DEVELOPING ARTIFICIAL INTELLIGENCE MODELS FOR CLASSIFICATION OF BRAIN DISORDER DISEASES BASED ON STATISTICAL TECHNIQUES

A Thesis submitted by

Hanan Ali Hammoodi Al-Hadeethi

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Abstract

The human brain is considered as a control centre of the human nervous system. It receives the signals from the body's sensory organs and conveys those information to the muscles. The brain contains millions of nerve cells named as neurons. Recently, brain signal analysis has become more advanced with numerous researchers using various techniques such as electroencephalogram (EEG), electrooculography (EOG) signals and electromyography (EMG). The most important studies were about investigating EEG signals during sleep stages, anaesthesia, epilepsy and alcoholism. The doctoral thesis focusses on building high performance artificial intelligence (AI) methods for modelling and analysis of three types of brain signals: *i.e.*, epilepsy, Focal & Non-Focal and alcoholism.

The first objective of this research is to propose an intelligent expert system that can detect the epileptic seizures which can provide a modelling framework for proactively supporting a neurologist's effort to improve authenticity, speed and accuracy of detecting signs of seizure. The second objective of this thesis proposes an intelligence AI framework tailored for epileptic EEG detection based on the determinant of a covariance matrix (*i.e.*, Cov–Det) method coupled with the AdaBoost Back-Propagation neural network (AB–BP–NN) algorithm. In the third objective of this research, an automatic brain modelling system, denoted as (CT-BS- Cov-Eig based FOA-F-SVM), is proposed to detect prevalence and health effects of alcoholism from multi-channel EEG signals.

The results of this doctoral research demonstrated the superiority and enhanced capability of the AI methods as promising medical diagnostic tools and their practicality for implementation in brain feature detection systems. As result, the first objective, second objective, and third objective yielded a high accuracy of 99%, 100%, and 99% respectively. Also, the research has confidently proposed that these AI approaches have good ability to aid clinicians in the diagnosis and intervention stages required to treat epileptic disease, Focal & Non-Focal and alcoholism including. The contributions and implications also arise from the potential utility of these methods in medical expert systems where EEG (or related time series) datasets need to be classified accurately through advanced pattern recognition algorithms.

Certification of Thesis

This Thesis is the work of *Hanan Ali Hammoodi Al-Hadeethi* except where otherwise acknowledged, with the majority of the authorship of the research papers are presented as a PhD Thesis by Publication that was undertaken by the Student. The work is original and has not previously been submitted for any other award, except where acknowledged.

Principal Supervisor: Dr Shahab Abdulla

Associate Supervisor: Professor Ravinesh C Deo

Associate Supervisor: Dr Mohammed Diykh

Student and supervisors signatures of endorsement are held at the University.

Statement of Contributions

The following provides the agreed share of contributions of the candidate and co-authors in publications arising from this thesis:

- **Article I: Al-Hadeethi, H.**, Abdulla, S., Diykh, M., Deo, R. C., & Green, J. H. (2020). Adaptive boost LS-SVM classification approach for time-series signal classification in epileptic seizure diagnosis applications. *Expert Systems with Applications*, *161*, 113676. https://doi.org/10.1016/j.eswa.2020.113676. [Impact Factor 5.452, *Q*1]

  The overall contributions by ***Al-Hadeethi, H.*** was 70%, including the concept development, analysis, drafting and revising the final submission; the contributions from all supervisors added to ~30%, in advising, editing and providing important guidance on technical inputs.

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- **Article III: Al-Hadeethi, H.**, Abdulla, S., Diykh, M., Deo, R. C., & Green, J. H. (2020). An Eigenvalue-based Covariance matrix Bootstrap Model Integrated with Optimised SVM for Multi-Channel EEG Signals Analysis. Submitted to *Journal of Expert Systems with Applications* (under review), [Impact Factor 5.452, *Q*1].

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The following list of papers are co-authored by Al-Hadeethi, H during the candidacy, but these do not form primary parts of the main thesis.

- Al-Hadeethi, I., Li, Y., Seneweera, S., & Al-Hadeethi, H. (2017, June). Estimating the effects of carbon dioxide, temperature and nitrogen on grain protein and grain yield using meta-analysis. In *Proceedings of the 1st International Conference on Quantitative, Social, Biomedical and Economic Issues 2017 (ICQSBEI2017)* (pp. 107-118). Greek Research Institute for the Study of Quantitative, Social and Biomedical Problems.

- HUSSEIN, M. J. M. & HAMODI, H. A. 2017. Comparison Count Regression Models for the Number of Infected of Pneumonia. *Global Journal of Pure and Applied Mathematics,* 13**,** 5359-5366.

- Al-Hadeethi, H., Li, Y., & Al-Hadeethi, I. (2017). Evaluating Individual Research Studies Using Statistical Techniques. In *Proceedings of the First MoHESR and HCED Iraqi Scholars Conference in Australasia 2017 (ISCA 2017)* (pp. 329-335). Swinburne University of Technology.

- AL-HADEETHI, I., LI, Y., ODHAFA, A. K. H., AL-HADEETHI, H., SENEWEERA, S. & LAM, S. K. 2019. Assessment of grain quality in terms of functional group response to elevated [CO2], water, and nitrogen using a meta-analysis: Grain protein, zinc, and iron under future climate. *Ecology and evolution,* 9**,** 7425-7437. [Impact Factor 2.540, Q1].

- ABBAS, N. S., CHONG, A., AL-KHARAZ, A. A. & AL-HADEETHI, H. Relationships between foot dimensions and plantar pressure distributed in older people. 2020 IEEE 10th Symposium on Computer Applications & Industrial Electronics (ISCAIE), 2020. IEEE, 198-202.

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Abbreviations

EEG	Electroencephalography
CNN	Convolutional Neural Network
GLM	Generalized Linear Model
EMD	Empirical Mode Decomposition
IEDs	Inter-ictal Epileptiform Discharges
RQA	Recurrence Quantification Analysis
DWT	Discrete Wavelet Transform
TLE	Temporal Lobe Epilepsy
LS_SVM	Least Square Support Vector Machines
SVM	Support Vector Machines
SampEn	Sample entropy
WHO	World Health Organization
MAS	Mean Amplitude Spectrum
TQWT	Tunable-Q Wavelet Transform
CTM	Central Tendency Measure
2D	Two-Dimensional
RPS	Reconstructed Phase Space
CFC	Cross-Frequency Coupling
MEMD	Multivariate Empirical Mode Decomposition
ApEn	Approximate Entropy
PCA	Principal Component Analysis
GVIX	Global Volatility Index
AB-LS-SVM	AdaBoost Least Square Support Vector Machines

ED	Euclidean Distance
WT	Wavelet Transform
CWT	Continuous Wavelet Transform
EWT	Empirical wavelet transform
PE	Permutation Entropy
RP	Recurrence Plots
AB-BP-NN	AdaBoost Back-Propagation neural network
Cov-Det	Covariance matrix with its Determinant
KST	Kolmogorov–Smirnov Test
MWUT	Mann Whitney U Test
NNM	Neural Network Model
FD	Fractal Dimension
CFC	Cross-Frequency Coupling
BC	Clustering technique- Bootstrap
COV-EIG	Covariance matrix- Eigenvalues
FOA	Fruit fly Optimisation Algorithm
F-SVM	Radius-margin-based SVM
ACC	Accuracy
Sen	Sensitivity
Spec	Specificity
NPV	Negative Predictive value
FOA-F-SVM	radius-margin-based SVM model-fruit fly optimisation algorithm
FFT	Fast Fourier transform
AR	Autoregressive

PSDs	Power Spectral Density
HHT	Hilbert-Huang Transformation
T-F	Time-frequency
KNN	K-nearest neighbour
SEPCOR	Separability and Correlation analysis

CHAPTER 1
INTRODUCTION

Statistics is one of the essential sciences that plays a vital role in many different sciences and studies. Also, it is considered one of the oldest sciences and emerged with the fundamental human need to deal with values and preparation for the conduct of daily life (Stigler, 1986). With the tremendous development in all sciences in the late twentieth century, statistics progressed to take advantage of computer technologies in a way that makes science more intertwined with other sciences (Woolf, 1989). It now uses statistics in commercial sciences, medical sciences, engineering, literature, and all other sciences without exception (David and Edwards, 2013). The era of information and the new global openness also contributed to highlighting the importance of activating the process of dealing with data in a manner that ensures control and reading it, which had a definite impact on the development of statistics (Stigler, 2002).

Statistics are used in a variety of fields, including many such as industry, agriculture, medicine, research, and other fields of administration, business, and science in general (Altman, 1990, Gower, 1988). Thus, statistical methods are applied in various aspects of the industry, such as monitoring the quality of production, marketing, storing and operating production lines (Hald, 2005). Furthermore, it is used in the medical field to study various diseases and research their causes and methods of treatment (Ramsay, 2004). In the field of agriculture, animal and plant wealth statistics are examined, and the relationship between fertiliser types and different agricultural methods and increased production is studied (Besag and Higdon, 1999). Population and housing are also considered through demographic statistics, and the workforce and its properties, wages, income, and spending are studied (Wardrop et al., 2018). In the field of business and trade, statistics play a vital role in the market study, consumer trends, price studies, and production quantities (Statistics, 2006).

The concept of statistics differs among the public, as it means data for some people, while it is used by others to indicate the process of data collection and the process of storing it. Some tend to understand statistics as the science that collects and describes data, to reconfigure it in a way that is easy to read and then is prepared to support

decision-making or obtain information related to a problem under consideration (Tufféry, 2011). Indeed, statistics represent the scientific tool through which data is collected and then described using tables and graphs to highlight the information contained in the data, which is otherwise challenging to read (Friel et al., 2001). Of course, the matter does not stop at the limit of data description but rather exceeds it to enter a crucial stage that depends on modern computer technology. The data analysed by advanced scientific methods through which the information in the data can be read with high accuracy and reliability, and it can be divided the statistics into two parts (Kirk, 2007):

1. Descriptive Statistics.
2. Inferential Statistics.

In the first part, statistical data is highlighted through graphical forms that are easy to read, while in the second part, the depths of data are entered into an understanding of what the numbers, and graphs mean is determined to be able to access information that is otherwise difficult to reach without knowledge of statistics (Jaggi, 2003). Statistical data are indicators of a quantitative or descriptive outcome of a specific situation or question. In addition, the data are divided into types that can be described in general through two main types (Mendenhall et al., 1996, McCarthy, 1982):

- Metadata.
- Quantitative data.

Metadata is divided into two main parts: nominal metadata and ordinal metadata (Grossmann, 2014). The difference between the two types is nominal metadata indicating different fields that do not represent a specific arrangement, while an arrangement has a particular meaning in the ordinal metadata (Grossmann, 2014). The other type of statistical data represents data that takes numbers and is called quantitative data (Blaikie, 2003). Most of the mathematical operations are done by dealing with numbers more than coping with adjectives or words.

In recent years, the need for using statistical principles in any project relies on the type of study that is carried out. However, biomedical researchers (biologists, physician-scientists, clinical trialists, and others) must have some insight into statistical principles to enable them to feel confident about carrying out a critique of published literature in their field. In this dissertation, the focus is on developing artificial

intelligence (AI) methods for analysing biomedical data (signals) using statistical techniques as an evaluation of the developed classification models and research methods. For that purpose, this study reviews the essential scientific details related to biomedical datasets starting with the backgrounds of the brain signals.

The human brain is considered a control centre for the human nervous system (Frackowiak, 2004, Boche et al., 2013). It receives all signals from the body's sensory organs and converts information to be sent to the muscles (Frackowiak, 2004). The brain contains millions of nerve cells named neurons. These cells produce electrical impulses and messages to create thoughts, feelings, movement and they control bodily functions (Kandel, 1991). Recently, brain signal analysis has become more advanced with numerous researchers using various techniques such as electroencephalogram (EEG), electrooculography (EOG) signals and electromyography (EMG). The most important studies were about investigating EEG signals during sleep stages, anesthesia, epilepsy and alcoholism. The focused of this thesis was on three types of brain signals: epilepsy, Focal & Non-Focal and alcoholism. This chapter is divided as follows: scientific background on the brain and how to capture the brain activities through a monitoring called an EEG and a brief history of this tool. Then, a detailed explanation of Epileptic EEG signals, Focal and Non-Focal EEG signals and Alcoholism EEG signals. Thereafter, research problems and the focus of the dissertation are discussed. Finally, the contribution of each chapter in this dissertation, are presented.

1.1 The Brain

The brain is considered one of the most significant and most complex parts of the human body (Herculano-Houzel, 2009). It consists of more than 100 billion nerves that work via connections called synapses. The brain can be divide into several parts that work together, and Figure 1 explains the essential elements of the brain, such as (Duncan and Owen, 2000):

- The first part is the cortex which is the outermost layer of brain cells; in this layer, the thinking and voluntary movements (expression of thought through action) begin.
- The second part is the brain stem; it is located between the spinal cord and the rest of the brain; the function of the brainstem is control of breathing and sleep.
- The third section is basal ganglia which are a cluster of structures in the centre of the brain, the function of this part is to co-ordinate messages between multiple other brain areas.
- The fourth part of the brain is the cerebellum and is located at the base, and the back of the brain, the primary function of the cerebellum is co-ordination and balance.

There is also another division of the brain, where it splits into several lobes (Goldberg, 2002):

1. The frontal lobes, its function is to control problem-solving, judgment and motor function.
2. The parietal lobes, its work on manage sensation, handwriting, and body position.
3. The temporal lobes, are involved with memory and hearing.
4. The occipital lobes are responsible for the brain's visual processing system.

