A Robust and Fast Seizure Detector for IoT Edge

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 Engineering Technology
University of North Texas, USA.
Email: elias.kougianos@unt.edu

Venkata P. Yanambaka
Dept. of Computer Science and Engineering
University of North Texas, USA.
Email: vy0017@unt.edu

Hitten Zaveri
Department of Neurology
Yale University, USA.
Email: hitten.zaveri@yale.edu

***Abstract*—Epilepsy is a neurological disorder which has negative impact on human life quality. Epilepsy affects almost 1% of the world population necessitating a unified system for fast seizure detection as well as remote health monitoring to enhance the daily lives of the epilepsy patients. We envision a smart seizure detection framework in the edge of the Internet of Things (IoT) which is capable of detecting seizures as well as monitoring the patient's healthcare activity remotely. Detection of seizure is performed using the discrete wavelet transform, statistical feature extraction, and a naive Bayes (NB) classifier. The proposed system was implemented and validated using Simulink®, ThingSpeak, and off-the-shelf microcontrollers. Experimental results show that the proposed system reduces latency by 44% compared to a cloud-IoT based system and reports a classification accuracy of 98.65%.**

***Index Terms*—IoT, Electroencephalogram (EEG), Epilepsy, Seizure Detection, Feature Extraction, Naive Bayes Classifier**

I. INTRODUCTION

Traditional healthcare is unable to accommodate the needs of the increasing population. Smart healthcare can be a solution for traditional healthcare which utilizes available resources in an efficient and intelligent way and fulfills everyone's healthcare needs [1]. One specific example of smart healthcare is edge-IoT based epileptic seizure detection. Epilepsy is characterized by recurrent and spontaneous seizures. A seizure is defined as an abnormal electrical activity in the brain marked by loss of consciousness and convulsions. People with epilepsy are more prone to sudden unexplained death (SUDEP) than normal people [2]. Anti-epileptic drugs cannot be an effective cure for refractory patients. Surgery is not an alternative to anti-epileptic drugs if the seizure focus is located on the eloquent area of the cortex. As a result, seizure detection is of high importance, as early detection leads to appropriate and timely treatment [3], [4]. The IoT is an integral part of smart healthcare; it refers to a cyber-physical system where all the real world components are connected together. The IoT acts as a bridge between doctor and patient and enables remote healthcare monitoring and consultations [5]. The IoT helps researchers to design potential frameworks which utilize limited resources to their maximum efficiency. The EEG (Electroencephalogram) contains relevant information related to different physiological states of the brain, which are useful for understanding brain behavior. Abnormal activities in epilepsy patients belong mainly in two types: the interictal state (between seizures) and the ictal sate (seizure). In this paper, we propose an EEG based epileptic seizure detection system in the edge-IoT framework which utilizes the Discrete Wavelet Transform (DWT), feature extraction, and a naive Bayes (NB) classifier (Fig. 1). EEG signals are decomposed using the DWT and statistical features are calculated from the decomposed signals. The extracted features are then applied to the naive Bayes classifier for classification. The EEG signal, as well as the output of the classifier are connected to an open data platform for remote healthcare monitoring.

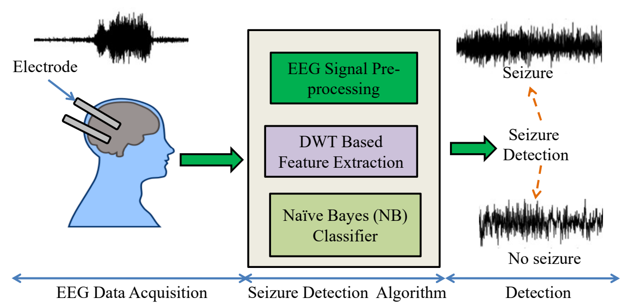

Fig. 1: Proposed seizure detection framework.

The remainder of this paper is organized as follows: Section II discusses the main and novel contributions of this work. Section III describes prior research on IoT-based seizure detection. Section IV discusses the proposed system from the edge-IoT perspective. Section V describes the architecture and design of the proposed seizure detection method. The implementation and validation of the proposed system is shown in Section VI. The paper concludes in Section VII.

