Neuro-Detect: A Machine Learning Based Fast and Accurate Seizure Detection System in the IoMT

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***Abstract*—Epilepsy, which is characterized by recurrent spontaneous seizures, has a considerably negative impact on both the quality and the expectancy of life of the patient. Approximately 3.4 million individuals in the USA and up to 1% of the world population are afflicted by epilepsy. This necessitates the real-time detection of seizures which can be done by the use of an IoT framework for smart healthcare. In this paper we propose an EEG based seizure detection system in the IoT framework which uses the discrete wavelet transform (DWT), Hjorth parameters (HPs), statistical features, and a machine learning classifier. Seizure detection is done in two stages. In the first stage, EEG signals are decomposed by the DWT into sub-bands and features (activity, signal complexity and standard deviation) were extracted from each of these sub-bands. In the second stage, a deep neural network (DNN) classifier is used to classify the EEG data. The prototype of the proposed Neuro-Detect was implemented using the hardware-in-the-loop approach. The results demonstrate a significant difference in HP values between interictal and ictal EEG with ictal EEG being less complex than interictal EEG. In this approach, we report an accuracy of 100% for a classification of normal vs. ictal EEG and 98.6% for normal and interictal vs. ictal EEG.**

***Index Terms*—Smart Homes, Ambient Intelligence, Smart Healthcare, Internet-of-Medical-Things (IoMT), Deep Neural Network (DNN), Electroencephalogram (EEG), Seizure Detection**

I. Introduction

ONGOING technological advancements offer considerable opportunities for the improvement of health care and reduction of cost, but also present a challenge for the incorporation of new technologies into clinical care [1–3]. A considerable amount of research effort is currently focused on smart healthcare to overcome the shortcomings of traditional healthcare and to meet the ever increasing demands for quality healthcare. Smart healthcare can be conceptualized as a combination of sensors, devices, applications, services and entities including: traditional healthcare, biosensors, wearable devices, information and communication technology (ICT), and smart emergency response services. The backbone of smart healthcare is the Internet of Medical Things (IoMT) or the Internet of Healthcare Things (IoHT), a collection of medical devices and applications that connect through the Internet to healthcare IT systems [4, 5]. The automated detection of epileptic seizures is one example of smart healthcare.

Epilepsy is a neurological disorder characterized by recurrent spontaneous seizures. A seizure is a sudden and transient interruption of brain function which may also be marked by convulsions and loss of consciousness [6]. Epilepsy has a considerably negative impact on the quality of life of patients. Epilepsy patients are more prone to sudden unexplained death (SUDEP) compared to the general population [7], underscoring the pernicious nature of this condition. Antiepileptic drugs (AEDs) can be used to control seizures, but 30% of epilepsy patients are refractory to AEDs [8]. Epilepsy surgery is useful for only a small fraction of refractory patients. Brain implantable devices show considerable potential for the control of seizure. The prediction and detection of seizures are of considerable importance, as warning and early detection can result in timely treatment [9–14].

This article presents technology for mass consumer electronics (CE) products in the form of wearable electronics for smart healthcare. Specifically, this article proposes an EEG-based seizure detection technology in the IoT framework, which uses the discrete wavelet transform (DWT), Hjorth parameters (HPs), statistical features, and a machine learning classifier for accurate and fast detection of seizure. A specific example of a wearable CE product is a medical-grade smartwatch for a neurological condition that alerts caregivers when someone is having an epileptic seizure [20, 21]. The smart healthcare market which is driven by CE in Internet-of-Medical-Things (IoMT) will have a projected market value of 57 Billion USD [22]. The scope of the research presented in the current paper is depicted in Fig. 1. In effect, this article advances the already existing CE research as summarized in Table I. It should be noted that the CE proof of concept and prototype with validation, using available medical databases in collaboration with medical schools, is presented in this article.

The EEG contains important information about different physiological states of the brain which is useful for understanding brain function and dysfunction. The identification of seizure can be done by visual inspection, but it requires considerable effort and time [23]. In epilepsy, the primary focus is in two states: interictal (between seizures) and ictal (seizure). Extracted features capture distinctive information which is useful for distinguishing EEG dynamics and can be central to the accuracy of classification [24, 25]. Hence, feature extraction is crucial for classification.

The remainder of this paper is organized as follows: Section II discusses the novel contributions of this work. Section III

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TABLE I: Existing Works on Smart Healthcare in the Consumer Electronics Literature.

