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Classification of Epilepsy EEG Signal based on Machine Learning in Edge/Fog Computing for Remote Patient Monitoring

A Thesis

Submitted to the Council of College of Science for Women, the University of Babylon in a Partial Fulfilment of the Requirements for the Degree of Master in Science\ Computer Science

By

Riyam Faisal Alwash

Prof.
Dr. Ali Kadhum Idrees
University of Babylon
College of Information Technology

Lect.
Dr. Salah Mahdi Al-Obaidi
University of Babylon
College of Science for Women

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بِسم الله الرَحْمن الرَحيم

وَقُلِ اعْمَلُوا فَسَيَرَى اللَّهُ عَمَلَكُمْ وَرَسُولُهُ
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صدق الله العلي العظيم

سورة التوبة

اية ١٠٥

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We are the members of the examination committee, certify that we have read this thesis entitled (**Classification of Epilepsy EEG Signal based on Machine Learning in Edge/Fog Computing for Remote Patient Monitoring**) and after examining the master student (**Riyam Faisal Majeed**) in its contents on 8/10/2023 and that in our opinion it is adequate as a thesis for the degree of Master in Science /Computer Science with degree (Excellent).

Committee Chairman

Signature:
Name: **Dr. Yossra Hussain Ali**
Scientific Degree: **Prof.**
Address: University of Technology /
Department of Computer Science
Date: / /2023

Committee Member

Signature:
Name: **Dr. Sura Zaki Alrashid**
Scientific Degree: **Asst. Prof.**
Address: University of Babylon/
College of Information Technology
Date: / / 2023

Committee Member

Signature:
Name: **Dr. Aladdin Abbas Abdulhassan**
Scientific Degree: **Asst. Prof.**
Address: University of Babylon/
College of Information Technology
Date: / / 2023

Committee Member (Supervisor)

Signature:
Name: **Dr. Ali Kadhum Idrees**
Scientific Degree: **Prof.**
Address: University of Babylon/
College of Information Technology
Date: / / 2023

Committee Member (Supervisor)

Signature:
Name: **Dr. Salah Mahdi Al-Obaidi**
Scientific Degree: **Lect.**
Address: University of Babylon/
College of Science for Woman
Date: / / 2023

Date of Examination: 8/10/2023
Deanship Authentication of College of Science for Woman
Approved for the College Committee of graduate studies.

Signature:
Name: **Dr. Abeer Fauzi Al-Rubaye**
Scientific Degree: **Prof.**
Address: **Dean of College of Science for Woman**
Date: / / 2023

Supervisor Certification

We certify this thesis entitled “**Classification of Epilepsy EEG Signal based on Machine Learning in Edge/Fog Computing for Remote Patient Monitoring*****” is written by** **“Riyam Faisal Alwash”** ***under our supervision at College of Science for Women a partial fulfilment of the requirements for the degree of a Master's in Computer Science.***

Signature:
Prof. Dr. Ali Kadhum Idrees
/ / 2023
University of Babylon
College of Information Technology

Signature:
Lec. Dr. Salah Mahdi Al-Obaidi
/ / 2023
University of Babylon
College of Science for Women

Head of the Department Certification

In view of the available recommendations, I forward the thesis entitled "**Classification of Epilepsy EEG Signal based on Machine Learning in Edge/Fog Computing for Remote Patient Monitoring*****" for debate by the examining committee*.**

Signature:
Asst. Prof.
Dr. Saif M . Kh. Al_Alak
/ / 2023
Head of computer science department
College of Science for Women

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Dedication

My deepest gratitude goes to all of my family members. It would not be possible to write this thesis without their support.

I would like to thank

my dearest father and my beloved mother

my lovely husband

for supporting and encouraging me with all love and patience…

my dear brothers for wishing happiness and success from the bottom of their hearts

my dear children for carrying with me the trouble of the journey

To all my dear loyal friends

I offer you that humble work….

Riyam

Abstract

In recent years, there has been a notable increase in the development of automated in-home monitoring systems according to the lack of human resources and medical services in health institutions. However, these systems produce a large amount of data because the monitoring takes a long time to collect significant information from the patient. This demand leads to increased interest in remote healthcare systems that use biosensors. These biosensors generate a significant amount of vital sensed data, which is then sent to the edge of the Internet of Medical Things (IoMT) for processing before transmitting to the next level of the network.

In this thesis, an Energy-efficient Two-level Epileptic Seizure Detection Approach (ETESeDA) is proposed for remote patient monitoring in edge/fog computing-based IoMT networks. The ETESeDA works on two levels in the IoMT network: edge and fog gateways. At the edge gateway, a data reduction method based on a proposing a time-frequency domain based feature extraction and Huffman encoding is used. The combination of Short-Time Fourier Transform (STFT), Gray Level Co-occurrence Matrix (GLCM) and Huffman encoding (HE) that is applied by the ETESeDA aims to extract useful features from the EEG signals and compress them before transmitting to the fog gateway. Then, a decision-making based machine learning model is proposed and implemented at the fog gateway using the transmitted data from edge gateway to determine the patient's situation and provide a suitable decision to the medical staff.

Several experiments have been conducted using the available Bonn University dataset. The results show that the ETESeDA highly reduces the transmitted data in terms of compression ratio, space saving, and accuracy of the decision-making. ETESeDA provides good compression ratio compared

with the HE method. The proposed ETESeDA offers a suitable level of accuracy for both binary and multi classifications, outperforming the state of the art and achieving accuracy 100% and 97% in binary and multi classifications, respectively.

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List of Abbreviations

Abbreviation	Meaning
EEG	Electroencephalography
ETESeDA	Energy-efficient Two-level Epileptic Seizure Detection Approach
FFT	Fast Fourier Transform
GB	Gradient Boosting
GLCM	Gray Level Co-occurrence Matrix
HE	Huffman encoding
IoMT	Internet of Medical Things
IoT	Internet of Things
KNN	K-Nearest-Neighbor
LR	Logistic Regression
MLP	Multi-Layer Perceptron
NB	Naive Bayes
RF	Random Forest
STFT	Short-Time Fourier Transform
SVM	Support Vector Machines

Chapter One
General Introduction

1.1 Introduction

The interaction between individuals and technology is widely regarded as a prominent aspect of our daily lives today, particularly with the pervasive presence of computers. This interaction means interpolating the sensor and computation into people’s daily activities by embedding it in the technology itself or through using computers. The Internet of Things (IoT) is one of the aspects of exploiting the technology to improve the conditions of living. IoT has been explored in the applications of smart homes, smart healthcare,smart environment monitoring and smart transportation[1].

There are numerous situations in which IoT can be implemented in real-life applications. The Internet of Medical Things (IoMT) encompasses a typical situation that incorporates both smart healthcare and smart home models. It involves the integration of connected devices and sensors in healthcare settings and homes to enable independent health monitoring and create smarter living environments [2]. IoMT is a new area of applications that can assist to find solutions for the raised remote healthcare monitoring problems, with the aim of specifically targeting the ability of the medical staff to carry out their in-home monitoring and diagnosis remotely. IoMT is made up of information gathered from medical and biosensor devices. These IoMT-based sensors are used to monitor the patient's health to collect and transmit the clinical data to professionals via the remote Cloud platform's data centres [3].

In recent years, remote patient monitoring has received an extensive interest for a significant role in the ageing world where patients can now be monitored at home while continuing to participate in their regular daily activities by exploiting the current communication and sensor technologies [4].

In the present day, there is extensive development and availability of various types of biosensor to monitor patients in smart homes and used to offer relevant information by analysing the acquired data [5].

Electroencephalography (EEG) is one of biosensor-based devices used to capture vital signs. These EEG signals are used to monitor brain activity to detect different type of diseases such as epilepsy [6]. The signals are generated by placing EEG sensors on the head of the patient, and then these signals are sent to an edge gateway before sending them to the cloud by the fog gateway to be processed. However, there are several issues, including the amount of recorder data and power consumption that need to be taken into consideration. In long term monitoring, such as during ambulatory EEG, a huge amount of data is produced which requires large memory space for saving and high bandwidth for transmitting. Furthermore, EEG signals are complicated and non-stationary, which are also considered challenges in this application [7]. Therefore, using an automated system to address these challenges could be very useful in tracking patients' conditions in both clinical and home settings, collecting objective and quantitative assessments to support both expert staff and medical diagnosis.

1.2 Problem Statement

In smart health systems, which are characterised by intelligent healthcare solutions, a huge amount of medical information is being recorded continuously, processed and transmitted via the network. This is particularly prominent in applications involving remote and constant monitoring. The data generated from advanced devices, comprising as many as 100 electrodes, can reach a rate of 1.6 Mbps per patient. In emergency situations, frequent reporting at ten-second intervals is essential. As a result, enhancing the transmission of patient health records over the network can lead to an increase in data volume, bandwidth utilisation, transmission errors, latency, and congestion within the IoT network. Moreover, the increasing number of chronic diseases, epidemics, and the ageing of the population represents a major challenge in hospitals, and more money needs to be spent to meet it.

1.3 Motivations

The main motivation behind reducing the transmitted data is to reduce the bandwidth usage, the latency and the congestion on the IoMT network. Moreover, remote patient monitoring allows healthcare professionals to monitor patients' physiological signals remotely. Continuous remote monitoring of EEG signals allows for early detection of abnormalities or changes in brain activity, enabling timely intervention and treatment.

1.4 Aims of Thesis

1. Proposing a new method, in time-frequency domain at edge gateway to extract meaningful features to improve the accuracy of decision making.
2. Developing an EEG data reduction framework at edge gateway to reduce the transmitted data.
3. Developing a decision-making based machine learning algorithm to provide the decision about the status of the patient that can be utilised efficiently at the fog gateway for remote patient monitoring.

1.5 Related Works

In this section, the existing work on EEG data analysis is conducted for remote monitoring and seizure detection. This thesis aims to develop a reliable and useful framework to address the issue of the large amount of data generated by monitoring seizure patients for long periods of time on their properties. It is also considered the issue of exploring the EEG-based data for detecting the patient's condition.

Zhang et al. [8] employed a deep convolutional network known as the Temporal Convolutional Network (TCN) to classify EEG signals. The suggested method had the ability to automatically acquire feature representations from unprocessed EEG signals, eliminating the need for any pre-processing steps. This research focused on binary classification, achieving an accuracy ranging from 96.57% to 100%.

Chowdhury et al. [9] proposed a method for classifying one-dimensional EEG signals by involving a compact and straightforward 1-D convolutional neural network. This architecture is designed to detect various types of seizure and non-seizure EEG signals, and it has been observed to achieve higher accuracy for binary classification from 97.60%-99.80% using Bonn EEG dataset.

Zhao et al. [10] is improved one-dimensional deep neural network architecture to effectively discriminate more than two classes of seizures. The performance of the proposed model is evaluated using the Bonn dataset. The results demonstrated high accuracy levels, ranging from 97.63% to 99.52% for binary classification and from 96.73% to 98.06% in the three-class EEG classification.

Aayesha, et al [11] suggested a method focused on extracting the most distinctive and discriminating features from EEG recordings of seizures in order to develop an approach that combines fuzzy-based and traditional machine learning algorithms for the detection of epileptic seizures. The proposed framework is designed to categorize unknown EEG signal segments into either ictal or inter-ictal classes. To validate the model, empirical evaluations were conducted on two widely recognized benchmark datasets, the Bonn dataset and CHB-MIT dataset. The results obtained indicate that, in both cases, the K-Nearest Neighbor (KNN) and Fuzzy Rough Nearest Neighbor (FRNN) algorithms consistently achieve the highest classification accuracy scores, arrange from 9.38 up to 81 and 92.97 for Bonn dataset and CHB-MIT dataset respectively.

Al-Hadeethi et al. [12] suggested a determinant of covariance matrix (Cov–Det) model for reducing EEG dimensionality .Each EEG signal is firstly segmented into small chunks and a determinant of covariance matrix (Cov–Det) is applied to shrink the dimensions of that data in each chunk. After that, a set of statistical features is extracted from each segment processed by Cov–Det. These features are filtered to remove the redundant values by integrating both the Kolmogorov–Smirnov (KST) and Mann–Whitney U (MWUT) to produce the most relevant features for the classification stage. These filtered features are used to train and test AdaBoost Back-Propagation neural network (AB_BP_NN) for binary classification. The obtained accuracy for the Bonn dataset was 98.86%. Such multi -level of dimensionality reduction can increase the time complexity of the proposed model.

Malekzadeh et al. [13] suggested approach comprises three stages: pre-processing, feature extraction, and classification. Initially, a band-pass filter with a cut off frequency of 0.5–40 Hz was applied to eliminate artifacts from the EEG dataset. The Tunable-Q Wavelet Transform (TQWT) was employed for decomposing the EEG signals. In the subsequent phase, a range of both linear and nonlinear features were extracted from the sub-bands produced by TQWT. In the classification step a CNN–RNN-based DL method with the number of layers proposed is applied. The results revealed that the proposed CNN–RNN method for Bonn datasets achieved an accuracy of 99.71%.

Mandhouj et al. [14] proposed an automated method for classifying EEG signals associated with the mentioned pathology. This research goal is to achieve effective seizure detection by categorizing the output into three classes:

normal, pre-ictal, and ictal. To accomplish this, they advocate the use of the Short-Time Fourier Transform (STFT) as a non-stationary signal processing technique for extracting valuable information from EEG signals. Following this, the STFT is converted into a spectrogram image, which serves as the input for the classification process. In this framework, we have developed a deep Convolutional Neural Network (CNN) model specifically designed to proficiently detect and classify epilepsy seizures based on the EEG spectrogram images. The experimental results confirm that the suggested approach is a robust tool for classifying EEG signals, achieving an impressive average accuracy rate of 98.22%.

Al-Salman et al. [15] proposed a binary model to discriminate between seizure and non-seizure individuals. EEG sensory signal is analysed in two steps: Complex Wavelet Transform (DT CWT) and Fast Fourier Transform (FFT), to extract signal properties from EEG data that can assist the classifier to accurately detect the seizure. LS-SVM (Least Square Support Vector Machine) classifier is used to classify the EEG signal into normal or seizure. The experimental results showed that the proposed method achieved an average accuracy of 97.7% and 96.8% for Bonn dataset and Bern dataset, respectively. Table 1.1 summarises the characteristics of seizure detection and classification models.

Table 1.1: Summarization of the Related Work on Seizure Detection and Classification

Ref No.	**Name**	**Year**	**Datasets**		**classifiers**	**Accuracy%**
			Bonn	**others**		
[8]	Zhang *et al.*	2018	✓	-	TCN	96.57% - 100%

[9]	Chowdhury *et al.*	2019	√	-	1-D CNN	97.60%-99.80%
[10]	Zhao *et al.*	2020	√	-	1D- DNN	97.63% to 99.52%, in the two-class and 96.73% to 98.06% in the three-class classification
[11]	Aayesha, et al	2021	√	√	FRNN	99. 38-99.81for Bonn dataset and 92.97 for CHB-MIT dataset
[12]	Al-Hadeethi *et al.*	2021	√	√	AdaBoost	98.86% for Bonn and 100%for Bern–Barcelona
[13]	Malekzadeh et al.	2021	√	-	CNN–RNN-based DL method	99.71%
[14]	Mandhouj et al.	2021	√	-	CNN	98.22%
[15]	Al-Salman *et al.*	2022	√	√	LS-SVM	97.7% for Bonn and 96.8% for Bern databases

1.6 Thesis Outline

The rest of thesis has the following arrangement:

Chapter Two: This chapter provided a comprehensive overview of the concepts of Internet of Things (IoT) and Internet of Medical Things (IoMT), edge computing, fog computing, fundamentals of EEG, data reduction techniques, remote patient monitoring, feature extraction, decision making, machine learning for EEG data classification, performance evaluation metrics.

Chapter Three: explains the proposed system to analyze the EEG sensory signal in time-frequency domain using STFT. This explanation also includes the description of the proposed descriptor to extract new features from time-frequency domain based coefficients.

Chapter Four: discusses and demonstrates the practical effort to evaluate the proposed methodologies. This chapter also shows the hardware and software Specifications, dataset and performance evaluation of our method and the comparison to the state of the art.

Chapter Five: presents the conclusions and future work.

Chapter Two
Theoretical Background

2.1 Introduction

The transmission of EEG signals plays a crucial role in providing real-time access to the brain activity of patients and enabling neurophysiologists to monitor and analyse data remotely. This remote access allows for timely diagnosis, monitoring, and treatment planning for individuals with brain disorders. However, the data of the patient consists of more sensitive information that should be sent without any lose or change in the contents [16].

The smart healthcare application encompasses several key requirements, including fast response times in emergency situations, and high bandwidth capabilities to handle the significant volume of daily sensed patient data transmitted in the network. The current limitations in network bandwidth, long delays, and high data costs indeed pose challenges in meeting the requirements of a smart healthcare application. The challenges faced in smart healthcare applications, such as limited bandwidth, long delays, and high data costs, have prompted the introduction of fog computing by Cisco[17]. Fog computing brings computing resources closer to the edge of the network, enabling local processing and analysis of data generated by healthcare devices and sensors. This approach reduces latency, optimizes bandwidth usage, and improves cost efficiency.

Resource-constrained devices, such as wearables, fitness tracker bands, and smartphones, are the primary consumers of edge services. These devices typically have limited computational power, memory, and battery life. Edge services cater to the needs of these devices by providing localized computing capabilities, reducing the reliance on cloud resources and minimizing data transfer to remote servers. This enables efficient data processing, real-time analytics, and responsive application functionalities on the resource-constrained devices themselves. By leveraging edge services, these devices can achieve enhanced performance, improved energy efficiency, and better user experiences in various domains, including fitness tracking, medical monitoring, and other IoT applications[18].

Edge and fog nodes serve as intermediate interfaces that connect resource-constrained devices to the cloud. These nodes facilitate the communication and interaction between the devices and the cloud infrastructure[19]. One of the important challenges in EEG analysis is that it contain variety of data and complex random and non-stationary signals, and so relying on visual scanning alone is time-consuming and impractical . The classification of EEG signals presents a problem in their analysis, and the key to solving it lies in extracting valuable information from the EEG using various methods [20]. In order to improve the classification task, it is necessary to transform the processed spectrogram into features that better represent the underlying patterns and characteristics of the data. This feature transformation step aims to extract relevant information and reduce the dimensionality of the data, making it more suitable for classification algorithms. When dealing with non-stationary EEG signals, it is important to consider techniques that can capture the time-varying dynamics of the EEG signals. One commonly used method is time-frequency analysis, which combines the advantages of both time and frequency domain [21]. Time-frequency techniques are effective tools that enable the decomposition of signals like EEG into both time and frequency domains. This decomposition facilitates the analysis of non-stationary signals, as it provides insights into how the signal's frequency content changes over time. Applying different distributions in time-frequency analysis of EEG signals, it becomes possible to visualize them as maps. As a result, it becomes possible to extract multiple features directly from the obtained mappings. These features capture important characteristics and information present in the time-frequency representations of the EEG signals. Then these extracted features can then be classified using many of machine learning algorithms. These techniques have shown good results in terms of accuracy for different applications [22].

