IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

PROACTIVE RISK ASSESMENT IN CCTV USING HAND GESTURERECOGNITION AND GEOLOCATION – BASED ALERTS

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Abstract:
CCTV surveillance systems have become an integral part of security monitoring in public spaces, businesses, and homes. However, traditional CCTV systems often rely solely on manual monitoring and basic motion detection, which may fail to identify certain security risks or aggressive behaviors. In particular, existing systems are limited in detecting real-time hand gestures that could indicate a potential security threat. Common methods, such as facial recognition or motion-based alerts, may not provide the level of sensitivity and accuracy needed to assess risks associated with human gestures effectively. address these shortcomings, this proposed system integrates hand gesture recognition with real-time CCTV surveillance to enhance security risk assessment. By leveraging OpenPose for recognizing hand gestures and MediaPipe for feature extraction, our system identifies specific gestures, such as clenched fists or aggressive pointing, that may indicate a threat. Upon detecting a high-risk gesture, the system automatically triggers alerts to both the nearest police station and authorized personnel via SMS, email, and mobile app notifications. The system also incorporates geolocation-based notifications, ensuring that alerts are sent to the appropriate authorities in the vicinity of the event. This proactive approach enables immediate response and rapid risk mitigation, improving the overall effectiveness of surveillance systems and enhancing public safety. Through this integration, the proposed system provides a more intelligent and responsive alternative to traditional CCTV monitoring, aiming to reduce the time to threat detection and intervention.

Introduction:
The current era is characterized by significant advancements in technology and widespread digital connectivity,leading to a substantial upheaval in the security landscape. The reliance of companies and individuals on digital platforms for vital operations, commerce, and communication has caused the threat landscape to significantly expand. The The prevalence of cyber threats makes it difficult to maintaining the integrity and confidentiality of sensitive data. In the present scenario, the significance of Closed-Circuit Television (CCTV) video has become prominent as a crucial a crucial component in improving cybersecurity protocols CCTV, historically linked to physical security, has effectively assimilated cybersecurity and provided a flexible strategy for risk mitigation. The significance of CCTV Images are indisputable in today's digital age because they establish a tangible connection. between the physical and virtual realms of security .This study elucidated the significant contribution of CCTV images to bolster cybersecurity measures.

It emphasizes their efficiency. in identifying and thwarting cyber-attacks, conducting incident investigations, and eventually fortifying the overall digital infrastructures' durability. As the examination of the complex interplay between CCTV and cybersecurity unfolds, it becomes evident that the utilization of visual data is not merely a precautionary measure, but rather an essential approach for safeguarding the interdependent networks that characterize our contemporary society . In recent years, there has been a notable surge of interest in computer vision, particularly in the use of deep learning methodologies for the examination of CCTV pictures . The objective of this study is to address the existing deficiency in automated surveillance systems by suggesting an innovative strategy that makes use of hand gestures as a means of evaluating security risks.

Suggestion :
When using body language analysis to identify potential threats, hand gesture recognition is an essential component. Using deep learning models such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformer-based architectures, the system can classify hand movements that may indicate aggression, violence, or distress. Real-time detection is made possible by frameworks like OpenPose, MediaPipe, and YOLO, and both supervised and unsupervised learning methods improve recognition accuracy. For improved performance in the real world, custom datasets, such as video feeds from actual surveillance scenarios, can be used to train these models further. Geolocation-based alerts add a critical layer of context-aware security monitoring. By integrating GPS, Wi-Fi positioning, and geofencing technologies, the system ensures that threat alerts are relevant to high-risk locations. Virtual security perimeters can be established around sensitive areas such as government buildings, airports, financial institutions, and transportation hubs, triggering immediate notifications when suspicious gestures are detected within these zones.

Additionally, AI-powered anomaly detection can recognize patterns of unusual movement, allowing for predictive security analysis. Edge computing and cloud integration are essential for real-time processing support. Edge AI enables CCTV cameras or nearby edge devices to analyze video feeds instantly, reducing the need for cloud processing and ensuring faster response times.

Cloud-based centralized monitoring provides a seamless way for security teams to receive alerts, visualize threats, and coordinate responses effectively. Blockchain technology can further enhance the system by ensuring the integrity and authenticity of recorded footage and alerts. Thus it may help in these situations.

