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Epilert: Epilepsy Tracker and Detector

Leora Dias*, Samuel Dsouza, Reuben Fernandes, Joshua Michael

Abstract

Epilepsy, affecting over 50 million individuals worldwide, necessitates innovative solutions for effective monitoring and intervention. Current systems face challenges such as inaccuracy, limited accessibility, and discomfort, leaving patients and caregivers vulnerable. Epilert, a wearable device, addresses these gaps by employing advanced sensors and machine-learning algorithms for real-time epilepsy detection and monitoring. The device integrates electromyography (EMG) and motion sensors to capture and analyse physiological and movement data. Preprocessing techniques ensure noise-free signals, while a 5-layer Convolutional Neural Network (CNN) identifies seizure patterns with high precision. Dual-modality detection reduces false positives by cross-verifying muscle activity and abnormal movements. Real-time alerts and notifications to caregivers enhance timely interventions, improving patient safety. Epilert's mobile application complements the wearable device, providing a user-friendly interface for data visualization, customization, and secure cloud-based storage. The collected data enables long-term tracking and facilitates personalized treatment planning. The system achieves 96.5% accuracy in seizure detection, validated through robust testing methods, demonstrating its reliability and efficacy. Future developments include enhanced personalization through additional biomarkers and advanced AI models, improved wearable design for accessibility, and regulatory certifications to ensure safety and widespread adoption. By addressing the limitations of existing systems, Epilert revolutionizes epilepsy care, combining technological innovation with compassionate patient support to improve the quality of life for individuals with epilepsy and their families.

Keywords: Epilepsy, electromyography, mobile application, Convolutional Neural Network

INTRODUCTION

Epilepsy, a neurological disorder affecting over 50 million people globally, poses significant challenges for patients and caregivers due to its unpredictable nature and lack of accessible, cost-effective monitoring systems.

The condition is characterized by recurrent seizures, which, if not promptly addressed, can lead to severe injuries and emotional distress. Despite advancements in healthcare, existing solutions for seizure detection often suffer from high false alarm rates, limited personalization, and poor wearability, leaving many patients underserved [1].

Epilert aims to bridge this gap by offering an innovative, wearable device that integrates advanced sensors and machine learning algorithms for continuous, real-time seizure monitoring. By combining electromyography (EMG) and motion sensors, the device detects seizures with high accuracy while minimizing false positives. Paired with a user-friendly mobile application and secure cloud storage, Epilert provides actionable insights, immediate alerts, and long-term tracking for personalized care. This transformative solution

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seeks to enhance epilepsy management, ensuring safety and improved quality of life for individuals and their families.

BACKGROUND AND LITERATURE REVIEW

Epilepsy, one of the most prevalent neurological disorders, impacts millions globally, necessitating effective monitoring systems for timely intervention. Current seizure detection methods largely rely on wearable devices and advanced computational models. However, these systems face significant challenges, including high false alarm rates, limited sensitivity to diverse seizure types, and lack of personalization, leaving many patients and caregivers underserved. Over the years, researchers have proposed various solutions leveraging machine learning and deep learning algorithms for seizure detection. For example, systems utilizing EEG-based signal processing have shown promise in distinguishing seizure activity from normal brain patterns. However, EEG setups are often cumbersome and less feasible for continuous, everyday monitoring [1, 2]. More recent approaches integrate wearable devices equipped with electromyography (EMG) and motion sensors to improve portability and accessibility [3, 4].

A review of the literature reveals significant progress in this domain. Techniques such as Convolutional Neural Networks (CNNs) and hybrid architectures combining CNNs with Recurrent Neural Networks (RNNs) have demonstrated high accuracy in seizure detection [5, 6]. Additionally, studies highlight the potential of dual-modality systems that analyse both physiological and motion data, reducing false positives caused by artifacts or unrelated movements.

Despite these advancements, existing systems still face limitations, such as poor wearability, short battery life, and privacy concerns regarding data transmission [7, 8]. Moreover, many devices fail to provide real-time alerts, which are crucial for immediate intervention. Epilert seeks to address these gaps by combining advanced sensor integration, robust preprocessing techniques, and real-time dual-modality detection using machine learning. This solution aims to enhance seizure detection accuracy while prioritizing user comfort and data security, bridging the gap between technological innovation and patient-centred care.