2.2 The Internet of Medical Things (IoMT)

The Internet of Things (IoT) refers to a network comprising interconnected devices, such as smart appliances and sensors, which have the capability to communicate and share data with each other via the internet. IoT plays an important role in smart cities, smart homes, and more [23]. The concept of IoT was originally introduced by Kevin Ashton in 1999, and it has gained significant traction over time. With the goal of enabling connectivity between all objects, regardless of location, IoT is expected to connect billions of devices in the foreseeable future [24].

The rapid development in medical devices and communication technologies has given rise to the Internet of Medical Things (IoMT) [25]. In the recent year, remote patient monitoring has received an extensive interest for significant role in aging world where patients can now be monitored at home while continuing to participate in their regular daily activities by exploiting the current communication and sensor technologies [26].

2.3 Edge/Fog Computing

A new generation of computational offloading, e.g. Edge and Fog gateways, is introduced to deal with distribution of resources in different environment, such as homes and offices. These gateways serve to be intermediate between the in-home/office devices, such as, mobile devices, IoT devices, clients and cloud computing. Regarding the physical location of the computer, edge computing differs from fog computing technology. Fog computing technology facilitates the provision of networking, computation, storage, and management services between edge gateway and cloud data center [27]. The architecture of edge/ fog is shown in Figure 2.1.

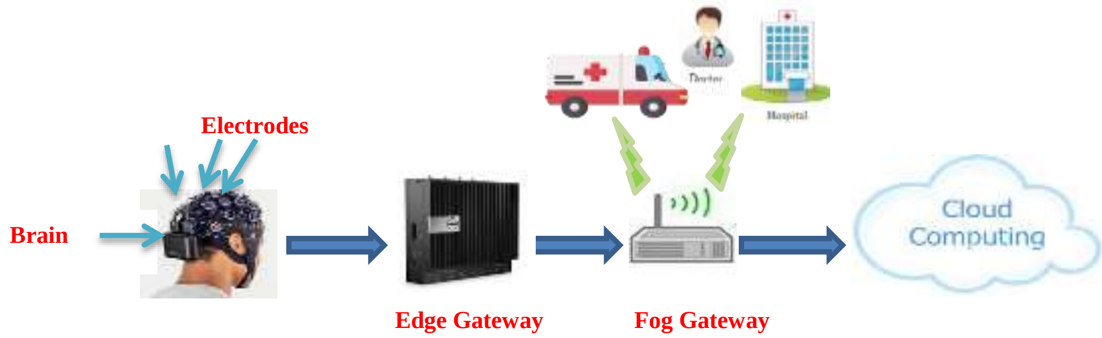


Figure 2.1: The Architecture of the Edge/Fog Computing

2.3.1 Edge Computing

Edge computing is a pivotal part of the IoT. The interest in Edge computing has increased rapidly in recent years in both industrial and research development. Physical accessibility and proximity serve as the bases for edge computing, with this critical aspect of Cloudlets affecting end-to-end latency, bandwidth being economically feasible, and the capacity to exist. Because the network's edge computing has lowered real transmission distances, less communication is required between a client and a server site [28].

Edge layer devices such as computer numerical control (CNC) machines, intelligent robots, sensors, terminals, and edge connection tools provide data and the ability to analyse and process these data, supporting edge computing and offering near edge smart services[29]. According to the given description, gateways such as routers, switches, or base stations are strategically placed near IoT devices to act as intermediaries between the devices and the fog or cloud layer. The purpose of this proximity is to enable traffic control and reduction, as data processing and analysis can be performed at the gateway level, minimizing the need for transmitting all data to the fog or cloud infrastructure.

2.3.1.1 Edge Computing Architecture

Edge computing consists of a set of infrastructure elements that are distributed from the central hub of a company's data centre to different edge locations, forming a comprehensive deployment strategy. This edge computing includes a range of resources such as computing power, storage capacity, applications, devices, and sensors. Micro data centres are employed to gather data from IoT sensors. These data centres perform data filtering and analysis, reducing the amount of data before transferring it to the fog gateway or cloud [30].

2.3.1.2 The Benefits of Edge Computing

Edge computing offers several benefits in terms of data processing, real-time analytics, reduced latency, and improved bandwidth efficiency. Here are some of the benefits of edge computing:

1. Reduced Latency: Edge computing is a paradigm that brings computational capabilities and processing power closer to the data source or edge devices. By doing so, it reduces the latency or delay that occurs when data needs to travel back and forth to a remote cloud server for processing.

The proximity of edge computing allows for faster data analysis and decision-making as the processing occurs in close proximity to where the data is generated [31].

2. Enhanced Data Privacy and Security: With edge computing, sensitive data can be processed locally, reducing the need to transmit it to a centralized cloud server. This approach helps address privacy concerns and can enhance data security by keeping critical information within the edge devices or local network [32].

3. Bandwidth Efficiency: Edge computing reduces the volume of data that needs to be transmitted to the cloud for processing. By performing data filtering, pre-processing, and analytics at the edge, only relevant information is sent to the cloud. This optimization minimizes bandwidth usage and helps alleviate network congestion [33].

4. Offline Operation: Edge computing enables applications to operate even in scenarios with limited or intermittent network connectivity. Local edge devices can continue to process and analyze data, ensuring uninterrupted functionality without relying on a constant internet connection [34].

5. Scalability and Cost Efficiency: Edge computing allows for distributed computation and storage resources, enabling scalability by adding more edge devices to the network. This approach reduces the need for extensive cloud infrastructure and can be more cost-effective, especially for applications that generate large amounts of data [35].

2.3.2 Fog Computing

Fog computing focuses on bringing cloud computing capabilities closer to the network's edge, making users access communication and software services more quickly. This framework is useful for offering the solutions of the cloud for highly mobile technologies like the IoT. In fog computing, the devices are connected directly to their location rather than through a complicated network infrastructure. This connection structure has significantly lower latency and better service quality[36].

2.3.2.1 The Benefits of Fog Computing

In the following, a list of fog computing's distinctive qualities and benefits: **1• Low latency**: this new paradigm's main driving force is to reduce data transmission latency while raising data transmission rate. Therefore, fog computing are used in time-sensitive applications [37].

2• Mobility support: the movement of nodes in applications like automotive networks might have an impact on the system performance, particularly when handling quick channel changes is required. This issue can be addressed by fog computing since fog gateway can help end users to be more mobile by delivering the compute and storage resources over the entire network [38].

3• Bandwidth: the data is pre-processed before being sent to the cloud for further analysis or storage. Fog computing makes this pre-processing stage possible to filter and aggregate data locally to speed up the completion of some operations that would otherwise require a lot of time due to very limited network bandwidth [38].

4• Scalability: in some IoT situations, it's important to manage massive volumes of end users as well as the vast amounts of data produced by billions of heterogeneous IoT items. Each one of these data resources has a different cost and performance profile [39].

2.4 Fundamentals of EEG

Electroencephalography (EEG) is biosensors-based device that are used to capture a vital signs. EEG signals are utilized for monitoring brain activity and detecting various conditions such as epilepsy [40]. These activities are detected by a set of biosensors placed on the head of the patients. The captured signals are then sent to an edge gateway before sending these signals to the cloud by the fog gateway [41].

However, there are several challenges, including the amount of recorder data and power consumption, need to be taken into consideration. In long term monitoring, such as during ambulatory EEG (AEEG), a vast quantity of data is produced which requires large memory space for saving and high bandwidth for transmitting. These issues restrict the resources of power, i.e. batteries, in such devices. In addition, EEG signals are complicated, non-stationary, which are considered challenges and making visual inspection time-consuming and imprecise [20].

An automated system could be very helpful in keeping track of patients' conditions in both clinical and home settings, collecting data and quantitative assessments to support both expert staff and medical diagnosis. This consists of extracting a meaningful features and exploiting these feature for classification [42].

2.4.1 Frequency Band of EEG

Ionic current flows occur as a result of the synchronized activation of neurons in the brain's sensory system produce the electrical activity and show as rhythmic voltage variations with amplitudes between 5 and 100 V and frequencies between 0.5 and 40 Hz. The five frequency bands into which brain waves are divided are as follows [43]:

• ***Delta*** (1-4 Hz): delta wave has the slowest frequency. It is characterized by its high amplitude; babies and adults both experience the delta band during deep sleep.

• ***Theta*** (4-8 Hz) is seen in youngsters, sleepy adults, and when recalling memories. Theta waves typically have amplitudes of less than 100 μV.

•***Alpha*** (8-12 Hz) generally appears while the eyes are closed or when in awareness relaxation as the main frequency band. The Alpha band's amplitude decreases with relaxation or focused attention while the eyes are open. These waves typically have a voltage of less than 50 μV.

•***Beta*** (12-25 Hz) is related to reasoning, active concentration, and precision. Additionally, making physical motions or seeing others make them improve beta power. Beta waves typically have amplitudes of less than 30μV.

•***Gamma*** (over 25Hz) during the processing of numerous sensory information. The amplitudes of gamma patterns are the smallest. All these waves are shown in Figure 2.3

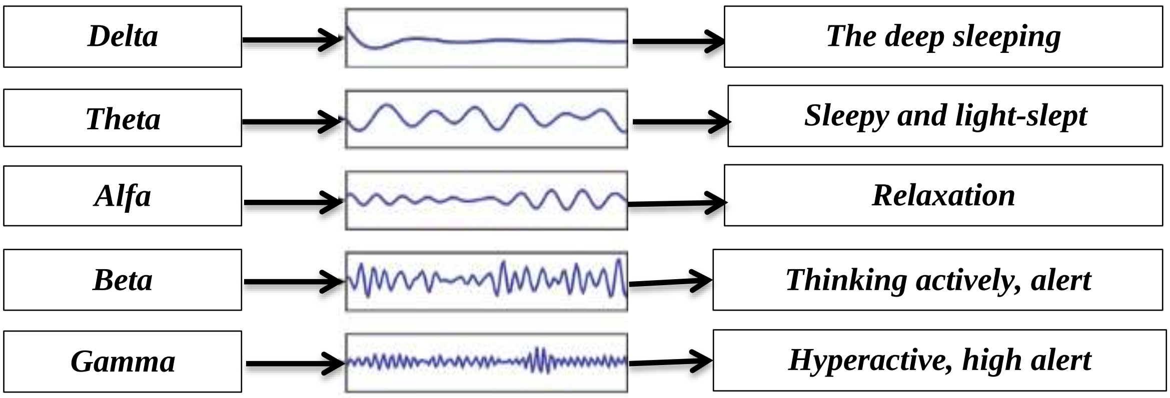


Figure 2.2: EEG Frequency Bands and Associated Mental States

EEG offers no radiation exposure dangers, ease of use, low costs, and tolerance for patient movements. Inadequate spatial resolution or high background noise level are the only two major downsides. The person wears an EEG hat on top of their head, with electrodes strategically placed on their scalp to record waves of electrical activity in the brain.

In addition to the frequency function correlations, each of the brain's area's is thought to perform a particular physical or intellectual function. As a result, it is important to pay more attention to the recording from the relevant part of the brain while identifying the brain waves associated with each desired task as well as determining the dominant frequency.

2.4.2 EEG Electrodes and Corresponding Brain Area

The electrodes are applied directly to the skin or through conductive gel. While dry electrodes may be easier to attach compared to traditional wet electrodes, they are more prone to motion artifacts. Motion artifacts refer to disturbances in the recorded signals caused by movement or physical contact between the electrode and the skin. There exist multiple standards for electrode positioning and labeling on the scalp, ranging from the 10-20 [44]. The electrodes in the 10-20 standard are identified according to the attached lobe and positioned at ten percent and twenty percent locations along latitude and longitude lines, respectively. In some electrode labeling systems, odd numbers are indeed assigned to electrodes on the left side of brain, while even numbers are assigned to electrodes on the right side of brain as shown in Figure 2.4.

The brain is divided into four lobes [45] as shown in Figure 2.4: The first lobe is the *occipital lobe* which is responsible for perception of visual sense. The second lobe is called *temporal lobe* is the center for memory, face recognition, hearing, and comprehension of language information. The third lobe is the *parietal lobe* record the information related to grammar, problem solving, attention, and sense of touch activities. Finally the fourth part, i.e. *front lobe*, is responsible for dealing with concentration, memory, and emotions.

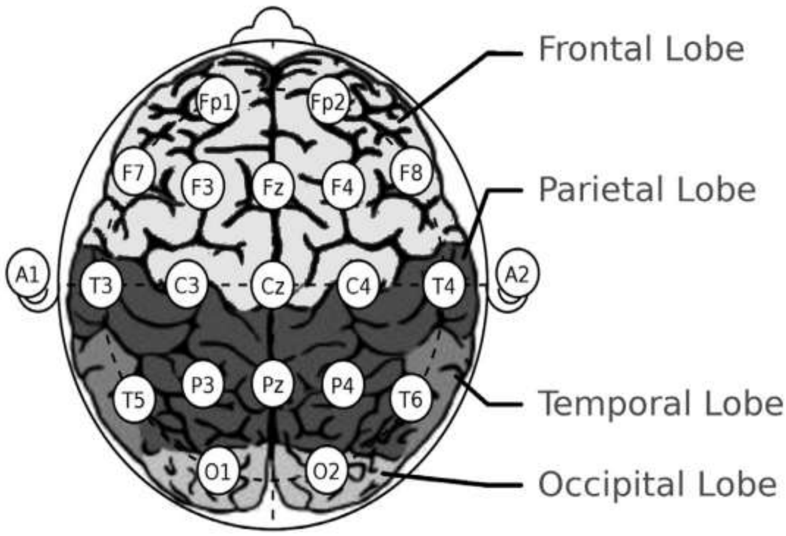


Figure 2.3: Show the Locations of the Electrodes with the Brain Regions that Each Electrode Corresponds to [45].

2.5 EEG Data Reduction Techniques

Medical decision support systems, intelligent control, and data clustering are all examples of when pattern recognition is put to use, and they all rely heavily on data reduction as an intermediate step. Reducing the size of data in such applications affects both the performance and computation time. In EEG based applications, data reduction techniques have become essential due to the large amount of recorded data [46].

The objective of data reduction is to classify epileptiform EEG signals more accurately while also reducing the calculation time. Up to 32 channels may be recorded by a typical AEEG device at a sampling rate of 200 Hz and the resolution of 16 bits. This framework produces 12.5 KBytes/s of data that can be broadcast from the portable device which could be up to 24 hours. The problem of producing a huge amount of data grows in long term monitoring systems.

Online data compression aims to reduce this average data rate while using the least amount of electricity possible. Therefore, it is vital to look for methods to compress this huge data and send less raw data while maintains the quality of compressed data. The reduction techniques would also minimise the amount of data supplied to the interpreting neurologist for long-term monitoring. There are two key techniques proposed for data reduction in EEG based applications. These techniques are reducing the recording's quantity and applying the compression to raw data**.**

2.5.1 Reduce the Recording's Quantity

Modern AEEG systems use digital recording to allow adjustment of both sampling resolution and rate. Applying data reduction in such case reduces the amount of data to be delivered. Although there is some higher frequency content, the majority of the examined EEG signals are in the range of 0.5–60Hz. Thus, a sampling frequency of at least 120Hz is needed. The lower end of this range would result in the least quantity of data because eight to sixteen sample bits are typically used in EEG devices. Simply monitoring fewer channels can reduce the amount of data collected. Clinically, an acceptable EEG recording of no more than four channels has been shown. However, all of these techniques degrade the quality of the EEG recording which affects the diagnosis of the EEG signal. Therefore, using more channels and better sample rates are required in the applications that depend on EEG [47].

2.5.2 Applying Compression Techniques to the Raw Data

Data compression refers to the process of reducing the size of text, audio, and video files without significantly compromising the quality or integrity of the information they contain [48].

Data compression involves reducing the size of data to save storage space and improve network transfer speed. It is a practical and effective approach because a significant portion of real-world data consists of duplicate information. Compression techniques can be either lossless, which allows for complete recovery of the original data in its original format, or lossy, where some original data bits may be irretrievable upon decompression. The algorithms used to restore the original data are known as decompression algorithms.

2.5.2.1 Lossy Compression

Lossy compression implies to the possibility of losing data during the decompression process. This compression technique operates under the assumption that modern data files contain an abundance of information that surpasses the comprehension of an average human. As a result, unnecessary information can be eliminated during the compression process [48].

2.5.2.2 Lossless Compression

Lossless compression is used when the original data preserved and can be fully recovered through file decompression. The data is effectively stored in its compressed form without losing information. This is particularly important for critical tasks where data must be restored without any loss [48].

One of the most important lossless compressions is the Huffman coding algorithm**.** It is a variable-length coding algorithm used for lossless data compression. It works by assigning variable-length codes to the input numbers, with the length of each code determined by the frequency of occurrence of the number in the input data. This means that more frequently occurring numbers are assigned shorter codes, while less frequently occurring numbers are assigned longer codes [49]. The following algorithm explains the main steps of Huffman coding algorithm.

Algorithm 2.1: Huffman Compression Algorithm

```
function CalcHuffLens (W , n)
    // initialize a priority queue, create and add all leaf nodes
    set Q ← [ ]
   for each symbol s ∈ ⟨0 . . . n − 1⟩ do
        set node ← new(leaf )
        set node.symb ← s
        set node.wght ← W [s]
        Insert(Q, node)
    // iteratively perform greedy node-merging step
    while |Q | > 1 do
        set node0 ← ExtractMin(Q)
        set node1 ← ExtractMin(Q)
        set node ← new(internal)
        set node.left ← node0
        set node.right ← node1
        set node.wght ← node0.wght + node1.wght
        Insert(Q, node)
    // extract final internal node, encapsulating the complete hierarchy of
mergings
    set node ← ExtractMin(Q)
    return node, as the root of the constructed Huffman tree
```

Huffman decompression, also known as Huffman decoding, is the process of reversing the Huffman coding algorithm to retrieve the original uncompressed data from a compressed file. Algorithm 2.2 shows the steps of Huffman decoding.

Algorithm 2.2: Huffman Decompression Algorithm

Input: HR*: Huffman tree root, B:* The decompression of the bit stream.
Output: ED : decompressed file

```
LL ← Length(B);
for i ← 1 to LL do
   ED ← HR;
   while ED .left /= NULL and  ED .right /= NULL do
      if (Bi = 0) then
         ED ← ED .left;
     end
```

```
    else
        ED ← ED .right;
    end
    i← i + 1;
  end
end
return ED ;
```

2.6 Remote Patient Monitoring

Different physiological data from patients are collected via systems for remote patient monitoring. Blood pressure, body/skin temperature, and electrocardiogram are the parameters that taken the most frequently ECG [50], EEG [51], heart rate, breathing rate, blood oxygen saturation or pulse oximetry, neurological system signals, and blood sugar level. Furthermore, weights, activity levels, and sleep information may also be gathered from patients. Hardware Meets Software (HMS monitoring)'s and diagnosis capabilities make it possible to diagnose and treat patients remotely without the need for them to visit the hospital [52].

2.6.1 The Advantage of Remote Patient Monitoring

The monitoring system offers many advantages that can help save the patient's life and provide a rapid alert system. One of these advantages is reducing overcrowding in health centers and hospitals. There is no waiting when recording the EEG data and the data can be recorded in home and then transmitted without the need for doctor visiting. In addition, there is no missing information because the readings are recorded to the database and clinicians can access the archive as they need it. Furthermore, after some minimal setup price, it is cheap [53].

