

Epilepsy Detection and Classification for Smart IoT Devices Using hybrid Technique

Sani Saminu

State Key Laboratory of
Reliability and Intelligence of
Electrical Equipment
Hebei University of Technology
Tianjin 300130, China
sansam4k@gmail.com

Guizhi Xu

State Key Laboratory of
Reliability and Intelligence of
Electrical Equipment
Hebei University of Technology
Tianjin 300130, China
gzxu@hebut.edu.cn

Shuai Zhang

State Key Laboratory of
Reliability and Intelligence of
Electrical Equipment
Hebei University of Technology
Tianjin 300130, China
zs@hebut.edu.cn

Abd El Kader Isselmou

State Key Laboratory of
Reliability and Intelligence of
Electrical Equipment
Hebei University of Technology
Tianjin 300130, China
isselmou_kader@yahoo.com

Rabiu S. Zakariyya

Micro/Nano-Electronic System
Integration R & D Centre
University of Science and
Technology of China (USTC)
230026 Hefei, China
rabiu123@mail.ustc.edu.cn

Adamu Halilu Jabire

School of Electronics and
Information Engineering
Hebei University of Technology
Tianjin 300130, China
adamu.jabire@tsuniversity.edu.ng

Abstract—Epilepsy is a type of neurological disorder which can happen without serious warning and affects people almost at any age. It is a brain disorder caused by sudden and unprovoked seizures as a result of excitation of a lot of brain cells simultaneously which may lead to physical symptoms abnormalities and deformation such as failure in concentration, memory, attention etc. therefore, proper and efficient method of continues monitoring and detection of these epileptic seizures is paramount. This work presents an effective and efficient technique suitable for smart, low cost, power and real time devices that can be easily integrated with recent 5G network IoT devices for mobile applications, home and health care centers for monitoring and alert the doctors and patients about its occurrence to prevent a sudden collapse and consciousness which may cause injury and death. We proposed a low computational cost features extraction method by utilizing the efficacy of time-frequency, statistical and non-linear features known as hybrid techniques. The efficiency and accuracy of these smart devices is highly depends on quality of feature extraction methods and classifier performance. Therefore, this work employed two machine learning classifiers, support vector machine (SVM) and feedforward neural network (FFNN) to detect and classify interictal (normal) and ictal (seizure) signals. Discrete wavelet transform (DWT) is employed to decomposes the signals into decomposition levels as sub-bands of the signals to capture the non-stationarity of the EEG signals. Mean, median, maximum, minimum etc. were calculated for each sub-band as statistical parameters, non-linear features such as sample entropy, approximate entropy and wavelet energy were also calculated. The combination of features is then fed to two classifiers for the classification. Based on the performance measures such as accuracy, sensitivity and specificity, our proposed approach reveals a promising result with highest accuracy of 99.6%.

Keywords— DWT, FFNN, SVM, EEG, 5G Network, Epilepsy Detection, Seizure Detection, Internet of Things

I. INTRODUCTION

Epilepsy is a serious neurological disorder which relate to the sudden seizures caused as a result of immediate change of the brain electrical activity which needs proper health care monitoring to minimize its occurrence before the condition is getting into critical situation [1]. However, detection of epilepsy seizure is one of the primary step to be taking by getting the symptoms data through healthcare devices.

Recently, internet of things (IoT) devices are integrated into healthcare system to improve the critical health system in real time situation to sense a biometric data, track, monitor, online consultation, and remotely wireless communicated to doctors easily at low cost. With the recent deployment of 5G network, IoT devices and machines with biometric sensors will be expected to deployed as smart hospital facilities to overcome healthcare challenges. In this paper we proposed an epilepsy detection and classification for smart IoT devices.

