A Multi-Tier Distributed fog-based Architecture for Early Prediction of Epileptic Seizures

by

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I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

Epilepsy is the fourth most common neurological problem. With 50 million people living with epilepsy worldwide, about one in 26 people will continue experiencing recurring seizures during their lifetime. Epileptic seizures are characterized by uncontrollable movements and can cause loss of awareness. Despite the optimal use of antiepileptic medications, seizures are still difficult to control due to their sudden and unpredictable nature. Such seizures can put the lives of patients and others at risk. For example, seizure attacks while patients are driving could affect their ability to control a vehicle and could result in injuries to the patients as well as others. Notifying patients before the onset of seizures can enable them to avoid risks and minimize accidents, thus, save their lives. Early and accurate prediction of seizures can play a significant role in improving patients' quality of life and helping doctors to administer medications through providing a historical overview of patient's condition over time.

The individual variability and the dynamic disparity in differentiating between the pre-ictal phase (a period before the onset of the seizure) and other seizures phases make the early prediction of seizures a challenging task. Although several research projects have focused on developing a reliable seizure prediction model, numerous challenges still exist and need to be addressed. Most of the existing approaches are not suitable for real-time settings, which requires bio-signals collection and analysis in real-time. Various methods were developed based on the analysis of EEG signals without considering the notification latency and computational cost to support monitoring of multiple patients. Limited approaches were designed based on the analysis of ECG signals. ECG signals can be collected using consumer wearable devices and are suitable for light-weight real-time analysis. Moreover, existing prediction methods were developed based on the analysis of seizure state and ignored the investigation of pre-ictal state. The analysis of the pre-

ictal state is essential in the prediction of seizures at an early stage. Therefore, there is a crucial need to design a novel computing model for early prediction of epileptic seizures. This model would greatly assist in improving the patients' quality of lives.

This work proposes a multi-tier architecture for early prediction of seizures based on the analysis of two vital signs, namely, Electrocardiography (ECG) and Electroencephalogram (EEG) signals. The proposed architecture comprises of three tiers: (1) sensing at the first tier, (2) lightweight analysis based on ECG signals at the second tier, and (3) deep analysis based on EEG signals at the third tier. The proposed architecture is developed to leverage the potential of fog computing technology at the second tier for a real-time signal analytics and ubiquitous response. The proposed architecture can enable the early prediction of epileptic seizures, reduce the notification latency, and minimize the energy consumption on real-time data transmissions. Moreover, the proposed architecture is designed to allow for both lightweight and extensive analytics, thus make accurate and reliable decisions. The proposed lightweight model is formulated using the analysis of ECG signals to detect the pre-ictal state. The lightweight model utilizes the Least Squares Support Vector Machines (LS-SVM) classifier, while the proposed extensive analytics model analyzes EEG signals and utilizes Deep Belief Network (DBN) to provide an accurate classification of the patient's state.

The performance of the proposed architecture is evaluated in terms of latency minimization and energy consumption in comparison with the cloud. Moreover, the performance of the proposed prediction models is evaluated using three datasets. Various performance metrics were used to investigate the prediction model performance, including: accuracy, sensitivity, specificity, and F1-Measure. The results illustrate the merits of the proposed architecture and show significant improvement in the early prediction of seizures in terms of accuracy, sensitivity, and specificity.

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Dedication

This thesis is dedicated to my parents for their prayers and unlimited support to me and for giving me the greatest love and care.

To my dear husband for being the most helpful person, I found during my graduate studies, who was always beside me.

To my daughter and my son for giving me the happiness and motivation to succeed.

To my dear brother and sisters, for their unconditional love and continued support.

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Chapter 1

This chapter discusses the motivation behind this work and highlights the scope of the research conducted in this thesis. A summary of the thesis outlines is also presented at the end of this chapter.

Introduction

Epilepsy is one of the most common chronic neurological diseases, which characterized by recurrent seizures. The severity and symptoms of epileptic seizure vary from patient to patient [1] [2]. According to the World Health Organization, epilepsy has affected more than 50 million people of all ages and genders around the world. According to Canada Statistics of 2016, approximately 0.6% of Canada's population has epilepsy, and an estimated 75-85% of epilepsy patient are under the age of 18, while 1.3% are over the age of 60 [1]. Epileptic seizures are classified into two main types, namely, partial seizures and generalized seizures. The type of seizure is determined based on the location of the epileptogenic zone in the brain. The partial seizure affects only one part of the brain and can be categorized into a simple and complex seizure, while the generalized seizure affects the whole brain and can be classified into several categories depending on the behavioral effects. According to [2], more than 33% of people with epilepsy experience partial seizures, and more than 30% of people with epilepsy experience generalized seizures.

The unpredictable seizures represent the main source of concern for patients and their families where daily activities such as using a knife, walking, or driving may turn into dangerous tasks. Epileptic seizure comprises of four states: inter-ictal state (period far from seizure), pre-ictal state (period before seizure), ictal state (period of seizure), and post-ictal (period after seizure) [3][4]. The development of a seizure prediction model based on the analysis of pre-ictal state is crucial to minimize the negative consequences of unpredicted seizures and improve patients' quality of life.

1.1 Research Motivation

During a seizure, patients may lose their consciousness, which leads to a lack of control over their feelings and movements. Epilepsy patients are at the risk of sudden death due to accidents caused by such unforeseen seizures. Although various methods were developed for seizure detection and prediction, several issues still exist and need to be addressed. Most of the existing approaches are not suitable for real-time settings, which requires bio-signals collection and analysis in real-time. In addition, most of the state-of-the-art research focused on the analysis of EEG signals to develop seizure prediction models. Limited methods were developed based on the analysis of ECG signals. However, seizure prediction based on EEG signals is not suitable for daily use due to the restrictions that are imposed by EEG sensors on the patient's mobility [8], while ECG sensors are more comfortable to use and suitable for light-weight real-time analysis. On the other hand, most existing approaches focused on the analysis of features that are relevant to seizures or non-seizures state and ignored the analysis of other seizures states such as the pre-ictal state, which is more relevant for early prediction. Moreover, most of the existing proposed algorithms still suffer from several limitations such as poor sensitivity, and high processing time. In contrast, the possibility of implementing the current approaches in clinical applications represent one of the debilitating aspects [4][5]. Therefore, there is a great need to design a new seizure prediction framework that supports real-time analysis and notifications to improve the patient's quality of life. Developing a new computing model for monitoring epilepsy patients based on advanced technology such as fog and mobile computing can improve the patients' Quality of Life (QoL), increase the independence, and reduce the hospitalization costs. Fog computing is an emerging technology that has been recently introduced to reduce the amount of data transported to the cloud for processing, analysis, and storage. Fog computing extends cloud computing services to the edge of the network to enable real-time data processing.

1.2 Research Contributions

The main goal of this research is to design, develop, and implement a novel computing system based on fog computing technology to analyze the vital signs of epilepsy patients that can enable the early prediction of seizures, and reduce latency and energy use for real-time data transmission and notification. Specifically, this thesis proposes a multi-tier architecture for early prediction of epileptic seizures based on the analysis of ECG and EEG signals, which allow for both lightweight analysis and extensive analysis to make more accurate and reliable decisions. The research contributions can be summarized as follows:

- Designing a distributed multi-tier fog-based architecture for early prediction of epileptic seizures, which enables real-time analysis and reduces the latency and energy use of signals transmissions and notifications over the network.
- Developing a lightweight prediction model based on the analysis of ECG signals by utilizing Least Squares-Support Vector Machine (LS-SVM).
- Proposing a deep learning framework for seizure prediction based on extensive analysis of EEG signals via Deep Belief Network (DBN).

1.3 Thesis Organization

This thesis consists of six chapters:

Chapter 1 provides a brief overview of the research problem, research motivations, and contributions.

Chapter 2 presents a comprehensive overview of the prime topics relevant to this thesis. First, it provides background about epilepsy, seizure states, seizure types, and seizures diagnosing tools. It also offers a broad discussion about various techniques and methods that were proposed in the literature for seizure prediction and highlights their limitations and gaps. Furthermore, this chapter provides an overview of fog computing and its benefits in developing healthcare applications, followed by a brief discussion of state-of-the-art applications based on fog computing in healthcare.

Chapter 3 proposes a multi-tier fog-based architecture for early prediction of epileptic seizure through the analysis of two vital signs including ECG and EEG signals. This chapter discusses the components of the proposed architecture, which comprises of three tiers namely, sensing at the first tier, fog computing at the second tier for lightweight analysis based on ECG signals, and cloud computing at the third tier for extensive analysis based on EEG signals. This chapter highlights the benefits of using fog computing technology at the second tier in distributing the analysis of patients' data and enabling real-time analysis and notifications. This chapter also presents the results for evaluating the performance of the proposed fog-based architecture in terms of latency minimization and energy consumption in comparison with the traditional cloud-based architectures.

Chapter 4 proposes a lightweight prediction model based on the analysis of ECG signals at the second tier of the proposed architecture. This chapter discusses in detail the proposed model for ECG analysis and provides a brief background about the techniques used to formulate the proposed model. This chapter also presents the results conducted to evaluate the efficiency of the proposed model in terms of accuracy, sensitivity, specificity in comparison with the state-of-the-art approaches.

Chapter 5 proposes a deep learning framework for seizure prediction based on the analysis of EEG signals at the third tier of the proposed architecture. This chapter discusses the details of the proposed deep learning framework and provides a brief background about the techniques that are used to formulate the proposed deep learning approach. This chapter also presents the results of the experiments conducted to investigate the performance of the proposed model in terms of accuracy, sensitivity, specificity, precision, recall, and F1 measure.

Finally, Chapter 6 provides a summary of this thesis and highlights the suggestions for future research.

Chapter 2

Background and Literature Review

2.1 Introduction

This chapter provides a brief background on the main topics related to this thesis. It first presents an overview of epilepsy, seizures, and seizures states, followed by a literature review of the state-of-the-art seizure detection and prediction methods. Second, provides a broad discussion of existing limitations and challenges that promote new research direction. Third, offers details about fog computing technology as a candidate solution for the issues of real-time data processing and low latency with regards to the developing of healthcare applications. This chapter also explains the main difference between fog and cloud computing and provides details on the characteristics of fog computing in healthcare applications, and a summary of the related work.

2.2 Overview of Epileptic Seizures

2.2.1 Epilepsy

Epilepsy is a common chronic disease that affects around 50 million individuals worldwide [2]. Epilepsy can influence both males and females of all ages and races. Epilepsy is a neurological disorder due to an abnormal electrical activity between the brain neurons which cause unexpected seizures. These unpredicted seizures lead to loss of awareness that could happen one or multiple times in which the severity and impact of seizures are different from person to person [2]. There are various types of epilepsy which are resulting from several known or unknown causes. In several cases, the epileptic condition is called epileptogenic focus when the epilepsy is caused by abnormalities in the structure of the brain or by several genetic factors. In many other cases, where there is no known cause, the epileptic condition is called idiopathic epilepsy [3].

2.2.2 Seizures

The seizure is a neurological upset resulting from abnormal brain activity. The seizure could happen during a day or sleeping time. During the seizures, the patients lose the control of their feelings and movements due to convulsions that result from abnormal electrical activity in nerve cells of the brain. Epilepsy patients are at risk of sudden unexpected death due to accidents caused by such unforeseen seizures.

2.2.2.1 Seizure Types

Epileptic seizures classified into three classes including partial seizures, generalized seizures, and unknown seizures as shown in Figure 2.1. Each class is subdivided into sub-classes depending on the behavior effect. The partial seizures affect only one part of the brain, while the generalized seizures affect the whole brain. Generalized seizures are categorized into clonic seizures, tonic seizures, tonic-clonic seizures, absence seizures, and myoclonic seizures. Focal or partial seizures are categorized into simple focal seizures, complex focal seizures, and secondarily generalized seizures.

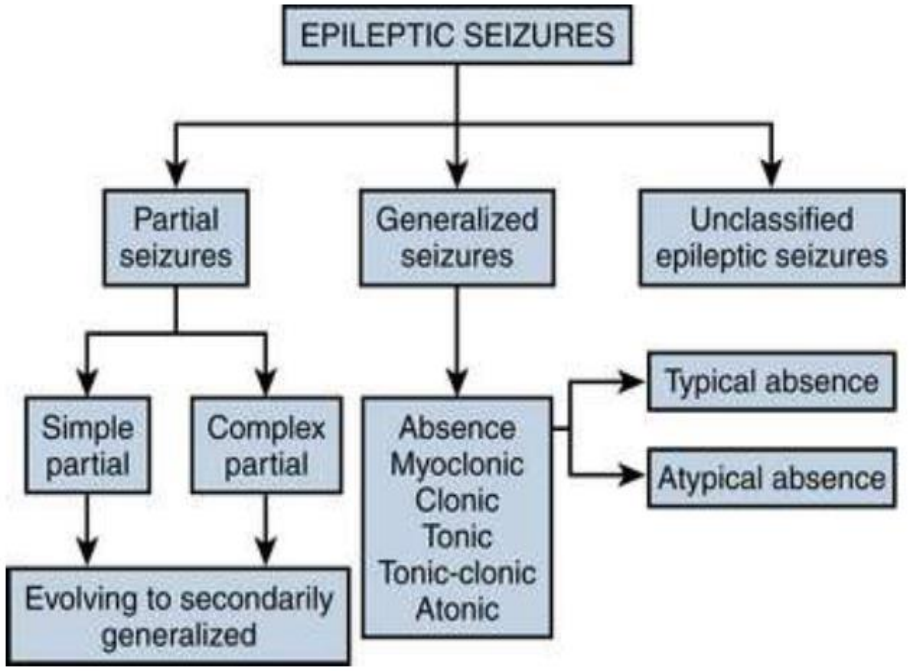


Figure 2.1: Types of Epileptic Seizures [3].

2.2.2.2 Seizure States:

The seizure consists of four states: inter-ictal (period far from seizure), pre-ictal (period before seizure), ictal state (period of seizure), and post-ictal (period after seizure) [3]. The symptoms of these stages can be different from person to person; more details about each stage presented in the following subsections:

Inter-ictal State: This stage represents almost 99% of the patient life, which refer to the normal period that comprises no seizure activity. The inter-ictal phase is considered as an essential stage in diagnosing of epileptic seizure [3].

Pre-ictal State: This stage represents the period before the onset of the seizure, which is different from the normal state [4]. The pre-ictal stage is one of the most critical stages that can be used to define the possible upcoming seizure at an early stage.

Ictal State: This stage refers to the period of seizure activity. During this stage, the convulsions can be patently observed on the patient's body and cannot be controlled. Tremors, confusion, twitching, loss of awareness, and loss of sensation are common symptoms associated with epileptic seizures [3]. These symptoms could continue due to the aftereffects that can happen during the seizure.

Postictal State: This stage refers to the period after the onset of the seizure and represents the transition from the ictal stage (seizure activity) back to the inter-ictal stage (normal). This period can be ranging from seconds to hours depending on several factors such as the severity of the seizure and health condition of the affected patient. Dizziness, memory loss, upset stomach, headaches, and fatigue are common symptoms that can happen during the postictal phase [3][4].

2.3 Literature Review of Seizure Prediction Methods & Techniques:

This section provides a comprehensive literature review of different methods and techniques that have been proposed in the field of seizure prediction.

Numerous research has been carried out to minimize the seizures negative consequences through the development of various seizure detection and prediction methods. As shown in Figure 2.2, seizure detection algorithms are classified into a seizure-onset detector or seizure-event detector [10]. The difference between these two categories is that the seizure-onset detector aims to identify the seizure starting time with minimum possible delay and ignored accuracy while the seizure-event detector attempts to recognize the seizure starting time with highest possible accuracy and ignored the delay time. Most of the seizure-onset and seizure-event detection algorithms are developed based on the analysis of EEG or iEEG signals, while limited methods are designed based on the analysis of ECG signals. Seizure detection algorithms were first developed to detect the onset of the seizures based on the analysis of patients-nonspecific data, which achieved limited detection accuracy due to the individual variability of patient's signals [10]. Several detection algorithms are also designed based on the analysis of patient-specific data from the same patient.

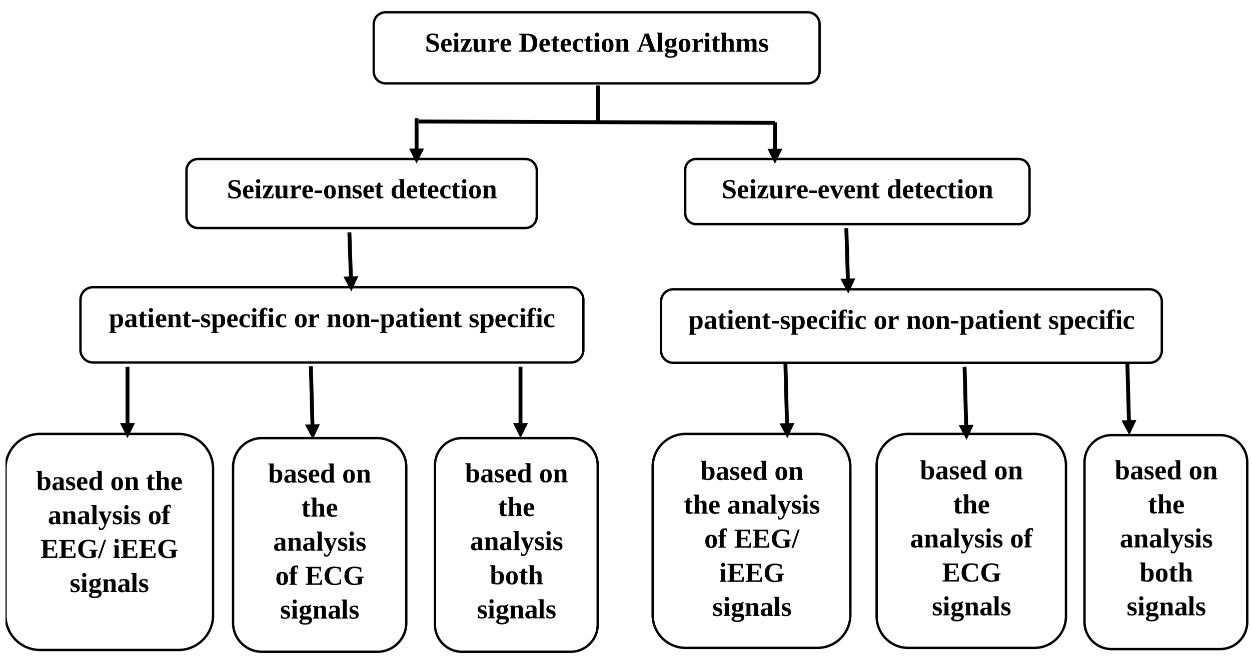


Figure 2.2: Seizure detection algorithms classification.

In general, the detection process in these proposed methods usually involves four main stage as shown in Figure 2.3 including; preprocessing, feature extraction, feature selection or reduction, and binary or multi-class classification.

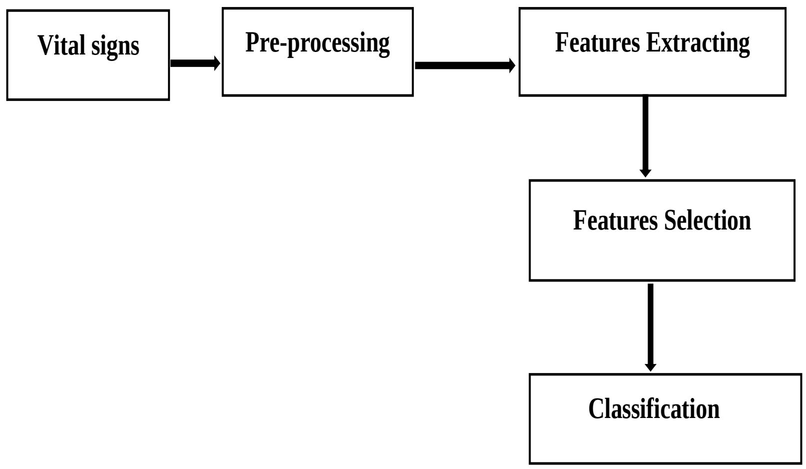


Figure 2.3: General Diagram of seizure detection algorithms stages.

In the preprocessing stage, the aim is to remove the artifact and noise from the signals. High pass filter (HPF), low pass filter (LPF), notch filter, and Butterworth filter are common signal filtering approaches that have been widely used for the preprocessing stage in seizure detection methods [11]. The objective of feature extraction stage is to capture the meaningful characteristics of the signal. Several feature extraction techniques for linear and nonlinear measures from the signals have been used in the literature [12]. Discrete wavelet transforms, Hilbert Huang transforms, and spectral analysis are common feature extraction techniques that have been applied in the field of seizure detection [12] [13] [14]. In seizure detection and prediction, usually high dimensions of features are extracted. Therefore, various feature selection techniques are used to select a subset of relevant features without loss of significant information to reduce the dimensionality of the features space. Principal component analysis (PCA), linear discriminant analysis (LDA), and independent component analysis (ICA) have been widely used in literature as feature selection techniques [13]. Classification is another essential procedure in seizure detection based on mathematical or machine learning techniques, which is used to map the extracted features into the set of labels to identify the signal state. SVM, k-nearest neighbors (KNN), K-nearest neighbor (KNN), neural networks (NN), probabilistic neural networks (PNN), self-organizing maps, and Recurrent Neural Networks RNN are common feature classification techniques that have been reported in the literature in the field of seizure detection to classify the signal into seizure or non-seizure state [15] [16] [17].

Most of these feature extraction and classification techniques have been applied for the analysis of EEG signals [11] [13] [16]. In [18], a novel methodology for the prediction of seizures based on the analysis of EEG and ECG signals was presented where a sequential forward selection (SFS) is used for feature selection while a linear Bayes and a k-Nearest Neighbors (KNN) classifiers are used for classifying EEG and ECG features respectively. In [19], epileptic seizure detection method based on EEG signals was proposed in which discrete wavelet transform (DWT) is used for feature extraction while artificial neural network (ANN) is implemented to classify these features. In [20], Classification method of epileptic EEG signals by making use of multilayer perceptron (MLP) neural network and discrete short time Fourier transform (STFT) was presented. In [21], seizure detection method based on thresholding technique and Short Time Fourier Transform (STFT) was presented. In [22], seizure prediction model based on the use of four different classifiers including decision tree, discriminant analysis, K-nearest neighbor, and support vector machines (SVM) was proposed to analyze the EEG signals. In this method, Higher Order Spectral Analysis (HOSA) is used for feature extraction where sample entropy (SE), and Hurst index (HI), and permutation entropy (PE) are computed. In [23], an automated detection method based on the discriminant analysis (DA) for classifying the EEG signal was presented. This method focuses on extracting sample and permutation of four entropies features in which permutation entropy achieved the best performance. In [24], a distributed computing model for epileptic seizure detection was developed. This model is developed by making use of cloud services to deal with processing of big data namely EEG data. In [25], another automated detection method based on the analysis of EEG signals was presented. This method is developed based extracting several statistical features accompanied by a Relief method for features ranking and four classifiers including support vector machine (SVM), Fuzzy k-Nearest Neighbor (Fuzzy k-NN), k-Nearest Neighbor(k-NN) and Naive Bayes to classifying the features into seizure and non-seizure. In [26], automatic classification method was presented to classify generalized epileptic and non-epileptic states from multi-channel EEG signals. In this method, time-frequency domain features are extracted followed by the Relief ranking algorithm for feature selection then the classification is done based on three different classifiers including Bayesian network, random forest, and Random Committee. Since the literature on seizure detection and prediction based on EEG signals are rich, only recent and relevant proposals are discussed. More discussion about other seizure prediction methods based on the analysis of EEG signals is presented in Chapter 5.

State-of-the-art work research stated that epileptic seizure prediction based on the analysis of EEG data may be unsuitable for daily life use as EEG sensors impose restrictions on the human mobility [8]. Moreover, although the performance of several approaches based on EEG signals analysis yielded good classification accuracy, these techniques suffer from poor sensitivity, in addition to focusing only on the differentiation between seizure and non-seizure state, not taking into consideration seizure prediction. In addition, over the past few years, it has been proven that not only the brain activity is affected during a seizure but also ECG signals, which can be used as a biomarker for seizure prediction [7][8]. In [27], a study of two patient groups with complex partial seizures and psychogenic non-epileptic seizures was introduced to investigate the changes in heart rate variability (HRV) in both groups. In this study, the HRV parameters in time and frequency domains were extracted from ECG signals of 26 patients. The obtained results indicate the apparent differences among ictal HRV features during epileptic and non-epileptic seizures. In [28], detection algorithm based on the analysis of ECG signals was presented in which an average of 85% positive predictive value (PPV) was obtained. This indicates that the changes in heart rate and respiration can be used as a biomarker for seizure onset detection. In [29], epileptic seizure detection algorithm based on the analysis of ECG was proposed in which four different heart rate variability (HRV) is evaluated by making use of a moving window of size 30, 50 or 100 R-R intervals. The proposed algorithm has shown a good performance in detecting 13 seizure onsets out of the 17 from the tested ECG data. In [30], another seizure detection method was presented based on the analysis of both ECG and EEG signals. In this method, support vector machines SVM algorithm is used to classify the time-domain and frequency domain features that are extracted from both signals. Recent several studies utilized different deep learning algorithms for seizure detection and prediction [31] [32] [33]. Most of these deep learning approaches such as Deep Recurrent neural network DRNN and Convolution neural network were designed based on the analysis of EEG signals. More discussion and details about other proposed methods for seizure prediction based on the analysis of ECG signals presented in Chapter 4.

