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Abnormal Activity Detection

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Abstract: *Abnormal Activity Detection (AAD) is an important research field in computer vision and artificial intelligence that focuses on identifying abnormal actions automatically from video or sensor data. With the increasing need for smart monitoring systems in healthcare, surveillance, and smart home environments, automated activity detection systems have gained significant attention. The proposed Abnormal Activity Detection and Abnormal Activity Detection System is developed using Pythonbased technologies including Flask, OpenCV, MediaPipe, NumPy, Pandas, and pyttsx3. The system captures live video through a webcam and processes each frame using the MediaPipe Pose model to detect the abnormal skeleton. MediaPipe Pose identifies 33 body landmarks such as the nose, shoulders, elbows, wrists, hips, knees, and ankles. These landmarks provide detailed information about the abnormal body posture and movement. During the training phase, the system records body landmark coordinates when the user performs specific activities such as sitting, standing, or falling. The coordinates are normalized relative to the body center to ensure consistency across different body positions and camera angles. These normalized landmark vectors are stored in a dataset file using the Pandas library. In the detection phase, the system continuously processes live video frames, extracts body landmarks, and compares them with the stored dataset vectors using distance-based comparison techniques. The closest matching vector determines the recognized activity. If the detected pose does not match any stored activity, the system labels it as unknown. The recognized activity is displayed on the video frame and announced through voice output using the pyttsx3 text-to-speech library. This system provides a lightweight and efficient solution for real-time abnormal activity monitoring and abnormal activity detection. The proposed system can be applied in healthcare monitoring, elderly fall detection, surveillance systems, and abnormal motion analysis*

Keywords*:* Abnormal Activity Detection, Computer Vision, MediaPipe Pose, Abnormal Activity Detection, OpenCV, Machine Learning

I. INTRODUCTION

Abnormal Activity Detection (AAD) has become an essential research topic in the fields of computer vision, artificial intelligence, and machine learning. The main objective of AAD systems is to automatically identify and analyze abnormal actions by interpreting visual or sensor-based data. These systems are widely used in many real-world applications such as healthcare monitoring, sports analysis, surveillance systems, and smart environments.

In traditional monitoring systems, abnormal observation is required to detect and analyze activities. However, manual monitoring is time-consuming, inefficient, and prone to abnormal errors. Automated activity detection systems help reduce the need for manual monitoring by detecting activities automatically using advanced computer vision techniques.

Recent developments in computer vision and machine learning have made it possible to recognize abnormal activities from video data using pose detection and skeleton tracking algorithms. MediaPipe Pose is one such framework that provides real-time abnormal pose detection with high accuracy. It detects 33 body landmarks that represent the positions of different joints and body parts.

The proposed system uses MediaPipe Pose detection to analyze abnormal body posture and recognize activities such as sitting, standing, and falling. By analyzing the spatial relationships between body landmarks, the system can identify

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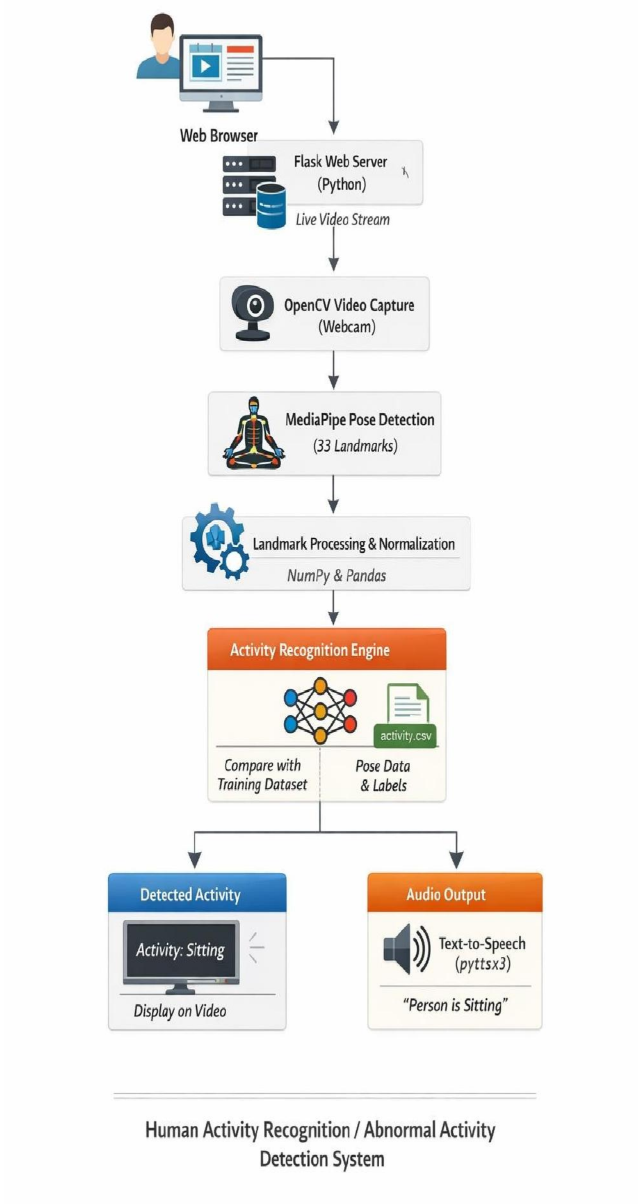
different body postures and movements. This enables the system to detect both normal and abnormal activities in real time.