The work also used Electroencephalography (EEG) signal to overcome the problem associated with traditional method of visual EEG interpretation which is tedious, time consuming and easily lead to errors. The proposed technique significant and novelties are:

1. The most robust features extracted from time domain, time-frequency and non-linear features
2. Developing an improved feature reduction method that used statistical parameters and features
3. Classifying the normal and seizures signals by applying two machine learning classifiers SVM and FFNN.
4. Experiment and search for the robust and efficient classifier

The organization of the rest of this paper is as follows. Studies from related work will be discuss in section II. Section III describe proposed seizure detection architecture and design. In section IV, proposed solution and experimental results, finally, conclusion remarks and future modification will be provided in section V.

II. RELATED WORK

One of the challenging task in development of monitoring and diagnosis of epilepsy with automatic and smart devices is extracting robust and efficient features from EEG signals which has effective computational performance as well as selecting appropriate and effective classifier. From the signal processing point of view, several techniques have been in existence for epileptic detection and classification.

One of the early and widely accepted method for automatic classification and detection of epileptic seizures is reported in [2]. In this work, continuous temporal analysis was performed to compare segment of EEG or epoch with a reference segment. Reference [3] used Empirical Mode Decomposition (EMD) method for epilepsy EEG signals feature extraction and used modified fuzzy clustering algorithm as a classifier to detect epilepsy signals. Simple random sampling technique (SRS) was employed by [4] to extract time domain features, thereafter, they applied algorithm of sequential feature selection (SFS) to extract the robust features and for dimensionality reduction.

Recently, several techniques for detection and classification of epilepsy have been in used and are developed based on different types of domain such as time, frequency, time-frequency linear and nonlinear techniques [5-10]. It was proved in literature that features extracted from frequency sub-bands provides higher discriminative information more than those from entire EEG signals [11]. Some of the previous works reported either low accuracy, used a single domain or linear features while some employed low efficient classifiers. Therefore, this work endeavor to address some of the reported drawbacks of those methods.

III. ARCHITECHTURE AND DESIGN

A. Background

1) Discrete Wavelet Transform

Discrete wavelet transform is quite popular and convenient approach for analyzing biomedical signals including EEG due to its ability of representing a signal in a time-frequency representation. DWT analyzed signals that are nonstationary like EEG signals conveniently. The approach in DWT is to decomposes the Epilepsy EEG signal into signal sub-bands or decomposition levels, thereafter, significant features are calculated and extracted from the decomposition levels selected. Selection of appropriate decomposition levels, type of mother wavelet to be used and identifying type of features from selected sub-bands are some of the challenging issues in using wavelet for classification of normal from seizure periods [12]. Wavelet function can be described as follows:

$$\Psi_{s,\tau} = \frac{1}{\sqrt{s}} \Psi\left(\frac{t-\tau}{s}\right) \quad (1)$$

Where τ is called shift parameter while, s is called scale parameter

Wavelet transform:

$$\gamma(s, \tau) = \int f(t) \Psi_{s,\tau}^*(t) dt \quad (2)$$

Inverse wavelet transform:

$$f(t) = \iint \gamma(s, \tau) \Psi_{s,\tau}(t) d\tau ds \quad (3)$$

To realize the DWT, a series of successive filters were designed by [13], they are made of low and high pass quadrature mirror filters with two downsamplers by 2. Fig. 1. shows a successive of low-pass represented by $g[n]$ and high-pass filter represented by $h[n]$ for three level of DWT decomposition. At every level of decomposition, there are two coefficients produced by the filters. Approximations coefficients and detail coefficients produced by low pass and high pass filters respectively, the process of filtering and decimation is continuous up to the last selected level of decomposition [14].

2) Support Vector Machine

SVM is a machine learning classifier highly suitable for binary classification with feature vectors of high dimension. It is very suitable and popularly used in biomedical signals processing and applications due to its capability of dealing with high number of predictors and also high accuracy. the distance of optimal hyper plane obtained by SVM from feature space of high dimension and that of each class closest data sample is maximized by SVM. It depends on its regularization parameter which control the level of overlap between the class and kernel functions which is used for mapping of training data to a feature space of higher dimensional from an input space. Fig. 2. depicts an example of 2-dimensional separable classification problem by denoting the maximum margin and optimal hyperplane. The support vectors are those data points on the margin line.