2.4 Challenges and Limitations in the Existing Methods for Seizure Prediction:

Although various seizure prediction algorithms have been widely studied, several limitations and gaps still exist and need to be addressed. One of the main challenges is to offer a balance between the predictive capability of seizures and false pre-ictal alarms in which the key features can be extracted to anticipate the seizure onset. On the other hand, most of the existing approaches focused on designing models to detect seizures or non-seizures state and did not consider the other seizures states such as inter-ictal and pre-ictal state, which is more relevant for early prediction. Most of the state-of-the-art methods have ignored the analysis of seizure detection speed as well as the computational cost such as energy consumption to validate the performance of their proposed methods. Limited advanced techniques have been applied for seizure prediction based on utilizing both ECG and EEG signals where the real-time prediction still an open issue. Developing prediction system based on lightweight signals such as ECG can enhance the detection latency, the real-time prediction, and decrease the computational complexity of the classification algorithm.

Most of the existing methods were developed without considering big data and notification latency issues to processes multiple patient’s data in real-time. For reliable real-time seizure prediction system, a massive amount of collected vital signs from various sensor need to be stored and processed in real-time. Wireless Body Area Networks (WBAN) have been used for acquiring different vital signs from the patients by establishing of implantable or wearable sensor nodes, which are used to transmit the data over a wireless network to end users for visualization and diagnosis. The WBAN-based systems have been used along with remote cloud servers to store and process the collected data from different sensor nodes. However, the health and medical systems based on the cloud computing platform have faced several challenges due to latency-sensitive and massive data transmission issues. Undoubtedly, transmitting of a massive amount of data over the network can result in increasing the possibility of error rate, especially in case of transmitting health data, a single error in analyzed data can crucially affect a treatment decision and human life. Fog computing platform is introduced to solve these challenges that are facing cloud computing platforms such as processing latency, and quality of service (QoS) guarantee. The integration of WBAN, cloud computing, and fog computing can play fundamental roles in monitoring various chronic diseases. This also could be a feasible solution to meet the current challenges in seizure prediction systems. Therefore, a new seizure prediction model should benefit from this emerging fog computing technology for real-time signals analysis and notification. More details about the role of emerging fog computing in healthcare systems are explained in the following sections.

2.5 An Overview of Fog Computing

2.5.1 Fog Computing

Fog computing was first introduced by Cisco in 2012 to overcome the existing limitations in cloud-computing platform [34]. Fog computing is an emerging technology in the context of Internet of Things (IoT) to extend cloud computing services to the edge of the network, which implies more computation power closer to the user and provides a practical solution to meet the needs of IoT applications for data processing in real-time. Fog computing also introduced to achieve the goal of designing and developing a scalable IoT platform to manage a large amount of distributed "things," support latency-sensitive applications, and serve a wide variety of IoT applications. In general, the following characteristics of IoT explain the main reason for introducing fog computing:

Huge volumes of data: IoT is expected to deal with vast amounts of data from hundreds of thousands or millions of edge devices. Therefore, it is not practical to transfer such huge data to the cloud for storage and computation that lead to consuming massive bandwidth [35]. Fog is a scalable networking model that can be used to process this data locally at the edge of the network.

Latency minimization: The applications such as latency sensitive applications require processing and filtering data close to the device that generated this data [36]. Fog as an intelligence network model closer to the network edge can minimize the latency and avert the system failure.

Scalability: It is necessary to introduce a scalable architecture that can support dense network with massively distributed devices. Fog provides distributed sensing nodes with capability for processing and storage locally and cooperation with the cloud for big data analytics.

Address security concerns: In many scenarios, IoT should be able to protect data in both directions sending and receiving to deliver critical and confidential data. This security concern can be solved since the fog nodes are distributed close to the vicinity of users. Thus, the ability to control end devices became possible [35] [36].

2.5.2 Characterization of Fog Computing:

Both fog and cloud computing platforms provide storage, compute, and network services to the end users, but the fog is different from the traditional cloud computing in terms of physical location, quality of service, and network structure. Fog computing can offer low latency, high computational power, better data management, and better quality of service (QoS) [37]. Moreover, fog allows real-time data processing with limited bandwidth. Other characteristics are explained as follows:

Physical location: Fog is closer to the user than the cloud, the fog nodes are distributed locally as the nearby sink points, while the cloud computing servers are centralized as the floating sink points. Since the fog nodes are close to the edge network, the overall delay can be reduced by exchanging data in the same Local Area Network (LAN).

Support for real-time interactions and low latency: Distribution of the fog nodes plays a significant role in the processing of the real-time data and providing network services of higher quality. Therefore, fog can support applications that involve real-time interactions such as video streaming and augmented reality.

Support for mobility: Fog nodes can communicate directly with the end devices and thus support mobility requirement that is an essential for several applications.

Support for various communications networks: Fog nodes can be supported by a wide range of communication networks. Fog can work with different types of protocols such as Wi-Fi, WiMAX, and 2G/3G/4G [37].

Geographical distribution: Fog can be deployed in wide geo-distribution locations with a large number of nodes in comparison with that in the centralized cloud.

Heterogeneity: Fog nodes can be distributed in the vast range of environments with the form of physical or virtual fog node. Fog nodes are heterogeneous at the various tier of networks hierarchy with the multi-tiered hierarchical organization.

2.5.3 Fog vs. Cloud:

Table 2.1 summarizes several differences between fog and cloud. Combined fog and cloud computing introduced a future platform for IoT applications that can exploit the benefits of the local distribution of the fog and the global centralized of the cloud. Fog computing can keep up with the rapid increase of IoT platforms in which more and more computational power is needed to execute intensive tasks for several applications such as augmented reality applications.

Table 2.1: Comparison between Fog and Cloud [34].

Main Features	**Cloud Computing**	**Fog Computing**
Latency	High	Low
Location of server nodes	Within the Internet	At the edge of the local network
Distance between the client and server	Multiple hops	One hop
Geographical distribution	Centralized	Distributed
Number of server nodes	Few	Very large
Real-time interactions	Supported	Supported
Support for Mobility	Limited	Supported
Location awareness	No	Yes
Delay jitter	High	Very low
Attack on moving data	High probability	Very low probability
Security	Undefined	Can be defined
Number of user/device	Tens/ hundreds of millions	Tens of billion
Scalability	Less (Big cloud centers - Cost prohibited)	More (Micro-fog centers – Easy to deploy)

2.5.4 Fog Architecture:

Figure 2.4 shows a simple architecture for fog computing that consists of three layers including end devices, fog, and cloud. In this framework, various smart devices can be connected to one or many fog nodes. The fog is the intermediate layer between the end devices and the cloud.

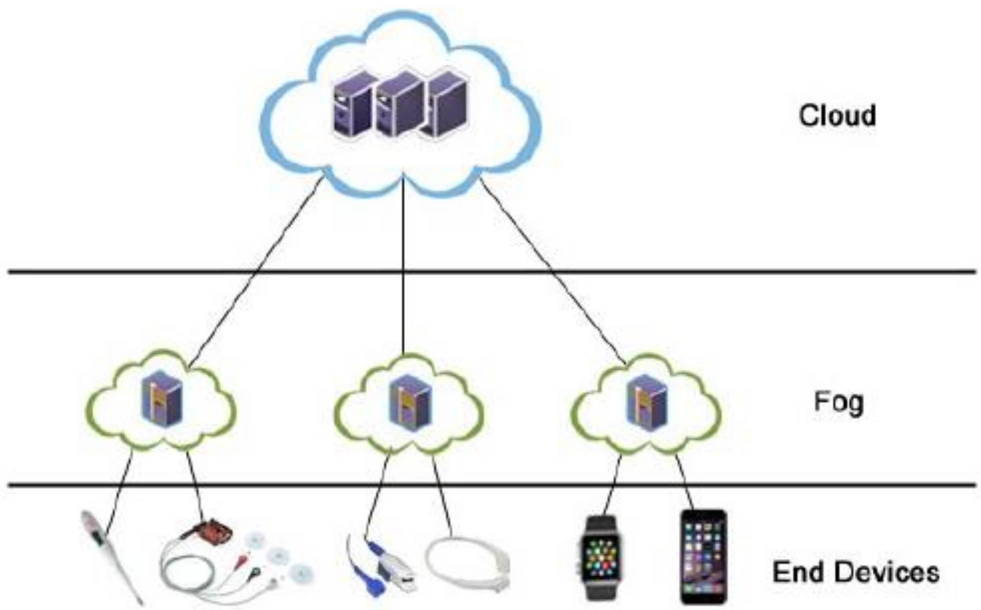


Figure 2.4: Fog computing architecture [37].

The architecture of fog computing is not a separate architecture from the traditional cloud; it is the architecture that extends the cloud capabilities to the edge of the network to enable real-time processing and analytics. Each layer has different properties, the first layer of this architecture consists of end devices such as sensors, which are used for collecting and filtering data and then send it to the higher layer for more processing. The second layer of this architecture consists of fog nodes, which distribute along the edge of the network to enable the local and real-time processing. The highest layer contains cloud servers that are responsible for future analytics and global storage.

2.5.5 Fog Applications:

This part discusses different applications that can benefit from fog computing platform. As stated in [38] [39] [40], several of the critical applications in which fog computing can play a significant role are the following:

Connected Vehicles: The unique features of fog computing, such as real-time interaction, is ideal for Connected Vehicles (CV) to support the communications among vehicles, traffic lights, and access points. Several applications for connected vehicles based on fog computing can be developed such as traffic information sharing, congestion mitigation, and traffic lights scheduling.

Smart Cities: Fog computing can support smart services by collecting data on city activities from different sensors. The capability of fog computing would be able to obtain sensor information for all levels and integrate mutually independent network to design smart applications.

Smart Grids: Fog computing offers a low-cost environment as energy consuming devices can be switched with devices that use other energies such as solar and winds. Fog backs semi-permanent capacity at the highest tier and temporary capacity at the lowest tier where the collected data is processed on the edge of the network through fog collectors and then generate control instructions to the actuators.

Health Care: Fog can provide many benefits for healthcare monitoring applications. Fog computing can play a significant role in improving the healthcare services and helping physicians to make an accurate decision. The following sections discuss the applications of fog computing in Healthcare with more details.

2.5.6 Fog Computing in Healthcare:

The healthcare services are evolving faster than ever before due to the growing interest in delivering high-quality services for low prices and expanded competitively among healthcare services providers. Fog computing technology, if implemented and used appropriately, can fulfill these requirements and offers the opportunity to improve the healthcare services, particularly for telehealth and telemedicine infrastructure for an elderly population and people with chronic conditions. Moreover, the distinctive characteristics of fog computing such as geographical distribution, location awareness, low latency, edge location, and scalability, offer a feasible solution for challenges in the existing IoT healthcare systems. Fog computing is considered as an intelligent technology for reliable services, especially for healthcare services that required low service response time [41].

Although cloud computing provides many benefits for health monitoring systems such as lower maintenance and services costs, and capability of large data storage volume, still many challenges exist in these systems [42]. Fog computing expands the applications and domains of the cloud computing that cannot fully support. These applications including real-time applications that require low latency, high bandwidth, and did not accept interrupted of services in case of losing connectivity. These previous characteristics are analogous to the characteristics of real-time health monitoring systems, which means that fog computing can deal with these requirements marvelously through cooperation and compatibility with the cloud.

2.5.6.1 Benefits of Fog Computing in Healthcare Systems:

In healthcare systems, it very important to analyze and process a collected data in milliseconds. Fog computing provides real-time processing at the edge of the network, which enables making a decision in real-time time. In fog, collecting data can be done at the utmost edge very close to a healthcare environment such as hospitals and smart home. Fog can keep up acceleration in the increasing number of devices connected to the future IoT, which include sensor used for healthcare such as wearable body sensors that will generate massive data. The following are several advantages of fog computing in the healthcare systems [36]:

Collaboration: Through the fog, the data can easily share and synchronize among different health services providers at the same time.

Easy and Fast Access: Since fog computing is close to the end users, the health services providers and their patients can get quick access to the vital health information without service interruption.

Better location: Fog can act as a smart gateway between the cloud data-centers and the end devices; this offers better delay performance, reduce data transmission, and saves high network bandwidth. These features can play an essential role in designing smart healthcare applications.

Decreased Costs: Since fog computing can be distributed as micro centers closer to the end-users compared to the cloud, the cost is typically minimal, which contributes to supporting human health monitoring Wireless Body Area Networks(WBAN)-based systems [42].

Security and Privacy: The privacy and security of patient's medical data are one of the most prominent challenges when stepping under new technology. Fog computing is a promising emerging technology to deal with the concerns.

2.5.6.2 General Architectures of Fog in Healthcare:

The topic of fog computing in the healthcare domain has attracted several research efforts recently. Several of these efforts seek to take advantage of fog computing to overcome the existing drawbacks in health monitoring systems. Applying the concept of fog computing for enhancing health monitoring IoT-based systems. The role of fog computing shown in Figure 2.5, in the architecture of IoT-based health monitoring system, fog computing is implemented as an intermediary layer between the cloud platform and the sensor nodes layer, which comprise gateways and distributed databases [43].

A health monitoring system either in a hospital or a smart home often comprises of various components, each with a specific function. Various devices or sensors used to collect bio-data such as ECG, EMG, blood pressure, temperature and EEG from a human body. Then processing and transmission of this collected bio-data are done via wireless or wire cables. Several limitations exist in this system such that unsupported remote monitoring and mobility, which results in numerous inconveniences to both patients and doctors [42]. A health monitoring system based on Wireless Body Area Networks (WBAN) can handle these drawbacks successfully. WBAN is one of the most important technologies used in healthcare IoT, which support mobility and wireless transmission. WBAN used for visualization and diagnosis through the data that collected from implantable or wearable sensor nodes and transmitted over the wireless network via communication protocols (i.e., Wi-Fi, 6LoWPAN or Bluetooth) to end users. The components of health monitoring WBAN-based systems can be divided into three fundamental parts, which are sensor nodes, gateways, and a back-end part [43] as described in the following section.

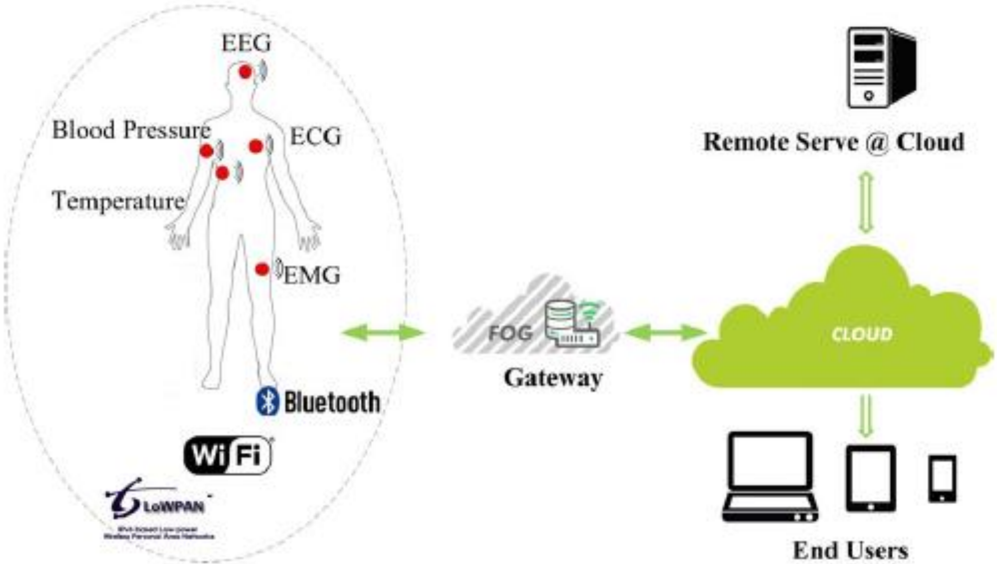


Figure 2.5: The IoT-based health monitoring system architecture [42].

Medical sensor node layer: The sensor node used for collecting bio-data, which can be implanted into patient's body or can be wearable sensors. These sensors should be as small as possible to be comfortable for patients use. The sensors in BAN is used for transmitting the data to a fog server (gateway) based on a direct link via different communication protocols such as Wi-Fi, Bluetooth, 6LoWPAN, and ZigBee [42].

Fog/Gateway layer: The gateway used for transmitting the collecting data to a remote cloud server. By implementing the fog concept, this gateway is also used for processing data locally and sending the rest of data to a higher layer. This layer connects the sensor nodes with a remote cloud server through fog computing.

Back-end part layer: This layer comprises of a cloud server, which can be different based on the type of services provided. The cloud server is responsible for storing and processing big-data while back-end services are used for visualization and diagnosis purposes.

2.5.6.3 State-of-the-art of Fog Computing in Healthcare:

Several research efforts have tried to outline the benefits of fog computing in designing smart healthcare applications [37] [43]. Different research tries to introduce more services and functions to expand healthcare monitoring systems, while others attempt to propose new architecture or platforms.

In [44] [45] [46], researchers have investigated the effectiveness of fog computing in health monitoring through developed fall detection algorithms and system. In [44], Cao et al. designed a real-time fall detection system, called U-Fall, and new fall detection algorithms for stroke mitigation that exploiting distributed analytics and edge intelligence from the fog computing paradigm. Compared to existing detection algorithms and systems, the experiments show that the proposed system achieved high sensitivity (low miss rate) and high specificity (low false positive rate). However, the authors stated that there is need to improve the specificity of future work. In [45], Cao et al. also proposed FAST; a fog computing assisted distributed analytics system for monitoring patients with stroke. The author's designed real-time fall detection system based on fog computing, which helped in the division of the fall detection task among edge devices and cloud computing. The proposed system accomplishes high sensitivity for real-world data. On the other hand, the obtained result of the response time and energy consumption are very close to the existing approaches. While the authors in [44] [45] used pervasive fall detection for stroke mitigation as a case study to explore the benefits of fog computing in health monitoring, the authors in [46] the proposed fog system implemented in the home of the user with the fall detection algorithm and the gas detection algorithm. In comparison with [44] [45], the proposed system implemented within the frames of the European funded project eWALL, which system consists of four sensing modules. The proposed system introduces a delay of maximum 1s comparing with the cloud that introduces an extra 2 to 4 seconds to process the same data.

In [42] [43] [47], the authors have exploited the benefits of fog computing at smart gateways to enhance a health monitoring system. The primary motivation in [42] is to enhance a health monitoring IoT-based systems architecture by exploiting the full benefits of fog computing and bring intelligence to the gateway. The results show that fog diagram helps in term of QoS assurance, emergency notification, and bandwidth utilization. However, Electrocardiogram (ECG) feature extraction is the only one case study that has been addressed to demonstrate the efficacy of fog computing in IoT-based healthcare systems. While in [47], the authors presented a smart gateway with fog computing capabilities, the authors in [42] implemented the fog computing and smart e-Health gateways concepts for body sensor networks to offer energy efficiency. In construct [43] evaluate the efficiency of the proposed system by comparing the power and energy characteristics of fog-based and traditional BSN networks, with fog computing service at a gateway can achieve more than 55% savings in energy consumption.

In [48], Monteiro et al. proposed fog computing interface (FIT) for remote processing of clinical speech data, where fog acts as a smart getaway between the smartwatch and the cloud. The results show the benefits of fog as a smart interface in reducing the data complexity and introducing computational intelligence at the edge compared to the cloud. In [49] [36] [50] [51], the authors proposed architectures for a u-healthcare monitoring system. In [49], Stantchev et al. introduced a three-tier architecture for a smart healthcare infrastructure through implementing fog computing, which provides a viable architecture for elderly care applications. The fog layer offers mobility support, location awareness, and low latency to improve the architecture. However, the blood pressure measurement is the only use case study used in this paper, which might make it difficult to evaluate the effectiveness of the proposed system. In [36], Nandyala et al. introduced architecture with benefits of fog to cloud (F2C) computing for IoT-based u-healthcare monitoring at home and hospital to overcome the limitations faced with the cloud. However, this paper did not validate the efficacy of using fog computing in such architecture. Conversely, [50] validated and evaluated the proposed architecture with fog computing used for telehealth big data applications. The case studies of this proposed system used for patients with either cardiovascular problems or speech motor disorders. Using the Fog Data architecture improve the system efficiency as shown in obtained results. Additionally, Ahmad et al. in [51] proposed a framework of Health Fog designed in a layered architecture where fog computing layer takes place between the system entities and the system consumer over the cloud. The proposed system exploit fog layer features that help in reducing the network flow and provide better control over data privacy and security.

In [41] [52], the authors discussed the benefits of fog computing for Chronic Obstructive Pulmonary Disease COPD. Designing monitoring systems for COPD patients with fog computing capacities can support patients' mobility, keep the privacy on the patient life, reduce the communications overload and healthcare costs. In [41], the authors proposed adopting F2C computing technology in handling and analyzing health service as a solution for COPD patients to carry out physical activity. The obtained results show that real-time processing with F2C computing helps to improve the COPD patients' quality of life and reduce health costs. In [52], the authors implemented part of the eWALL project in a home environment to monitor the patients with COPD and Mild Dementia. They address the aspects of fog computing in such environment for eHealth and ambient assisted living, and exam how to integrate such system in the Romanian healthcare ecosystem. However, both papers did not clarify the implementation process for the proposed system. Other related work focused on evaluating the e-Health applications with fog computing. In [53], Ramalho et al. have evaluated the performance of their previously proposed system, which is a cloud-based approach called Multi eHealth Cloud Service Framework in fog computing scenario. The evaluation results of this approach with fog achieving good performance rates to run mobile eHealth applications and overcome the performance of the cloud. However, the authors stated that other challenges might face the integration of fog and cloud to improve the performance of smart eHealth applications. It should mention that these proposed methods did not exploit the benefits of fog computing to address the problem of seizure prediction.

2.6 Summary

This chapter presents background information about epilepsy, different seizures states, and seizures types. It also offers a comprehensive review of the state-of-the-art techniques and methods that proposed for seizure prediction. This chapter also highlights the limitations and challenges of the existing methods and followed by an overview of fog computing technology and its benefits as a candidate solution in the context of healthcare applications.

The following chapter proposes a novel multi-tier fog-based architecture for early prediction of epileptic seizures based on the analysis of both ECG and EEG signals.

Chapter 3

Multi-Tier Fog-based Architecture for Early Prediction of Epileptic Seizures

3.1 Introduction

Epilepsy patients may lose their consciousness during daily activities such as driving or walking due to unexpected seizures. Such unpredicted seizures may result in a situation that imposes serious threat not only to the patients' lives but also to the people around them. The best strategy to protect such patients is to predict the onset of the seizure accurately to alert them at an early stage, thus improving the quality of life and increasing the safety considerations.

Different factors and challenges make the early prediction of seizure a complicated task. Over the past few years, several algorithms and methods were developed to predict the seizure and minimize its negative consequences. However, several limitations still exist in the state-of-the-art approaches, which need to be addressed. Most of the existing approaches are not suitable to support real-time settings, which requires bio-signals collection and analysis in real-time. Numerous methods were developed without considering the notification latency and computational cost for processing big data to support monitoring of many patients. Limited advanced techniques have been implemented for seizure prediction based on the analysis of different vital signs. Also, many prediction methods were developed based on the analysis of seizure state and ignored the investigation of pre-ictal state, which is more relevant to predict the seizure at an early stage. Early prediction methodology should be able to differentiate the pre-ictal state accurately from other seizure states with minimum latency to send a real-time notification. Recently, several seizure prediction models were developed based on the cloud. However, there is a significant need for supporting the real-time seizure notification and location awareness requirements. Therefore, there is a crucial need to design a new seizure prediction framework based on advanced computing technology such as fog computing which would greatly assist the patients' care and improve their quality of lives.

