International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 04 | April - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

AI - Enhanced Nighttime Seizure Surveillance

Mr. JAGAN M
Department of Artificial Intelligence and Machine Learning
Sri Shakthi Institute of Engineering and Technology, Coimbatore, India

Mr. RAJAGUHAN A
Department of Artificial Intelligence and Machine Learning
Sri Shakthi Institute of Engineering and Technology, Coimbatore, India

Mr. PRANESH N S
Department of Artificial Intelligence and Machine Learning
Sri Shakthi Institute of Engineering and Technology, Coimbatore, India

Mr. PRATHAP E
Department of Artificial Intelligence and Machine learning
Sri Shakthi Institute of Engineering and Technology, Coimbatore, India

Ms. NIVEDHA S
Assistant professor
Department of Artificial Intelligence and Machine Learning
Sri Shakthi Institute of Engineering and Technology, Coimbatore, India

Abstract – Nighttime seizures pose serious health risks to individuals with epilepsy, often going undetected until critical complications occur. This system tackles these challenges by using advanced computer vision and AI to create a non-invasive, real-time seizure detection solution. It integrates technologies like MediaPipe, OpenCV, and edge computing to analyze video streams and detect seizure-specific patterns through body pose estimations and physiological inputs. High-resolution video feeds, enhanced by infrared capabilities, enable effective nighttime surveillance. MediaPipe's Pose Estimation and Face Mesh modules ensure accurate real-time tracking of body movements, facial expressions, and hand gestures. OpenCV aids in preprocessing by removing noise, segmenting motion areas, and capturing subtle body changes critical for detection. Designed with efficiency and patient comfort in mind, the system uses local edge computing to reduce latency and enhance data privacy by avoiding cloud transmissions. Training with annotated datasets helps distinguish between regular sleep movements and seizure-related activities, reducing false alarms. Integration with wearable and environmental sensors strengthens the system by capturing physiological changes and contextual room data. Outputs include real-time alerts, visual overlays on detected video frames, and detailed activity logs. This innovative solution combines machine learning, real-time analytics, and advanced vision technologies, paving the way for reliable, non-invasive seizure detection systems in epilepsy care and broader healthcare monitoring scenarios.

Key Words: *OpenCV, MediaPipe, Vision Transformers (ViG), Artificial Intelligence (AI), Electronic Health Records (EHR), Machine Learning (ML), Convolutional Neural Networks (CNNs),*

1. INTRODUCTION

Nighttime seizures often go undetected due to lack of continuous surveillance during sleep, posing life-threatening risks. The AI-Enhanced Nighttime Seizure Surveillance project proposes a real-time monitoring system combining AI and computer vision technologies for seamless seizure detection and analysis, enhancing patient safety and supporting medical research.

The system utilizes multimodal data from video feeds, audio signals, and environmental sensors, featuring real-time video processing, movement analysis, and pose estimation. Integration of MediaPipe, OpenCV, and edge computing ensures robustness, scalability, and efficiency.

In MediaPipe, the tracks body landmarks, analyzes seizure movements, and provides real-time alerts. Key features include facial detection, hand tracking, and object detection, improving precision and reducing false positives.

In OpenCV, the complements MediaPipe with image and video analysis, edge detection, contour mapping, motion tracking, and pre-processing tasks.

In Edge Computing, the processes data locally to reduce latency, enhance privacy, and ensure uninterrupted functionality during network outages.

2. LITERATURE REVIEW

The integration of artificial intelligence (AI) into healthcare, particularly in seizure detection and monitoring, has been a subject of increasing research interest. This literature review examines the existing studies and technologies addressing nighttime seizure surveillance, focusing on their methodologies, effectiveness, and limitations.

2.1. Wang Et Al. (2020) EEG-Based Seizure Detection:

Wang et al. conducted an in-depth analysis of EEG-based seizure detection, which remains the gold standard for identifying epileptic events due to its direct measurement of brain activity. The study emphasized the accuracy of EEG systems in capturing the electrical signatures of seizures, making them highly reliable in controlled clinical environments. However, the reliance on specialized equipment, including scalp electrodes and recording devices, poses significant challenges for widespread adoption. This work serves as a foundational reference for understanding the strengths and limitations of EEG-based methods, emphasizing the need for innovative solutions that can extend seizure detection capabilities beyond traditional clinical settings.