3) Artificial Neural Network

The Artificial neural network used a predefined algorithm to mimic learning the input-output behavior. Its structures are inspired by human nervous system and widely used for system modeling and function approximation. Multi-layer feedforward neural network with backpropagation learning is the simplest and most common ANN structure as shown in Fig. 3.

The ANN process is to choose structure of the system, number of layers, and number of neurons in each layer, training samples are fed to ANN and weights are determined based on the learning algorithm. Steepest descent direction is used by backpropagation algorithm to adjusts its weight and this direction is where the performance function rapidly decreased.

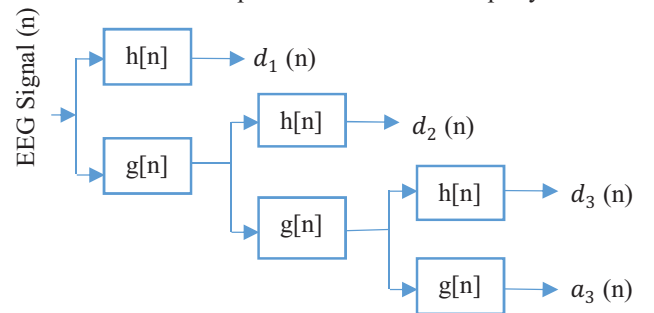


Fig. 1. Three level Wavelet decomposition tree

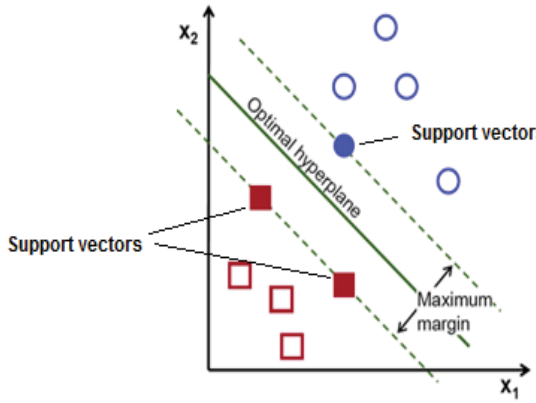


Fig. 2. An example of a separable problem in a 2 dimensional space

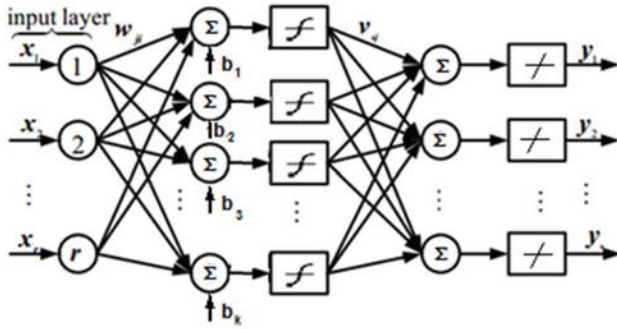


Fig. 3. Multi-layer feedforward neural network

B. System Design

The block diagram of the overall working principle of the proposed system is given in Fig. 4.

1) EEG Epilepsy Data Acquisition

To enable easy validation and comparison with related works in literature, this work used the widely acceptable publicly dataset from the Bonn University Germany, department of Epileptology [15]. It consists of five groups A-E or Z, O, N, F, S classes and standard system of 10-20 electrode placement was used during signal acquisition. Each group consist of 100 single channels EEG signals of 23.6 s with 128 amplifier channels and digitized with 12 bit A/D converter with 173.6Hz as sampling frequency. The detail of this datasets will be found in [16]. This work used set C dataset which is recorded from five epileptic patients at time of non-seizure activity (interictal) and set E which is recorded during epileptic seizure activity of five pre-surgical epileptic patients (seizure). Fig. 5. shows the EEG signals from these two groups.

