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eSeiz 2.0: An Optimized Pulse Exclusion Mechanism for Accurate and Energy Efficient Seizure Detection in the IoMT

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Abstract Approximately 50 million people worldwide are impacted by epilepsy, necessitating the development of a seizure detection system that is low-power, low-latency, and capable of providing accurate and real-time monitoring to address the issue. In this paper, a low-power wearable device for epilepsy has been presented that uses a novel pulse exclusion (PEM) algorithm to characterize seizure and normal activities. PEM resolves the issue of heavy computational burden by reducing the number of channels or features. The feature vectors of reduced size become input to an optimized deep neural network (DNN) classifier for seizure identification. The proposed PEM-based approach has been extensively validated with 10 epileptic subjects obtained from the CHB-MIT Scalp datasets. PEM in combination with DNN classifier shows huge potential in eliminating false detections, and the average specificity of the specified subjects is recorded as 100%, which may be useful for seizure detection and subsequent epilepsy treatment.

Keywords Electroencephalography (EEG) · Pulse Exclusion Mechanism (PEM) · Internet-of-Medical-Things (IoMT) · Deep neural network · Energy Efficiency · Feature vector

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1 Introduction

The conventional healthcare system is inadequate for the expanding population, but modern smart healthcare that utilize Internet of Medical Things (IoMT) technology has the potential to improve the current healthcare system and cater to the rising demand [1–3]. Smart healthcare systems are built on a network of biomedical applications and devices known as the Internet of Things (IoT), with the goal of improving the quality and experience of the user [4,5]. An example of how healthcare can be made smarter is through the use of automated seizure detection.

Epilepsy is a condition of the nervous system marked by recurring seizures. Approximately 1% of the global population is afflicted with this disorder. Epilepsy has a devastating impact on the quality of life. Epileptics cannot perform daily activities and lead normal life [6–8]. In contrast to the general population, people with epilepsy are more susceptible to sudden unexplained deaths (SUDEP). Epilepsy may affect breathing and reduce the oxygen level in the blood, which creates a dangerous situation such as suffocation and lead to death. It may also alter the heart rhythm and cause cardiac arrest. Every year, one in a thousand patients with epilepsy dies from SUDEP [9]. Different treatments exist for epilepsy, such as antiepileptic drugs (AEDs), surgery, deep brain stimulation, responsive neurostimulation, external nerve stimulation, and focal drug delivery. Drug-resistant patients do not benefit from AEDs, even though they can be taken orally to treat epilepsy. Surgery has the potential to harm the

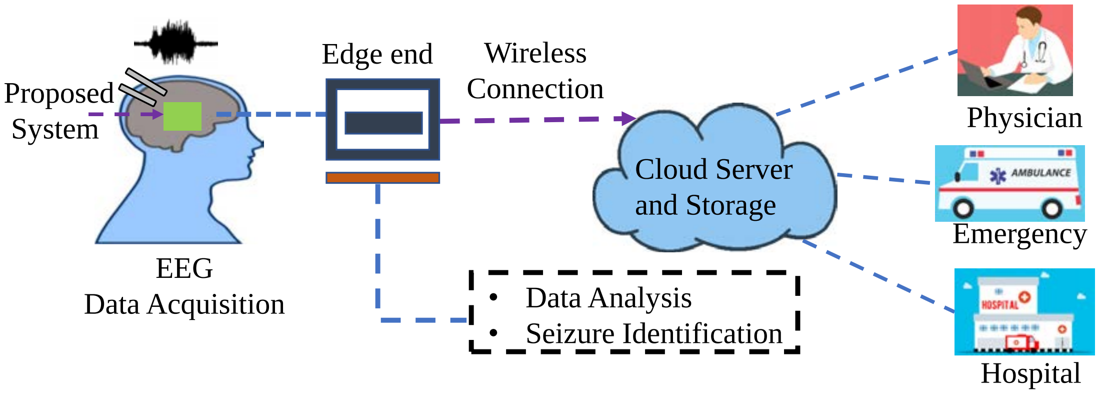


Fig. 1: The proposed Edge-IoT module.

eloquent cortex [10,11]. Therapies can be useful, but they are expensive and time-consuming. Automated detection of seizures is gaining importance in addressing epilepsy.

Different clinical tests exist for epilepsy diagnoses, such as magnetic resonance imaging (MRI), electrocardiogram (ECG), magneto-encephalogram (MEG), or electroencephalogram (EEG). For the precise diagnosis of epilepsy, the EEG's excellent temporal resolution is beneficial [12,13]. Electroencephalography (EEG) records neural activity in terms of electric voltage. The amplitude of the voltages varies for different psychological states, and EEG can be used to identify the varying state of the brain. Electrodes as a cap have been placed safely and painlessly across various brain zones to monitor brain activity. The traditional and manual way of seizure detection through clinical tests is becoming obsolete and inconvenient to the user and medical professionals. In the manual diagnosis, a subject may need to wear a cap for several hours to a few days, and massive amounts of data are recorded on the database. An expert can analyze the data and locate if there is any abnormality. The user is notified later about the abnormality. The whole process may take a few weeks and costs a lot of money [14].