Although fog-based framework has been proposed in the literature for monitoring patients with diseases such as stroke [45], and Mild Dementia [52], these approaches have not considered the real-time analysis based on collecting the data from different bio-sensors, which is crucial for epilepsy patients. We hypothesize that the development of a novel distributed prediction methodology based on fog and mobile computing can enable the real-time prediction and notification of seizure state. This chapter proposes an intelligent multi-tier fog-based architecture for early prediction of epileptic seizures based on the analysis of ECG and EEG signals. The proposed architecture comprises of three tiers; sensing tier, fog computing tier, and cloud computing tier. This proposed architecture is designed to leverage the emerging fog computing technology at the second tier to enable data collection and analysis in real-time. The proposed architecture consists of two-level prediction models; a local decision based on lightweight analysis of ECG signals, and global decision based on extensive analysis of EEG signals. The main contribution of this chapter is proposing a multi-tier fog-based architecture for early prediction of epileptic seizures that 1) enables real-time signals analysis, 2) reduce the notification latency and energy consumption on real-time transmission and notification.

The rest of this chapter is organized as follows: Section 3.2 provides a brief overview of the related work. Section 3.3 presents a comprehensive description of the proposed multi-tier fog-based architecture for seizure prediction. Section 3.4 explains the properties of fog networking and presents mathematical formulation that used to evaluate the performance of the proposed architecture. Section 3.5 shows the primary results to evaluate the performance of the proposed fog-based architecture in comparison with that based on the traditional cloud computing framework. Section 3.6 provides a summary of this chapter.

3.2 Related Work

This section highlights the use of computing platforms in the context of healthcare applications and discusses the current cloud-based methods for seizure prediction.

In the last few years, the use of cloud computing technology grabbed considerable attention in the context of monitoring-healthcare applications. In [54], a cloud-based computing system is proposed to collect different biomarkers from patients in healthcare institutions, which support ubiquitous access. In [55], an architecture based on a combination of body sensor networks and cloud computing platform was proposed for assisted living monitoring. In this architecture, the data is collected using wearable sensors, while the analysis of this data is done at the remote cloud server. In [57], another cloud-based architecture was proposed for monitoring patients by using wireless sensor networks. This architecture supports sharing the patient's health state among different healthcare providers.

Several cloud-based approaches were designed for seizure prediction. In [58], a distributed platform based on cloud computing was proposed for seizure detection. In this model, the seizure decision is made based on the analysis of EEG patterns via random subspace ensemble learning approach. In [59], a cloud monitoring framework based on the analysis of EEG data was proposed for automatic seizure detection. In this framework, an accuracy of 94.6% was achieved based on the fast Walsh-Hadamard transform method for feature extraction and the k-means classifier for classification. However, a significant challenge was raised in this framework due to the limited memory and communication bandwidth for the processing of EEG data in real time. In [60], a cloud-based model for seizure detection based on the analysis of EEG signals was proposed. In this model, six support vector machines (SVMs) are collaboratively trained to classify the features that are extracted from EEG data, while a native genetic algorithm (GA) is used to determine a feature set. Although most of these proposed models indicated the benefits of cloud computing in the processing of vital signs of epileptic patients, there is a significant lack of supporting the real-time requirements in the cloud-based approaches.

The development of seizures-prediction model that is useful for real-time settings considered as a complex task due to several challenges. The biomedical sensors have lower capabilities regarding transmission speed, processing time, memory size, and energy supply compared with those sensors in other networking domains. In addition, location awareness and latency sensitivity are two main prominent challenges that face the cloud-based seizure-prediction models. Recently, fog computing technology is introduced as an intelligent solution to deal with these issues. However, the state-of-the-art methods have not considered utilizing the full benefits of such computing platform to address the problem of seizure prediction. The proposed method for seizure prediction in this chapter exploits the capabilities of fog computing for bio-signals collection and analysis in real-time.

3.3 The Proposed Multi-tier fog-based Architecture for Early Prediction of Seizures

The present work proposes a distributed multi-tier fog-based architecture to enable the early prediction of epileptic seizures and reduce the energy and latency on real-time data transmission and notification. This proposed architecture aims to distribute the data analytics between the edge device and server in the cloud. The proposed model is developed to exploit the intelligent services of emerging fog computing technology as a middle tier between the bio-sensors and remote cloud data servers. This tier enables the data collection and analysis through pervasive gateways at the edge of the network, thus providing significant support for monitoring the vital signs of epilepsy patients in real-time. This proposed architecture comprises of three-tiers and exploits the benefits of both fog and cloud in the early prediction of seizures as shown in Figure 3.1.

In the proposed architecture, the first tier is responsible for collecting data from patients. The fog tier is responsible for local decision making based on lightweight analysis of ECG signals. The cloud tier is responsible for making global decision based on extensive analysis of EEG signals as well as global data storage. Since the EEG signal is usually composed of multiple channels with higher fidelity data, analyzing such data on a limited-resource fog node may reduce the efficiency of the system. Allowing the single-channel ECG to be processed on the fog node allows for light-weight decision making and real-time patient notification. Coupling that with the analysis of EEG signals on the cloud provides a robust system with reliable decisions.

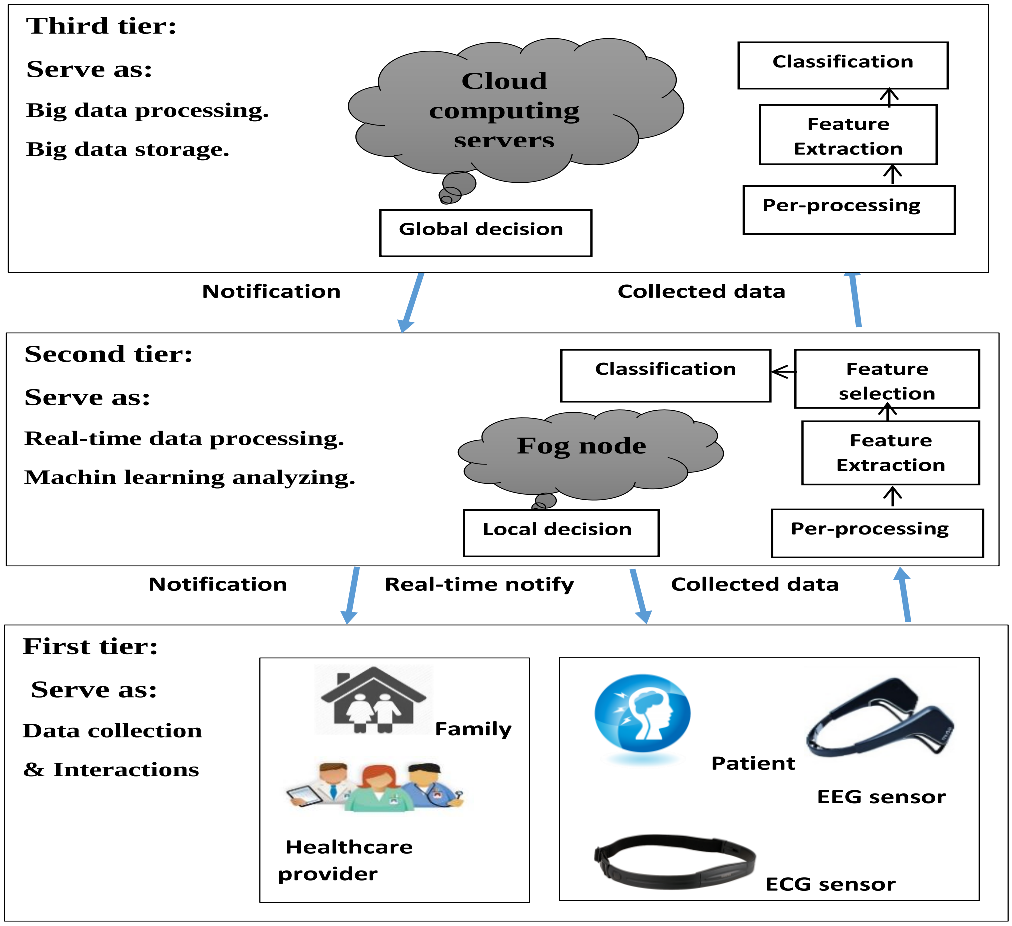


Figure 3.1. An overview of multi-tier fog-based architecture for seizure prediction.

The flow of the data and notification within the proposed three-tier architecture can be explained as follows:

At the first tier, the ECG signals are collected from a patient based on a window size of five seconds, which has been proven to be a suitable window for the analysis of epileptic ECG signals; more details can be found in Chapter 4. The collected data from the first tier then transferred to the next tier. At the second tier, the ECG signals are analyzed within the nearest gateway (fog node) to make the local decision upon the seizure state. If the proposed system does not detect signs of seizure, the system continues monitoring the ECG signals at the second tier. If the proposed system detects the signs of oncoming seizure, the fog node sends a real-time notification to the patient at the first tier and start the analysis of EEG signals from the same window to make a global decision at the third tier in the cloud. If the decision of EEG analysis matches that of the local decision, the system sends a notification to the patient, family members, and healthcare provider to help in case of emergency. If the local decision is different from the global one, the system relies on the global decision and discards the local decision. This may be attributed to the fluctuation of ECG signals due to factors other than seizure such as a sport activity carried by patients. The proposed ECG and EEG analysis model are presented in more details in Chapters 4 and 5, respectively. The following subsections provide in-depth discussion of each tier in the proposed architecture.

3.3.1 First tier (Sensing):

The first tier serves as a data collection and interaction. This tier comprises of multiple biosensors, which is used for monitoring and collecting different health parameters from the patient. In this tier, different biomarkers such as brain activity, blood pressure, and heart rate can be collected using the wearable biosensors. The wearable sensors can interact with wireless communication protocols, such as Bluetooth or Wi-fi, to transmit the received bio-signals to the next tier. The wearable sensors can also be used to send an alert message to the patients to warn them before the seizure onset. The family members and healthcare provider at this tier are also notified to provide first aid and emergency assistance.

3.3.2 Second tier (fog computing/edge gateway):

This tier exploits the fog computing technology. In fog computing, the edge gateway act as a middle tier between the wearable biosensors and cloud server. The edge gateway can be used not only for forwarding data to the cloud but also for processing data in a distributed manner. These gateways are equipped with intelligent capabilities for local storage and lightweight computing. Although the cloud servers have the computing and storage power to perform advanced analytics, these cloud servers are often located at a server farm far from the patient's location which hinders analysis and response of the data in real-time. In fog environment, the fog nodes are located at the local area network where the processing can be performed in the nearest data hub to the patient such as a smart device, smart router or gateway. Such data hubs can reduce the transmission delay over the network and support patient mobility [37]. Moreover, this tier can be used for data aggregation, compression, filtering, and processing. Therefore, such intelligent gateway is exploited to make the local decisions based on lightweight analysis of ECG signals to predict the seizure state and send a real-time notification.

3.3.3 Third tier (cloud computing):

This tier exploits the cloud computing services for bio-signals analysis. The cloud computing is characterized by the ability for massive storage, massive computing capabilities, and big data processing. Therefore, this tier is used for an extensive analysis based on EEG signals to make accurate global decisions. Moreover, this tier can be used for storing long-term patients' medical data and providing access to the family and healthcare provider.

The following section illustrates the role of the proposed fog-based architecture in enhancing the seizure prediction performance and defines the performance metrics for modeling the performance in terms of latency minimization and energy consumption over the network.

3.4 Properties of the Proposed Fog-based Architecture

In the proposed architecture, the intermediate or fog tier can provide intelligent services to enhance the seizure prediction performance in real-time. The clear advantage of the proposed fog-based architecture is the ability to perform signal processing locally (closer to the end user), which significantly reduces the data movement across the network and thus minimizing the network congestion and latency. Moreover, enable real-time services such as alert notification due to the nearness of edge gateways to the patient.

In this chapter, the following performance metrics are modeled to evaluate the performance of the proposed fog-based architecture and compare its performance against the use of traditional cloud computing:

- Service latency
- Energy consumption

The following subsections provide a discussion about each one of these performance metrics.

3.4.1 Service Latency:

In the proposed architecture, the collected bio-signals from the sensors at the first tier are processed at two different tiers. The ECG signals are processed at the fog tier while the EEG signals are forwarded through the fog for further analysis at the cloud tier. In the context of fog computing platforms; the service latency is defined as response time (i.e., time for getting a notification), which calculated as a sum of the transmission time and the processing time [61] [62]. In addition, the communication latency between sensors at the first tier is considered negligible as it does not impact the latency over the network [62] [63]. Figure 3.2 shows an overview of the flow of data and notification between the three tiers of the proposed architecture for seizure prediction.

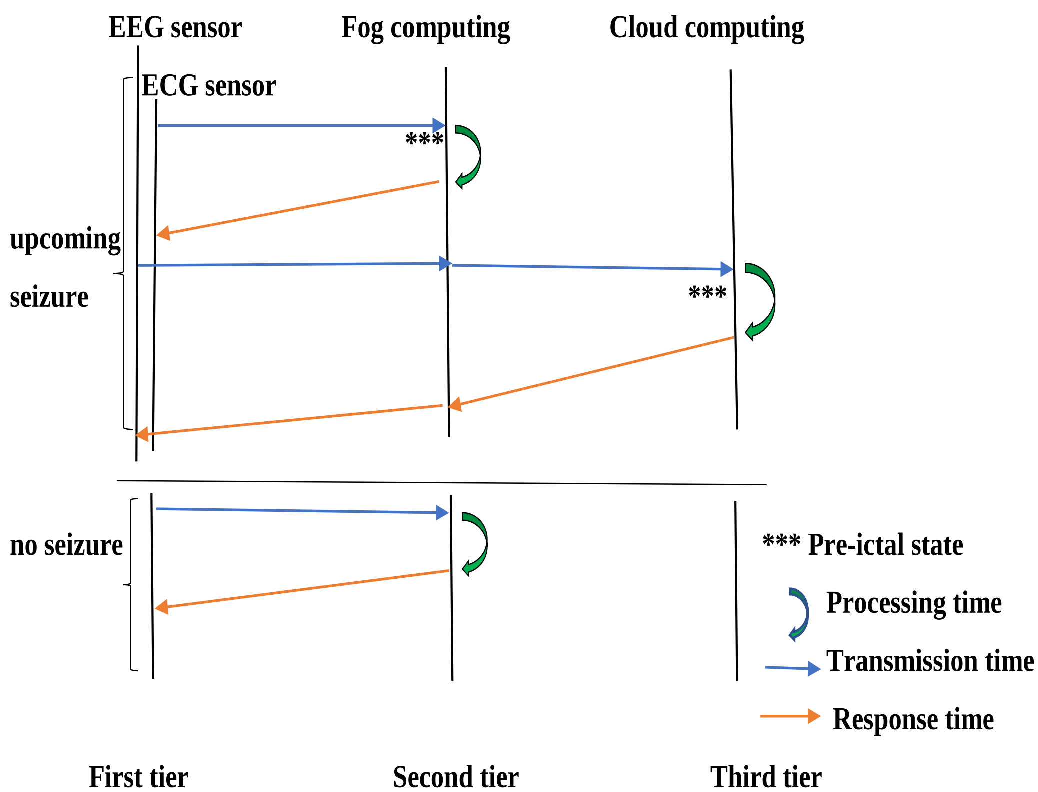


Figure 3.2. An overview of latency in the proposed multi-tier architecture.

To show the benefit of using the fog tier in the proposed architecture; the latencies for transmitting the bio-signals from the sensor to the edge gateway and from the gateway to the remote cloud server need to be measured and compared. In the proposed architecture, the service latency (i.e., end to end delay) can be calculated at the fog tier in case of detecting normal state using equation (3.1), while in the case of detecting upcoming seizure using equation (3.2) as follows:

$$L(fog)_{Normal} = Tt(ECG)_{sf} + Pt(ECG)_f + Rt(ECG)_{fs} \quad (3.1)$$

$$L(fog)_{Seizure} = Tt(ECG)_{sf} + Tt(EEG)_{sf} + Tt(EEG)_{fc} + Pt(ECG)_f + Pt(EEG)_c + Rt(ECG)_{fs} + Rt(EEG)_{cf} + Rt(EEG)_{fs} \quad (3.2)$$

In contrast, the service latency (*i.e.*, end-to-end delay) at the cloud tier (*i.e.*, without using the fog tier for analysis) can be computed in case of detecting normal state using equation (3.3), while in case of detecting upcoming seizure using equation (3.4) as follow:

$$L(cloud)_{Normal} = Tt(ECG)_{sf} + Tt(ECG)_{fc} + Pt(ECG)_c + Rt(ECG)_{cf} + Rt(ECG)_{fs} \quad (3.3)$$

$$L(cloud)_{Seizure} = Tt(ECG)_{sf} + Tt(ECG)_{fc} + Tt(EEG)_{sf} + Tt(EEG)_{fc} + Pt(ECG)_c + Pt(EEG)_c + Rt(ECG)_{fs} + Rt(EEG)_{fs} + Rt(EEG)_{cf} + Rt(EEG)_{fs} \quad (3.4)$$

- $Tt(ECG)_{sf}$, $Tt(EEG)_{sf}$: represent the transmission time of ECG or EEG packets from the sensor at first tier to the corresponding fog node (gateway) at the second tier.
- $Tt(ECG)_{fc}$, $Tt(EEG)_{fc}$: represent the transmission time of ECG or EEG packets from the fog node at second tier to the cloud at the third tier.
- $Pt(ECG)_f$, $Pt\ (EEG)c$: represent the processing time of ECG or EEG packets in the fog $(.)_f$ node at the second tier or in the cloud $(.)_c$ at the third tier, respectively.
- $Rt(ECG)_{fs}$, $Rt(EEG)_{fs}$: represent the response time for ECG or EEG packets analysis from the fog node at the second tier to the sensor at first tier.
- $Rt(ECG)_{cf}$, $Rt(EEG)_{cf}$: represent the response time for ECG or EEG packets analysis from the cloud at the third tier to the fog at second tier.

According to the mathematical formulation of fog computing architecture in [62], the mean of service latency for data packets from N_i $a$applications running at the first tier and served by fog is computed as follows:

$$L(fog) = \frac{\delta_{tf} \sum_{i=1}^{w} \left[B_i + {b_i}^r + (B_i - b_i)^r \right] + \delta_{fc} \sum_{i=1}^{w} [B_i + {b_i}^r]}{\sum_{i=1}^{w} B_i} \tag{3.5}$$

$$L(cloud) = \frac{\delta_{fc} \sum_{i=1}^{w} (B_i + {B_i}^r)}{\sum_{i=1}^{w} B_i} \tag{3.6}$$

- δ_{tf} , δ_{fc} : represent the delay in transmission of a data packet from the sensor to fog node and from the fog to the remote cloud, respectively.
- b_i , B_i: represent the total number of packets sent by N_i applications from sensor and served at the fog or at the cloud data server, respectively.
- X^r : denote a total number of packets that are sent as response to the X request data packets.

Based on equation (3.5) and (3.6), the service latency of our proposed architecture presented in equation (3.2) and (3.4) in case of detecting upcoming seizure can be reformulated as follows:

$$\begin{aligned} L(fog)_{Seizure} = & \left(\frac{Tt \sum_{i=1}^{x} (p_i)_{sf} + Rt \sum_{i=1}^{x} (p_i)_{fs} + Pt \sum_{i=1}^{x} (p_i)_f}{\sum_{i=1}^{X} (p_i)_{sf}} \right) \\ & + \left(\frac{Tt \sum_{j=1}^{y} [(q_j)_{sf} + (q_j)_{fc}] + Rt \sum_{j=1}^{y} [(q_j)_{cf} + (q_j)_{fs}] + Pt \sum_{i=1}^{y} (q_j)_c}{\sum_{j=1}^{y} [(q_j)_{sf} + (q_j)_{fc}]} \right) \end{aligned} \tag{3.7}$$

The first part of this equation, $\left(\frac{Tt \sum_{i=1}^{x} (p_i)_{sf} + Rt \sum_{i=1}^{x} (p_i)_{fs} + Pt \sum_{i=1}^{x} (p_i)_f}{\sum_{i=1}^{X} (p_i)_{sf}} \right)$, refers to the delay in transmission Tt, processing Pt, and response time Rt for ECG signals analysis at the fog tier. The second part of the equation, $\left(\frac{Tt\sum_{j=1}^{y}[(q_j)_{sf}+(q_j)_{fc}]+Rt\sum_{j=1}^{y}[(q_j)_{cf}+(q_j)_{fs}]+Pt\sum_{i=1}^{y}(q_j)_c}{\sum_{j=1}^{y}[(q_j)_{sf}+(q_j)_{fc}]}\right)$, refers to the delay in transmission Tt, processing Pt, and response time Rt for EEG signals analysis, which forwarded through the fog and served at the cloud. To consider the analysis of bio-signals from multiple patients, we use x to refer to the total number of ECG sensors, while y refers to total number of EEG sensors. Also, p_i is the total number of ECG packets per sensor, and q_j is the total number of EEG packets per sensor. In contrast, in case of using the cloud tier (*i.e.;* without using the fog tier for the analysis), both ECG and EEG are analyzed at the cloud where the end to end latency in case of detecting upcoming seizure can be computed as follow:

$$L(cloud)_{Seizur} = \left(\frac{Tt\sum_{i=1}^{x}[(p_i)_{sf}+(p_i)_{fc}]+Rt\sum_{i=1}^{x}[(p_i)_{cf}+(p_i)_{fs}]+Pt\sum_{i=1}^{x}(p_i)_c}{\sum_{i=1}^{X}[(p_i)_{sf}+[(p_i)_{fc}]}\right) + \left(\frac{Tt\sum_{j=1}^{y}[(q_j)_{sf}+(q_j)_{fc}]+Rt\sum_{j=1}^{y}[(q_j)_{cf}+(q_j)_{fs}]+Pt\sum_{i=1}^{y}(q_j)_c}{\sum_{j=1}^{y}[(q_j)_{sf}+(q_j)_{fc}]}\right) \quad (3.8)$$

The first part of this equation refers to the delay in transmission Tt, processing Pt, and response time Rt for the analysis of ECG signals at the cloud tier. The second part of the equation refers to the delay in transmission Tt, processing Pt, and response time for the analysis of EEG signals at the cloud tier.

3.4.2 Energy Consumption:

Energy is a scarce commodity in sensor networks, hence, it is imperative that the network resources are managed to prolong the lifetime of the network as much as possible. Fog computing provides a practical solution for saving the sensors energy via shifting the data processing from these sensors to the edge gateway. Despite the growth of local fog servers at the edge of the network, limited studies investigated the energy consumption based on using such distributed fog servers in comparison with the centralized data servers in the cloud [63]. Therefore, this study compares the energy consumption of data processing of the proposed architecture with and without the fog tier. Thus, the analysis of energy consumption is essential to investigate the performance of the proposed fog-based architecture against the cloud architecture in optimizing the seizure prediction performance. The primary source of energy consumption at each tier needs to be identified to analyze the energy consumption in the proposed architecture. Bio-sensor at the first tier, a gateway at the second tier, and cloud server at the third tier are the three main sources of energy in the proposed architecture. The energy expended in the context of computing platforms is computed as a sum of energy spent due to the transmission and processing of data from an application running within the end devices [61] [62]. Thus, in general, the energy expended can be calculated as follow:

$$E = E_{tr} + E_{proc} \qquad (3.9)$$

- E_{tr}: denote the energy expended due to the transmitting of data.
- E_{proc}: denote the energy expended due to the processing of data.

To show the advantage of using the fog tier in the proposed architecture in terms of energy consumption; the end-to-end energy expended due to the transmission and processing of bio-signals based on using fog server (edge gateway) at the second tier and without using the fog tier (based on the cloud server) is computed and compared. In this way, we can compare the performance of our proposed architecture, as fog-based, versus cloud-based concerning energy consumption. The end-to-end energy expended due to the transmission and processing of patient data in case of detecting upcoming seizure while using the edge gateway at the second tier can be computed as follows:

$$E(fog)_{Seizure} = E_{tr}(ECG)_{sf} + E_{proc}(ECG)_{f} + E_{tr}(EEG)_{sf} + E_{tr}(EEG)_{fc} + E_{proc}(EEG)_{c} \quad (3.9)$$

On the other hand, based on using the cloud computing (*i.e.*, without using fog) the data is forwarded to the cloud through the core of the network for storage and analysis. Thus, the end to end energy expended due to the transmission and processing of patient data can be estimated as follows:

$$E(cloud)_{Seizure} = E_{tr}(ECG)_{sf} + E_{tr}(ECG)_{fc} + E_{proc}(ECG)_{c} + E_{tr}(EEG)_{sf} + E_{tr}(EEG)_{fc} + E_{proc}(EEG)_{c} \quad (3.10)$$

According to the mathematical formulation in [62], the average of energy expended due to the transmission and analysis of data packets in fog computing framework computed as follows:

$$E(fog(t)) = \left[\gamma_{tf} \sum_{i=1}^{w} \sum_{j=1}^{t} \Lambda_i(j)\right] + \gamma_{fc} \sum_{i=1}^{w} \sum_{j=1}^{t} \Lambda_i(j) \,\big]/t + \alpha_{fog} \sum_{i=1}^{w} \sum_{j=1}^{t} \Lambda_i(j) + \alpha_{cloud} \sum_{i=1}^{w} \sum_{j=1}^{t} \Lambda_i(j) \quad (3.11)$$

In contrast, the rate of energy consumption at the cloud is given as follows:

$$E(cloud(t)) = \left[\gamma_{tc} \sum_{i=1}^{w} \sum_{j=1}^{t} \Lambda_i(j)\right]/t + \left[\alpha_{cloud} \sum_{i=1}^{w} \sum_{j=1}^{t} \Lambda_i(j)\right] \quad (3.12)$$

- γ_{tf}, γ_{fc}: represent the rate of energy expended due to the transmission of one data byte from (the sensors to the fog nodes) and (from the fog nodes to the cloud), respectively.
- α_{fog} , α_{cloud}: denote the required energy to process one data byte at the fog or at the cloud respectively.