The primary goal of this project is to develop a lightweight and efficient abnormal activity detection system that can operate in real-time using only a webcam and computer vision algorithms without requiring any wearable devices.



II. LITERATURE REVIEW

Abnormal Activity Detection (AAD) has emerged as an important research area in the fields of computer vision, artificial intelligence, and machine learning. It focuses on automatically identifying abnormal actions and behaviors from sensor data or visual inputs. In earlier years, many researchers developed activity detection systems using wearable sensors such as accelerometers, gyroscopes, and motion sensors attached to the abnormal body. These sensors collect motion data which is then analyzed using machine learning algorithms to recognize activities such as walking, running, sitting, or standing. Although these sensor-based approaches provide accurate results, they require users to continuously wear devices, which may cause inconvenience and limit their usability in real-world environments.

With advancements in computer vision technologies, researchers began developing vision-based abnormal activity detection systems that use cameras instead of wearable devices. These systems analyze images or video streams to identify abnormal posture and body movements. One of the most important developments in this field is the use of pose estimation algorithms, which can detect key points or landmarks of the abnormal body. Popular frameworks such as MediaPipe Pose, OpenPose, and PoseNet have been widely used for detecting abnormal body skeleton structures in real time. These frameworks identify key body landmarks such as the nose, shoulders, elbows, wrists, hips, knees, and ankles, which can then be used to analyze abnormal posture and movement patterns.

Recent studies have also applied deep learning techniques such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) networks for activity detection. These models are capable of learning complex motion patterns from large datasets of video sequences. However, deep learning models require large computational resources, extensive training data, and high-performance AADdware such as GPUs. Therefore, lightweight systems that can perform activity detection with lower computational requirements are still an active area of research.

The proposed system focuses on a lightweight computer vision-based approach for detecting abnormal activities using pose landmark analysis. By using MediaPipe Pose to detect body landmarks and storing these landmarks as numerical vectors in a dataset, the system can recognize activities by comparing real-time pose data with previously recorded activity samples. This method eliminates the need for complex neural network training while still providing efficient real-time performance. The system is particularly useful in applications such as abnormal activity detection, fall detection, healthcare monitoring, surveillance systems, and smart home environments where continuous abnormal activity monitoring is required.

III. PROPOSED SYSTEM

The proposed Abnormal Activity Detection and Abnormal Activity Detection System is designed to recognize abnormal activities using computer vision techniques and pose estimation algorithms. The system captures real-time video using a webcam and processes each frame using the MediaPipe Pose detection framework.

MediaPipe Pose detects the abnormal body skeleton by identifying 33 key landmarks that represent various joints and body parts. These landmarks include the nose, shoulders, elbows, wrists, hips, knees, and ankles. The coordinates of these landmarks provide detailed information about the abnormal body posture.

After detecting the body landmarks, the system extracts their coordinates and processes them using the NumPy library. The coordinates are normalized relative to the body center, which helps eliminate variations caused by camera position or body size.

During the training phase, the user performs specific activities such as sitting, standing, or falling. The system captures the landmark coordinates for each activity and stores them in a dataset file called activity.csv using the Pandas library. Each row in the dataset represents a pose vector with its corresponding activity label.

In the detection phase, the system continuously reads frames from the webcam and extracts the current body landmarks. These landmarks are processed in the same way as the training data. The system then compares the current pose vector with the stored dataset vectors by calculating the distance between them.

The activity corresponding to the closest matching vector is identified as the detected activity. If the calculated distance is greater than a predefined threshold, the system classifies the activity as unknown.

The detected activity is displayed on the video frame, and the system also provides voice feedback using the pyttsx3 text-tospeech engine.

