RSeiz: A Channel Selection based Approach for Rapid Seizure Detection in the IoMT

Md Abu Sayeed
Dept. of Computer Science and Engineering
University of North Texas, USA.
Email: mdsayeed@my.unt.edu

Saraju P. Mohanty
Dept. of Computer Science and Engineering
University of North Texas, USA.
Email: saraju.mohanty@unt.edu

Elias Kougianos
Dept. of Electical Engineering
University of North Texas, USA.
Email: elias.kougianos@unt.edu

Laavanya Rachakonda
Dept. of Computer Science and Engineering
University of North Texas, USA.
Email: rl0286@unt.edu

***Abstract*—Epilepsy affects 1% of the world population, which necessitates a fast seizure detection system for practical epilepsy solutions. The reduction of seizure detection delay is a critical problem which needs to be addressed as rapid detection provides effective treatment. In this paper an electroencephalogram (EEG) based, patient-specific seizure detection system is proposed in the Internet of Medical Things (IoMT) framework which can detect seizures at a minimum delay. The proposed system uses neighborhood component analysis (NCA) for channel selection, statistical features for optimal feature extraction, and a ReliefF-based optimization (RBO) in conjunction with a κ-nearest neighbor classifier for feature classification. A publicly available database (CHB-MIT EEG) has been used for evaluation of the proposed algorithm. The simulation results show that the proposed algorithm provides a sensitivity of 100% while maintaining a low average latency of 1.49 sec, which may be useful for practical epilepsy treatment and biomedical applications.**

***Index Terms*—Internet of Medical Things (IoMT), Smart Healthcare, Seizure Detection, Seizure Early Detection, Electroencephalogram (EEG), Epilepsy**

I. Introduction

In this paper, a real time seizure detection is proposed in the IoMT framework. EEG Signals are initially analyzed using neighborhood component analysis (NCA) and optimal channels are determined. The EEG signals of selected channels are then partitioned continuously by a moving window. Features are then extracted from each segment which form a feature vector, and finally feature vectors are trained and classified using an optimized κ-nearest neighbor (κ-NN) classifier. The IoMT framework enables recording of a patient's day to day activities and allows access to healthcare data anywhere, anytime [1]. The proposed system is conceptualized in Fig. 1.

This paper clarifies the basic terms of seizure detection in section II. Section III discusses novel contributions. Section IV describes related prior research. The seizure detection algorithm is discussed in section V. The architecture of the proposed system is illustrated in Section VI. Section VII discusses the implementation and experimental results. Section VIII concludes the paper with suggestions for further research.

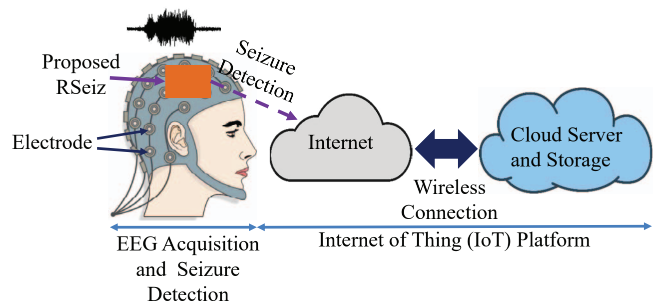

Fig. 1: Module of the proposed system.

II. Seizure - Detection, Early Detection, Real-Time Detection, and Prediction

The term "Seizure Detection" generally refers to the detection of a seizure occurrence using biological signals obtained from the epileptic subjects. Seizure detection algorithms analyze the input signals and classify the segmented signals into seizure or non-seizure states. In early detection input signals or data points are continuously analyzed and a seizure state is detected at a minimum delay. Seizure prediction is the forecasting of an impending seizure and is different from seizure detection. Fig. 2 conceptualizes and clarifies the definition of seizure detection, early detection, and early prediction. A denotes the typical detection delay associated with existing algorithms, which is approximately 6 sec or more, whereas B is the delay for early detection, which is expected to be 1$\sim$2 sec. C is the time before the seizure onset, which indicates seizure prediction.