- w: represent a total number of sensors.
- $\Lambda_i(j), \Lambda_i(j)$: denote the total number of bytes transferred (from sensors to the fog nodes) and (from the fog nodes to the cloud) at time t=j where $\Lambda_i(j) > \Lambda_i(j)$.
- γ_{tc}: denote the energy expended due to transferring of one data byte between the sensor and cloud.

Based on equation (3.11) and (3.12), the energy expended in our proposed architecture, presented in equation (3.9) and (3.10) in case of detecting upcoming seizure can be reformulated as follows:

$$E(fog)_{Seizure} = \left[\left(E_{tr} \sum_{i=1}^{x} \sum_{k=1}^{t} p_i(K)_{sf}\right) \Big/ t + E_{proc} \sum_{i=1}^{x} \sum_{k=1}^{t} p_i(K)_f\right] +$$

$$\left[\left(E_{tr} \sum_{j=1}^{y} \sum_{k=1}^{t} q_j(K)_{sf} + q_j(K)_{fc}\right) \Big/ t + E_{proc} \sum_{j=1}^{y} \sum_{k=1}^{t} q_j(K)_c\right] \quad (3.13)$$

$$E(cloud)_{Seizure} = \left[\left(E_{tr} \sum_{i=1}^{x} \sum_{k=1}^{t} p_i(K)_{sf} + p_i(K)_{fc}\right) \Big/ t +\right.$$

$$\left. E_{proc} \sum_{i=1}^{x} \sum_{k=1}^{t} p_i(K)_c\right] + \left[\left(E_{tr} \sum_{j=1}^{y} \sum_{k=1}^{t} q_j(K)_{sf} + q_j(K)_{fc}\right) \Big/ t +\right.$$

$$\left. E_{proc} \sum_{j=1}^{y} \sum_{k=1}^{t} q_j(K)_c\right] \quad (3.14)$$

The first part of equations (3.13) and (3.14), refer to the energy expended due to the transmission and processing of ECG signals (x), while the second part of these equations refers to the energy expended due to the transmission and processing of EEG signals (y). In case of using the cloud tier (without using fog for the analysis), both ECG and EEG signals are analyzed at the remote cloud data server. $p_i(K)_{sf}$, $p_i(K)_{fc}$ denote the total number of bytes transferred (from ECG sensors to the fog nodes) and (form fog to the cloud), respectively at time t=k, while

$q_j(K)_{sf}$, $q_j(K)_{fc}$ denote the total number of bytes transferred (from EEG sensors to the fog nodes) and (form fog to the cloud), respectively at time t=k.

3.5 Performance Evaluation and Discussion:

This section presents the primary results for evaluating the performance of the proposed fog-based architecture in terms of latency minimization and energy consumption. The described equations in the previous section were used to model and evaluate the performance of the proposed architecture. The performance evaluation is presented as a comparative study of fog computing and traditional cloud computing.

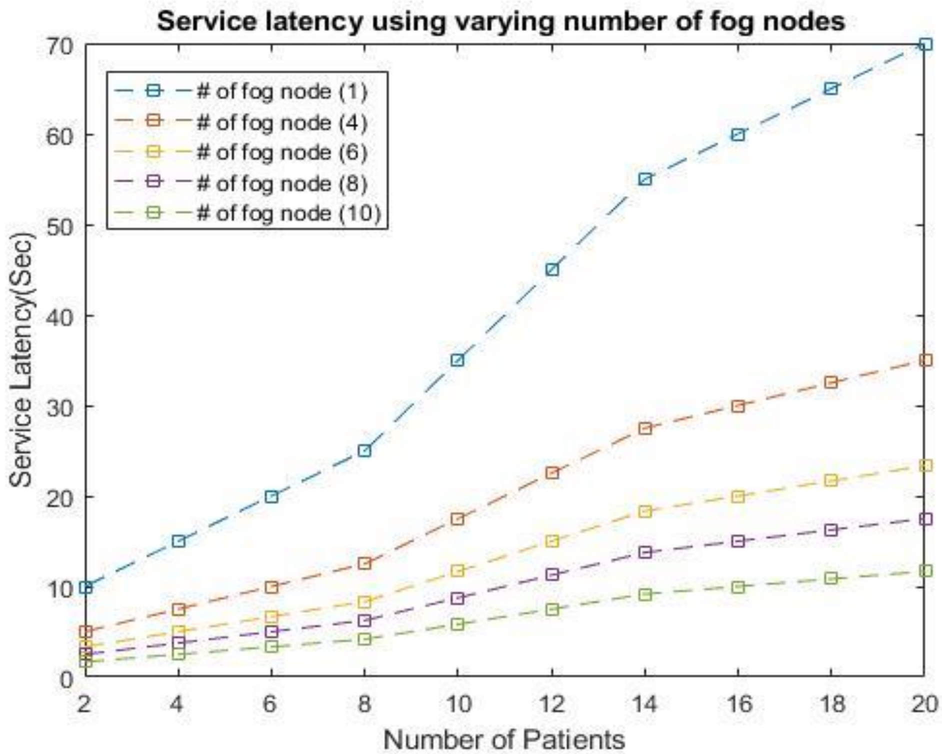
We consider an architecture with a varying number of patients between 1 to 10 at the first tier; each has two bio-sensors. These sensors are connected to a few fog nodes (gateways) at the second tier. The number of gateways at the second tier is set in the range of 1 to 10 nodes, which then is connected to a single cloud service provider (CSP) at the third tier. In this way, we can assess the performance of the proposed fog-based architecture to support multiple patients under varied network conditions.

In this architecture, the collected data from the sensors at the first tier are transmitted to the fog tier in the form of packets. The packet arrival rate is considered as one packet per node every five seconds. The size of the data packet includes two parts namely, payload, and instruction. The payload size is different based on the type of sensor; ECG or EEG sensors, while the size is the instruction is same for both ECG and EEG packets, which comprises 64 bits. The edge gateway can communicate with various network protocols; including 6LoWPAN, Wi-Fi, and Bluetooth. The link capacity between the sensors and edge devices is considered as 1 Gb per second, while the link capacity between the edge devices and cloud data server is taken as 10 Gb per second. The processing speed at the cloud data centers within the cloud tier is higher than that in the devices at the fog computing tier. Table 3.1 shows the rest of the parameters that used in the experiments.

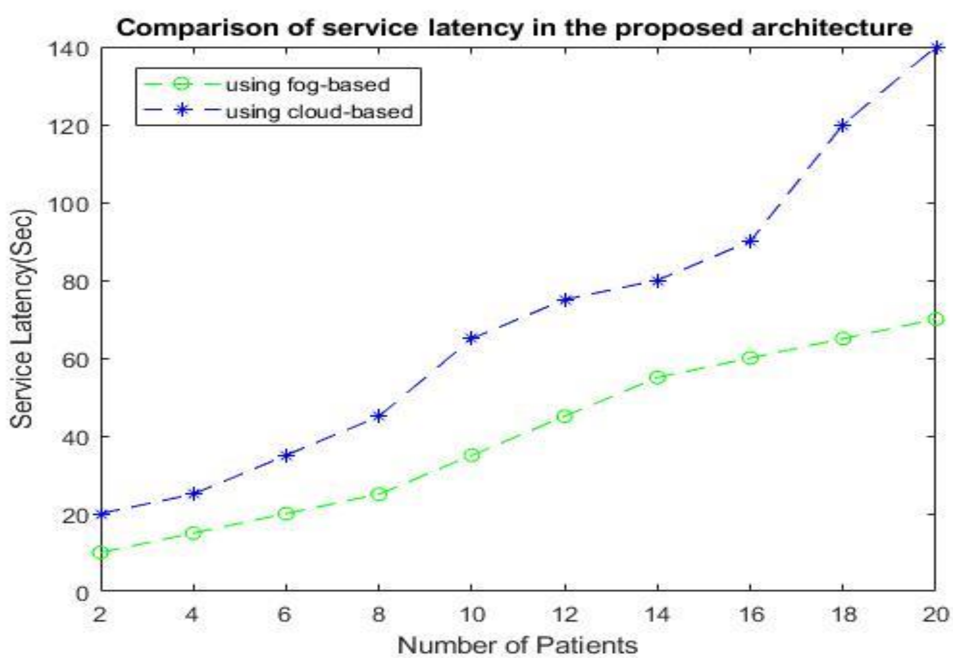
Table 3.1: Parameters used in the experiments.

Parameters	**Values**	**Comments**
# number of patients	from 1 to 10	Each has two sensors (20 sensor nodes)
Time	86400 sec.	One-day monitoring
Data generation rate	1 packet every 5 sec	Transmission rate for each sensor
Length of ECG packet	34,032 bytes	272,256 bits
Header size of ECG packet	64 bits.	8 bytes
Length of EEG packet	65,536 bytes	524288 bits
Header size of EEG packet	64 bits.	8 bytes
# number of fog node	From 1 to 10	
Processing speed at fog tier	1256 MIPS	(ARM Cortex A5)
Processing speed at cloud tier	124,850 MIPS	(Intel Core i3)
Transmission energy	20_{N}	Energy for transmission a single data byte
processing energy	10 J/GB data	Energy expended per hour

For the analysis of services latency in case of detecting an upcoming seizure, a varying number of fog nodes is used to analyze the total number of bytes generated from all EEG and ECG sensors. Figure 3.3 (a) shows the analysis of service latency within the fog tier based on a varying number of gateways. Figure 3.3 (b) shows a comparison of service latency between fog and cloud.



(a) Latency using varying fog nodes.

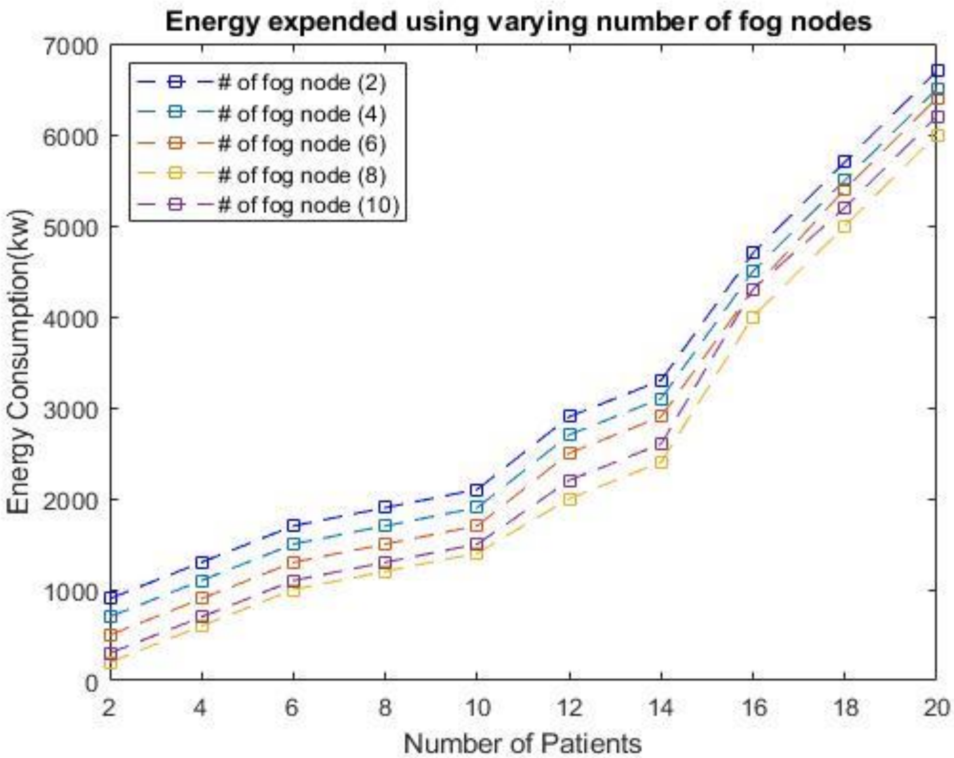


(b) Latency: fog vs. cloud.

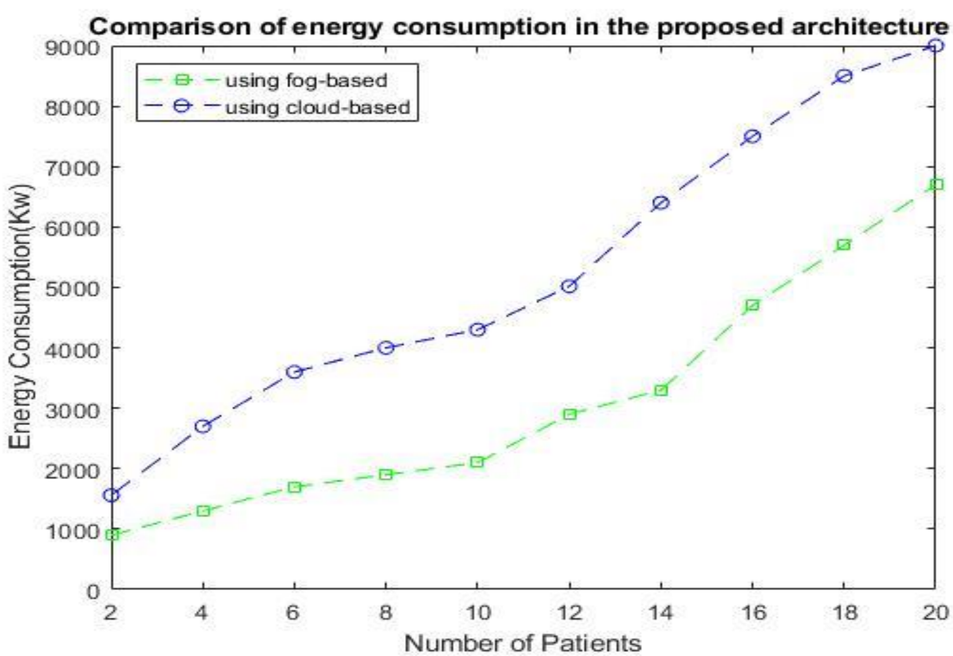
Figure 3.3. Analysis of Service Latency

As seen from Figure 3.3 (a), when the number of fog nodes (gateways) at the edge of the network increases, the service latency decreases. This attributed to the distributed processing of the collected data from the sensors. Moreover, even when there is a high load based on using only one gateway, the service latency using fog architecture is still much better than that using the cloud as we can see in Figure 3.3 (b). This indicates the significant benefits of using fog computing tier for the analysis of bio-signals locally and sending the real-time notification upon the detection of seizure state. It also demonstrates the significant success of using fog computing not only for latency minimization but also for reducing the congestion and communication overhead, thus optimizing the seizure prediction performance.

The energy expended in case of detecting an upcoming seizure is analyzed concerning a varying number of fog nodes (from one to ten) to analyze the data collected at the second tier. To show the benefit of the proposed fog architecture in reducing the end-to-end energy consumption, the energy expended based on the fog tier and without the use of fog tier (cloud-based), is also analyzed. Figure 3.4 (a) shows the analysis of energy expended within the fog tier based on varying number of gateways. Figure 3.4 (b) shows a comparison of energy consumption as fog-based or cloud-based architecture.



Energy using varying fog nodes.



(b) Energy consumption: fog vs. cloud.

Figure 3.4. Analysis of Energy Consumption

As we can see from Figure 3.4 (a), when the number of fog node increases, the energy expended to process and forwards data bytes that generated from the sensors at the first tier is decreased. On the other hand, as we can see from Figure 3.4 (b), the energy expended based on using the cloud tier is higher than that based on using fog computing as a middle tier between the sensor and the cloud. Therefore, the energy consumption in case of using fog-based architecture is much lower than that in case of cloud-based architecture, where the data is redirected to the remote server.

3.6 Summary

This chapter proposes a multi-tier fog-based architecture for early prediction of epileptic seizures. This chapter discusses the properties of the proposed architecture in comparison with that in traditional cloud computing as an intelligent computing platform for real-time prediction. By leveraging the use of emergent fog computing in epilepsy, the main contributions of the proposed approach lie in enabling real-time signals analysis, reducing latency and energy, and sending real-time notifications. The obtained results show that the proposed fog-based architecture can significantly optimize the seizure prediction performance where the decisions can be made with minimum latency and energy.

The proposed model is developed to exploit the benefits of emerging fog computing technology in the prediction of seizures based on the analysis of different vital signs; including EEG and ECG signals. This chapter focused only on the networking aspect to investigate the use of such computing architecture for seizure prediction. In the following chapters, the proposed models for ECG analysis at the second tier and EEG analysis at the third tier are presented in detail.

Chapter 4

Lightweight Analysis based on ECG signals for Early Prediction of Epileptic Seizures

4.1 Introduction

The development of suitable approaches to predict the onset of seizures at an early stage is crucial to prevent the unexpected risks, avoid traumatic accidents, and improve the quality of life. EEG sensors are the most commonly used tool for seizure onset detection. State-of-the-art research developed various methods for seizure detection and prediction based on the analysis of EEG signals [5][6][7][8]. However, epileptic seizure prediction based on the EEG data is not suitable for daily activities due to the restrictions of the EEG sensors that may impose on the human mobility [8]. In recent years, several studies have shown that not only the brain activity but also the Heart Rate Variability (HRV) of Electrocardiogram (ECG) signal during seizures can enable the identification of focal and generalized seizures [7][8]. Seizures can lead to ictal tachycardia, bradycardia, and fluctuation of ECG signals that occurs before the EEG seizure onset. Therefore, ECG signals can be an efficient biomarker for early prediction of epileptic seizures. The prediction of epileptic seizures based on the analysis of ECG signals has multiple advantages over EEG signals; including (1) the availability of the ECG sensors in many commodity hardware like wearables, (2) Such sensors are not invasive and are easy to use, (3) These sensors are suitable to use in a long-term setting, and (4) the ECG signals is suitable for light-weight real-time analysis.

A limited number of studies has focused on investigating the ECG signals for early prediction of epileptic seizure [64-70]. However, there is still major gaps and challenges that need to be addressed. One challenge is to maintain a balance between the predictive capability and false alarms to anticipate the seizure onset, which is essential as false alarms can cause a great deal of stress to the patients. Another limitation is that the existing approaches are focused on feature extraction relevant to seizures and non-seizures states, ignoring the inter-ictal and pre-ictal state of seizures. Discrimination between the pre-ictal and ictal states of seizure is essential to ensure enough time for intervention at an early stage. Furthermore, most of the state-of-the-art algorithms still suffer from limitations such as poor sensitivity and high processing time. Thus, there is a lack of algorithms suitable for practical uses in clinical applications. Therefore, a significant need for a novel seizure prediction algorithm that could address these limitations and enable the real-time signals analysis and prediction.

This chapter proposes a novel lightweight algorithm for seizure prediction based on the analysis of ECG signals to enable real-time notification. This algorithm can be implemented at the second tier of the proposed multi-tier fog-based architecture in Chapter 3. In this architecture, the lightweight analysis of ECG is used for making the local decision at the fog tier to predict the onset of seizures and send real-time notifications. The proposed method aims to differentiate between the pre-ictal and ictal states of seizures from ECG signals based on utilizing a fast and robust machine learning approach. The proposed method involves several stages including pre-processing of the ECG signals, feature extraction, feature selection, and classification. The performance is evaluated in terms of accuracy, specificity, and sensitivity. The experimental results show that the proposed method yields a promising performance based on the analysis of ECG signals. The contribution of this chapter can be summarized as follows:

- Proposing a robust and fast prediction model based on ECG signals, which allows for lightweight analysis and enables the real-time notification.
- Designing seizure prediction model based on the analysis of pre-ictal, inter-ictal, and ictal state of the seizures using Least Squares Support Vector Machines (LS-SVM).

The rest of this chapter is organized as follows: Section 4.2 provides a brief background about the ECG signals as well as Principal Component Analysis (PCA) and Least Squares Support Vector Machines (LS-SVM) and their role in the classification of bio-signals. Section 4.3 presents an overview of the related work in the field of seizure prediction based on the analysis of ECG signals. Section 4.4 explains the design details of the proposed lightweight algorithm based on ECG signals. Section 4.5 discusses the results of the proposed methodology and provides a brief comparison between the proposed method and the state-of-the-art approaches. Section 4.6 summarizes this chapter.

4.2 Background

This section provides an overview of the ECG signal and presents a brief background of the key techniques used in the formulation of the proposed approach including PCA and LS-SVM.

4.2.1 ECG signal:

The ECG signal is a record of waves that graphically measures and registers the electrical activity of the heart in detail. ECG signal consists of three graphical deflections (waves), which is well known as QRS complex as shown in Figure 4.1. R wave is the highest peak in the signal, which also known as R-peaks. The Q wave is the downward deflection sequent with the P wave while the S wave is any downward deflection posterior to the R wave [69]. RRI is a well-known phenomenon that reflects the fluctuation of ECG signals and defined as the time between R-peaks. The time duration between the series R-peaks or the RRI interval is also known as heart's beat-to-beat interval.

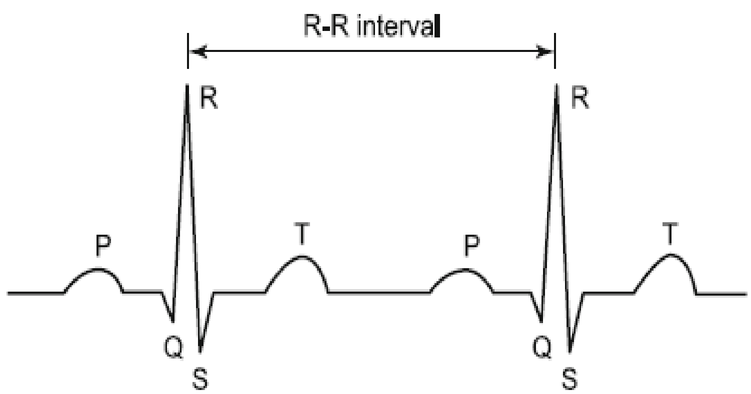


Figure 4.1. ECG signal and RRI [78].

In the recent years, several studies have proven that the fluctuation of the R-R interval (RRI) in ECG signal, or what is known as heart rate variability (HRV), is affected during the pre-ictal state of the seizures [7] [8] [65] [75]. Therefore, extracting features based on HRV analysis is an essential stage for the early prediction of epileptic seizures [8]. The following subsections provide a brief background about the role of PCA and LS-SVM in the bio-signals analysis.

4.2.2 Principal Component Analysis (PCA):

PCA is one of the most commonly used tools in dimensionality reduction and information extraction. PCA reduces the dimensionality of the data through embedding the data from high dimension space to linear subspace with a lower dimension that consists of high variance of data.

In mathematical terms, the linear projection is the most popular derivation in which PCA is trying to find a linear mapping M to maximize the variance for the given data [71]. PCA performs the linear mapping based on the cost function $(M^t\ cov(x)\ M)$, where $cov(x)$ is a matrix of data variance. In this context, the linear mapping is created based on principal components of the sample variance matrix of given data where the PCA solves the Eigen problem $(cov(x)M = \Lambda M)$ for the d principal eigenvalues Λ [71]. For the given xi data points, the low-dimensional representation (yi) is calculated through mapping these points into linear basis M.

4.2.3 Least Squares-Support Vector Machine (LS-SVM):

LS-SVM classifier is a reformulation to the standard Support Vector Machine SVM that has been widely used in pattern recognition problems and machine learning. SVM is a hyperplane classifier used to find the optimal hyperplane. The hyperplane is a decision boundary to maximize the margin of separation between two classes (linearly separable) of training data for binary classification [72]. A set of different kernels were also developed to make SVM able to classify nonlinear data. The most common SVM kernels are dot product, polynomial, and the (Gaussian) radial basis function RBF kernels. By using these kernels, the nonlinear input data can be converted into linear space with high dimensional.