Existing works	System Details	Contributions to the Smart Healthcare	Features
Khan, et al. 2011 [15]	Abnormal human activity detection using R-transform and Linear Discriminant Analysis (LDA)	Healthcare monitoring of elderly people at home	Improved detection accuracy
Ivanov, et al. 2012 [16]	Wireless body area network (WBAN) and medium access control (MAC) layer	ECG healthcare monitoring	Low cost and low power consumption
Wang, et al. 2016 [17]	Outdoor healthcare monitoring device using GPS and Zigbee module	Remote monitoring of falling events for the elderly people	Reduction in detection time and improvement in detection accuracy
Dey, et al. 2017 [18]	Wireless sensor network (WSN) and Zigbee wireless unit	Continuous ECG healthcare monitoring	Reduction in cost, improved reliability and latency
Sundaravadivel, et al. 2018 [19]	Nutrition monitoring system using deep learning method	Balancing the nutrient intake for healthy development	low cost and high accuracy
Proposed System	Seizure detection using DWT and DNN classifier	Remote EEG healthcare monitoring and IoT implementation	High detection accuracy and low power consumption

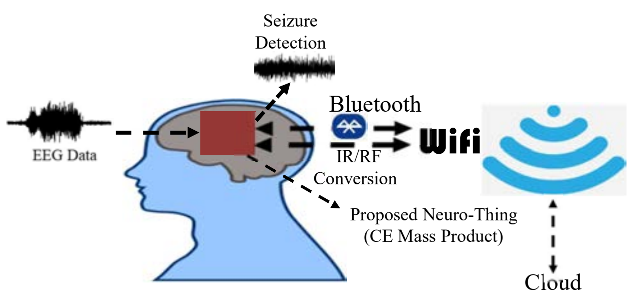


Fig. 1: Neuro-Detect for automatic seizure detection for smart healthcare.

describes current research on seizure detection. Section IV presents a design and architecture overview of the proposed solution. Section V discusses the implementation and CE proof-of-concept of the proposed design. Experimental results and validation procedures are discussed in Section VI. Section VII presents conclusions and future directions for research.

II. Novel Contributions of This Study

The detection of abnormalities in biomedical signals is a difficult task because of its complexity. Several algorithms have been proposed for the detection of seizure and some of them show promising results. Still, current smart healthcare necessitates a smart detection system which can detect seizure mores accurately and can provide ubiquitous connectivity to the users for remote healthcare monitoring. The main contributions of this paper are discussed below:

1) We propose a seizure detection system using the discrete wavelet transform (DWT), Hjorth parameters (HP), statistical features, and a deep neural network (DNN) classifier. DWT provides the time frequency (TF) localization which is useful for non-stationary EEG signal processing. The quantification of the complexity of the EEG is important as it helps to characterize the signal. Statistical features and HPs are very effective in capturing the complexity of the biomedical signals. The use of HPs and statistical features leads to an improved classification accuracy and makes the detection method more efficient. The mathematical modeling of the seizure pattern is a challenging task. A DNN provides a large set of functions to quantify seizure and non-seizure patterns without any internal mathematical modeling. This also allows a change in the weighting given to the different bands to permit adjustment of the classifier to possible changes in seizure and signal characteristics.
2) The proposed "Neuro-Detect" system performs the analysis and detection of seizure at the user end and sends EEG data and seizure state to the cloud.

III. Related Previous Research

It has been predicted that IoT-based smart healthcare will have a market value of 350 Billion USD by 2025 [1]. CE integrated in the IoT framework in the heatlhcare domain, such as smart pills and smart RFID cabinets are receiving significant attention. Different CE systems for elderly healthcare have been presented [15, 17, 26, 27]. A wireless body area network (WBAN) has been proposed to transfer sensor monitoring physiological parameters including ECG, blood oxygen level, body temperature and pressure [16]. A method has been proposed for transmission of Electrocardiogram (ECG), Electroencephalography (EEG), and Electromyography (EMG) data from respective sensors [28]. A wireless sensor network (WSN) has been proposed for continuous monitoring of elderly people [3]. However, there is a need for CE products for automatic seizure detection in the IoT framework to advance the state-of-art in smart healthcare. The proposed system enriches CE by adding epileptic seizure detection and remote health monitoring to smart healthcare. Existing papers on CE applications to smart healthcare are discussed in Table I.

Several methods have been proposed for epileptic seizure detection. An approximate entropy (ApEn) based seizure detection method [29] has been presented which found that the ApEn value drops significantly during seizure activity. A correlation dimension (CD) based method [30] reported that CD values are low in the epileptegenic zone. Artificial neural network (ANN) based classifiers have been proposed [31], [32] for the detection of seizure, with improved classification accuracy. Multilayer perception neural network (MLPNN) [33] based seizure detection has been shown to enhance the detection performance. ANN and wavelet transform based feature extraction [34] were used to classify seizure and non-seizure patterns. In the short term Fourier transform (STFT) based approach [35], feature extraction is performed using the smoothed-pseudo Wigner-Ville distribution. The classification of seizure using a radial basis function (RBF) network and a multilayer perception network (MLP) has been investigated [36]. Permutation entropy [37] based classification also demonstrates a significant drop in permutation entropy during seizure. A support-vector-machine (SVM) based method [38] for seizure detection has been proposed, which provided better accuracy. A signal rejection algorithm based seizure detector [39] has been proposed, which improved detection accuracy and reduced power consumption. Other classifiers have been used including naive bias [40], decision tree [41], surrogate data analysis [25], adaptive fuzzy logic [42], recurrent neural network (RNN) [43], convolutional neural network (CNN) [44], and Markov modeling [45]. Existing algorithms use different features to enhance classification accuracy. In this work, we investigate classification accuracy, sensitivity, and specificity using DWT based HPs and statistical features.