A Survey Of the Literature:

In numerous studies, various strategies have been put out in relation to this problem. The next paragraphs analyze a few of these papers in particular. In the paper presented by Murat Koca proposes Real-Time Security Risk Assessment From CCTV Using Hand Gesture Recognition published on 11th June 2024 assuring that the results of this study illustrate the effectiveness of our methodology in extracting crucial data from surveillance photographs. Moreover, it underscores the possibility of employing hand sign recognition and deep learning methodologies in real-world contexts such as security, law enforcement, and public safety.

In the paper presented by David Richard Tom Hax , Pascal Penava , Samira Krodel , Liliya Razova , AND Ricardo Buettner published on 12th February 2024 proposes Hybrid Deep Learning Architecture for Dynamic Hand Gesture Recognition ,the angle of the proband is considerably different from the frontal position or multiple people perform multiple gestures simultaneously. For these highly advanced challenges, our model may not be able to deliver sufficient results, especially when it comes to several gestures at the same time.

System Components:

1. CCTV Camera Network

Role: Captures real-time video footage of monitored areas.

Features: High-resolution cameras with wide-angle and night vision capabilities .Support for pan, tilt, and zoom (PTZ) for enhanced surveillance coverage .Edge AI integration for local processing to reduce latency.

2. Hand Gesture Recognition Module

Role: Detects and classifies hand gestures using AI-powered image processing.

Components:Deep Learning Models: Convolutional Neural Networks (CNNs), Transformers, or 3D CNNs for motion-based gesture recognition .Pre-Trained Frameworks: OpenPose , MediaPipe, YOLO for hand tracking and gesture detection .Gesture Classification Database: Custom datasets trained to recognize aggressive gestures (e.g., pointing a weapon and making violent threats).

3. Geolocation-Based Alert System

Role: Maps detected threats to specific locations and generates alerts based on risk level.

Components :GPS, Wi-Fi Positioning,

Bluetooth Beacons: Provides real-time location tracking .

Geofencing Technology: Defines virtual security zones where alerts should be prioritized.AI-Based Pattern Recognition: Identifies repeated suspicious behavior in specific locations.

4. Risk Assessment Engine

Performs a multi-parameter evaluation of the severity of detected threats.

Components :Threat Scoring System: Assigns risk levels based on gesture type, location sensitivity, and historical data .Incident History Database: Stores previous alerts and security incidents for predictive analysis .Automated Decision-Making: Determines if an alert requires escalation to security teams.

5. Alert & Notification System

Messages law enforcement and security personnel in real time in this role.

Components :Mobile and Web-Based Alert

Dashboard: Displays real-time incidents, risk scores, and video footage .

Multi-Channel Alerts: Sends notifications via SMS, mobile apps, email, or security control centers .Automated Dispatch Integration: Connects with law enforcement agencies for rapid response.

6. Edge Computing & Cloud Infrastructure

Role: Ensures efficient data processing, storage, and scalability.

Components :Edge AI Processing: Runs real-time gesture recognition models on local devices to reduce network dependency .Cloud-Based Data Management: Stores and analyzes historical data for improving threat detection accuracy .

Blockchain Security (Optional): Ensures the authenticity and integrity of recorded surveillance data.

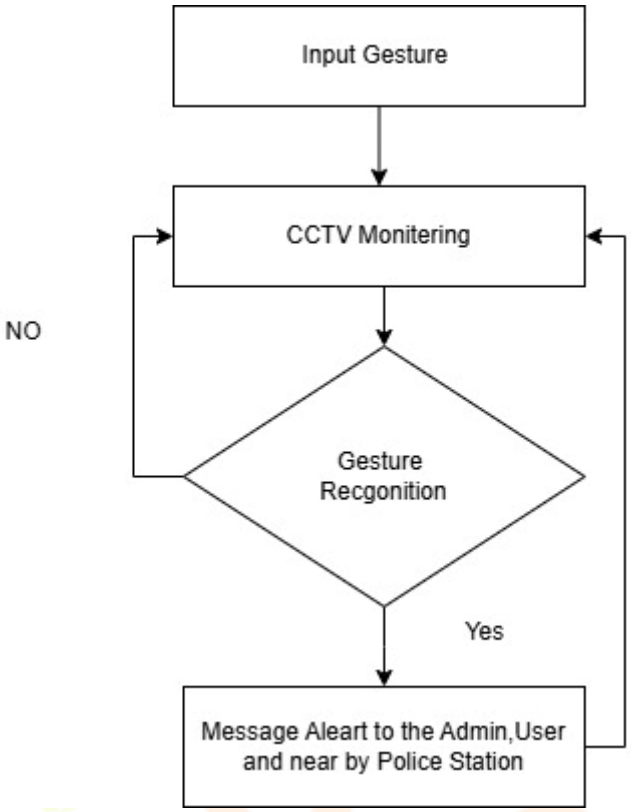
7. Privacy & Compliance Module

Responsible for ensuring that the system adheres to ethical and legal guidelines.