III. Novel Contributions of This Paper

In this paper, a real time seizure detection system which monitors EEG signals continuously and detects seizure quickly is proposed. The proposed algorithm removes unnecessary and less significant channels and features, which eliminates redundant computations and reduces the latency of the system. The extracted feature values are highly effective in capturing

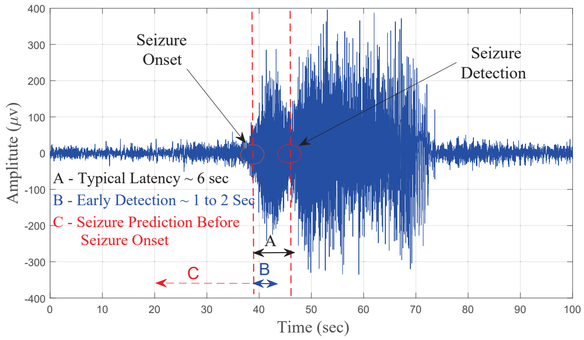

Fig. 2: Time domain characterization of an epileptic seizure.

complex EEG dynamics, which helps in distinguishing seizure and non-seizure behavior. The IoMT framework provides remote connectivity with other healthcare devices. Experimental results show that proposed system reduces detection latency considerably while maintaining high sensitivity, which makes it a suitable candidate for practical epilepsy treatment.

IV. Related Previous Research

A scalp EEG dataset is analyzed for epileptic seizure using a wavelet transform based algorithm in [2], with a reported sensitivity and latency of 76% and 10 sec, respectively. A seizure detection algorithm [3] is introduced in the edge-IoMT framework which uses a Naive Bayes classifier for classification of the query point. A support vector machine (SVM) based seizure classification method is presented in [4], which is extensively validated with scalp EEG dataset and results in a sensitivity and mean detection latency of 96% and 4.6 sec, respectively. The signal rejection algorithm (SRA) based algorithm in [5] eliminates unwanted signal and noise which in turn improves the classification accuracy and provides a sensitivity and latency of 96.9% and 3.6 sec, respectively. A deep neural network (DNN) based detection technique is explored in the short duration icEEG dataset. The extracted Hjorth parameters from the icEEG dataset capture the seizure and non-seizure activities effectively and improve the detection performance considerably [6]. An non-invasive approach alternative to EEG was proposed recently [7] for the detection of convulsive seizure using a wrist-worn accelerometer device. A temporal synchronization based seizure detection method has been proposed in [8] where a complex model represents the recurrence pattern of normal EEG and ictal EEG and results in a latency of 6 sec. In the local mean decomposition (LMD) based approach [9], the EEG signal is decomposed to several product functions (PF) and features are extracted.

V. The Proposed Novel Algorithm for Seizure Rapid Detection

EEG signals are preprocessed through a band pass filter and are then passed to the neighborhood component analysis (NCA) module for channel selection. The extracted features from the selected channels are then submitted to the optimized κ-NNalgorithm for seizure classification. The flowchart of the proposed system is shown in Fig. 3.

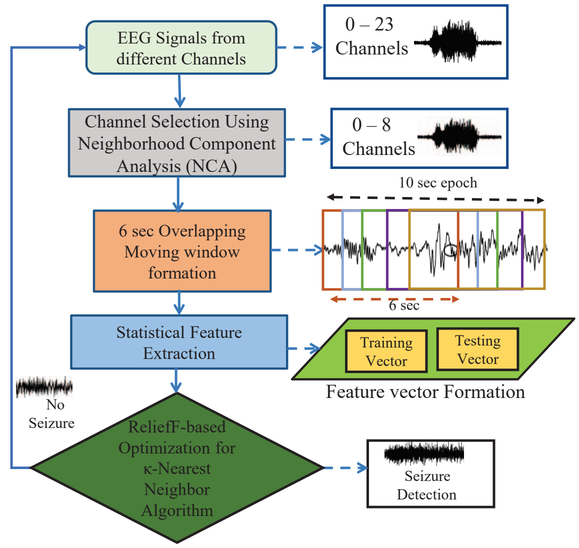

Fig. 3: Flowchart of the proposed algorithm.

