SmartEye Surveillance System using AI Detection

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Abstract- With the growing demand for intelligent surveillance systems, real-time abnormal activity detection has become an essential feature in security monitoring, aged care, and public safety applications. Traditional deep learning algorithms frequently necessitate big datasets, significant processing capacity, and complex training procedures. This study introduces the SmartEye Surveillance System, a lightweight, real-time anomalous activity detection platform based on MediaPipe pose estimation and absolute inter-frame distance analysis.

To achieve translation and scale invariance, the system uses MediaPipe to extract 33 human body landmarks and then applies center and scale normalization. Abnormal activity is discovered by calculating the absolute Euclidean distance between consecutive frames' landmarks. If the estimated motion intensity exceeds a predetermined threshold, the system considers the activity abnormal and issues an alarm. The suggested strategy reduces the requirement for massive training datasets while yet preserving real-time performance and computational economy. Under single-person observation, the experimental results show that abrupt falls, aggressive gestures, and strange posture changes can be reliably detected..

Key Words: Smart Surveillance, Abnormal Activity Detection, MediaPipe Pose, Pose Normalization, Absolute Distance, Computer Vision

1. INTRODUCTION

With rising urbanization and increased reliance on automated systems, the need for intelligent monitoring is greater than ever. Security monitoring systems are commonly used in residential buildings, corporate offices, banks, hospitals, and educational facilities. Conventional surveillance systems, on the other hand, are largely recording equipment that require regular human monitoring by security professionals. This technique is inefficient and frequently fails to respond quickly to unusual or suspicious behaviour.

Modern research has introduced artificial intelligence and deep learning techniques for activity recognition and behavior analysis. Although these techniques are highly accurate, they require large training datasets, powerful GPUs, and complicated computational models. These constraints make them unsuitable for lightweight and cost-effective solutions.

The SmartEye Surveillance System tackles these issues by implementing a computationally efficient abnormal activity detection system that use pose-based motion analysis. Instead than processing raw video frames with large neural networks, the system concentrates on human skeletal landmarks collected with MediaPipe. Abnormal actions can be recognized in real time using inter-frame landmark displacement analysis, which does not require model training.

2. LITERATURE SURVEY

Research in abnormal activity detection has been extensively carried out using computer vision and AI-based methods. Several approaches have been proposed to improve accuracy, reliability, and real-time usability.

1. Process-based Activity Monitoring

According to Noghre et al. (2023), aberrant human activities can be diagnosed by examining departures from typical posture and movement patterns. Their findings underline that abnormality is frequently described as a detectable departure from a learnt baseline of normal human motion. Instead of depending exclusively on event detection, their method emphasizes continuous monitoring of skeletal joint locations and posture transitions.

The study shows that not every deviation is dangerous; rather, abrupt or excessive posture alterations typically suggest potential risk circumstances such as falling, collapse, or violent activity. Their framework compares current posture vectors to previously recorded stable posture distributions to determine anomaly scores.

This approach immediately inspired the SmartEye Surveillance System to use pose deviation as its major criteria for detecting suspicious behavior. Rather than evaluating raw pixel data, our approach identifies skeletal landmarks with MediaPipe and assesses deviation intensity using inter-frame absolute distance computations. Using motion magnitude as a deviation indicator, the system detects anomalous behavior in a lightweight and effective manner without the need for complex model training.

3. Deep Learning for Pose Classification

This method instantly prompted the SmartEye Surveillance System to employ pose deviation as a primary criterion for

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detecting suspicious activity. Rather of analyzing raw pixel data, we use MediaPipe to identify skeletal landmarks and assess deviation intensity via inter-frame absolute distance computations. Using motion magnitude as a deviation indicator, the system detects abnormal behavior in a lightweight and effective manner, eliminating the need for complex model training.

This strategy immediately encouraged the SmartEye Surveillance System to use pose deviation as its key criterion for detecting suspicious activities. Rather than examining raw pixel data, we use MediaPipe to locate skeletal landmarks and determine deviation intensity using inter-frame absolute distance computations. Using motion magnitude as a deviation indicator, the system detects anomalous behavior in an efficient and lightweight manner, reducing the need for extensive model training.

This method quickly prompted the SmartEye Surveillance System to use pose deviation as the primary criterion for detecting suspicious activity. Rather than looking at raw pixel data, we use MediaPipe to find skeletal landmarks and calculate deviation intensity using inter-frame absolute distance computations. Using motion magnitude as a deviation indicator, the system detects abnormal behaviour in an efficient and lightweight manner, eliminating the need for significant model training.

4. Occlusion-Aware 3D Motion Interpretation

This strategy immediately led the SmartEye Surveillance System to adopt pose deviation as the key criterion for detecting suspicious activities. Rather of inspecting raw pixel data, we use MediaPipe to locate skeletal landmarks and compute deviation intensity via inter-frame absolute distance computations. Using motion magnitude as a deviation indicator, the system detects anomalous behavior in an efficient and lightweight manner, reducing the need for extensive model training.

