eSeiz 2.0: An IoMT Framework for Accurate Low-Latency Seizure Detection using Pulse Exclusion Mechanism

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***Abstract*—Epilepsy is a neurological disorder marked by recurrent seizures. At least 3 million Americans and 1% of the global population have epilepsy, requiring a low-latency seizure detection system necessary for effective epilepsy treatment. In this paper, a pulse exclusion mechanism (PEM) based novel seizure detection system has been presented in the internet of medical things (IoMT), which uses a PEM to eliminate unnecessary features or channels and allocate desired pulses in a time frame. An optimized deep neural network (DNN) algorithm is used for feature classification. The proposed approach has been evaluated using CHB-MIT Scalp database. The results of the experiments indicate that the proposed eSeiz 2.0 offers a high specificity of 100% and a low latency of 1.05 sec, which can be useful for wearable biomedical applications as well as real-world epilepsy treatment.**

***Index Terms*—Pulse Exclusion Mechanism (PEM), Internet of Things (IoT), Epilepsy, Low Latency System, Feature Extraction**

I. Introduction

Epilepsy is a neurological condition defined by recurring seizures and a seizure refers to abnormal brain activity [1]. Since 1 in every 100 people worldwide has epilepsy, an automated seizure detector is becoming essential. [2] . Different clinical examinations are available to diagnose epilepsy, such as magneto- encephalogram (MEG), electrocardiogram (ECG), magnetic resonance imaging (MRI), or electroencephalogram (EEG). Electroencephalography (EEG) is a data acquisition approach that monitors and measures activity in the brain. The EEG has high temporal resolution, which is particularly useful for the accurate diagnosis of epilepsy [3], [4]. The development of an automated seizure detection system is becoming more and more necessary because the manual seizure detection system requires lot of time. A key performance metric of the system is latency, which is the disparity between the seizure detection point provided by a seizure detector and the actual seizure onset determined by a professional.

In this paper, an IoT enabled real time seizure detection system has been presented. The PEM algorithm analyzes the EEG signals, eliminates unwanted pulses, and captures the seizure and non-seizure behavior. A time frame of 6 sec length has been created and the non-overlapping portions have been used to extract features. This features on the time frame creates a feature vector which trains the optimized DNN classifier. The IoT architecture enables it to record patients' everyday activities and obtain medical data at any time, anywhere. Fig. 1 conceptualizes and illustrates the proposed system.

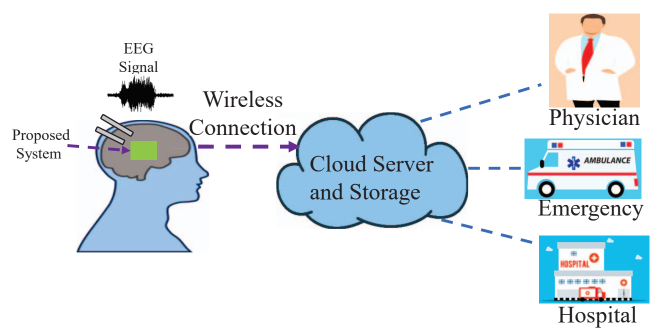

Fig. 1: Module of eSeiz 2.0.

Section II covers novel contributions of the proposed approach. Related earlier research is described in Section III. Section IV illustrates proposed eSeiz 2.0's architecture. The application and outcomes of the experiments are covered in Section V. Section VI suggests ideas for future research.

II. Novel Contributions of This Paper

1) In this paper, a NEP based novel seizure detection algorithm has been proposed. This algorithm allows a greater number of pulses in the seizure prone area which helps in removing less significant channels and features. The reduction of number of channels and features enhances the latency of the system.

2) Existing algorithms associate with significant number of false detections. The combination of PEM algorithm and machine learning technique helps in removing false detection associated with the existing algorithms, which is highly useful for practical epilepsy treatment. The IoT framework allows universal connectivity and enables the smart healthcare system.