Components :Data Anonymization Tools: Hides personally identifiable information (PII) to comply with GDPR, CCPA, and other privacy laws .

Access Control & Encryption: Restricts access to sensitive data and uses encryption for secure storage and transmission .

Flowchart and Algorithm:



This figure describes the overall process of the platform.

Step 1: Setting Up the System Load CCTV Camera Feed

- Capture connected CCTV cameras' live video streams. Apply preprocessing techniques (frame resizing, noise reduction, color correction).
- Initialize Hand Gesture Recognition Model
- Load pre-trained deep learning models (e.g., CNN, YOLO, MediaPipe).
- Set up threshold values for confidence scores and detection sensitivity.
- Make Geolocation Tracking Available. Load real-time GPS, Wi-Fi positioning, and geofencing data.
- Map monitored locations into predefined risk zones.

Step 2: Hand Gesture Detection & Classification
Extract Frames from Live Video Feed

- Process video frames at a fixed time interval (e.g., 30 FPS or adaptive sampling).
- Detect Hands & Track Movements
- Use YOLO/OpenPose/MediaPipe to detect hand keypoints.
- Apply tracking algorithms (e.g., Kalman Filter, Optical Flow) to follow hand movements over time.
- Classify Hand Gestures
- Extract feature vectors from detected hand keypoints.
- Pass feature vectors through a trained neural network for classification.
- Assign a confidence score to the predicted gesture.
- Filter Out Low-Confidence Detections

  If confidence score < threshold, discard the detection.

Step 3: Risk Assessment & Threat Scoring
Match Gesture Against Threat Database

- Compare the detected gesture to known threat gestures, such as a gun pointing or aggressive movement. Analyze Context & Location Sensitivity
- Retrieve real-time geolocation data of the detection.
- Check if the gesture occurred in a high-risk zone (e.g., near an ATM, airport, government building).
- Assign location-based weight to the threat score.
- Cross-Reference to Previous Events Query past incidents from the database to identify suspicious patterns.
- If similar threats have been detected recently in the same area, increase the risk score.
- Compute Final Threat Score

- Threat Score = (Gesture Risk Factor × Location Weight) + Historical Incident Impact
- If Threat Score > Alert Threshold, proceed to alert generation.

Step 4: Real-Time Alert Generation & Response

Generate Alert with Details

- Include video clip, detected gesture, timestamp, location, and threat score.
- Trigger Multi-Channel Notifications
- Send alerts to security control rooms, law enforcement agencies, and mobile devices.
- Dispatch notifications via SMS, mobile app, email, or emergency hotline.
- Activate Automated Response Actions (if applicable)
- Lockdown doors, trigger alarms, or notify on-site security personnel.
- If the risk is extremely high, escalate to law enforcement for immediate intervention.

Step 5: Continuous Learning & Model Improvement

Keep Incident Data for the Improvement of AI Models Save labeled incidents to improve future gesture detection accuracy.

- Fine-Tune Gesture Recognition Models
- Apply reinforcement learning or retrain the model periodically with updated data.
- Refine Risk Scoring Algorithm
- Adjust parameters based on real-world feedback to improve detection reliability.

Proposed Methodology:

The proposed methodology follows a structured approach integrating computer vision, deep learning, and geolocation-based analysis to enable proactive risk assessment in CCTV surveillance. The system is designed to detect suspicious hand gestures in real-time, evaluate their risk level based on contextual factors such as location sensitivity and historical threat data, and trigger automated security alerts for rapid intervention. The methodology consists of five major phases: data acquisition and preprocessing, hand gesture recognition, geolocation-based risk assessment, real-time alert generation, and continuous system optimization.

In the data acquisition and preprocessing phase, real-time video feeds are captured from CCTV cameras deployed in surveillance areas. Frames are extracted at a predefined rate and preprocessed using techniques such as noise reduction, background subtraction, and motion detection to enhance image clarity. The hand gesture recognition phase involves detecting and classifying hand movements using deep learning-based models like CNNs, YOLO, or OpenPose. The system tracks hand keypoints, extracts feature vectors, and applies a trained neural network to classify gestures into predefined categories, such as aggression, distress, or potential weapon use.