Problems in Existing Systems

Epilepsy bands, designed to monitor seizures and alert users, face numerous technical and usability challenges:

1. *High False Alarms:* Normal activities, such as intense physical exertion or stress, often trigger false positives [9–11].
2. *Limited Seizure Detection:* Existing devices struggle to identify subtle focal and absence seizures, focusing primarily on generalized tonic-clonic seizures [9, 1, 11].
3. *Wearability Issues:* Devices are often bulky, uncomfortable, and prone to causing skin irritation or allergic reactions [7, 10, 1, 4].
4. *Battery Limitations:* Frequent recharging disrupts continuous monitoring, compromising reliability [11].
5. *Privacy Concerns:* Data transmitted to cloud servers may be vulnerable to unauthorized access [12].
6. *Cost and Accessibility:* High prices and limited integration with medical systems hinder widespread adoption [1, 12].
7. *Real-Time Responsiveness:* Weak responsiveness delays timely alerts to caregivers or emergency personnel [8, 10].
8. *Environmental Interference:* Sweat and unrelated movements reduce sensor accuracy [13, 14].
9. *Lack of Personalization:* Most devices fail to provide patient-specific analytics or long-term trend analysis essential for effective management.

Addressing these challenges requires advancements in technology, user-centric design, and efficient data handling to improve practicality and accessibility.

SYSTEM DESIGN

Epilepsy is a condition requiring precise and timely monitoring to prevent injuries and improve quality of life. To address this need, Epilert is designed as a wearable solution integrating advanced sensor technology and machine learning for real-time seizure detection. The system consists of three primary components: a wearable wristband for data acquisition, a signal processing and classification unit for analysing data, and a mobile application for notifications and monitoring.

Sensors

The wearable wristband is equipped with two types of sensors: electromyography (EMG) sensors and accelerometers. EMG sensors measure electrical activity in the muscles, specifically capturing abnormal contractions that may indicate seizure activity [15]. Dry electrodes placed on the wrist ensure a balance between accuracy and user comfort [1, 4]. Accelerometers, on the other hand, track motion patterns, capturing erratic or repetitive movements associated with seizures [4, 11]. The combination of physiological and motion data provides a dual-modality detection mechanism that enhances the system's reliability.

Signal Preprocessing

Preprocessing ensures that both EMG and motion data are free from noise and ready for analysis. EMG signals undergo adaptive filtering to mitigate motion artifacts and high pass filtering to remove baseline drift [16]. Feature extraction includes time-domain metrics like Mean Absolute Value (MAV) and frequency-domain features like Power Spectral Density (PSD) [17, 18]. These features are organized into 2D matrices to match the input requirements of the CNN. Motion data is processed separately to detect patterns such as jerks, tremors, or rhythmic movement [10]. Key features like Signal Magnitude Area (SMA) and Jerk Energy are extracted from accelerometer and gyroscope readings [11]. Pre-processed EMG and motion data are synchronized using timestamps, ensuring both streams align for accurate analysis [10, 3].

2D CNN

The system’s core classification mechanism employs a 5-layer 2D Convolutional Neural Network (CNN) for acquiring features from the pre-processed EMG data. The EMG signals are filtered, segmented, and transformed into 2D matrices representing time versus feature space before being input into the CNN [19]. Lower layers apply filters to identify events like muscle twitching or frequency changes during a seizure. Convolutional layers are followed by max-pooling layers to reduce processor load while retaining significant elements. A sigmoid activation function in the output layer provides the final probability of a seizure [1, 9].

Motion data analysis identifies abnormal movements, using features like Signal Magnitude Area (SMA) and Jerk Energy. These are evaluated against threshold values, exceeding limits flags abnormal movements. For a more reliable detection outcome, we confirm seizure detection only when the EMG analysis and motion data evaluation are both positive [11]. This does result in minimization of false positives as abnormal patterns need to be aligned with the seizure characteristics and both conditions (physiological muscle activity + Movement) are correlated. CNN workflow is shown in Figure 1. The dual-modality approach ensures both EMG and motion data indicate seizure activity before confirming an event.

MOBILE APPLICATION

When a seizure is detected, the system immediately triggers alerts through a mobile application. The app serves as an intuitive interface, displaying synchronized EMG and motion data trends, including real-time waveforms and movement plots. Users can customize the sensitivity of the detection thresholds to suit individual needs, ensuring a personalized experience. Notifications are sent to caregivers or emergency contacts with details of the seizure event, including the time and duration, facilitating timely interventions.