2.6.2 The Challenges of Remote Monitoring Application

There are several challenges are found in applying a remote monitoring application. The difficulty in developing monitoring systems for these illnesses derives from the possibility that some of them may be closely related to other illnesses, necessitating the use of systems that can monitor vital signs, autonomous nervous system reactions, and psychological responses [54].

Healthcare applications and services are considered time-sensitive and require real-time processing. These systems are become critical for monitoring the patients, whose physiological parameters may rapidly deteriorate, and require immediate response and decision making. Delivery of health data may experience excessive latency under erratic network conditions, rendering the data incomplete, inaccurate, and occasionally even unusable. For data requiring cascade-based processing, such as ECG or EEG signals, this issue may result in even worse findings [55].

2.6.3 Developing of Remote Patient Monitoring

In general, contact-based remote patient monitoring (RPM) systems have been extensively reviewed. The concept of (RPM) originated from the use of contact-based techniques, which involve the integration of sensors, processing, communication, post-processing, database, and receiver/end-terminal technologies [50].

2.7 Feature Extraction

In order to make the features accessible, the important data or features from the signal are extracted through the process of feature extraction. The information extract depicts the anatomy and physiology of the brain's active processes. It required a lot of memory or a strong algorithm to analyze the data because it involved numerous variables in a sizable batch of data. To resolve these variables or information such that it may be comprehended simply and precisely in this situation, the feature extraction approach is required.

There are two techniques for feature extraction and selection, feature subset selection and feature extraction, can be recognized to get a meaningful representation from data collected by EEG. These techniques are applied in different domains including spatial, time, frequency and time frequency domains.

2.7.1 The Methods of Feature Extraction

There are two primary approaches for extracting features from EEG signals: manual extraction and automatic extraction. In manual extraction, experts or researchers analyze the EEG signal and identify relevant characteristics in both the frequency and time domains. These characteristics can be either multivariate or univariate, and they are selected based on specific attributes of interest.

Indeed, automated feature extraction methods encompass various techniques, including the calculation of Horthy parameters and statistical moments. Horthy parameters are a set of statistical descriptors used to characterize the shape and distribution of a signal. Statistical moments, including kurtosis, skewness, entropy, mean, and variance, are widely employed as feature extraction measures [56]. These features are computed using algorithms or mathematical formulas without manual intervention. They provide quantitative measures of the EEG signal characteristics and can be extracted automatically from the signal data.

There are several commonly used methods for analyzing EEG signals, including the discrete wavelet transform (DWT), continuous wavelet transform (CWT), Fourier transform (FT), time-frequency domain (TFD), time domain (TD) and frequency domain (FD)-based features [57]. These methods analyse different aspects of the EEG signal to extract relevant information in terms of time, frequency, or both. Each method has its own advantages and can provide valuable insights into the characteristics of the EEG signal.

2.7.2 Short Time Fourier Transform (STFT)

The short-time Fourier transform (STFT) is a widely used time-frequency analysis technique for EEG signal processing, especially in the context of epileptic seizure detection [58]. The STFT allows extracting frequency-based features from the EEG signal by dividing it into short-time segments using a time window function with some degree of overlap. The resulting spectrogram provides a visualization of the frequency content of the EEG signal over time [57].

The choice of time windowing function, w_n, determines whether the resulting spectrogram is narrowband or wideband. Shorter time windows result in a wider band spectrogram, while longer time windows produce a narrower band spectrogram [58]. The segments, or frames, of the EEG signal can be expressed as a function of time and frequency using the STFT [59].

$$xl[n] = w_n * x\,[n + lL] \qquad , 0 \leq n \leq N - 1, \qquad (2.1)$$

Eq. 2.1 represents sliding window and hop size used in the STFT algorithm to partition a signal into frames for frequency analysis. The window size (N) and hop size (L) can be adjusted depending on the desired time-frequency resolution of the spectrogram. The notation $x[n + lL]$ indicates a specific location within the signal, where n is the starting point of the window and l is the index of the frame. The $*$ operator represents the complex conjugate operation. Finally, each frame of the signal is subjected to the Fast Fourier Transform (FFT), as follows:

$$X[j, l] = \sum_{n=0}^{N-1} w_n * x[n + lL]\, e^{-i2\pi nj/J} \text{ , (2.2)}$$

The STFT provides a frequency spectrogram of a specific time frame segment of the input signal after applying the window across time; *X[j, l]* can be interpreted as a function of the frequency j for each value of the time index l, the STFT relates to a number of temporally situated series of spectra. In addition to being a frequency function for each time frame, the STFT can also be viewed as a time series function for each frequency, by interpreting *X[j, l]* as a function of *l*. The STFT can be seen as a filter bank that breaks down an input signal into sub-bands or frequency channels [59]. Regarding the time-frequency plane, these two STFT interpretations are represented.

The STFT process involves applying a window function to the signal in short overlapping segments, and then computing the FFT of each segment separately [60] and after this, the results are typically represented as a 2D array or matrix can be constructed where the columns denote the time intervals and the rows the frequency bins. This 2D representation is known as the spectrogram (image), and it provides a visual representation of the signal's frequency content over time.

2.7.3 Gray Level Co-occurrence Matrix (GLCM)

To perform classification, texture features are extracted from EEG signals. Utilizing the statistical moments of an image based on an image's intensity-histogram is one of the methods for presenting texture [61]. The spatial relationships between two or more of the texture's pixels cannot be described by our study of texture, instead, the histogram that is only used to characterize the distribution of intensities. To obtain the statistical texture features, the gray level co-occurrence matrix (GLCM) is exploited [62]. The

GLCM matrix for an image I with r*c dimension, parameterized by an offset $C_{Dx,Dy}$ is defined as:

$$C_{Dx,Dy}(i,j) = \sum_{i}^{r}\sum_{j}^{c}\begin{cases} 1 & ,if\ I(r,c)=i\ and\ I(r+D_x,c+D_y)=j \\ 0 & otherwise \end{cases} \qquad (2.3)$$

Where

$D_x = d * \cos(\theta)$

$D_y = d * \sin(\theta)$

where i and j are the image intensity values of the image, r and c are the spatial positions in the image I and the offset (*Dx,Dy*) depends on the direction used θ and the distance d at which the matrix is computed. Different co-occurrence matrices are generated by changing the values of d and θ. A range of statistics can be derived from the co-occurrence matrix to obtain a more meaningful set of features. In total, in our research, 11 statistical features are used that can be extracted from GLCM: contrast, homogeneity, correlation, ASM, entropy, energy, dissimilarity, variance, slandered division, Skewness and Root Mean Square (RMS).

1- Contrast: refers to a variation in the degree of contrast between a pixel and its adjacent pixels within an image as follows [63]:

$$Contrast = \sum_i \sum_j (i-j)^2 p(i,j) \qquad (2.4)$$

where $p(i,j)$ represents the probability at location (i,j) in the image.

2- Homogeneity*:* is an indicator of the uniformity of pixel distribution within an image as follows [63]:

$$H = \sum_{i,j} \frac{p(i,j)}{i+|i-j|} \qquad (2.5)$$

3- Correlation: measures the degree of correlation between each pixel in an image and its neighbouring pixels across the entire image as follows [64]:

$$r_{i,j=}\frac{(i-\mu i)(j-\mu j)p(i,j)}{\sigma_i\sigma_j}, \quad (2.6)$$

where μi and μj are the mean for i and j

σ_i and σ_j are the **s**tandard deviations of i and j, respectively.

4- Angular Second Moment (ASM): ASM is a statistical measure that reflects the homogeneity or uniformity of an image and it is calculated by summing the squared values of the elements of GLCM. The ASM is calculated as follows [63]:

$$\text{ASM} = \sum_i \sum_j p(i,j)^2 \qquad (2.7)$$

5- Entropy: Entropy is a statistical concept that reflects the level of randomness or uncertainty present in a signal or dataset. In the context of GLCM, entropy is calculated as the sum of the product of each element in the matrix and its logarithm [65].

$$Entropy = -\sum_i \sum_j p(i,j)\ \log\ (p(i,j)), \qquad (2.8)$$

6- Energy: The concept of "energy" is used to measure the evenness of the texture throughout an image as follows [63]:

$$\text{E} = \sqrt{ASM} \qquad (2.9)$$

7- Dissimilarity: Dissimilarity refers to the extent of difference or dissimilarity between two objects or entities. Manhattan distance, which is one of the oldest dissimilarity measures, is computed by the sum of absolute intensity differences as follows [63]:

$$\text{D} = \sum_i \sum_j p(i,j)|i-j| \qquad (2.10)$$

8 -Standard deviation: Standard deviation is a statistical measure that indicates how many the values in a dataset deviate or differ from the mean value. It is computed by the square root of the variance [65].

$$\sigma = \sqrt{\frac{\sum_i \sum_j (p(i,j) - \mu)^2}{n}} \qquad (2.11)$$

9- Variance: Variance is a statistical metric that indicates how much a dataset varies or deviates from its mean value. The variance value is obtained by averaging the squared differences between each data point and the mean value [65].

$$\sigma^2 = \frac{\sum_i \sum_j (p(i,j) - \mu)^2}{n} \qquad (2.12)$$

10-Skewness: Skewness is a statistical measure that describes the asymmetry or lack of symmetry in a probability distribution. It provides information about the shape of the distribution. A distribution can be either positively skewed (tail extends more towards the right) or negatively skewed (tail extends more towards the left), or it can be symmetric (no skewness). The skewness, Sk, is calculated as follows [65]:

$$S = \frac{\sum_i \sum_j (p(i,j) - \mu)^3}{n * \sigma^3} \qquad (2.13)$$

11-Root Mean Square (RMS): RMS, also known as quadratic mean, is calculated by taking the square root of the mean of the squares of the values in the set. It provides a way to determine the typical or average magnitude of the values, considering both positive and negative values. The equation for root mean square is [65]:

$$RMS = \sqrt{\frac{\sum_i \sum_j p(i,j)^2}{n}} \qquad (2.14)$$

2.8 Decision Making

Smart devices, in the context of healthcare, collect physiological signals from patients and transmit this data to fog devices. Each fog device stores the gathered data for a maximum of three hours. Each fog device uses its computational capability to deploy machine learning algorithms while the data is being retained in the devices to test. This framework is used to determine whether the physiological signals acquired in real-time indicate any requirement the patient to be attended by the attendant. After that, a notification will be sent to the attendant's mobile device. The notification contains the most recent information gathered about physiological signals as well as the message that the patient needs to be attended to. Upon receiving the notification, the caregiver will visit the patient to determine whether the situation is fatal or whether it can be resolved by the attendant. The attendant will notify the doctor responsible for treating the patient in question if the situation is serious [66]

2.9 Machine Learning for EEG Data Classification

Machine learning is the process of gradually enhancing the performance of a single task using a collection of mathematical models and algorithms. The most well-known machine learning technique utilized in medical applications is classification since it corresponds to problems that occur in daily life [67].

The classification algorithms build a model using the training data, which is then used to the test data to generate a prediction. There are many different tasks in this area, but they can be divided into two basic categories: supervised learning and unsupervised learning [68].

By evaluating EEG data, the suggested machine learning models are utilized to interpret the epileptic disease type being treated and assess the therapy options. Acquisition of signals is the initial step. Essentially, this is unfiltered raw data [69].

Pre-processing involves taking outliers and other erratic data points. The spectrogram of the data point groupings and the corresponding features are determined through feature extraction. The isolation of the required classifiers that the machine learning approach will be tested for the subsequent training is known as feature selection. To improve the classification process, machine learning training makes use of training data sets, either with or without known outputs. The processing of testing step consists of actual test data sets and comparisons of the desired feature's overall accuracy [70].

Researchers aim to develop algorithms and models that can accurately differentiate between these distinct brain states. This classification helps in understanding the underlying patterns and dynamics of EEG signals, assisting in the diagnosis and management of neurological conditions (epilepsy) [71].

2.9.1 Machine learning Techniques

The choice of algorithm in machine learning depends on various factors, such as the specific problem to be solved, the number of variables involved, and the type of model that would be most suitable. Here is an overview of some commonly used algorithms in machine learning.

1. Logistic Regression (LR)

Logistic regression is indeed a supervised learning algorithm that is commonly used for predicting a dependent categorical target variable based on a set of independent variables.

This algorithm is utilized to categorize individuals into specific categories based on the logistic function [72]

Algorithm 2.3: Logistic Regression Algorithm
Input: The Normalized Features vector for each user
1- ***for*** *i* ← *1* ***to*** *k* 2- for each training data instance d_i : 3- set the target value of regression to $z_i \leftarrow \frac{yi-P(1\|dj)}{[P(1\|dj).(1-P(1\|dj))]}$ 4- Nationalize the weight of instance d_j to $P(1\|dj).(1-P(1\|dj)$ 5- Finalize the f(j) to the data with class value(zj) and weights (wj) 6- Assign (class label :1) if $P(1\|dj)$ >0.5 otherwise (class label :2)

2. Multi-Layer Perceptron (MLP)

MLP is a non-linear neural network-based method that contains of three layers: input, hidden, and output. The input layer receives the input data, which is then transmitted through the hidden layer to the output layer. However, it is important to note that the MLP model can be prone to overfitting when the number of neurons in the hidden layer is insufficient or excessive [73].

Algorithm 2.4: Multi-Layer Perceptron Algorithm
Input: The Normalized Features vector for each user
1- Start with random initial weights 2- Do 3- For all patterns P 4- For All output Nodes j 5- Calculate activation (j) 6- Error_j= Target value_j_for_Pattern_p= Activation_j

7- For all input Nodes i to output node j

Delta_weight = learning constant = Error_j* Activation_i

Weight= weight * Delta_weight

8- End

9- End

10- End

10- Until Error is sufficiently small or "Time_out"

Output : MLP results.

3. K-Nearest-Neighbor (KNN)

The K-Nearest Neighbors (K-NN) method is a classification algorithm that dates back to the early 1950s. It is based on the principle of learning by analogy, where a given test data point is compared to similar training data points. The training data points are characterized by multiple attributes, representing points in an n-dimensional space.

In the K-NN algorithm, the training data points are stored in an n-dimensional pattern space. When a new, unknown data point is given, the K-NN classifier searches the pattern space to find the k training data points that are closest to the unknown point. These k nearest neighbors are identified based on their proximity in the n-dimensional space [74].

Algorithm 2.5: K-Nearest-Neighbor Algorithm
Input: The Normalized Features vector for each user
1. Set the value of k 2. Loop: 1 to N // To get predicted class Calculate the distance Di between data instance in training data and test data.

3. Increasingly arrange the computed distances (Di)
4. Populate the upper k results from the arranged list
5. Pick up the most frequent class from the list
Output: resultant class

4. Support Vector Machine (SVM)

SVM is a popular supervised learning algorithm used for classification and regression tasks. It is particularly effective for solving binary classification problems, but can also be extended to handle multi-class classification [75].

Algorithm 2.6: Support Vector Machine Algorithm
Input: α: =0 or α: =trained SVM, X and y
1- C:= Approximate upper bound constant value 2- Loop :∀ { Xi, yi } and { Xj, yj } 3- Do 4- Optimize αi and αj 5- End loop 6- Until no change in **α** **Output:** Hold merely Support Vector (SV) , (αi >0)

5. Gradient Boosting (GB)

Gradient Boosting is a machine learning technique that combines multiple weak learners to create a strong predictive model. It is an ensemble learning method where each weak learner is trained sequentially, with each subsequent learner focusing on the mistakes made by the previous learners.

The basic idea behind GB is to iteratively build a series of weak models (often decision trees) that are trained to correct the errors or residuals of the previous models. In each iteration the model is trained to reduce a loss function, typically using gradient descent optimization [76].

Algorithm 2.7: Gradient Boost algorithm
Inputs: • input data (x, y)Ni=1 • number of iterations M • choice of the loss-function (y, f) • choice of the base-learner model h(x, θ)
1: initialize f0 with a constant 2: for t = 1 to M do 3: compute the negative gradient g t (x) 4: fit a new base-learner function h(x, θt) 5: find the best gradient descent step-size ρt :ρt = arg minρNi=1yi, f t−1(xi) + ρh(xi, θt) 6: update the function estimate:f t ← f t−1 + ρt h(x, θt) 7: end for

6. Naive Bayes (NB)

The Naive Bayes algorithm is a popular machine learning algorithm that is known for its good classification efficiency and stable classification effect. It is based on the idea of calculating the probability of each condition when given a classification.

It is called "naive" due to the fact that it supposes that the features are conditionally independent of each other, which simplifies the computation.

The NB algorithm can be built using different distribution models such as Gaussian, Multinomial, and Bernoulli. The selection of a distribution depends on the characteristics of the data being analyzed and the specific problem being addressed [77].

Algorithm 2.8: Naive Bayes Algorithm
Input: The Normalized Features vector for each user
1: Count : table of observed counts of combination of 1 attribute value and the class label 2: for instance inst ∈ D train do 3:   get the value of class variable in inst, suppose it is the yth value 4:   for Xi, i ∈ {1, 2, . . . , a} do 5:   get the value of attribute Xi in inst, suppose it is the jth value 6:   increase the element in Count with index (i, j, y) by 1 7:   end for 8: end for

7. Random Forest (RF)

Random Forest is a popular machine learning algorithm that utilizes an ensemble of decision trees for classification and regression tasks. It is a bagging-based algorithm that combines the predictions of multiple individual decision trees to make a final prediction.

The main idea behind Random Forest is to create an ensemble of decision trees, where each tree is trained on a different subset of the training data and uses a random subset of the features. This randomness helps to reduce overfitting and improve the generalization performance of the model [78].

Algorithm 2.9: Random Forest Algorithm
Input: training set S with F features
1- Randomly pick ‘P’ features in ‘F’ features 2- Using ‘P’ features, find node ‘d’ by the best split 3- Break the node into child nodes by applying the best split method 4- Iterate steps 1to 3 until the ‘1’ number of nodes has been reached 5- Repeat steps 1 to 4 and build the forest by generation n numbers of desision trees **Output** :Random Forest Tree

2.10 Energy Consumption

Energy Consumption is the total amount of energy consumed at the edge gateway. It has been observed that data transmission consumes more energy compared to processing tasks. Energy consumption can be calculated using the following equations [79]:

$$Energy\ Consumption^{send} = \text{Eelec} * h + \beta\text{amp} * h * \text{dis}^2 \qquad (2.15)$$

The consumed energy is computed for the reception as follow:

$$Energy\ Consumption^{recieve} = \text{Eelec} * h \qquad (2.16)$$

where the "Eelec" is used to denote the energy consumption of the electronic components in a radio. The energy consumed by the amplifier is denoted by βamp. The size of the data packet is indicated by the variable "h." that refers to the size of the compressed file, typically measured in kilobytes (KB). The dis is the distance between the edge gateway and fog gateway in this dissertation. It is supposed to be 50 meters.

2.11 Performance Evaluation

This section outlines key performance measures for evaluating the proposed strategy. These measures are described as follows:

1. Compression Ratio (CR): this metric is defined in the following manner:

$$\textbf{CR (\%)} = \frac{\mathrm{E}comp}{\mathrm{E}or} \qquad (2.18)$$

Where E_{Comp} represents the compressed size of the EEG data obtained using the recommended method, and E_{Or} represents the uncompressed size of the EEG data.