2) Preprocessing and Feature extraction

Preprocessing stage involves the removal of noise which affect the signal from various sources. The data used in this work was already denoised and therefore no need for noise removal. Therefore, the epilepsy data from class C and class E datasets each of 100 single channels EEG signal were prepared

for decomposition using DWT. It is possible to use the raw EEG signal as classifier's input but these full length data is a poor representation of the input signal due to a lot of redundant information and large dimensionality which can make a classification more complex.

To extract significant information and smaller number of parameters and still maintain the accuracy of the system is particularly important in EEG epilepsy detection and classification using smart IoT devices. To realize this aim, DWT is employed to decompose the signal into a number of sub-bands. To cover all the frequency of these signals level 10 decomposition was chosen and Daubechies mother wavelet was selected as it is proved in literature as one of the suitable wavelet for EEG analysis. Here we proposed a feature extraction in three stages as follows:

- DWT statistical features: in this stage, statistical parameters were calculated at each sub-band of DWT decomposition with details and approximations coefficients, $d_1 - d_{10}$ combined with a_{10} respectively as shown in Fig. 6. The standard statistical features are

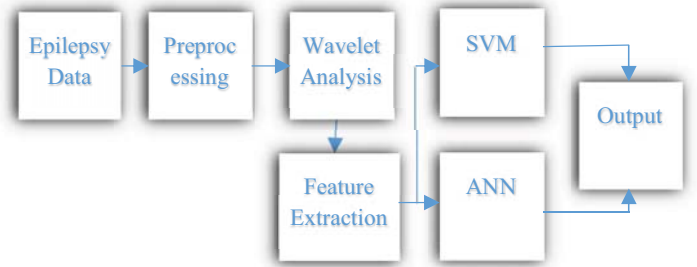


Fig. 4. Block diagram of the proposed technique

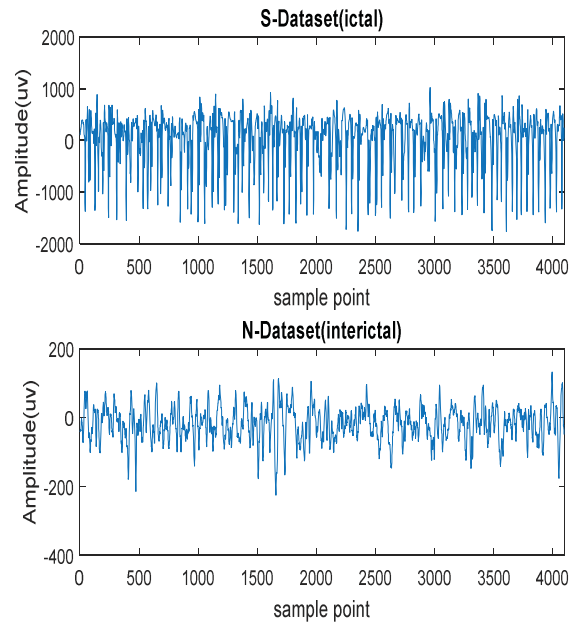


Fig. 5. Example of EEG signals from set C and set E

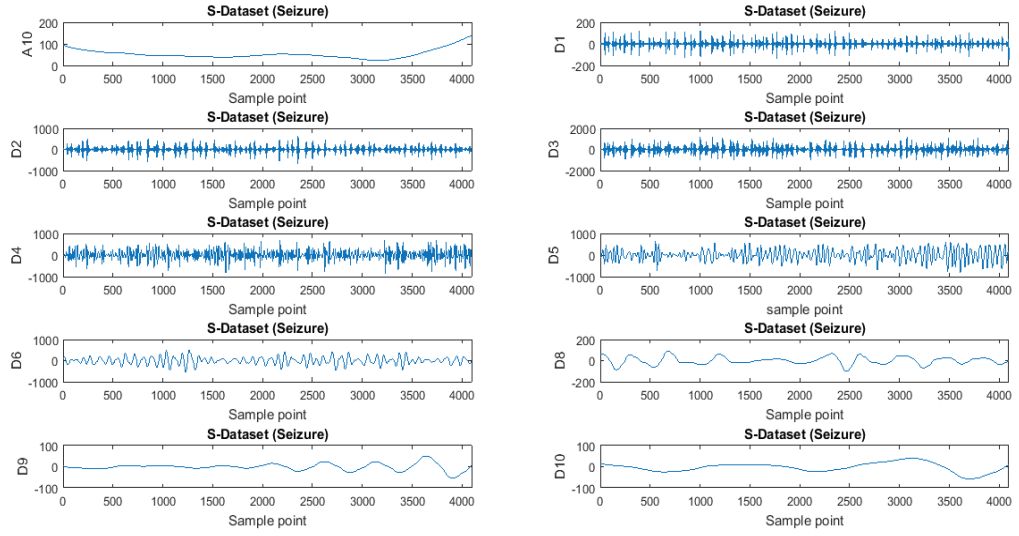


Fig. 6. Decomposition levels of DWT

mean, median, mode, maximum, minimum and standard deviation.

- Nonlinear features: to further capture the significant characteristics of EEG signals nonlinearity, nonlinear features were extracted as Approximate entropy and Sample entropy.
- Energy features: To further capture the EEG Epilepsy signals significant characteristics and information, energy of the signal was also calculated as features to be used for classification.

The above features are combined in one file and serve as our features for training and testing SVM and ANN classifiers.