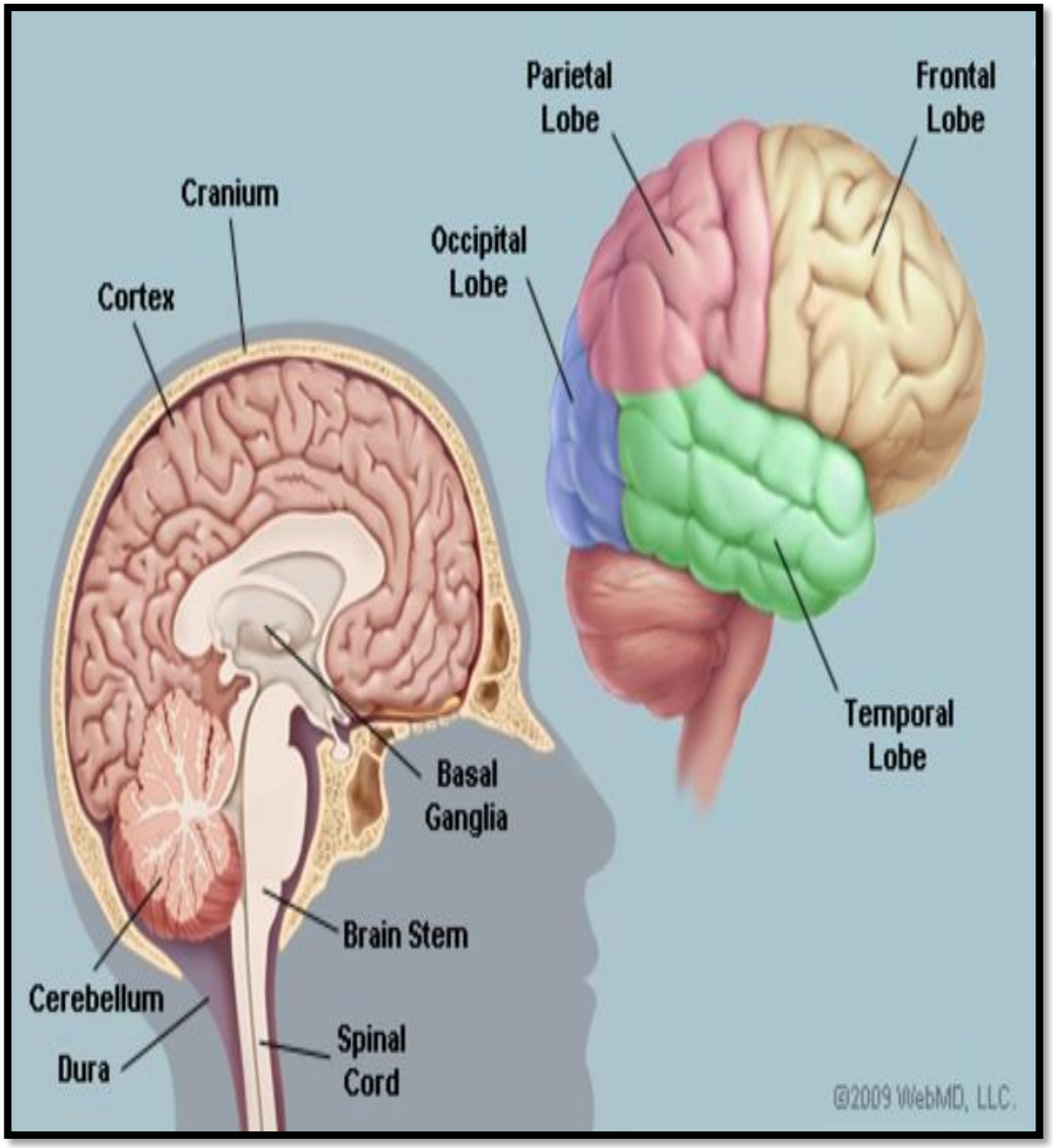

Figure 1.1 The human brain parts (Holmberg and Hoffman, 2014) https://www.webmd.com/brain/picture-of-the-brain#1.

1.2 The Neurons

The brain consists of more than 100 billion nerves, cells within the nervous system, called neurons, and they communicate with each other in distinctive ways (Kandel, 1991). The nerve cell is the essential working unit of the brain, a particularised cell designed to convey information to other neurons, muscle, or gland cells (Bullock, 1959). All of the nerve cells have a cell body, an axon, and dendrites. The cell body includes the cytoplasm and nucleus. The axon extends from the cell body and often provides rise to many smaller branches before ending at nerve terminals (Comer and

Robertson, 2001). Dendrites extend from the nerve cell body and extradite messages from other neurons. The function of synapses is to connect points where one neuron communicates with another (Fields and Stevens-Graham, 2002). The dendrites create synapses together with the ends of axons from other nerve cells. Figure 2 shows the morphology of the nerve cell.

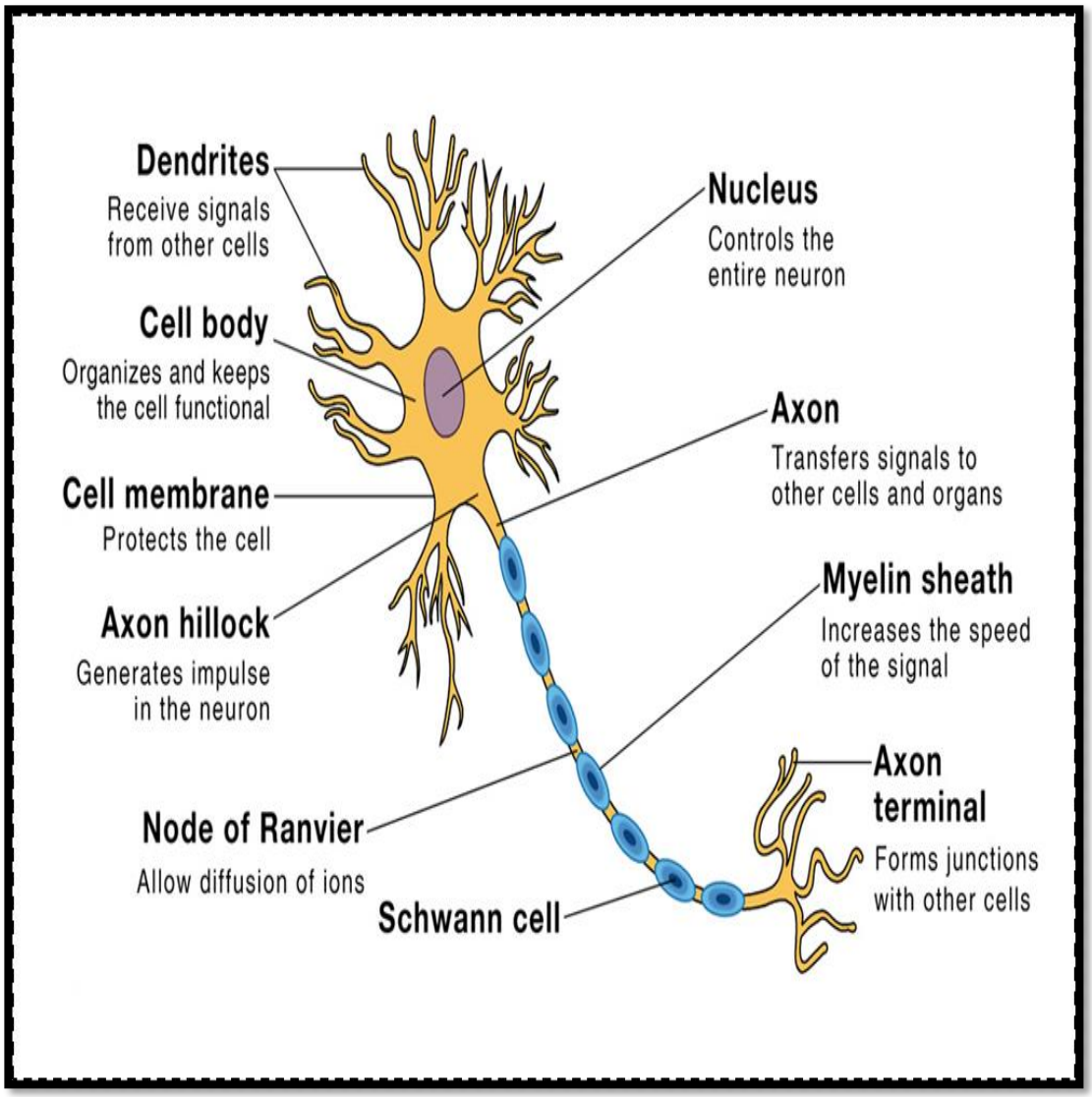

Figure 1.2 The shape of neurons https://www.sciencefacts.net/parts-of-a-neuron.html.

1.3 History of EEG

Called the electrophysiological monitoring method, the Electroencephalography (EEG), it used to record the electrical activity of the brain. The first human EEG was recorded in 1924 by German physiologist and psychiatrist Hans Berger (1873–1941) (Haas, 2003, Tudor et al., 2005, La Vaque, 1999). Also, Hans Berger has invented the

electroencephalogram and gave the device its name, EEG. This invention can be described as one of the most astonishing and fundamental developments in the history of clinical neurology (Millet, 2002). Figure 3 shows the first EEG signal together with its inventor. An EEG considered helpful for diagnosing or treating the following disorders (Sutter and Kaplan, 2013, Wallace et al., 2012, Rossi et al., 1995, Geocadin and Eleff, 2008):

- Brain tumour.
- Brain damage from a head injury.
- Brain dysfunction with a variety of causes (encephalopathy).
- Stroke.
- Sleep disorders.
- Epileptic seizures.
- Differentiate "organic" encephalopathy.
- Brain death in comatose patients.
- Prognosticate in comatose patients.

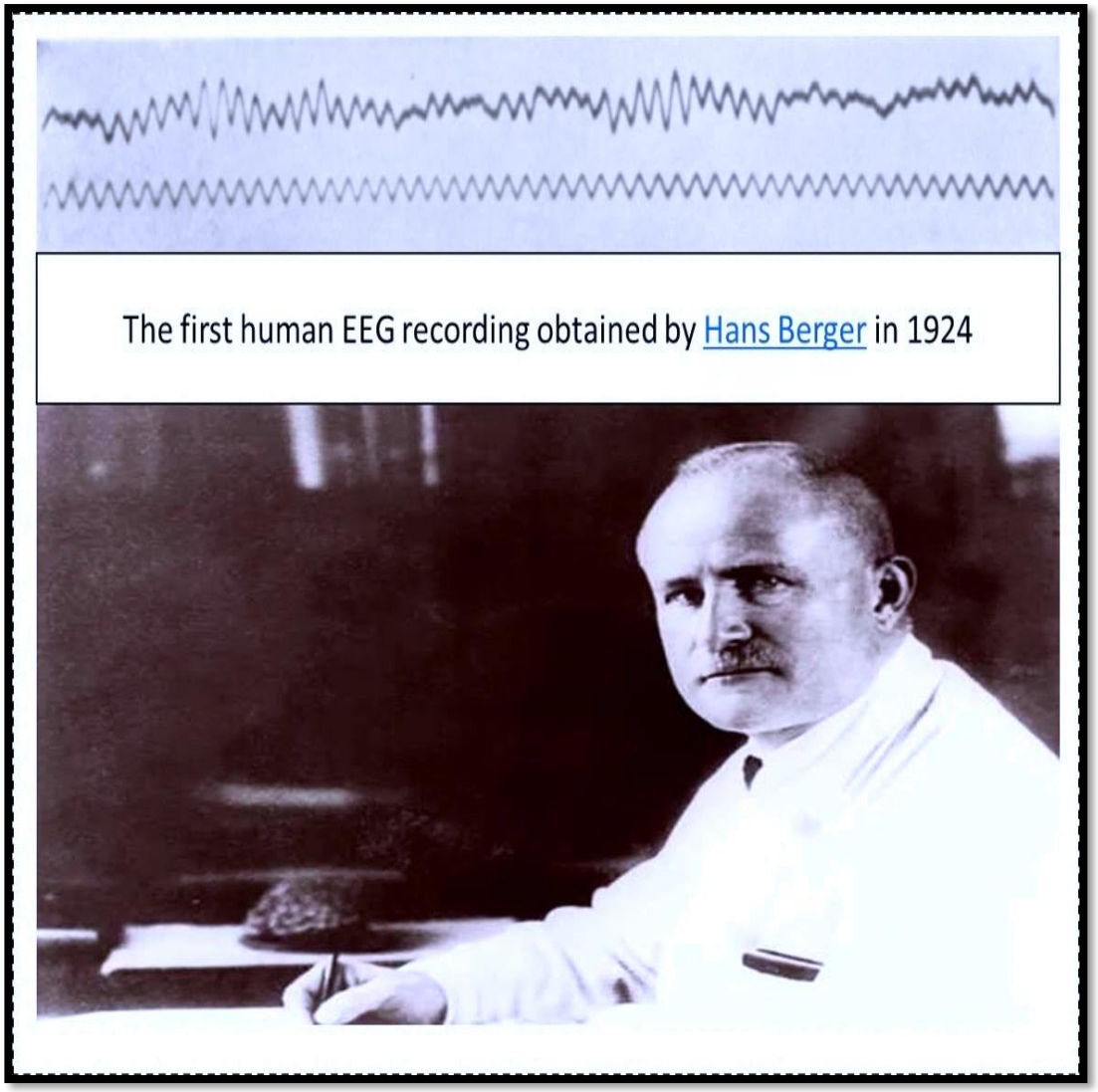

Figure 1.3 The first EEG recording that was taken by Hans Berger in 1924 https://medium.com/voice-tech-podcast/the-history-of-eeg-bbec859633ee.

However, with the improvements in digital technologies, systems of EEG recording have become more sophisticated. Various types of metal electrodes were designed to detect brain signals; tin, gold platinum and silver (Geddes and Roeder, 2003, Tallgren et al., 2005). These electrodes have the capability to measure any small potential produced by the brain nerve cells.

The 10/20 system is known as the international system for measuring brain activity. It is a standard system that has the ability to describe the locations of electrodes on the scalp (Herwig et al., 2003). The relationships between the location of an electrode and the underlying area of the cerebral cortex, resulted in the design of the 10/20 system (Technologies, 2012). The numbers 10 and 20 were chosen on the basis of the distance

between each pair of electrodes that is either 10% or 20% of the overall left-right or front-back of the human cranium (Jurcak et al., 2007). Each electrode is identified by a specific number and letter to distinguish lobe and hemisphere location, respectively. Figure 4 gives a stylised representation of those locations, and Figure 5 provides a clear idea of the 10/20 system.

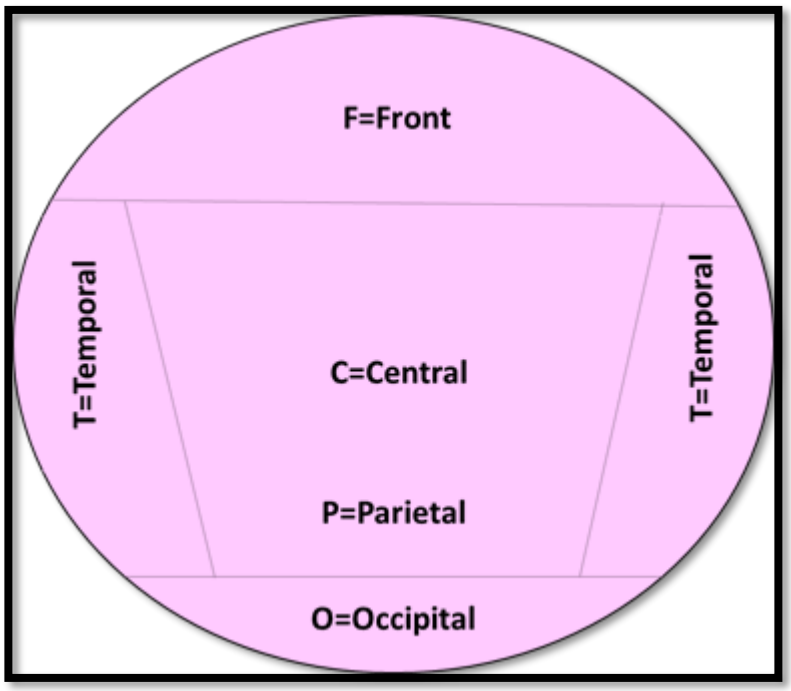

Figure 1.4 Human brain lobes and their hemispheric location.