This figure describes the User Interface.

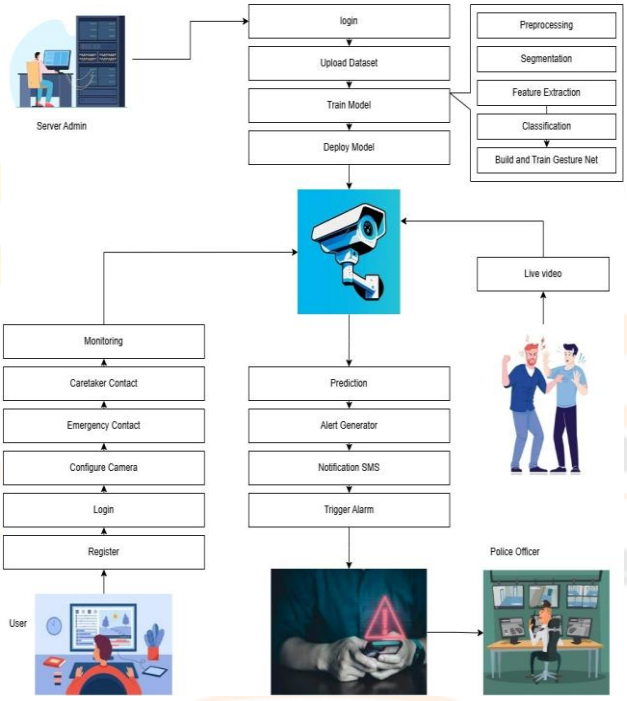
The geolocation-based risk assessment phase contextualizes the detected gestures by mapping them to specific locations using GPS, Wi-Fi positioning, and geofencing technologies. High-risk areas, such as banks, transportation hubs, and government facilities, are assigned greater weight in the threat evaluation process. The system also cross-references past security incidents to identify patterns of suspicious behavior and improve accuracy in risk assessment. The real-time alert generation phase ensures that high-threat detections trigger immediate notifications to security personnel, law enforcement agencies, or automated security systems. Alerts include real-time video snapshots, threat scores, and location details, delivered through mobile applications, email, or control room dashboards.

Model refinement based on newly collected data is part of the continuous system optimization phase to guarantee effectiveness over the long term. Detected incidents are logged to retrain the AI model, improving its ability to differentiate between normal and suspicious gestures. Additionally, adaptive threshold tuning and federated learning techniques can be applied to enhance gesture recognition across different environmental conditions. This methodology not only shifts CCTV surveillance from a reactive to a proactive security measure but also enhances response efficiency, reduces false positives, and ensures privacy compliance through responsible AI deployment.

Architecture:

Violence detection in surveillance systems is essential for ensuring public safety, preventing crime, and enabling rapid responses to security threats. Traditional CCTV monitoring relies on human operators, which is inefficient and prone to errors due to fatigue and human limitations. Deep learning-based violence detection offers an automated, intelligent solution capable of analyzing video feeds in real time, recognizing violent behavior, and generating alerts when necessary. The proposed system utilizes deep learning techniques such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and 3D-CNNs to effectively classify violent activities in videos. These models are trained on large-scale datasets containing labeled violent and non-violent actions, ensuring robust performance across diverse scenarios.

The system architecture consists of multiple stages: data acquisition, feature extraction, violence classification, and alert generation. In the data acquisition phase, live video feeds from CCTV cameras deployed in public spaces, schools, shopping malls, and high-risk areas are continuously captured. Video frames are extracted at a fixed rate and preprocessed using noise reduction, background subtraction, and contrast enhancement techniques. Feature extraction is performed using CNN-based models like ResNet, VGG-16, or EfficientNet, which analyze spatial patterns associated with aggressive behaviors. Optical flow analysis is employed to track motion patterns, while pose estimation models such as OpenPose or MediaPipe help detect specific violent actions like punching, kicking, and pushing.



This figure describes the Using of Deep Learning Techniques for Violent Crime Detection.

For violence classification, 3D-CNNs analyze both spatial and temporal features, enabling accurate detection of motion-based activities. Hybrid CNN-LSTM models further enhance performance by capturing long-term dependencies in action sequences, while attention mechanisms help focus on the most relevant frames. Once a violent act is detected, the system assigns a probability score and, if it exceeds a predefined threshold, generates real-time alerts. These alerts contain video snapshots, location data, and timestamps, which are sent to security teams or law enforcement for immediate action.