III. Related Previous Research

For seizure detection, several techniques have been proposed. A hybrid model [5] has been proposed that combines both supervised learning (SL) and unsupervised learning (UL), in which UL distinguishes between determinate and indeterminate subjects and SL performs the classification. In order to minimize the dimensionality and increase the accuracy of seizure detection, Tian et al. [6] created a method that makes use of the fast Fourier transform (FFT) to create multiview features and the convolutional neural network (CNN) to train deep features. Peng et al. [7] proposed a unique method that uses dictionary learning-based sparse representation. Their works are evaluated using both MIT-scalp and Bonn dataset, and the results show high potential for accurate seizure detection. Li et al.[8] presented an approach that can effectively detect seizures using convolutional NLSTM. In terms of sensitivity and precision, this work performs excellently without the need for extensive preprocessing. The utilization of a wrist-worn accelerometer device [9] is proposed as a non-invasive convulsive seizure detection alternative to EEG. The existing EEG-based system requires a lot of effort and resources, but the non-invasive approach alleviates this problem by including an accelerometer sensor. Fan et al. proposes a technique [10] that uses a temporal synchronization based complex model to distinguish normal EEG and ictal EEG. This work reduces the latency of the seizure detection system. EEG signals are broken down into multiple product functions (PFs) based on a local mean decomposition based detection technique [11], from which features are obtained and fed to 5 different classifiers for seizure detection. This work is evaluated using the publicly available Bonn dataset, which offers high detection accuracy.

IV. The Proposed Seizure Detection System

EEG signals of specified time frames are applied to pulse exclusion mechanism (PEM), which eliminates unwanted pulses and capture EEG behavior. DNN classifier detects seizure from the extracted features. Both the EEG and information on seizure activities have been sent to the cloud. Medical practitioners can access the cloud-based data and take preventative measures. The proposed system's architecture is illustrated in Fig. 2.

A. Time frame Formation Unit

Six second time frames have been used to divide up the EEG signals. (Fig. 3). This time frame acts as a moving window to implement real time seizure detection. A further division of this timing window into three separate EEG segments of 2 sec each has been made. The timing window consists of 1536 samples which captures the progression of seizure or non-seizure characteristics. The length of the window has been chosen in a heuristic approach that maintains trade off between accuracy and latency. The increase of the length of the timing window or non-overlapping segments improves the accuracy, but it increases the latency as well. A smaller length of timing window or non-overlapping segments enhances the latency. The number of elements N in a feature vector is denoted by the below equation:

$$N = FXEXC \tag{1}$$

where F is the number of feature, E is the number of non-overlapping epoch in each moving window, and C is the number of channels.

B. PEM (Pulse Exclusion Mechanism)

The novel PEM algorithm has been used for the following reasons: 1. Eliminate unwanted noises 2. Allocate more pulses in the seizure area compared to non-seizure area. It has mainly two parts: a. level detection unit b. pulse exclusion unit

1) Level detection unit (LDU): : EEG signals from EEG data acquisition system contains unwanted signals and noise. The unwanted signals and noise need to be eliminated to capture seizure and non-seizure behavior. The level detector unit contains a filter that discards unnecessary pulses and keeps the EEG signals of desired frequency range. Band pass filter keeps the pulses within the frequency range and that allow the elimination of low frequency noise. The EEG signals with seizure contains distinctive amplitude level and the level detector keeps the EEG pulses within the amplitude range of seizure characteristics. The exclusion of pulses can be expressed as:

$$V(n) = \begin{cases} 1, & \text{for } V_{high} > V(k-1) > V_{low} \\ zero, & \text{otherwise,} \end{cases} \tag{2}$$

Where V_{low} and V_{high} are the lowest and highest amplitude that characterizes hyper-synchronous signal

2) Pulse exclusion unit: : Each time frame of the EEG signals contains pulses. This algorithm will keep a greater number of pulses in the seizure area in compared to non-seizure area, which is very useful for distinguishing seizure and non-seizure characteristics. A time frame with a higher number of pulses can be better distinguished from a time frame with a lower number of pulses. However, there are false detection because of human emotion, stress, sneezing, e.t.c. The PEM algorithm captures seizure and non-seizure dynamics and makes the EEG signals simplified. As a result, it requires a smaller number of features or channels for the detection of seizure, which reduces the latency of the system.