This method instantly prompted the SmartEye Surveillance System to use pose deviation as the primary criterion for detecting suspicious activity. Rather of reviewing raw pixel data, we use MediaPipe to find skeletal landmarks and calculate deviation intensity using inter-frame absolute distance computations. Using motion magnitude as a deviation indicator, the system detects abnormal behavior in an efficient and lightweight manner, eliminating the need for significant model training.

This study inspired the SmartEye system by emphasizing the value of resilience and computing efficiency. Although SmartEye is currently operating in a single-person, controlled indoor environment, the normalization approach used in our methodology improves tolerance to scale fluctuation and tiny occlusions. Furthermore, the lightweight MediaPipe-based approach guarantees faster processing than bulky 3D reconstruction models. In future updates, occlusion-aware techniques can be included to improve detection performance in real-world deployment circumstances.

2. METHODOLOGY

The SmartEye Surveillance System is developed with a tiered architecture that includes an input layer, a processing layer, and an output layer. The technique detects anomalous activity in real time for single-person monitoring by evaluating human pose markers retrieved from live video feeds. The design provides continuous monitoring, computational efficiency, and modular implementation that is appropriate for lightweight surveillance applications.

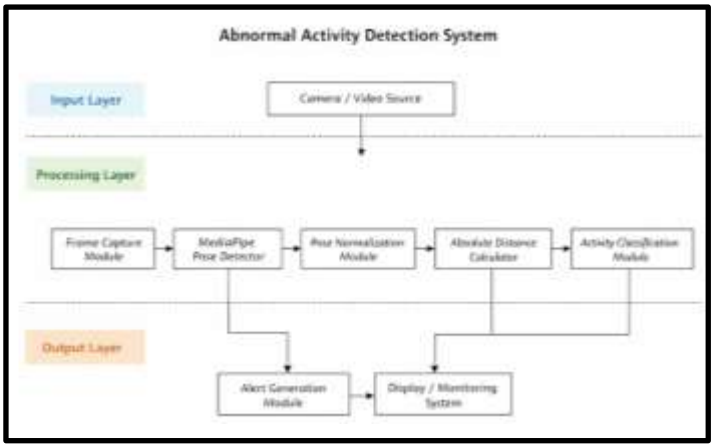

Figure 1. System Architecture

3.1Input Layer

The Input Layer collects live video data from a webcam or CCTV camera. The continuous video stream is broken down into discrete frames for sequential processing. Each frame is scaled and preprocessed to ensure consistency and minimize computational overhead. The input module ensures that frames are acquired smoothly and continuously, allowing for latency-free real-time activity analysis.

3.2 Processing Layer

The Processing Layer is the fundamental component of the SmartEye Surveillance System. It is made up of several modules that work consecutively to detect anomalous human behavior. The Frame Capture Module takes individual frames from the live video source and saves them in a sequence for comparison. The MediaPipe Pose Detector then recognizes 33 human body markers in each frame, including important joints like the shoulders, elbows, hips, knees, and ankles. These landmarks offer coordinate values that represent the person's skeletal structure and are the fundamental features used in activity analysis.

To increase robustness, a Pose Normalization Module is used. To achieve translation invariance, the body center is first calculated as the average of all landmark coordinates, and then each landmark is adjusted relative to this center. Scale normalization is then conducted by estimating torso size based on shoulder distance. A normalization factor is applied to all

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landmark coordinates to guarantee that they are represented consistently independent of subject height or camera distance.

Following normalization, the Absolute Distance Calculator calculates the motion intensity between consecutive frames using Euclidean distance measurement. The displacement of the related landmarks is calculated and added to get a total motion score. This score indicates the degree of bodily movement between frames. The activity classification module then compares the motion score to a predetermined threshold value. If the motion score exceeds the threshold, the system considers the activity abnormal; otherwise, it is regarded as normal. This rule-based threshold technique allows for efficient abnormal activity identification without requiring extensive training datasets.

3.3 Output Layer

The Output Layer creates the system response based on the classification results. When the system detects anomalous behavior, an alarm message appears on the monitoring interface. The live camera feed is displayed, together with position landmarks and an activity status labeled Normal or Abnormal. The device then monitors in a continuous loop to ensure real-time surveillance.

4. WORKING MODULE

The SmartEye Surveillance System operates on a continuous real-time monitoring process that includes sensing, processing, and alarm production stages. The system starts by capturing live video input from a webcam. Each frame of the video stream is analyzed sequentially by the MediaPipe Pose framework to extract 33 human body landmarks representing important skeletal joints. These landmarks are then adjusted to remove any discrepancies caused by camera location and subject distance.
After normalization, the system computes the absolute Euclidean distance between adjacent landmarks in consecutive frames to measure motion intensity. The displacement values of all landmarks are added together to generate a total motion score. This motion score indicates the extent of body movement between frames. The generated score is then compared to a predetermined threshold value. If the motion score exceeds the threshold, the system flags the activity as abnormal and displays an alert message on the monitoring screen; otherwise, the activity is labeled normal. To assure constant observation, the system repeatedly runs this operation.
The module is implemented using the Python computer language, with OpenCV handling video frames and MediaPipe detecting poses in real time. The normalization and motion calculation logic is achieved using mathematical operations on landmark coordinates. The threshold-based classification is integrated into the processing loop, allowing for fast decision-making. The system runs fast on CPU-based devices and does not require GPU acceleration or model training, making it portable and appropriate for single-person interior surveillance scenarios.