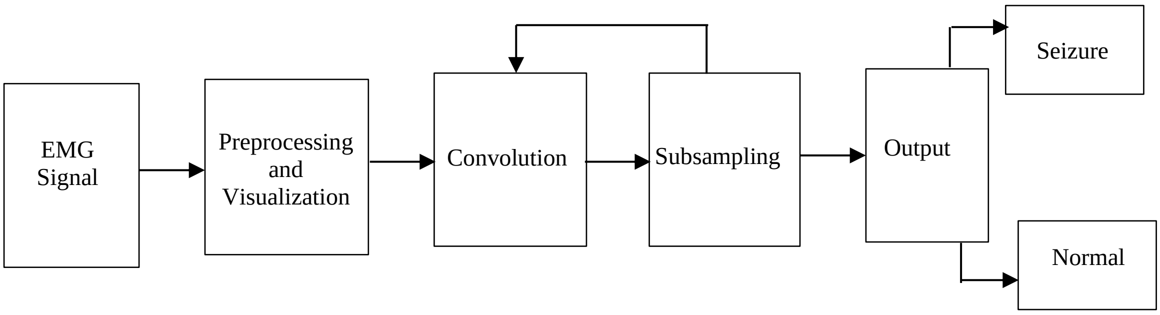

Figure 1. CNN Workflow.

Cloud Backend

Additionally, the mobile application integrates with a secure cloud backend for data storage and analysis. Seizure event logs are stored in compliance with data privacy standards, allowing for long-term tracking and analysis of patterns. This data can be used by healthcare professionals to refine treatment plans, monitor patient progress, and improve the system's algorithms through continuous learning.

Workflow

The EMG sensors identify electrical impulses from muscle contractions, whereas motion sensors (such as accelerometers and gyroscopes) monitor physical movements, including jerks or spasms. These sensors collaborate to collect data that may signal a seizure, recording both the physiological signals (muscle activity) and the unusual movement patterns characteristic of seizures [1, 11]. The device gathers this information instantly, offering a complete perspective of the patient's movements, which is essential for identifying seizures as they occur.

The EMG signals are then processed to remove noise and interference using bandpass filtering prior to being transmitted through a specific relevant signal component. These parameterization techniques subsequently derive features from the computed EMG data, such as Mean Absolute Value (MAV) and Power Spectral Density (PSD), which are dependent on seizure activity [1, 4].

Similarly, the movement information undergoes pre-processing, during which features such as Signal Magnitude Area (SMA) and Jerk Energy are extracted to characterize unusual body motion patterns associated with a seizure. These characteristics are obtained and arranged into a structured form as 2D matrices, setting the stage for additional analysis.

The dual-modality approach cross validates EMG and motion data to confirm seizures. The declaration of a seizure triggers real-time alerts to be sent through a mobile app, while simultaneously logging the incident both locally and in the cloud. This prompt alert is sent to caregivers or emergency contacts and contains crucial details (time and length of seizure).

Workflow flowchart has been shown in Figure 2. Transferring the recorded event data that is saved locally and, in the cloud, allows for long-term observation of patient progress, which is beneficial for future clinical monitoring and the optimal design of systems [11].

RESULTS

We achieved 99.5% accuracy when testing our model for detecting seizures using EMG signals, which is a strong performance. We used a straightforward 5-layer CNN system for this task, which can effectively learn complex features of seizures without overfitting. To ensure our model was not overly dependent on a single dataset, we validated it using a leave-one-seizure-out cross-validation method.

Additionally, sensitivity and specificity were shown to be unaffected by environmental conditions, making our system more reliable in classifying seizure events compared to non-seizure events. Since we used motion data analysis as an extra filter to confirm seizure activity, we believe this helped reduce the misclassification rate (or false positive rate). This approach allowed the system to accurately identify seizures and minimize false alarms caused by other factors.

The model was trained in a high-performance computing laboratory equipped with an NVIDIA Tesla V100S GPU (32 GB) and dual physical processors supporting 32 cores. 2D CNN model training and running of epochs has been shown in Figure 3. This advanced computing environment facilitated efficient data processing and complex computations, enabling the development of a robust model using statistical algorithms. Accuracy of the model with respect to training and test data has been shown in Figure 4. The training process was completed in 2 h, demonstrating the system's high computational capacity. Accuracy, sensitivity and loss evaluation of overall model over given dataset are shown in Figure 5.