II. NOVEL CONTRIBUTIONS OF THIS PAPER

Smart healthcare requires a smart seizure detection system which can provide accurate detection, fast responses and universal connectivity to other healthcare applications. In this paper, an edge-IoT based seizure detection system is proposed. The main contributions of this paper are the following:

1) The proposed seizure detection method utilizes the DWT, statistical features, and a naive Bayes classifier. DWT provides time frequency (TF) localization of the EEG signal. The statistical features show considerable potential to distinguish seizure and non-seizure behavior and the use of the naive Bayes classifier leads to an improved classification accuracy.
2) Cloud computing offers high computational ability and storage with slow response time, whereas edge computing provides less computational capability and storage with fast response time. Internet of Medical Things (IoMT) applications demand fast response with tolerable computation capacity to deal with critical health conditions of the patient. The proposed edge-IoT framework reduces latency compared to cloud-IoT frameworks and provides universal connectivity with ambient intelligence. In the edge-IoT framework, the patient's healthcare data can be accessed from anywhere or at any time for remote consultation.

III. Related previous research

The IoT is becoming an integral part of smart health care. A significant portion of the biomedical research is focused on addressing the new issues on the healthcare domain [5]. The proposed IoT-based seizure detection system can be useful for epileptic patients and enrich smart healthcare considerably.

Several methods have been proposed for seizure detection such as: the κ-Nearest Neighbor (k-NN) algorithm [6][7], support vector machines (SVM) [8], [9], weighted permutation entropy [10], surrogate data analysis, [11], neural networks [12] and deep neural networks [13]. Most of these methods are useful to enhance detection accuracy to a certain amount. As traditional healthcare advances towards smart healthcare, faster seizure detection as well as remote connectivity are becoming more important. So far, few methods have been proposed for seizure detection in the an IoT framework. In [14], an efficient seizure detection has been proposed for portable IoT devices, which eliminates unnecessary features and reduces EEG channel data while maintaining accuracy. A deep learning based seizure prediction has been proposed in the IoT [15], which provides safe storage and large computational resources for the large number of electrodes in the system. A seizure detecting smartwatch [16] shows good potential to detect epileptic seizure, and has been approved by the Food and Drug Administration (FDA). A signal rejection algorithm (SRA) that reduces false detection in is presented in [17]. An accurate edge device has been proposed for seizure detection in the IoT [18], which enables remote health monitoring for patients with medically intractable epilepsy.

IV. Edge Computing : Edge-IoT Perspective

Fig. 2 shows the basic architecture of edge computing for seizure detection, which is divided into the following units:

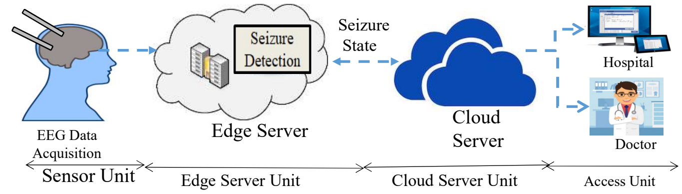

Fig. 2: Architecture of the proposed system in the edge-IoT perspective.

A. Sensor Unit

Millions of sensors and devices are scattered in the large IoT network. The sensor unit is crucial for the IoT as it consumes most of the resource requirements. Most cannot be fulfilled at the sensor unit due to its limited capacity [19], [5]. EEG data acquisition is carried out by the sensor unit. Once data acquisition is complete, it is then sent to the edge server for further processing.

B. Edge Server Unit

In the conventional cloud based IoT, most of the computations are done on the cloud. In edge computing, most of the resource requirements such as EEG data analysis, data processing, and temporary data storage are performed on the edge servers, which enhances the performance of the data computation and storage. EEG data is analyzed and processed here and seizure detection is carried out using the proposed algorithm. This unit also acts as temporary storage for the EEG patient's data [20]. Upon seizure detection, the information corresponding to the patient's seizure state is sent to the cloud. The edge servers only allow necessary information to be sent to the cloud [19].

C. Cloud Server Unit

In edge computing, the cloud servers are deployed far away from the end devices and can provide high computation and large data storage. In practical real time services, the computational requirements of the IoT devices can be satisfied by edge nodes as IoT devices do not demand high computation. Moreover, the power consumption has been significantly reduced through the offloading of computation tasks. The cloud server stores the necessary information relating to seizure and non-seizure states.

D. Access Unit

Health professionals can access the cloud data from anywhere and anytime, which provides universal connectivity to the IoT devices and enables remote health services. In the case of a health abnormality, the doctor will be notified by a message. The doctor will then prescribe the required dosage by analyzing the patient's medication history [18].

The edge-IoT based seizure detection provides the following advantages over cloud-IoT based seizure detection.