2. Compression and Decompression processing time (T): the total time required for both the compression and decompression processes.

3. Size of sent data: the amount of transmitted data from the edge gateway to the fog gateway is determined by the size of the compressed EEG data, expressed in kilobytes (KB).

4. Compression Power: the data compression ratio, often referred to as CP, is defined as the ratio of the uncompressed size (EOr) to the compressed size (ECompr) of the data.

$$\textbf{CP} = \frac{\mathrm{E}or}{\mathrm{E}comp} \qquad (2.19)$$

5. **Average Compression Power (ACP):** refers to the average value of CP calculated for all the dataset records (Z, F, N, O,and S). It can be defined as follows:

$$\textbf{ACP} = \frac{CP^S + CP^F + CP^N + CP^O + CP^Z}{5} \qquad (2.20)$$

The parameters $CP^{S,}$ CP^{F}, CP^{N}, CP^{O} and CP^{Z} refer to the compression power of dataset records S, F, N, O, and Z respectively.

6- Compression gain: refers to the reduction in data size achieved through the compression process.. The equation for compression gain can be represented as follows:

Compression Gain = $10\log_{10}(E_{comp})$ (2.21)

7- **Space saving:** refers to the amount of storage space saved as a result of data compression. The equation for space saving can be represented as follows:

Space Saving = $(1-(\frac{Ecomp}{Eor}))*100$ (2.22)

8- Confusion Matrix: the confusion matrix is commonly employed to visualize and analyze the performance of a classifier on a specific dataset. It is a square matrix of size n*n, where n represents the number of classes. Each element of the matrix corresponds to the number of occurrences for each combination of the actual and predicted classes.

In binary classification, where n=2, the confusion matrix represents two classes: positive and negative. The matrix helps in understanding the classification results by providing information about true positives, true negatives, false positives, and false negatives as show in Figure 2.4 [80].

Here are some key terms related to the Confusion Matrix:

- **True Positives (TP):** the number of instances correctly classified as positive.

- **True Negatives (TN):** the number of instances correctly classified as negative.

- **False Positives (FP):** the number of instances incorrectly classified as positive.

- **False Negatives (FN):** the number of instances incorrectly classified as negative.

Total		Predict classes	
		positive	Negative
Actual classes	positive	TP	FN
	Negative	FP	TN

Figure 2.4: The Confusion Matrix Specifically Designed for Binary Classification

The Confusion Matrix for multi-class classification extends the binary confusion matrix to accommodate three distinct classes. It is a square matrix of size 3x3, representing the combination of actual and predicted classes for each instance in the dataset as show in Figure 2.5

Total		Predict classes		
		A	B	C
Actual classes	A	TP	FN	FN
	B	FP	TP	TN
	C	FP	TN	TP

Figure 2.5: The Confusion Matrix Specifically Designed for Multi-Class Classification

In Figure 2.6, the element A_A represents the count of instances that are correctly classified as class A (TP for class A). Similarly, B_B and C_C represent TP for classes B and C, respectively. The other elements in the matrix represent misclassifications or false predictions.

Analyzing the confusion matrix can provide insights into the classifier's performance for each class, enabling the calculation of metrics such as accuracy, precision, recall, and F1-score for the three-class classification problem.

- **Recall:** is calculated as the ratio of TP to the sum of TP and FN. It represents the ability of a classification model to correctly identify positive instances out of all actual positive instances. The formula for recall is as follows:

$$\textbf{Recall} = \frac{TP}{TP+FN} \quad (2.23)$$

- **Precision:** is calculated by dividing the number of TP by the sum of TP and FP. It measures the convergence or accuracy of positive predictions made by the classifier. The formula for precision is as follows:

$$\textbf{Precision} = \frac{TP}{TP+FP} \quad (2.24)$$

- F1-score, also known as the F1 measure, is a metric that combines precision and recall into a single value to assess the performance of a classifier. The formula for F1-score is as follows:

$$\textbf{F1-score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \quad (2.25)$$

- Accuracy is a measure of how close the measured value or predicted value is to the true or real value. It is calculated by dividing the number of correct predictions (true positives and true negatives) by the total number of instances in the dataset. The formula for accuracy is as follows:

$$\textbf{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (2.26)$$

2.12 Summary

This chapter provides a theoretical introduction about the topic of this thesis. The definition of edge, fog computing and their characteristics are presented. Data compression, along with its two main types, lossless and lossy compression, is also illustrated in this chapter. In addition, the remote patient monitoring application is discussed and its advantages, challenges are also explained. Feature extraction to the EEG data is applied. Different machine learning algorithms are demonstrated and discussed in the context of their applications. Finally, the performance evaluation metrics that are used in this research are introduced in detail.

Chapter Three
The Proposed System

3.1 Introduction

This chapter focuses on explaining the steps used to design the proposed system for seizure detection from EEG signals. Different approaches were employed to analyze EEG signals. The designed system is aimed at enhancement Seizure detection systems. Seizure detection systems play a crucial role in remote patient monitoring, particularly for individuals with epilepsy or other seizure disorders. These systems are designed to monitor and detect seizures in real-time, enabling rapid response, data collection for healthcare providers, and improved patient safety and quality of life.

3.2 Proposed System

This chapter proposes system for an edge-fog computing enabled lossless EEG data compression with epileptic seizure detection in IoMT Network. This method depends on processing the EEG signal in the time-frequency domain using STFT in order to consider the nonstationary behaviour of the EEG sensory data. Processing the signal by Short Time Fourier Transform (STFT) improves the ability to utilize the data for detecting seizure. Figure 3.1 depicts the structure of the proposed ETESeDA based on Edge-Fog computing architecture. The proposed system involves two stages of processing: edge gateway processing and fog gateway processing. The next sections will explain these stages in more detail.

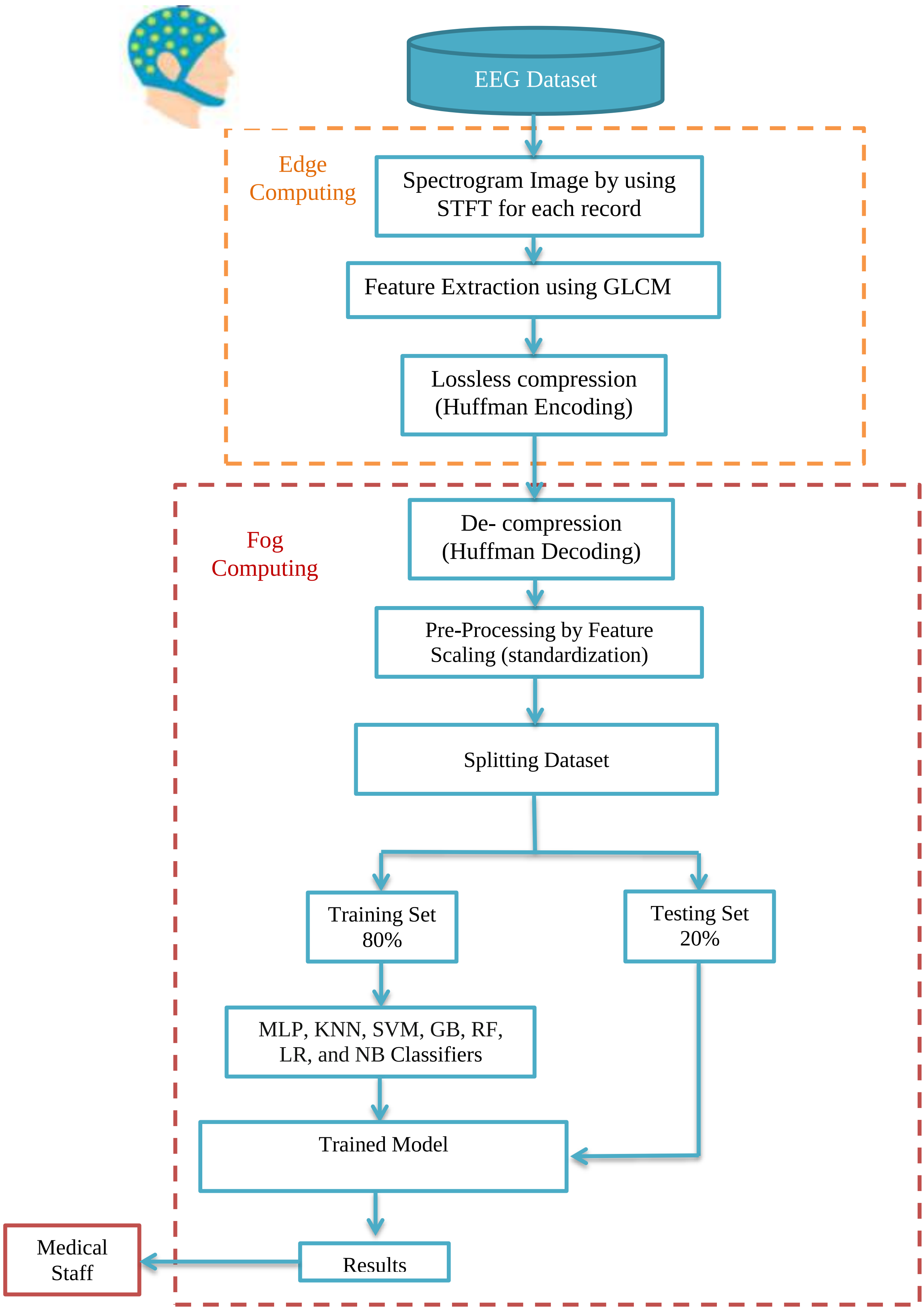


Figure 3.1: The Block Diagram of the Proposed System.

3.2.1 Edge Gateway Processing

The huge amount of vital sign signals that are captured by EEG sensor is processed in the edge gateway to decrease their size and extract the most significant features from the data. In this context, fusing the EEG sensor and signal processing are exploited to achieve a powerful framework for remote patient monitoring. The EEG signals recorded from the patient are processed in the edge gateway to improve the quality of the data.

3.2.1.1 Spectrogram Image

Generating the best representation for the raw EEG signal consists of the following steps. Let *s* be the EEG signal with *s* readings of a specific patient. First, *s* is processed by STFT in order to measure the spectrogram of *s* in the time-frequency domain. A crucial stage of the STFT is the windowing, during which parameters such as Hann window, length of the segment is 256, and 50% overlapping are chosen. Accordingly, the EEG signal, *s*, is partitioned into several segments by adapting Eq. 2.1 in Chapter Two.

Second, for each segment obtained by Eq. 2.1, FFT is applied to obtain the spectrogram image. Each spectrogram of all segments is concatenated to construct the final time-frequency domain representation of the signal *s*. Figure 3.2 shows an example of the time-frequency spectrogram of a sampled EEG signal from Bonn dataset. This spectrogram map provides a visual representation of the original signal in the time-frequency domain. This representation of *s* in the time-frequency domain is explored to extract a set of features that are used to discriminate between the EEG readings from different patients.

After computing the FFT of each window in the EEG signal, a two dimensional map can be constructed by collecting the FFT of all windows to represent the frequency density each time.

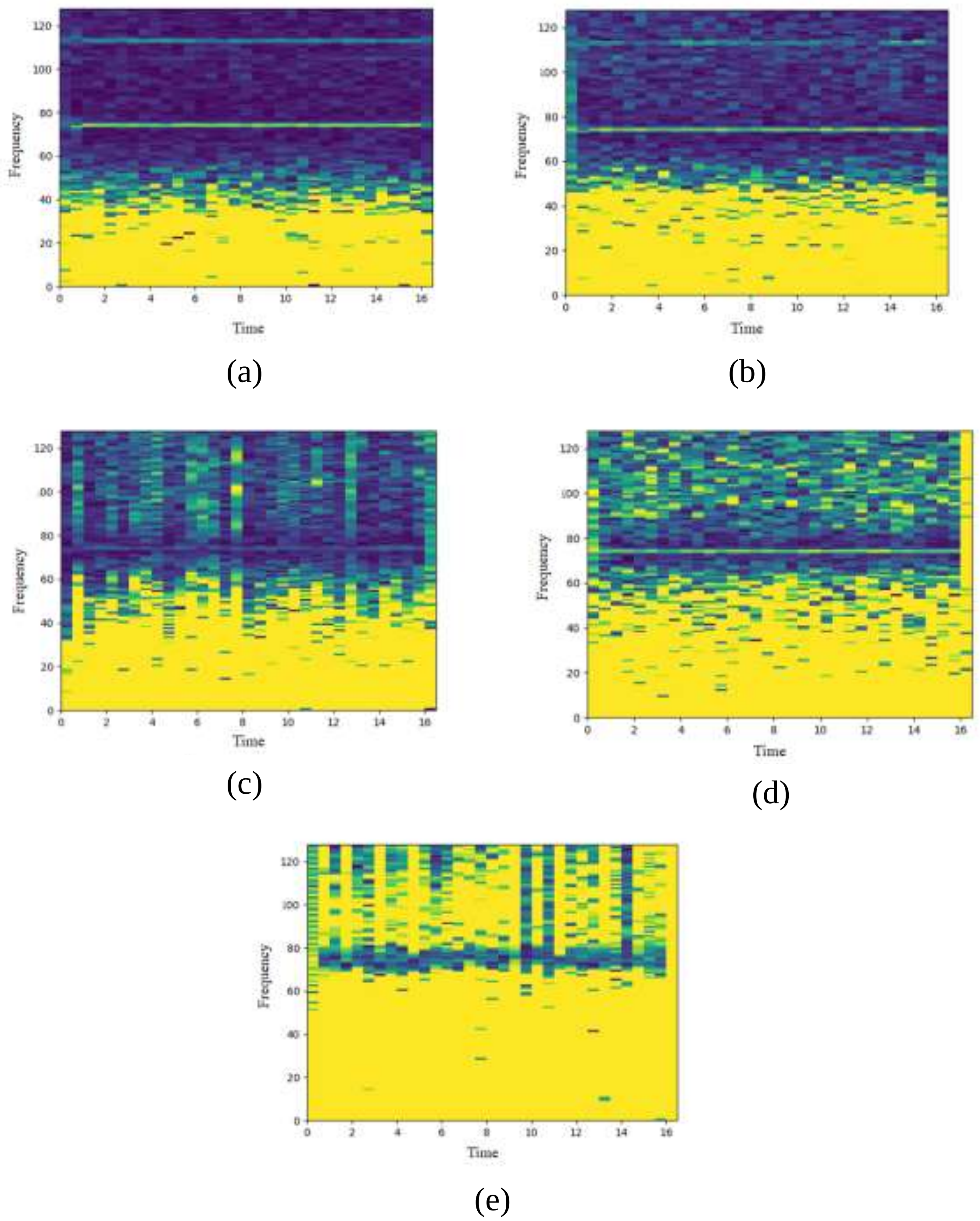


Figure 3.2: STFT Spectrogram Samples Generated from Different EEG Signals: (a) O for Healthy Patients, (b) Z for Healthy Patients, (c) F for Inter-ictal Patients,(d) N for Inter-ictal Patients and (e) S for an Epileptic Patients.

Algorithm 3.1 summarises the STFT Algorithm steps in the edge gateway.

Algorithm 3.1: STFT

Input: s: The input EEG data of the patient, T: the number of overlapped segments in s, L: The hop size.

Output: *I:* spectrogram image

1 Initialize $stft \leftarrow [\,]$
2 Initialise n ← 0
3 For $t \leftarrow 1$ to T
  Applying Eq. 2.1
  $\hat{S}_t \leftarrow FFT\ (\hat{s}_t)$.
  $stft[t, 1{:}size(\hat{S}_t)] \leftarrow\ abs(\hat{S}_t)$.
  $n \leftarrow n + L$.
4 Endfor
5 $I \leftarrow\ ConvertToImage\ (\ stft)$
6 Return *I*;

Algorithm 3.1 shows the processing of EEG data for each record to obtain the spectrogram image of the time-frequency analysis. The original signal is partitioned into several short time based segments using Hann window. The FFT is applied on each segment. Then the results of applying FFT on all segments are formed the time-frequency representation, i.e. spectrogram. In last step, the spectrogram is converted into image.

3.2.1.2 Feature Extraction

The proposed descriptor is applied on the time-frequency spectrogram map to extract a set of discriminative features, instead of sending the whole map to the fog gateway. This can help in two folds: reducing the size of the spectrogram map into one dimensional vector and presenting a set of features that are used in fog gateway to classify the seizures. In the current proposed system, Gray-level-Co-occurrence Matrix (GLCM) is exploited to extract the features from the time-frequency spectrogram of each EEG data. In the current work, texture features are employed to classify EEG signals, which are derived from the statistical moments of an intensity-histogram based representation. GLCM produces a feature vector, v, that includes 176 distinct features obtained from 11 features, 4 distances and 4 angles. These 11 features are dissimilarity, correlation, homogeneity, contrast, energy, ASM, variance, standard deviation, entropy, skew and root mean square. All feature vectors of all patients are collected to form the final representation, V, where V= $\{v_1, v_2, v_3, \ldots, v_P\}$ and p is the total number of patients.

3.2.1.3 Lossless Compression Technique

Finally, a further data reduction in the form of data compression is applied on V to reduce its dimensions. Applying the compression on the features rather than the original spectrogram reduces the time complexity of compression. In addition, this compression considers the limitations of transmission media. To perform the compression, Huffman encoding technique is used as in Algorithm 2.1 to compress these features for further decreasing in the amount of data being sent to the fog gateway.

These three stages of EEG signal based model, i.e. time-frequency based signal representation, feature extraction and compression, aim to reduce the transmitted data, and save bandwidth in the IoMT network to meet the limitations in such networks. Moreover, representing EEG signals as features can improve the performance in Fog gateway because the model deals with meaningful information rather than raw data. Algorithm 3.2 summarises the GLCM and Huffman encoding steps.

Algorithm 3.2: GLCM-Huffman Encoding

Input: *I*: Input spectgrum, r , c: The spatial positions**,** distance ={4,6,8,10}, θ = {0,45,90,135}, and G: Number of gray levels (=256).

Output: enF: Decoded file of the EEG data features

$M_{G\times G} \leftarrow \emptyset$;
For each pixel (r, c) in *I* do
    $c_1 \leftarrow r + d * cos(\theta)$;
    $c_2 \leftarrow c + d * sin(\theta)$;
    If (pixel (c_1, c_2) within the bounds of the image)
        Increment the value of $M_{I(r,c),I(r+d*cos(\theta),c+d*sin(\theta))}$ $by\ 1$;
    Endif
Endfor
$M_s \leftarrow symmetric(M)$;
$M_n \leftarrow$ *normalization* (M_s);
$F \leftarrow ExtractFeatures\ (M_n)$ *by applying Eq.(2.4) - Eq.(2.14);*
enF← Applying Huffman Algorithm (2.1) ;
Send *enF* file to fog gateway;
Return *enF*;

In Algorithm 2.3 the spectrogram image is explored by GLCM to extract a set of statistical feature that describe the texture of the spectrogram image. These features provide information about the spatial distribution and relationships between different intensity levels in the image. The computation of GLCM involves taking into account the intensity values of the image at positions *r* and *c* as well as the spatial positions denoted by c_1 and c_2, and an offset that is determined by the direction of θ at distance d to calculate the matrix. The foundation that is using d = {4, 6, 8, 10} and θ = {0, 45, 90, 135} produces the best results. To compute GLCM, all pixels in the image and increment the corresponding element G (r, c) based on the occurrence of pixel pairs (c1, c2) with intensity values r and c is iterated .