The first iteration of pulse exclusion is represented as:

$$V(n) = \begin{cases} 0, & V(k-3) = 0 \text{ or } V(k-2) = 0 \\ & \text{or } V(k-1) = 0, \text{ if } V(k) = 0 \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

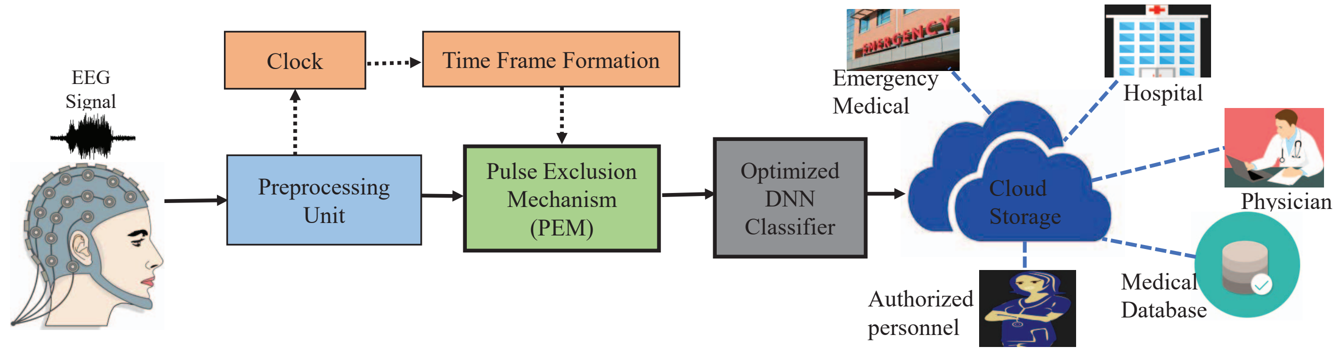

Fig. 2: Architecture of the proposed eSeiz 2.0.

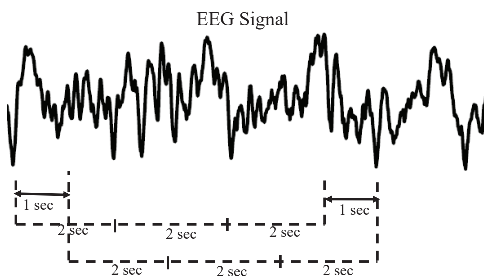

Fig. 3: Time Frame formation

The second iteration of pulse exclusion is represented as:

$$V(n) = \begin{cases} 1, & V(k-3) = 1 \text{ and } V(k-2) = 1 \\ & \text{and } V(k-1) = 1, \text{ if } V(k) = 0 \\ 0, & \text{otherwise.} \end{cases} \tag{4}$$

C. *Feaure Extraction and Deep Neural Network (DNN) Classifier*

The EEG signals obtained from the PEM are subjected to feature extraction. Each moving window is used to extract the standard deviation and variance statistical characteristics, which are then used to create the training vector for the DNN classifier. The testing vector is continually FED into the DNN algorithm during the real-time classification phase to determine classification.

A standard multilayer perceptron neural network (MLPNN) is referred to as a deep neural network when it contains more than one hidden layer (DNN). MLPNN requires lesser training data, hence the operation is fast compared to other classifier [12]. A DNN structure is illustrated in Fig. 4. A Gradient Descent optimization technique has been used, which is reliant on the first derivative of the loss function. It establishes how the weights ought to be adjusted in order for the function to minimize.

Consider a deep neural network where v^t is the output vector for the ith layer and N signifies the overall hidden layers. The input and output layers are indicated by 0 and N+1. The following equation express the output vector:

$$v^t = f(W^t v^t - 1 + b^t) \qquad 0 < t < N, \tag{5}$$

W^t indicates weight matrix and b^t represents bias vector. The type of classification defines which activation function is chosen. The proposed work incorporates a sigmoid transformation as an activation function.

$$f(g) = \frac{1}{1 + e^{-g}}. \tag{6}$$

The normalizing condition has been satisfied by employing the softmax function [13]. The back propagation algorithm, which is based on the gradient descent algorithm, is used to optimize the posterior probability of the DNN.

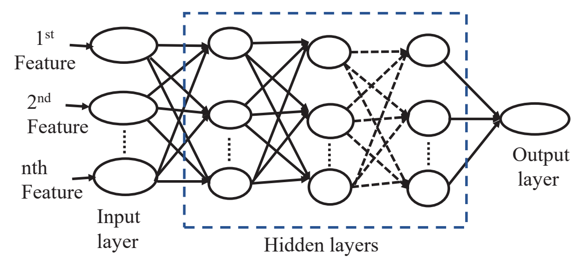

Fig. 4: An example of an optimized DNN structure.