In our previous work [46], a k-NN classifier based seizure detection method has been proposed in which Hjorth parameters (HPs) are used as a feature. In the current extended paper, both statistical parameters and Hjorth parameters are considered as features to distinguish seizure and non-seizure pattern; a deep neural network (DNN) was utilized as a classifier. Hardware in the loop based simulations were performed to validate the proposed system. The proposed DNN based approach provides better detection performance compared to the previous k-NN based approach and proved to be useful for larger datasets. Overall, the current paper improves the prior results significantly in terms of accuracy.

IV. The Proposed Seizure Detection Approach

The architecture of the proposed Neuro-Detect is shown in Fig. 2. EEG signals are initially processed and decomposed to several sub-bands using the DWT. HP and statistical values are extracted from different sub-bands which form a feature vector. The feature vectors and class labels are applied by the DNN classifier. The classifier is trained and validated using the available training datasets. The class label in the testing dataset is obtained using the estimated posterior probability from the DNN. The IoMT module enables remote connectivity by transferring data to the physician through the Internet. Fig. 3 shows the working algorithm of the proposed Neuro-Detect.

The training of Neuro-Detect is critical for accurate detection of seizure. There are several alternatives for training Neuro-Detect as follows:

1) *Weekly Training*: Data comes from the cloud server. This training uses significant data but can be accurate as historic information is included.
2) *Daily Training*: Data comes from the cloud server. This training uses a medium amount of data but can be moderately accurate as some historic information is included.
3) *Real-Time Training*: Few times in an hour using a window of data which is of the order of few hours. The data comes from the on-chip memory. This is fast, but can be less accurate.

A. Discrete Wavelet Transform based Preprocessing Unit

The Fourier transform is useful for the analysis of stationary signals. EEG signals, however, are nonstationary in nature [47]. The Fourier transform cannot resolve both time and frequency aspects of signals. In the Fourier series, frequency localization is compromised to achieve time domain localization. On the contrary, a longer time window is required to achieve frequency localization, compromising time localization information. The analysis of nonstationary signals can be performed through a TF decomposition of the signal [47].

The wavelet transform (WT) enables time frequency (TF) decomposition by capturing both low frequency and high frequency information. The WT has been broadly used in various biomedical applications and proven to be a useful tool for biomedical signal processing. There are two types of WTs: the continuous wavelet transform (CWT) and the discrete wavelet transform (DWT). The computation of CWT coefficients is expensive. For the DWT, in contrast, the decomposition of signals can be achieved through filters. The signal is decomposed into approximation and detail coefficients at a first level. The approximation coefficients are then further decomposed to subsequent approximation and detail coefficients through a second application of the same decomposition step. The decomposition is achieved by the following [48] equations:

$$HPF(S) = A_{1p} = \sum_{q} S(q)h(2p-q) \tag{1}$$

$$LPF(S) = D_{1p} = \sum_{q} S(q)g(2p-q) \tag{2}$$

Fig. 4 shows the decomposition of the EEG signal using a filter bank. In the first stage, the EEG signal $x[n]$ is submitted to a low pass filter and a high pass filter. The output of the filters is known as approximate coefficient and detail coefficient. The decomposition is performed up to 4th level using Daubechies wavelet. The subsequent detail and approximate coefficients are known as D2, D3, D4, and A4, respectively. The breakdown of sub-band frequencies is shown in Table II.

TABLE II: Frequency characterization of the proposed system

Parameters	Value
Detectable seizure frequency range	0-29 Hz
D1	43.4-86.8 Hz
D2	21.7- 43.4 Hz
D3	10.85-21.7 Hz
D4	5.43-10.85 Hz
A4	0-5.43 Hz

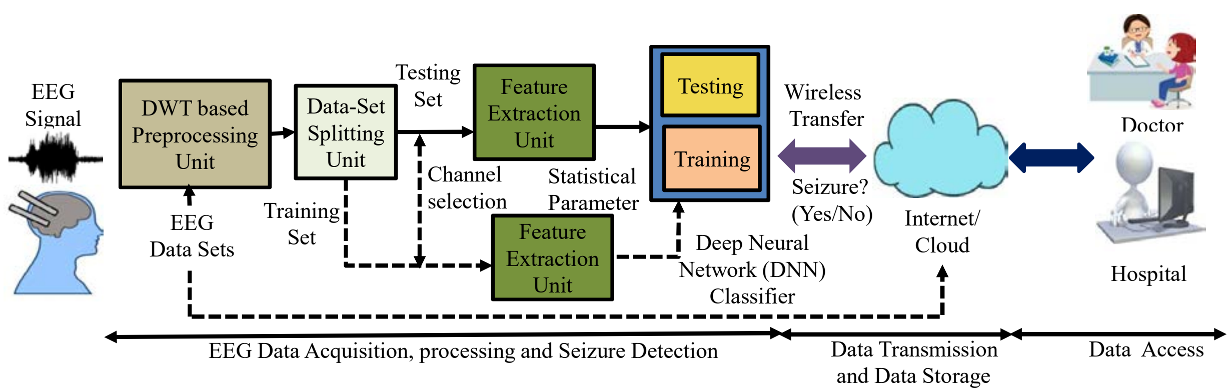


Fig. 2: Block diagram of the proposed architecture.