2.2. Shah Et Al. (2019) Deep Learning for Video-Based Seizure Detection:

Shah et al. (2019) introduced a deep learning approach for detecting seizures using video data, specifically targeting convulsive seizures. Their framework utilized convolutional neural networks (CNNs) to analyze visual patterns and detect abnormal motion indicative of seizures. The results were promising, demonstrating the feasibility of using non-invasive video data for seizure detection.

2.3. LIU ET AL. (2021) Skeleton-Based Human Activity Recognition:

Liu et al. conducted a comprehensive study on skeleton-based models for recognizing human activities, employing pose estimation tools like OpenPose to extract key joint positions. The skeleton-based approach focuses on analyzing skeletal representations, which capture the positions and movements of various body joints. This method eliminates distractions from background noise and irrelevant visual data, making it highly effective for activity recognition tasks.

This work laid the groundwork for using similar techniques in medical applications, such as seizure detection. Liu et al. highlighted the potential of skeleton-based methods to accurately capture seizure-related movement patterns while minimizing false positives caused by background activities. Their findings serve as a stepping stone for integrating skeletal data with spatiotemporal models to develop reliable, real-time detection systems for healthcare purposes.

2.4. Dosovitskiy Et Al. (2020) Vision Transformers (VIG) For Motion Analysis:

Dosovitskiy et al. introduced Vision Transformers (ViG) as a revolutionary framework for analysing spatiotemporal data, challenging the dominance of convolutional and recurrent neural networks. Unlike traditional models, ViG processes sequential data more effectively by modelling long-term dependencies, making it ideal for tasks involving complex motion analysis.

The ability to process motion data in detail while preserving computational efficiency highlighted its suitability for real-time systems. This research established ViG as a state-of-the-art approach for spatiotemporal modelling, paving the way for its application in medical and healthcare fields.

2.5. Zhang Et Al. (2021) Challenges in Real-time Seizure Detection:

Zhang et al. explored the unique challenges associated with real-time seizure detection, particularly focusing on computational efficiency and adaptability to diverse scenarios. The study underscored the importance of lightweight models capable of running on resource constrained devices, such as smartphones and edge devices, without compromising accuracy. Their findings highlight the importance of designing adaptable systems that balance accuracy, speed, and resource efficiency. This research provides valuable guidance for developing practical, real-time seizure detection solutions suitable for both clinical and non-clinical applications.

3. PROPOSED SYSTEM

The AI-Enhanced Nighttime Seizure Surveillance System is designed to monitor individuals during sleep, aiming to detect and respond to seizures in real time with exceptional accuracy and reliability. Leveraging advanced technologies such as MediaPipe, OpenCV, and edge computing, the system integrates multimodal data processing, real-time video analysis, and AI-driven abnormal movement detection to ensure comprehensive monitoring. It utilizes high-resolution cameras, optionally paired with audio and environmental sensors, to capture detailed video feeds and sound patterns that are indicative of seizures. The acquired data serves as the foundation for further analysis, helping identify movements, postures, and seizure-specific behaviors with minimal latency. By relying on edge computing, the system processes data locally on devices like edge servers or smart cameras, reducing reliance on cloud infrastructure while enhancing data privacy.

Core Components

The core components of the proposed system include:

3.1. MediaPipe:

The MediaPipe is a versatile, cross-platform framework for building pipelines to process multimodal data, such as audio, video, and sensor streams. It is highly optimized for real-time applications and offers state-of-the-art machine learning models for tasks such as face detection, hand tracking, body pose estimation, object detection, gesture recognition, and more.

3.2. Pose Landmark Detection:

The MediaPipe Pose Landmarker task lets you detect landmarks of human bodies in an image or video. You can use this task to identify key body locations, analyze posture, and categorize movements. This task uses machine learning (ML) models that work with single images or video. The task outputs body pose landmarks in image coordinates and in 3-dimensional world coordinates.

The Pose Landmarker uses a series of models to predict pose landmarks. The first model detects the presence of human bodies within an image frame, and the second model locates landmarks on the bodies.

- **Pose detection model**: detects the presence of bodies with a few key pose landmarks.
- **Pose landmarker model**: adds a complete mapping of the pose. The model outputs an estimate of 33 3-dimensional pose landmarks.