A. Channel selection using neighborhood component analysis

If all EEG channels are considered for feature extraction, the computation time as well as latency will be high. It would be useful to select an optimal number of channels which could provide high detection accuracy and low latency. Consider a training set T of n observations which include both seizure and non-seizure instances:

$$T = (B_i, b_i) \qquad i = 1, 2, \ldots, N, \tag{1}$$

where B_i is the feature vector and b_i is the corresponding class label. The weighted distance between two observations (B_i, B_j) is [10]:

$$D_w(B_i, B_j) = \sum_{q=1}^{d} {w_q}^2 |B_{iq} - B_{jq}|, \tag{2}$$

where w_q denotes the weight of the q-th channel. In the training set, the leave one out classification accuracy is maximized. The probabilistic distribution function is used for choosing the reference point. The probability of B_j being chosen as a reference point for B_i is [10]:

$$P_{ij} = \begin{cases} \frac{k(D_w(B_i,B_j))}{\sum_{k \neq i} k(D_w(B_i,B_j))}, & \text{if } i \neq j \\ 0, & \text{if } i = j \end{cases} \tag{3}$$

The probability of the correct classification of B_i is:

$$p_i = \sum_j b_{ij} p_{ij} \tag{4}$$

The approximate leave one out classification accuracy is [10]:

$$\epsilon(w) = \frac{1}{N} \sum_i p_i = \frac{1}{N} \sum_j \sum_j b_{ij} p_{ij} \tag{5}$$

A regularization term λ is introduced for mitigating the problem of over-fitting and channel selection, which leads to the following error function:

$$\epsilon(w) = \sum_{j}\sum_{j} b_{ij}p_{ij} - \lambda \sum_{q=1}^{d} {w_q}^2 \tag{6}$$

The best value of λ leads to minimum classification loss.

B. Feature extraction using statistical parameters

Statistical features such as variance, signal mobility, and signal complexity are useful for describing complex biomedical signal. Variance refers to the variations of the sample points from the mean. Complexity and mobility refer to the 1st and 2nd order variations along a signal. Frequency information of the signal is contained in these parameters and as a result, non-stationary EEG signals are better characterized and distinguished using these features [6], [11].

1) Variance: It is calculated by:

$$VAR_{EEG-seg} = \frac{1}{L-1}\sum_{k=1}^{L} |x_k - \mu_{EEG-seg}|^2, \tag{7}$$

where x_k is the k^{th} sample of the epoch, $\mu_{EEG-seg}$ is the mean of the epoch or segment and L is the length of the segment.

2) Mobility: The 1st order variations can be represented by:

$$MOB_{EEG-seg} = \sqrt{\frac{VAR_{EEG-seg}(x'(t))}{VAR_{EEG-seg}(x(t))}} \tag{8}$$

where $x(t)$ is the raw EEG signal.

3) Complexity: The 2nd order variations along a EEG segment are [6]:

$$COM_{EEG-seg} = \frac{MOB_{EEG-seg}(x'(t))}{MOB_{EEG-seg}(x(t))} \tag{9}$$

C. ReliefF-based optimization (RBO) for κ Nearest Neighbor (κ-NN) algorithm for feature classification

The RelifF algorithm (RBA) [12], [13] calculates the score for each feature iteratively. The features with top scores are applied to the classifier for feature classification. The elimination of irrelevant features reduces computational burden of classifiers. Consider a set of features or predictors $F1, F2, \ldots, Fn$ with predictor weights $FW1, FW2, \ldots, FWn$. Initially all weights are set to zero. The algorithm selects a random instance z_u and finds κ nearest instances and all the weights are updated for each nearest neighbor z_v. If z_u and z_v are within the same class, the weight of the feature F_j at the ith iteration are computed by [13], [14]:

$${FW_j}^i = {FW_j}^{i-1} - \frac{\Delta_j(z_u, z_v)}{q_{EEG}} * d_{uv}. \tag{10}$$

