(Extended Abstract)

Consumer Grade Wearable for Epilepsy Seizure Prediction in Preictal Stage with Pneumatic Safety Mechanism

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1. Introduction

Epilepsy, a chronic neurological disorder affecting 50 million people worldwide, is marked by recurrent seizures caused by abnormal brain activity. These seizures often lead to unconsciousness or loss of motor control, posing severe safety risks during daily activities like driving or near water and fire.

Traditional epilepsy seizure detection systems rely on expensive, stationary EEG setups, limiting their practical use. This study proposes a portable, affordable EEG cap with minimal electrodes designed for real-time seizure prediction. Integrated with a pneumatic safety mechanism, the device protects the user during falls, enhancing safety and quality of life for epilepsy patients.

2. Methodology

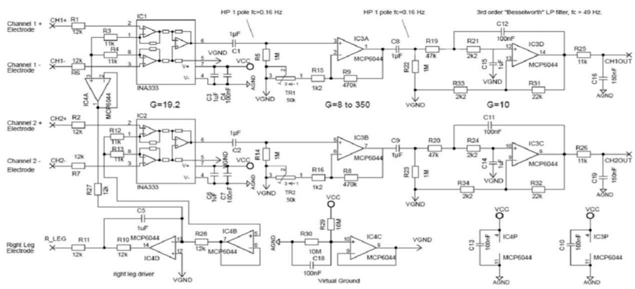
The CHB-MIT Scalp EEG Dataset is a publicly available dataset of long-term seizure EEG data with a sampling rate of 256 Hz[1]. The data, originally in EDF format, has been converted to CSV for preprocessing and training the predictive model.

2.1 Wearable Cap and Hardware

The cap uses four electrodes in the positions F7-T7 and FP1-F3 (based on the 10-20 system as shown in Figure 1) targeting frontal and temporal lobes for effective detection of epileptiform activity. This design integrates an MSP430 microcontroller and ADS1299 ADC for signal processing.

Data is transmitted via Bluetooth to an Android app for seizure prediction using TensorFlow Lite. The circuit for amplification and processing is adapted from Muse 2 [2] and detailed in Figure 2.

Figure 2: Schematic diagram of a two channel EEG amplifier based on OpenEEG Project with reduced power consumption.



2.2 AI Model for Prediction

The preictal stage involves irregular brainwave patterns, but not all lead to seizures. Limited electrodes in consumer-grade EEGs challenge differentiation of "true preictal" from non-seizure anomalies, as shown in Figure 3.Using unsupervised methods (Isolation Forest, K-means), signals are clustered into probable preictal states, followed by LSTM[3] training for accurate pattern recognition. Feature extraction techniques like rolling mean, spectral (e.g., power spectral density), and time-domain transforms (e.g., energy, entropy) enhance the CHB-MIT dataset's extensive labelled data for precise predictions.

2.3 Pneumatic Actuator for Protection

To mitigate prediction inaccuracies, a safety mechanism detects falls using an MPU6050 6-axis accelerometer and gyroscope with an ATMEGA328P microcontroller as shown in Figure 4.

A time window confirms fall patterns through acceleration spikes and angular velocity changes. On detection, a valve inflates a TPU layer in the cap, cushioning the head during falls or seizures, thus reducing injury risk.

2.4 Personalized Fine-Tuning

Since seizure patterns vary across individuals, the model is fine-tuned using manually annotated ictal data from the first few days of use. Data augmentation multiplies this limited dataset. During fine-tuning, earlier model layers are frozen to retain general learning while adapting final layers to patient-specific patterns, ensuring better prediction accuracy.

This approach combines practicality, safety, and adaptability for wearable seizure monitoring.

3. Results

Table 1: Prediction Scores (This table summarises the accuracy of different methods for predicting seizures)

Model	Accuracy	F1 Score
LSTM(Long Short Term Memory)	0.94	0.92
LGBMClassifier	0.91	0.89
XGBClassifier	0.90	0.89
BaggingClassifier	0.89	0.88
ExtraTressClassifier	0.89	0.86
RandomForestClassifier	0.87	0.87
NuSVC	0.81	0.80

The concept of data labelling with unsupervised algorithms is far from new. However, using it for signal data labelling led to more precise data labelling compared to defining fixed preictal periods. The best model achieved was trained on data labelled with KMeans algorithm where number of clusters = 5. The optimal cluster number is selected from the elbow method .

The best model was achieved using LSTM(Long Short Term Memory) with 2 LSTM and 2 Dense layers on ReLU and Softmax activation function along with Adam Optimiser. The confusion matrix is as Figure 6.

4.Conclusion

This study presents a cost-effective, wearable EEG cap with minimal electrodes for seizure prediction. Combining targeted electrode placement, deep learning, and a pneumatic safety mechanism, it balances practicality and accuracy while enhancing patient protection. This innovation bridges clinical-grade technology and real-world accessibility for improved epilepsy management.

References

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