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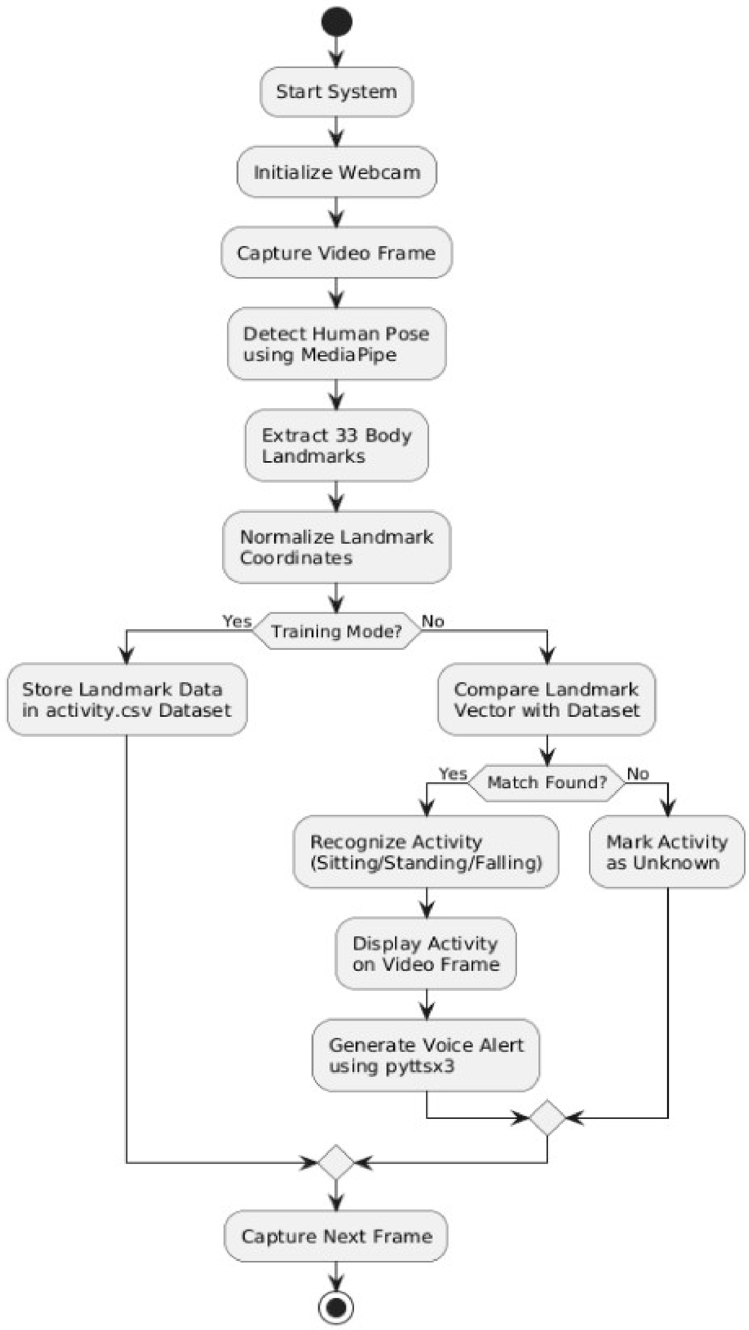
FLOW DIAGRAM :-



IV. OBJECTIVES

The primary objective of the Abnormal Activity Detection and Abnormal Activity Detection System is to design and develop a real-time monitoring system capable of identifying abnormal activities using computer vision techniques. The system aims to automatically detect abnormal body movements and recognize specific activities by analyzing body posture and skeletal landmarks captured from live video streams. By utilizing advanced pose estimation algorithms, the system can accurately identify body joints and use their spatial relationships to classify different abnormal actions.

Another important objective of the system is to detect abnormal activities such as falls or unusual body movements that may indicate potential danger or emergency situations. Detecting such abnormal events is particularly important in environments such as hospitals, elderly care facilities, rehabilitation centers, and surveillance systems where continuous monitoring of individuals is required. The system aims to provide immediate feedback when abnormal activities are detected so that appropriate actions can be taken.

The project also aims to create a lightweight and efficient activity detection model that does not require expensive AADdware or complex deep learning training processes. Instead of relying on computationally intensive neural networks, the system uses pose landmark comparison techniques to identify activities. This approach reduces processing time and allows the system to run smoothly on standard computing devices.

Additionally, the system aims to provide both visual and audio feedback to the user. Detected activities are displayed on the video stream while voice announcements are generated using text-to-speech technology. This improves user interaction and ensures that activity detection results are clearly communicated in real time.