3.3. Pose Land Marker Model:

The pose landmarker model tracks 33 body landmark locations, representing the approximate location of the following body parts:

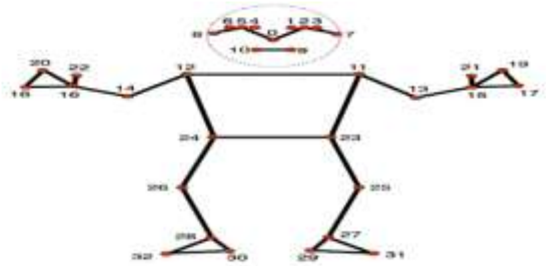

Fig 1: Real-time Posture Tracking Model

3.4. OpenCV:

OpenCV (Open-Source Computer Vision Library) is a robust, open-source library designed for real-time computer vision tasks, offering cross-platform compatibility and extensive functionality for image and video analysis. Its key features include real-time performance optimized for high-speed processing, comprehensive tools for tasks such as face detection, object tracking, and motion analysis, and seamless integration with AI frameworks like TensorFlow and PyTorch. OpenCV also supports hardware acceleration via CUDA and OpenCL, ensuring efficient computation, and provides bindings for multiple programming languages, including Python, C++, and Java. Widely used in domains like robotics, surveillance, and healthcare, OpenCV's scalability and flexibility make it an ideal choice for complex applications, such as the AI-Enhanced Nighttime Seizure Surveillance Project, where it facilitates tasks like image preprocessing, motion tracking, pose estimation, and real-time video analysis to enhance detection accuracy and responsiveness.

3.5. Pose Estimation and Skeleton Tracking:

OpenPose is a widely used tool for human pose estimation, capable of detecting and tracking the key points of the human body, including the head, shoulders, elbows, wrists, hips, knees, and ankles. OpenPose will be used in the proposed system to generate skeleton-based data from video inputs, which will then be processed for seizure detection.

Developed by Google, MediaPipe is another powerful framework for real-time pose estimation that is optimized for performance on mobile devices. It offers high accuracy in detecting body landmarks and can operate in real-time. MediaPipe’s lightweight implementation makes it suitable for deployment on low-power edge devices.

3.6. Real-Time Video Processing:

OpenCV (Open-Source Computer Vision Library) will be used to process real-time video streams. OpenCV will help capture video frames, extract the relevant portions, and feed them into the pose estimation models. It will also allow for image preprocessing and enhancement, which is crucial for maintaining the quality of video inputs in various lighting conditions.

FFmpeg is a powerful multimedia framework that will be used for handling video streams and converting between different video formats, enabling compatibility with various cameras and video devices.

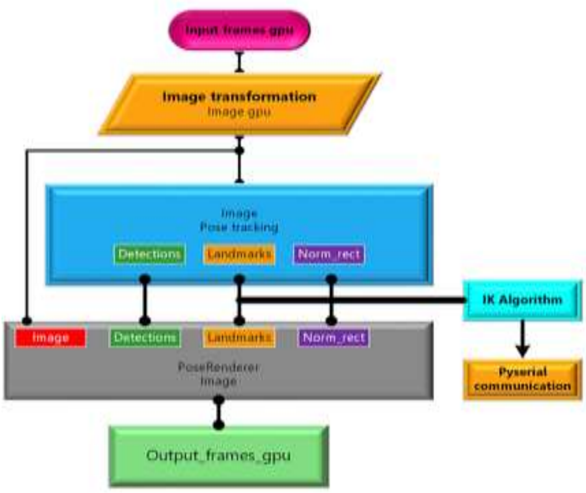

Fig 2: Open CV flow diagram

4. EXPERIMENTAL RESULT

4.1. Result:

In Pose Estimation and Movement Tracking, the person is monitored through pose estimation using red dots marking key body points to detect abnormal motions, which may indicate a seizure.
In Right Hand Jerk, it indicates an involuntary, abnormal movement during a seizure, detected using pre-trained AI models.
In Detection Box, the green box labelled "SEIZURE" indicates the system has identified seizure-related movement requiring immediate attention.
In Real-Time Feedback, the system provides instant visual and textual feedback on abnormal movements and seizure detection.
In Overall System Function, the system uses computer vision techniques like MediaPipe and OpenCV to continuously monitor and analyze movements, providing immediate feedback on potential seizure events.
In Normal Pose Example, the system does not detect a seizure because the person is in a normal, controlled pose with no sudden or irregular movements.