The main difference between the traditional SVM and LS-SVM is that a set of quadratic optimization equations (4.1) used in the training of SVM while a set of linear equations (4.2) used in the training of LS-SVM. The LS-SVM work to reduce the classification error by determining the optimal separating hyperplane and maximizing the distance between the different classes from the hyperplane [73] [74].

$$\text{Q (w, b, } \alpha, \varepsilon) = 1/2\|w\|^2 + \frac{c}{2}\sum_{i=1}^{n} \varepsilon_i^2 - \sum_{i=1}^{n} \alpha_i \{y_i[(w * x_i) + w0] \geq 1 - \varepsilon_i \ . \quad (4.1)$$

$$1/2\|w\|^2 + \frac{c}{2}\sum_{i=1}^{n} \varepsilon_i^2 \ . \quad (4.2)$$

where the slack variables (ε_i) is used to allow misclassification within the inequalities, α refer to positive real constants, w refer to separating hyperplanes, and x_i, y_i denote the data with n datum $\{(x_1, y_1), \ldots, (x_n, y_n)\}$, where x ∈ R^n and y ∈ {1,-1}, all further details can be found in [73]. The other difference between them is that the parameter α_i, which is Lagrange multipliers can be positive or negative with LS-SVM, but with SVM it should be positive [73] [74].

In this research, LS-SVM is used for binary classification with the Gaussian Radial Basis Function (RBF) as a kernel. Mathematically, the decision function of LS-SVM classifier is given as follow [72]:

$$L = sign[\sum_{k=1}^{P} \alpha_k y_k G(z, z_k) + b]. \quad (4.3)$$

In this equation, the $G(z, z_k)$ is a kernel function.

The RBF kernel can be defined as:

$$G(z, z_k) = exp\left[\frac{-|x - x_m|^2}{2\sigma^2}\right]. \quad (4.4)$$

In this equation, the σ parameter controls the width of the kernel [72].

4.3 Related work

This section summarizes the recent state-of-the-art techniques that have been introduced for seizure prediction based on the analysis of ECG signals. Several algorithms have been recently proposed for seizure prediction based on the analysis of ECG signals. In [8], a seizure prediction method was introduced based on the extracted features from ECG signal. This proposed method developed through integrating of the HRV analysis and Multivariate Statistical Process Control (MSPC) to make prediction decision. The obtained results showed that the seizures could predict with a sensitivity of 91% and false prediction rate of 0.7. However, the proposed method did not consider the real-time analysis. In [7], seizure prediction method was presented based on Support Vector Machines (SVM) classifier to classify the ECG signals as epileptic or non-epileptic. The obtained results showed that the performance improved with using a combination of time domain, frequency domain, and statistical features extracted from ECG signals. Although the accuracy of 97% was achieved, this method focused on the analysis of seizure and non-seizure states and ignored the pre-ictal state. In [64], seizure prediction method based on the analysis of EEG and ECG signals was presented in which a sequential forward selection (SFS) was used for feature selection while a linear Bayes and a k-Nearest Neighbors (KNN) classifiers were utilized with EEG and ECG respectively. The obtained results indicated that the ECG signal is an appropriate resource for prediction of seizure where an average accuracy of 93% was achieved from both signals. However, this method was developed to perform off-line and did not consider the implementation in the real-time world. In [75] an algorithm for detection of epileptic seizures based on a single-lead ECG was proposed. This algorithm aims to investigate the possibility of identifying the changes in ECG morphology that can occur during seizures through means of principal component analysis. The performance of this method achieved 80% detection accuracy based on the analysis of ECG signals of 5 mins from four patients, which is one the limitations of this work. In [76], epileptic seizure monitoring method was proposed based on the analysis of heart rate variability (HRV). This method was utilized with One-Class Support Vector Machine

(OCSVM) for monitoring the HRV features. The obtained results showed that the seizures could be predicted at least one minute before the onset of a seizure. This method ignored the analysis of the pre-ictal and ictal seizures states in real-time. In [77], a new feature extraction method based on Hilbert-Huang transform was employed to determine the appropriate features from EEG and ECG to use for early prediction of epileptic seizures. This method was developed to evaluate the use of ECG in seizure prediction and showed that the RR interval of ECG signals significantly dropped down around 30 seconds before the onset of a seizure. In [78], seizure prediction algorithm for the analysis of the HRV features based on threshold approach was presented. The experiment results showed that the HRV signal consists valuable information to use for seizure prediction. In [79], an epileptic seizure detection method was proposed based on the analysis of the ECG signals during normal and abnormal conditions of the seizures. This method utilized two different approaches including threshold and linear support vector machine to analyze time and frequency domain features that extracted from ECG signals.

Although different seizure detection and prediction algorithms have been proposed based on ECG signals, these approaches still suffer from several limitations where it's still not possible to be used in clinical applications and the performance can be further improved. Therefore, a new model is needed to optimize the seizure prediction performance where the pre-ictal state can be used to predict a seizure in advance through the lightweight analysis of ECG signals in real-time. The design of seizure prediction method based on lightweight analysis of ECG signals can enhance the detection latency, enable real-time notifications, and reduce the computational complexity. The next section provides details about the proposed approach.

4.4 The Proposed Approach

In this chapter, a novel seizure prediction method is proposed based on the analysis of ECG signals to enable lightweight analysis and real-time notification at an early stage. The proposed model aims to accurately identify the pre-ictal state compared to the other seizure states to enable an early prediction of epileptic episodes. Since the post-ictal state is away from the region-of-interest in the ECG signal and has high similarity with the inter-ictal state, this study focuses on the analysis of pre-ictal, inter-ictal (including post-ictal state), and ictal states. The proposed algorithm aims to reach an accurate differentiation between the three states of the seizures, which allow for making seizure prediction decision in real-time. The proposed method for seizure prediction is formulated based on utilizing fast and robust machine-learning techniques including PCA and LS-SVM. Figure 4.1 shows an overview of the proposed method for seizure prediction based on the analysis of ECG data.

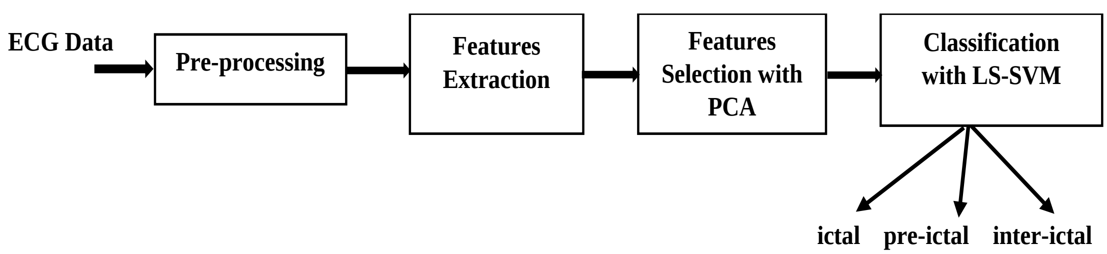


Figure 4.2: Block diagram of the proposed method for the analysis of ECG signals.

The proposed model involves several stages to make the seizure prediction decision. As we can see from Figure 4.2, the proposed method initially preprocesses the ECG signals at the first stage to remove the artifacts and noise. Then, different features from the three seizures state are extracted over each ECG signals. At the next stage, PCA is applied to reduce the dimensions of extracted features. Finally, the data processed from the previous stages are fed into the LS-SVM to discriminate between the seizure states. The following sub-sections provide more details about each one of these stages.

4.4.1 Pre-processing of ECG signals:

ECG signal is one of the non-stationary bio-signals that is sensitive to noise and artifacts [78]. De-noising and filtering the artifacts from the signal is an important process to obtain accurate information about the heart activity. Therefore, the preprocessing stage to remove such noise can play a significant role in increasing the reliability of the features extracted from the signals and optimizing the signals quality.

In this research, all ECG signals were preprocessed to remove the noise from each signal. The preprocessing stage is utilized to remove the noise based on a specific band of interest (5–15 Hz), which chosen based on Pan– Tompkins algorithm for heart rate analysis proposed in [80]. A combination of a low pass filter with (5 Hz) and high pass filter with (15 Hz) is applied to eliminate the artifacts and muscle noise from the ECG signals.

4.4.2 Feature Extraction:

As the excessive neuronal activity of epilepsy affects the fluctuation of ECG, a seizure can be predicted through the analysis of heart rate variability (HRV). Extracting features based on HRV analysis is an essential stage for the early prediction of epileptic seizures [8]. Since the heart rate of every person is different from that of other people and it changes at different ages, an appropriate analysis of HRV features from different seizure states, specifically the pre-ictal, inter-ictal, and the ictal states can lead to design an accurate prediction method. The proposed method in this chapter developed based on the analysis of HRV features that extracted from different seizure periods. Extracting critical HRV features from raw ECG signals, including time and frequency domain features, involves three main stages as shown in Figure 4.3. The following subsections explain each stage with more details.

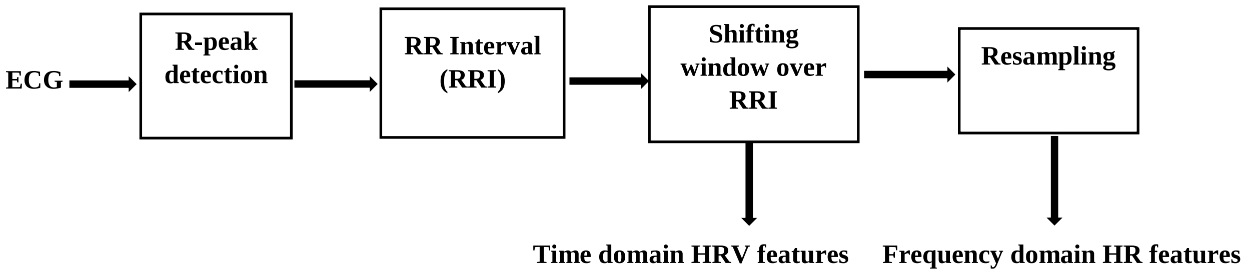


Figure 4.3: HRV feature extraction process.

4.4.2.1 R-peak Detection:

Obtaining information about HRV requires efficient detection of R-peaks from ECG signals to guarantee the proper calculation of the RR Interval (RRI). In this research, the R-peaks were detected using the Pan– Tompkins algorithm proposed in [80]. This algorithm defines a threshold value to ensure that all R-peaks of ECG signals are detected. The Pan– Tompkins algorithm works through searching for the local maxima, which predefined by the threshold value and uses the following strategy to avoid misclassification of R-peaks. After the identification of first R-peak, the algorithm holds for a short period before searching for the second R-peak. This process continues until the detection of all consecutive R-peaks, which then used to calculate the RR interval.

4.2.2.2 RR Interval (RRI):

Upon the detection of all consecutive R-peaks from the signals, the raw RRI data can be easily obtained through finding the difference between the sequence R-peaks. The collected raw RRI then used to gain multiple features.

4.2.2.3 Shifting window over RRI:

Based on the calculated raw RRI data, multiple time and frequency domain HRV features can be obtained over a shifting window. A shifting window with a width of 150 samples over the RRI is used to collect the features. The size of the window was chosen based on a previous study for the analysis of HRV for seizure detection [78], which proved that the time intervals of 1–10 seconds before the seizure is suitable for feature extraction. Different HRV features including those proposed in [8] and [78] were tested in this work for seizure prediction. Eleven HRV features were computed in the proposed model from each window; six features corresponded to the time-domain HRV features and five features corresponded to the frequency-domain HRV features. The time domain features can be derived directly from RRI data, while power spectrum density (PSD) is used to calculate the frequency-domain features over the resampled RRI data. The time and frequency domain features were calculated from both periods pre-ictal and ictal state of the seizures, which more relevant to predict and investigate the seizure prediction accuracy. Table 4.1 summarize the extracted features over the raw RR data.

TABLE 4.1: Summary of extracted features from RRI raw data.

Description	**Features**	**Number of Features**
Time-domain features	(MeanNN),(SDNN), (TP),(RMSSD),(NN50), (PNN50).	6
Frequency-domain features	(LF), (HF), (Ratio LF/HF).	3
Normalized Frequency Domain Features	(nuLF), (nuHF).	2

Time-Domain Features:

The following time-domain features were extracted from the original raw RRI data:

- meanNN: mean of RRI.
- SDNN: standard deviation of RRI.
- TP: Variance of RRI.
- RMSSD: root mean square value of SDNN.
- NN50: number of pairs adjacent RRI whose difference is more than 50ms.
- pNN50: the NN50 divided by the total of RRI.

Frequency-Domain Features:

The following frequency-domain features were obtained through the power spectral density (PSD) over the resampled raw data:

- LF: the low-frequency power of RRI (0.04Hz- 0.15Hz).
- HF: the high-frequency power of RRI (0.15Hz- 0.4Hz).
- LF/HF: the ratio of LF to HL.

In addition, the following normalized frequency domain features were also used in the present work to obtain accurate frequency analysis as stated by the HRV analysis guidelines [81]:

- nuLF: the normalized unit of LF (LFnu = LF/TP).
- nuHF: the normalized unit of HF (HFnu = HF/TP).

In the proposed algorithm, all these essential features were extracted from each ECG signals to achieve an accurate differentiation between the pre-ictal and ictal periods of seizures. The feature extraction stage leads to produce high dimensional features. The next section provides information about the feature selection stage in the proposed method.

4.4.3 Feature selection:

In seizure prediction task, dealing with high dimension features is not appropriate for real-time analysis due to the time consuming and computational complexity. Therefore, feature selection stage is critical to developing an efficient prediction model. The feature selection stage is useful for selecting a subset of relevant features without loss of meaningful information and identifying the best patterns from ECG signals.

In the proposed algorithm, PCA is applied in the feature selection stage to reduce the extracted HRV features into two dimensions, which are NN50 and pNN50. The use of feature selection improves the seizure prediction performance. The following section presents details of features classification stage in the proposed method.

4.4.4 Classification using Least Squares Support Vector Machine (LS-SVM):

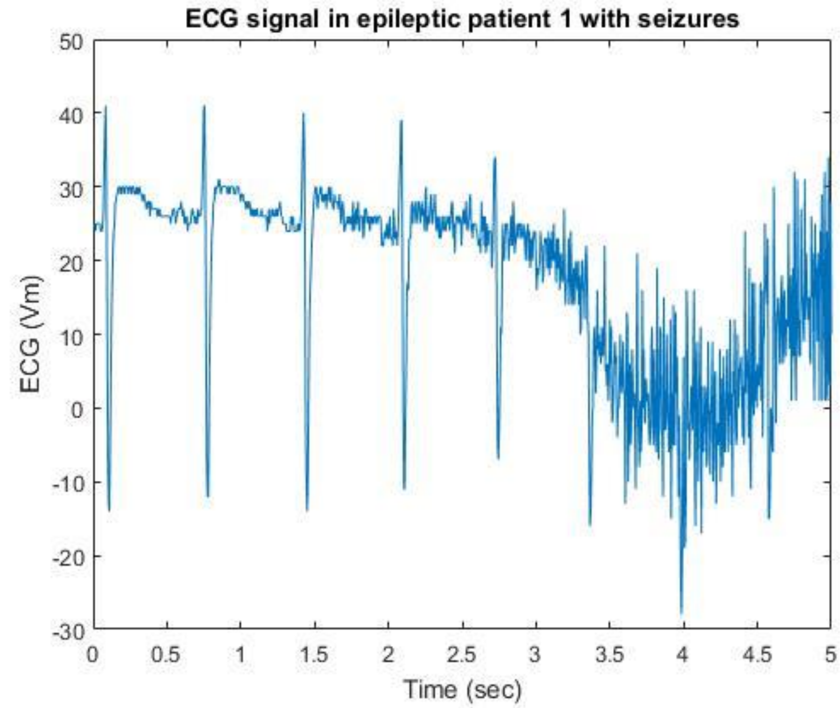
Different techniques have been proposed in the literature to develop an efficient, accurate, and sensitive method to classify various patterns. LS-SVM considered as an excellent classifier for classification of different features extracted from bio-signals [70] [72]. More important, LS-SVM has powerful generalization and fast learning abilities, which make it more suitable for the real-time analysis of epileptic ECG data.

The proposed model in this work investigated the use of LS-SVM technique in discriminating the extracted features from the ECG signals into an ictal or pre-ictal state of seizure. The performance of LS-SVM evaluated with different kernels including linear, polynomial, Gaussian radial basis function (RBF) kernels. The following section presents the performance results of the proposed method.

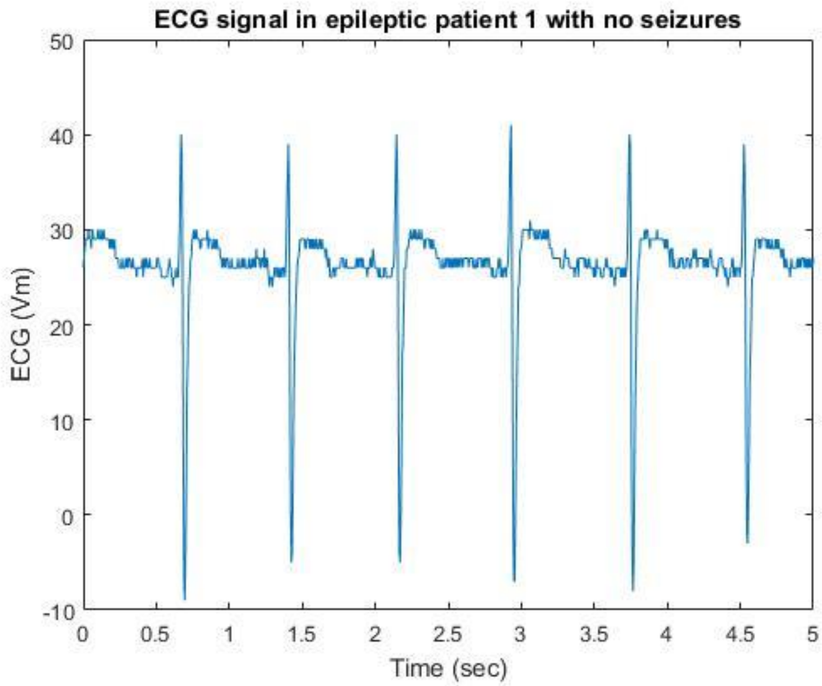
4.5 Results and discussions

4.5.1 Dataset Description

The performance of the proposed method for seizure prediction based on ECG signals was evaluated based on a dataset of Post-Ictal Heart Rate Oscillations in Partial Epilepsy, which is available in [83]. The length of each ECG signals in this dataset is ranged from one hour and 30 mins to three hours and 45 mins. [83]. This dataset consists of continuous single-lead ECG signals that were collected from seven women who have epilepsy; their age ranged from 31 to 48 years. They had no cardiac diseases based on clinical evidence, and they had partial seizures with or without secondary generalization. This dataset consists of ictal state of the seizures, while we re-labeled to obtain the pre-ictal state, inter-ictal state of the seizure. Figure 4.4 shows an ECG samples of this dataset for a patient with and without seizures.



a)



b)

Figure 4.4: ECG signal in a patient without a seizure (a) with seizure (b).

4.5.2 Performance Evaluation

In the present work, the proposed method was implemented using the MATLAB software and its toolboxes, specifically LS-SVM toolbox in [84]. All the experiments were performed on HP laptop with Intel Core i3 processor and 6 GB RAM.

The objective of the proposed algorithm is to achieve accurate discrimination between the different seizure states based on the lightweight analysis of HRV features of ECG signals using PCA and LS-SVM. Figure 4.5 shows the obtained raw RR interval data of ECG signals in a patient during both ictal and pre-ictal periods.

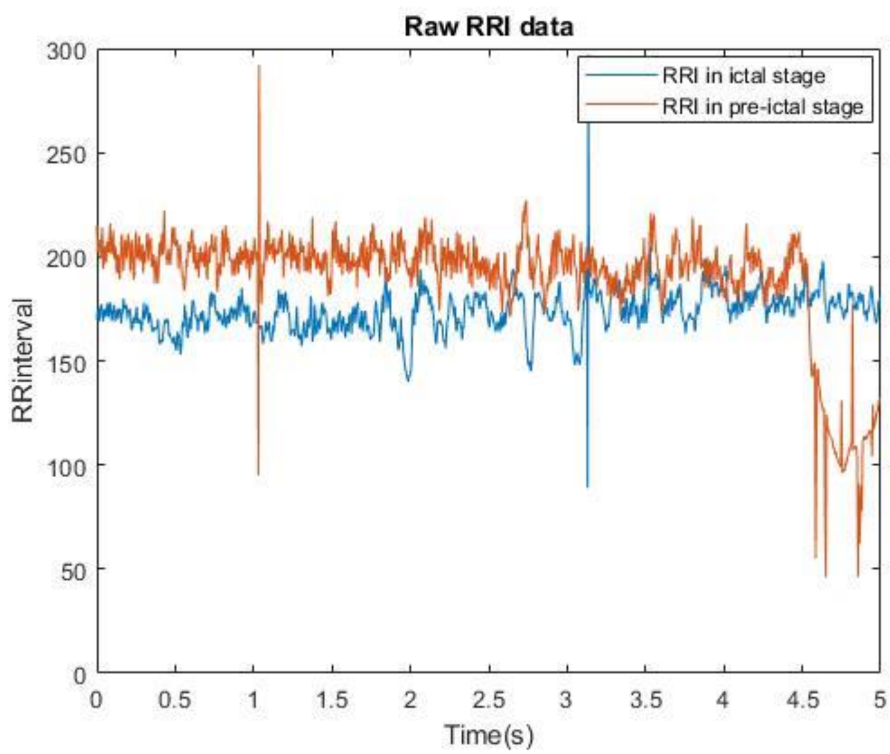


Figure 4.5. Raw RR interval during ictal and pre-ictal periods.

As we can see from Figure 4.5, the raw RRI affected due to large ECG artifacts associated with the beginning of the seizure onset (at the pre-ictal state). This indicates that the relevant key features extracted from the pre-ictal state can enable an accurate prediction performance at an early stage.

During the experiment, it was observed that with the sudden change in heart rate during the beginning of the seizure, the time domain features, such as meanNN increased, and the rest of such as SDNN and RMSSD decreased. Most of the frequency domain features reduced upon the occurrence of the seizure. Therefore, analyzing the variations of heart rate activity under multiple domains including time and frequency ones is essential for the successful prediction of seizures.

All extracted features were used to form one matrix of dimension (N*M) in which N represents the number of features (=columns), and M represents the number of samples (data points=row) for each ECG record, which then used to train and test the performance with LS-SVM. The data were divided into 80% training and 20% testing along with training and testing labels. Also, 5-fold cross-validation technique was also used to avoid the prospect of overfitting, which segments the data into five random subsets. This training and testing data were first normalized and standardized before feeding to the LS-SVM. The following performance metrics were used to evaluate the performance of the proposed method. These metrics including accuracy, sensitivity (true positive rate), and specificity (true negative rate), that measured as follows:

$$\text{Sensitivity (SEN)} = TP / (TP + FN). \tag{4.5}$$

$$\text{Specificity (SPC)} = TN / (TN + FP). \tag{4.6}$$

$$\text{Accuracy (ACC)} = (TP + TN) / (TP + FP + FN + TN). \tag{4.7}$$

TP, TN, FP, and FN denote the number of true positive, number of true negative, number of false positive, and number of false negative respectively. Confusion Matrix and Receiver operating characteristic (ROC) curve were also used for performance evaluation.

In this work, PCA was implemented to compute the principal components and reduce the dimensions of the training and testing data into two dimensions. The performance of the proposed model is enhanced from 97% to 99% by a combination of PCA and LS-SVM. This indicates the benefit of using the PCA to improve the classification performance through reducing the dimensions of extracted features.

In the classification stage with LS-SVM, three different kernels were used separately; including Linear kernel, Polynomial kernel, and Gaussian or RBF kernel. Training the LS-SVM with RBF kernel requires a calculation of two parameters; including the optimization of kernel width parameter (σ), and regularization parameter (γ). Table 4.2 shows the performance results based on the three kernels to differentiate between the ictal and pre-ictal state of the seizure, while Table 4.3 shows the performance results based on the three kernels to differentiate between the pre-ictal and inter-ictal state of the seizure. As we can see from this table, the best performance was achieved by using LS-SVM with Gaussian (RBF) kernel. Figures 4.6 ,4.7, and 4.8 show the performance of LS-SVM with RBF kernel to differentiate between the ictal and pre-ictal states, and between the inter-ictal and pre-ictal state of the seizure, respectively.

Table 4.2 LS-SVM performance between the ictal and pre-ictal states.