The article outlines a system for detecting seizures in real time that utilizes the Internet of Things (IoT). A module of the proposed approach is illustrated in Fig 1. The research problem and potential solution have been discussed in Sec.2. Existing algorithms for seizure identification have been presented in Sec. 3 . The mathematical model of the PEM and DNN classifier are illustrated in the Sec. 4. Sec. 5.1 shows the Simulink structure of the proposed algorithm and describes each block. Sec. 5.2 presents a dataset for 10 epileptic subjects and discusses the results. Sec. 5.2 discusses possible integration with seizure prediction and cybersecurity.

2 Problem Statement and proposed Solution

2.1 Problem Statement

1. One of the drawbacks of the existing epileptic seizure detector is that the false detection rate is relatively high, which hinders epilepsy treatment through drug delivery or stimulation process. A synchronous seizure control system stops the seizure development by stimulating the onset area or drug injection. False detection enables unnecessary drug delivery or stimulation process to the onset area, which essentially reduces the volume of the drug. The device life of an implantable device is a crucial factor, as frequent implantation through a non-invasive approach is inconvenient to the user.
2. Power usage is a crucial parameter for wearable or implantable devices as the device's life depends on power usage. Existing literature mainly focused on improving the accuracy of the classification. Few algorithms were presented to address the issues with power consumption. The recorded active power usage of those algorithms is high. How is low-power seizure detection possible with a minimum false detection? This question has been addressed in this paper.

2.2 Proposed Solution

1. The deep learning (DL) method uses many functions to examine EEG signals and eliminate extraneous pulses and noise. When DL algorithm is used alone, it provides a specificity around 90%. The reason behind the issue is that EEG signals contain

noises of varied frequency and amplitude. Human emotions also constitute false detection.
2. To solve this problem and to improve the specificity, a combination of DL and PEM has been utilized to get the best possible true negative rate. PEM simplifies the EEG signals by assigning 0's and 1's in the ictal and normal EEG regions, eventually making the seizure and non-seizure activities more distinguishable. There is a noticeable improvement in specificity when EEG signals are first processed using PEM and classification is carried out using DL.

2.3 Novel Contributions of This Work

1. The proposed PEM effectively accumulates the desired number of 0's, and 1's in the targeted brain area and eradicates unneeded pulses. Using both PEM and DNN provides better distinction among different EEG activities and enhances the specificity of the detection. The simplified EEG structure leads to a reduction in features which decreases the latency of the system.
2. PEM reduces the necessity of heavy feature size, which requires a smaller number of functions to capture EEG dynamics. A smaller set of functions enables the system to be implemented using simple circuitry and leads to a considerable reduction in active power usage.

3 Related previous research

Several algorithms have been proposed for seizure identification. A deep learning (DL) based early detection approach [21] has been introduced that uses synthetic minority techniques to balance the sampled EEG data and convolutional neural network (CNN) with truncated backpropagation to extract temporal and spatial features. It overcomes the issue of computational complexity with a conventional DL-based approach. Hand-crafted features have been combined with automated features to characterize abnormal behavior [6]. The proposed hybrid model provides better accuracy compared to the hand-crafted method alone. An EEG-based early detection scheme [3] has been presented that uses multichannel EEG recordings. The features have been derived from the Flower Pollination Algorithm (FPA) which is later submitted to the convolutional neural network (CNN) for seizure identification and feature labeling. A residual network has been extended with mean amplitude spectrum (MAS) to combine the temporal and spatial relevance of EEG channels. The proposed model [22] fully represents the varying activities of the brain. The spatio-temporal features significantly enhance the performance of epileptic seizure detection. Stack autoencoder and random vector functional network [23] have been applied to characterize abnormal EEG activities. The unsupervised features have been extracted using stack autoencoder and fed to the functional network for seizure classification. The adjustment of the cost function enables efficient training and improves detection accuracy.

Nested Long Short-Term Memory (NLSTM) based approach [13] has been presented that analyzes temporal dependencies and determines high-rank features. The features have been fed to softmax layer for feature classification. This method does not require heavy pre-processing of EEG data, which is useful for low-latency biomedical applications. Adversarial Representation Learning (ARL) based patient-independent and robust seizure detection model [24] is proposed. The complex deep neural network (CDNN) model uses the ARL to capture the dynamics of EEG signals during seizures and non-seizure periods. The effectiveness of this method was assessed on the TUH EEG dataset, and the findings indicate a significant reduction in latency. The non-linear property of the epileptic signals has been retained by a unified model [13], which extracts time and frequency domain features. The model is assessed with a large set of datasets and results in a better performance. Intracortical microelectrode arrays (MEAs) can help in the early detection [25] of epileptic seizures in humans. The use of nonlinear support vector machines (SVMs) is utilized to differentiate between features that are indicative of a seizure and those that are not. The utilization of intracortical MEAs may have the potential for synchronous seizure control. The use of Stockwell transforms (S-transform), and bidirectional long short-term memory (BiLSTM) is incorporated to obtain time-frequency blocks and classify seizures [26]. The enhancement in the detection performance is achieved by processing the EEG signals after they have been acquired.