If z_u and z_v are from different classes this becomes:

$${FW_j}^i = {FW_j}^{i-1} - \frac{p_{y_v}}{1-p_{y_u}}\frac{\Delta_(z_u, z_v)}{m_{EEG}} * d_{uv}, \tag{11}$$

where d_{uv} is the distance function. p_{y_v} and p_{y_u} denote the prior probability of the class to which z_u and z_v belong, respectively. m_{EEG} indicates the update for iterations. The difference in feature values for two instances z_u and z_v is given by [14]:

$$\Delta_(z_u, z_v) = \frac{|z_{uj} - z_{vj}|}{\max(F_j) - \min(F_j)} \tag{12}$$

The κ-NNalgorithm consists of two phases: a training phase and a classification phase. The updated feature vectors from the RBO and class labels of the training samples are stored in the training phase. In the classification phase, a query point to be tested is submitted to the classifier, the algorithm determines the κ nearest neighbors and a class is assigned to the query point by voting among the neighbors. To achieve high classification accuracy, only two parameters need to be tuned: the κ value and the distance metric. The selection of the κ value for the computation of nearest distance is a critical task. The effect of noise can be reduced by using a larger value of κ but a larger κ also weakens the boundary between different classes. The performance of the classifier depends on distance metric and the value of κ. If $G = (g1, g2, g3, \ldots, gn)$ and $H = (h1, h2, h3, \ldots, hn)$ are two points in the feature vector space, their Euclidean distance is [15] :

$$d_{EEG-feature}(g, h) = \sqrt{\sum_{i=1}^{n}(g_i - h_i)^2}, \tag{13}$$

VI. The Proposed Rapid Seizure Detection System

The architecture of the proposed real time system is shown in Fig. 4. EEG signals are passed through a band pass filter, which eliminates unwanted noise and retains only useful signals. The filtered signal is applied to NCA for channel selection. The EEG signals of desired channels are divided to a 6 sec moving window. The moving window is further subdivided into three 2 sec segments. Signal complexity, signal mobility and variance are extracted from each segment and then the window is moved by 1 sec. The feature vector is formed by repeating the process [16]. The classifier is trained using training feature vectors of specified length, as discussed above. In the classification phase, the moving window is continuously given to the system which forms the feature vector for the specified window, which is then given to κ-NNclassifier for the detection of seizure.

A. Preprocessing and Channel Selection Unit

EEG signals are applied to a low pass filter with cutoff frequency of 32 Hz. Scalp electrodes are placed in different areas of the scalp. The EEG data acquisition system generally includes more than 20 channels. The analysis and computation from all the channels is cost and time expensive. The channel selection unit analyzes all the channels based on NCA and keeps only the useful channels.

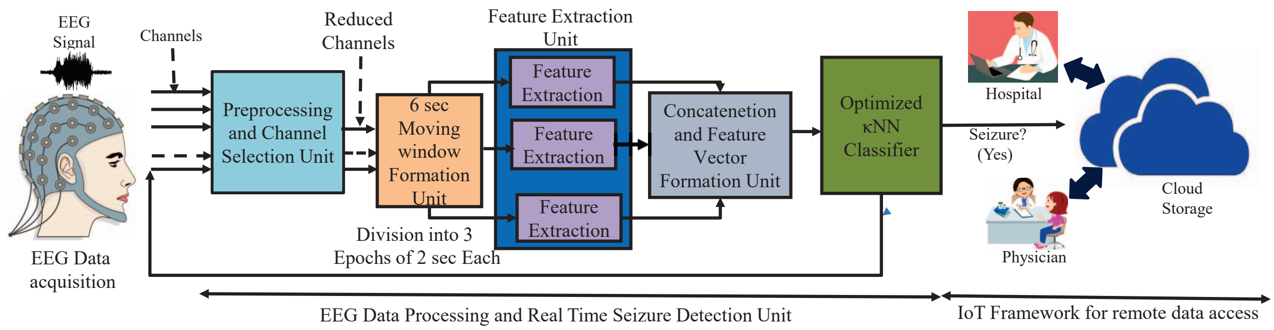

Fig. 4: Architecture of the proposed system.