V. Implementation and Validation of The Proposed eSeiz 2.0

EEG data was gathered from the CHB-MIT scalp database [14], a publicly accessible database. EEG data was sampled at a 256f Hz sampling frequency. MATLAB and ThingSpeak were used to implement the proposed system. The epileptic subjects (chb01, chb03, chb05, chb07, and chb08) are chosen randomly for the evaluation. EEG signals have been applied to the PEM algorithm. The band pass filter associated with the PEM algorithm has a frequency range:0-30 Hz. The output of the band pass filter only retains the signals within the frequency (0-30 Hz) range. The filtering output was amplified and then fed to the amplitude level detector. The hypersynchronous activities occur within the range between 200 mV to 500 mV. The threshold calculation is performed using heuristic approach. The upper threshold and lower threshold for the amplitude level detector were considered as 200 mV, and 500 mV, respectively for the specified database. The threshold value may change for varied number of EEG datasets. It is evident from the experimental data that the seizure (ictal) area contains a greater number of pulses than the non-seizure area. The aim is to simplify the EEG signals by reducing number of pulses in the non-seizure area. To achieve that, the EEG signals from the output of the LDU were applied to the PEM. In the algorithm, a pulse is indicated by a 1 and a non-pulse is indicated by 0. In a time frame, this algorithm tends to eliminate 1 (pulse) if the majority of the surrounding area contains 0 (non-pulse). On the other hand, if the majority of the surrounding area is composed of 1, this method tends to keep 1 (pulse).

Table I illustrates PEM mechanism on non-seizure area, where LDU output contains a 0 on the following columns: [0], [2-3], [6-8], [12], and [14-15]. After 1st iteration, the columns [0-4],[6-9], and [12-15] also become 0 and after the second iteration, the columns [0-9] and [12-15] become 0. The illustration of PEM mechanism on the seizure area is shown in Table II. The following columns [2-5], [9-12], and [15-16] hold a 0 (non-pulse). After the second iteration, the columns [2-7] and [9-16] become 1. Fig. 5 and Fig. 6 illustrate, respectively, the PEM output during non-seizure and seizure activities.

TABLE I: Pulse Exclusion Mechanism (PEM) on Non-seizure area

Location	Normal EEG area
LDU output	0 1 0 0 1 1 0 0 0 1 1 1 0 1 0 0
PEM (1^{st} iteration)	0 0 0 0 0 1 0 0 0 0 1 1 0 0 0 0
PEM (2^{nd} iteration)	0 0 0 0 0 0 0 0 0 0 1 0 0 0 0

TABLE II: Pulse Exclusion Mechanism (PEM) on Seizure area

Location	Seizure area
LDU output	0 1 1 1 1 0 0 0 1 1 1 1 0 0 1 1
PEM (1^{st} iteration)	0 1 1 1 1 1 0 0 1 1 1 1 1 0 1 1
PEM (2^{nd} iteration)	0 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1

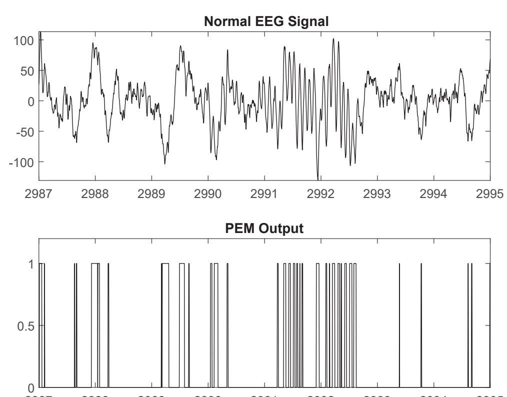

Fig. 5: PEM Output for non-seizure activities (Normal EEG).