The next step is to make the GLCM matrix symmetrical by adding the GLCM matrix to the GLCM transpose matrix. Then the normalization step is applied to the symmetric GLCM matrix by dividing each element value by the total number of elements.

The features are extracted for each record of EEG data by applying the equations from (2.4) to (2.14) as describe in Chapter Two.

The file of features are finally encoding by using Huffman encoding using algorithm (2.1) as described in Chapter Two. Following the encoding process, each encoded file is transmitted to the fog gateway for further processing and analysis. The fog gateway receives the encoded file and decodes it before doing any process.

3.2.2 Fog Gateway Processing

In fog gateway, the compressed file of features is received from edge gateway. Before the decision is making there are some

3.2.2.1 Decompression Technique

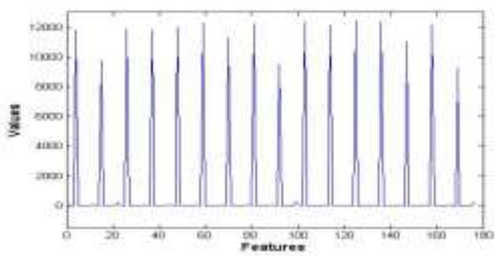
The Huffman decoding algorithm, described in chapter two in Algorithm (2.2), is used to ensure that the original feature vector is recovered without losing information.

3.2.2.2 Feature Scaling Method (Standardization)

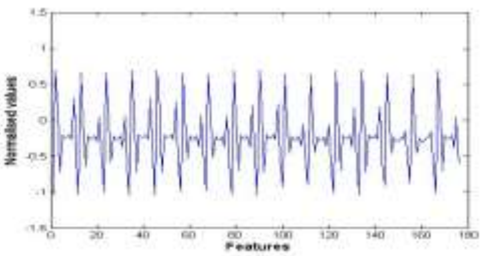
In machine learning, standardization is a common pre-processing step that helps to normalize the training data from different dimensions. The retrieved feature vectors are normalised to reduce the variation between features and to ensure that machine learning models can learn effectively from all dimensions of the data.

The normalised vectors are collected to form the final data representation that are used to evaluate the proposed using the classifier. By applying the standardisation, it is aimed to bring all the features onto a similar scale, which can be beneficial for training machine learning models. In addition, the normalisation increases the discrimination among the categories of the elliptic disease as it can be seen in Figure 3.3. This figure shows sample feature vectors obtained from dataset to illustrate the effect of applying the normalisation.

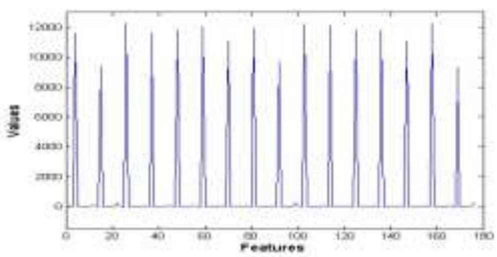
Figure 3.3 shows the improvement of features quality by modelling the features of each sample differently by increasing the dissimilarity among epileptic seizure cases. All these advantages resulting from feature normalization help the classifier to differentiate between classes easily and accurately.



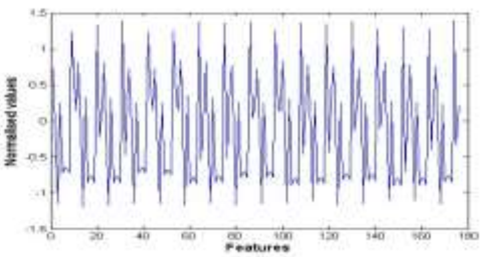
(a)



(b)



(c)



(d)

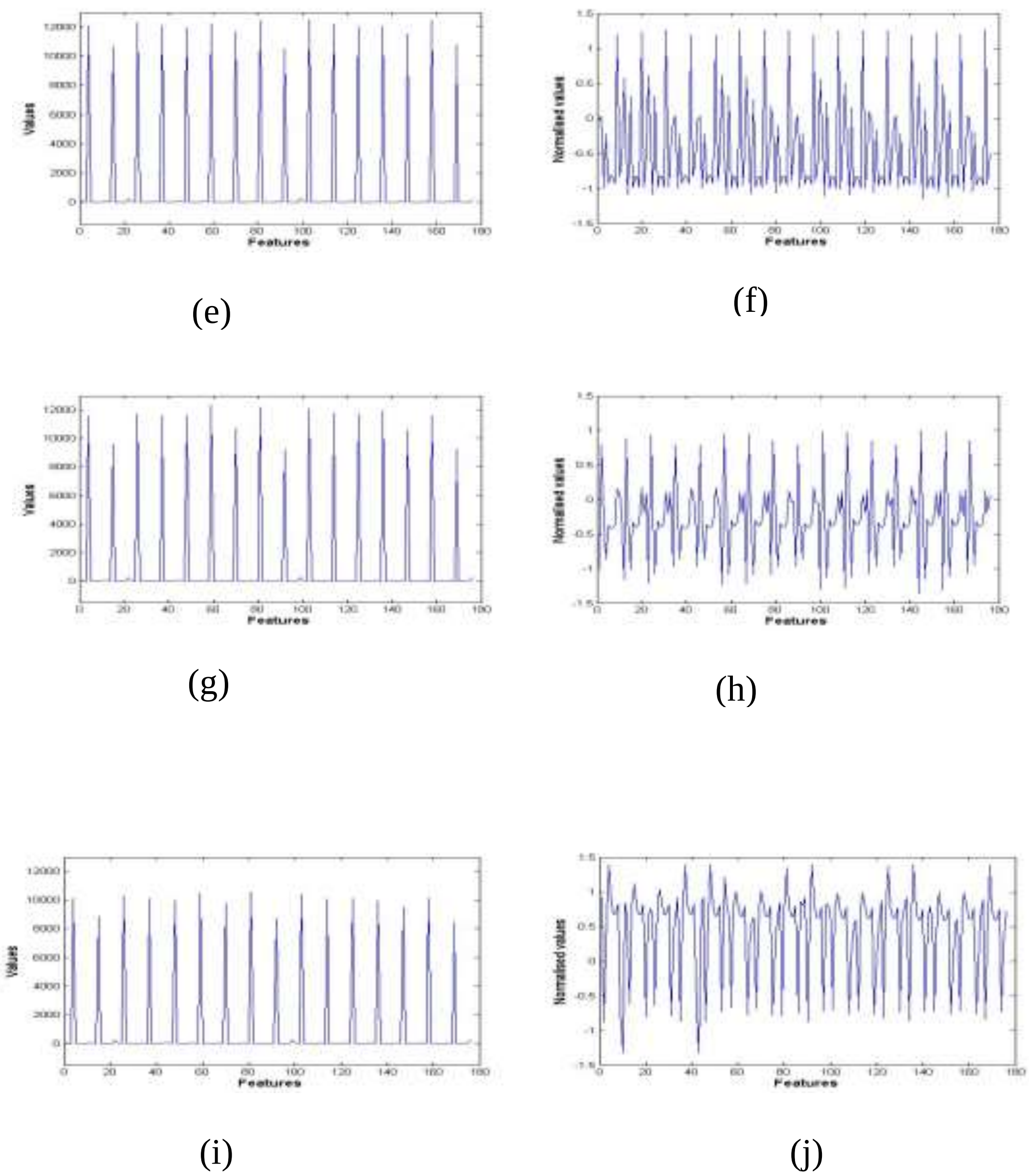


Figure 3.3: The Feature Vectors: 1st Column without Normalization and 2nd Column After Applying the Normalization. (a, b) F State, (c,d) N State, (e,f) Z State, (g,h) O State and (i,j) S State.

3.2.2.3 Seizure Detection and Classification

To make the decision, the standardised vectors are exploited for identifying and diagnosing the patient's condition. This diagnosis is made in fog gateway using several classifiers in order to find the best one in terms of the accuracy of classification for our scenarios. These classifiers are MLP, KNN, SVM, GB, RF, LR, and NB. The binary classification and multi classifications are used to evaluate the performance of the proposed system.

After the decision is made and the case of the patient is determined, the model will send a notification message to medical staff. This automated decision-making and notification improves the remotely medical treatment without the need for in-site diagnosis. It also takes into account the lack of medical staff that is needed to monitor the increased numbers of patients.

3.3 Summary

This chapter highlights the proposed ETESeDA based in edge-fog gateway of the present work. In edge gateway, first STFT was explained with its parameters and equations in order to measure the spectrogram of the time-frequency domain. Second GLCM and its features is discussed. Third the Huffman encoding method was explained for lossless compression. The STFT-GLCM-Huffman encoding algorithm of proposed ETESeDA is explained.

In the fog gateway, the decompression Huffman method was discussed as well as the binary and multi class classifications of machine learning were mentioned. Also using normalization and its effect on the result of accuracy is compared between data with and without normalization. At last the Decision making based machine learning algorithm with its steps is explained.

Chapter Four
Results and Discussions

4.1 Introduction

This chapter presents the evaluation of the proposed ETESeDA system in both edge and fog gateways using several performance metrics to diagnose epileptic seizure patients. At the edge gateway, several experiments have been achieved and the results show that the ETESeDA highly reduces the transmitted data in terms of compression ratio, compression gain, space saving, Energy consumption, compression time and decompression time**.** At the fog gateway, several experiments were conducted to evaluate the proposed ETESeDA to address the problem of epileptic seizure recognition. To do this, the proposed system is trained with seven classifiers, MLP, KNN, SVM, GB, LR, RF and Naïve Bays, to show the performance of the proposed system. The proposed system is evaluated based on different dataset combinations and using various evaluation metrics such as accuracy, recall score, precision score, Hamming loss, and F1 score macro. Furthermore, the system is compared with the state of the art to show the efficiency of ETESeDA. The Bonn University dataset, which comprises diverse EEG data files (Z, F, N, O, S), is used to test the proposed system. The proposed system is periodic and it processes a data size equal to 4097 EEG data readings per period.

4.2 Hardware and Software Specifications

The proposed system is implemented by using Lenovo laptop with 8.00 GB RAM, Intel(R) Corei5-4200U, CPU 1.60GHz, running at 2.30 GHz, and Windows 10 Pro-64-bit operating system. Programmatically, these projects carried out through utilizing Python 3.9 language.

4.3 EEG Bonn Dataset

There are several datasets for EEG data signals are used by many researchers and authors. In this thesis, the suggested strategies are based on the Bonn dataset.

The Bonn dataset is a widely used EEG dataset in the field of neuroscience and brain-computer interface (BCI) research. It is commonly used by vast number of authors which is publicly available. The proposed system in the mentioned work was tested using the epilepsy EEG dataset from Bonn University [81]. The dataset consists of five subsets labeled as Z, O, N, F, and S. Each subset contains 100 EEG signals, and each signal has 4097 samples. The data recordings were conducted at a sampling rate of 173.61 Hz, meaning that each second of the EEG signal was sampled 173.61 times to capture the electrical activity of the brain. The recordings were acquired using a 128-channel amplifier system, which implies that 128 different EEG electrodes were placed on the scalp to measure brain signals from various regions.

Sets Z and O were collected from five healthy volunteers, while Sets N, F, and S were recorded from five epileptic patients. Records from Set S were obtained during seizure activity, while Sets N and F were gathered during seizure-free intervals as shown in Table 4.1.

This dataset provides researchers and practitioners with a valuable resource for studying and analyzing EEG signals in the context of epilepsy. It allows for investigations into the differences between healthy individuals and those with epilepsy and facilitates the development and evaluation of various algorithms and techniques for seizure detection, classification, and other related tasks.

Table 4.1 Distribution of Study Sample

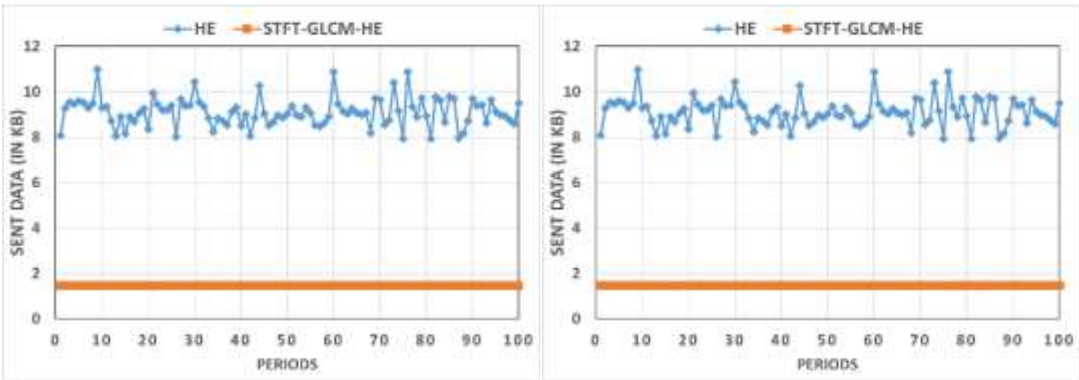
Set	Sample	No. of signals	State
Z	Healthy	100	Open eyes
O	Healthy	100	Closed eyes
F	Epilepsy	100	Inter-ictal
N	Epilepsy	100	Inter-ictal
S	Epilepsy	100	Seizure(Ictal)

4.4 Performance evaluation of ETESeDA on the Edge gateway

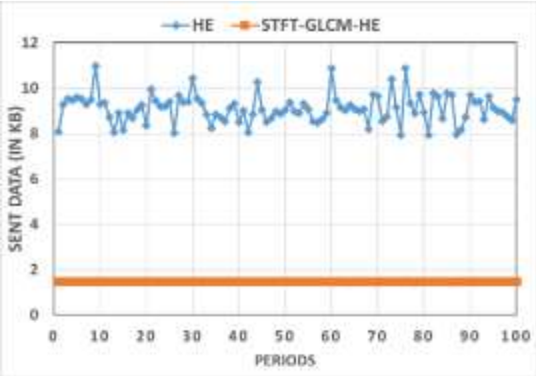
This section provides the results of a data reduction method that is proposed in ETESeDA to decrease the size of transition data at the edge gateway. The evaluation explains the comparison in the performance between STFT-GLCM-HE and Huffman encoding (HE). The proposed STFT-GLCM-HE data reduction is applied on the time-frequency domain based GLCM while HE is applied on the original EEG sensory data, i.e. the patients' data recordings, F, N, O, S, and Z.

4.4.1 Transmitted Data

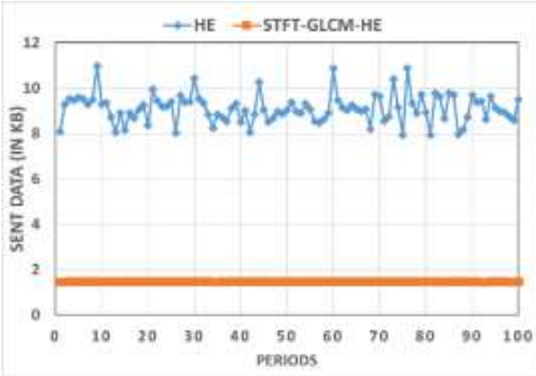
This experiment shows the effect of applying data reduction proposed by the ETESeDA on data that are sent to the fog gateway. Figure 4.1 depicts the amount of data that are sent using the proposed data reduction method, STFT-GLCM-HE and HE.



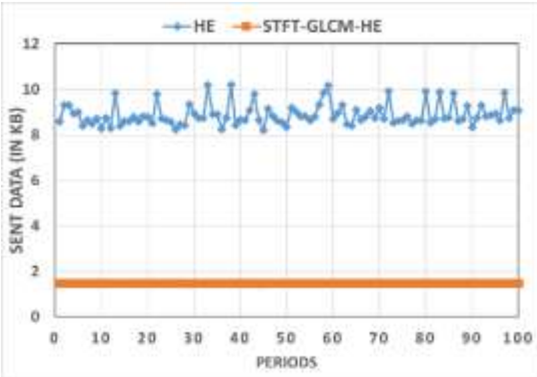
(a) F (b) N



(c) O



(d) S



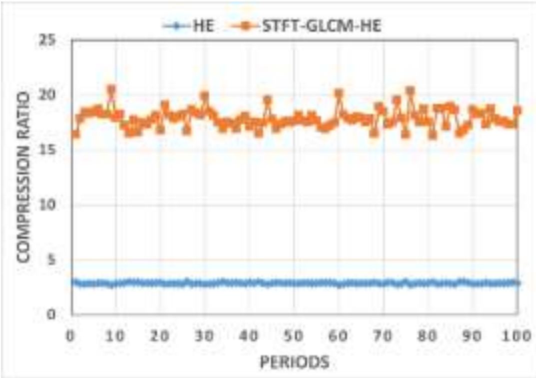
(e) Z

Figure 4.1: The Amount of Transmitted Data using STFT-GLCM-HE and HE for Different Dataset Records.

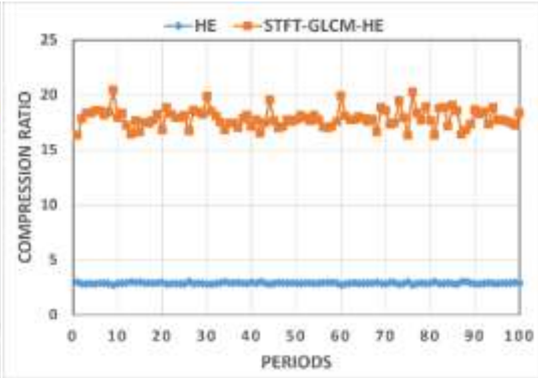
It has been shown in Figure 4.1 that the proposed STFT-GLCM-HE decreases the size of transmitted data from 1.48 to 1.45 KB per period while HE transmitted data from 7.94 up to 10.99 KB. This means that STFT-GLCM-HE is superior to the conventional HE method in terms of transmitting data from edge gateway to fog gateway. The stability of compressed data transmission by STFT-GLCM-HE is compared to HE. This outperformance is due to dealing with features instead of raw data since the features are highly reduced compared to the original raw data.

4.4.2 Compression Ratio

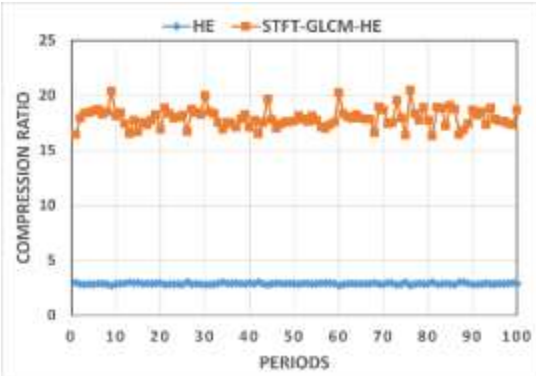
In this section, the compression ratio metric is used to evaluate the proposed STFT-GLCM-HE to show the ratio of reduction achieved by the proposed system. Figure 4.2 shows the compression ratio using STFT-GLCM-HE and HE.