B. Moving Window Formation Unit

The moving window formation unit is the crucial part of the real time seizure detection and consists of three non-overlapping 2 sec EEG segments. The current window will be overlapping by 5 sec with the next window (Fig. 5). The length of the moving window and non-overlapping segment play a pivotal role for characterizing seizure progression and maintaining detection delay. The non-overlapping 2 sec segment contains 512 samples, which are sufficient for characterizing the signals and for further analysis.

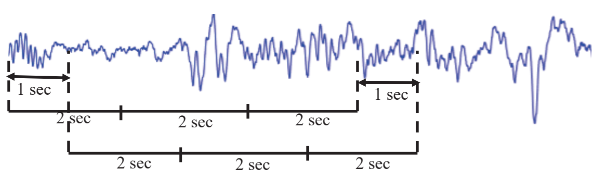

Fig. 5: 6 sec moving window and 5 sec overlap.

C. Feature Extraction Unit

Each non-overlapping segment is submitted to the feature extraction unit and variance, signal mobility, and complexity are extracted. These parameters measure the level of variations along a signal and these parameters are very useful in characterizing non-stationary EEG dynamics.

D. Concatenation and Feature Vector Formation Unit

Extracted features from non-overlapping segments are concatenated and form the feature vector. During offline training, features are concatenated to form a training feature vector. Its length is dependent on training time. The training time is a crucial factor for controlling detection accuracy and latency. In the online classification phase, features are concatenated to form testing feature vectors continuously from the moving window and applied to the machine learning classifier for further analysis.

E. Optimized κ-Nearest Neighbor Classifier

The classification of query points based on distance is simple but highly effective [15]. The ReliefF-based optimization (RBO) discards irrelevant features and reduces the size of the training and testing feature vectors. In the offline training, the training feature vector is given to the κ-NNclassifier and the classifier is trained. In the real time classification phase, the system continuously forms testing feature vectors from the moving window and passes them to the classifier. The classifier analyzes the feature vectors and determines the κ nearest neighbors and finally, a class is assigned to the testing vector by voting among the neighbors.

VII. Implementation and Validation of The Proposed System

EEG data were taken from the CHB-MIT scalp EEG database [17], [4] with sampling frequency of 256 Hz. 6 epileptic subjects (chb01, chb02, chb03, chb05, chb08, and chb11) were considered. EEG signals were given to a 32 Hz low pass filter. The filtered signals were submitted to NCA for channel selection. The dataset was analyzed and significant channels were selected. The regularization parameter λ for NCA was computed from 10-fold cross validation. As an example, for epileptic subject 1 (chb01) in each fold, average loss value was calculated and the minimum loss corresponds to the best λ = 0.000264. The ictal or interictal patterns are not identical for different subjects, hence, the best λ value may vary according to epileptic subjects. The significant channels were selected according to channel weights. The weights of the following significant channels were greater than the threshold value: F7-T7 (2), P7-O1 (4), FP1-F3 (5), FP2-F8 (13), F8-T8 (14), FZ-CZ (17), T7-FT9 (20), FT9-FT10 (21). 8 significant channels were retained and the other 15 channels were removed. Fig. 6 show the variation of channel weight with channel index.

The moving window consists of 1536 points and was subdivided into P=3 non-overlapping epochs of 512 points (2 sec each). The Q=3 features signal complexity (SC), signal mobility (SM), and variance were extracted from each P segments which were then concatenated. For N=8 channels, the obtained feature vector contains $N \times P \times Q$ =72 elements for the 6 sec moving window. RBO ranked the elements from 1 to 72 and 1-30 ranked elements from different positions of the timing window were used to form the updated feature vector. The κ-NNclassifier was trained with 2-4 hours of inter-ictal data and 0.5-2 hours of normal EEG, whereas for a patient with s seizures, $s-1$ number of ictal EEG was used for the