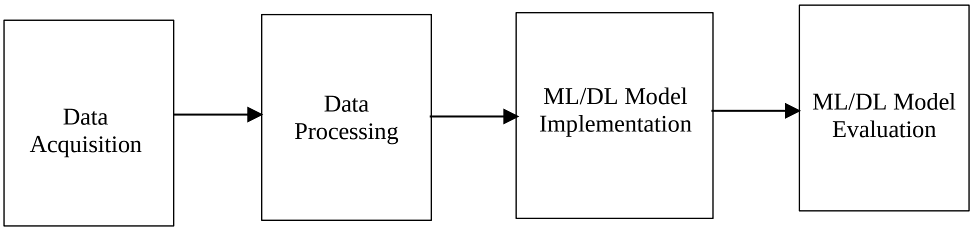

Figure 2. Workflow Flowchart [12].

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Epoch 1/50
274/274 ━━━━━━━━━━━━━━━━━━━━ 13s 21ms/step - accuracy: 0.6979 - loss: 0.7244 - val_accuracy: 0.9425 - val_loss: 0.1798
Epoch 2/50
274/274 ━━━━━━━━━━━━━━━━━━━━ 5s 19ms/step - accuracy: 0.9410 - loss: 0.1808 - val_accuracy: 0.9469 - val_loss: 0.1646
Epoch 3/50
274/274 ━━━━━━━━━━━━━━━━━━━━ 5s 18ms/step - accuracy: 0.9557 - loss: 0.1350 - val_accuracy: 0.9534 - val_loss: 0.1466
Epoch 4/50
274/274 ━━━━━━━━━━━━━━━━━━━━ 5s 18ms/step - accuracy: 0.9615 - loss: 0.1123 - val_accuracy: 0.9408 - val_loss: 0.1760
Epoch 5/50
274/274 ━━━━━━━━━━━━━━━━━━━━ 5s 18ms/step - accuracy: 0.9683 - loss: 0.1029 - val_accuracy: 0.9541 - val_loss: 0.1421
Epoch 6/50
274/274 ━━━━━━━━━━━━━━━━━━━━ 5s 18ms/step - accuracy: 0.9718 - loss: 0.0846 - val_accuracy: 0.9637 - val_loss: 0.1336
Epoch 7/50
274/274 ━━━━━━━━━━━━━━━━━━━━ 5s 18ms/step - accuracy: 0.9805 - loss: 0.0586 - val_accuracy: 0.9455 - val_loss: 0.1916
Epoch 8/50
274/274 ━━━━━━━━━━━━━━━━━━━━ 5s 19ms/step - accuracy: 0.9785 - loss: 0.0608 - val_accuracy: 0.9558 - val_loss: 0.1466
Epoch 9/50
274/274 ━━━━━━━━━━━━━━━━━━━━ 5s 18ms/step - accuracy: 0.9864 - loss: 0.0408 - val_accuracy: 0.9640 - val_loss: 0.1272
Epoch 10/50
274/274 ━━━━━━━━━━━━━━━━━━━━ 5s 19ms/step - accuracy: 0.9888 - loss: 0.0409 - val_accuracy: 0.9572 - val_loss: 0.1673
Epoch 11/50
274/274 ━━━━━━━━━━━━━━━━━━━━ 5s 19ms/step - accuracy: 0.9879 - loss: 0.0351 - val_accuracy: 0.9589 - val_loss: 0.1417