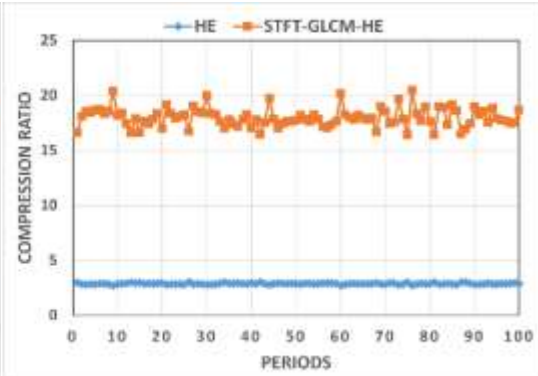
(a) F



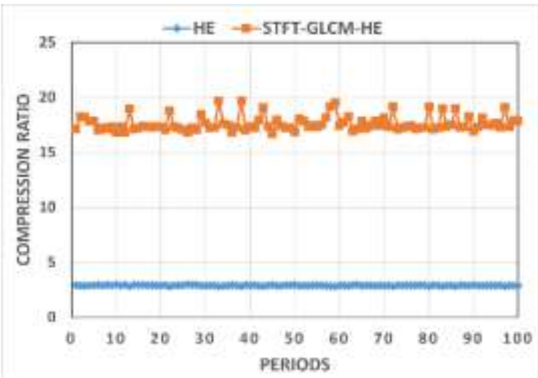
(b) N



(c) O



(d) S



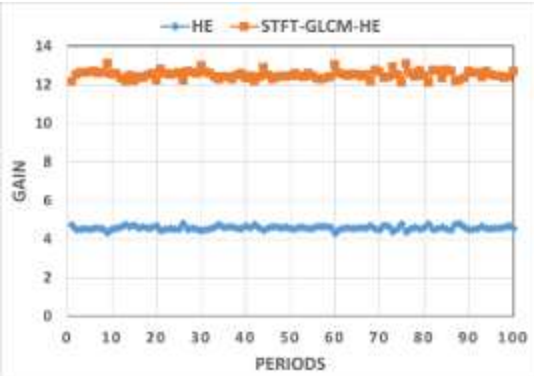
(e) Z

Figure 4.2: The Compression Ratio of STFT-GLCM-HE and HE for Different Dataset Records.

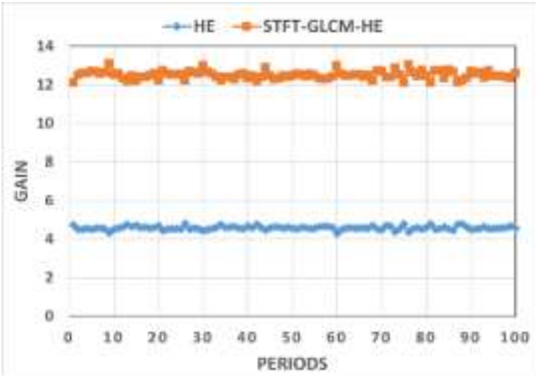
From the results in Figure 4.2 it can be seen that STFT-GLCM-HE offers the best compression ratio compared to HE. It provides a compression ratio from 16.29 to 20.5 per period while the maximum compression ratio obtained by HE does not exceed 3.02. This means that the proposed STFT-GLCM-HE compresses data six times more than the HE method.

4.4.3 The Compression Gain

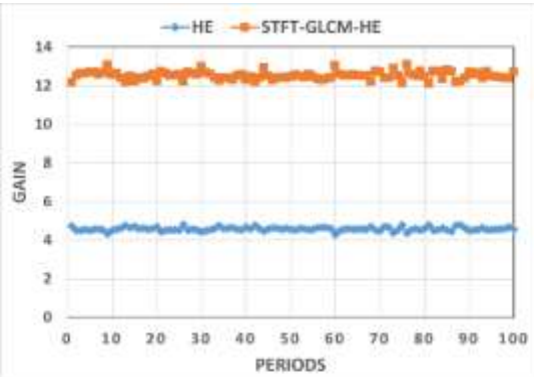
The compression gain is another metric used to evaluate the performance of the proposed STFT-GLCM-HE data reduction Figure 4.3 shows the compression gain using STFT-GLCM-HE and HE.



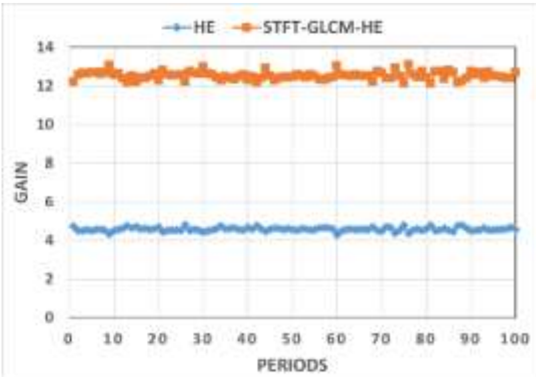
(a) F



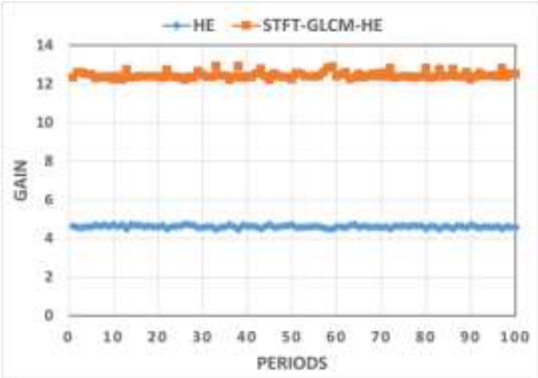
(b) N



(c) O



(d) S



(e) Z

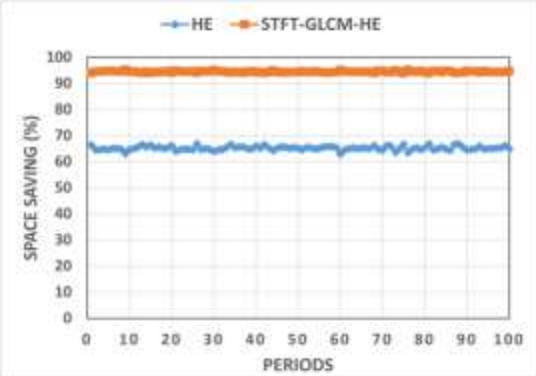
Figure 4.3: The Compression Gain of STFT-GLCM-HE and HE for Different Dataset Records: a Comparison.

The findings in Figure 4.3 indicate that the proposed STFT-GLCM-HE data reduction method demonstrates superior performance compared to the HE. It provides a compression gain 8.2 times the HE method. This ensures the validation of the STFT-GLCM-HE in decreasing the transmitted data to enhance the performance of the IoMT network.

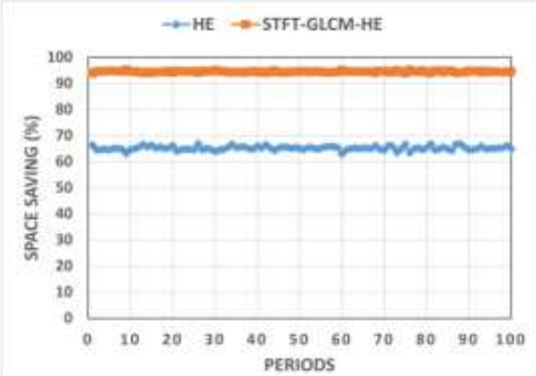
4.4.4 Space Saving

In this experiment, the space saving is used in the evaluation of STFT-GLCM-HE. Figure 4.4 shows the space saving using STFT-GLCM-HE and HE.

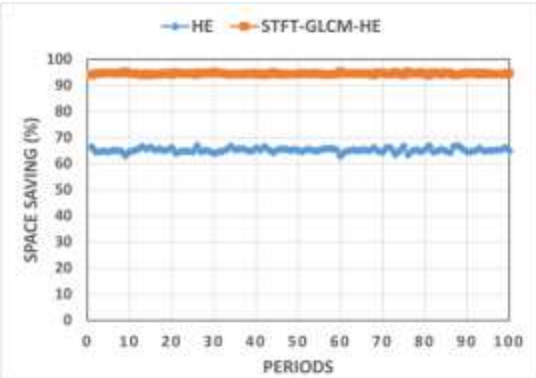
The results presented in Figure 4.4 highlight that the STFT-GLCM-HE data reduction method achieves an average space saving of over 94%, outperforming the HE method which achieves a space saving of 64%. These two percentages means that STFT-GLCM-HE provides 30% saving more than HE. This is because the proposed STFT-GLCM-HE method highly reduces the data transmitted on the edge gateway to improve the performance of the IoMT network.



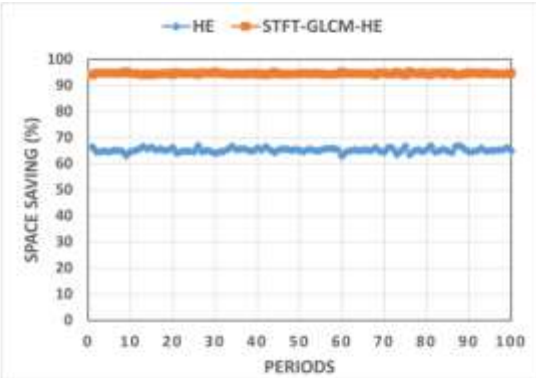
(a) F



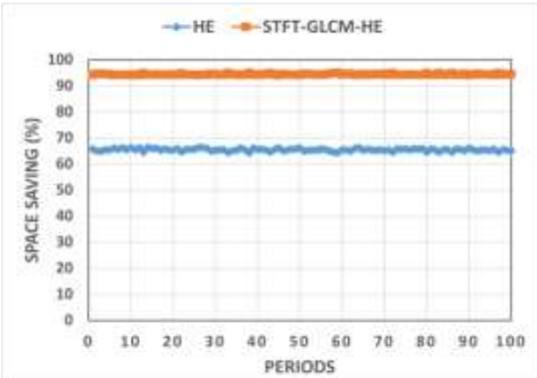
(b) N



(c) O



(d) S

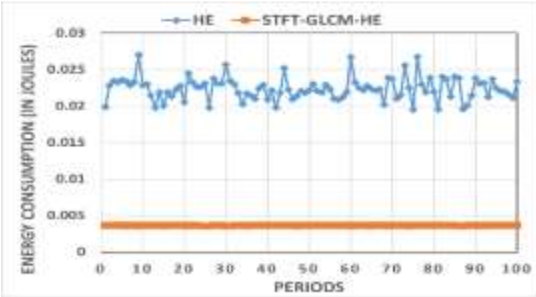


(e) Z

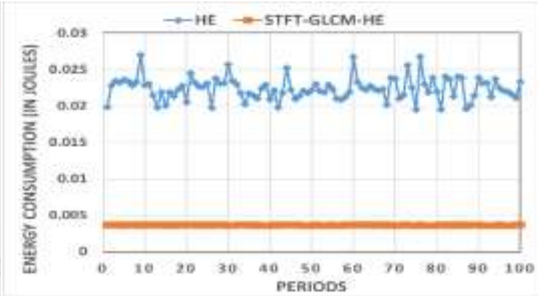
Figure 4.4: The Space Saving for Different Dataset Records.

4.4.5 Energy Consumption

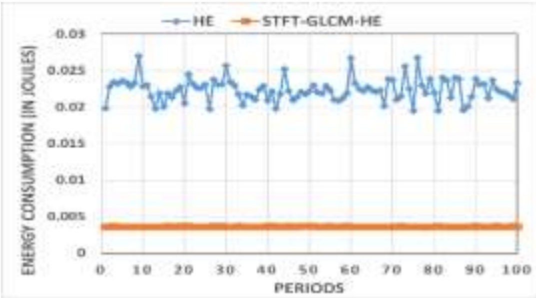
Measuring the amount of power consumed by the remote monitoring system is necessary since these systems use limited sources of power. Therefore, the energy consumed by the proposed STFT-GLCM-HE was measured. Figure 4.5 shows the energy consumption by STFT-GLCM-HE compared to HE.



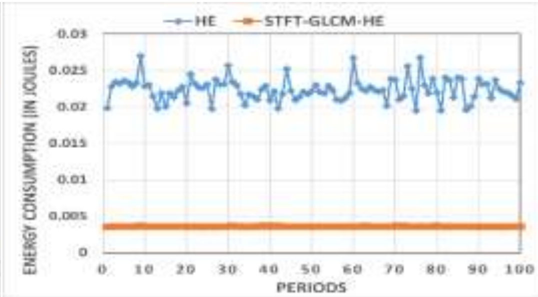
(a) F



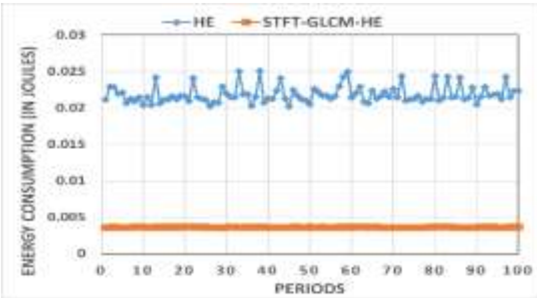
(b) N



(c) O



(d) S



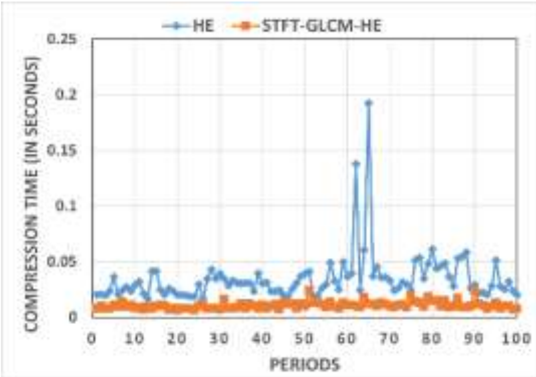
(e) Z

Figure 4.5: The Energy Consumption for Different Dataset Records.

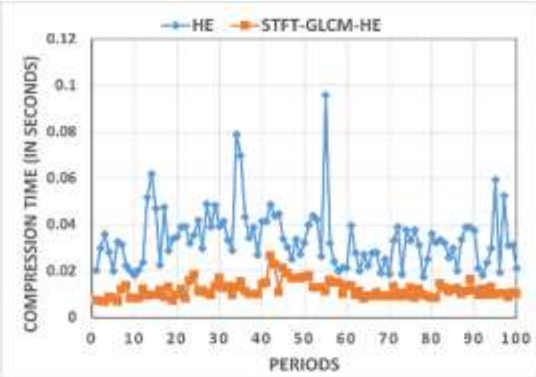
The results in Figure 4.5 have shown that the data reduction method, STFT-GLCM-HE consumes energy from 81.74% up to 86.56% compared to the HE method. This is because the proposed ETESeDA is highly reduced the data on the edge gateway before sending them to the fog gateway.

4.4.6 Compression Time

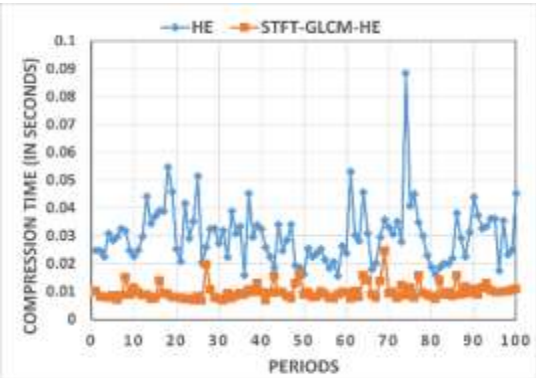
The compression time is also used to evaluate the complexity of STFT-GLCM-HE. Figure 4.6 shows the compression time that is required by STFT-GLCM-HE to compress EEG data-based features.



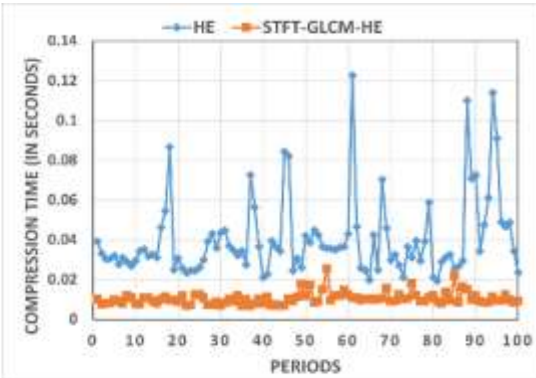
(a) F



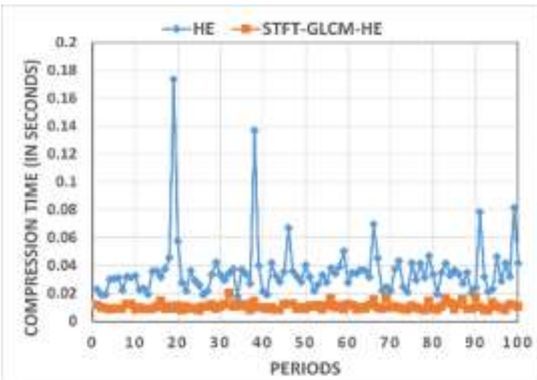
(b) N



(c) O



(d) S



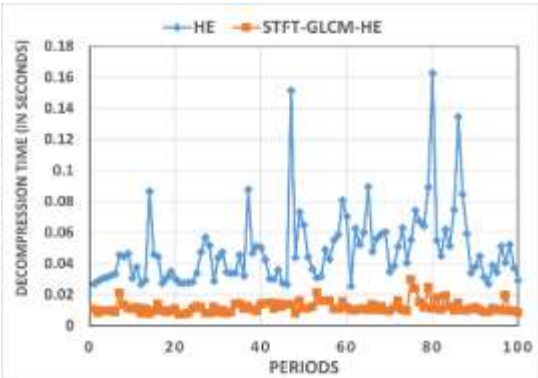
(e) Z

Figure 4.6: The Compression Time for Different Dataset Records.

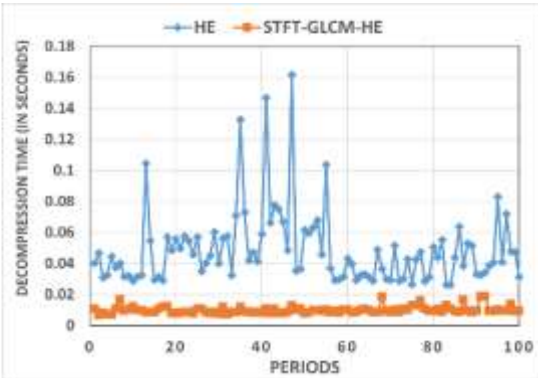
From the results in Figure 4.6, STFT-GLCM-HE reduces the required compression time compared to the HE method. This difference in the time means that STFT-GLCM-HE is less complex.

