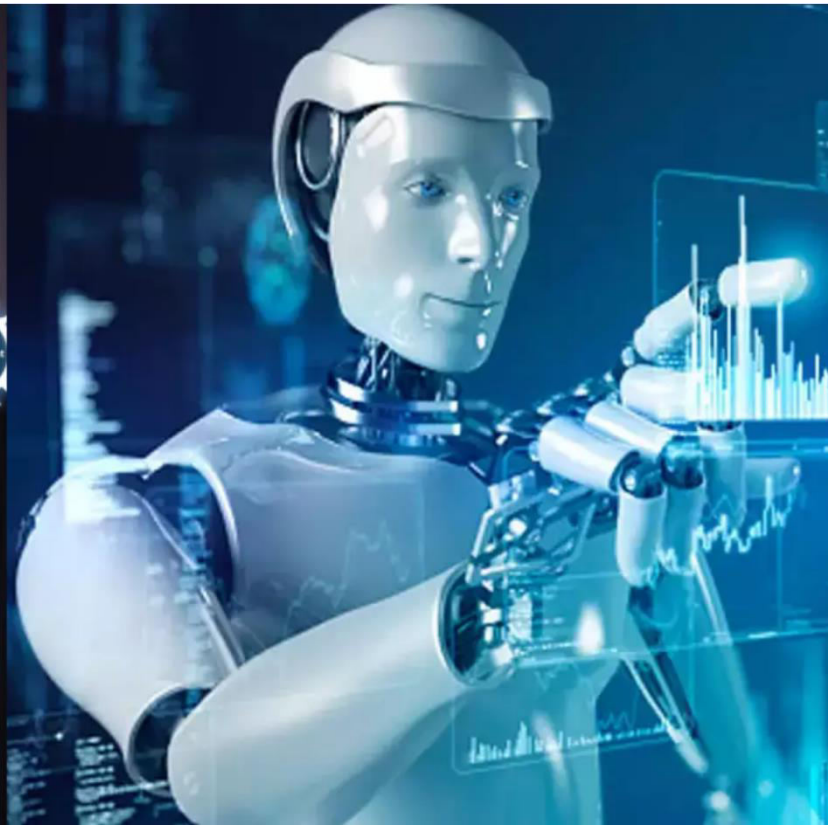
IJIRSET
International Journal of Innovative Research in Science | Engineering | Technology

ISSN(O): 2319-8753
ISSN(P): 2347-6710

International Journal of Innovative Research in Science Engineering and Technology (IJIRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 8.699

Volume 14, Issue 4, April 2025

International Journal of Innovative Research of Science, Engineering and Technology (IJIRSET)

Impact Factor 8.699

|www.ijirset.com |A Monthly, Peer Reviewed & Refereed Journal| e-ISSN: 2319-8753| p-ISSN: 2347-6710|

Volume 14, Issue 4, April 2025

|DOI: 10.15680/IJIRSET.2025.1404218|

Vigilanteye: Densenet121-Powered Suspicious Activity Detection in Real-Time Surveillance

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ABSTRACT - Suspicious Activity Detection System is a real-time monitoring and analysis tool developed using Python with Tkinter, OpenCV, and Image AI libraries. The system integrates a modern graphical user interface (GUI) to facilitate video processing, frame generation, and suspicious activity detection from both live camera feeds and pre-recorded CCTV footage. Leveraging the DenseNet121 deep learning model for image classification, the system processes video frames to identify potential suspicious activities, employing temporal consistency and confidence thresholding to enhance detection accuracy. Key features include live feed toggling, video recording with timestamped storage, and automated frame extraction, with suspicious frames flagged and saved for further review. The GUI, styled with a sleek dark theme and gradient aesthetics, provides intuitive controls and dual text areas for logging frame generation and detection results. Advanced visualization overlays detection metrics on frames, while the system ensures robust error handling and resource cleanup. Designed for security applications, this tool demonstrates a scalable approach to real-time video analysis, balancing usability and performance. Future enhancements could include multi-camera support and expanded activity classification capabilities.

KEYWORDS: Suspicious Activity Detection, Deep Learning, Convolutional Neural Networks (CNN), Computer Vision, Object Detection, Gesture Recognition.