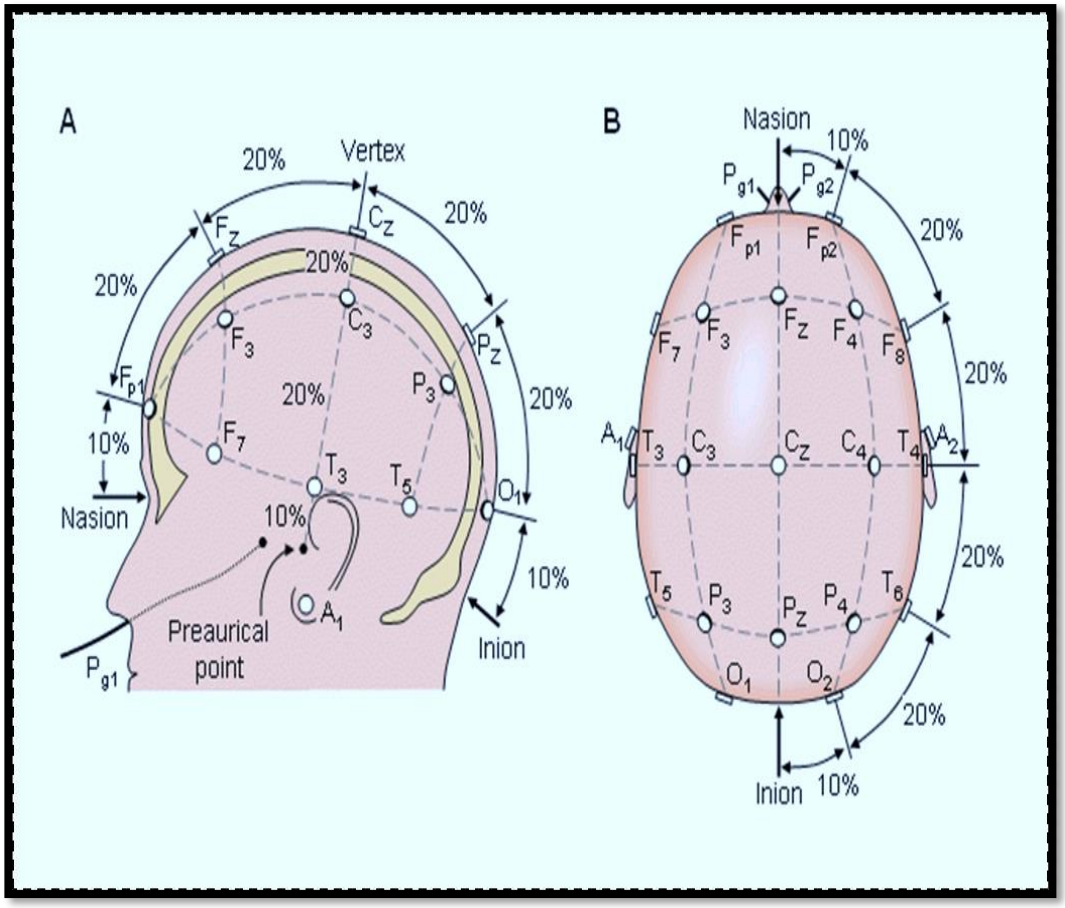

Figure 1.5 The 10–20 system of electrode placement for the recording of EEG signals https://www.slideshare.net/prema5252/eeg-by-prc.

As mentioned previously, the EEG is a tool for recording electrical activities from the scalp area, and the recorded waveforms reflect the cortical electrical activity. The signal intensity can be measured in microvolts (μV) and there are many frequencies of the human EEG waves, Figure 6 illustrates the human EEG waves:

- ⇒ Gama: The range of this wave is 30-100 Hz, and the gamma frequency appears during kinetic and cognitive functions.
- ⇒ Beta: The beta activity frequency ranges between 13-30 Hz, and this type of frequency appears through active movements and kinetic behaviours.
- ⇒ Alpha: The frequency range of this wave activity is between 8-13 Hz, and it is called the basic background rhythm, and it usually appears when the subject is in a state of relaxation with closed eyes.
- ⇒ Theta: Theta activity range is between 4-8 Hz, and this wave observed during drowsiness in adults and young children.

⇒ Delta: The delta activity frequency range is between 0.5-4 Hz with the lowest waves and the highest amplitude. This type of signal is associated with two stages, namely deep sleep and the stages of awakening, and sometimes with the brain disorder.

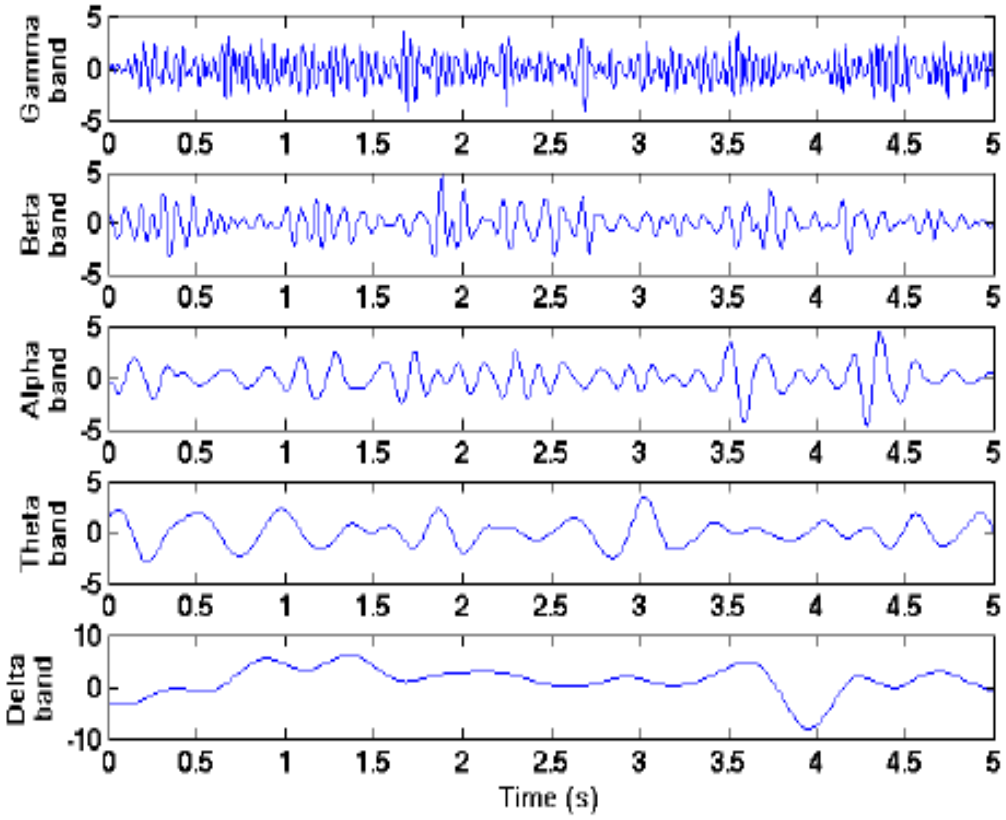

Figure 1.6 The main frequencies of the human EEG waves (Abhang et al., 2016).

1.4 Background of different types of EEG Signals

This thesis will focus on developing robust statistical methods that can analyse and classify several types of EEG signals such as Focal and Non-Focal, Epileptic and Alcoholism EEG signals.

1.4.1 Epileptic EEG signals

According to the latest report of World Health Organization https://www.who.int/news-room/fact-sheets/detail/epilepsy (Megiddo et al., 2016), epilepsy is a chronic brain disorder that affects more than 50 million people globally, with almost 2.4 million people diagnosed with epilepsy annually (Megiddo et al., 2016). Thus, it affects about 1 per cent of the global population. Epilepsy is distinguished by frequent episodes that cause involuntary movement of a particular

part of the body, or the whole body, followed by a loss of consciousness. People who experience epileptic seizures might, therefore, be susceptible to premature death; up to three times higher than people who do not experience seizures (Megiddo et al., 2016).

From the viewpoint of neurology, the fundamental cause of most cases of epilepsy is unknown or is ill-defined. However, some cases could be a result of brain injuries, genetic factors and tumours (Delanty, 2014). Most medical professionals adopt EEG –an electrophysiological monitoring technique – to capture the electrical activities of the brain through placing electrodes on specific locations on a patient's scalp (Tatum IV, 2014). This can supply important information to discover human brain activities, and differentiate neurological diseases, such as sleep disorders, epilepsies, encephalopathies, brain deaths and comas. Figure 7 and 8 show the EEG signals and shape of the human brain of epileptic and normal subjects.

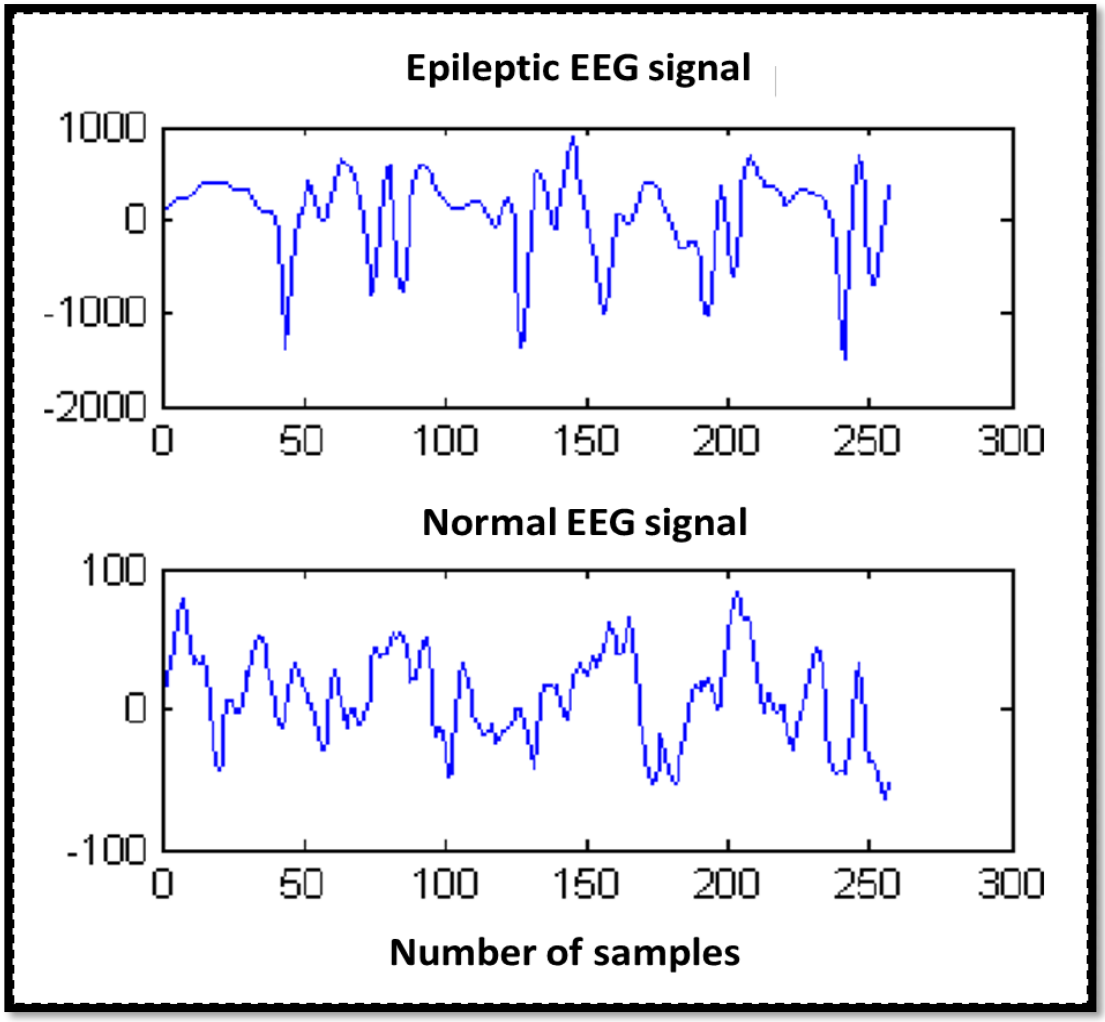

Figure 1.7 An example of EEG signals of epileptic and healthy subjects (Naderi and Mahdavi-Nasab, 2010).

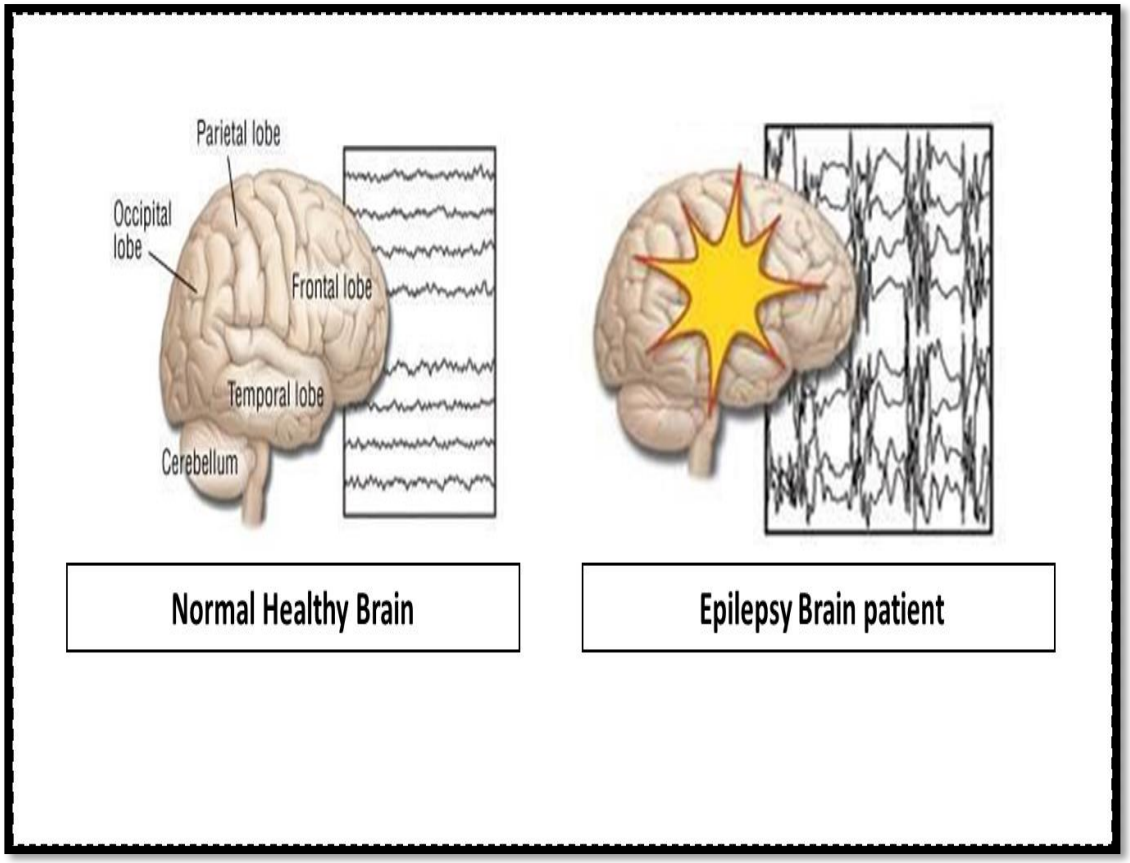

Figure 1.8 The shape of a healthy subject brain and epilepsy patient https://www.health.harvard.edu/a_to_z/epilepsy-a-to-z.