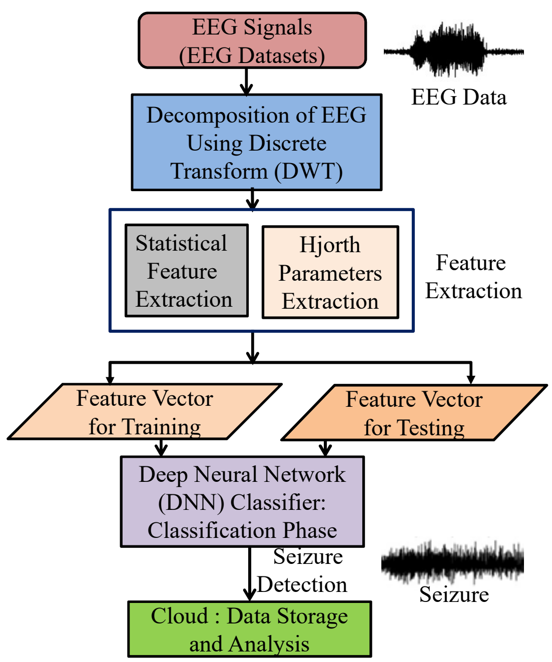


Fig. 3: The proposed algorithm for accurate seizure detection.

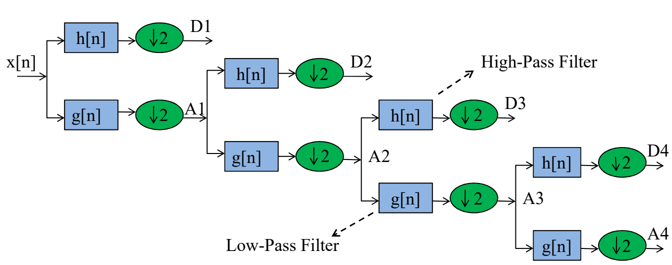


Fig. 4: Four level wavelet decomposition of the EEG.

B. Feature Extraction Unit

Hjorth parameters and statistical features are extracted from the decomposed EEG signals, as discussed in this Section.

1) Hjorth Parameter Extraction: Hjorth parameters (activity and signal complexity) are useful in capturing complex EEG dynamics [49]. The level of variations along a signal can be quantified by signal complexity. Signal mobility captures the first order variations while signal complexity addresses second order variations along a signal.
Consider an EEG signal X_i, where $i = 1, 2, 3, ..., N$. The vector of the first order variations in x is represented by a signal m_j, $j = 1, 2, ...N-1$,

$$m_j = x_{j+1} - x_j. \tag{3}$$

The vector of the second-order variations in x is defined by a signal n_k, where $k = 1, 2.....N-2$,

$$n_k = m_{k+1} - m_k, \tag{4}$$

$$\text{Activity} = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \mu)^2}{N}}, \tag{5}$$

where μ is the mean. The first and second-order factors are defined using x, m and n:

$$Z_0 = \sqrt{\frac{\sum_{i=1}^{N}(x_i)^2}{N}}, \tag{6}$$

$$Z_1 = \sqrt{\frac{\sum_{j=2}^{N-1}(m_j)^2}{N-1}}, \tag{7}$$

$$Z_2 = \sqrt{\frac{\sum_{k=3}^{N-2}(n_k)^2}{N-2}}. \tag{8}$$

The signal mobility and complexity can be defined as follows:

$$\text{Signal Mobility} = \frac{Z_1}{Z_2}, \tag{9}$$

$$\text{Signal Complexity} = \sqrt{\frac{Z_2^2}{Z_1^2} - \frac{Z_1^2}{Z_0^2}}. \tag{10}$$

2) Statistical Feature Extraction: Standard deviation refers to the amount of variation of a signal from its mean value, which is represented by the following equation;

$$\text{Standard deviation} = \frac{1}{M-1}\sum_{j=1}^{M}(x_j - \mu)^2, \tag{11}$$

where x_j denotes the j^{th} sample of the decomposed EEG segment, μ is the mean of the decomposed segment and M indicates the length of the segment.