3) Classification

At this stage, ANN and SVM were used for classification of pre-ictal and ictal (normal and seizure) classes. To optimized the classifier's performance and to select efficient and robust classifier for 5G IoT devices, different types of SVM classifier as well as different number of neurons were selected and tested.

IV. EXPERIMENTAL RESULTS

In this paper, EEG epilepsy signal from University of Bonn, Germany database were used for training and testing. 200 EEG records from two classes of pre-ictal and ictal were downloaded as .txt files and distributed randomly for classification of normal and seizure beats. 200 EEG records are fed to artificial neural network and SVM, approximately 70% is used for training and the remaining is used for validation and testing. The classification performance is considered in terms of sensitivity, specificity and accuracy. The used measures are defined as

$$Sensitivity = \frac{TP}{TP + FN} * 100\%$$

$$Specificity = \frac{TN}{TN + FP} * 100\%$$

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} * 100\%$$

where TP is True Positive (correctly identified), FP is False Positive (incorrectly identified), FN is False Negative (incorrectly rejected), TN is True Negative (correctly rejected).

Classification of interictal and ictal is very crucial and challenging as both the EEG classes are recorded from patients, one without seizure and the other during the seizure. the performance of our hybrid features is evaluated with different types feed forward neural network structure and that of SVM structure. Fig. 7. shows the performance of experimented FFNN with various selected hidden layers. FFNN with 15 neurons outperforms other structures as its sensitivity, specificity and accuracy reached 99.7%, 99.3% and 99.6% respectively.

Table I. indicates the performance of our approach with different SVM kernel functions. From the table polynomial function gives better result compared to other functions. Also, SVM method was experimented with different types of methods and the result does not yield improvement in accuracy as shown in fig. 8. compared to SVM with polynomial kernel function.