I. INTRODUCTION

In an age of extensive video surveillance, manually monitoring for suspicious activities are increasingly unfeasible, risking missed threats and slow responses. This project presents an Automated Suspicious Activity Detection System, utilizing real-time video analysis and deep learning to pinpoint anomalies accurately. Built with OpenCV for video processing, ImageAI's DenseNet121 for classification, and a Tkinter interface, it handles both live feeds and recorded footage. Employing temporal consistency and adjustable confidence thresholds, the system reduces false positives while flagging suspicious frames effectively. Designed to transform security, this solution automates detection, eases human workload, and boosts real-time decisions. Applicable to live monitoring and forensic review, it offers a scalable, intelligent approach to enhance safety across varied settings.

II. LITERATURE REVIEW

Suspicious activity detection in video surveillance has progressed remarkably, fueled by breakthroughs in computer vision, deep learning, and real-time processing technologies. These advancements seek to automate security monitoring, improving detection accuracy and efficiency in environments overwhelmed by vast video data. Traditional manual oversight struggles to cope with this scale, often missing critical anomalies and delaying responses. By leveraging sophisticated algorithms and models, recent research addresses these challenges, offering intelligent solutions to enhance safety across diverse applications, from public spaces to private facilities, setting the stage for more reliable and scalable surveillance systems.

1. **Vision-Based Activity Recognition:** Vision- based techniques are central to anomaly detection in surveillance systems. Studies have leveraged Convolutional Neural Networks (CNNs) such as ResNet to classify video frames with high accuracy, focusing on spatial feature extraction from complex scenes [1–2]. OpenCV, a cornerstone in

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this project's process_live_feed() for capturing and displaying frames, supports real- time video processing [3]. Research also explores object detection frameworks like YOLO, which enhance recognition by identifying specific elements within frames [4]. These approaches underpin this system's ability to process live feeds and generate frames for analysis, ensuring effective monitoring.

2. **Deep Learning Approaches:** Deep learning has revolutionized surveillance by enabling sophisticated pattern recognition. DenseNet121, implemented via ImageAI in prediction.classifyImage(), uses dense connectivity to achieve superior image classification, leveraging pre-trained weights for efficiency [5–6]. While this project employs frame-by-frame analysis, studies suggest integrating Long Short-Term Memory (LSTM) networks to model temporal dependencies across sequences [7], a potential enhancement for future iterations. Dense CNN architectures, as explored in related work, optimize performance in video-based tasks [8], reinforcing DenseNet121's suitability for detecting suspicious activities in this system.

3. **Suspicious Activity Detection Systems**: Automated detection systems employ temporal consistency via a 3-frame check in detectActivity() to reduce false positives by tracking prediction stability over time [9–10]. Frames are preprocessed like OCR using OpenCV [10]. A Tkinter GUI logs detections to enhance operator decisions in real time [11]. ImageAI's DenseNet121 classifies activities. Python code demonstrates a design with gradient styling and multi-threaded feed processing.

4. **Optical Character Recognition (OCR) and Frame Preprocessing:** OCR techniques are widely used in text detection but also play a role in frame preprocessing for video analytics. The system preprocesses frames using OpenCV, similar to OCR pipelines, where image enhancements improve text recognition accuracy. Studies highlight the importance of preprocessing for feature extraction in deep learning models [10]. The system applies frame extraction, resizing, and contrast adjustments, ensuring high- quality input for DenseNet121-based classification. This preprocessing stage helps eliminate noise, making it easier for the model to focus on relevant patterns. Such techniques are crucial for ensuring high detection accuracy in dynamic surveillance environments.

5. **Graphical User Interface (GUI) for Real- Time Surveillance:** A well-designed Graphical User Interface (GUI) plays a crucial role in real- time surveillance, improving operator efficiency and response time. The given system employs Tkinter to create an interactive and user-friendly interface, displaying live video feeds, logging detected activities, and generating alerts. Studies indicate that an intuitive GUI enhances situational awareness, allowing security personnel to respond promptly to threats [11]. The system includes real- time activity logging, detection confidence scores, and frame visualization, ensuring operators can verify suspicious events before taking action. Additionally, the interface provides easy access to recorded footage for post-event analysis. The integration of color-coded alerts and dynamic updates makes navigation more efficient. Future enhancements may include speech-based commands, touchscreen compatibility, and multi- window support, making the system even more accessible and effective for security professionals in high-risk environments**.**

Challenges: Activity Variability and Scene Complexity, Real-Time Processing Demands, and Detection Accuracy and False Positives.
Future Research: Future enhancements for the suspicious activity detection system could involve training DenseNet121 in prediction.classifyImage() on varied datasets to adapt to diverse activities, optimizing process_live_feed() with efficient algorithms for real-time performance on edge devices, and integrating advanced temporal models into detectActivity() to improve consistency and minimize errors.