1) Millions of IoT devices create a large amount of data. The transmission of these large data sets to the cloud

consumes huge network bandwidth and leads to a large transmission delay. IoT gateways migrate pre-processing and aggregation of the data into the edge which reduces transmission delay and bandwidth requirements.

2) IoT devices generate vast amounts of data which need to be stored in a storage server. In cloud computing, the simultaneous storage of massive data in the cloud leads to obstruction in the network. For instance, EEG produces massive data which should be stored in the storage device and processed within a time constraint. The performance of the cloud computing based storage is not satisfactory because of traffic in the network. In edge computing, the traffic in the network can be mitigated by offloading the storage demand to the different edge storage nodes.

V. The Proposed Seizure Detection Approach

Initially EEG signals are decomposed using the DWT and then the decomposed signals are applied to the feature extraction unit. Once feature extraction is complete, the extracted features are given to the NB classifier for classification. The architecture of the proposed seizure detection approach is shown in Fig. 3.

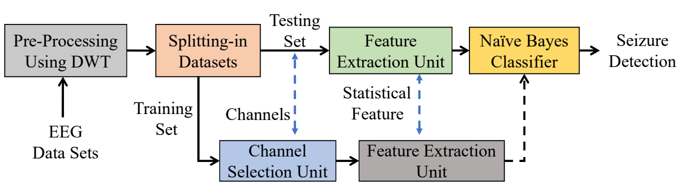

Fig. 3: Architecture of the proposed seizure detection approach.

A. Feature Extraction From Discrete Wavelet Transform (DWT)

EEG signals are complex and non-stationary in nature. The analysis of EEG signals requires time-frequency (TF) decomposition to capture both low and high frequency information. The DWT is useful in analyzing EEG signals and provides TF localization by using both long and short timing windows [21], [22]. The signal is decomposed through a filter bank comprising of both low pass filters and high pass filters. The Daubechies wavelet of order 4 has been used for the decomposition. The decomposition is carried out in four stages. In the first stage, the signal is decomposed to approximate coefficient A_1 and detail coefficient D_1. In the second stage the approximate coefficient A_1 is further decomposed to approximate coefficient A_2 and detail coefficient D_2. The decomposition steps continue up to 4th stage. The subsequent approximate and detail coefficients are denoted as A_4, D_3, and D_4 respectively. The sub-band frequency ranges are: D_1 (43.4-86.8Hz), D_2 (21.7-43.4Hz), D_3 (10.85-21.7Hz), D_4 (5.43-10.85Hz), and A_4 (0-5.43Hz).

The following statistical parameters are extracted from the decomposed EEG signals:

1) Variance and Standard Deviation: Variance and its square root (standard deviation) refer to the dispersion of the data from its main value.

2) Energy: The energy of the kth epoch is denoted by

$$\text{Energy} = \sum_{k=1}^{L} (A_k)^2, \tag{1}$$

where A_k is the amplitude of the kth sample and L is the total number of samples in an epoch.

B. Naive Bayes (NB) Classifier

The Naive Bayes classifier is based on Bayesian theory and requires fewer data for the training [23]. The algorithm for the NB classifier is:

Consider an attribute vector z of n features. The posterior probability of the class C_p for the attribute z is calculated from:

$$p(C_p|z) = \frac{p(z|C_p)\, p(C_p)}{p(z)}, \tag{2}$$

where $p(C_p)$ is the prior probability of the class, $p(z)$ is the prior probability of the attribute, and $p(z|C_p)$ is the probability of z for a given class. Naive Bayes models employ conditional independence where z_i is independent of z_j for a given class C_p. The above equation can be written as:

$$p(C_p|z) = p(C_p) \prod_{i=1}^{n} p(z_i|C_p). \tag{3}$$

A class label is given to the attribute based on highest posterior probability, which is defined by the following equation:

$$p(C_1) \prod_{i=1}^{n} p(z_i|C_1) > p(C_2) \prod_{i=1}^{n} p(z_i|C_2). \tag{4}$$

VI. Implementation and Validation of The Proposed System

The proposed system was implemented using Simulink®, an ATmega328P microcontroller (Arduino) and ThingSpeak. The DWT structure was created in Simulink® as presented in Fig. 4. EEG datasets were initially decomposed using the DWT. DWT structure was created in Simulink®. The decomposed signals were divided to a training set and a testing set. Both the training data set and the testing data set were then fed to the feature extraction unit. A Simulink® user defined function was created to construct the feature extraction unit. The statistical features which were extracted the from feature extraction unit were then input to the naive Bayes (NB) classifier. The structure of the NB classifier was constructed using a Simulink® function. The training data sets were used to train the classifier. The detection was carried out based on the highest posterior probability of the class.