C. Deep Neural Network (DNN) Classifier

A conventional multilayer perceptron neural network with more than one hidden layer is considered as a deep neural network (DNN) [33, 50]. MLPNN is chosen as it requires a smaller training data set and provides faster operation with simple implementation. Fig. 5 shows an example of a DNN structure. Consider a deep neural network, where N denotes the total number of hidden layers and v^n represents the output vector of the i^th layer. The layers 0 and N+1 denote the input and output layers. The output vector is calculated by:

$$v^n = f(W^n v^n - 1 + b^n) \qquad 0 < n < N, \tag{12}$$

where W^n is the weight matrix and b^n is the bias vector. In this work, a sigmoid transformation [51] has been used as an activation function:

$$f(x) = \frac{1}{1 + e^{-x}}. \tag{13}$$

The selection of the activation function depends on the type of classification. The normalization requirement can be fulfilled by a softmax function. The weight matrix W and bias b are calculated during the training phase. Consider a training set $S = (x_q, y_q)$ of P sample pairs, where x_q denotes the input vector, and y_q represents the posterior probability vector corresponding to x_q. The network is trained by optimizing the cost function [33] as follows:

$$J(W, b : S) = \frac{1}{P} \sum_{q=1}^{P} J_{CE}(W, b : x_q, y_q) + \lambda |W|^2{}_F, \tag{14}$$

where $J_{CE}(W, b : x_q, y_q)$ represents the cross entropy, $\lambda |W|^2{}_F$ denotes the Frobenius norm of matrix W, and λ is a scalar. The posterior probability of the DNN is optimized using back propagation which is based on the gradient desecent algorithm.

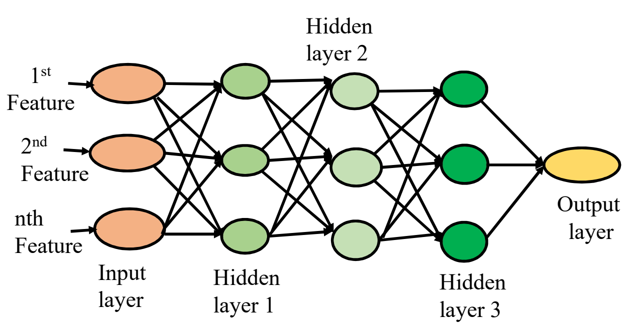


Fig. 5: An example of a DNN structure.

V. Proof of Concept of the Proposed Neuro-Detect Device

Fig. 6 shows the prototype of the proposed system for a single statistical feature: signal complexity. The DWT structure was obtained via user defined functions. EEG signals were applied to DWT for decomposition. Daubechies wavelets of order 4 were used for the decomposition. Each decomposition doubles the frequency resolution and halves the time resolution. The filtered signal halves the bandwidth of the original signal which could be further down-sampled by two according to the Nyquist rule. Hjorth parameters and statistical features were obtained from the decomposed signals. The first and second order variations of the signal were measured using the DSP system toolbox and math operations library available in the simulator software. The proposed system was validated with both k-NN and DNN classifiers. The k-NN classifier was constructed using another user-defined function available in the simulator software. The HP and statistical values formed the feature vectors. In the training phase, the classifier was trained with feature vectors and class labels of different EEG datasets. In the classification phase, when a unknown point was given to the system, the algorithm computed nearness of data using Euclidean distance metric and a label was assigned to the query point based on voting among the neighbors. In the later DNN based approach, the DNN structure was created using a user defined function. The DNN classifier was trained and validated with the training datasets. The classification of the testing dataset was obtained using the posterior probability from the DNN.

In general, power estimation is determined through pattern dependent or pattern independent approaches. In the pattern dependent approach, power estimation is done using simulation. In the pattern independent approach, a number of simulations are performed to study the design for different inputs. The average power dissipation is calculated from the simulation results and used as the power estimate. We employed a pattern-independent approach to calculate power dissipation. The current and voltage values are computed using the sensors and power blocks available in the simulator library, and provide an estimation of the power dissipation [52]. The characterization of the proposed system is shown in Table III.

TABLE III: Characterization of the proposed system

Parameters	Value
Data sampling rate	173.61 Hz
Bandwidth of the acquisition system	0.53-40 Hz
Wavelet type	Daubechies wavelet of order 4
k value for k-NN classifier	2
Average SC (normal EEG - set A)	0.71
Average SC (inter-ictal state - set D)	0.65
Average SC (ictal state - set E)	0.48
Power consumption	34.5 μW

The prototyping of the proposed Neuro-Detect was done using a hardware-in-the-loop based simulation approach. The simulator was configured using a hardware support package provided by vendor. The actual board was constructed and then the proposed Neuro-Detect was run on the board. The user's EEG data were continuously stored on the 'Neuro-Detect' channel in the IoT cloud storage. A buzzer was turned on and the designated user was informed by a message for any seizure activity. An LCD displayed the state of the seizure, where '0' denotes non-seizure activity and '1' represents seizure activity. The IoT cloud storage permits medical professionals, stake holders, and users to access the patient's database using API (Application Programming Interface) via IoT [53], [54]. The prototyping of the proposed Neuro-Detect is shown in Fig. 7.

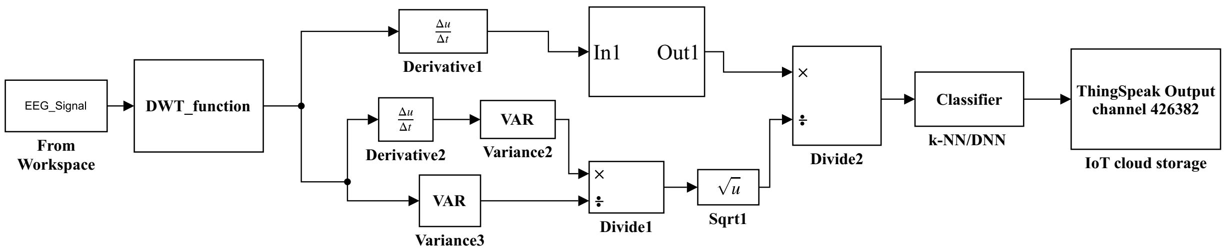


Fig. 6: System level model of the Proposed Neuro-Detect.