1.4.2 Focal and Non-Focal EEG signals

Focal epilepsy, this term is used when an epileptic seizure starts on one side of the brain, while the signals that are captured from another part of the epileptogenic area called non-focal epilepsy (Acharya et al., 2019). However, there are different types of focal seizure and these can be divided into two main classes according to what level of awareness the patient has during the seizure (Sharma et al., 2014). The first type is called 'aware of focal seizures: during these seizures, the person is aware and may experience feelings such as an unpleasant smell or taste, or sensations such as 'butterflies' or nausea. These seizures may also involve motor activity (such as involuntary and brief jerking of an arm or leg) or autonomic behaviours (such as fiddling with clothing or pointing). These seizures used to be called 'simple partial seizures,' and the second one is 'focal impaired awareness seizures: a seizure that starts in one area or side of the brain and the person is not aware of their surroundings during it is called focal impaired awareness seizure' (Hussein et al., 2018). The properties of

focal epilepsy signals are more nonlinear and less random when compared to the non-focal epilepsy signals. The latest reports indicate that more than 20% of patients are affected by generalised epilepsy which is apparent throughout the entire brain.

In comparison, more than 60% of patients suffer from focal epilepsy, localised to a smaller region of the brain (Pati and Alexopoulos, 2010). It is difficult to treat patients with focal epilepsy using medication alone (Pati and Alexopoulos, 2010). Figure 9 illustrates two samples of signals from Focal and Non-Focal epilepsy, respectively.

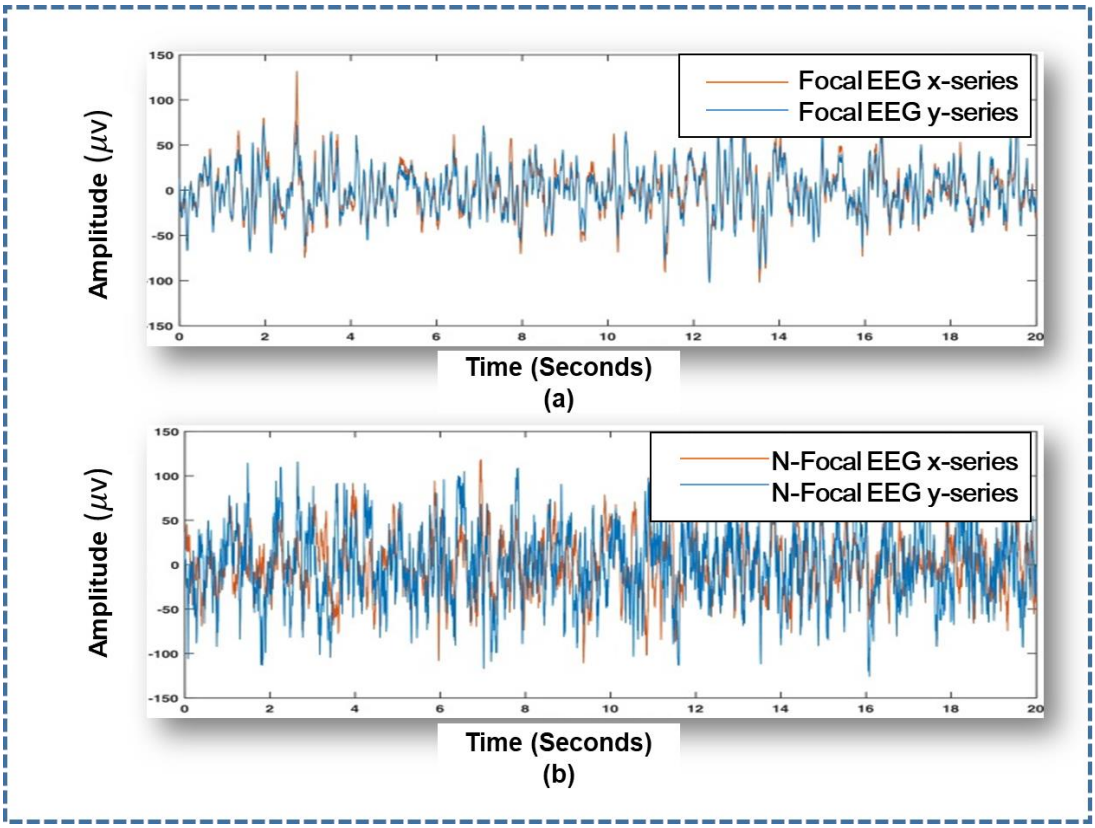

Figure 1.9 The sample of Focal and Non-Focal EEG signals (Arunkumar et al., 2018).

1.4.3 Alcoholism EEG signals

Alcoholism is a common neurological disorder caused by excessive and repetitive drinking of alcoholic beverages to the extent that the drinker is repeatedly harmed. The harm could be physical or psychological; as well as social, legal and economic (Lieber, 1995). As well, alcoholism and chronic heavy drinking can have earnest repercussions for the functioning of the entire nervous system, especially the brain. It not only destroys the brain system but also leads to cognitive and mobility weakness (Oscar-Berman et al., 1997). Thus, alcoholism is considered by most clinicians as an addiction

and a disease. Based on the latest reports issued by the World Health Organization (WHO) https://www.who.int/health-topics/alcohol#tab=tab_1, 3 million deaths every year are caused by the consumption of harmful levels of alcohol. Besides this, more than 200 disease and injury conditions are caused by the extensive use of alcohol. Recognising alcoholics from healthy subjects in a reasonable way is likely to decrease unnecessary economic losses and social problems as well as supply a prompt way for doctors in clinical settings to diagnose alcoholism. Figure 10 shows the EEG signal shapes for an alcoholic versus a non-alcoholic subject. Figure 11 shows the significant difference in the shape of the brain between alcoholic and healthy people. Table 1 provides some information about the data used in this thesis.

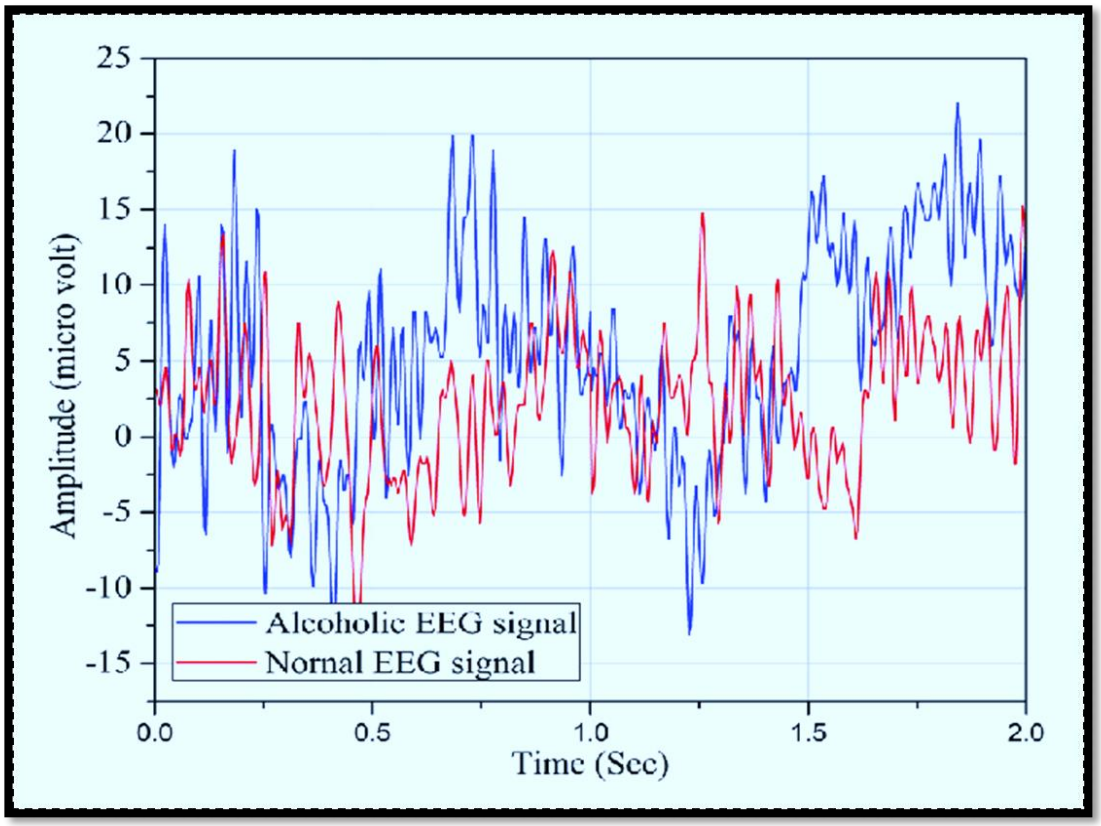

Figure 1.10 Alcoholic and normal EEG signal (Bavkar et al., 2019).

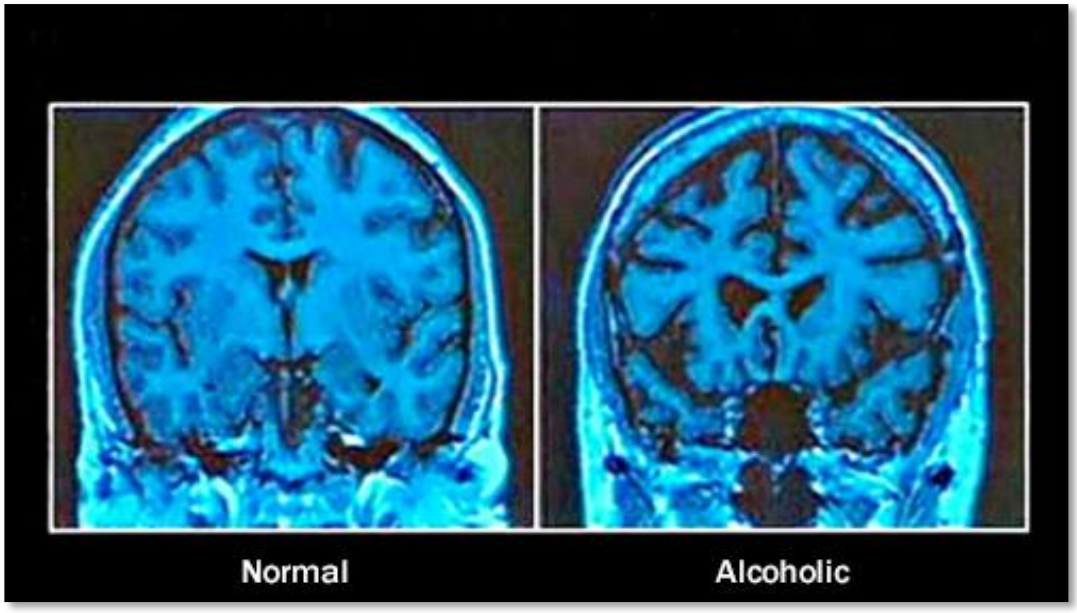

Figure 1.11 the brain's shape of alcohol and normal people. https://www.webmd.com/mental-health/addiction/ss/slideshow-alcohol-body-effects

Table 1 Datasets description

Source description for the data sets used in the work covered by this thesis		
No.	Type of data	Sources
1	Epileptic	Collected at Epileptic Department of the University of Bonn located in Germany (Andrzejak et al., 2001), are publicly accessible through a web link http://epileptologie-bonn.de/cms/front_content.php?idcat=193&lang=3.
2	Focal & Non-Focal	Collected at the University of Bern Department of Neurology (Andrzejak et al., 2012).
3	Alcoholism	It is a public database known as the UCI Knowledge Discovery in Databases (KDD) Archive www.kdd.ics.usi.edu from Irvine, CA: the University of California, Department of Information and Computer Science (Hettich and Bay, 1999).

1.4 Research Problems and Focus of the Dissertation

The main objective of this research is to effectively develop an intelligent Machine Learning model to detect and analyse miscellaneous brain disorders.

The work presented in this dissertation focuses on how diverse EEG signals from various brain activities can be detected and used to analyse miscellaneous brain disorders using statistical methods. Three types of EEG data are analysed and studied: epileptic, Focal & Non-Focal and alcoholism. A covariance matrix, when integrated with several other methods, it is considered a powerful extraction technique to reduce the dimensionality. A statistical approach was utilised that included non-parametric methods applied for feature selection. A newly designed Adaptive Boost Least Square Support Vector Machines (LS-SVM) method, designated as the AB-LS-SVM algorithm was proposed, as well as, intrducing AdaBoost Back-Propagation neural networks (AB-BP-NN) algorithm additionally, and radius-margin-based SVM (F-SVM) model with fruit fly optimisation algorithm (FOA), (i.e., FOA-F-SVM), all were aimed at predicting the occurrence of seizures in an alcoholic patient's EEG signal. This thesis examines and explores the best intelligent ML modelling framework addressing the following research quastions:

1. How to evaluate and reduce the dimension of EEG signals (data) based on the covariance matrix coupled with several other methods?
2. How to employ arithmetic operators based on the non-parametric methods to eliminate the noisy features in EEG signal datasets?
3. How to develop an intelligent ML modelling framework for epileptic, Focal & Non-Focal and alcoholism EEG detection based on the AdaBoost Back-Propagation neural networks (AB-BP-NN), Adaptive Boost Least Square Support Vector Machines (AB-LS-SVM) algorithms and finally with Fruit fly Optimization with the radius-margin-based Support Vector Machine (FOA-F-SVM)?