V. RESULTS AND DISCUSSION

The Abnormal Activity Detection and Abnormal Activity Detection System was implemented and tested using a webcam-based setup in a controlled environment. Several abnormal activities including standing, sitting, and falling were recorded and stored in the dataset during the training phase. The system successfully extracted body landmarks using MediaPipe Pose and converted them into numerical vectors for activity classification.

During testing, the system demonstrated the ability to detect abnormal activities in real time with a high level of accuracy. The activity detection process was able to correctly identify different body postures by comparing real-time landmark vectors with stored dataset samples. The system also provided immediate visual feedback by displaying the detected activity on the video frame.

In addition to visual output, the system generated voice alerts using the pyttsx3 text-to-speech engine. This feature enhances usability by allowing users to receive audio notifications about detected activities. The combination of visual and audio feedback makes the system suitable for monitoring environments where immediate alerts are necessary.

However, certain challenges were observed during the testing process. Factors such as poor lighting conditions, occlusion of body parts, or multiple individuals appearing in the camera frame can affect the accuracy of pose detection. Despite these limitations, the proposed system provides a reliable and efficient solution for real-time activity detection using lightweight computer vision techniques.

VI. METHODOLOGY

The proposed system follows a systematic methodology for recognizing abnormal activities and detecting abnormal events using computer vision and pose estimation techniques. The first step in the methodology involves capturing live video frames from a webcam using the OpenCV library. The webcam continuously streams video data which is processed frame by frame to analyze abnormal body movements in real time.

Once a video frame is captured, the MediaPipe Pose detection model is applied to identify the abnormal body skeleton and extract key body landmarks. MediaPipe Pose is capable of detecting 33 different body landmarks representing important joints of the abnormal body such as the nose, shoulders, elbows, wrists, hips, knees, and ankles. These landmarks provide detailed information about the position and orientation of the abnormal body in each frame.

During the training phase, the user performs different activities such as sitting, standing, or falling in front of the camera. For each activity, the system captures the corresponding body landmarks and converts them into numerical coordinate vectors. These vectors are then normalized relative to the body center to ensure that the activity detection process is independent of camera position or body orientation. The normalized landmark vectors are stored in a dataset file named **activity.csv** using the Pandas data processing library.

In the detection phase, the system continuously captures new video frames and extracts the current body landmarks using MediaPipe Pose. These landmarks are processed in the same way as the training data to generate a pose vector. The system then compares this pose vector with all stored vectors in the dataset by calculating the distance between them. The activity corresponding to the closest matching vector is identified as the detected activity. If the calculated distance exceeds a predefined threshold, the activity is classified as unknown.

Finally, the recognized activity is displayed on the video frame using OpenCV visualization techniques. In addition, the system uses the pyttsx3 text-to-speech library to generate voice announcements that inform the user about the detected activity. This combination of visual and audio feedback allows the system to provide real-time monitoring and alert functionality.

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REFERENCES

[1]. Z. Cao, G. Hidalgo, T. Simon, S. Wei, and Y. Sheikh, “OpenPose: Realtime Multi-Person 2D Pose Estimation Using Part Affinity Fields,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 43, no. 1, pp. 172–186, 2019.

[2]. C. Lugaresi, J. Tang, H. Nash, et al., “MediaPipe: A Framework for Building Perception Pipelines,” Google Research, 2019.

[3]. G. Bradski, “The OpenCV Library,” Dr. Dobb’s Journal of Software Tools, vol. 25, no. 11, pp. 120–125, 2000.

[4]. F. Pedregosa, G. Varoquaux, A. Gramfort, et al., “Scikit-learn: Machine Learning in Python,” Journal of Machine Learning Research, vol. 12, pp. 2825–2830, 2011.

[5]. N. Dalal and B. Triggs, “Histograms of Oriented Gradients for Abnormal Detection,” Proceedings of IEEE Conference on Computer Vision and Pattern Detection (CVPR), pp. 886–893, 2005.

[6]. Krizhevsky, I. Sutskever, and G. Hinton, “ImageNet Classification with Deep Convolutional Neural Networks,” Advances in Neural Information Processing Systems (NIPS), pp. 1097–1105, 2012.

[7]. K. Simonyan and A. Zisserman, “Very Deep Convolutional Networks for Large-Scale Image Detection,” International Conference on Learning Representations (ICLR), 2015.

[8]. J. Redmon and A. Farhadi, “YOLOv3: An Incremental Improvement,” Computer Vision and Pattern Detection (CVPR), 2018.

[9]. O. D. Lara and M. A. Labrador, “A Survey on Abnormal Activity Detection using Wearable Sensors,” IEEE Communications Surveys & Tutorials, vol. 15, no. 3, pp. 1192–1209, 2013.