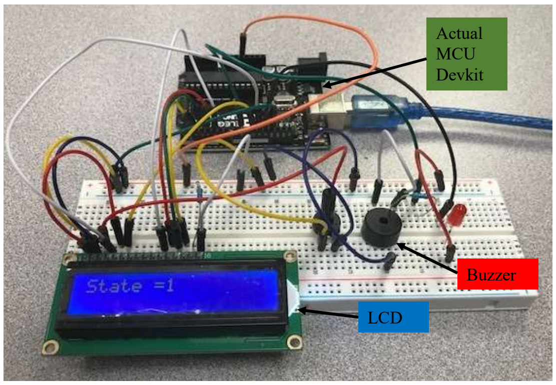


Fig. 7: Prototyping of the proposed Neuro-Detect.

VI. Experimental Results

EEG datasets were taken from widely used open source databases [55]. The database comprised of five datasets: A, B, C, D, and E.In this work, dataset A, D, and E have been used. Each dataset comprised of 100 EEG segments and each segment contains 4097 data points of 23.6 sec duration. Datasets A consists of scalp EEG which is recorded from a healthy subject with eyes open (A), whereas dataset D is recorded from the epileptegenic zone during interictal states. Dataset E comprises of seizure activity. Datasets D and E were obtained with icEEG. The data sampling rate and spectral bandwidth of the acquisition system were 173.61 Hz and 0.53-40 Hz, respectively. EEG epochs from different datasets are shown in Fig. 8a. The approximation and detail coefficients (D1, D2, D3, D4 and A4) for the decomposed sample EEG epoch are shown in Fig. 8b. The Hjorth parameters and statistical feature were calculated from the decomposed sub-bands.

Tables IV, V, and VI show the activity (AC), signal complexity (SC), and standard deviation (SD) of the different sub-bands. The average signal complexity (SC) values for A, D, and E were computed as 0.71, 0.65, and 0.48. It is evident from the experimental results that the signal complexity drops whenever a seizure occurs, which supports the findings reported in [30]. However, the activity and standard deviation value are lower in datasets A and D compared to dataset E. Dataset A, which consists of normal scalp EEG, is almost identical to dataset D (seizure free icEEG). Extracted features from different sub-bands were applied to a k-NN and DNN classifier. The following cases were tested in this work:

(1) Case 1: Set A versus Set E

(2) Case 2: Set A and Set D versus Set E.

TABLE IV: Extracted feature coefficients for dataset A

Coefficient	Activity	Signal Complexity	Standard Deviation
D1	18.44	0.9371	4.29
D2	362.5	0.4688	19.03
D3	3.88e+03	0.7145	62.33
D4	7.33e+03	1.2315	85.66
A4	1.91e+04	1.4909	138.14

TABLE V: Extracted feature coefficients for dataset D

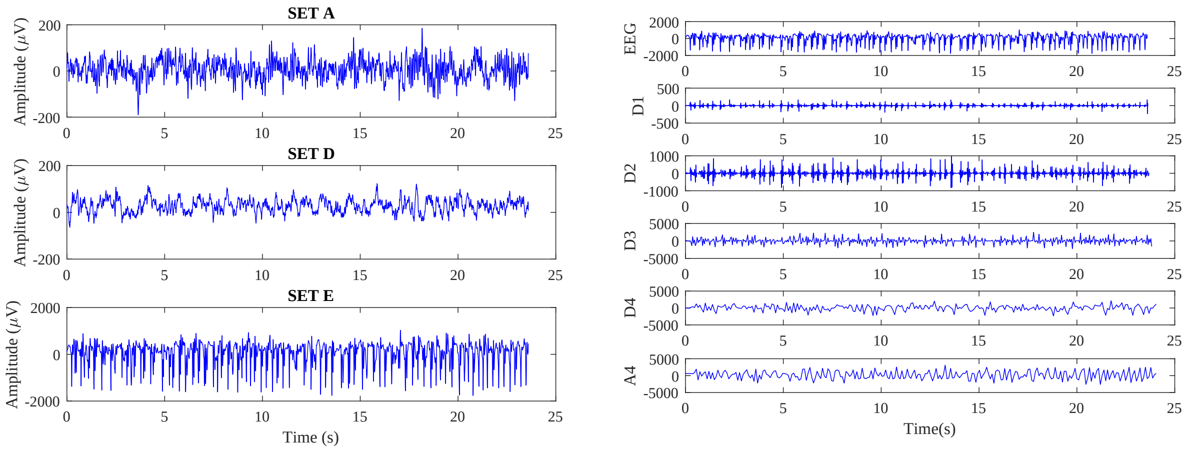
Coefficient	Activity	Signal Complexity	Standard Deviation
D1	24.73	0.8951	4.97
D2	252.48	0.4432	15.88
D3	3.07e+03	0.7043	55.43
D4	1.41e+04	1.0251	118.75
A4	6.07e+04	1.3509	246.54