The focus is on the classification and analysis of EEG signals in this study, to improve a new computerised model of an epileptic seizure, Focal & Non-Focal and alcoholism detection that is based on the covariance matrix coupled with the AdaBoost Back-Propagation neural network (AB-BP-NN), Adaptive Boost Least Square Support Vector Machines(AB-LS-SVM), and (F-SVM) model with fruit fly optimisation

algorithm (FOA), (i.e., FOA-F-SVM) approaches. The results demonstrate that the proposed model characteristics exhibit clear and significant improvement when applied to different types of EEG signals.

1.5 Contribution of Each Chapter in This Dissertation

The work presented in this thesis focuses on how to study human brain behaviour utilising an intelligent ML modelling framework. Investigation of different EEG signals acquired from different channels was applied to study the functioning of the human brain in healthy and non-healthy subjects. Various types of brain networks are assessed through epileptic, Focal& Non-Focal and alcoholism EEG signals. Covariance matrix with Eigenvalue, covariance matrix with its determent, bootstrapping coupled with clustering technique, non-parametric methods, (AB-LS-SVM), (AB-BP-NN), and (FOA-F-SVM) are employed to study these EEG signals. Three types of data were used to evaluate the performance of these brain networks EEG analysis; thorough investigations are made through the design of extensive experiments. The following contributions are proposed:

- Generate a reliable EEG classification model, based on a covariance matrix to reduce the dimensionality of data to be later employed in the proposed AB-LS-SVM model. To achieve that, the eigenvalues of the covariance matrix derived from EEG signals were investigated using a statistical model, and different sets of statistical features arising from these eigenvalues and tested using performance criteria metrics.
- An efficacious automated detection model of abnormal events in the EEG signals, named the Cov_Det based AB-BP-NN model, was proposed, and its efficacy was evaluated using two separate medical datasets.
- Proposed robust detection model which designed based on the CT-BS-COV-EIG technique coupled with a new radius-margin-based SVM (F-SVM) model with fruit fly optimisation algorithm (FOA) called FOA-F-SVM model to detect alcoholism EEG signals.

These algorithms are entered into Matlab R2020b; all experiments were performed on a desktop computer with the following capabilities: Dell P2018H, Intel (R) Core 7 CPU and RAM of 8.0 GB. Each algorithm is simulated and assessed utilising various EEG signals acquired from diverse channels. A brief discussion of these contributions is provided below.

1.6 Epileptic seizure diagnosis based on the covariance matrix coupled with AdaBoost LS-SVM

Epileptic seizures are distinguished by abnormal neuronal discharge, causing a notable disturbance in electrical activities of the human brain. Designing an automated and intelligent expert system to classify the epileptic seizure can proactively support a neurologist's effort to ameliorate authenticity, speed and accuracy of detecting signs of seizures. A novel two-phase classification technique for detection of seizures from an EEG signal, applying the covariance matrix coupled with AdaBoost LS-SVM frameworks was proposed. In the first stage, the covariance matrix is used as a dimensionality reduction tool together with a feature extraction applied to analyse an epileptic patient's EEG record. Initially, each single EEG channel was divided into its respective k segment with m clusters. Subsequently, the covariance method is utilised with eigenvalues of each cluster extracted and tested employing statistical metrics to distinguish most representative, optimally classified features. In the second stage, a robust classifier (i.e., AB-LS-SVM) is proposed to resolve issues of unbalanced data and detect epileptic events, yielding a high classification accuracy compared to its competing counterpart methods. The results demonstrate that AB-LS-SVM technique (optimised by a covariance matrix) can achieve satisfactory results (>99% accuracy) for eleven prominent features in EEG signals. The results are compared with state-of-the-art algorithms (i.e., k-means, SVM, k-nearest neighbour, Random Forest) on identical databases, demonstrating the capability of the AB-LS-SVM method as a promising medical diagnostic tool and its practicality for implementation in seizure detection systems. The study also stated that the proposed approach can aid clinicians in diagnosis and interventions to treat epileptic disease, including its potential use in expert systems where EEG data needs to be classified through advanced pattern recognition.

1.7 Abnormal Event Detection Based on Determinant of the Covariance Matrix Method Coupled with the Hybrid AdaBoost Neural Network

Much research, based on machine learning algorithms, has been conducted on the phenomena of epileptic EEG seizure detection. This study adds to this body of research by proposing an intelligent ML modelling framework for epileptic EEG detection based on the determinant of a covariance matrix (Cov_Det) method integrated with the AdaBoost Back-Propagation neural networks (AB-BP-NN) algorithm. The objective model is constructed by segmenting EEG signals into small, empirically-chosen intervals, followed by employing the Cov_Det each of these intervals to decrease the dimensionality and extract the representative features. Consequently, the statistical features are extracted from each interval to construct a feature-based vector for each single EEG channel. To eliminate the noisy features generally prevalent in EEG signals, the Kolmogorov–Smirnov (KST) Mann Whitney U (MWUT) Tests are coupled, with the extracted features ranked based on KST, and MWUT metrics and arithmetic operators utilised to figure out the most successful features for each pair of EEG groups. The selected features are fed then to the proposed AB-BP-NN model to classify EEG signals into different EEG groups. The proposed Cov_Det, coupled with AB-BP-NN is conducted on two EEG datasets: epileptic EEG data; and focal and non-focal EEG data. The percentage elucidate the superiority of the proposed Cov_Det model coupled with AB-BP-NN compared with traditional methods and confirm that the proposed Cov_Det model coupled with AB-BP-NN model surpasses the existing state-of-the-art techniques with a high rate 100% of accuracy. The proposed model can be utilised by doctors and neurologists for accurate diagnosis of epileptic seizures.

1.8 An Eigenvalue-based Covariance Matrix Bootstrap Model Integrated with Optimised SVM for Multi-Channel EEG Signals Analysis

The identification of alcoholism is clinically important because of the way the disease affects the operation of the brain. Alcoholics are more vulnerable to health issues, such as immune disorders, high blood pressure, brain anomalies, and heart problems. These health issues also cause a significant cost to the national health system. To help health professionals diagnose the disease with high rate of accuracy, there is an urgent need to create accurate and automated diagnosis systems capable of classifying human bio-signals. An automatic system, denoted as (CT-BS- Cov-Eig based FOA-F-SVM), has been proposed to detect prevalence and health effects of alcoholism from multi-channel EEG signals. The EEG signals are segmented into small intervals, with each segment passed to a clustering technique-based bootstrap (CT-BS) for selection of modelling samples. A covariance matrix method with its eigenvalues (Cov-Eig) is integrated with the CT-BS system and applied for useful feature extraction related to alcoholism. To select most relevant features, a non-parametric approach is adopted, and to classify the extracted features, a radius-margin-based support vector machine (F-SVM) with a fruit fly optimisation algorithm (FOA), (i.e., FOA-F-SVM) is utilised. To assess the performance of the proposed CT-BS model, different types of evaluation methods are employed, and the proposed model is compared with state-of-the-art models to benchmark the overall effectiveness of the newly designed system for EEG signals. The results show that the proposed CT-BS model is more effective than other methods, and a high accuracy rate of 99% is obtained. In comparison with state-of-the-art algorithms (i.e., KNN, k-means and SVM) tested on identical databases describing the capability of the FOA-F-SVM method, the study shows the CT-BS model as a promising medical diagnostic tool with the potential for implementation in automated alcoholism detection systems. The proposed model, as an expert system where EEG data needs to be classified through advanced pattern recognition techniques, can assist neurologists and other health professionals in the accurate and reliable diagnosis of alcoholism.

CHAPTER 2

ADAPTIVE BOOST LS-SVM CLASSIFICATION APPROACH FOR TIME-SERIES SIGNALS CLASSIFICATION SEZURE DIAGONOSIS APPLICATIONS

2.1 Foreword

With more than 65 million people affected worldwide, epilepsy is the most common, chronic, serious neurological disease. People with epilepsy suffer from discrimination, misunderstanding, social stigma, and the stress of living with a chronic unpredictable disease that can lead to loss of autonomy for activities of daily living. It is characterized by frequent episodes that cause involuntary movement of a specific part of the body, or the whole body, followed by a loss of consciousness. From a neurological viewpoint, the primary cause of most cases of epilepsy is unknown or is rather ill-defined. Most medical professionals adopt EEG–an electrophysiological monitoring technique – to capture the electrical activities of the brain by placing electrodes on certain locations of a patient's scalp. In this regard, a robust and intelligent medical diagnosis and early intervention technique developed to identify epileptic seizures can help medical clinicians to address this problem.

In general, visually analysing EEG signals can be considered a tedious, time-consuming and a largely inaccurate task if performed manually, introducing significant errors that can lead, in turn, to catastrophic consequences for epileptic disease treatments. To address such issues, automatic and intelligent methods, based on the covariance matrix coupled with the AB-LS-SVM is proposed to predict seizures in patient's recordings. Therefore, several clinical studies have been conducted using standard EEG epileptic databases recorded at the University of Bonn in Germany. In most of the earlier studies, a maximum of seven different groups were formed. While, in the present study, a much wider combination of eleven possible classification groups ({*A*}vs{*E*}, {*B*}vs{*E*}, {*C*}vs{*E*}, {*D*}vs{*E*}, {*AB*}vs{*E*}, {*AC*}vs{*E*}, {*AD*}vs{*E*}, {*ACD*}vs{*E*}, {*ABCD*}vs{*E*}, {*A*}vs{*C*}vs{*E*}, and {*AB*}vs{*AC*}vs {*AD*}vs{*E*}) was generated. Hence, in this study, a novel contribution is made by constructing the AB-LS-SVM classification approach and finally applying the newly designed method to detect epileptic seizures in patients' EEG records.

The AB-LS-SVM method was designed to classify eleven groups of features in the efficient epileptic detection technique, and results compared with state-of-the-art methods in identical databases. The results of this research demonstrated that the proposed AB-LS-SVM classification method (coupled with covariance matrix method) was able to achieve highly satisfactory results, yielding more than 99% classification accuracy (on average) for eleven classification issues. Moreover, the present findings show that the proposed AB-LS-SVM model has a high potential to be used for real-time detection of epileptic seizure as it entailed less of a time complexity factor compared to several other studies in the existing literature.

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Adaptive boost LS-SVM classification approach for time-series signal classification in epileptic seizure diagnosis applications

Hanan Al-Hadeethi [a,*], Shahab Abdulla [b], Mohammed Diykh [a,d], Ravinesh C. Deo [a,*], Jonathan H Green [b,c]

[a] School of Sciences, University of Southern Queensland, QLD 4300, Australia
[b] Open Access College, University of Southern Queensland, Australia
[c] Faculty of the Humanities, University of the Free State, South Africa
[d] University of Thi-Qar, College of Education for Pure Science, Iraq

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ABSTRACT

Epileptic seizures are characterised by abnormal neuronal discharge, causing notable disturbances in electrical activities of the human brain. Traditional methods based on manual approaches applied in seizure detection in electroencephalograms (EEG) have drawbacks (e.g., time constraint, lack of effective feature identification relative to disease symptoms and susceptibility to human errors) that can lead to inadequate treatment options. Designing an automated expert system to detect epileptic seizures can proactively support a neurologist's effort to improve authenticity, speed and accuracy of detecting signs of a seizure. We propose a novel two-phase EEG classification technique to detect seizures from EEG by employing covariance matrix coupled with Adaptive Boosting Least Square-Support Vector Machine (*i.e.,* AdaBoost LS-SVM) framework. In first phase, the covariance matrix is employed as a dimensionality reduction tool with feature extraction applied to analyse epileptic patients' EEG records. Initially, each single EEG channel is partitioned into respective k segment with m clusters. Subsequently, covariance matrix is adopted with eigenvalues of each cluster extracted and tested through statistical metrics to identify the most representative, optimally classified features. In the second phase, a robust classifier (*i.e.,* AB-LS-SVM) is proposed to resolve issues of unbalanced data, to detect epileptic events, yielding a high classification accuracy compared to its competing counterparts. The results demonstrates that AB-LS-SVM (optimised by a covariance matrix) is able to achieve satisfactory results (>99% accuracy) for eleven prominent features in EEG signals. The results are compared with state-of-art algorithms (*i.e., k-means*, SVM, k-nearest neighbour, Random Forest) on identical databases, demonstrating the capability of AB-LS-SVM method as a promising diagnostic tool and its practicality for implementation in seizure detection. The study avers that the proposed approach can aid clinicians in diagnosis or interventions to treat epileptic disease, including a potential use in expert systems where EEG needs to be classified through pattern recognition.

1. Introduction

According to World Health Organization (Megiddo et al., 2016), epilepsy is a chronic brain disorder that is likely to affect more than 50 million people globally, with approximately 2.4 million people identified with epilepsy annually (Megiddo et al., 2016). Consequently, it affects around 1 per cent of the global population. Epilepsy is characterized by frequent episodes that cause involuntary movement of a specific part of the body, or the whole body, followed by a loss of consciousness. People experiencing epileptic seizures could therefore be susceptible to a major life risk, such as premature death up to three times higher than people who do not experience seizures (Megiddo et al., 2016). In this regard, a robust and intelligent medical diagnosis and early intervention technique developed to identify epileptic seizures can help medical clinicians to address this problem.

From a neurological viewpoint, the primary cause of most cases of epilepsy is unknown, or is rather ill defined. However, some cases could be a result of brain injuries, genetic factors and tumours (Delanty, 2014). Most medical professionals adopt electroencephalography (EEG) – an electrophysiological monitoring technique – to capture the electrical activities of the brain by plac-

* Corresponding authors.
E-mail addresses: HananAliHammoodi.Al-Hadeethi@usq.edu.au (H. Al-Hadeethi), Shahab.abdulla@usq.edu.au (S. Abdulla), mohammed.diykh@usq.edu.au (M. Diykh), ravinesh.deo@usq.edu.au (R.C. Deo), Jonathan.Green@usq.edu.au (J.H Green).

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0957-4174/

ing electrodes on certain locations of a patient's scalp (Tatum IV, 2014). This can provide significant information to explore human brain activities, and distinguish neurological diseases, such as sleep disorders, epilepsies, encephalopathies, brain deaths and comas. In general, visually analysing EEG signals can be considerably a tedious, time-consuming and a largely inaccurate task if performed manually, introducing significant errors that can lead, in turn, to catastrophic consequences for epileptic disease treatments.