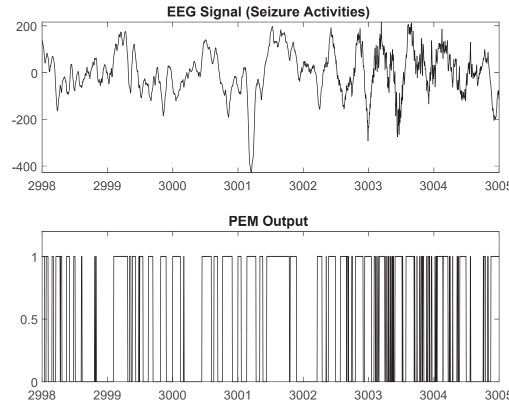

Fig. 6: PEM Output for Seizure activities.

The following five significant channels F7-T7 (2), F8-T8 (14), FZ-CZ (17), FP1-F3 (5), and FT9-FT10 (21) were selected. For each time frame, the number of elements contained in a feature vector N = 2 X 3 X 5 = 30. The testing data was utilized to perform the classification after the DNN classifier had been trained on the training set of data. For non-seizure behavior, three hours of inter-ictal and two hours of normal EEG were used to train the DNN classifier. For seizure characteristics, the classifier was trained with 80% of the seizure instances. The training feature vectors were formed by continually collecting data across a 6 sec time frame. The time frame was continually monitored during the real-time classification phase to determine whether a seizure had occurred. Proposed system is characterized in Table IV. The incorporation of PEM algorithm with DNN classifier reduces the computational burden, hence, there is a significant reduction in latency of the system. Fig. 7 shows latency for different epileptic subjects. PEM algorithm is very effective in capturing non-seizure pulses, hence, it improves the specificity. The sensitivity, specificity, and latency of the proposed system are reported to be 96.4 %, 100 %, and 1.05 sec, respectively, which represents a significant improvement over the existing method. The comparison is shown in Table III.

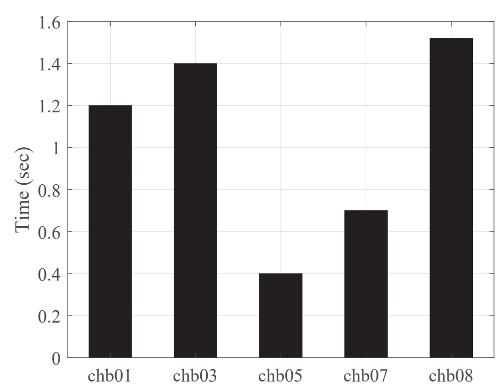

Fig. 7: Various epileptic individuals' latency variations

TABLE III: Performance evaluation with relation to existing works

Reference	Methods utilized	Sensitivity (%)	Specificity (%)	Latency (sec)	IoT Implementation
Guo, et al. (2022) [5]	Unsupervised learning (UL) and supervised learning (SL)	95.55	92.57	NA	NA
Peng, et al. (2021) [7]	Dictionary Learning and sparse representation	95.38	94.33	NA	NA
Olokodana, et al. (2020) [15]	DWT, fractal dimension, and kriging model	87.6	NA	0.85	Yes
Sayeed, et al. (2020) [16]	RBO based κ-NN classifier and Neighborhood component analysis (NCA)	100	NA	1.49	Yes
Sayeed, et al. (2019) [2]	Signal rejection algorithm (SRA)	96.9	97.5	3.6	Yes
Fan, et al. (2019) [10]	Temporal synchronization, spectral graph, and feature extraction	98	NA	6	NA
Vidyaratne, et al. (2017) [3]	HWPT, Feature Extraction, and Relevance Vector Machine	96	0.1/hour	1.89	NA
Proposed approach	Pulse exclusion mechanism (PEM) and optimized DNN classifier	96.4	100	1.05	Yes

TABLE IV: Characterization of the proposed system

Parameter	Value
Sampling frequency	256 Hz
frequency	0 - 30 Hz
Sensitivity	96.4%
Specificity	100%
Latency	1.05 sec

VI. Conclusions and Future Directions

We propose a system in the IoMT paradigm that can identify seizures in real time. The novel PEM algorithm eliminates low weighted features and channels, which reduces system's latency and computation time. The average latency is 1.05 sec, which is significantly less than the latency of existing algorithms. The combination of PEM algorithm and deep learning method leads to a significant enhancement in specificity of 100%. Future research includes incorporation of the PEM algorithm to develop a model for seizure prediction, and create a wearable sensor for low-power biomedical uses.

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