TABLE VI: Extracted feature coefficients for dataset E

Coefficient	Activity	Signal Complexity	Standard Deviation
D1	1.42e+03	0.7797	37.75
D2	5.82e+04	0.3881	241.38
D3	5.45e+05	0.5904	738.63
D4	3.07e+05	0.6281	554.08
A4	6.33e+05	0.7126	796.08

The k-NN classifier was trained using a training dataset and the accuracy of the classification was evaluated through the testing data. For case 1, the classifier was trained on 80% (80 EEG epochs) of each set, and 20% (20 EEG epochs) of each set was used for testing. For case 2, 85% (85 EEG epochs) of the datasets was similarly used for training, whereas 15% (15 EEG epochs) was used for testing. k =2 was used for the classification. In the later approach, the DNN is trained and validated using the training datasets and the performance of the classification was measured using the testing data. In both case 1 and case 2, 70% of each dataset was used for training, whereas 15% was used for validation, and 15% was used for testing. Case 1 (A-E) only considered seizure and normal EEG. The comparison of A-E with existing algorithms provides an idea on the effectiveness of the proposed algorithm. On the other hand, case 2 (AD-E) considered normal, interictal, and seizure activities which is more useful for practical applications. The distribution of EEG epochs is shown in Table VII.

The performance parameters were calculated for both the individual and the combined features using the k-NN and



(a) (b)

Fig. 8: (a) Example scalp EEG and icEEG from datasets A, D, and E. (b) Decomposed EEG from set E (ictal icEEG).

TABLE VII: Distribution of EEG Epochs for Training and Testing

Methods and cases	Training Epoch	Testing Epoch
k-NN training and testing for Normal VS ictal (A-E)	80 Epoch (A) 80 Epoch (E)	20 Epoch (A) 20 Epoch (E)
DNN training and testing for Normal and interictal VS ictal (AD-E)	85 Epoch (A) 85 Epoch (D) 85 Epoch (E)	15 Epoch (A) 15 Epoch (D) 15 Epoch (E)

DNN algorithm. Table VIII summarizes the results showing the classification accuracy, precision, recall, and F1-score with individual and combined features. The accuracy, precision, recall, and F1-score of the classifier were evaluated as follows:

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{Total Instances}} \quad (15)$$

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \quad (16)$$

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \quad (17)$$

$$\text{F1-score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \quad (18)$$

For both k-NN and DNN based approaches, in case 1 (dataset A versus E), the classification accuracy was measured as 100% for combined and individual features. In case 2 (dataset A and D versus E), the k-NN classifier shows an accuracy of 97.8% for AC. The classification accuracy dropped to 95.3% for the individual feature SD and 95.1% for the combined feature AC+SD. In case 2, the DNN reported a highest accuracy of 98.6% for the combined feature AC+SC+SD. The classification accuracy dropped to 94.3% for the individual feature SD. A Network with sigmoid activation reports a better and consistent accuracy for the varied features that have been extracted from EEG dataset. The experimental results show that the DNN classifier provides better performance for two hidden layers (Hl) with 10 neurons in each layer. The number of neurons on the hidden layers has been determined by trial and error and it is seen that an excessive increase in hidden neurons negatively affects the accuracy. A random combination of hidden neurons also reported a reduction in accuracy. Fig. 9 shows the variation of accuracy with the change in the number of neurons in each hidden layer. Table VIII shows the comparison between k-NN and DNN classifiers and it is evident that DNN provides better accuracy for normal and interictal vs. ictal EEG (case2). Figure 10 compares existing competitive methods and demonstrates the suitability of the proposed system. The average latency of the proposed system is negligible (a few milliseconds). The estimated power consumption for the proposed system is 34.5 μW. A comparison with existing seizure detection algorithms is shown in Table IX.

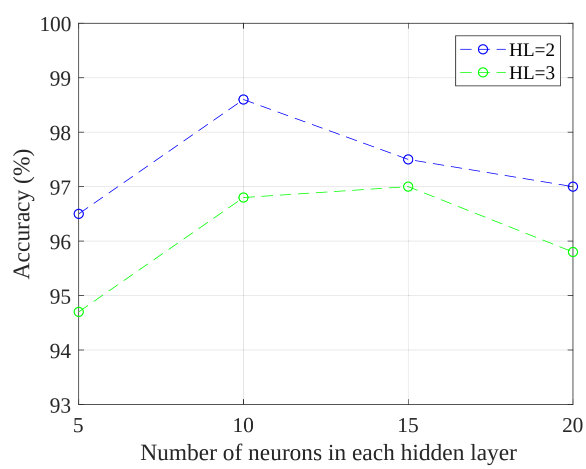


Fig. 9: Variation of accuracy with number of hidden neurons: Case 2: (Normal and interictal vs. ictal) AC+SC+SD