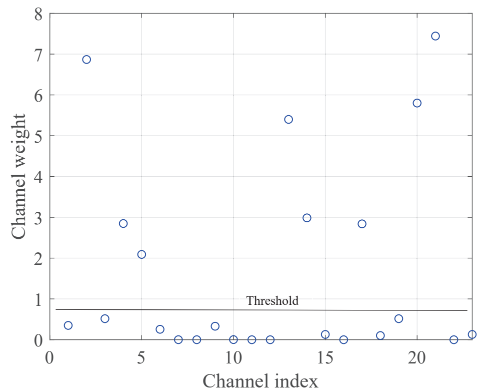

Fig. 6: Variation of channel weight with channel index.

training. For the proposed patient specific seizure detection, NCA selected the channels in the training phase which helped to reduce detection delay in the testing or classification phase. Seizure is denoted as '1' and non-seizure (inter-ictal or normal) EEG is denoted as '0'. In the training phase, data was continuously taken as a 6 sec overlapping window and formed the training feature vectors. In the real time classification phase, the window was continuously analyzed whether it is seizure or not. κ=2 was used for the κ-NNclassifier. The system was implemented using MATLAB® and ThingSpeak. Fig. 7 shows the variation of feature values with time. It is clear from the extracted features that the feature value drops during inter-ictal activities. The performance of the proposed algorithm is evaluated by sensitivity and latency. The sensitivity is defined as follows [5]:

$$\text{Sensitivity} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \tag{14}$$

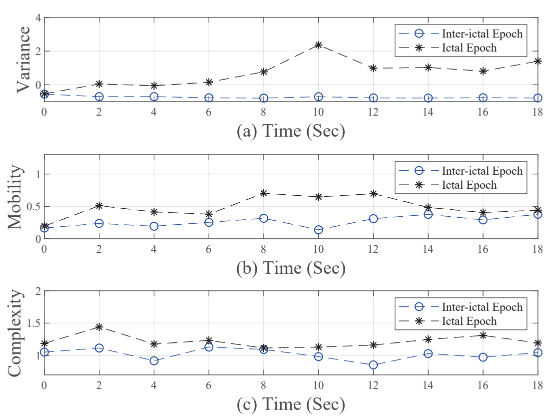

Fig. 7: Variation of Variance, Mobility, and Complexity for ictal and inter-ictal EEG.

Seizure detection delay is the difference between the actual seizure onset point marked by an expert and the seizure detection point determined by the seizure detection system. The proposed approach was validated with 6 epileptic subjects of 30 seizures. All the seizures were correctly detected providing a sensitivity of 100%. Fig. 8 shows the average latency of each patient and the average latency for 6 subjects is 1.49 sec. The highest average latency of 2.6 sec was found for epileptic subject 5 (chb08) whereas subject 3 (chb03) reported the lowest average latency of 0.53 sec.

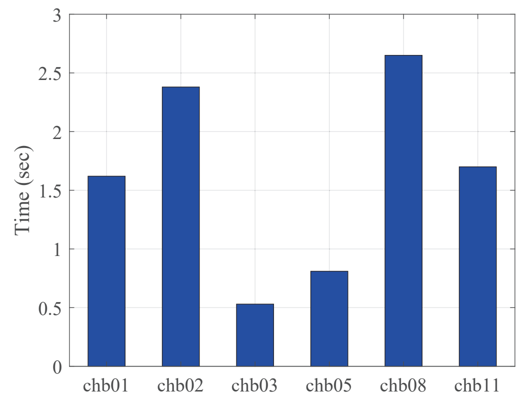

Fig. 8: Variation of latency for different epileptic subjects.

The characterization of the proposed system is shown in Table I. Without ReliefF based optimization (RBO), the proposed system reported an average latency of 1.6 sec, since irrelevant features increase the computational burden. Table II shows the performance comparison with existing algorithms. The short duration nature of the Bonn dataset would not provide proper evaluation of the latency, hence, it was not considered for latency comparison. Simulation results reported a sensitivity and latency of 100% and 1.49 sec, respectively, which is a considerable improvement compared to existing algorithms.