4.4.7 The Decompression Time

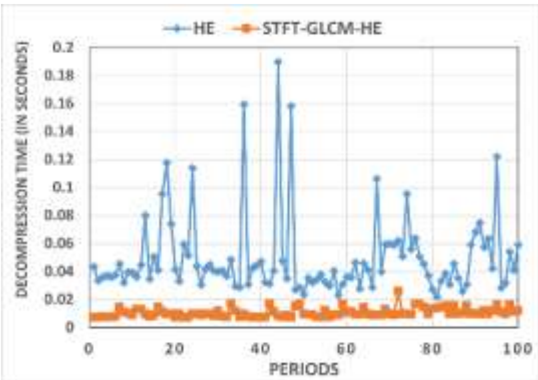
The last metric to evaluate STFT-GLCM-HE is the decompression time. Figure 4.7 shows the decompression time using STFT-GLCM-HE and HE.



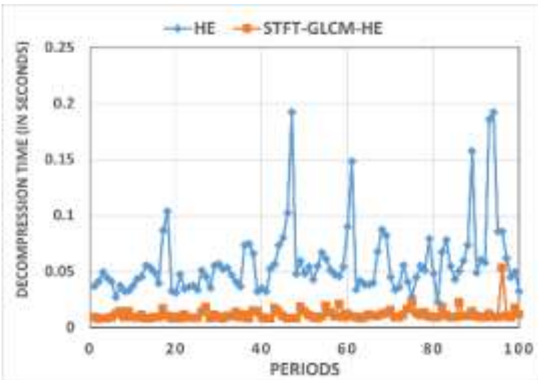
(a) F



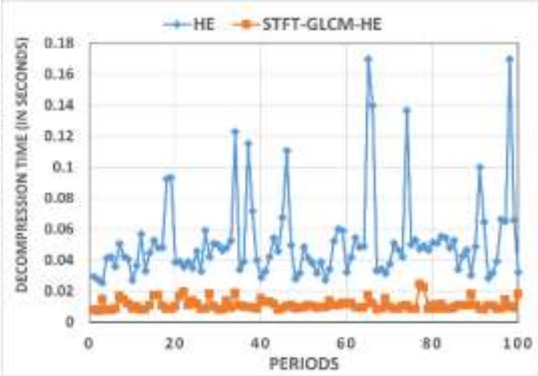
(b) N



(c) O



(d) S



(e) Z

Figure 4.7: The Decompression Time for Different Dataset Records.

The results presented in Figure 4.7 demonstrate that the STFT-GLCM-HE data reduction method reduces the required decompression time in comparison to the HE method because the proposed ETESeDA greatly reduces the data on the edge gateway before it is sent to the fog gateway.

4.5 Performance Evaluation of ETESeDA on the Fog Gateway

This section presents the outcomes of decision-making utilizing machine learning models at the fog gateway. In addition, the results are discussed regarding the proposed decision-making method based on machine learning is implemented by the proposed ETESeDA system at the fog gateway.

4.5.1 Epileptic Seizure Detection Based Binary Class Decision Making

In the binary classification scenario, the input EEG signal is classified into epileptic seizure or not. The experiments are conducted using different combinations from the Bonn dataset. The following combination *S_(Z,O,F,N)* (ictal and (healthy with pre-ictal)) is used to evaluate the proposed method for binary classification. The performance of different classifiers is compared in terms of the accuracy of binary recognition. Table 4.2 shows the results of the accuracy and the comparison among different classifiers.

Table 4.2: Accuracy Recognition of Binary Classification for Different Classifiers using Bonn Dataset.

Dataset combination	*Accuracy (%)*						
	STFT+GLCM +MLP	*STFT+GLCM +KNN*	*STFT+GLCM +SVM*	*STFT+GLCM +GB*	*STFT+GLCM +LR*	*STFT+GLCM +RF*	*STFT+GLCM +Naïve Bayes*
S_(F,N,O,Z)	**100**	99	98	90	**98**	98	93

According to Table 4.2, the proposed system with STFT+GLCM+MLP and STFT+GLCM+LR achieved the best results compared to other models. These two models achieve average recognition accuracy 100% in determining the patient's condition at the fog gateway. The high accuracy for MLP and LR belong to the use of standardization method. Tables 4.3 and 4.4 show other performance metrics for evaluating the performance of the proposed system using STFT+GLCM+MLP and STFT+GLCM+LR, respectively.

Table 4.3: The Performance Metrics for STFT+GLCM+MLP.

Data set combination	Accuracy %	Precision score	Recall score	F1 score macro	Hamming loss
S_(F,N,O,Z)	100%	1.0	1.0	1.0	0.0

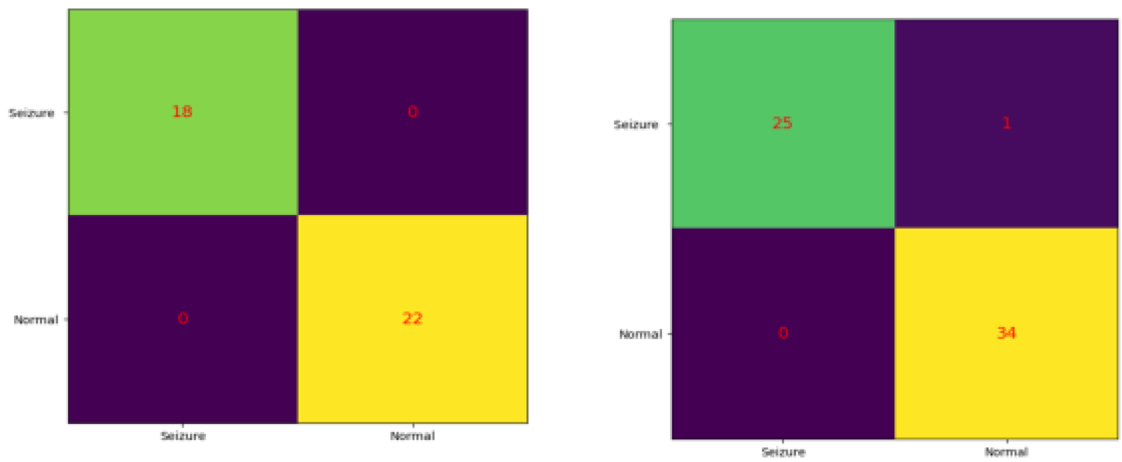
From Table 4.3 it can be seen that the accuracy of proposed system by using STFT+GLCM+MLP is 100%.

Table 4.4: The Performance Metrics for STFT+GLCM+LR.

Data set combination	Accuracy %	Precision score	Recall score	F1 score macro	Hamming loss
S_(F,N,O,Z)	98%	0.969	0.969	0.969	0.02

It can be seen from Table 4.4 that the class is recognized with 98% accuracy by using STFT+GLCM+LR method.

The confusion matrix of the ETESeDA for the **STFT+GLCM+MLP** and **STFT+GLCM+LR** is shown in Figure 4.8 for the **S_(F,N,O,Z)** combination. It can be seen that the proposed system using **STFT+GLCM+MLP** and **STFT+GLCM+LR** achieves recognition accuracies of 100%, 98% respectively. This achievement means that the proposed system produces high discriminating features that accurately discriminate between the seizure classes.



(a) STFT+GLCM+MLP (b) STFT+GLCM+LR

Figure 4.8: Confusion Matrices of STFT+GLCM+MLP and STFT+GLCM+LR for Binary Classification.

The ETESeDA with the **STFT+GLCM+MLP** and **STFT+GLCM+LR** is compared with the existing models on binary classification proposed by Ramos-Aguilar et al. in [82], Orhan et al. [83], Raghu et al.[84], Liu et al. [85] and Khan et al. [86] in order to demonstrate the efficiency of the proposed method. Table 4.5 shows the comparison between proposed system and the state of the art. The proposed system outperforms the existing work and achieves improvement of accuracy.

Table 4.5: The Accuracy for Binary Classification of the Proposed System and Other Models using Bonn dataset.

Ref. No.	Name	ML model	S _(Z,O, F, N)
[82]	Ramos et al.	MLP	96.8
		SVM Linear	96.2
		SVM Polynomial	96.2
		kNN	95.2
[83]	Orhan et al.	MLPNN	99.6
[84]	Raghu et al.	DWT based sigmoid entropy + SVM	96.2
[85]	Liu et al.	Unigram and bigram ordinal pattern + 1NN	95
[86]	Khan et al.	SVM	-
Proposed System		**STFT+ GLCM+MLP**	**100**
		STFT+ GLCM+LR	**98**

According to the results presented in Table 4.5, the proposed system can serve as a robust seizure identifier due to the obtained level of accuracy for binary classification compared to the existing methods.

This improved accuracy comes from the integration of the STFT with GLCM that contributed in providing a more accurate decision regarding the situation of the patient.

4.5.2 Epileptic Seizure Detection Based Multi Classes Decision Making

In the second context, the proposed method will be tested to more complicated problems, i.e. multiclass classification tasks. In multiclass classification, the EEG data is classified into three classes, ictal, normal and inter-ictal. Several experiments are conducted to evaluate the proposed method. Different data combinations are used in the evaluation. The combination used is **S _ (O,Z) _(F,N)** for **(** *(Ictal, healthy, pre-ictal)***.** The method is firstly evaluated using several classifiers. This evaluation allowed us to assess the performance of different algorithms and identify the most accurate system for classifying the data into the three categories Table 4.6 depicts the results of accuracies for different classifiers for the multi class classification task.

Table 4.6: Multi-Class Classification Performance for Different Classifiers.

Dataset combination	Accuracy%						
	STFT+GLCM+ MLP	STFT+GLCM+ KNN	STFT+GLCM+ SVM	STFT+GLCM+ GB	STFT+GLCM+ LR	STFT+GLCM+ RF	STFT+GLCM + Naïve Bayes
S _(F,N),(O,Z)	**97**	91	94	89	**97**	85	82

It can be seen from Table 4.6 that the accuracy is lower than the accuracy of the binary classification scenario because multi class classification is more complex compared to binary classification. However, MLP and LR achieve 97% accuracy compared to other classifiers. These results prove the powerful of the proposed descriptor in discrimination the classes. Tables 4.7 and 4.8 show other performance metrics for STFT+GLCM+MLP and STFT+GLCM+LR, respectively

Table 4.7: The Performance Metrics for STFT+GLCM+MLP.

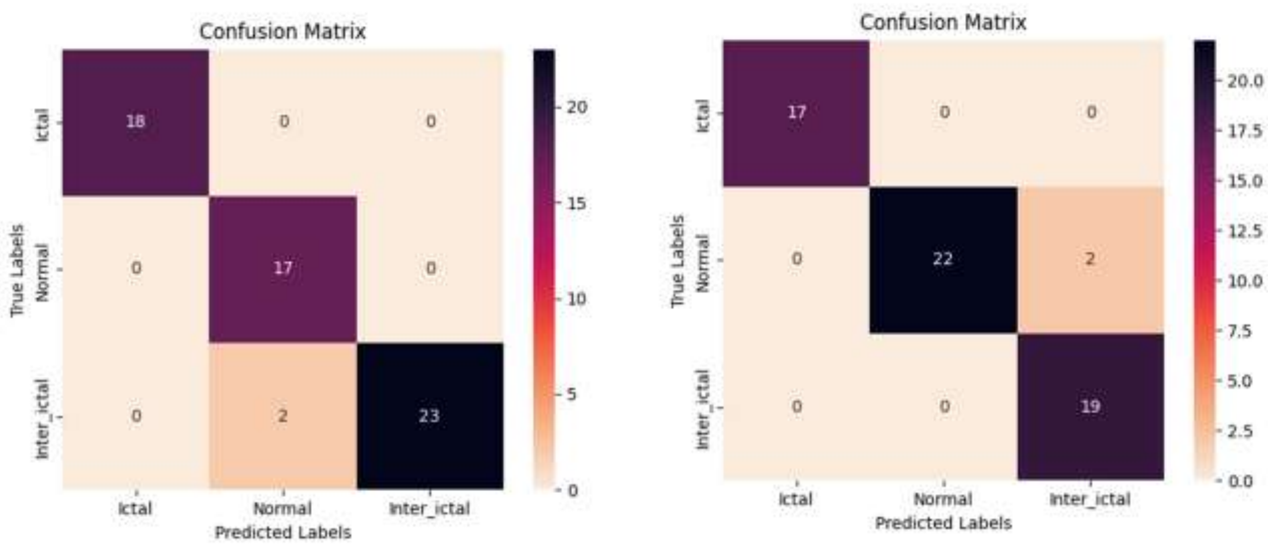
Data set Combination	Accuracy %	Precision score	Recall score	F1 score macro	Hamming loss
S _(F,N)_(O,Z)	97%	0.973	0.973	0.973	0.03

Table 4.8: The Performance Metrics for STFT+GLCM+LR.

Data set Combination	Accuracy %	Precision score	Recall score	F1 score macro	Hamming loss
S _(F,N)_(O,Z)	97%	0.974	0.974	0.974	0.03

In Tables 4.7 and 4.8, it can be seen that the combination **S _(F,N)_(O,Z)** achieved 97%.

The confusion matrices of the ETESeDA for the **STFT+GLCM+MLP** and **STFT+GLCM+LR** are shown in Figures 4.9 for **S _(F,N)_(O,Z)** case.



(a) STFT+GLCM+MLP (b) STFT+GLCM+LR

Figure 4.9: Confusion Matrices of STFT+GLCM+MLP and STFT+GLCM+LR for multi -Classes Classification.

The confusion matrices in Figure 4.9 show that the proposed system discriminates the multi class accurately in classification. Again, this outperformance is the result of using GLCM in the time-frequency domain. This descriptor proved its ability to extract high quality features for accurate recognition.

To assess the efficiency of proposed system compared to other models in the context of multi class classification, the accuracy metric is used to compare the performance of STFT+GLCM+MLP and STFT+GLCM+LR with the existing work. Table 4.9 depicts the results of the performance of the proposed system and the current models. We notice that the proposed system achieved good recognition improvement compared to the state of the art.

Table 4.9: The Accuracy for Multi- Class Classification of the Proposed System and Other Models using Bonn dataset.

Ref. No.	**Name**	**ML model**	**S_ (F, N)_ (O, Z)**
[83]	Orhan et al.	MLPNN	95.60
[84]	Raghu et al.	DWT based sigmoid entropy + SVM	90.89
[85]	Liu et al.	Unigram ordinal pattern and bigram ordinal pattern representations + 1NN	96
[87]	Acharya et al.	13-layer deep CNN structure	88.7
proposed system		**STFT+GLCM+MLP**	**97**
		STFT+GLCM+LR	**97**

Table 4.9 refers to the comparison between proposed system and several other related existing works in terms of accuracy. Based on the results presented in Table 4.8, the proposed system can serve as a robust seizure identifier, as it offers a satisfactory level of accuracy for multi class classification problem compared with other methods. Table 4.9 also indicates that MLP and LR achieved high levels of accuracy compared to the existing methods. The proposed system accuracy value is larger than Orhan et al. [83], Raghu et al. [84], Liu et al. [85] and Acharya et al. [87] accuracy value. This improvement is attributed to the integration of STFT and GLCM. This integration has proven to be effective in making more accurate decisions regarding the patient's condition compared to other methods leading to reliable remote patients monitoring systems.

4.6 Summary

This chapter presented the results, analysis, Hardware and Software Specifications. The Bonn university dataset, which is used in our research, and performance evaluation of the proposed ETESeDA are explained. The effectiveness of the ETESeDA is proven by using several performance parameters such as the sent data compression ratio, compression time, decompression time, compression gain, energy consumption and space saving for the proposed data reduction method executed by the ETESeDA at the edge gateway. The efficiency of the proposed ETESeDA in decision-making based on machine learning at the fog gateway has been demonstrated. The performance of ETESeDA in recognition and the results of the comparison with existing work showed that our system outperforms the state of the art in the scenarios of binary and multiclass classification. The success of ETESeDA in multiclass classification, which is considered complicated compared to binary classification, proves that powerful of the proposed integration between STFT and GLCM for such application.

Chapter Five
Conclusions and Future works

5.1 Conclusions

This thesis presents a remote patient monitoring system that addresses the problems of the huge amounts of data generated by EEG and the diagnosis of epileptic seizures. In the following, we will review the most important conclusions of this thesis:

1. A lossless EEG data compression method, i.e. Huffman encoding, is applied at the edge gateway. This method aim to decrease data traffic and improve network performance by compressing the EEG data without any loss of information. The ETESeDA offers efficient solution to reduce the volume of data transmitted through the network from 1.48 to 1.45 KB, ultimately improving overall system performance. The achievement of the compression method is due to applying the compressing on the feature vectors instead of the raw EEG data. The performance of the compression algorithm in feature domain is improved from the perspective of compressing ratio and time complexity. In addition, using lossless compression algorithm satisfies the utility of using data for diagnosis at the fog gateway.
2. A descriptor is proposed by exploring GLCM in the time-frequency domain to extract more comprehensive information and improve the accuracy of classification. The integrating of GLCM and time-frequency domain analyses using STFT leads to reduce the dimensionally of original EEG data and extract a meaningful representation.
3. The results obtained from proposal system that the ETESeDA outperforms the existing work in various aspects. Specifically, the methods demonstrate superior performance in terms of compression ratio, sent data, compression, decompression time, compression power and the accuracy for binary and multi class classification. These findings validate

the effectiveness and efficiency of the ETESeDA and highlight their superiority compared to existing models.

4. Overall, the integration of data reduction, feature extraction, remote patient monitoring, and classification offers significant benefits in terms of improved healthcare management, early intervention, and enhanced patient outcomes.

5.2 Future works

Here are some potential future works that can be performed in the given context:

1- Since the proposed time-frequency domain descriptor presents a useful data representation. However, this descriptor can be improved by applying an optimization to select the best representative features to improve the accuracy of recognition.

2- Proposing another domain for analysis EEG data, e.g. wavelet domain. Wavelet domain proved its ability to deal with nonstationary signal. Therefore, exploring wavelet transform can lead to outstanding results

3- As remote patient monitoring involves the transmission and storage of sensitive healthcare data, future research can address privacy and security concerns. This could involve developing robust encryption techniques, secure data sharing protocols, and privacy-preserving machine learning algorithms to ensure patient data confidentiality and integrity.

4- Proposing another method of feature extraction with GLCM to improve performance of the decision making.

References

References

[1] Muhammad, Ghulam, M. Shamim Hossain, and Neeraj Kumar. "EEG-based pathology detection for home health monitoring." *IEEE Journal on Selected Areas in Communications* 39.2 (2020): 603-610.

[2] Ning, Zhaolong, et al. "Mobile edge computing enabled 5G health monitoring for Internet of medical things: A decentralized game theoretic approach." *IEEE Journal on Selected Areas in Communications* 39.2 (2020): 463-478.

[3] Pioli, Laércio, et al. "An overview of data reduction solutions at the edge of IoT systems: a systematic mapping of the literature." *Computing* 104.8 (2022): 1867-1889.

[4]Malasinghe, Lakmini P., Naeem Ramzan, and Keshav Dahal. "Remote patient monitoring: a comprehensive study." *Journal of Ambient Intelligence and Humanized Computing* 10 (2019): 57-76.

[5]Pateraki, Maria, et al. "Biosensors and Internet of Things in smart healthcare applications: Challenges and opportunities." *Wearable and Implantable Medical Devices* (2020): 25-53.

[6] Feng, Guibo, et al. "Prognostic value of electroencephalography (EEG) for brain injury after cardiopulmonary resuscitation." *Neurological Sciences* 37 (2016): 843-849.