A wavelet packet decomposition (WPD) based approach [27] is proposed to create multiview features which are then applied to a convolutional neural network (CNN) to capture the characteristics of deep features. The method enhances identification accuracy and reduces the dimensionality of the feature vector. The EEG-based data acquisition approach requires electrodes to be placed on the scalp or brain, which requires a considerable amount of time and effort. An accelerometer sensor, a non-invasive method [28], captures seizure activities, which resolves the issues with existing invasive seizure detection approaches. Passive InfraRed (PIR) sensors [29] detect seizure activities by track-

Table 1: Assessment of the proposed approach in comparison to the existing methods

Reference	Methods Employed	Latency (sec)	Sensitivity (%)	specificity (%)	IoMT Framework
Yedurkar et al. (2023) [3]	Flower polination algorithm and convolutional neural network (CNN)	NA	97.85	98.38	NA
Guo, et al. (2022) [15]	Reduction in heavy computation and data labelling through UL and seiZURE identification by SL	NA	95.55	92.57	NA
Peng, et al. (2021) [16]	Sparse representation of EEG data segments and dictionary learning	NA	95.38	94.33	NA
Song, et al. (2020)[17]	Model driven method to characterize dynamic features and identify seizure activities	7.1	100	NA	NA
Olokodana, et al. (2020) [18]	Extracting fractal dimension features using discrete wavelet transform (DWT) and kriging model for classification	0.85	87.6	NA	Yes
Sayeed, et al. (2019) [12]	An amplitude level detector and a signal rejection algorithm (SRA) for seizure onset detection	3.6	96.9	97.5	Yes
Fan, et al. (2019) [19]	Temporal synchronization and feature extraction to track the recurrence pattern of normal and ictal activities	6	98	NA	NA
Wu, et al. (2019) [20]	Combination of continuous EEG and amplitude EEG, multi-domain features, and Random forest classification	NA	99.41	82.98	NA
Sayeed et al. (2023)[current paper]	Optimized pulse exclusion mechanism for feature reduction and deep neural netwrok (DNN) for feature classification	0.96	98.2	100	Yes

ing the body's movement. Distinguishing between body movement during an epileptic seizure and normal sleep can be accomplished by machine learning algorithms. The distinct body movement patterns are identified by combining a hidden Markov model (HMM) and a convolutional neural network, with data collected from a PIR sensor being fed into these models for classification. The recurrence pattern of seizure and non-seizure characteristics is quantified using a spectral graph. The proposed temporal synchronization-based approach [30] leads to an increase in seizure detection accuracy. The local mean decomposition (LMD) based seizure detection approach divides the EEG signals into multiple product functions, and features are taken from each function which is then fed to different classifiers to evaluate the accuracy.

A technique that relies on PEM and utilizes a small dataset was introduced in the previous work [31]. However, the method necessitates validation using a vast amount of data. The proposed method is thoroughly validated by utilizing a broad set of EEG datasets. This paper uses an optimized PEM in combination with DNN classifier, which significantly reduces the false detection and latency of the system. Table 1 demonstrate that the proposed method improves current state of the art and makes a valuable contribution to the development of smart healthcare systems.

4 The Proposed Seizure Detection Approach

The EEG data acquired from the data acquisition system is applied to the pulse exclusion mechanism (PEM). PEM processes the EEG data in two steps. In the first stage, EEG samples of low amplitudes were eliminated using a level detector, and in the second stage, the unnecessary EEG samples were further eradicated using PEM algorithm. The features of non-seizure and seizure activities were recorded and applied to DNN classifier for seizure identification. The detection system is connected to the IoT framework, which allows medical data