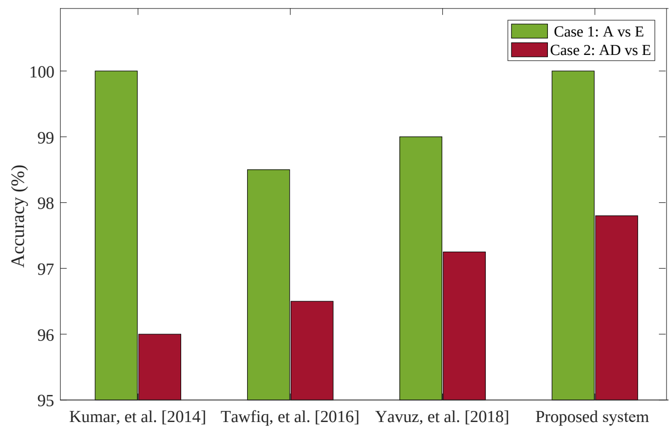


Fig. 10: Comparison of accuracy (in %) with existing methods

TABLE VIII: Performance of DNN and k-NN classifier for different features.

Method	Case	Performance	AC+SC+SD	AC+SC	AC+SD	SC+SD	AC	SD
k-NN	A-E	Accuracy (%)	100	100	100	100	100	100
		Precision (%)	100	100	100	100	100	100
		Recall (%)	100	100	100	100	100	100
		F1-score (%)	100	100	100	100	100	100
	AD-E	Accuracy (%)	96.4	96.6	95.1	96.7	97.89	95.3
		Precision (%)	97.3	97.8	94.5	95.5	98.5	94.5
		recall (%)	94.1	93.7	97	97	94.7	97
		F1-score (%)	95.6	95.7	95.7	96.2	96.5	95.7
DNN (No. of Hidden Layer=2)	A-E	Accuracy (%)	100	100	100	100	100	100
		Precision (%)	100	100	100	100	100	100
		Recall (%)	100	100	100	100	100	100
		F1-score (%)	100	100	100	100	100	100
	AD-E	Accuracy (%)	98.65	97.8	97.3	97.6	95.6	95.7
		Precision (%)	99.1	96.9	97.2	98.4	94.1	97.8
		Recall (%)	97.3	100	97	95.4	100	92
		F1-score (%)	98.2	98.4	97.1	96.8	96.9	94.8
DNN (No. of Hidden Layer=3)	A-E	Accuracy (%)	100	100	100	100	100	100
		Precision (%)	100	100	100	100	100	100
		Recall (%)	100	100	100	100	100	100
		F1-score (%)	100	100	100	100	100	100
	AD-E	Accuracy (%)	96.8	96.5	95.2	96.1	94.6	94.3
		Recall (%)	95.6	98.3	96.1	94.4	96	93.5
		Precision (%)	97.5	95.9	94.8	97.1	93.4	95.5
		F1-score (%)	96.5	97.1	95.4	95.7	94.6	94.4

A-E: Normal VS Ictal, AD-E: Normal and Interictal VS Ictal, AC: Activity, SC: Signal Complexity, SD: Standard deviation

TABLE IX: Comparison with the Existing Seizure Detection Methods.

Works	Methods	Cases	CA (%)
Subasi, et al. 2010 [24]	PCA, ICA and LDA	A-E	98.75 (PCA)
		A-E	99.50 (ICA)
		A-E	100 (LDA)
Orhan, et al. 2011 [40]	κ–means clustering - MLPNN	A-E	99.56
		ABCD-E	99.6
Nicolaou, et al. 2012 [37]	Permutation entropy and SVM	A-E	93.55
		D-E	79.94
Kumar, et al. 2014 [56]	Discrete wavelet transform and neural network classifier	A-E	100
		A, D-E	95
Tawfik, et al. 2016 [57]	Weighted permutation entropy (WPE) and support vector machine (SVM)	A-E	98.5
		A, D-E	96.5
Yavuz, et al. 2018 [58]	Cepstral analysis and generalized regression neural network	A-E	99
		A, D-E	97.25
Current Paper 2018	DWT based feature extraction and DNN classifier	A-E	100
		A, D - E	98.65

A-E: Normal VS Ictal, AD-E: Normal and Interictal VS Ictal

VII. Conclusions

In this paper, a machine learning based automated seizure detection method has been proposed in the IoT framework, which utilizes Hjorth parameters as well as statistical features, and DWT based feature extraction. The system was validated using a hardware-in-loop based simulation approach. The experimental results show that the proposed approach is highly effective in understanding complex EEG dynamics, which leads to an improved classification accuracy as compared to existing algorithms. Future research includes prototyping the architecture at a board level using to realize a high-speed version which can be better integrated within an IoT and smart healthcare framework. The proposed framework can be expanded to include wireless icEEG sensors, biosensors, or other wearable sensors such as limb worn accelerometers to detect users' abnormal activity including convulsive seizures [59, 60]. The information from these sensors can be fused with information from EEG sensors to provide a much richer and more holistic capture of users' activity and state.

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