LS-SVM Kernel Type	**Accuracy**	**Sensitivity**	**Specificity**
Linear kernel	94.4%	98.6%	84.3%
Polynomial kernel	96.3%	97.5%	90.1%
Gaussian (RBF) kernel	**99.1%**	**99.2%**	**98.3%**

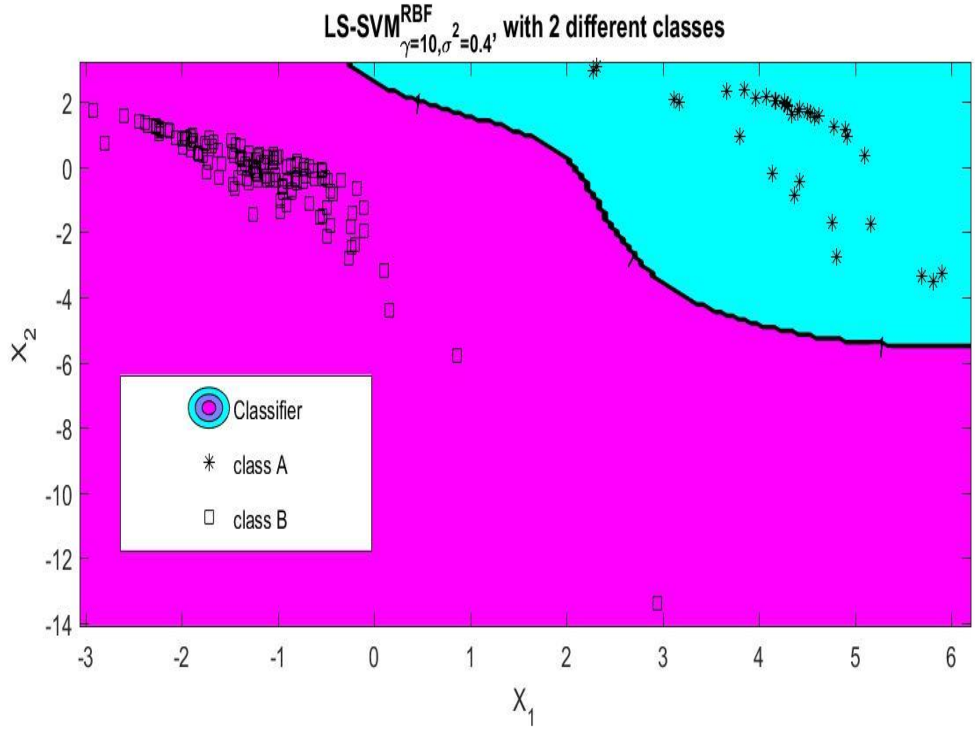


Figure 4.6. Classification of ECG signals as ictal (class A) or pre-ictal (class B) by LS-SVM with RBF kernel.

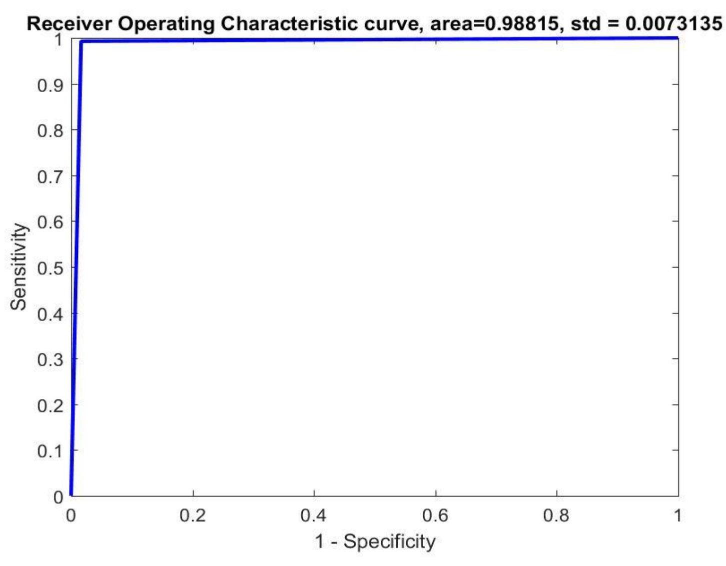


Figure.4.7: ROC curve for LS-SVM with RBF kernel to differentiate between ictal and pre-ictal state of the seizure.

Table 4.3 LS-SVM performance between the inter-ictal and pre-ictal states.

LS-SVM Kernel Type	**Accuracy**	**Sensitivity**	**Specificity**
Linear kernel	93.5%	91.5%	78.1%
Polynomial kernel	94.4%	93.7%	84.3%
Gaussian (RBF) kernel	**96.2%**	**95.0%**	**87.5%**

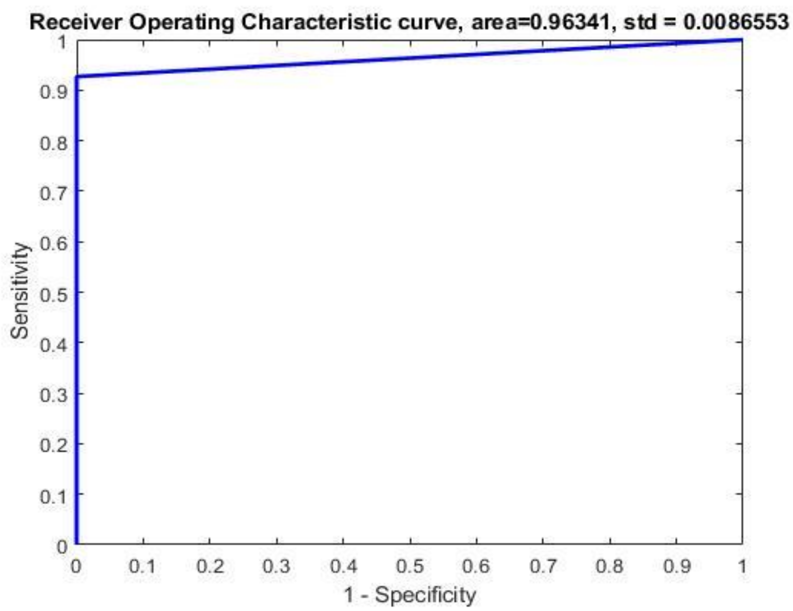


Figure.4.8: ROC curve for LS-SVM with RBF kernel between inter-ictal and pre-ictal state.

The performance of the proposed for the lightweight analysis of ECG signals was also tested by using other machine learning techniques; including linear discriminant analysis (LDA), k-nearest neighbor's algorithm (KNN), and support vector machine (SVM). The same extracted features were used as input data to each one of these methods. The obtained results are summarized in Tables 4.4.

Table 4.4: Comparison of the proposed work with other learning algorithms.

Implemented method	**Accuracy**	**Sensitivity**	**Specificity**
LDA	76.8%	69.7%	80.1%3
KNN	80.5%	89.1%	62.3%
SVM	93.5%	97.2%	81.1%
The proposed model	**99%**	**99.2%**	**98.3%**

The performance of the proposed model with LS-SVM was then extended to analyze ECG signals to differentiate the three key seizure states; pre-ictal, ictal, and inter-ictal to enable the early prediction of epileptic seizure and notifying the patients. Figures 4.6 and 4.7 show the obtained results of LS-SVM with RBF kernel. Due to high inference between the pre-ictal and inter-ictal state, an average accuracy of 86.6%, specificity of 79.8%, and sensitivity of 99.0% are achieved to differentiate between the three seizure states.

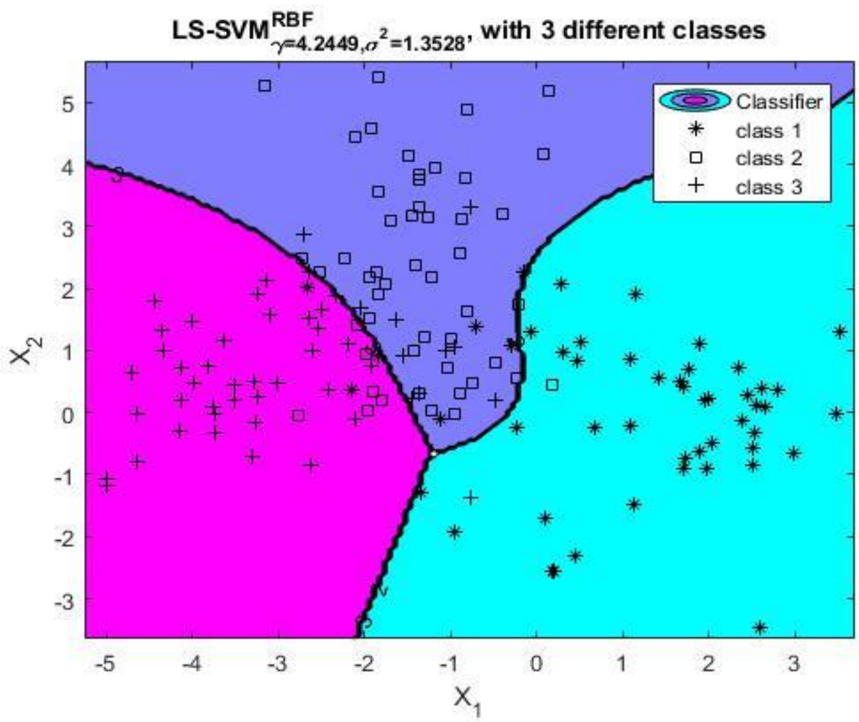


Figure 4.6. Classification of ECG signals as ictal (class 1), pre-ictal (class 2), and inter-ictal (class 3), by LS-SVM with RBF kernel.

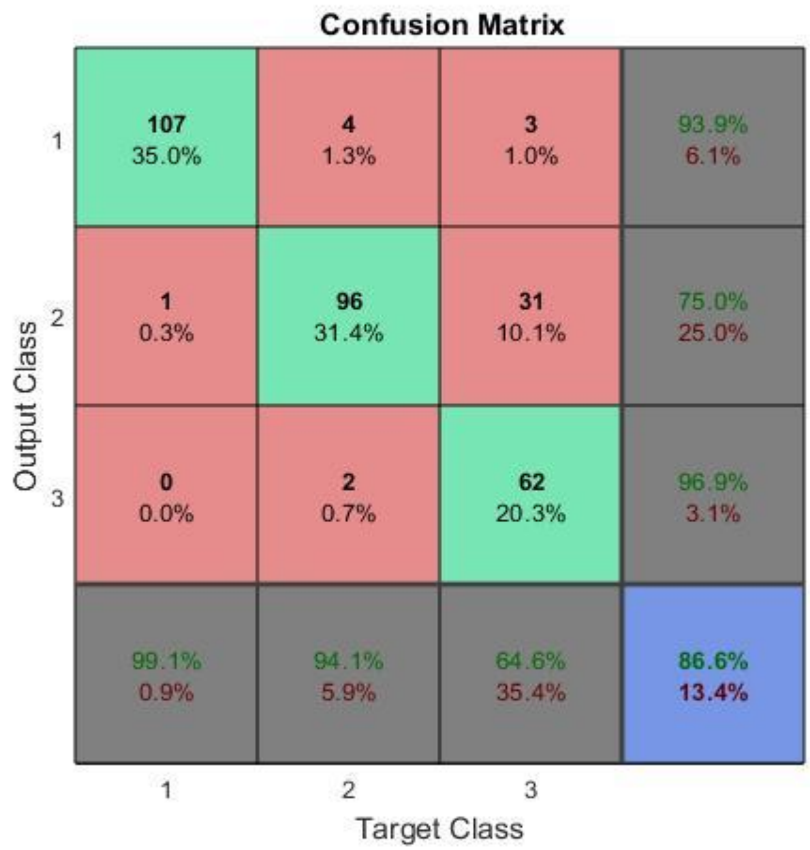


Figure 4.7. Confusion Matrix for analysis of ECG signals into ictal, pre-ictal, and inter-ictal.

A comparison between the proposed model and state-of-the-art approaches is also presented to evaluate the efficacy of the proposed seizure prediction model. Table 4.5 provides a summary to compare the performance of the proposed method with previous studies introduced in the field of epileptic seizures detection and prediction. These methods are focused on the analysis of ECG signals to identify the signals state as a seizure or not without considering the use of cross-validation to evaluate the performance. The best performance results are highlighted in bold fonts as shown in the table.

The proposed method achieves higher performance against almost all the compared methods regarding accuracy and specificity. The performance in terms of sensitivity is only 1% lower than the sensitivity of the proposed method in [7], which is focused on the classification of epileptic and nonepileptic states.

Table 4.5: Comparison between the proposed method and previous studies

Authors	**Year**	**Method**	**Performance**
Varon et al. [75]	2015	Principal Component Analysis (PCA).	86.6% Positive predictive values. 90% sensitivity.
Fujiwara et al. [8]	2016	Multivariate Statistical Process Control (MSPC).	91% sensitivity. False prediction rate 0.7/Hr.
Valke, & Karthikeyan [7]	2016	Support Vector Machines (SVM).	97% accuracy 95% specificity 100% sensitivity
Behbahani, et al. [65]	2016	An adaptive decision threshold method.	78.59% sensitivity. False prediction rate 0.21/Hr.
Proposed work	2017	**Least squares support vector machines (LS-SVM).**	**99.1% accuracy** **98.3% specificity** 99.2% sensitivity

4.6 Summary

This chapter has proposed novel prediction method to differentiate between the pre-ictal state and other epileptic seizures states based on the analysis of ECG analysis, which allows for lightweight analysis and real-time notification at an early stage. The proposed method makes use of PCA and LS-SVM in discrimination of the real-time ECG data into ictal, inter-ictal, or pre-ictal state. The implementation of the proposed approach involves four stages to analyze the ECG signals, which including pre-processing, multiple feature extraction, feature selection, and features classification.

Based on the experiment results, the proposed method shows a promising performance with 99% accuracy, 98.3% specificity, and 99.2% sensitivity to differentiate between the pre-ictal and ictal state of the seizure, and 96.2% accuracy, 95.0% specificity, and 87.5% sensitivity to differentiate between the pre-ictal and inter-ictal state of the seizure. Moreover, the obtained results showed that the performance of the proposed method outperforms other proposed approaches in the literature. This indicates the potential success of implementing this proposed algorithm at the second tier of fog-based architecture introduced in the previous Chapter, thus, enabling the lightweight local analysis of ECG signals and real-time notifications. Although the results of ECG were promising, the fluctuation of ECG signals could also be affected by patient activities. Thus, the EEG analysis becomes significant complementing for seizure prediction. The upcoming chapter proposes seizure prediction model based on the analysis of EEG signals to be implemented at third-tier to make more accurate and reliable decisions.

Chapter 5

A Deep Learning Framework for Prediction of Seizures Using EEG Signals.

5.1 Introduction

Although the previous chapter proposed lightweight seizure prediction model based on ECG signals, an extensive analysis based on long-term EEG signals is also critical due to the following reasons: (1) The fluctuation of ECG signals could be affected by factors other than seizures, such as sport activities carried by patients, which could lead to a false warning. (2) Combining the analysis of ECG and EEG signals can enable more accurate and reliable decisions, thus, reduce the false alarms. (3) Deep analysis of EEG signals based on cloud computing technology could lead to several advantages; such as sharing the patient data among different healthcare provider, storing the historical patient data for long-term analysis, developing a reliable monitoring model to process multiple patients' data.

In the past few years, several algorithms were proposed for seizure detection and prediction based on the analysis of EEG signals [85-90]. However, several limitations still exist in the state-of-the-art approaches that need to be addressed. Although such approaches offered good performance, in terms of accuracy, most of them were designed without considering multiple EEG channel analysis and large patients' data. A reliable seizure prediction system should be able to process a massive amount of data from different patients and different EEG electrodes. Several seizure prediction methods ignored the analysis of normal/health state against the seizures states, which could lead to the development of a generalized model that can be used not only for epilepsy patients but also for general diagnostic purposes. Most of the state-of-the-art approaches were designed to classify, not predict, an EEG record to indicate a seizure or not. Such approaches have not considered the pre-ictal state of seizure, which is crucial in predicting an upcoming epileptic episode. On the other hand, most of the existing seizure prediction approaches were developed based on utilizing simple machine learning techniques. These techniques have faced difficulty in recognizing the underlying characteristics of non-stationary signals such as (EEG) as its frequency is changing over time [89]. Moreover, the use of deep learning approaches for the analysis of time series signals has proven to outperform several approaches such as SVM, K-nearest neighbor KNN, and ANN [89] [90]. Nevertheless, a limited number of studies has investigated the use of advanced deep learning techniques, such as DBN, in seizure prediction based on the analysis of EEG signals. Furthermore, state-of-the-art approaches for seizure prediction still suffer from a lack of generalization across different patient datasets. Therefore, these limitations indicate crucial need to design new prediction model to improve and optimize seizure prediction performance based on the analysis of EEG signals.

This chapter proposes a deep learning framework for seizure prediction based on the analysis of EEG signals. This proposed model is used in the third tier of the proposed architecture in Chapter 3 to enable an extensive analysis, make more accurate decisions, and reduce the error rate. The integration of cloud computing technology in the third tier can allow for higher accuracy seizure prediction based on analyzing large patients' dataset over extended periods of time. The proposed framework investigates the benefits of using Deep Belief Networks (DBN) in developing seizure prediction models that can accurately discriminate between normal, pre-ictal, and ictal states. Since most of epilepsy patients' datasets consist of a small ictal period in comparison with other seizures states, the performance of the proposed framework is evaluated in terms of accuracy, sensitivity, specificity, precision, recall, and F-Measure. The key contribution of this chapter is:

- Designing deep learning framework for the analysis of time series signals, which is formulated with Wavelet packet transform (WPT) features and Deep Belief Networks (DBN).
- Proposing a seizure prediction model to differentiate between normal, pre-ictal, ictal states accurately.

The rest of this chapter is organized as follows: Section 5.2 provides a brief background about the EEG signals, WPT, and DBN. Section 5.3 presents an overview of the related work in the field of seizure prediction based on the EEG signals analysis. Section 5.4 explains the proposed model. Section 5.5 discusses the results and compare its performance with the state-of-the-art approaches. Section 5.6 summarizes this chapter.

5.2 Background

This section provides a brief background about EEG signal and its role in the diagnosis of seizures. The section also presents an overview of techniques used in the formulation of the proposed approach.

5.2.1 EEG signal:

EEG stands for electroencephalogram that is used to measure and visualize the electrical activity in the brain. EEG signal recorded the electrical activity as waves to show the prominent activity of the brain. These waves have different frequencies and names based on the area of the brain. Time series EEG signals are mainly described with four main brain waves including; Alpha [7.5-13] Hz, Beta [13-30] Hz, Delta [0-3.5] Hz, and Theta [3.5-7.5] Hz [4]. These waves of EEG signal are widely used for exploring abnormal activities in the brain.

EEG signals are used as a diagnostic tool in many diseases such as stroke, head trauma, and epilepsy. During the seizure, the EEG waves become sharp and variable, which indicate the occurrence of local and generalized seizures across a subset or all brain waves. Figure 5.1 shows five channels EEG signal that represents different seizure states [4]. An efficient seizure prediction model should be able to capture, as early as possible, the gradual transition between ictal and ictal states, which well known as the pre-ictal state of seizure.

Figure 5.1: Different seizure states in EEG signal [4].

5.2.2 Wavelet Packet Decomposition:

Wavelet packet transform (WPT) is a specific type of wavelet transform (WT). WPT is a useful tool for the analysis of nonstationary and time-varying signals such as EEG. WPT is different from WT where the decomposition is done not only for the approximation coefficients but also for the detail coefficients [92]. WPT outperforms other transform methods such as short time Fourier transform due to its flexibility in time and frequency resolution of the signal based on variable window sizes [91] [92]. Hence, WPT can offer time and frequency features at all frequency ranges.

WT is based on a set of basic functions for decomposing the signal $x(t)$, where each function is a scaled and translated version of the mother wavelet (basic waveform). Feature extraction based on WPT can be divided into two steps; feature construction and bases selection [91]. The goal of feature construction step is to use WPT coefficients that are produced from each sub-band in the WPT tree to capture the best properties from the signal. In contrast, the objective of the bases selection step is to identify the best sub-bands to recognize the differences between the signals. Figure 5.2 shows an example of a three-level decomposition using WPT.

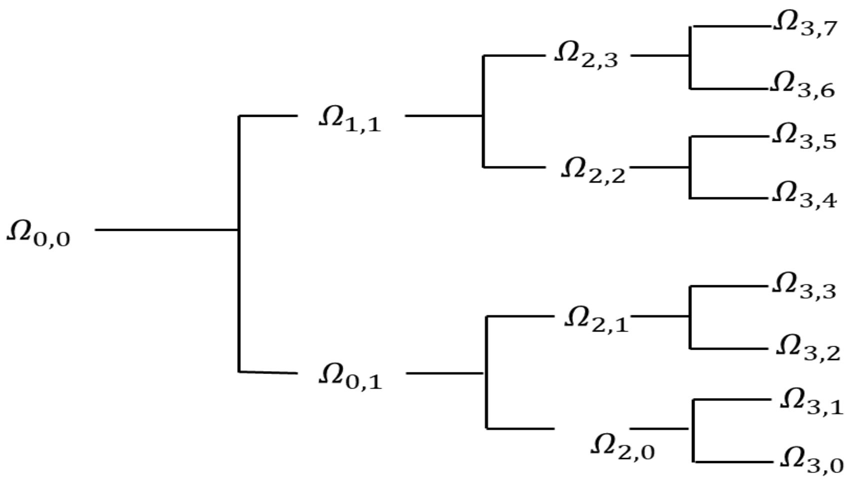


Figure 5.2: Decomposition tree of WPT with tree-structured subspaces.

WPT can be represented as a tree of subspaces in which $\Omega_{0,0}$ refer to the original signal space (the root of the tree) while $\Omega_{1,1}$ and $\Omega_{0,1}$ refer to the decomposed orthogonal subspaces. The left number represents the scale while the right number represents the sub-band index within the scale [91]. In general, the node $\Omega_{(j,k)}$ can be decomposed into lower resolution space $\Omega_{(j,k)} \rightarrow \Omega_{(j+1,2k)}$ and detail space $\Omega_{(j,k)} \rightarrow \Omega_{(j+1,2k+1)}$. This type of decomposition can be achieved through division of the orthogonal basis $\{\varphi_j(t-2^j k)\}\ of\ \Omega_{(j,k)}$ into two new orthogonal bases $\{\varphi_{j+1}(t-2^{j+1}k)\}\ of\ \Omega_{(j+1,2k)}$ and $\{\psi_{j+1}(t-2^{j+1}k)\}\ of\ \Omega_{(j+1,2k+1)}$ [91]. The scaling $\varphi_{j,k}(t)$and wavelet functions $\psi_{j,k}(t)$ is given as [91]:

$$\varphi_{j,k}(t) = \frac{1}{\sqrt{2^j}}\ \varphi\left(\frac{t-2^j k}{2^j}\right). \tag{5.1}$$

$$\psi_{j,k}(t) = \frac{1}{\sqrt{2^j}}\ \psi\left(\frac{t-2^j k}{2^j}\right). \tag{5.2}$$

where $\varphi(t)$ and $\psi(t)$ refer to scaling and wavelet functions respectively, j indicate the scale and k indicate the sub-band index in the scale.

5.2.3 Deep Belief Networks:

Numerous characteristics distinguish the deep neural network (DNN) from other types of learning methods in pattern recognition. DNNs able to recognize the internal representation of features from the input layers and allows modeling more complex and nonlinear relationship between the network layers [93]. DNN was utilized as a potential candidate for learning features and classification to solve various pattern recognition problems [94] [95]. DBN is a type of DNN, which defined as a probabilistic generative model that consists of a stack of N Restricted Boltzmann Machines (RBMs). DBN enable the representation of high nonlinear diverse patterns by combining a set of nonlinear RBMs. This type of structure can be easily expanded to use the output of one RBM as input for other RBM to achieve fast training.

5.2.3.1 Restricted Boltzmann Machines (RBMs):

RBMs are mainly networks of type Boltzmann Machine (BM) that consist of one visible input layer and one hidden layer, where there is no connection between the visible and hidden units as shown in Figure 5.3. In RBM, the probability distribution on the visible unit (v) and hidden unit (h) are given in the form of energy function.

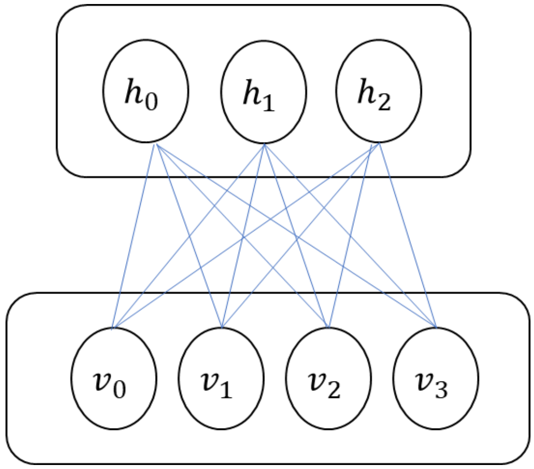


Figure.5.3 Architecture of RBM with one input layer (v) and one hidden layer (h).