To address such issues, automatic and intelligent methods, known as expert systems, designed to help neurophysiologists in detecting the presence of epileptic seizures in EEG recordings, can promote identification and treatment of this condition. For this reason, a vast body of clinical studies has been developed to detect epileptic seizures, as evidenced through EEG signals (Samiee, Kovacs, & Gabbouj, 2014). For example, Li and Wen (2009) have employed a sampling technique based on least square support vector machines (LS-SVM) to extract useful features from EEG; in this study, an average accuracy ranging from 80.31% to 80.05% was evident. In another study, the empirical mode decomposition (EMD) algorithm was adopted by Bhardwaj, Tiwari, Krishna, and Varma (2016) in order to distinguish epileptic seizures in EEG signals where a genetic programming algorithm was used to classify the extracted features. A neural-network approximate entropies model was employed by the studies of Srinivasan, Eswaran, and Sriraam (2007), obtaining an accuracy of nearly 100%. Gotman (1982) proposed an automatic method to detect seizures based on an EEG signal's rhythm, evaluated on a set of 24 superficial recordings and 44 recordings from the intracerebral region in which numerous kinds of seizures were marked.

Similar to the context of the present study, a previous investigation by Lee, Lim, Kim, Yang, and Lee (2014) proposed a wavelet transform model with neural networks and a weighted fuzzy membership function to classify EEG signal from epileptic patients. This work illustrated that their approach was able to identify abnormalities in EEG, and could, thus, support decisions made in respect to medical diagnosis of epilepsy. Sharma, Pachori, and Acharya (2015) developed an automated expert system to classify focal and non-focal EEG signals based on the entropy measure whereas Subasi (2007) suggested a double-loop Expectation-Maximization approach that was used to classify epileptic EEG signals. A study by Ocak (2009) used discrete wavelet transform with an approximate entropy to analyse EEG signals recorded into normal and epileptic classes, while a study by Acharya et al. (2013) utilized wavelet transform-based higher order spectra to extract EEG features in which support vector machine was used with radial basis functions to classify features (*e.g.*, *normal*, *interictal* and *ictal*).

An epileptic detection scheme based on the Tunable-Q factor wavelet transform and the bootstrap aggregation, utilising EEG signals, was proposed by Hassan, Siuly, and Zhang (2016). Sharmila and Geethanjali (2016) introduced a new framework to detect epileptic seizures from EEG signals based on a discrete wavelet transform, and showed that the use of statistical features of the DWT coefficients yielded a high accuracy rate. Empirical wavelet transform-based Hilbert marginal spectrum was used by Bhattacharyya, Gupta, and Pachori (2017) to classify epileptic seizures through EEG signal, with their method achieving a classification accuracy of 99.3%. Fathima, Bedeeuzzaman, Farooq, and Khan (2011) utilized a wavelet-based statistical features approach for seizure detection in EEG signals: a linear classifier was used to classify the extracted features into seizure and seizure-free epochs with an accuracy of 99.5%. Kumar, Dewal, and Anand (2014) adopted discrete wavelet transform from EEG to explore EEG signals to detect epileptic seizures; an approximate entropy was extracted and used to detect seizure activities in EEG. From a plethora of studies, it is therefore evident that machine-learning algorithms developed to extract useful information from EEG signals and classify the features are becoming an important tool in the health informatics area.

The detection of seizures based on entropies have also received significant attention by many researchers who have generally aimed to improve the existing methods and render them suitable for medical diagnosis of epilepsy. A study by Arunkumar et al. (2017), for example, proposed a classification methodology of focal and non-focal EEG based on an approximate entropy (ApEn), Sample entropy (SampEn) and Reyni's entropy as the input features. Kannathal, Min, Acharya, and Sadasivan (2006) compared various entropy features to detect seizures in EEG signal whereas Nicolaou and Georgiou (2012) used permutation entropy, obtaining an average sensitivity of 94.38% and an average specificity of 93.23%. Acharya, Molinari, Sree, Chattopadhyay, Ng, and Suri (2012) tested different types of entropy features, whereas Patidar and Panigrahi (2017) proposed Kraskov entropy for analysis of epileptic EEG signals. Srinivasan et al. (2007) designed a model based on neural-network and approximate entropy, whereas Wang et al. (2017) proposed multi-domain features models to automatically detect epileptic seizure. Acharya, Sree, Chattopadhyay, Yu, and Ang (2011) employed recurrence plots (RP) to classify epileptic EEG signals where recurrence quantification parameters were extracted to classify EEG signals into preictal and ictal groups. The study of Mohseni, Maghsoudi, and Shamsollahi (2006) suggested a variance-based method for detection of epileptic seizures with results showing that the variance-based method was able to gain higher detection rates than the other methods. Recently, Sharma, Dhere, Pachori, and Acharya (2017) used wavelet filter banks to detect focal and non-focal epileptic signals, obtaining an average accuracy, sensitivity and specificity of 94.25%, 91.95% and 96.56%, respectively. Diykh, Li, and Wen (2017) proposed a graph-based technique approach to detect seizures in EEG signal. To sum up, many other research studies have presented reported epileptic detection methods with the various datasets, as per Table 1.

Table 1 illustrates that previous studies focused largely on exploring two to seven classification problems (or EEG features). Despite a number of attempts were made in the design of an automatic system for seizures detection, still to this day no approach has been approved formally by the Federal and Drug Administration. In this paper, the AB-LS-SVM coupled with covariance matrix is developed to predict epileptic seizures effectively. In addition, we aim to expand this scope by considering eleven different classification problems. The present study also addresses issues due to the model input data redundancy that have largely been ignored by previous studies focused on EEG classification. It is noteworthy that previous methods have focused on feature selection, but their approaches were computationally expensive. To address these research gaps and improve the performance of algorithms used previously, this study attempts to improve the classification accuracy of EEG signals relative to previous studies, and also to reduce the computational time by using the following additional approaches:

A covariance matrix method is proposed to reduce the EEG signal (and data) dimensionality whilst extracting most important features for better classification accuracy; A statistical method is used that includes non-parametric methods applied for feature selection; and A newly designed Adaptive Boost Least Square Support Vector Machines (LS-SVM) method, designated as the AB-LS-SVM algorithm, is proposed aimed at predicting the occurrence of seizures in a patient's EEG signal.

Our proposed approach (*i.e.,* AB-LS-SVM algorithm) resulted from several previous methods, albeit on different application problems, where a covariance method was found to be relatively useful in classification-based studies. It should be noted, however,

Table 1
Different epileptic seizures detection approaches with the various datasets.

Investigating authors	Datasets	Proposed method	Accuracy
(Li & Wen, 2009)	EEG database from University of Bonn*, two sets (*A* and *E*)	Sampling techniques (ST)	80.31%
(Bhardwaj et al., 2016)	The whole database consists of five EEG data sets from University of Bonn (denoted as Set A, Set B, Set C, Set D, Set E)	Empirical mode decomposition (EMD)	–
(Srinivasan et al., 2007)	Two sets (Normal EEG and Epileptic EEG)	Approximate entropy (ApEn)	100%
(Gotman, 1982)	24 surface recordings and 44 recordings from intracerebral electrodes	Decomposition of the EEG into elementary waves and the detection of paroxysmal bursts of rhythmic	–
(Lee et al., 2014)	The whole database consists of five EEG data sets from University of Bonn (denoted as Set A, Set B, Set C, Set D, Set E)	Wavelet transform (WT), phase-space reconstruction (PSR) and Euclidean distance (ED)	98.17%
(Sharma, Pachori, et al., 2015)	The dataset consists of 3750 pairs of focal EEG signals and 3750 pairsof non-focal EEG signals	Butterworth filter and wavelet filter banks	87%
(Subasi, 2007)	EEG database from University of Bonn, two sets (*A* and *E*)	Discrete wavelet transform (DWT)	–
(Ocak, 2009)	EEG data used in this study consists of four different sets (Surface, Intracranial, Intracranial, Intracranial)	Approximate entropy (ApEn) and discrete wavelet transform (DWT)	96%
(Acharya et al., 2013)	Different sets(a) normal, (b) interictal and (c) ictal	Continuous Wavelet Transform (CWT), Higher Order Spectra (HOS) and textures	96%
(Hassan et al., 2016)	Inter-ictal, ictal and healthy seizure and non-seizure; ictal and inter-ictal; and seizure and healthy	Tunable-Q factor wavelet transform(TQWT and bootstrap aggregating (Bagging)	98.40%
(Sharmila & Geethanjali, 2016)	The whole database consists of five EEG data sets from University of Bonn (denoted as Set A, Set B, Set C, Set D, Set E)	Discrete wavelet transform (DWT)	100%
(Bhattacharyya, Gupta, et al., 2017)	Seizure (subset S) and seizure-free EEG (subsets *D* and *C*)	Empirical wavelet transform (EWT) based Hilbert marginal spectrum (HMS)	99.3%
(Fathima et al., 2011)	EEG database from University of Bonn, two sets (*A* and *E*)	Wavelet	99.5%
(Kumar et al., 2014)	The whole database consists of five EEG data sets from University of Bonn (denoted as Set A, Set B, Set C, Set D, Set E)	Discrete wavelet transform (DWT) and approximate entropy (ApEn)	95%
(Arunkumar et al., 2017)	50 pairs of focal and non-focal signals	Approximate entropy (ApEn), Sample entropy (SampEn) and Reyni's entropy	98%
(Kannathal et al., 2006)	Normal EEG and Epileptic EEG	Entropies	90%
(Nicolaou & Georgiou, 2012)	The whole database consists of five EEG data sets from University of Bonn (denoted as Set A, Set B, Set C, Set D, Set E)	Permutation Entropy (PE)	88.5%
(Acharya et al., 2012)	Three classes, namely, normal, epileptic background (pre-ictal), and epileptic seizure (ictal)	Approximate Entropy (ApEn), Sample Entropy (SampEn), Phase Entropy 1 (S1) and Phase Entropy 2 (S2)	98.1%
(Patidar & Panigrahi, 2017)	The whole database consists of five EEG data sets from University of Bonn (denoted as Set A, Set B, Set C, Set D, Set E)	Kraskov entropy	97.75%
(Srinivasan et al., 2007)	Two sets of EEG data (normal and epileptic subjects)	Approximate entropy (ApEn)	100%
(Wang et al., 2017)	The whole database consists of five EEG data sets from University of Bonn (denoted as Set A, Set B, Set C, Set D, Set E)	Multi-domain features model	99.25%
(Acharya et al., 2011)	(a) normal (b) ictal and (c) pre-ictal	Recurrence Plots (RP)	95.6%
(Mohseni et al., 2006)	EEG database from University of Bonn, three sets (*A* and *E*)	Variance-based method	100%
(Sharma et al., 2017)	50 pairs of focal and 50 pairs of non-focal	Entropy measures	94.25%
(Diykh et al., 2017)	The whole database consists of five EEG data sets from University of Bonn (denoted as Set A, Set B, Set C, Set D, Set E)	Graph-based machine learning technique	98%

* Synopsis of the clinical data from University of Bonn: set (A = Z) from 5 healthy participants with Eyes open; set (B = O) from 5 healthy participants with Eyes closed; set (C = N), set (D = F) and set (E = S) from 5 epileptic patients, set (C & D) with Seizure free (Inter-ictal) while set (E) with Seizure activity (Ictal).

that in the present study, the covariance matrix has been adopted to reduce an EEG signal's dimensionality and extract the key features from a time-series-based EEG signal. This approach is consistent with some of the earlier methods, for example, that of Sofolahan (2013), which utilized a covariance matrix to predict the behaviour of high dimensional datasets and the study of Bilinski and Bremond (2015), which presented a technique for action recognition in real videos depending on a descriptor (denoted as a video covariance matrix logarithm). Moreover, the study of Ergezer and Leblebicioğlu (2016) studied trajectories using covariance matrix features, whereas Ergezer and Leblebicioğlu (2018) used covariance matrices as a features extractor for time-series signals.

To the best of the author's knowledge, no previous study has utilised the covariance matrix for reducing EEG signals dimensionality and developed AB-LS-SVM for detection epileptic seizures in EEG signals. The contributions and novelty of this research study lies in the incorporation of a covariance matrix approach in a LS-SVM algorithm to reduce the dimensionality of data, leading to improved classification accuracy in the problem of detecting epileptic disease in EEG signals. From a practical point of view, dimensionality reduction can be considered a crucial data pre-processing step required to attain a fast model with accurate performance, given that the most relevant features of EEG signal are used in LS-SVM algorithm. To facilitate this objective, the EEG signals representing important information on epileptic disease conditions were arranged systematically to generate a square matrix prior to reducing the dimensionality, followed by each single channel segmented into four clusters with each cluster further divided in sub-clusters for feature identification. A covariance matrix, with eigenvalues, was applied to reduce dimensionality, employing different sets of statistical features extracted and then evaluated with statistical score metrics. Finally, the study also aimed to apply the newly designed AB-LS-SVM classification model to classify a wider comparison of eleven groups of features, with these comparisons made in respect to state-of-the-art methods, employing the same database for consistency and cross-validation.

2. Datasets

The data utilised in this study were collected at Epileptic Department of the University of Bonn located in Germany. These EEG data, whose details have been provided in an earlier study (Andrzejak et al., 2001), are publicly accessible through a web link http://epileptologie-bonn.de/cms/front_content.php?idcat=193&lang=3. To construct this particular database, the 10/20 international system, which is an internationally recognized method adopted to describe the location of scalp electrodes where relationships between the location of an electrode and the underlying area

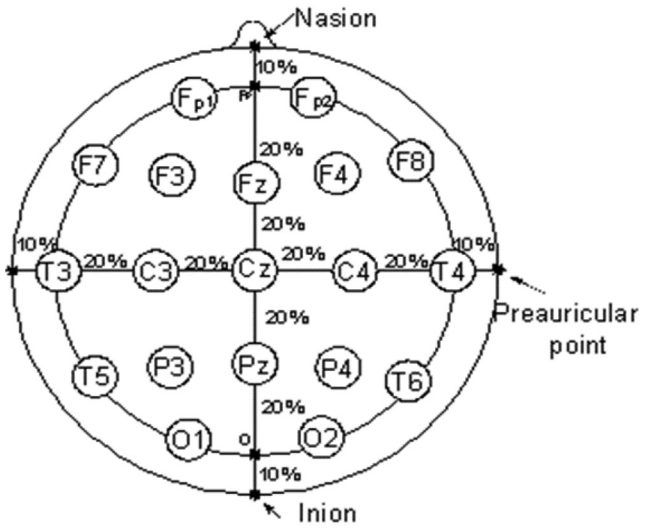

Fig. 1. The 10/20 electrodes placement scheme for data obtained from Epileptic Department at University of Bonn located in Germany. www.aha.ru.

of cerebral cortex can be studied, was utilised to record EEG signals.