4.2. Discussion:

The combination of MediaPipe and OpenCV enables seamless data collection and processing. MediaPipe provides powerful pre-built solutions for tasks like pose estimation, face detection, and hand tracking, which are integral to detecting seizures. By tracking 33 body landmarks, MediaPipe's Pose Estimation module is particularly useful for identifying abnormal movements such as jerking, rigidity, or sudden postural changes typically associated with seizures. The Pose Landmarker model adds another layer of accuracy by providing both image coordinates and 3D world coordinates, which improves detection in varied environments.

The AI-Enhanced Nighttime Seizure Surveillance System leverages the latest advancements in AI, computer vision, and edge computing to provide a reliable and efficient solution for monitoring seizures during sleep. By integrating MediaPipe, OpenCV, and edge computing, the system offers real-time, low-latency seizure detection that ensures timely alerts for caregivers and healthcare professionals. While the system has faced challenges, such as real time processing and data privacy concerns, it offers significant potential for improving patient safety and providing life-saving interventions. Continuous model training enhanced multimodal data integration, and the exploration of cloud-based updates will further elevate the system's accuracy and effectiveness, making it an invaluable tool in the future of seizure monitoring.

5. CONCLUSION

The AI-Enhanced Nighttime Seizure Surveillance system introduces an innovative approach for managing seizures outside traditional clinical settings. By integrating technologies like MediaPipe, OpenCV, and edge computing, it offers highly accurate, real-time seizure detection. The system monitors body movements, facial expressions, and hand gestures through advanced video processing, pose estimation, and movement analysis, alerting caregivers and medical professionals immediately when a seizure is detected. This proactive monitoring reduces the risk of Sudden Unexpected Death in Epilepsy (SUDEP) and other complications, enabling prompt interventions.

The integration of multimodal data, including audio and physiological signals from wearable devices, enhances the system's accuracy by distinguishing between normal sleep movements and seizures. Predictive analytics further allow the system to forecast potential seizures, enabling preventive actions. Future enhancements include cloud-based model updates for continuous learning, expanding capabilities to detect daytime seizures, and integrating with electronic health records (EHR) for seamless communication with healthcare providers. Furthermore, its user-friendly design, scalability, and adaptability position it as a practical solution for home and clinical use.

Ultimately, this solution underscores the transformative role of AI in healthcare, offering a proactive and life-enhancing tool for epilepsy care and beyond.

7. REFERENCES

[1]. Arnab, A., Dehghani, M., Heigold, G., Sun, C., Lučić, M., Schmid, C.: Vivit: A video vision transformer. In: ICCV. pp. 6836–6846 (2021)

[2]. Bazarevsky, V., Grishchenko, I., Raveendran, K., Zhu, T., Zhang, F., Grundmann, M.: Blazepose: On-device real-time body pose tracking. arXiv preprint arXiv:2006.10204 (2020)

[3]. Cai, J., Jiang, N., Han, X., Jia, K., Lu, J.: Jolo-gcn: mining joint-centered lightweight information for skeleton-based action recognition. In: WACV. pp. 2735–2744 (2021)

[4]. Cao, Z., Hidalgo Martinez, G., Simon, T., Wei, S., Sheikh, Y.A.: Openpose: Realtime multi-person 2d pose estimation using part affinity fields. IEEE TPAMI (2019)

[5]. Cao, Z., Simon, T., Wei, S.E., Sheikh, Y.: Realtime multi-person 2d pose estimation using part affinity fields. In: CVPR (2017)

[6]. Chen, J., Ho, C.M.: Mm-vit: Multi-modal video transformer for compressed video action recognition. In: WACV. pp. 1910–1921 (2022)

[7]. Chen, Y., Zhang, Z., Yuan, C., Li, B., Deng, Y., Hu, W.: Channel-wise topology refinement graph convolution for skeleton-based action recognition. In: ICCV. pp. 13359–13368 (2021)

[8]. Han, K., Wang, Y., Guo, J., Tang, Y., Wu, E.: Vision gnn: An image is worth graph of nodes. NeurIPS 35, 8291–8303 (2022)