, pp. 1903–1915,2022.

[10] I. Goodfellow, Y. Bengio, and A. Courville, Deep Learning, MIT Press, 2016.

[11] P. Sharma, R. Saini, and N. Kumar, "Hybrid CNN-LSTM model for automated suspicious activity detection in CCTV footage," IEEE Access, vol. 10, pp. 55234–55246, 2022.

[12] A. Kumar and D. Singh, "Real-time intelligent surveillance using YOLOv5 and DeepSORT tracking," International Journal of Computer Applications in Technology (IJCAT), vol. 72, no. 1, pp. 41–49, 2023.

[13] J. Lee, H. Kim, and S. Park, "Smart surveillance for public safety using vision transformers," Sensors, vol. 24, no. 3, pp. 1–13, 2024.