The International 10–20 System was adopted to record EEG signals. All of the electrodes were used to record Groups A and B, while the depthless electrodes were used to record the groups C and D, and the electrodes were employed to record group E. Fig. 1 clarifies the pre-surgical assessment of the epileptic patients based on the scheme of intracranial electrodes embedded. With all the EEG recordings, a 128-channel amplifier with a medium mutual reference was utilised. Using a 12-bit resolution, the EEG recordings were observed at 173.61 per second. 0.3–40 Hz a band pass filter was used. EEG signals for all groups were obtained using 100 single EEG channels of 23.6 s. 10 subjects were involved to obtain EEG signals A–E. The datasets were obtained with open eyes in set A and closed eyes in set B, while sets C, D and E were gained from five epileptic patients. The EEG signals of classes C and D were gained from five participators during seizure free (Inter-ictal). While set E was selected from all recording sites displaying ictal activity. To design and evaluate the proposed AB-LS-SVM classification model, all of these classification groups (*i.e., A, B, C, D* and *E*) have been utilized in this research paper.

Fig. 2 illustrates the five classes of epileptic EEG signals (Raghu, Sriraam, Hegde, & Kubben, 2019).

3. Methodology

Based on clinical studies, several devices have been developed to identify and predict seizures prevalent in a patient's recordings using heart-rate monitors, motion sensors, and electrodermal activity sensors. Most of these devices can detect seizures activity in real time, however, predicting a seizure activity well in advance with an intelligent expert system, that can improve the lives of patients with epilepsy, requires more accurate, and effective intelligence model to identify any abnormalities in patient's recordings. In this paper, the covariance matrix coupled with the AB-LS-SVM is proposed to predict seizures in patient's recordings. Therefore, several clinical studies have been conducted using standard EEG epileptic databases recorded at the University of Bonn in Germany (Andrzejak et al., 2001). In most of the earlier studies, a maximum of seven different groups was formed.

It is noteworthy the EEG data used in this paper reflect the actual clinical situation in which most of the acquired EEG signals were non-ictal representing groups *i.e.,* A, B, C, D). To assess the proposed AB-LS-SVM model for this particular situation, several experiments were carried out in which different sets of non-ictal EEG were combined and then classified against set E representing the ictal EEG. In the present study, a much wider combination of eleven possible classification groups (or features) were generated. These included group features from {*A*}vs{*E*}, {*B*}vs{*E*}, {*C*}vs{*E*}, {*D*} vs{*E*}, {*AB*}vs{*E*}, {*AC*}vs{*E*}, {*AD*}vs{*E*}, {*ACD*}vs{*E*}, {*ABCD*}vs{*E*}, {*A*} vs{*C*}vs{*E*}, and {*AB*}vs{*AC*}vs {*AD*}vs{*E*}. The classes were subsequently applied to evaluate the newly proposed AB-LS-SVM approach. In respect to EEG signal classification studies by specific application of a covariance matrix, as proposed in this study, no previous study has derived the data features from such a wide range (eleven) of groups. Hence, in this study, a novel contribution is made by constructing the AB-LS-SVM classification approach and finally applying the newly designed method to detect epileptic seizures in patients' EEG records.

Fig. 3 illustrates the proposed AB-LS-SVM classification method for epileptic EEG signal analysis, where the dimensionality of an EEG signal input is firstly reduced based on the covariance matrix method. This requires the partitioning of each single EEG channel into four different segments of lengths 1024, 1024, 1024 and 1025 respectively. Due to the non-stationary nature of most EEG signals that are recorded in a real-world scenario, each segment is then divided into 32 clusters and the covariance matrix is applied to reduce dimensionality of each of these clusters.

To detect possible abnormalities in the prescribed EEG signal, the eigenvalues of covariance matrix are investigated by means of a statistical test so that the 10 different statistical features could be extracted from each eigenvector. This involved a process where each EEG single channel, which contained (4097) data points, was segmented into window size of 1024, 1024, 1024 and 1025, respectively, to consider the EEG signal's quasi-stationary behaviour, and following this, each segment was further spilt into 32 clusters. To reduce the dimensionality of each cluster, the covariance matrix was applied whereas from the eigenvalues of covariance matrix, a total of 10 statistical characteristics were extracted. As a result, the dimensionality of each segment was reduced from 1024 to 320 (32×10) data points. Consequently, the dimension of each single-channel providing the optimal EEG features was reduced from 4097 to 1280 data points to build the proposed AB-LS-SVM classification system.

Following this, the extracted features are investigated using non-parametric tests. Based on simulation results, not all of the EEG cases can be identified using the same feature set. As result, each EEG group is represented by a set of unique statistical features. More discussion in this respect to this methodology are provided in Section 5. To categorize the extracted features into 'seizure and seizure-free' groups, as prevalent in EEG signals, a new classification model, denoted as the AB-LS-SVM for time series analysis utilizing support vector machine algorithm was designed. Subsequently, the AB-LS-SVM model was validated to ascertain its capability to detect epileptic seizures from real-life datasets recorded at the University of Bonn, Germany (Andrzejak, Lehnertz, Mormann, Rieke, David, & Elger, 2001).

3.1. Segmentation technique

Considering that an EEG signal can exhibit a non-stationary nature, which can also influence the accurate classification capability of the proposed classification model, it is important to examine this issue by dividing the EEG signal set into its respective segments in such a way that these signals can be considered approximately stationary prior to applying the actual classification model. In this study, each single EEG channel is partitioned into four segments of length 1024, 1024, 1024 and 1025, based on a specific

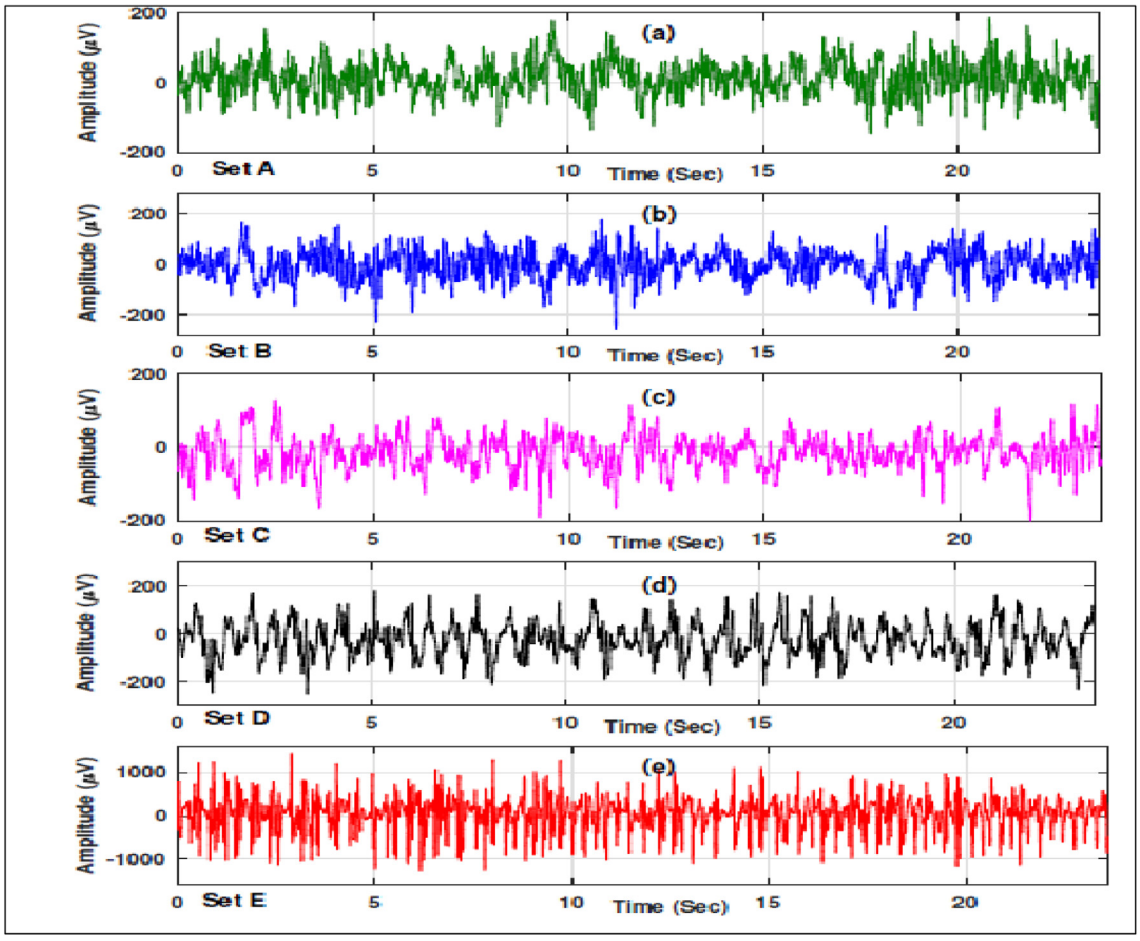

Fig. 2. The five classes of epileptic EEG signals used to design the AB-LS-SVM classification approach applied on eleven possible classification groups using EEG epileptic databases recorded at the University of Bonn in Germany.

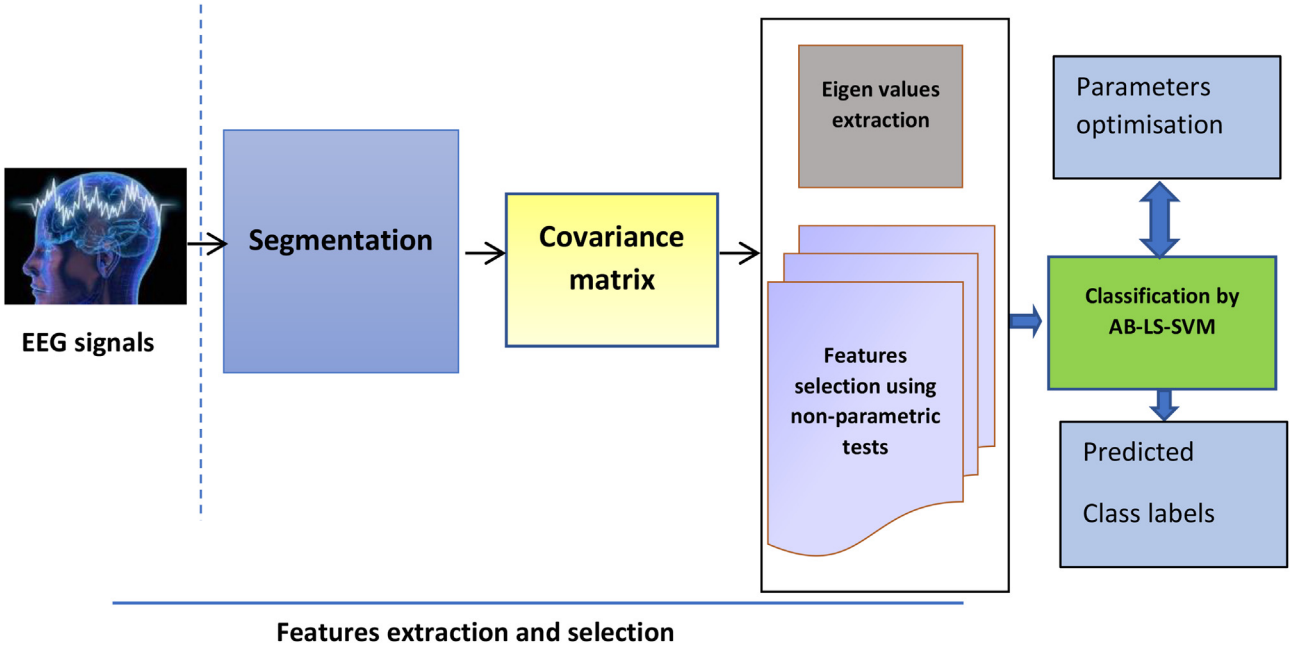

Fig. 3. The newly proposed AB-LS-SVM methodology for epileptic EEG signal classification and detection of the epileptic disease.

period of time (≈5.9 s) for each segment. Further attention is given to the non-stationary nature of the EEG signal where each segment is sub-divided into its sub-clusters. The covariance matrix is then applied to reduce the cluster's dimensionality.

To detect abnormalities in EEG signal, the eigenvalues of covariance matrix are investigated using a statistical method by extracting ten statistical features from eigenvalues of the covariance matrix. These features, based on the mean, median, maximum, minimum, mode, range, standard deviation, variation, skewness and kurtosis, are the key attributes normally used to represent any EEG time series data.

3.2. Covariance matrix and feature extraction process

The covariance matrix, indicated by an asymmetric array of numbers, can potentially reveal several important properties in any continuous signal (Bai & Shi, 2011). This method is a statistical approach based on probability theory. In the mathematical form, the covariance matrix of a random vector $A \in R^n$ and mean vector m_A is defined as:

$$H_A = E\left[(A-m)(A-m)^T\right] \tag{1}$$

The elements $(i,j)^{th}$ of the covariance matrix H_A is given by

$$H_{ij} = E\left[(A_i - m_i)(A_j - m_j)\right] = \sigma_{ij} \tag{2}$$

The diagonal entries of H_A are the vars of the components of the A such as

$$H_{ii} = E\left[(A_i - m_i)^2\right] = \sigma_i^2. \tag{3}$$

$$H_{jj} = E\left[(A_j - m_j)^2\right] = \sigma_j^2. \tag{4}$$

The trace (tr) of H_A is positive because the all diagonal entries are positive such as

$$tr(H_A) = \sum_{i=1}^{n} H_{ii} > 0. \tag{5}$$

Where, H_A is symmetric, $H_A = H_A^T$ because $H_{ij} = \sigma_{ij} = \sigma_{ji} = H_{ji}$, and H_A is positive semidefinite, for all $b \in R^n$

$$E\left\{\left[(A-m)^T b\right]^2\right\} = E\left\{\left[(A-m)^T b\right]^T\left[(A-m)^T b\right]\right\} \geq 0 \tag{6}$$

$$E\left[b^T(A-m)(A-m)^T b\right] \geq 0, b \in R^n \tag{7}$$

$$b^T H_A b \geq 0, b \in R^n \tag{8}$$

where the H_A is symmetric matrix that represents the mean self-adjoint matrix with the usual inner output as its eigenvalues (all real and positive) and the eigenvectors that belong to distinct eigenvalues are orthogonal,

$$H_A = \vee \wedge \vee^T = \sum_{i=1}^{n} \gamma_i \vec{v}_i \vec{v}_i^T. \tag{9}$$

As a result, the determinant of the H_A is positive, *i.e.*,

$$Det(H_A) = \prod_{i=1}^{n} \gamma_i \geq 0. \tag{10}$$

The eigenvectors of the H_A act to convert the random vector into statistically uncorrelated random variables, *i.e.,* into a random vector with a diagonal of H_A. In this work, the covariance matrix is used to reduce the dimensionality of EEG signals. Therefore, let $A_i = (A_1, A_2, \cdots, A_N)^T$ be a $N \times 1$ vector of random variables. N is referred to the number of series, the covariance matrix of the H_A can be calculated as

$$cov(H_A) = \frac{1}{N-1} \sum_{i=1}^{N} (A_i - m)(A_i - m)^T \tag{11}$$

where m is the mean vector of A,$m = \frac{1}{N}\sum_{i=1}^{N} A_i$

3.3. Feature selection method

In this study, the eigenvalues of the covariance matrix are investigated using different statistical metrics to select most the influential features as per our earlier studies (*e.g.*, (Diykh, Miften, Abdulla, Saleh, & Green, 2019)) and, also, to discern and subsequently discard the largely irrelevant features in the EEG signal (Abdulla, Diykh, Laft, Saleh, & Deo, 2019; Diykh, Abdulla, Saleh, & Deo, 2019). The number of observation used in this paper for epileptic EEG data is represented as a matrix of 100 rows (all channels) and 4098 columns (data points) for each EEG group (A-E), while for focal and non-focal EEG signals a total of 3750 pairs of focal EEG segments and 3750 pairs of non-focal EEG segments were used in this paper (Diykh, Li, & Abdulla, 2020).