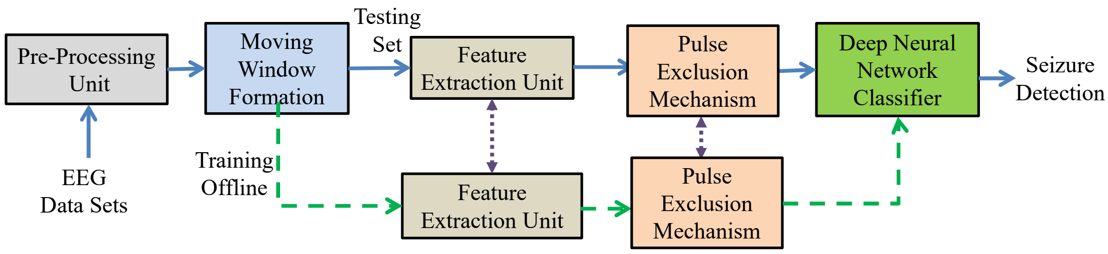


Fig. 2: Architecture of the proposed Detection

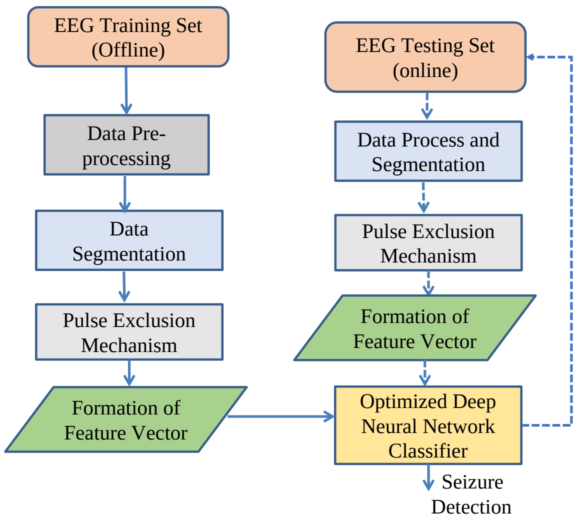


Fig. 3: Flow of algorithm for seizure identification

to be recorded on the cloud [32]. Proposed architecture and flowchart have been illustrated in Fig. 2 and Fig. 3, respectively.

4.1 Time Frame Formation

A biomedical wearable or implantable chip should be able to monitor individuals in real-time. Data could be analyzed offline for important feature extraction, and the chip is trained with limited training vectors. In the real-time classification phase, the bulk amount of testing data is analyzed and only a limited number of features were formed in the testing vector, which was then fed to the classifier for seizure detection. One of the issues addressed in the current paper is the real-time monitoring and analysis of EEG signals from stationary EEG data. The question is how to use stationary EEG data for real-time analysis. The real-time EEG data monitoring is performed using a continuous 6-sec moving window. The moving window captures the seizure propagation at a certain time. The window of a lower length decreases the detection accuracy, whereas a higher length window increases the accuracy. The detection latency is inversely proportional to the window length. 6-sec window provides enough samples that can accurately capture seizure progression along a signal with a reasonable delay. Each moving window consists of three segments of 2-sec duration. The following expression computes the total elements N in a certain feature vector [33].

$$N = B.P.C \tag{1}$$

Where, B is the total feature, P indicates EEG segments, and C is the number of channels in the data acquisition system.

4.2 Pulse Exclusion Mechanism (PEM) for feature reduction

4.2.1 Level Detector (LD)

Distinctive amplitudes and a certain frequency range can characterize the samples at the seizure onset point. Raw EEG signals are associated with low-frequency noise and redundant pulses. LD employs a band pass filter which keeps EEG signals within 0 to 30 HZ frequency and eradicates EEG samples outside the given frequency range. A sudden increase in amplitude marks seizure onset. For a certain epileptic subject chb01, the normal EEG activities span from 0 μV to 500 μV, and during seizure activities, the amplitude has been increased from 0 μV to 1000 μV. LD introduces minimum and maximum voltage to extract the distinctive amplitude ranges. LD keeps the EEG samples that fall within the desired voltage range. LD is the first step in eliminating unwanted samples. They are further eliminated by PEM algorithm. The desired pulses can be obtained using the following expression [31,34]:

$$S(n) = \begin{cases} 1, & \text{for } S_{up} > S(l-1) > S_{low} \\ zero, & \text{otherwise,} \end{cases} \tag{2}$$

The hyper-synchronous signal can be ider its amplitude range, which is defined by the r (S_{low}) and maximum (S_{up}) values.

4.2.2 Pulse Exclusion Mechanism

PEM analyzes EEG signals and creates two d regions: pulse and non-pulse regions. A pulse (a biomedical abnormality in the EEG signals, ular EEG activity is characterized by a non-] The output of LD in the region with seizu ties contains a significant number of 1's, wh area with normal EEG possesses a higher numl PEM reduces 0's in the seizure region, and 1 non-seizure part. The seizure region contains a higher number of 1's, and a greater number of 0's is occupied in the normal EEG region. The transient analysis of the EEG signals demonstrates that the two areas are distinguishable. PEM makes EEG signals more distinctive, which requires fewer features or channels to distinguish seizure and normal activities. It is also observed that brain behavior can be altered by emotional activities (laughing, crying, stress, sneezing). The pulse elimination through LD and PEM maintains the false detection at a minimum level.