TABLE I: Characterization of the proposed system

Parameter	Value
Sampling frequency	256 Hz
Low cut-off frequency	0 Hz
High cut-off frequency	32 Hz
Best λ (NCA)	0.000264 (varies)
κ value (κ-NN)	2
Distance metric (κ-NN)	Euclidean
Sensitivity	100%
Latency	1.49 sec

VIII. Conclusions and Future Directions

We propose a real time system for seizure detection in the IoMT framework using feature extraction, NCA, and RBO with a κ-NNclassifier. The proposed IoMT-based seizure detection system was implemented using MATLAB® and ThingSpeak. The experimental results evaluated using the CHB-MIT database show that the statistical feature values for seizure and non-seizure EEG are different, providing a high sensitivity of 100 %. NCA eliminates low weighted channels, RBO discards irrelevant features and reduces computation time, rendering an average detection latency of 1.49 sec, which is considerably less compared to existing algorithms. The proposed system can be useful for low latency implantable or wearable applications.

TABLE II: Performance comparison with existing works

Reference	Dataset	Methods	Sensitivity (%)	Latency (sec)
Saab, et al. [2]	Private database from Montreal neurological institute and hospital	Feature extraction, Five level Wavelet decomposition, Bayesian formulation	78	9.8 (median)
Shoeb, et al. [4]	CHB-MIT scalp EEG database	Temporal and spectral features, Support Vector Machines (SVMs)	96	4.6 (mean)
Kusmakar, et al. [7]	CHB-MIT scalp EEG database	Spatial Temporal synchronization using complex network model	98	6
Fan, et al. [8]	Freiburg (Bonn) Database	Loacl mean decomposition (LMD), k-NN, LDA, SVM, GA-SVM	98.1	NA
Vidyaratne, et al. [16]	CHB-MIT scalp EEG database	Fractal dimension (FD), harmonic wavelet packet transform (HWPT), Relevance Vector Machine	96	1.89
Sayeed, et al. [6]	Bonn Database	DWT based deep neural network (DNN)	98.65	NA
Sayeed, et al. [5]	CHB-MIT scalp EEG database	Signal amplification and signal rejection algorithm (SRA)	96.9	3.6
Proposed System	CHB-MIT scalp EEG database	NCA, Feature extraction, and ReliefF based optimization (RBO), and κ-NNclassifier	100	1.49

Future research includes validation of the proposed system with large scale databases, including both scalp EEG and intracranial EEG (icEEG). We will also explore integrating with drug-delivery systems for fast seizure control [18]. Security consideration as the overall system in IoMT enabled is an important research direction [19], [20].

ACKNOWLEDGMENTS

The authors would like to acknowledge the inputs of Dr. Hitten P. Zaveri, Department of Neurology at Yale University, USA, on this work.

REFERENCES

[1] A. Zanella, N. Bui, A. Castellani, L. Vangelista, and M. Zorzi, “Internet of Things for Smart Cities,” *IEEE Internet of Things Journal*, vol. 1, no. 1, pp. 22–32, Feb 2014.

[2] M. Saab and J. Gotman, “A System to Detect the Onset of Epileptic Seizures in Scalp EEG”,” *Clinical Neurophysiology*, vol. 116, no. 2, pp. 427 – 442, 2005.

[3] M. A. Sayeed, S. P. Mohanty, E. Kougianos, V. P. Yanambakha, and H. Zaveri, “ A Robust and Fast Seizure Detection in IoT Edge ,” in *Proceedings of IEEE International Symposium on Smart Electronic System (iSES)*, Hyderabad, India, 2018, pp. 156–160.

[4] A. Shoeb and J. Guttag, “Application of Machine Learning to Epileptic Seizure Detection,” in *Proceedings of the 27th International Conference on International Conference on Machine Learning*, Haifa, Israel, 2010.

[5] M. A. Sayeed, S. P. Mohanty, E. Kougianos, and H. P. Zaveri, “eSeiz: An Edge-Device for Accurate Seizure Detection for Smart Healthcare,” *IEEE Transactions on Consumer Electronics*, vol. 65, no. 3, pp. 379–387, August 2019.