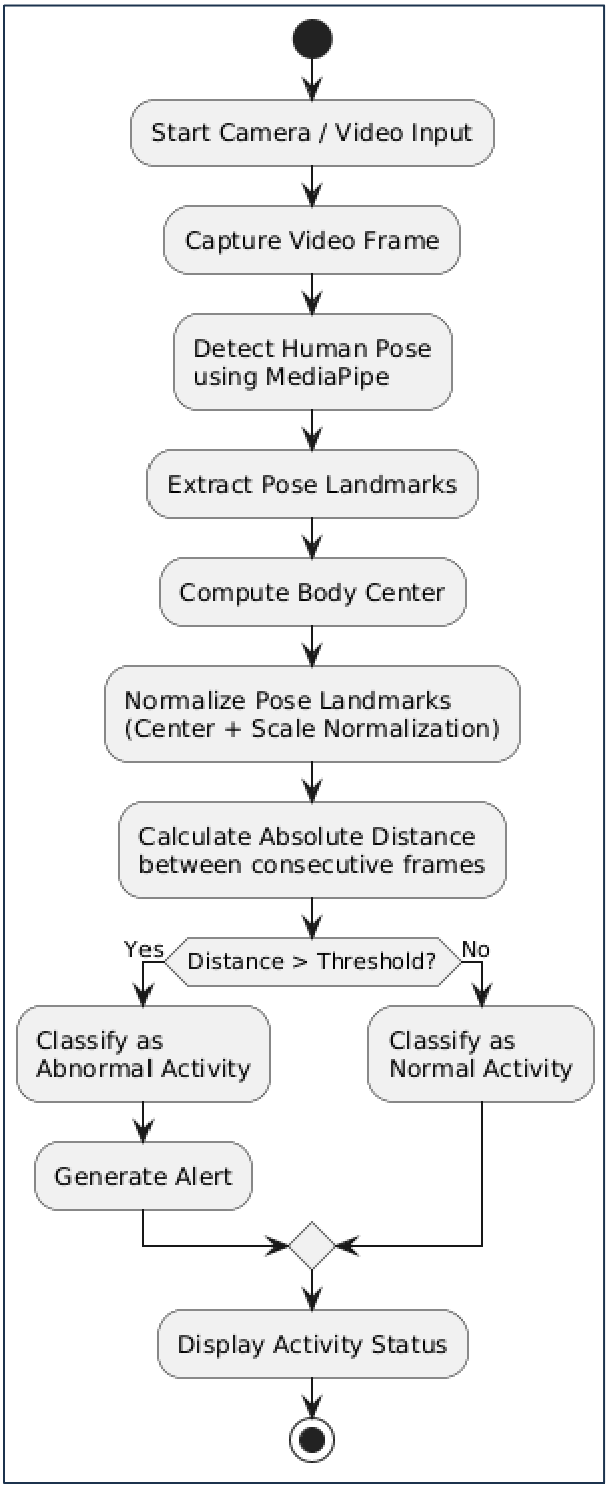

Figure 2. Activity Detection Flow

Used modules and devices in implemented system are as follow:

1. The Camera Module captures live video input for continuous monitoring.
2. The Frame Capture Module extracts individual frames from a video stream for processing.

3. MediaPipe Pose Module detects and extracts 33 human body landmarks each frame.
4. The Pose Normalization Module ensures translation and scale invariance by performing center and scale normalization.
5. The Absolute Distance Calculation Module measures motion intensity by calculating the Euclidean distance between landmarks across multiple frames.
6. The Activity Classification Module compares motion scores to predefined thresholds to determine whether activity is normal or pathological.
7. The Alert Generation Module generates visual alert notifications when suspicious activity is identified.
8. Display Interface Module: Displays live video stream with pose landmarks and activity status.

5. CONCLUSION

The SmartEye Surveillance System, described in this paper, is a lightweight and real-time abnormal activity detection platform that employs MediaPipe-based posture estimation and absolute distance motion analysis. The technology identifies atypical human movements by analysing normalised skeletal landmark displacement between consecutive frames. The technique is robust against fluctuations in camera location, subject distance, and body size thanks to the use of centre and scale normalisation.

Unlike deep learning-based surveillance systems, which require large training datasets and significant processing capacity, the suggested method employs a threshold-based classification approach, making it computationally inexpensive and appropriate for CPU-based devices. Under single-person monitoring conditions, the system accurately detects unexpected falls, quick body movements, and uncommon posture abnormalities. The modular architecture promotes scalability and ease of future enhancement. Overall, the SmartEye Surveillance System is a useful, affordable, and real-time solution for smart surveillance applications in homes, offices, and healthcare settings.

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