Non-seizure region can be expressed as:

$$S(n) = \begin{cases} 0, S(l-6) = 0 \text{ or } S(l-5) = 0 \\ \quad \text{or } S(l-4) = 0, \text{if } S(l-3) = 0 \\ 1, \quad \text{otherwise.} \end{cases} \tag{3}$$

The accumulation of 0's can be optimized by:

$$S(n) = \begin{cases} 0, S(l-5) = 0 \text{ or } S(l-4) = 0 \\ \quad \text{or } S(l-3) = 0, \text{if } S(l-2) = 0 \\ \quad 1, \quad \text{otherwise.} \end{cases} \tag{4}$$

Seizure region can be represented as:

$$S(n) = \begin{cases} 1, S(l-6) = 1 \text{ and } S(l-5) = 1 \\ \quad \text{and } S(l-4) = 1, \text{if } S(l-3) = 0 \\ 0, \quad \text{otherwise.} \end{cases} \tag{5}$$

The accumulation of 1's can be optimized by:

$$S(n) = \begin{cases} 1, S(l-5) = 1 \text{ and } S(l-4) = 1 \\ \quad \text{and } S(l-3) = 1, \text{if } S(l-2) = 0 \\ 0, \text{otherwise.} \end{cases} \tag{6}$$

In the earlier work, the accumulation of 1's and 0's was constituted using three neighboring samples. The proposed approach utilizes four or more neighboring samples to create 0 and 1 region, which is more effective for distinguishing seizure activities.

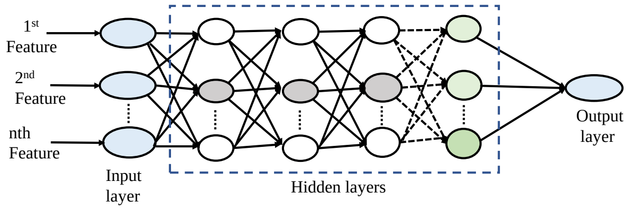


Fig. 4: Deep neural network with more than two hidden layers

A neural network that has multiple hidden layers and follows the conventional multilayer perceptron structure is referred to as a deep neural network (DNN) [35, 36]. The structure of a deep neural network is illustrated in Fig. 4.

In this network, denoted as DNN, the total number of hidden layers is represented by N, and each layer is characterized by the function g^j. The input and output layers are represented by layers 0 and N+1, respectively. The output vector is computed using the following equations:

$$g^j = f(W^j g^j - 1 + bias^j) \qquad 0 < j < N. \tag{7}$$

In the equation, the weight matrix is denoted as W^j and the bias vector as $bias^j$. Sigmoid transformation can be expressed as:

$$f(h) = \frac{1}{1 + e^{-h}} \tag{8}$$

Assume, the training set $S = (x_c, y_c)$ comprised of d sample points, where the the input vector x_c is associated with the posterior probability of y_c. The Frobeneius norm of matrix W is represented by $|W|^2{}_F$, while λ stands for a scalar value.The cost function can be optimized as follows [14]:

$$J(W, bias; S) = \frac{1}{d} \sum_{c=1}^{d} J(W, bias; x_c, y_c) + \lambda |W|^2{}_F \tag{9}$$

5 Implementation and Validation of the Proposed System

5.1 Implementation of the Proposed System

The diagram in Fig. 5 illustrates the system-level overview of the proposed system for detecting seizures. The EEG

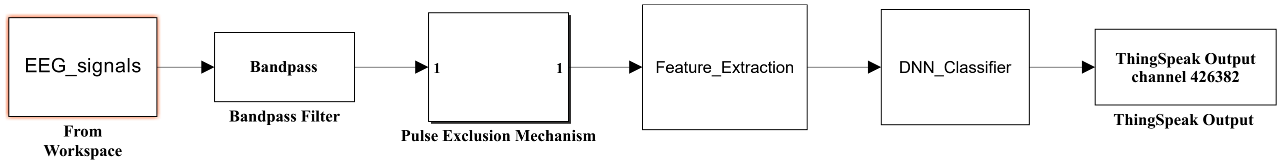


Fig. 5: System implementation using Simulink

signals were brought into the Simulink workspace and fed into the PEM. Simulink user-defined functions were employed to design the structure of the PEM. The feature vectors minimized from the designated timeframe were consistently given to the DNN classifier. The dataset was chosen randomly from different epileptic individuals, and the interictal activities constitute the major portion of the training. The system's training time does not impact the overall latency because it is conducted offline. The primary source of delay is attributable to the testing time and the length of the testing vectors.

To illustrate the PEM operation clearly, 10 samples have been chosen from the ictal and normal EEG areas. In the beginning, the samples at the seizure area are 1010101011, which includes six 1's and four 0's. PEM tends to convert all the remaining 0's to 1's. After the execution of PEM in the first and second iterations, the area should be 1110111011 and 1111111011, respectively. The resulting PEM output contains nine 1's and one 0, 1 prevails in this area, indicating a seizure. Let's consider the samples at the normal EEG area is 0010101001, which consists of six o's and four 1's. Applying PEM to the non-seizure area leads to a conversion of 1's to 0's. The resulting samples become 0000000000, which can be distinguished from the abnormality. Table 2 illustrates PEM mechanisms for a specified number of samples.