There are two types of RBM namely, Bernoulli-Bernoulli RBM (BBRBM) and Gaussian-Bernoulli RBM (GBRBM). In training of RBM, the following equations are used to update the weight and bias of RBM of type GBRBM [96]:

$$\Delta W_{ij} = \varepsilon \left(v_i h_j / \sigma^2\right)_{data} - \left(v_i h_j / \sigma^2\right)_{model} . \tag{5.3}$$

$$\Delta a_i = \varepsilon \ (v_i / \sigma^2)_{data} - (v_i / \sigma^2)_{model} . \tag{5.4}$$

$$\Delta b_j = \varepsilon \ \left(h_j / \sigma^2\right)_{data} - \left(h_j / \sigma^2\right)_{model} . \tag{5.5}$$

The expression $(.)_{data}$ and $(.)_{model}$ are used to denote the expected amount of data and model distribution. The parameter ε indicates the learning rate and σ^2 denotes the deviation. In RBMs, the units inside the hidden and visible layers are not connected, thus the unbiased samples can be obtained from $\left(v_i h_j\right)_{data}$. Furthermore, the activations of the hidden or visible layers are independent in a conditional way by given the visible (v) or hidden (h) units, where the conditional property of the hidden (h) unit of given (v) is computed as follows [93]:

$$P\ (h_j |\ v) = \prod_j P\ (h_j |\ v). \tag{5.6}$$

When the type of RBM is GBRBM, the following equations are used to compute the activations of the hidden and visible nodes [96]:

$$P\ (h_j = 1|\ v)\ = \sigma(\ b_j +\ 1/\sigma^2 \sum_{i=1}^{m} v_i\ W_{ij}). \tag{5.7}$$

$$P\ (v_i = 1 \mid h)\ = N(a_i\ + \sum_{j=1}^{n} h_j\ W_{ij}\ \ \sigma^2). \tag{5.8}$$

RBMs use Contrastive Divergence (CD) algorithm to calculate the approximation of $\left(v_i h_j\right)$ which is faster than Gibbs algorithm [93] [96].

5.2.3.2 Deep Belief Network Architecture:

Figure 5.4 shows a general structure of DBN. While this structure is superficially analogous to multi-layer feedforward, its different in the way of training. In DBN, the training process consists of two stages namely, pre-training and the fine-tuning stage. In the pre-training stage, a greedy layer-wise training algorithm is used for training in which the lowest RBM is trained first, and then the obtained representation from this RBM is used for training the next RBM, and this continues until the last layer in the network. In the fine-tuning stage, the learned generative model of the final layer is used to adjust the parameters of the whole network with a supervised learning algorithm. Back-propagation algorithm is used in the fine-tuning stage to obtain an optimal classification. The use of back-propagation in fine-tuning phase with DBN outperforms the use of back-propagation with the traditional neural network [118].

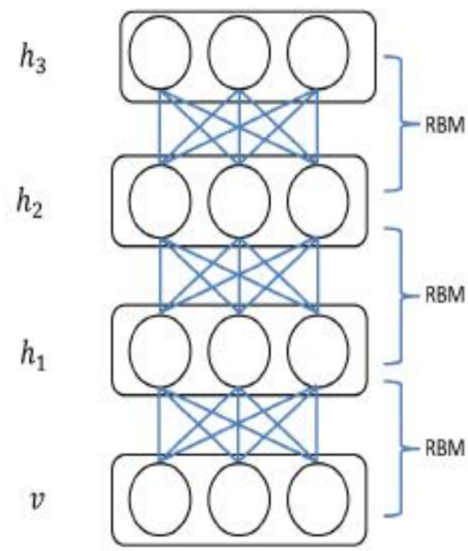


Figure.5.4 Architecture of DBN with one input layer (v) and three hidden layers (h) [93].

5.3 Related work

This section provides an overview of the state-of-the-art methods for detection and prediction of seizures based on the analysis of EEG signals.

The prediction process in state-of-the-art methods usually involves four main stages including, preprocessing, feature extraction, feature selection, and classification. Different seizure prediction and detection methods were developed based on utilizing wavelet packet technique for extracting features from EEG signals. In [97], seizure detection method was proposed based on utilizing wavelet technique for EEG feature extraction and recurrent Elman neural network (REN) for features classification. In [98], seizure prediction approach was proposed in which discrete wavelet transform (DWT) is used for feature extraction, while linear and nonlinear classifier is used for classification. In [99], EEG seizure detection method was proposed, which used a dual-tree complex wavelet transform (DT-CWT) for feature extraction and support vector machine

(SVM) for classification. In [100], detection method was proposed to classify the EEG data into a seizure and non-seizure state with wavelet analysis for feature extraction and radial basis function neural network, unsupervised-means clustering, and linear and quadratic discriminant analysis for features classification. Most of these methods indicate the benefits of using wavelet packet technique for feature extraction in the analysis of epileptic EEG signals. However, these approaches were focused on the analysis of seizure and non-seizure states and ignored the pre-ictal state.

Feature selection and preprocessing techniques were also utilized besides the feature extraction for the analysis of EEG signals in many seizure prediction methods. In [101], [102], and [103], seizure detection methods were proposed for the analysis of EEG signals based on using genetic algorithms for feature selection. In [105], automatic seizure detection method was proposed based on Multilayer Perceptron (MLP) and approximate entropy features. In [106], seizure detection method was presented based on Common Spatial Pattern (CSP) algorithm and SVM to analyze the EEG signals. In [107], seizure prediction approach was proposed based on Relief ranking algorithm for feature selection, and Bayesian Network, Random Committee, and Random Forest for classification. In [109], a multistage nonlinear pre-processing filter and Artificial Neural Network (ANN) were used for automated diagnosis of seizures from EEG signals. In [112], automatic seizure detection model was presented in which smoothing, collar, and threshold judgment techniques are used for post-processing of EEG signals. In [108], [110], and [111] seizure prediction methods were proposed for the analysis of EEG signals based on different machine learning techniques including, Fuzzy k-Nearest Neighbor (Fuzzy k-NN), Decision tree, Support Vector Machine(SVM), and k-Nearest Neighbor(k-NN). Although these methods achieved good performance in terms of accuracy, most of these methods still suffer from poor sensitivity due to the complexity of EEG signals analysis. Moreover, most of these approaches were evaluated based on patient-specific data where the same patient data is used for training and testing.

Recently, deep learning approaches were used in designing of seizure detection and prediction models. In [113], a deep learning method based on 13-layer convolutional neural network (CNN) was introduced for seizure prediction based on the analysis of EEG signals. This method has faced difficulty in recognizing the underlying characteristics of non-stationary signals such as (EEG) and achieved an accuracy of 88%. In [114], a deep learning approach with Gated Recurrent Unit (GRU) RNN was introduced for seizure prediction based on EEG signals. However, the performance of this approach was evaluated without considering the analysis of normal state against the seizure states in EEG signals. Other deep learning methodologies for seizure prediction based on the analysis of EEG signals were also presented in the literature [116] [117] [118]. However, most of the state-of-the-art approaches still suffer from a lack of generalization across different patient datasets and ignored the analysis of the pre-ictal state of the seizure, which is more relevant to making a decision at an early stage. Thus, there is a significant need for a generalized model to analyze large patient's data based on single and multiple channels of EEG signals. The proposed model in this chapter is designed to deal with the existing issues in the current seizure prediction approaches by making use of advanced and robust deep learning framework. The following section presents more details about the proposed model.

5.4 The Proposed Approach

In this Chapter, a novel seizures prediction model is proposed based on the analysis of EEG signals with deep learning framework. This proposed model is developed to make more accurate and reliable decisions based on the analysis of EEG signals at the third tier of the proposed multi-tier architecture in Chapter 3. While the use of the Recurrent neural network (RNN) has been widely used for time-series forecasting, this chapter investigates the use of DBN in time-series analysis and seizure prediction. This proposed method is formulated via wavelet packet transform and DBN to reach high separability between normal and seizure states. Figure 5.5 shows an overview of the proposed method for prediction of the epileptic seizure based on the analysis of EEG signals.

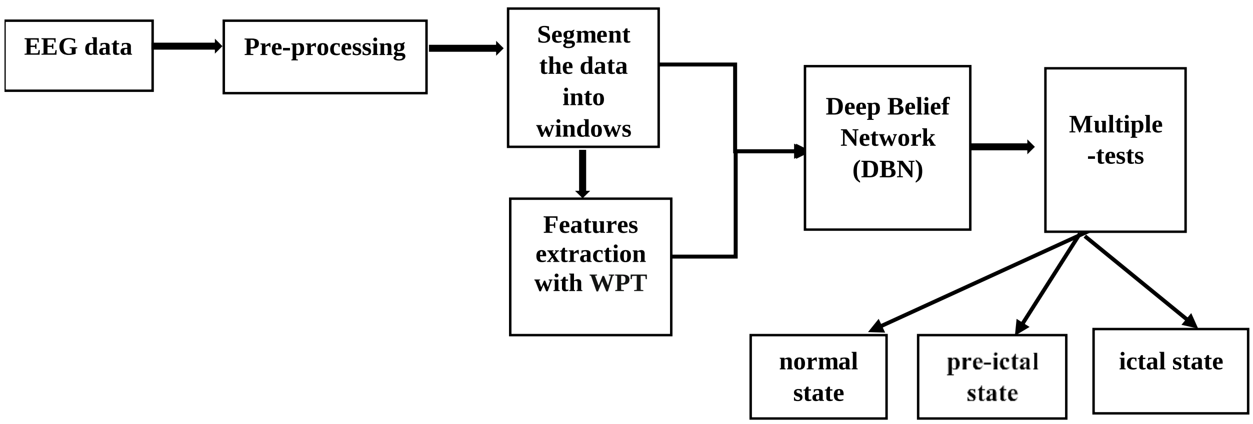


Figure 5.5: Flowchart of the proposed model for the analysis of EEG time series data.

The analysis of EEG signals in the proposed model investigate the three conditions, healthy/normal, pre-ictal, interictal. As illustrated in Figure 5.5, the proposed analysis of EEG signals involves several stages. At the first stage, the raw EEG is pre-processed to remove the effect of line noise (50 Hz). At the second stage, the de-noised raw EEG data is split into multiple windows; each is of size N seconds. At the third stage, several features are extracted from each window based on WPT. At the fourth stage, these features are grouped as an input to the DBN model. The following sub-sections discuss in detail each stage in the proposed model.

5.4.1 Preprocessing of EEG signals:

Obtaining high-quality electrical signals, such as EEG signals from biological sensors, is difficult due to the following reasons; (1) EEG signals basically have a low amplitude in the domain of M-volts, (2) During EEG recordings, the artifacts and electrical noise are easily coupled into the signal. The power line with 50 and 60 Hz is well-known as the primary source of such noise, which could lead to wrong analysis. Therefore, several techniques were developed for de-noising and filtering the bio-signals. Spectrum estimation technique has shown promising results in the analysis of the brain signals.

In the proposed model, the 50 Hz power line noise was removed using the spectrum estimation technique presented in [115]. In spectrum estimation, the power spectrum of the corrupted signal is considered as a continuous curve. This curve is an overlie peak with a power line of frequency ω. The interpolation of this curve can be used to estimate the extent of the current signal frequency. In this technique, the correct value $S'(\omega)$ is estimated using frequency resolution $(d\omega)$ and the interpolation between $S(\omega - d\omega)$ and $S(\omega + d\omega)$. Then the entire EEG signal is transformed using discrete Fourier transform (DFT). Finally, the interference in the EEG signal is reduced by taking the reverse DFT of the corrected spectrum.

5.4.2 Feature Extraction based on WPT:

Among the variety of existing feature extraction approaches from EEG signals, WPT is considered as a powerful tool that enables the estimation of multi-resolution representation of time and frequency domains in EEG signals [116]. This makes WPT an appropriate feature extraction tool for capturing and localizing the transient features in the EEG epileptic data. In addition, WPT can deal with the analysis of different window sizes. Thus, specific time and frequency information, at both low and high frequencies, can be captured.

WPT consists of two main types including; Discrete wavelet transform (DWT) and Continuous wavelet transform (CWT). DWT is rated as a useful tool in more than one study for seizure detection [116]. It is well known that WT composes only approximation coefficients, while WPT composes both the approximation and detail coefficients of the signal. In the proposed method, DWT is used to decompose the EEG signals into various frequency bands. The DWT decomposes the signal into approximation and detail coefficients [116]. In DWT, the number of decomposition levels is essential to achieve an accurate analysis. According to a previous study in the field of seizure detection [116], it was proved that 5-level of decomposition is an appropriate choice for the analysis of epileptic EEG signals. DWT also used with different window sizes in which the long-term EEG signals are segmented into windows of size N seconds before feature extraction. Therefore, the proposed approach utilized DWT with 5-level of decomposition to extract several features from time and frequency domains. In this study, the extracted features have the dimension of (S*M*N) where S denotes the number of EEG channels, M denotes the number of features and N denotes the number of Windows. Energy, entropy, mean, and standard deviation of wavelet coefficients were calculated from each window.

5.4.3 Prediction based on Deep Belief Network (DBN):

In this study, a deep framework is used to analyze the extracted features from time series EEG data. This framework is a hybrid approach of DBN with Back Propagation. DBN consist of

N RBM of type Gaussian-Bernoulli RBM (GBRBM) to deal with continuous EEG data. Each GBRBM is trained based on Contrastive Divergence (CD) method.

DBN consists of one visible layer in which the features are its input. This layer then linked to a series of hidden layers, each one of them is an RBM. The output of each RBM is used as input to the next one. The last hidden layer then connects to an output layer, which consists of two nodes. The output layer is used to predict and differentiate the features into a normal, pre-ictal, or ictal state of seizure. In the proposed DBN model, the type of each RBM is Gaussian- Bernoulli RBM (GBRBM). GBRBM was introduced to deal with continues data through Gaussian distribution for the visible layer instead of the probability distribution that used with the Bernoulli-Bernoulli RBM (BBRBM). The number of the hidden layers and the number of their RBMs nodes are selected based on empirical analysis. In the training of DBN model, the extracted features are used as input data to the first RBM, which learns and passes the data to the next RBMs. Then the pre-trained phase starts in which all RBMs are trained in an unsupervised manner where only the training data is fed to the network without labels. This followed by the main training process where the data and labels are fed together in a supervised manner, and the process of learning and pass continues until the last layer is reached. Once each RBM layer is trained in a layerwise manner (one layer each time), the output of the last RBM is used for fine-tuning phase with backpropagation. Table 5.1 presents a pseudo-code for training the DBN model.

Table 5.1: pseudocode for training the DBN model with Back Propagation

Training DBN Model: GBRBM with Back Propagation
See listing below

```
Begin
    Initialization:
    Initialize the number of RBMs (3 layers).
    Initialize the number of hidden units for each RBM.
    Initialize type of RBMs= GBRBM.
    Initialize weights W randomly weights.
    Set (v_i) data = time series input
    Set y = time series output
  repeat
    for every layer L do
      for every input k in training dataset do
        for all hidden units' j do
        update (h_j)_data based on equation (5.7)
        end
        for all visible units i do
         update (v_i)_model based on equation (5.8)
        end
        for all hidden units' j do
        update (h_j)_model based on equation (5.7)
        end
      update weights W based on equation (5.3)
      update bias (a) based on equation (5.4)
      update bias (b) based on equation (5.5)
      end
    end
  end
 until total number of iterations is reached
  for every input k in training data do
    for all layers i do
      for all hidden units' j do
       update h_ij based on equation (5.7)
      end
     Set v_i+1 = h_i
    end
  end
The output of final layer performs fine-tuning phase
Set output to Backpropagation (final-layer, y)
return output
end
```

5.5 Results and discussion

5.5.1 Dataset Description:

The performance of the proposed method for seizure prediction based on the analysis of EEG signals was tested with two different EEG datasets (dataset 1, dataset 2). The dataset 1 obtained from University of Bonn, Germany [119]. This dataset consists of three conditions; normal/healthy (set A), pre-ictal state (set D) and epileptic seizure state (set E). Each subset contains 100 single channel EEG signals with a sampling rate of 173.6 Hz. Subset A contains EEG records belong to five healthy volunteers with eyes open and closed. The EEG records of subset D belong to five epileptic patients during seizure-free intervals. Subset E contains EEG records taken during seizures activity from five patients. Table 5.2 shows a summary description of the three subsets. Figure 5.6 shows EEG samples of normal, pre-ictal, and epileptic from set A, D, E respectively. Although Dataset 1 has been widely used in the field of seizure detection and prediction, the type of electrode and placement is different between the sets, which may impose different noise models. This motivates the use of another dataset to evaluate the performance of the proposed work.

Table 5.2: Summary of EEG data in dataset 1

Description	**Set A**	**Set D**	**Set E**
Subjects	Healthy subject	Epilepsy patient	Epilepsy patients
Subjects state	(normal)	Seizure-free (pre-ictal)	Seizure activity (ictal)
Electrode type	Surface	Intracranial	Intracranial
Number of records	100	100	100
Time duration (m) for each record	23.6	23.6	23.6
Electrode placement	International 1020 System	Opposite to epileptogenic zone	Within epileptogenic Zone

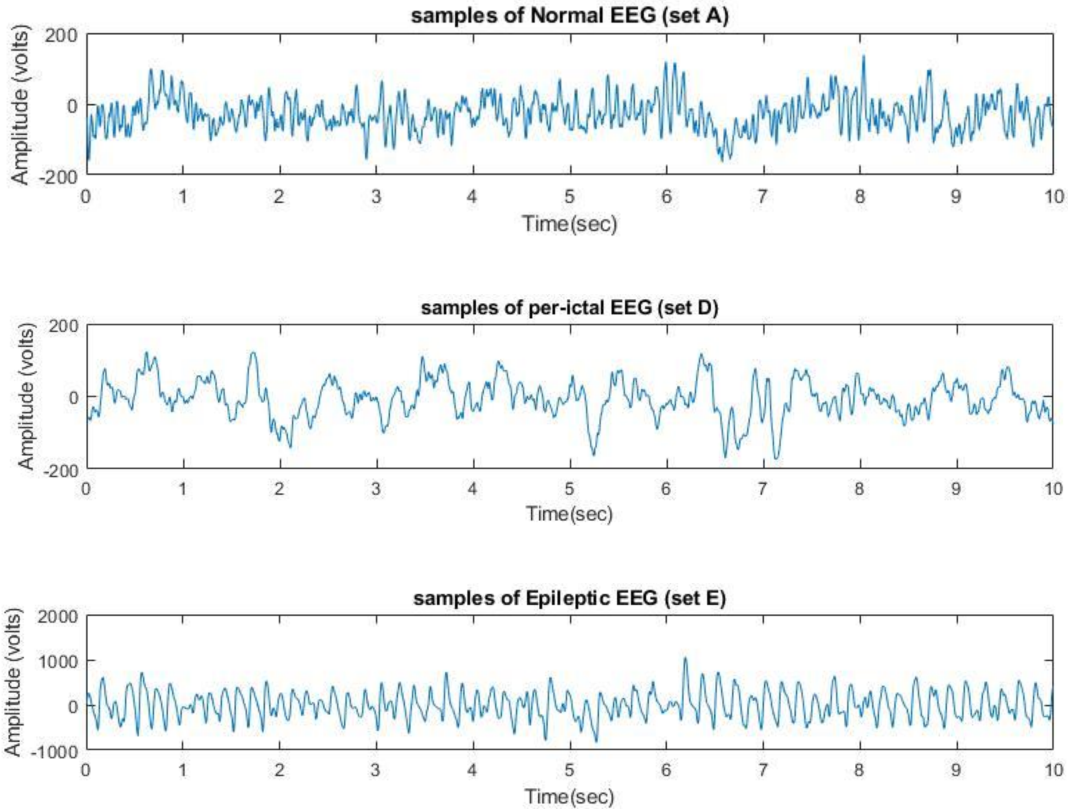


Figure 5.6: EEG samples from the three subsets A, D, E.

Experiments in this chapter were also carried on another dataset (dataset 2: CHB-MIT database), which is available in [120]. This dataset collected at the Children's Hospital Boston from twenty patients; including male and female, whose ages range between 1.5 and 18 years. This dataset comprises multi-channel EEG signals recorded from 23 channels for each patient. The sampling rate is 256 Hz with 16-bit resolution. The dataset contains two conditions; including pre-ictal and ictal seizure states. The electrode placement of this dataset is used based on international10–20 systems to record all EEG signals [120]. EEG signals of six patients were used in the experiments to evaluate the performance of the proposed method, which summarized in Table 5.3.

Table 5.3: Summary of EEG data in dataset 2.

No. of patient	**Gender**	**Age**	**No. of records& duration**	**No. of seizures**	**No. of channels**
1	F	11	22*(1:00:00)	7	23
2	M	11	5*(1:00:00)	3	23
3	F	1.5	14*(1:05:06)	10	23
4	M	3.5	20*(1:00:00)	7	23
5	F	13	6*(1:05:06)	7	23
6	F	9	22*(1:00:00)	16	23

5.5.2 Performance Evaluation

In this study, the proposed method was implemented using MATLAB software with DBN toolbox [121]. The following performance metrics were used to evaluate and compare the performance of both datasets. These metrics including; accuracy (ACC), sensitivity (SEN), and specificity (SPE), which are defined in equations (4.7), (4.8), and (4.9) respectively. In addition to the use of precision (PRE), recall (REC), and F1-Measure (F1-M), which are defined follows:

Precision(PRE)= TP/ (TP+ FP). (5.21)

Recall(REC) = TP / (TP + FN). (5.22)

F1-Measure(F1-M) = 2*((Precision*Recall)/ (Precision + Recall)). (5.23)

Where TP, TN, FP, and FN denote the number of true positive, number of true negatives, number of false positive, and number of false negative, respectively. Confusion Matrix is also used for performance measurement.

In this study, each EEG channel was first pre-filtered to remove the noise based on the spectrum estimation method. Then the varying window sizes were used with WPT to extract features from each sub-band. The performance was tested based on different window sizes, the window size of 150 samples (corresponding to ~1 second) produced the best performance based on the training and testing of each dataset separately. This matches the finding by other research [105], which indicate that the window size of one second is appropriate to demonstrating any sudden changes in the brain activity. Table 3 shows the effects of different window sizes on the performance.

Table 5.4: performance based on different window sizes

Window size	Accuracy
265 (~2 second)	93.2%
250 (~1.70 second)	95.3%
175 (~1.50 second)	97.1%
150 (~1 second)	**99.2%**
75(~0.5 second)	94.2%

For feature extraction based on 1 s window and DWT of 5 levels, all EEG signals from each dataset were decomposed to calculate different EEG patterns. Figure 5.7 shows the five levels of decomposition with DWT including; the five details (d1-d5) and the fifth approximate (a5) from each subset in the dataset 1. The energy, entropy, mean, and standard deviation features were extracted from ictal, pre-ictal, and normal periods.

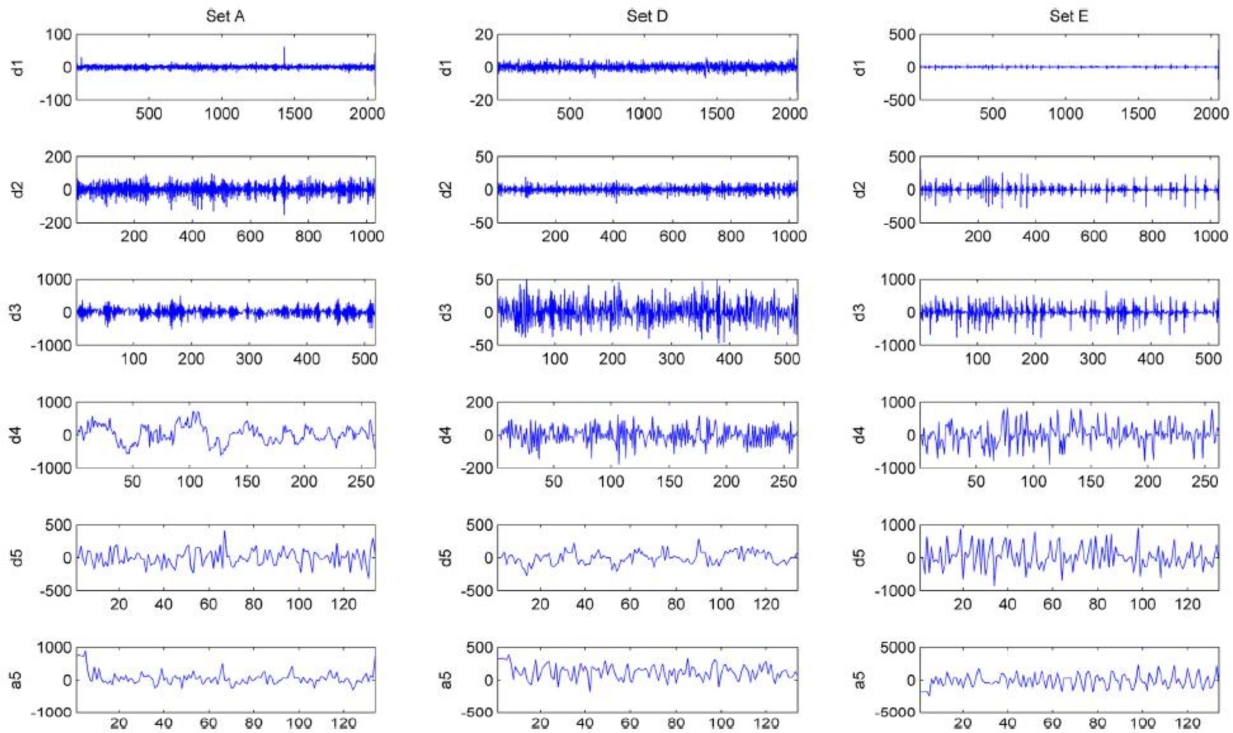


Figure 5.7: EEG samples from set A, D, E with WPT.