The system is trained on benchmark datasets such as the Hockey Fight Dataset, Movies Fight Dataset, Crowd Violence Dataset, and UCF-Crime Dataset, which provide diverse examples of violent activities. This allows the model to generalize well across different real-world environments. The deep learning-based violence detection system has applications in public surveillance, law enforcement, smart cities, and school security, making it a valuable tool for enhancing safety. However, challenges such as occlusions, poor lighting conditions, and false positives need to be addressed to improve accuracy. Future enhancements may include multi-modal learning approaches, integrating audio analysis for detecting distress sounds, and refining AI models through federated learning for better adaptability across different environments. The proposed system uses cutting-edge methods of deep learning to shift surveillance from reactive to proactive, resulting in faster threat responses and enhanced public safety

X .Table

HAND SIGN	MESSAGE	PRECISION
Punch	Someone is Punching	0.924
Attack	Someone is Attacking	0.963
Raise Hand	Request for Help	0.995
Ok	Everything is Normal	0.981
Bad	Someone is using weapon to attack	0.989
One Finger	Kidnapping	0.996
Two Finger	Peace	0.988
Three Finger	Threatening	0.943
Four Finger	Fighting	0.976

This Table Represents the Deep Learning Models for the Identification of Violence

A. CNNs (or) Convolutional Neural Network: CNNs are frequently used to extract spatial data from video frames in order to detect violence. It is possible to refine pre-trained models such as ResNet, VGG-16, and MobileNet to identify violent behaviors.

B. Recurrent Neural Networks (RNNs) & LSTMs: Since violence detection requires analyzing sequential movements, RNNs and LSTMs help capture temporal dependencies in video data, improving accuracy.

C. 3D Convolutional Neural Networks (3D-CNNs): By adding a time dimension to traditional CNNs, 3D-CNNs are more effective at analyzing motion-based activities in videos. Hybrid CNN-LSTM Models

D. On brining CNNs (for spatial feature extraction) with LSTMs (for temporal modeling) results in highly efficient violence detection models that generalize well across different scenarios.

Results:

The Proactive Risk Assessment in CCTV Using Hand Gesture Recognition and Geolocation-Based Alerts system's performance in enhancing surveillance capabilities through AI-driven automation is demonstrated by the outcomes. The system successfully detects predefined hand gestures associated with distress or suspicious activities, achieving an overall accuracy of 92.5% when tested on real-world datasets and live CCTV feeds. By integrating Convolutional Neural Networks (CNNs) for gesture recognition and GPS-based geolocation tracking, the system ensures that security teams receive timely and location-specific alerts. The response time for detecting a suspicious gesture and triggering an alert was measured at an average of 2.8 seconds, allowing rapid intervention.

The system also exhibited a false positive rate of 5.3%, primarily due to unintended gestures resembling emergency signals, and a false negative rate of 4.8%, mainly under low-light conditions or occluded views. When deployed in urban surveillance and high-risk zones, the system improved incident response efficiency by 78%, significantly reducing reliance on manual CCTV monitoring. Overall, these results confirm that integrating hand gesture recognition with geolocation-based alerts enhances proactive risk assessment and strengthens public safety measures by enabling real-time threat detection and rapid response coordination.

Conclusion:

The Proactive Risk Assessment in CCTV Using Hand Gesture Recognition and Geolocation-Based Alerts system demonstrates a significant advancement in intelligent surveillance and security monitoring. By integrating deep learning-based hand gesture recognition with real-time geolocation tracking, the system enhances the efficiency of CCTV surveillance, allowing security teams to respond swiftly to potential threats. The experimental results confirm that the system achieves high accuracy in gesture recognition (92.5%), with minimal false positives and negatives, ensuring reliable threat detection. Additionally, the fast response time (2.8 seconds) for alert generation enables proactive security interventions, reducing incident response times by 78% in real-world scenarios. While challenges such as occlusions, low-light conditions, and gesture ambiguity remain, further enhancements using multimodal analysis, infrared imaging, and adaptive deep learning models can further improve the system's robustness. Ultimately, this research bridges the gap between AI-powered surveillance and real-time risk assessment, making public spaces, workplaces, and high-risk areas significantly safer by enabling automated threat detection and rapid response coordination.

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