Table 2: Analysis of PEM output

Iteration	Seizure area	Non-seizure area
1	1 0 1 0 1 0 1 0 1 1	0 0 1 0 1 0 1 0 0 1
2	1 1 1 0 1 1 1 0 1 1	0 0 0 0 1 0 0 0 0 0
3	1 1 1 1 1 1 1 0 1 1	0 0 0 0 0 0 0 0 0 0

One critical aspect of performance for biomedical sensors is power usage, which must be minimized to prolong battery life. The proposed system is viewed as a black box to compute the power consumption and applied to an additional Simscape circuitry for power measurement. EEG signals of varying individuals became an input to the power measurement circuitry. The power consumption for varied input EEG signals was measured, and the resulting data were averaged to yield the actual power consumption. The Simulink-PS converter links the proposed Simulink model to the Simscape network. The power measurements tools, such as the current sensor, voltage sensor, and voltage source have been contained in the Simscape environment. The connection between Simscape output and a Simulink block is facilitated by a PS-Simulink converter [37]. The voltage and current data is obtained through the voltage and current sensor, which is then used to assess the system's total power usage.

ThingSpeak, an open data platform, incorporated IoT devices and established two separate channels: one for EEG recordings of patients and another for seizure recordings and relevant information. While the EEG channel stored patient EEG recordings, the seizure channel exclusively held seizure recordings and associated useful information.

5.2 Validation With CHB-MIT Scalp Dataset

The CHB-MIT EEG data [38] is selected for the purpose of validation. Table 3 contains details of the patients' age, gender, and seizure, including six female and four male participants.

Table 3: Epileptic Patient's information

Epileptic Subject	Subject's Gender and age	Quantity of seizures
chb01	Female - 11 years	7
chb02	Male - 11 years	3
chb03	Female - 14 years	7
chb04	Male - 22 years	4
chb05	Female - 7 years	5
chb06	Female - 1.5 years	10
chb07	Female - 14.5 years	3
chb08	Male - 3.05 years	5
chb09	Female - 10 years	4
chb10	Male - 3 years	7
	Total No. of seizures:	55

Fig. 6 depicts transient analysis of EEG signal for epileptic subject *chb*01_18. The samples have an amplitude lower than 300μV prior to the seizure starting point. However, during ictal activity, the amplitude level increases to 800 μV. This indicates that the beginning of the seizure is linked to a discharge of high amplitude. Epileptic brain activity can result in irregular amplitude patterns within frequency bands. For instance, seizure activity may give rise to sudden amplification or reduction in amplitude within designated frequency ranges. To remove unwanted pulses and incorrect detections from EEG signals, a band pass filter of frequency range (0-30)Hz is employed [39, 14] The resulting signals include EEG signals from 23 channels, which are fed into PEM to remove unimportant channels and shrink the feature size.

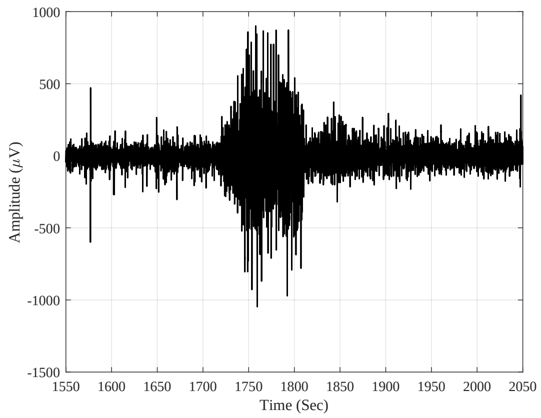


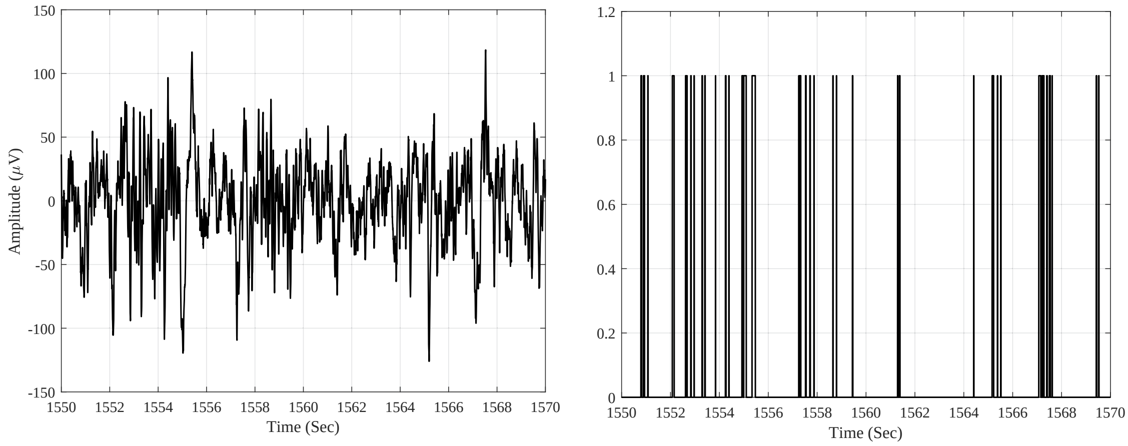
Fig. 6: Transient analysis of EEG Signals at channel 10 (1550 sec - 2050 sec)