The performance of the proposed model with DBN was tested based on three different approaches including; raw data (without feature extraction stage), wavelet packet features, and statistic features (without wavelet packet) features. Table 5.5 shows a summary of extracted statistical features. Based on the obtained results, it was found that the best performance is achieved by using the wavelet packet features along with DBN as shown in Table 5.5.

Table 5.5: Summary of statistic features

Statistic Features	**Description**
Mean (M)	Mean value of signal.
Standard Deviation (SD)	Amount of variation in the signal.
Median Absolute Deviation(MAD)	A statistical dispersion measures.
Kurtosis(K)	Represent the sensitivity of the signal to outliers.
Skewness(S)	Represent the asymmetry in the signal concerning the mean.

Table 5.6: Performance based on different implementation approaches

Implementation approach	Accuracy
Raw EEG data & DBN	81.2%
Extracted statistic features & DBN	88.5%
Wavelet packet features & DBN	**99.2%**

The extracted features based on the wavelet packet from each EEG signal were employed as input to feed the DBN. The obtained features were first divided into 80% training and 20% testing to test the performance of automated seizure prediction model.

In DBN, several parameters are needed to initialize the model. A summary of the layered architecture of DBN in the proposed model is presented in Table 5.7. DBN was trained using 100 epochs or iterations, such that the error of training was minimized in each iteration. The training data was also divided into mini-batch of size 100. The learning rate of the algorithm was set to 0.1, which utilized with all layers in the network. DBN was designed with three hidden layers or RBMs each one with 200, 500, and 500 neurons respectively. DBN consist of two outputs which corresponding to predicted condition (pre-ictal or ictal) and (pre-ictal or normal). In addition, dropout-DBN was also used to avoid the possibility of overfitting. The idea of dropout-DBN is that a random number of hidden layer neurons is ignored to prohibit the correlation among features during each iteration. The dropout-DBN was set to 0.4.

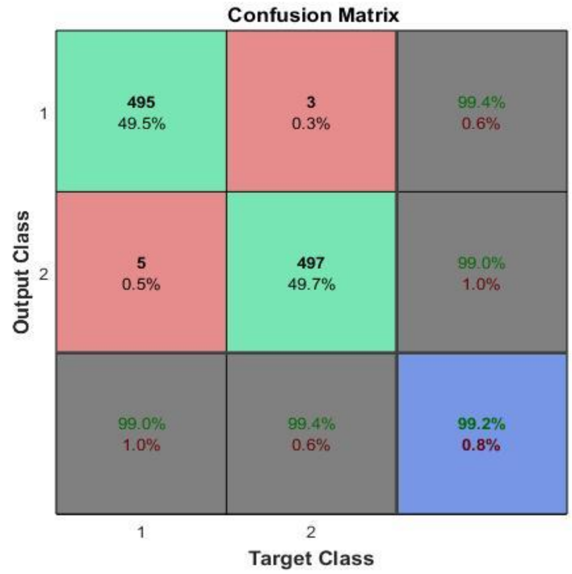
Table 5.7: Architecture of DBN in the proposed model

Layer in DBN	**#number**	**#type**	**#activation function**	**#training algorithms**
Input layer	One (corresponding to input data)	RBM of type (GBRBM)	_	Contrastive Divergence (CD).
Hidden layers	Three each with 200,500,500 neurons	RBM of type (GBRBM)	Sigmoid	Contrastive Divergence (CD) method.
One output layer	One (corresponding to seizure stage)	RBM of type (GBRBM)	_	Backpropagation.

Figure 5.8 and Figure 5.9 show the results of the proposed model for analysis of EEG signals with DBN. Table 5.7 and 5.8 show the overall evaluation based on the different performance metrics. The obtained results indicate the robust performance of the proposed model and the success of using WPT with DBN as robust techniques for seizure prediction. The proposed model yielded high-performance accuracy in differentiation between the pre-ictal, ictal, and normal states based on EEG signals analysis. As we can see in these figures, an accuracy of 99.2% between the pre-ictal and ictal states was achieved, while the accuracy of 99.3% between the pre-ictal (set A) and normal condition was obtained. The accuracy of differentiation between the normal or health condition and pre-ictal state was a little higher than that between the pre-ictal and ictal state, which may result due to the significant similarity and interference between the extracted features from the former seizures states.

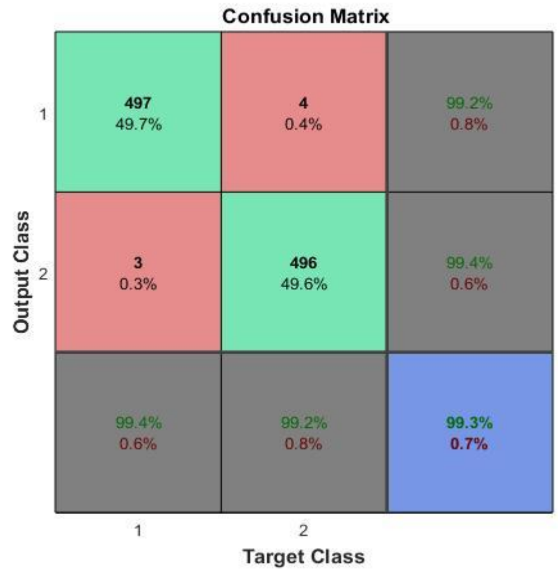
Tables 5.8 and Figure 5.8: Prediction results between pre-ictal and ictal states:

# of training samples	4000
# of testing samples	1000
Accuracy	99.2%
Sensitivity	99.0%
Specificity	99.4%
Precision	99.4%
Recall	99.0%
F1-Measure	99.2%



Tables 5.9 and Figure 5.9: Prediction results between pre-ictal and normal state:

# of training samples	4000
# of testing samples	1000
Accuracy	99.3%
Sensitivity	99.4%
Specificity	99.2%
Precision	99.2%
Recall	99.4%
F1-Measure	99.3%



The performance of the proposed DBN model was also compared with other methods including linear discriminant analysis (LDA), k-nearest neighbor's algorithm (KNN), support vector machine (SVM) with RBF kernel, and logistic regression (LR).

The same extracted features were used as input data to each one of these methods. The obtained results are summarized in Tables 5.9 and 5.10 along with Figures 5.9 and 5.10. As shown in these Figures, the proposed approach has yielded higher performance than the other techniques over all the evaluation metrics.

Table 5.10: Prediction results between pre-ictal and normal state based on various methods:

Prediction Method	**Accuracy**	**Sensitivity**	**Specificity**	**Precision**	**Recall**	**F1-Measure**
LDA	59.8%	53.0%	66.0%	61.3%	53.0%	56.8%
KNN	77.4%	74.8%	80.0%	78.8%	74.8%	76.8%
SVM	78.8%	95.8%	61.8%	71.4%	95.8%	81.8%
LR	88.1%	95.8%	80.4%	83.0%	95.8%	88.9%
Proposed method	**99.3%**	**99.4%**	**99.2%**	**99.2%**	**99.4%**	**99.3%**

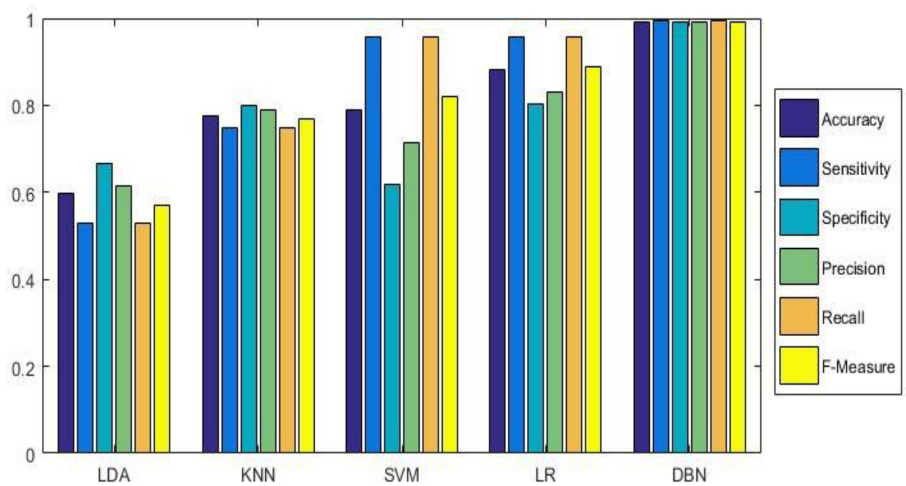


Figure 5.10: Performance results between pre-ictal and normal state using different machine learning methods.

Table 5.11: Prediction results between pre-ictal and ictal state based on various methods:

Prediction Method	Accuracy	Sensitivity	Specificity	Precision	Recall	F-Measure
LDA	75.2%	56.6%	88.1%	88.8%	56.6%	67.1%
KNN	87.2%	89.0%	85.4%	85.9%	89.0%	87.4%
SVM	91.0%	90.8%	91.2%	91.1%	90.8%	90.9%
LR	90.4%	81.2%	95.4%	95.5%	81.2%	89.4%
Proposed method	**99.2%**	**99.0%**	**99.4%**	**99.0%**	**99.4%**	**99.2%**

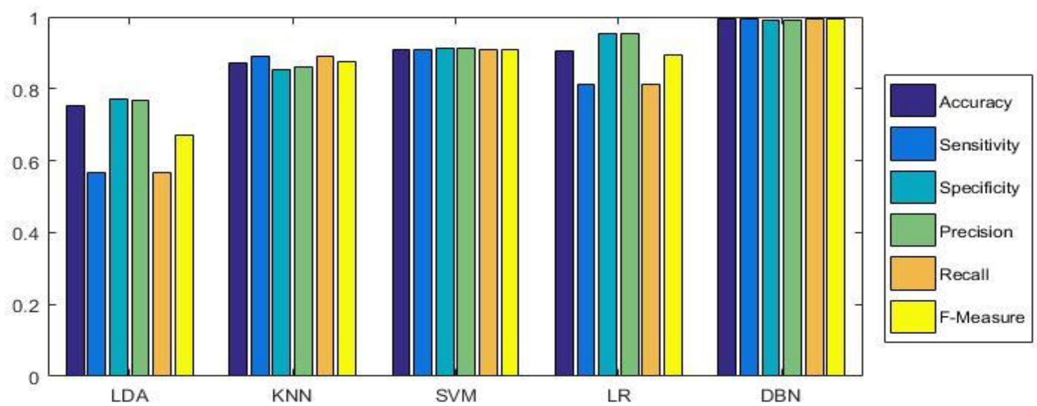


Figure 5.11: Performance results between pre-ictal and ictal state using different machine learning methods.

The proposed DBN approach extended for the analysis of the EEG data from dataset 2. Figure 5.11 shows a sample boxplot of dataset 2 with 23 channels. DBN was used to analyze the 23 channels of six patients along with DBN. Leave-one-out-cross-validation methodology was also used to evaluate the performance where each time one patient is left out of the training so that such unseen data is used for testing. Table 5.11 shows the prediction results based on multi-channel EEG signals.

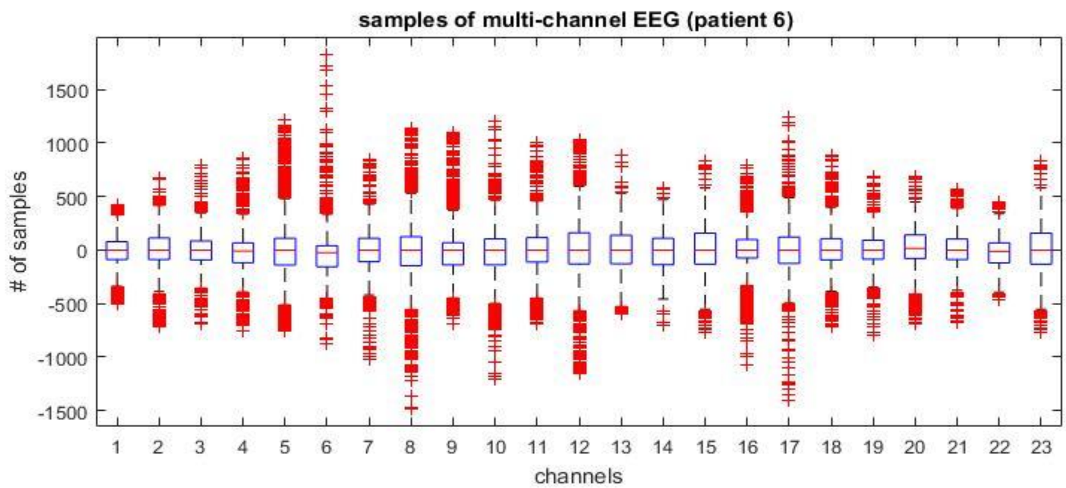


Figure 5.12: boxplot for 23 channels of patient 6.

Table 5.12: Results on leave-one-out-cross-validation:

Patient ID	# of seizures	# of training	# of testing	ACC	SEN	SPC	PRE	REC	F1-M
P1	7	4105	1000	95.4%	84.4%	100%	93.8%	100%	95.4%
P2	3	5800	1000	98.1%	92.4%	93.8%	92.5%	93.7%	98.1%
P3	10	6800	1000	94.1%	88.1%	100%	89.4%	100%	93.1%
P4	7	4000	1000	93.0%	89.6%	96.3%	90.3%	96.1%	93.1%
P5	7	4486	1000	92.4%	85.3%	100%	82.8%	100%	92.4%
P6	16	4699	1000	96.8%	100%	94.0%	100%	93.6%	96.8%

This set of experiments illustrated the merits of the proposed approach as it was generalized from one channel EEG data to 23 channel data. Moreover, the proposed approach yielded an average testing accuracy of 94.97% and an average testing F1 score of 94.82% based on dataset 2 with leave-one-out-cross-validation. Table 5.12 illustrates the performance of the proposed model in comparison with the state-of-the-art techniques that analyze the EEG signals from the same datasets. As we can see from Table 5.12, the proposed DBN approach with the WPT features outperforms the state-of-the-art techniques. The obtained results indicate the potential success of implementing this method as a valuable tool in the proposed architecture in chapter 3 to make more reliable and accurate decision.

Table 5.12: A Comparison between the proposed method and other existing methods

Author(s)	**Method Description**	**Accuracy**
[100] Ghosh et al.	Wavelet analysis & radial basis function, backpropagation neural network.	96.7%
[104] Panda et al.	Wavelet transform & support vector machine (SVM).	91.2%
[105] Guo et al.	Approximate entropy features & multilayer Perceptron (MLP).	95.2%
[106] Alotaiby et al.	Common Spatial Pattern (CSP) algorithm &SVM.	93.15%
[107] Pippa et al.	Time and frequency domain features & Bayesian network.	95%
[108] Chaurasiya et al.	Hilbert Huang transforms & SVM.	96.25%
[109] Nigam & Graupe	Non-linear preprocessing filter & ANNs.	97.2%
[110] Gopan et al.	Entropy & fuzzy inference system.	89.8%
[111] Martis et al.	Time-scale decomposition (ITD) features & decision tree classifier	95.7%
[112] Zhou et al.	Wavelet decomposition& Bayesian Linear Discriminant Analysis(BLDA).	96.2%
[113] Acharya et al.	13-layer deep convolutional neural network (CNN).	88.7%
[114] Vidyaratne et al.	a deep learning framework with Gated Recurrent Unit (GRU) RNNs	98%
Proposed method	**Wavelet analysis & Deep Belief Network**	**99.2%**

The performance of the proposed DBN model was also extended to analyze EEG signals to identify the three key seizure states; pre-ictal, ictal, and inter-ictal. This enables the early prediction of the seizure for notifying the patients. Figure 5.13 represents the confusion matrix of the proposed approach. An average accuracy of 91.9% is reported for classifications of the 3 states. Table 5.13 shows the various performance metrics of the proposed approach. The accuracy of identifying the pre-ictal state is 96.8%, however, the sensitivity is 83.4% due to the confusion of some of inter-ictal and pre-ictal state samples.

Figure 5.13: Prediction results between three seizure states:

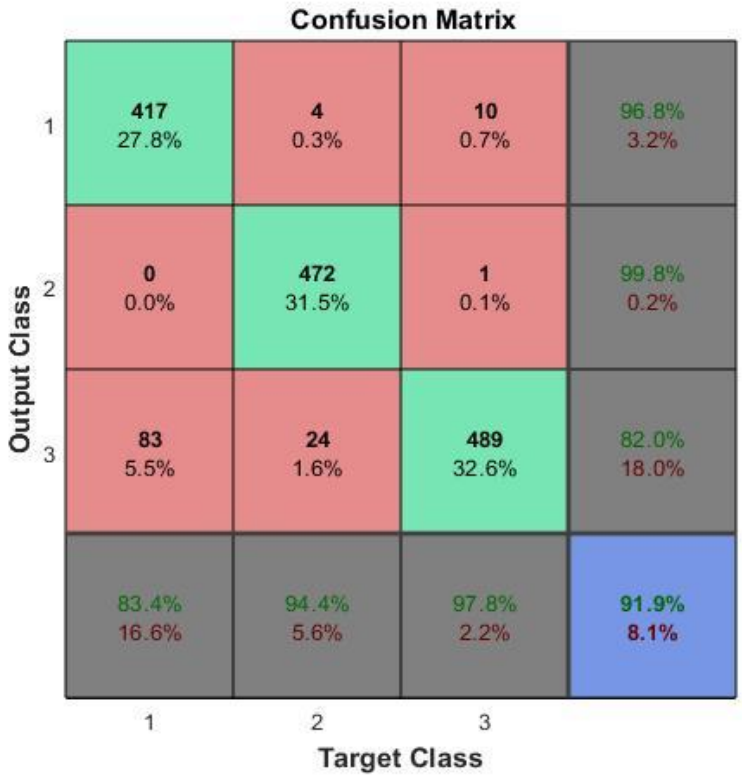


Table 5.13: Prediction results between tree seizure states

	Pre-Ictal	Ictal	Inter- Ictal
# of training samples	2000	2000	2000
# of testing samples	431	473	596
Accuracy	96.8%	99.8%	82.0%
Recall	83.4%	94.4%	97.8%
Precision	96.7%	99.7%	82.0%
F1-Measure	89.6%	97%	89.2%

5.6 Summary

This chapter proposed a new deep learning framework for seizure prediction model based on the analysis of EEG signals. The proposed model has exploited the benefits of WPT for feature extraction and DBN for differentiation between normal, pre-ictal, ictal states. Based on the experimental study, the proposed model has shown promising results in the analysis of time series EEG data in comparison to the state-of-the-art methods. This indicates the benefits of using Wavelet packet features along with DBN in making accurate prediction decision.

The proposed model for the analysis of EEG signals yields a high accuracy, sensitivity, and specificity, which indicates the success of implementing the model in the cloud tier of the proposed multi-tier architecture. In the proposed model, an accuracy of 99.3 % was achieved between the normal and pre-ictal state, while the accuracy of 99.2 % was obtained between the pre-ictal and ictal states was obtained based on the analysis of single-channel EEG signals. The proposed model also achieved a promising performance in the analysis of multi-channel EEG signals.

Chapter 6

Conclusion and Future Work

This chapter highlights the benefits of the proposed multi-tier architecture for early prediction of the epileptic seizure. It also presents the suggestions for future research.

6.1 Conclusion

This thesis proposes a novel distributed fog-based architecture for early prediction of epileptic seizures. The proposed architecture is multi-tier prediction model based on the analysis of ECG and EEG signals. The proposed architecture comperes of three tiers, each tier has its role in making the seizure prediction decision. The first tier is responsible for data collection and transmission to the next tier. The second tier of the proposed architecture exploits the benefits of emerging fog computing technology for lightweight analysis based on ECG signals. The third tier is responsible for extensive analysis based on EEG signals and data storage in the cloud. In the proposed architecture, the proposed model for lightweight analysis of ECG signals is formulated via Least Squares Support Vector Machines (LS-SVM), while the proposed model for deep analysis of EEG signals is formulated via Deep Belief Network (DBN). In addition, various features were extracted through the analysis of both signals, which are relevant to pre-ictal and ictal states of the seizures.

In Chapter 3, an overview of the proposed multi-tier fog-based architecture for early prediction of epileptic seizures was introduced. This chapter provided a discussion about the role of fog computing at the second tier of the proposed architecture in reducing the latency and energy over real-time data transmission and notifications. This chapter also offered a comparative study to evaluate the performance of the proposed fog-based architecture against the traditional cloud as an intelligent computing platform for early prediction of epileptic seizures.

In Chapter 4, the proposed model for seizure prediction based on lightweight analysis of ECG signals was presented. This chapter explained the details of each stage in the proposed model for ECG analysis. This chapter also presented the obtained results, which showed that the proposed model for ECG analysis with PCA and LS-SVM achieved 99% accuracy, 98.3% specificity, and 99.2% sensitivity in differentiate between the ictal and pre-ictal states of seizure. The performance of the proposed model with PCA and LS-SVM demonstrated higher performance in comparison with the state-of-the-art approaches.

In Chapter 5, the proposed deep-learning framework for the analysis of EEG signals was introduced. This chapter investigated the benefits of using wavelet packet features and DBN in discriminating between the pre-ictal state, ictal state, and normal/health state. The obtained results showed that the performance of DBN outperformed several approaches including; SVM, KNN, LDA, and LR. The performance of the proposed deep learning framework was tested based on two different datasets.

The advantages of the proposed architecture can be summarized as follows:

- The proposed multi-tier fog-based architecture enables the collection and analysis of vital signs in real-time.
- The proposed architecture optimizes the seizure prediction performance where the decisions can be made with minimum latency and energy.

- The exploitation of fog computing technology at the second tier of the proposed architecture enables a lightweight analysis of ECG signals and real-time notifications.
- The use of deep learning framework at the third tier allows for extensive analysis based on EEG signals to make accurate and reliable decisions.
- The proposed models for the analysis of ECG and EEG signals achieved promising performance in terms of accuracy, sensitivity, specificity, and outperformed several proposed seizure prediction methods in literature.

6.2 Future work

- The proposed architecture can be implemented for monitoring patients with different neurological diseases other than epilepsy such as strokes, coma, brain necrosis, and sleep disorders, which might lead to mitigate the risks and save the lives of patients with various neurological diseases.
- Other biometrics such as magnetic resonance imaging (MRI), Electrocorticography (ECoG), or intracranial Electroencephalography (iEEG) can be included besides ECG and EEG signals to develop a comprehensive computing system for real-time signals analysis.
- Although the results have demonstrated the effectiveness of the proposed models for the analysis of ECG and EEG, each one could further be tested using different datasets.
- Testing the performance of the proposed models for the analysis of ECG and EEG signals based on different machine learning approaches other than LS-SVM and DBN.

- Examining the performance based on using different window sizes for extracting the features from ECG signals.
- Expanding the proposed architecture by considering the contextual data besides the ECG and EEG signals such as patient medical records, which could make the prediction decision more realistic.
- The full integration of the three tiers of the proposed architecture including the local decision based on ECG signals analysis and the global decision based on EEG signals analysis can be tested in a real-world setting.
- Extending the proposed model through the use of multi-classifier fusion method for the analysis of ECG and EEG signals to develop more precise classification.
- Evaluating the performance not only based on the traditional standard metrics such as accuracy but also based on other clinical relevant metrics.

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