III. PROBLEM STATEMENT

3.1 Existing System: Current video surveillance relies heavily on human operators to monitor feeds for suspicious activities, using basic tools like CCTV systems and manual frame review. Some automated systems employ traditional image processing with OpenCV or simple classifiers, as seen in early attempts to flag anomalies, but these lack advanced intelligence and real-time capabilities.

3.2 Limitations:

1. **Requires Constant Oversight:** Manual monitoring demands uninterrupted human attention, causing fatigue and overlooked threats in extensive video feeds.
2. **Limited Scalability:** Physical review restricts handling multiple camera inputs efficiently, overwhelming

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operators as surveillance networks grow.

3. **Accuracy Shortfalls:** Basic automated tools using OpenCV lack adaptability, misidentifying activities and generating frequent false alerts.
4. **Processing Lag:** Retrospective analysis of recorded footage, like frames in frames/, delays threat detection, impeding swift security responses.
5. **Lack of Contextual Insight:** Existing systems miss nuanced behavior patterns, limiting depth in distinguishing normal from suspicious actions effectively**.**

3.3 Proposed System:

This system automates suspicious activity detection using OpenCV for video capture, DenseNet121 for classification, and Tkinter for real-time monitoring, enhancing security efficiency:

- Processes camera feeds instantly with OpenCV.
- Identifies activities precisely using DenseNet121.
- Shows detection logs through a Tkinter GUI.
- Handles both live and recorded videos.

Video Processing: OpenCV in process_live_feed() captures and manages video frames, supporting real-time surveillance and storage in videos/ for later review.

Real-Time Detection: The system leverages OpenCV in process_live_feed() to detect threats as they occur, ensuring prompt identification within live streams.

Activity Classification: DenseNet121, utilized in prediction.classifyImage(), analyzes frames with pre- trained precision, distinguishing suspicious behaviors effectively.

Temporal Consistency: A 5-frame buffer with confidence thresholds (60%, 85%) in detectActivity() ensures stable detection across sequences, minimizing false alarms.

Desktop Interface: Tkinter in main provides a desktop interface, presenting detection results in text1 and frame logs in text for user convenience.

Frame Storage: Frames flagged in detectActivity() are saved to suspicious_frames/, providing a repository for post-event analysis and evidence.

Video Recording: The system records live feeds to videos/ via process_live_feed(), supporting forensic examination of captured footage.

Confidence Tracking: Confidence tracking computes a moving average over five frames, mitigating transient noise and boosting detection reliability, as implemented idetectActivity(), thereby enhancing real-time decision- making accuracy.

III. METHODOLOGY

System Overview: The system aims to detect suspicious activities in real-time and recorded video, integrating OpenCV for frame capture, DenseNet121 for activity classification, and Tkinter for result visualization. It operates in two modes: live feed analysis via process_live_feed() and recorded footage processing through upload() and generateFrame(), with outputs stored in suspicious_frames/ and videos/ for review.

Key Technologies Used:

- **OpenCV**: For video capture, frame processing, and real-time display.
- **DenseNet121**: A pre-trained deep learning model from ImageAI for classifying activities within frames.
- **Threading**: Ensures seamless execution of live feed processing without interrupting the user interface.

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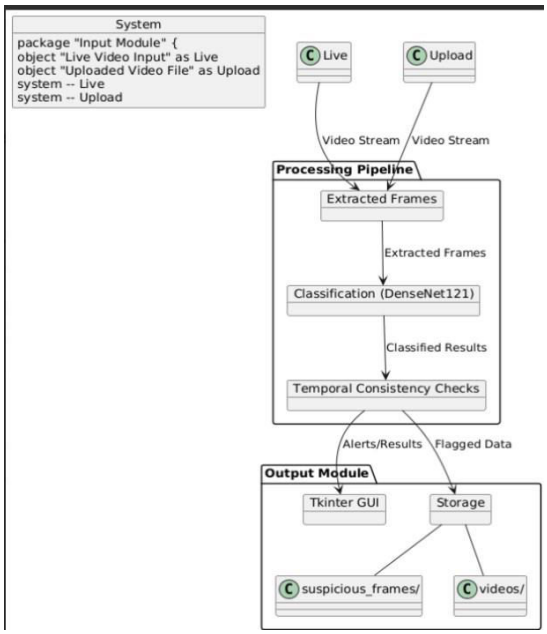
6. System Architecture:

The system is structured into three interconnected modules: Input, Processing, and Output, each designed to handle specific tasks efficiently:

i. Input Module (Video Capture)

This module manages video input acquisition. In live mode, process_live_feed() captures footage from the default camera at 20 frames per second (FPS), storing frames in frames/ and recording video segments in videos/. For offline mode, upload() imports a video file, and generateFrame() extracts up to 500 frames, saving them as individual images in frames/ for further processing.



Activity Detection Module:

The core processing unit performs suspicious activity detection:

1. **Frame Extraction:** Frames are saved as JPEG files (e.g., live_frame_1.jpg).
2. **Classification:**DenseNet121,via prediction.classifyImage(),generates activity labels and confidence scores, returning the top three predictions.
3. **Temporal Consistency:** A 5-frame sliding window evaluates prediction consistency. An activity is flagged as suspicious if its label persists for at least 3 consecutive frames with an average confidence exceeding 85% (minimum threshold of 60%).

Temporal Consistency Formula:

- Average Confidence: $C_{avg} = \frac{1}{n}\sum_{i=1}^{n} C_i$, where C_i is the confidence per frame, $n = 5$.
- Detection Condition: If $C_{avg} > 85\%$ and consecutive occurrences ≥ 3, the activity is marked suspicious.

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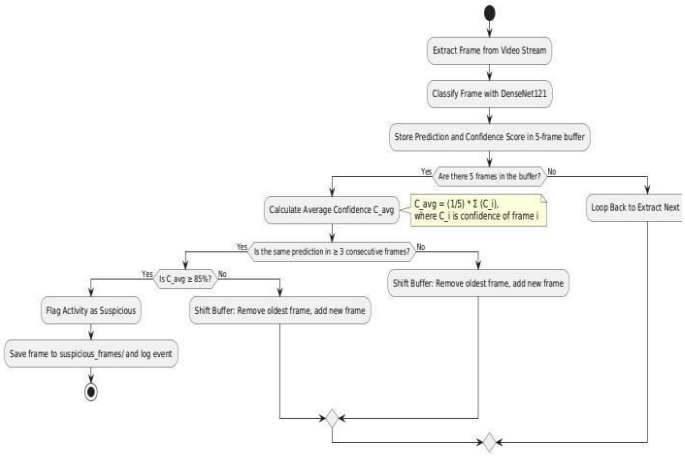
Figure 2: Temporal Consistency Flowchart for the Suspicious Activity Detection System

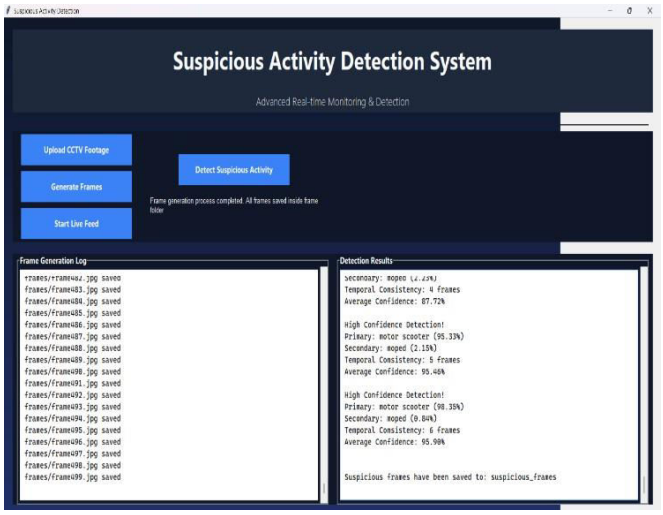


Output Module (Visualization and Storage)

This module delivers results to the user:

1. **Real-Time Feedback:** OpenCV overlays labels and confidence scores on live frames (e.g., "Suspicious: 91.8%").
2. **GUI Display:** Tkinter's text1 widget logs detection events, while text monitors frame generation progress.
3. **Persistent Storage:** Suspicious frames are archived in suspicious_frames/, and full videos in videos/.