PEM reduces the necessity for a large number of channels and features that can capture EEG behavior. PEM employs limited functions to analyze EEG signals and extract weighted channels and features to differentiate EEG activities. A high-amplitude discharge, also known as a hypersynchronous discharge, occurs in the onset area of a specific frequency limit during a seizure. The occurrence of this high-magnitude discharge results in a greater number of 1's being present in samples taken from areas that are prone to seizures. In contrast, the non-seizure area has a larger number of 0's as the normal EEG area is dominated by low amplitude pulses. In this context, 1 refers to pulses that exceed the amplitude threshold of the epileptic individual, whereas 0 signifies that the pulses are below the threshold level. The amplitude threshold detects the hypersynchronous discharge and creates a likeness in a specific segment of the EEG.

The samples at the ictal and normal EEG area have been converted to 0's, and 1's according to the threshold set by hypersynchronous discharge. When PEM extracts samples of a particular time frame, it sets the samples to 1 if 1 prevails in the surrounding areas, and 0 is set to a particular sample if 0 is leading. The counting of 0's and 1's is conducted through two different counters. Two counters, A and B, have been employed to count the number of 0's and 1's in a particular time frame. For example, a time frame contains 1000 samples, counter A value is 800, and counter B value is 200. It means that 1 prevails in this time frame, and the progression of associated signals indicates seizure. Assume another example in which B value is higher than A; B is 900, whereas A is 100. B is dominant, which suggests that the specified time frame indicates a non-seizure. Certain human actions like stress, sneezing, or emotional responses can generate samples of similar amplitude to hypersynchronous pulses, leading to incorrect detections. To overcome this issue, the PEM algorithm includes a frequency range between 0 and 30 HZ, which helps to eliminate false detections. Fig. 7 shows the PEM output for a normal EEG signal, whereas Fig. 8 depicts the PEM output for seizure activities.

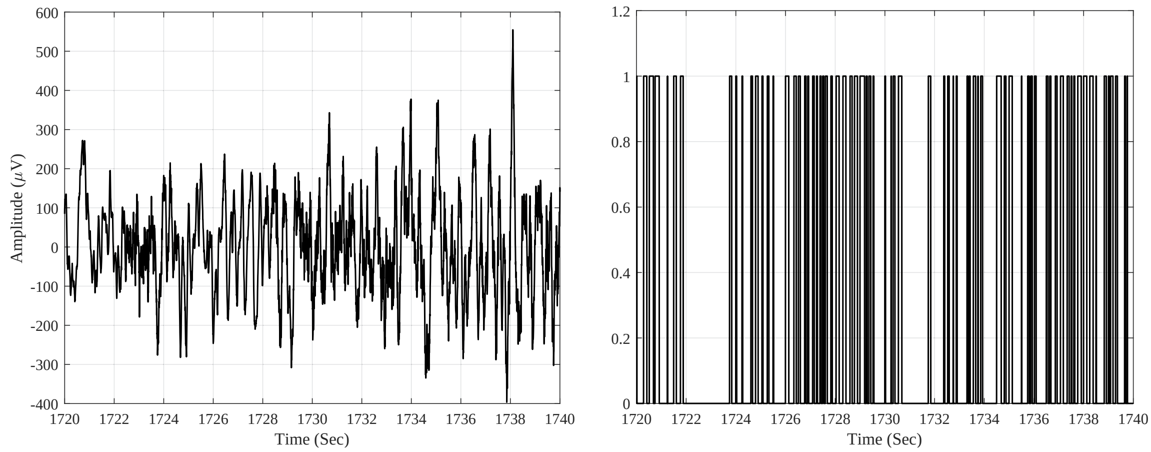
EEG signals were utilized and analyzed during the feature extraction to generate statistical features. These features were then compiled into feature vectors for a particular time. To determine the size of the feature vector, the result can be computed by multiplying the number of features, channels, and non-overlapping EEG epochs. The feature vector had 8 x 23 x 3 = 552 elements in each time frame when PEM was not considered. PEM eliminates five features and keeps three features for feature vector formation. Twenty-three channels shrink down to eight. When PEM is employed, the feature vector size is reduced to 3 x 3 x 3 = 27 elements for the 6-sec moving window. Eight hours of normal and interictal data and 70% of seizure instances were used to train the DNN classifier. Training the data offline involves using feature vectors from the time frames, and this process demands a considerable amount of training time. The testing of seizures is done online in real-time using reduced-size training and testing vectors.