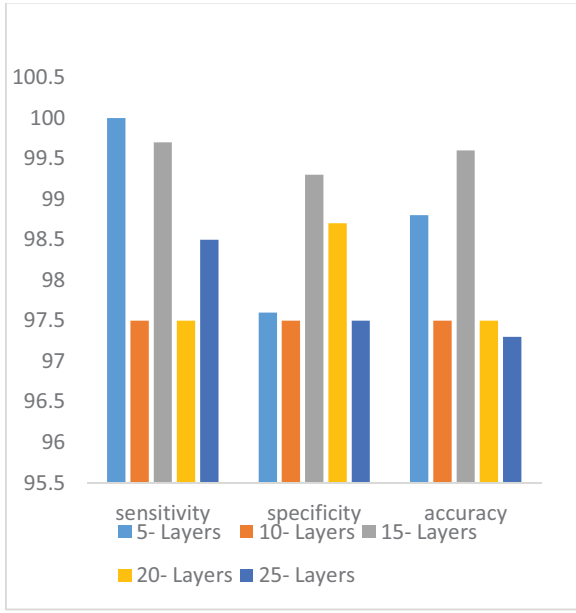


Fig. 7. Performance of FFNN with different number of neurons

TABLE I. DIFFERENT KERNEL FUNCTION OF SVM

Kernel Function	Sensitivity(%)	Specificity(%)	Accuracy(%)
Linear	97.5	97.5	97.5
Quadratic	97.4	92.9	95.0
Polynomial	97.5	100	98.8
rbf	58.82	100	65.0

Table II. provides the comparison of the two chosen classifiers FFNN and SVM with our proposed hybrid features. The result reveals that FFNN performs better than SVM with 99.6% and 98.8% accuracy respectively. Also, the performance of our proposed method with other related works in literature that used the same dataset is shown in table III. Our proposed approach performs better than some reported works in literature.

Finally, based on the results obtained from our proposed approach, we provide some comments as follows: our method proved and emphasized the use of joint time-frequency domain compared to using time or frequency domain alone. Moreover, searching for simple but accurate approach for feature extraction that simplify the classifier operation, computation and increased speed to cater for the need of our smart IoT network and devices is highly needed.

V. CONCLUSION

In this work, we have proposed a hybrid based features which can represents the epilepsy EEG signals effectively for the classification of interictal as normal and ictal as seizure. the method employed less computational approaches of DWT features combined with statistical and nonlinear features as well as effective and widely used FFNN and SVM classifiers in order to meet the increasing demand of integrating smart devices and embedded system in our health care facilities. For

validation of our proposed approach, we used widely and publically available dataset from the University of Bonn Germany in which dataset of class C and that of class E for interictal (normal) and ictal (seizure) respectively. Our proposed approach achieved highest accuracy compared with some recent works in literature with sensitivity, specificity and accuracy of 99.7%, 99.3% and 99.6% respectively.

However, although our approach yields a promising result, the dataset considered is less than some works reported in literature. Therefore, as part of our calibration of the proposed method in future, more datasets will be used, more realistic datasets will be tested for real time application. Incorporating deep learning in epilepsy detection and classification need to be considered.

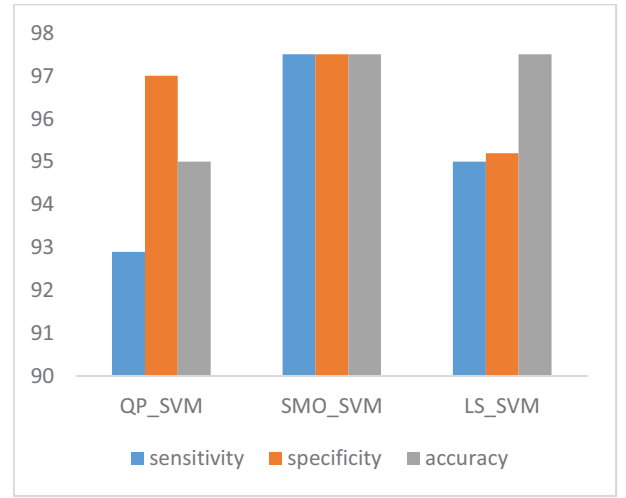


Fig. 8. Performance of SVM Methods

TABLE II. COMPARISON BETWEEN SVM AND FFNN

Classifier	Sensitivity(%)	Specificity(%)	Accuracy(%)
SVM	97.5	100	98.8
FFNN	99.7	99.3	99.6

TABLE III. COMPARISON OF PROPOSED METHOD WITH SOME RECENT METHODS IN LITERATURE

Method	Sensitivity(%)	Specificity(%)	Accuracy(%)
Kroskov entropy and LS_SVM[17]	97.0	99.5	97.8
Sample entropy and SVM[18]	-	-	97.7
Time domain exponential Energy features[19]	-	-	99.5
This study	99.7	99.3	99.6

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