ThingSpeak, an open data platform, was utilized to store the data in the cloud. Upon seizure detection, a notification is sent to ThingSpeak from Simulink®. Medical professionals including the doctor and other stake-holders can access health care data using an API (Application Programming Interface)

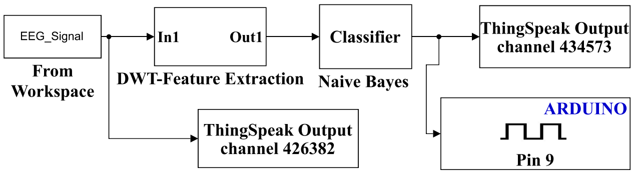

Fig. 4: Simulink and Arduino based prototyping of the proposed system.

via the Internet. The proposed Simulink® model was run on Arduino board.

EEG datasets were taken from the widely used Bonn database [11], which contains five datasets denoted as A, B, C, D and E. We analyzed datasets A, D, and E. Dataset A was recorded from a healthy person whereas dataset D was recorded during the interictal state. Dataset E was recorded from the epileptegenic zone during seizure activity (ictal state). Each dataset includes 100 EEG epochs and each epoch is comprised of 4097 samples.The sampling rate for the EEG data acquisition was 173.61 Hz. Fig. 5 shows an EEG epoch from datasets A and E. The approximate coefficient A_4 and detail coefficients D_1, D_2, D_3 and D_4 for datasets A and E are shown in Fig.6 and Fig. 7 . The statistical parameters were then extracted from the sub-bands, and are shown in Tables I and II. It is evident that the values of all statistical parameters are higher for dataset E. The extracted feature values are almost identical for dataset A and dataset D. In this work, classification was tested for the following case: Dataset A, D versus Dataset E.

Datasets A, D, and E contain altogether 300 EEG epochs. 85% of the EEG epochs from each dataset were utilized to train the classifier and the remaining 15% of EEG epochs were used for testing purposes. The lowest classification accuracy was found as 96.58% for the individual feature SD (Standard Deviation) and the highest accuracy of 98.65% was obtained for the combined feature SD+VAR (Variance). Table IV shows an accuracy comparison with existing methods. The latency of the proposed system was measured using Simulink® and ThingSpeak. The latency for the cloud based IoT was measured as 2.5 seconds, whereas the edge based IoT offered a reduced latency of 1.4 seconds (Table III). The latency includes both computation time as well as transmission delay. In real world cloud based IoT applications, millions of devices are connected to the cloud server and the unnecessary information in the transmission line will cause higher transmission delays as well as system latency. The edge based IoT provides 44% reduction in latency which is highly important for critical biomedical applications.

VII. Conclusions

We proposed a smart seizure detection system in the edge-IoT framework which utilizes statistical feature extraction and naive Bayes classification. The prototype of the system was implemented using Simulink® and ThingSpeak. It is evident from the experimental results that the proposed edge-IoT framework reduces latency by a sizable portion while maintaining high classification accuracy. Future research includes implementing a drug delivery system with the proposed framework for seizure detection and drug injection, simultaneously.

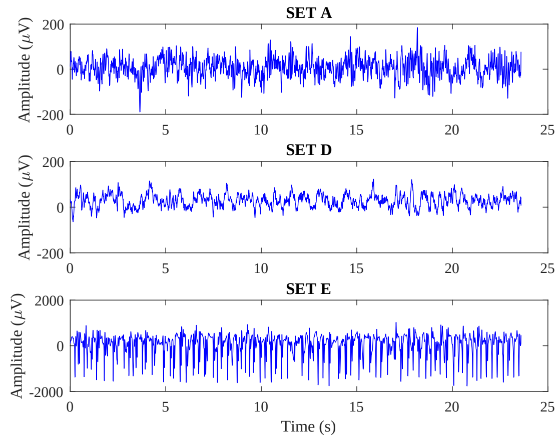

Fig. 5: Sample EEG epoch from datasets A, D, and E.