[7] Ambulkar, Narendra Kumar, and S. N. Sharma. "Detection of epileptic seizure in eeg signals using window width optimized s-transform and artificial neural networks." *2015 IEEE Bombay section symposium (IBSS)*. IEEE, 2015.

[8] Zhang, Jiuwen, et al. "A new approach for classification of epilepsy eeg signals based on temporal convolutional neural networks." *2018 11th International Symposium on Computational Intelligence and Design (ISCID)*. Vol. 2. IEEE, 2018.

[9] Chowdhury, Tanima Tasmin, et al. "Seizure and non-seizure EEG signals detection using 1-D convolutional neural network architecture of deep learning algorithm." *2019 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT)*. IEEE, 2019.

[10] Zhao, Wei, et al. "A novel deep neural network for robust detection of seizures using EEG signals." *Computational and mathematical methods in medicine* 2020 (2020).

[11] Aayesha, et al. "Machine learning-based EEG signals classification model for epileptic seizure detection." *Multimedia Tools and Applications* 80 (2021): 17849-17877.

[12] Al-Hadeethi, Hanan, et al. "Determinant of covariance matrix model coupled with AdaBoost classification algorithm for EEG seizure detection." *Diagnostics* 12.1 (2021): 74.

[13] Malekzadeh, Anis, et al. "Epileptic seizures detection in EEG signals using fusion handcrafted and deep learning features." *Sensors* 21.22 (2021): 7710.

[14] Mandhouj, Badreddine, Mohamed Ali Cherni, and Mounir Sayadi. "An automated classification of EEG signals based on spectrogram and CNN for epilepsy diagnosis." *Analog integrated circuits and signal processing* 108 (2021): 101-110.

[15] Al-Salman, Wessam, et al. "Extracting epileptic features in EEGs using a dual-tree complex wavelet transform coupled with a classification algorithm." *Brain Research* 1779 (2022): 147777.

[16] Hayajneh, Thaier, et al. "Secure authentication for remote patient monitoring with wireless medical sensor networks." *Sensors* 16.4 (2016): 424.

[17] Ometov, Aleksandr, et al. "A survey of security in cloud, edge, and fog computing." *Sensors* 22.3 (2022): 927.

[18] Mäkitalo, Niko, et al. "The internet of bodies needs a human data model." *IEEE Internet Computing* 24.5 (2020): 28-37.

[19] Mukherjee, Mithun, et al. "Security and privacy in fog computing: Challenges." *IEEE Access* 5 (2017): 19293-19304.

[20] Alçin, Ömer F., et al. "Multi-category EEG signal classification developing time-frequency texture features based Fisher Vector encoding method." *Neurocomputing* 218 (2016): 251-258.

[21] Ashokkumar, S. R., et al. "Implementation of deep neural networks for classifying electroencephalogram signal using fractional S-transform for epileptic seizure detection." *International Journal of Imaging Systems and Technology* 31.2 (2021): 895-908.

[22] Ridouh, Abdelhakim, Daoud Boutana, and Salah Bourennane. "EEG signals classification based on time frequency analysis." *Journal of Circuits, Systems and Computers* 26.12 (2017): 1750198.

[23] Kumar, Prabhat, et al. "A Distributed framework for detecting DDoS attacks in smart contract-based Blockchain-IoT Systems by leveraging Fog computing." *Transactions on Emerging Telecommunications Technologies* 32.6 (2021): e4112.

[24] Harbi, Yasmine, et al. "A review of security in internet of things." *Wireless Personal Communications* 108 (2019): 325-344.

[25] Joyia, Gulraiz J., et al. "Internet of medical things (IoMT): Applications, benefits and future challenges in healthcare domain." *J. Commun.* 12.4 (2017): 240-247.

[26] Malasinghe, Lakmini P., Naeem Ramzan, and Keshav Dahal. "Remote patient monitoring: a comprehensive study." *Journal of Ambient Intelligence and Humanized Computing* 10 (2019): 57-76.

[27] Singh, Simar Preet, et al. "Fog computing: from architecture to edge computing and big data processing." *The Journal of Supercomputing* 75 (2019): 2070-2105.

[28] Rahmani, Amir M., et al. "Exploiting smart e-Health gateways at the edge of healthcare Internet-of-Things: A fog computing approach." *Future Generation Computer Systems* 78 (2018): 641-658.

[29] Zheng, Tao, et al. "A survey of computation offloading in edge computing." *2020 International Conference on Computer, Information and Telecommunication Systems (CITS)*. IEEE, 2020.

[30] Aslanpour, Mohammad S., Sukhpal Singh Gill, and Adel N. Toosi. "Performance evaluation metrics for cloud, fog and edge computing: A review, taxonomy, benchmarks and standards for future research." *Internet of Things* 12 (2020): 100273.

[31] Satyanarayanan, Mahadev. "The emergence of edge computing." *Computer* 50.1 (2017): 30-39.

[32] Phillips Jr, Ira J. *Maintaining Small Retail Business Profitability by Reducing Cyberattacks*. Diss. Walden University, 2020.

[33] Shi, Weisong, et al. "Edge computing: Vision and challenges." *IEEE internet of things journal* 3.5 (2016): 637-646.

[34] Mehrabi, Mahshid, et al. "Device-enhanced MEC: Multi-access edge computing (MEC) aided by end device computation and caching: A survey." *IEEE Access* 7 (2019): 166079-166108.

[35] Barbarossa, Sergio, et al. "The edge cloud: A holistic view of communication, computation, and caching." *Cooperative and Graph Signal Processing*. Academic Press, 2018. 419-444.

[36] Naha, Ranesh Kumar, et al. "Fog computing: Survey of trends, architectures, requirements, and research directions." *IEEE access* 6 (2018): 47980-48009.

[37] Ren, Ju, et al. "A survey on end-edge-cloud orchestrated network computing paradigms: Transparent computing, mobile edge computing, fog computing, and cloudlet." *ACM Computing Surveys (CSUR)* 52.6 (2019): 1-36.

[38] Salaht, Farah Ait, Frédéric Desprez, and Adrien Lebre. "An overview of service placement problem in fog and edge computing." *ACM Computing Surveys (CSUR)* 53.3 (2020): 1-35.

[39] Iranmanesh, Saam, and Esther Rodriguez-Villegas. "A 950 nW analog-based data reduction chip for wearable EEG systems in epilepsy." *IEEE Journal of Solid-State Circuits* 52.9 (2017): 2362-2373.

[40] Feng, Guibo, et al. "Prognostic value of electroencephalography (EEG) for brain injury after cardiopulmonary resuscitation." *Neurological Sciences* 37 (2016): 843-849.

[41] Prieto, Javier, et al. "IoT approaches for distributed computing." *Wireless communications and mobile computing* 2018 (2018).

[42] Siuly, Siuly, et al. "Electroencephalogram (eeg) and its background." *EEG Signal Analysis and Classification: Techniques and Applications* (2016): 3-21.

[43] Sun, Yi, et al. "Electroencephalography: clinical applications during the perioperative period." *Frontiers in Medicine* 7 (2020): 251.

[44] Demos, John N. *Getting started with EEG neurofeedback*. WW Norton & Company, 2019.

[45] Bidgoly, Amir Jalaly, Hamed Jalaly Bidgoly, and Zeynab Arezoumand. "A survey on methods and challenges in EEG based authentication." *Computers & Security* 93 (2020): 101788.

[46] ur Rehman, Muhammad Habib, et al. "Big data reduction methods: a survey." *Data Science and Engineering* 1 (2016): 265-284.

[47] Alotaiby, Turky, et al. "A review of channel selection algorithms for EEG signal processing." *EURASIP Journal on Advances in Signal Processing* 2015 (2015): 1-21.

[48] Pandey, Manak, et al. "An enhanced data compression algorithm." *2020 International Conference on Emerging Trends in Information Technology and Engineering (ic-ETITE)*. IEEE, 2020.

[49] Rajasekar, P., and M. Pushpalatha. "Huffman quantization approach for optimized EEG signal compression with transformation technique." *Soft Computing* 24 (2020): 14545-14559.

[50] Merdjanovska, Elena, and Aleksandra Rashkovska. "Comprehensive survey of computational ECG analysis: Databases, methods and applications." *Expert Systems with Applications* (2022): 117206.

[51] Luján, Miguel Ángel, et al. "A survey on eeg signal processing techniques and machine learning: Applications to the neurofeedback of autobiographical memory deficits in schizophrenia." *Electronics* 10.23 (2021): 3037.

[52] Swaroop, K. Narendra, et al. "A health monitoring system for vital signs using IoT." *Internet of Things* 5 (2019): 116-129.

[53] Morosetti, Massimo, Michelina Peccerillo, and Maria Iolanda Famà. "Clinical and social advantages of remote patient monitoring in home dialysis." *Giornale Italiano di Nefrologia: Organo Ufficiale Della Societa Italiana di Nefrologia* 37.2 (2020).

[54] Gallant, Alisa L. "The challenges of remote monitoring of wetlands." *Remote Sensing* 7.8 (2015): 10938-10950.

[55] Shaik, Thanveer, et al. "Remote patient monitoring using artificial intelligence: Current state, applications, and challenges." *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery* (2023): e1485.

[56] Malasinghe, Lakmini P., Naeem Ramzan, and Keshav Dahal. "Remote patient monitoring: a comprehensive study." *Journal of Ambient Intelligence and Humanized Computing* 10 (2019): 57-76.

[57] Usman, Syed Muhammad, Shahzad Latif, and Arshad Beg. "Principle components analysis for seizures prediction using wavelet transform." *arXiv preprint arXiv:2004.07937* (2020).

[58] Zabidi, A., et al. "Short-time Fourier Transform analysis of EEG signal generated during imagined writing." *2012 International Conference on System Engineering and Technology (ICSET)*. IEEE, 2012.

[59] Sandoval, Steven, and Phillip L. De Leon. "The instantaneous spectrogram: A general framework for time-frequency analysis." *IEEE Transactions on Signal Processing* 66.21 (2018): 5679-5693.

[60] Goodwin, Michael M. "The STFT, sinusoidal models, and speech modification." *Springer handbook of speech processing* (2008): 229-258.

[61] Sethares, William A. "Transforms." *Rhythm and Transforms* (2007): 111-145.

[62] Pratiwi, Mellisa, Jeklin Harefa, and Sakka Nanda. "Mammograms classification using gray-level co-occurrence matrix and radial basis function neural network." *Procedia Computer Science* 59 (2015): 83-91.

[63] Hall-Beyer, Mryka. "GLCM texture: A tutorial v. 3.0 March 2017." (2017).

[64] Singh, Vibhav Prakash, et al. "Mammogram classification using selected GLCM features and random forest classifier." *International Journal of Computer Science and Information Security (IJCSIS)* 14.6 (2016): 82-87.

[65] Junaedi, Imam, Erni Yudaningtyas, and Rahmadwati Rahmadwati. "Tuberculosis detection in chest X-ray images using optimized gray level co-occurrence matrix features." *2019 International Conference on Information and Communications Technology (ICOIACT)*. IEEE, 2019.

[66] Banerjee, Anwesha, et al. "A secure IoT-fog enabled smart decision making system using machine learning for intensive care unit." *2020 International Conference on Artificial Intelligence and Signal Processing (AISP)*. IEEE, 2020.

[67] Alić, Berina, Lejla Gurbeta, and Almir Badnjević. "Machine learning techniques for classification of diabetes and cardiovascular diseases." *2017 6th mediterranean conference on embedded computing (MECO)*. IEEE, 2017.

[68] Nasteski, Vladimir. "An overview of the supervised machine learning methods." *Horizons. b* 4 (2017): 51-62.

[69] Srinath, Rajagopalan, and Rajagopal Gayathri. "Detection and classification of electroencephalogram signals for epilepsy disease using machine learning methods." *international Journal of imaging Systems and technology* 31.2 (2021): 729-740.

[70] Aayesha, et al. "Machine learning-based EEG signals classification model for epileptic seizure detection." *Multimedia Tools and Applications* 80 (2021): 17849-17877.

[71] Supriya, Supriya, et al. "Automated epilepsy detection techniques from electroencephalogram signals: a review study." *Health Information Science and Systems* 8 (2020): 1-15.

[72] Shah, Kanish, et al. "A comparative analysis of logistic regression, random forest and KNN models for the text classification." *Augmented Human Research* 5 (2020): 1-16.

[73] Ramchoun, Hassan, et al. "Multilayer perceptron: Architecture optimization and training." (2016).

[74] Moldagulova, Aiman, and Rosnafisah Bte Sulaiman. "Using KNN algorithm for classification of textual documents." *2017 8th international conference on information technology (ICIT)*. IEEE, 2017.

[75] Nayak, Janmenjoy, Bighnaraj Naik, and H. S. Behera. "A comprehensive survey on support vector machine in data mining tasks: applications & challenges." *International Journal of Database Theory and Application* 8.1 (2015): 169-186.

[76] Peter, Sven, et al. "Cost efficient gradient boosting." *Advances in neural information processing systems* 30 (2017).

[77] Salmi, Nafizatus, and Zuherman Rustam. "Naïve Bayes classifier models for predicting the colon cancer." *IOP conference series: materials science and engineering*. Vol. 546. No. 5. IOP Publishing, 2019

[78] Parmar, Aakash, Rakesh Katariya, and Vatsal Patel. "A review on random forest: An ensemble classifier." *International Conference on Intelligent Data Communication Technologies and Internet of Things (ICICI) 2018*. Springer International Publishing, 2019.

[79]Liu, Xuesong, and Jie Wu. "A method for energy balance and data transmission optimal routing in wireless sensor networks." *Sensors* 19.13 (2019): 3017.

[80] Andrzejak, Ralph G., et al. "Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state." *Physical Review E* 64.6 (2001): 061907.

[81] Luque, Amalia, et al. "The impact of class imbalance in classification performance metrics based on the binary confusion matrix." *Pattern Recognition* 91 (2019): 216-231.

[82] Ramos-Aguilar, Ricardo, et al. "Feature extraction from EEG spectrograms for epileptic seizure detection." *Pattern Recognition Letters* 133 (2020): 202-209.

[83] Orhan, Umut, Mahmut Hekim, and Mahmut Ozer. "EEG signals classification using the K-means clustering and a multilayer perceptron neural network model." *Expert Systems with Applications* 38.10 (2011): 13475-13481.

[84] Raghu, Shivarudhrappa, et al. "Performance evaluation of DWT based sigmoid entropy in time and frequency domains for automated detection of epileptic seizures using SVM classifier." *Computers in biology and medicine* 110 (2019): 127-143.

[85] Liu, Yunxiao, et al. "Representation based on ordinal patterns for seizure detection in EEG signals." *Computers in Biology and Medicine* 126 (2020): 104033.

[86]Khan, Gul Hameed, et al. "A Shallow Autoencoder Framework for Epileptic Seizure Detection in EEG Signals." *Sensors* 23.8 (2023): 4112.

[87] Acharya, U. Rajendra, et al. "Deep convolutional neural network for the automated detection and diagnosis of seizure using EEG signals." *Computers in biology and medicine* 100 (2018): 270-278.

Publications

1-Riyam Faisal Alwash, Ali Kadhum Idrees, Salah Al-Obaidi. (2023). A Methodological Review on EEG Data Reduction in Edge/Fog computing-based IoMT networks, In 2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT), IEEE. Accepted.

2- Riyam Faisal Alwash, Ali Kadhum Idrees, Salah Al-Obaidi. (2023). EEG Data reduction with Epileptic Seizure Detection based machine learning in IoMT Networks, In 2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT), IEEE. Accepted

3- Riyam Faisal Alwash, Ali Kadhum Idrees, Salah Al-Obaidi.” Energy-efficient Two-level Epileptic Seizure Detection Approach for Remote Patient Monitoring in Fog Computing based IoMT Networks”, submitted to the journal Future Generation Computer Systems, Elsevier.

الخلاصة

شهدت السنوات الأخيرة ارتفاعا ملحوظا في تطوير أنظمة المراقبة المنزلية الآلية نظرا لقلة الموارد البشرية والخدمات الطبية في المؤسسات الصحية. ومع ذلك، تنتج هذه الأنظمة كمية كبيرة من البيانات لأن المراقبة تستغرق وقتًا طويلاً لجمع معلومات مهمة من المريض. يؤدي هذا الطلب إلى زيادة الاهتمام بأنظمة الرعاية الصحية عن بعد التي تستخدم أجهزة الاستشعار الحيوية. تولد أجهزة الاستشعار الحيوية هذه كمية كبيرة من البيانات المستشعرة الحيوية، والتي يتم إرسالها بعد ذلك إلى حافة إنترنت الأشياء الطبية (IoMT) للمعالجة قبل إرسالها إلى المستوى التالي من الشبكة.

في هذه الرسالة، تم اقتراح نهج موفر للطاقة على مستويين للكشف عن نوبات الصرع (ETESeDA) لمراقبة المرضى عن بعد في شبكات IoMT القائمة على حوسبة الحافة/الضباب. يعمل نهج ETESeDA على مستويين في شبكة IoMT: بوابات الحافة والضباب. عند بوابة الحافة، يتم استخدام طريقة تقليل البيانات القائمة على اقتراح استخراج الميزات المستندة إلى مجال التردد الزمني وترميز هوفمان. يهدف الجمع بين تحويل فورييه قصير الأمد (STFT) ومصفوفة التواجد المشترك للمستوى الرمادي (GLCM) وترميز هوفمان (HE) الذي يتم تطبيقه بواسطة ETESeDA إلى استخراج ميزات مفيدة من إشارات تخطيط كهربية الدماغ (EEG) وضغطها قبل إرسالها إلى الضباب. بوابة. بعد ذلك، يتم اقتراح نموذج التعلم الآلي القائم على اتخاذ القرار وتنفيذه في بوابة الضباب باستخدام البيانات المرسلة من بوابة الحافة لتحديد حالة المريض وتقديم القرار المناسب للكادر الطبي.

تم إجراء العديد من التجارب باستخدام مجموعة بيانات جامعة بون المتاحة Bonn University Dataset. أظهرت النتائج أن ETESeDA يقلل بشكل كبير من البيانات المرسلة من حيث نسبة الضغط وتوفير المساحة ودقة اتخاذ القرار. توفر ETESeDA نسبة ضغط جيدة مقارنة بطريقة HE. يوفر نهج ETESeDA المقترح مستوى مناسبًا من الدقة لكل من التصنيفات الثنائية والمتعددة، ويتفوق على أحدث التقنيات ويحقق دقة ١٠٠% و٩٧% في التصنيفات الثنائية والمتعددة، على التوالي.

وزارة التعليم العالي و البحث العلمي
جامعة بابل كلية العلوم للبنات
قسم علوم الحاسوب

تصنيف اشارة EEG لمرض الصرع بالاعتماد على تعلم الالة في حوسبة الحافة / الضباب لمراقبة المريض عن بُعد

رسالة مقدمة الى مجلس كلية العلوم للبنات في جامعة بابل وهي جزء من متطلبات الحصول على درجة الماجستير في علوم الحاسبات

بواسطة

ريام فيصل علوش

الاستاذ الدكتور

علي كاظم ادريس

جامعة بابل

كلية تكنولوجيا المعلومات

المدرس الدكتور

صلاح مهدي العبيدي

جامعة بابل

كلية العلوم للبنات

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