The accuracy and latency of the detector have been measured and compared for both 6-sec and 9-sec time frames. A time frame with a longer period contains more samples compared to a time frame with a shorter period. A longer time frame has enough samples to capture seizure progression, which is useful for accurate detection. While a 9-second time frame offers excellent sensitivity and specificity of more than 98%, it suffers from the drawback of having higher latency. However, a time frame of less than 3-sec improves the delay, but the drawback is that it sharply reduces the system's accuracy. By utilizing a medium-length time frame of 6 seconds, it is possible to overcome the challenges related to sensitivity and latency, resulting in optimal perfor-



(a) (b)

Fig. 7: Transient analysis (a) Normal EEG signals (1550 sec - 1570 sec) (b) PEM output (1550 sec - 1570 sec)



(a) (b)

Fig. 8: Transient analysis (a) Seizure activities (1720 sec - 1740 sec) (b) PEM output (1720 sec - 1740 sec)

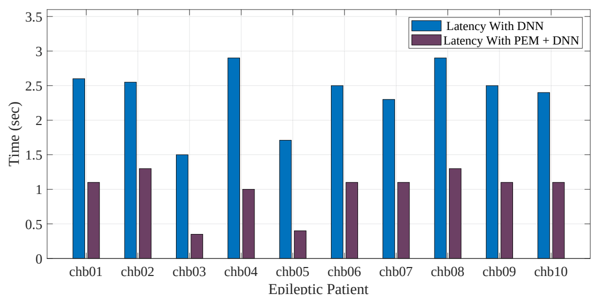


Fig. 9: Variation of latency for each epileptic subject

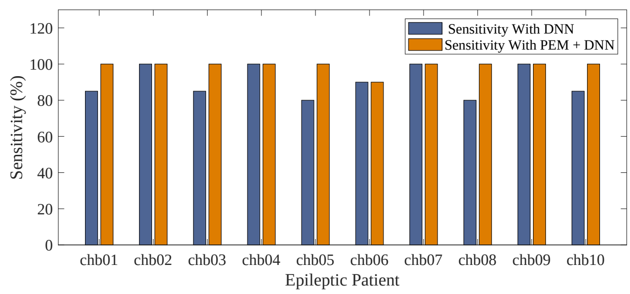


Fig. 10: Variation of sensitivity for each epileptic subject

mance. The measurement for active power consumption is recorded at 126 μw.

Fig. 9 shows the detection delay for each individual with epilepsy. Latency is calculated from two different structures. The first setup did not include PEM, and the extracted features were directly applied to DNN for classification. It reported an average delay of 2.35 sec. In the second setup, the extracted features were shurnk using PEM, and later they were submitted to

DNN for detection. The PEM-based structure reported a reduced delay of 0.96 sec. Incorporating PEM significantly decreases the total latency. PEM employs simple and uncomplicated functions that entail minimal computation. The individual with epilepsy labeled as chb03 has the shortest latency, which is 0.3 sec, whereas chb04 has the longest delay of 2.9 sec. The average sensitivity is less than 95% when PEM is not incorporated. PEM inclusion raised the average sensitivity to 98.2%. Fig. 10 shows average sensitivity for each individuals. Proposed system is characterized in Table 4.

Table 4: Proposed eSeiz 2.0 Characterization

Parameter	Value
Sampling rate	256 Hz
Sensitivity (DNN Classifier)	≤92%
Sensitivity (PEM + DNN Classifier)	98.2%
Specificity (DNN Classifier)	≤95%
Specificity (PEM + DNN Classifier)	100%
Latency (DNN Classifier)	2.35 sec
Latency (PEM + DNN Classifier)	0.96 sec
Power usage	126 μw

6 Conclusions and Future Work

This article introduces an optimized PEM algorithm that has been tested and validated for its ability to identify seizures efficiently and accurately in real-time. PEM uses simple functions iteratively to remove redundant pulses, features, and channels, which eventually shrink the size of the feature and lead to a sharp reduction in computation time and the system's delay. The proposed system demonstrated a specificity of 100%, and a delay of 1.05 seconds, resulting in a notable advancement over the current state-of-the-art approaches.

The potential area of future research is seizure prediction which is gaining importance and will be explored. If a seizure can be predicted before its occurrence, it can be prevented by applying different seizure termination techniques such as drug injection, responsive neurostimulation, or electrical stimulation. The pro-posed model will be analyzed for seizure prediction. To validate its efficacy in predicting seizures, the proposed model will undergo analysis using both scalp and icEEG databases. Another potential future application for the proposed system is enhancing security measures [40], particularly given that healthcare devices often contain highly sensitive financial and healthcare information. Measures for enhancing the system's robustness and se-curity will be explored.

Acknowledgements This article is an expanded version of our prior conference paper that was presented at [31].

Compliance with Ethical Standards

The authors declare that they have no conflict of interest and there was no human or animal testing or participation involved in this research. All data were obtained from public domain sources.

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