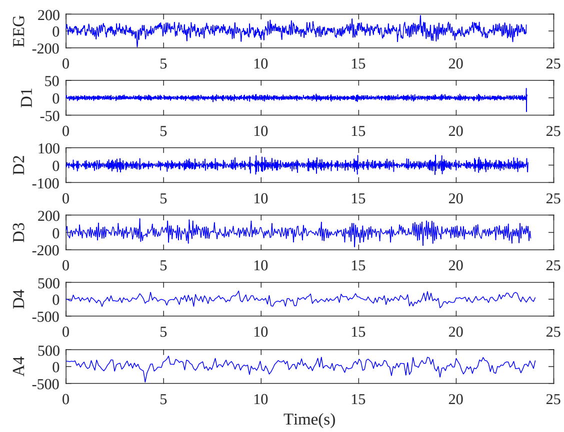

Fig. 6: DWT decomposed EEG epoch from set A.

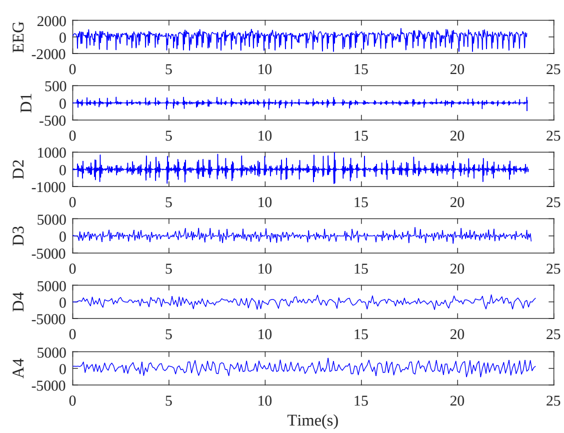

Fig. 7: DWT decomposed EEG epoch from set E.

TABLE I: Extracted feature coefficients for dataset A

Coefficient	Variance	Standard Deviation	Energy
D_1	25.2164	5.0216	2.8564e+04
D_2	587.553	24.2395	3.0435e+05
D_3	5.3957e+03	73.4555	1.4426e+06
D_4	9.9058e+03	99.5279	1.9874e+06
A_4	1.5439e+04	124.2539	4.0502e+06

TABLE II: Extracted feature coefficients for dataset E

Coefficient	Variance	Standard Deviation	Energy
D_1	1.4426e+03	37.9819	1.8934e+06
D_2	6.4382e+04	253.736	4.8707e+07
D_3	7.0151e+05	837.560	3.0676e+08
D_4	6.9684e+05	834.769	1.8874e+08
A_4	1.7177e+06	1.310e+03	4.0854e+08

REFERENCES

[1] S. P. Mohanty, U. Choppali, and E. Kougianos, "Everything You wanted to Know about Smart Cities," *IEEE Consumer Electronics Magazine*, vol. 6, no. 3, pp. 60–70, July 2016.

[2] L. A. Jones and R. H. Thomas, "Sudden Death in Epilepsy: Insights from the last 25 years," *Seizure*, vol. 44, pp. 232–236, Jan 2017.

[3] N. Verma, A. Shoeb, J. Bohorquez, J. Dawson, J. Guttag, and A. P. Chandraksan, "A Micro-power EEG Acquisition SoC With Integrated Feature Extraction Processor for a Chronic Seizure Detection System," *IEEE J.Solid-State Circuits*, vol. 45, no. 4, pp. 804–816, April 2010.

[4] P. Kwan and M. J. Brodie, "Early Identification of Refractory Epilepsy," *N Engl J Med*, vol. 342, no. 5, pp. 314–319, Feb 2000.

[5] P. Sundaravadivel, E. Kougianos, S. P. Mohanty, and M. Ganapathiraju, "Everything you wanted to know about Smart Healthcare," *IEEE Consumer Electronics Magazine*, vol. 8, no. 1, pp. 18–28, January 2018.

[6] S. Supriya, S. Siuly, H. Wang, J. Cao, and Y. Zhang, "Weighted Visibility Graph With Complex Network Features in the Detection of Epilepsy," *IEEE Access*, vol. 4, pp. 6554–6566, 2016.

[7] A. Sharmila and P. Geethanjali, "DWT Based Detection of Epileptic Seizure From EEG Signals Using Naive Bayes and k-NN Classifiers," *IEEE Access*, vol. 4, pp. 7716–7727, 2016.

[8] 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.

[9] A. Shoeb, "Application of Machine Learning to Epileptic Seizure Onset Detection and Treatment," Ph.D. dissertation, Massachusetts Institute of Technology, September 2009.

[10] N. S. Tawfik, S. M. Youssef, and M. Kholief, "A Hybrid Automated Detection of Epileptic Seizures in EEG Records," *Comput. Electr. Eng.*, vol. 53, pp. 177–190, July 2016.