[6] M. A. Sayeed, S. P. Mohanty, E. Kougianos, and H. P. Zaveri, “Neuro-Detect: A Machine Learning Based Fast and Accurate Seizure Detection System in the IoMT,” *IEEE Transactions on Consumer Electronics*, vol. 65, no. 3, pp. 359–368, August 2019.

[7] S. Kusmakar, C. K. Karmakar, B. Yan, T. J.O’Brien, R. Muthuganapathy, and M. Palaniswami, “Automated Detection of Convulsive Seizures Using a Wearable Accelerometer Device,” *IEEE Transactions on Biomedical Engineering*, vol. 66, no. 2, pp. 421–432, Feb 2019.

[8] M. Fan and C. Chou, “Detecting Abnormal Pattern of Epileptic Seizures via Temporal Synchronization of EEG Signals,” *IEEE Transactions on Biomedical Engineering*, vol. 66, no. 3, pp. 601–608, March 2019.

[9] T. Zhang and W. Chen, “LMD Based Features for the Automatic Seizure Detection of EEG Signals Using SVM,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 25, no. 8, pp. 1100–1108, Aug 2017.

[10] W. Yang, K. Wang, and W. Zuo, “Neighborhood Component Feature Selection for High-Dimensional Data.” *Journal of Computers*, vol. 7, no. 1, Jan. 2012.

[11] D. Shon, K. Im, J.-H. Park, D.-S. Lim, B. Jang, and J. Kim, “Emotional Stress State Detection Using Genetic Algorithm-Based Feature Selection on EEG Signals,” *International Journal of Environmental Research and Public Health*, vol. 15, no. 11, p. 2461, Nov. 2018.

[12] M. Robnik-Šikonja and I. Kononenko, “Theoretical and Empirical Analysis of ReliefF and RReliefF,” *Machine Learning*, vol. 53, no. 1, pp. 23–69, Oct 2003.

[13] R. J. Urbanowicz, M. Meeker, W. L. Cava, R. S. Olson, and J. H. Moore, “Relief-based Feature Selection: Introduction and Review,” *Journal of Biomedical Informatics*, vol. 85, pp. 189 – 203, 2018.

[14] MathWorks, *Statistics and Machine Learning Toolbox: Users Guide (R2019a)*. Natick, Massachusetts: The MathWorks Inc., 2019. [Online]. Available: https://www.mathworks.com/help/pdf_doc/stats/stats.pdf

[15] I. Saini, D. Singh, and A. Khosla, “QRS Detection Using K-Nearest Neighbor Algorithm and Evaluation on Standard ECG Databases,” *J. Adv. Res.*, vol. 4, no. 4, pp. 331–344, July 2013.

[16] L. S. Vidyaratne and K. M. Iftekharuddin, “Real-Time Epileptic Seizure Detection Using EEG,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 25, no. 11, pp. 2146–2156, Nov 2017.

[17] A. L. Goldberger, “PhysioBank, PhysioToolkit, and PhysioNet: Components of a New Research Resource for Complex Physiologic Signals,” *Circulation*, vol. 101, no. 23, pp. e215–e220, June 2000.

[18] M. A. Sayeed, S. P. Mohanty, and E. Kougianos, “cSeiz: An Edge-Device for Accurate Seizure Detection and Control for Smart Healthcare,” *arXiv Electrical Engineering and Systems Science*, vol. arXiv:1908.08130, 2019.

[19] S. P. Mohanty, V. P. Yanambaka, E. Kougianos, and D. Puthal, “PUFchain: Hardware-Assisted Blockchain for Sustainable Simultaneous Device and Data Security in the Internet of Everything (IoE),” *arXiv Computer Science*, vol. 1909.06496, Sep 2019.

[20] V. P. Yanambaka, S. P. Mohanty, E. Kougianos, and D. Puthal, “PMsec: Physical Unclonable Function-Based Robust and Lightweight Authentication in the Internet of Medical Things,” *IEEE Transactions on Consumer Electronics*, vol. 65, no. 3, pp. 388–397, Aug 2019.