User Interface Screenshot



3. Performance Evaluation

The system's effectiveness is assessed using:

These metrics validate the system's accuracy and operational efficiency.

- **Accuracy**: $Accuracy = \frac{\text{Correctly Detected Frames}}{\text{Total Frames Analyzed}} \times 100.$
- **Frame Processing Rate**: $FPS = \frac{\text{Frames Processed}}{\text{Processing Time}}.$
- **Precision**: $Precision = \frac{TP}{TP + FP}$, where TP denotes true positives and FP false positives.

4. Deployment:

The system is deployed on a local Python environment, executed via the main function, which initializes the Tkinter GUI and threading for live feed handling. It operates on a standard computer with a webcam, requiring no external network connectivity for primary functions.

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IV. EXPERIMENT RESULT

V. CONCLUSION

The Suspicious Activity Detection System successfully automates the identification of potential threats in video surveillance, leveraging OpenCV for real-time frame capture, DenseNet121 for precise activity classification, and Tkinter for user-friendly result visualization. By implementing a 5-frame buffer with temporal consistency checks in detectActivity(), the system achieves reliable detection, minimizing false positives through confidence thresholds (60% minimum, 85% high). The dual-mode functionality—supporting both live feeds via process_live_feed() and recorded footage through upload()—ensures versatility, while storage in suspicious_frames/ and videos/ facilitates forensic analysis.

This solution significantly reduces manual monitoring efforts, enhancing security efficiency in diverse scenarios, from public spaces to private facilities, and sets a foundation for scalable surveillance advancements.

VI. FUTURE WORK

To enhance the efficiency, accuracy, and scalability of the **Suspicious Activity Detection System**, several key improvements can be implemented in future iterations. These advancements will focus on **adaptive learning, multimodal integration, and real-time performance optimization.**

a. Adaptive Learning for Evolving Threat Patterns

- Implement self-learning models that adapt to emerging security threats.
- Utilize reinforcement learning to refine detection accuracy over time.
- Develop a feedback-based system where flagged activities improve model predictions.

b. Multimodal Surveillance Integration

- Combine video data with thermal imaging and motion sensors to detect anomalies in low-light conditions.
- Use acoustic event detection to enhance the accuracy of suspicious activity recognition.
- Develop a fusion model that integrates different sensory inputs for improved reliability.

c. Federated Learning for Privacy-Preserving Training

- Enable decentralized training across multiple surveillance locations while preserving data privacy.
- Reduce reliance on centralized databases, minimizing potential security risks.
- Enhance cross-location detection capabilities by leveraging collaborative AI training.

d. Cloud-Based Real-Time Monitoring & Analytics

- Deploy the system on cloud platforms for scalable real-time monitoring.
- Utilize edge computing for low-latency processing of video feeds.
- Implement a dashboard-based analytics system for security teams to access live alerts and statistics.

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5. **Explainable AI (XAI) for Detection Transparency**
- Integrate explainability frameworks like SHAP and LIME to provide insights into why a detection was flagged as suspicious.
- Develop an interactive visualization tool to display confidence scores and decision paths in real time.

6. **Blockchain-Backed Secure Logging**
- Use blockchain technology to create immutable logs of detected suspicious activities.
- Ensure auditability and prevent tampering of security logs by unauthorized entities.
- Develop a decentralized security ledger to share logs across multiple institutions.

7. **Real-Time Model Optimization with Edge AI**
- Implement lightweight deep learning models that can run efficiently on edge devices.
- Optimize DenseNet121-based classification to reduce computational overhead.
- Deploy quantization techniques to enhance real- time performance without sacrificing accuracy.

8. **Cross-Domain Adaptability for Multi-Environment Use Cases**
- Train models on diverse datasets including airports, retail stores, and public transit hubs.
- Develop domain-specific detection modes for different security scenarios.
- Implement transfer learning techniques to adapt models for varied environments without extensive retraining.

These future advancements will significantly improve the scalability, adaptability, and transparency of the Suspicious Activity Detection System, ensuring it remains a cutting- edge security solution in real-world applications.

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