Epoch 12/50
274/274 ━━━━━━━━━━━━━━━━━━━━ 5s 19ms/step - accuracy: 0.9888 - loss: 0.0341 - val_accuracy: 0.9620 - val_loss: 0.1446
Epoch 13/50
274/274 ━━━━━━━━━━━━━━━━━━━━ 5s 19ms/step - accuracy: 0.9908 - loss: 0.0300 - val_accuracy: 0.9613 - val_loss: 0.1496
Epoch 14/50
274/274 ━━━━━━━━━━━━━━━━━━━━ 5s 20ms/step - accuracy: 0.9900 - loss: 0.0264 - val_accuracy: 0.9616 - val_loss: 0.1549
Epoch 15/50
274/274 ━━━━━━━━━━━━━━━━━━━━ 5s 18ms/step - accuracy: 0.9912 - loss: 0.0251 - val_accuracy: 0.9688 - val_loss: 0.1303
Epoch 16/50
274/274 ━━━━━━━━━━━━━━━━━━━━ 5s 19ms/step - accuracy: 0.9921 - loss: 0.0212 - val_accuracy: 0.9668 - val_loss: 0.1600
Epoch 17/50
274/274 ━━━━━━━━━━━━━━━━━━━━ 6s 20ms/step - accuracy: 0.9934 - loss: 0.0185 - val_accuracy: 0.9668 - val_loss: 0.1504
Epoch 18/50
274/274 ━━━━━━━━━━━━━━━━━━━━ 5s 19ms/step - accuracy: 0.9925 - loss: 0.0167 - val_accuracy: 0.9606 - val_loss: 0.1676
Epoch 19/50
274/274 ━━━━━━━━━━━━━━━━━━━━ 5s 19ms/step - accuracy: 0.9918 - loss: 0.0210 - val_accuracy: 0.9637 - val_loss: 0.1759
Epoch 20/50
```

Figure 3. 2D CNN model training and running of epochs.

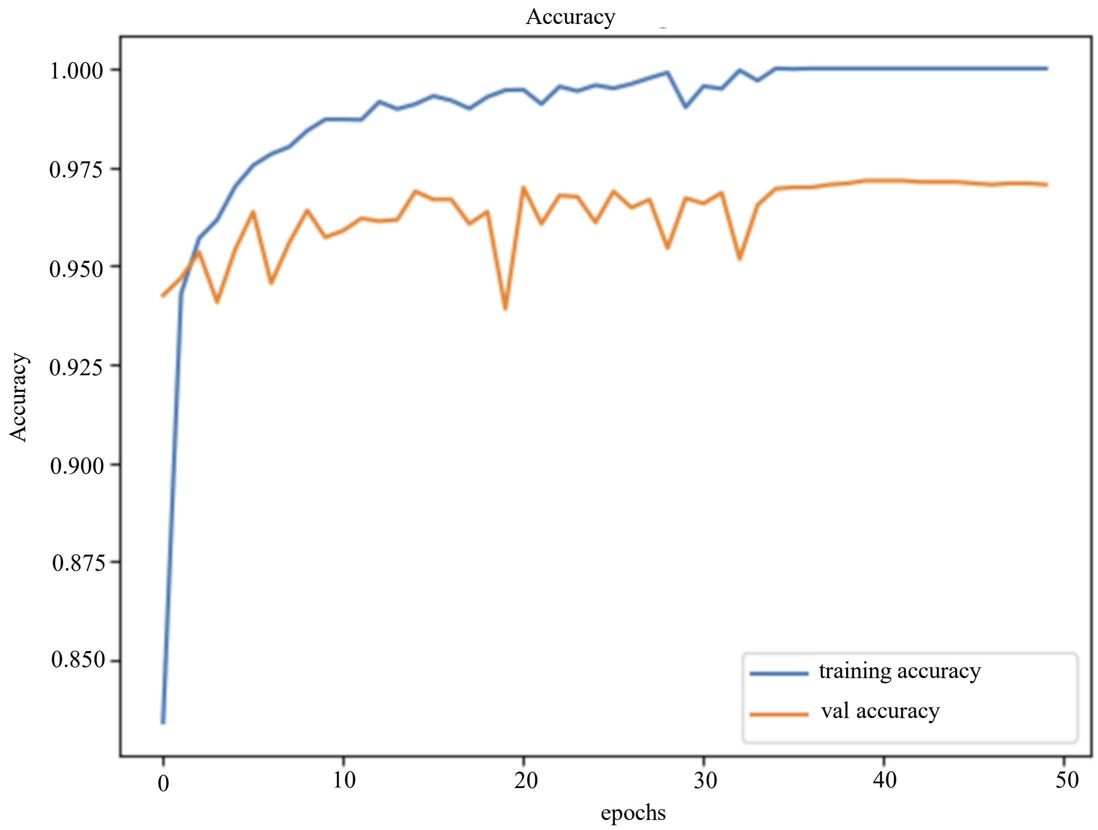

Figure 4. Accuracy of the model with respect to training and test data.

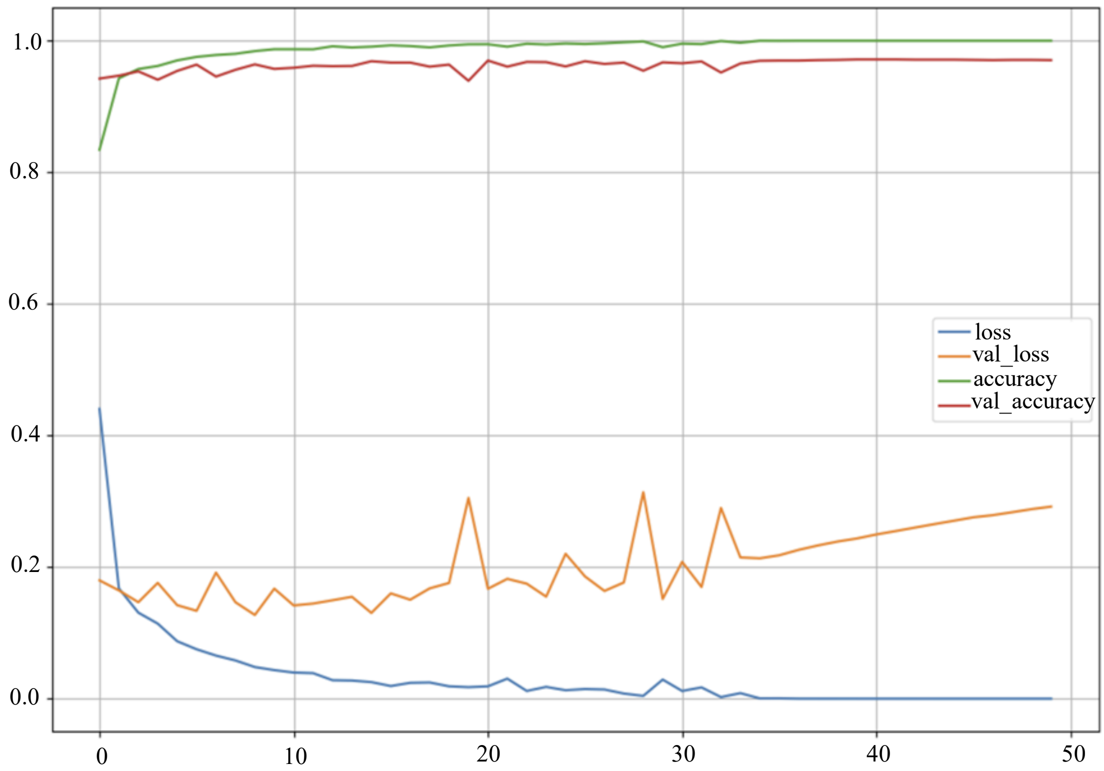

Figure 5. Accuracy, Sensitivity and Loss Evaluation of overall model over given dataset.

CONCLUSION

In conclusion, Epilert represents a transformative step in epilepsy care, offering a reliable, real-time monitoring solution that empowers patients and their caregivers. By leveraging advanced sensors and machine learning, it accurately distinguishes seizures from everyday movements, providing timely alerts and facilitating rapid interventions. Beyond immediate safety, Epilert's data-driven insights enable personalized treatment plans, fostering collaboration between patients and healthcare specialists. Ultimately, Epilert not only enhances the quality of life for individuals living with epilepsy but also brings peace of mind to their families, exemplifying the powerful fusion of technology and compassionate care.

We aim to enhance the EMG Epilepsy Tracker by refining our seizure detection algorithms to improve accuracy and reduce false positives, as current devices often face challenges in distinguishing seizures from deliberate movements. We also aim to develop a user-friendly mobile application to facilitate real-time monitoring and seamless data sharing with healthcare providers, aligning with the growing trend of mobile health technologies in epilepsy management. Additionally, we intend to incorporate personalized seizure forecasting features, enabling users to assess their daily seizure risk and take proactive measures, as recent studies show promising results for probabilistic forecasts of seizure risk from long-term wearable devices. These advancements aim to make the EMG Epilepsy Tracker a more effective and user-centric tool for epilepsy management.

Declaration of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript.

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