TABLE III: Cloud-IoT VS Edge-IoT.

System Details	Latency
Cloud-IoT based Detection framework	2.5 sec
Edge-IoT based Detection framework	1.4 sec

TABLE IV: Accuracy Comparison With Existing Systems

Works	Methods	Accuracy (%)
Shoeb, et al. [9]	Support Vector Machines	78.74
Kumar, et al. [12]	Neural Network	95
Tawfiq, et al. [10]	Weighted Permutation Entropy	96.5
Sharmila, et al. [7]	Feature Extraction, k-NN classifier	97.08
Proposed System	DWT and naive Bayes classifier	98.65

[11] R. G. Andrzejak, K. Lehnertz, F. Mormann, C. Rieke, P. David, and C. E. Elger, "Indications of Nonlinear Deterministic and Finite-dimensional Structures in Time Series of Brain Electrical Activity: Dependence on Recording Region and Brain State," *Phys. Rev. E*, vol. 64, no. 6, p. 061907, Nov 2001.

[12] Y. Kumar, M. Dewal, and R. Anand, "Epileptic Seizures Detection in EEG Using DWT-based ApEn and Artificial Neural Network," *Signal, Image and Video Processing*, vol. 8, no. 7, pp. 1323–1334, October 2014.

[13] H. G. Daoud, A. M. Abdelhameed, and M. Bayoumi, "Automatic Epileptic Seizure Detection Based on Empirical Mode Decomposition And Deep Neural Network," in *Proceedings of the IEEE 14th International Colloquium on Signal Processing Its Applications*, 2018, pp. 182–186.

[14] F. Samie, S. Paul, L. Bauer, and J. Henkel, "Highly Efficient And Accurate Seizure Prediction on Constrained IoT Devices," in *Proceedings of the Design, Automation Test in Europe Conference Exhibition*, 2018, pp. 955–960.

[15] M. P. Hosseini, D. Pompili, K. Elisevich, and H. Soltanian-Zadeh, "Optimized Deep Learning for EEG Big Data and Seizure Prediction BCI via Internet of Things," *IEEE Transactions on Big Data*, vol. 3, no. 4, pp. 392–404, Dec 2017.

[16] E. Dolgin, "This Seizure-Detecting Smartwatch Could Save Your Life," https://spectrum.ieee.org/the-human-os/biomedical/diagnostics/this-seizuredetecting-smartwatch-could-save-your-life, February 2018, online; accessed 19-February-2018.

[17] M. A. Sayeed, S. P. Mohanty, E. Kougianos, and H. Zaveri, "An Energy Efficient Epileptic Seizure Detector," in *Proceedings of the IEEE International Conference on Consumer Electronics (ICCE)*, 2018, pp. 1–4.

[18] M. A. Sayeed, S. P. Mohanty, E. Kougianos, and H. Zaveri, "A Fast and Accurate Approach for Real-Time Seizure Detection in the IoMT," in *Proceedings of the IEEE International Smart Cities Conference (ISC2)*, 2018.

[19] W. Yu, F. Liang, X. He, W. G. Hatcher, C. Lu, J. Lin, and X. Yang, "A Survey on the Edge Computing for the Internet of Things," *IEEE Access*, vol. 6, pp. 6900–6919, 2018.

[20] D. Puthal, M. S. Obaidat, P. Nanda, M. Prasad, S. P. Mohanty, and A. Y. Zomaya, "Secure and Sustainable Load Balancing of Edge Data Centers in Fog Computing," *IEEE Communications Magazine*, vol. 56, no. 5, pp. 60–65, May 2018.

[21] H. P. Zaveri, W. J. Williams, L. D. Iasemidis, and J. C. Sackellares, "Time-frequency Representation of Electrocorticograms in Temporal Lobe Epilepsy," *IEEE Transactions on Biomedical Engineering*, vol. 39, no. 5, pp. 502–509, MaY 1992.

[22] O. Salem, A. Naseem, and A. Mehaoua, "Epileptic Seizure Detection from EEG Signal Using Discrete Wavelet Transform and Ant Colony Classifier," in *Proceedings of the IEEE International Conference on Communications*, 2014, pp. 3529–3534.

[23] R. Bayindir, M. Yesilbudak, M. Colak, and N. Genc, "A Novel Application of Naive Bayes Classifier in Photovoltaic Energy Prediction," in *Proceedings of the 16th IEEE International Conference on Machine Learning and Applications*, 2017, pp. 523–527.