To reduce the dimensionality of the input (EEG) data used in the classifier algorithm, the features extracted from these EEG signal are studied more closely using non-parametric tests depending on the statistical theory of each method and their hypotheses, we obtain the set that has the most distinguishing features. Tables 2 and 3 below show the different sets of features in EEG signals that pass the prescribed test. Following this method, nonparametric tests are applied to study robustly the classified features of the EEG signals to detect epileptic disease.

3.3.1. Non-Parametric methods

A Kolmogorov–Smirnov Two-sample test (*K–S* test) is one of the beneficial and common nonparametric approaches for comparing two samples. It is a nonparametric hypothesis test that evaluates the difference between the CDFs of the distributions of the two sample data vectors over the range of x in each data set. The two-sided test uses the maximum absolute difference between the CDFs of the distributions of the two data vectors, calculated using the following (Lilliefors, 1967):

$$K^* = \max_x \left(\left|\widehat{P}_1(x) - \widehat{P}_2(x)\right|\right) \tag{12}$$

where (*) means the sizes of first and second sample respectively, $\widehat{P}_1(x)$ is the proportion of x_1 values less than or equal to x and $\widehat{P}_2(x)$ is the proportion of x_2 values less than or equal to x. In this paper, the number of sample size considered large so the null hypothesis is rejected at level α if:

$$K^* > c(\alpha)\sqrt{\frac{size\ of\ first\ sample + size\ of\ second\ sample}{size\ of\ first\ sample \times size\ of\ second\ sample}} \tag{13}$$

A Wilcoxon Rank Sum Test or Wilcoxon–Mann–Whitney test is a non-parametric method that can be used to test the null hypothesis that two samples come from the same population (have the same median) or, alternatively, whether observations in one sample tend to be larger than observations in the other. Although it is a non-parametric method but it does assume that the two distributions are similar in shape, calculated utilising the following (Mann & Whitney, 1947; Shier, 2004):

$$W_1 = S_1 - \frac{n_1(n_1+1)}{2} \tag{14}$$

Table 2
Feature selection based on Wilcoxon metric.

Feature statistics	A vs E (1)	B vs E (2)	C vs E (3)	D vs E (4)
Mean	8.8850×10^{-51}	3.5644×10^{-34}	3.0679×10^{-34}	1.4805×10^{-30}
Max	2.6403×10^{-34}	2.9506×10^{-33}	5.2605×10^{-34}	1.7111×10^{-28}
Min	0.0859	0.1147	0.1205	0.1755
Mode	0.0859	0.1147	0.1205	0.1755
Median	2.5058×10^{-17}	8.7550×10^{-14}	9.3038×10^{-25}	5.9617×10^{-28}
Range	2.6403×10^{-34}	3.4202×10^{-33}	5.2605×10^{-34}	1.7111×10^{-28}
Var.	2.5621×10^{-34}	5.7540×10^{-34}	3.3569×10^{-34}	2.4999×10^{-29}
St	2.5621×10^{-34}	1.8926×10^{-33}	1.1424×10^{-33}	2.4999×10^{-29}
Skew	0.1295	0.2873	1.8976×10^{-18}	2.4057×10^{-11}
Kur	0.05	0.5149	8.9044×10^{-18}	6.0631×10^{-11}

Table 3
Features selection based on Kolmogorov metric.

Feature statistics	*A* vs *E*	*B* vs *E*	*C* vs *E*	*D* vs *E*
Mean	9.0430×10^{-57}	5.3352×10^{-42}	5.3352×10^{-42}	8.6551×10^{-34}
Max	1.5506×10^{-45}	1.3166×10^{-38}	8.8103×10^{-38}	5.0583×10^{-30}
Min	1.4660×10^{-09}	9.1220×10^{-09}	2.2056×10^{-08}	5.2233×10^{-08}
Mode	1.4660×10^{-09}	9.1220×10^{-09}	2.2056×10^{-08}	5.2233×10^{-08}
Median	6.6643×10^{-19}	1.0553×10^{-11}	8.2362×10^{-24}	3.5891×10^{-27}
Range	1.5506×10^{-45}	1.3166×10^{-38}	8.8103×10^{-38}	5.0583×10^{-30}
Var.	1.5506×10^{-45}	2.7628×10^{-40}	2.7628×10^{-40}	2.9582×10^{-32}
St	1.5506×10^{-45}	2.7628×10^{-40}	2.7628×10^{-40}	2.9582×10^{-32}
Skew	0.003	0.2606	3.9632×10^{-16}	5.6969×10^{-10}
Kur	5.8125×10^{-04}	0.2606	1.1514×10^{-16}	5.6969×10^{-10}

$$W_2 = S_2 - \frac{n_2(n_2+1)}{2} \tag{15}$$

where n_1, n_2 sample size of sample 1 and 2 respectively, S_1, S_2 are the sum of the ranks in sample 1 and 2 respectively.

3.4. Performance evaluation

To evaluate the performance of the epilepsy classification and detection system based on the proposed AB-LS-SVM method, the following metrics are used.

3.4.1. Accuracy

The term of accuracy is used to evaluate the performance of the AB-LS-SVM method based on the following formula

$$\text{Accuracy} = (TP + TN)/(TP + TN + FP + FN) \tag{16}$$

In Eq. (15), the true negative (TN) refers to the actual non-epileptic correctly classified as non-epileptic and true positive (TP) means the actual epileptic segments correctly identified. Also, the false negative (FN) refers to the epileptic segments incorrectly marked as non-epileptic, while false positive (FP) denotes to the number of epileptics incorrectly determined by the AB-LS-SVM method (Baldi, Brunak, Chauvin, Andersen, & Nielsen, 2000); (Polat & Güneş, 2007).

3.4.2. Sensitivity

Sensitivity is a statistical metric employed to calculate the rate of real positive classification values (Sokolova, Japkowicz, & Szpakowicz, 2006):

$$\text{Sensitivity} = TP/TP + FN \tag{17}$$

3.4.3. Specificity

Specificity refers to the proportion of real negative prediction, defined as follows (Sokolova et al., 2006):

$$\text{Specificity} = TN/(TN + FP) \tag{18}$$

3.4.4. Predictive positive value

Predictive Positive Value (PPV) is defined as the rate of positive classification samples that correspond to the presence of the epileptic conditions, as described by Altman and Bland (Altman & Bland, 1994).

$$PPV = TP/TP + FP \tag{19}$$

3.4.5. Predictive negative value

Predictive Negative Value (PNV) is the ratio of negative classification samples that correspond to the absence of the epileptic condition (Altman & Bland, 1994).

$$PNV = TN/TN + FN \tag{20}$$

3.5. AdaBoost based LS-SVM technique (AB-LS-SVM classifier)

Over the last few decade, the demand for automated expert systems to reliably predict seizure has increased, in order to improve current epileptic warning devices that can be used to identify the onset of such events in the absence of a clinical symptom. Generally, the presence of non-epileptic segments and its features in any real-world EEG data are higher than that of the epileptic-based segments. To differentiate the relatively smaller quantity of non-epileptic segments from the epileptic type segments and also to balance the EEG data (as a requirement for machine learning algorithm), the newly proposed hybrid technique denoted as AB-LS-SVM classifier is proposed. Fig. 4 describes the proposed AB-LS-SVM classifier technique that was established for the present EEG classification problem.

Firstly, the EEG data are partitioned into the training and the testing sub-sets from the full dataset. Next, the important features related to epileptic conditions are extracted based on the techniques described in Section 3.4. Within the proposed AB-LS-SVM algorithm, the AdaBoost technique has been used for training purposes to attain a robust classifier system that is able to discern the epileptic events from the non-epileptic events. The LS-SVM classi-

fication method (*i.e.*, Stage 2 of Fig. 4) is employed to discriminate the features for non-epileptic events, to classify them into different classes such as *A*, *B*, *C* and *D*. If one EEG segment is recognised as a non-epileptic event using the AdaBoost classifier, the LS-SVM is employed hereafter to identify the specific category of the predictive non-epileptic segments (*i.e.*, Stage 3 of Fig. 4). The details of the proposed AB-LS-SVM algorithm are described next.

3.5.1. AdaBoost classifier: Stage 1

In this study, we adopt the AdaBoost classifier, which is a well-known machine learning algorithm that has been used to train different classifier systems (Freund, Schapire, & Abe, 1999). Based on AdaBoost classifier mechanism, the alpha (or the 'weights') and the theta (or the 'error rate') values of the training samples are updated after each iteration step. The weights of the training sets, which remain misclassified, are increased and the weights of the training sets with the correct classification rate are decreased. As a result, the weaker classifiers are combined to construct an overall robust classifier system.

3.5.2. Non-epileptic EEG events classification based on LS-SVM: Stage 2

In pattern recognition, the LS-SVM algorithm has been employed for different classification problems, comparing relatively well with other classification algorithms, including artificial neural networks. In principle, an LS-SVM model is relatively easy to develop, and apply, and it provides acceptable classification rates in several application domains, such as image classification and biomedical signals. In the proposed AB-LS-SVM model, we apply this algorithm to specifically classify the non-epileptic EEG events.

3.5.3. Testing based on the AB- LS-SVM: Stage 3

The testing phase is implemented based on the trained AB-LS-SVM classifier (*i.e.*, Stage 3 of Fig. 4). This model's useful patterns are first extracted from EEG signals, and then, a further selection of the most optimal features is carried out using a set of statistical score metrics. The set of extracted features is passed through trained AdaBoost classifier. If an EEG segment is classified as a non-epileptic event, the learned SVM model is then utilized to recognize its class; otherwise, this testing sample is allocated to an epileptic segment.

3.6. Feature selection

To improve the efficiency of the proposed AB-LS-SVM, the noisy features are removed and the optimal once are selected to represent each EEG signal group using statistical score metrics. The results show that not all EEG groups can be represented with the same feature set. Two non-parametric methods were chosen to achieve the concept of dissimilarity which provides an initial idea of the shape of the data. Thus, we demonstrate that not all features are valid for classification. Tables 2 and 3 report the results of feature analysis, showing that some features fail to pass these tests using the Wilcoxon Rank Sum to test the null hypothesis that two samples are from continuous distributions with equal medians, against the alternative that they are not. Based on the Wil-

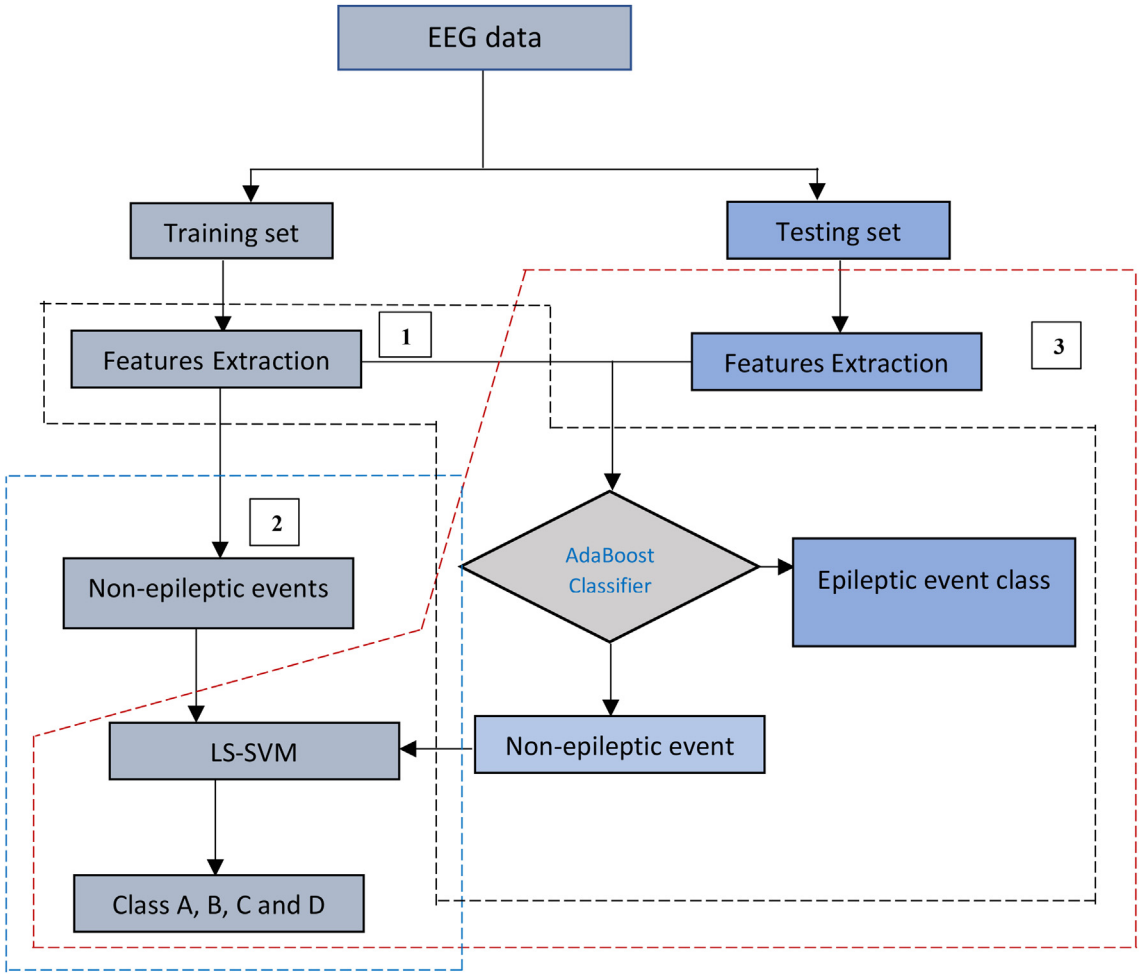

Fig. 4. The newly proposed AB-LS-SVM classifier technique to split and identify EEG data into classes *A, B, C* & *D*.

coxon test, to differentiate group B against E, the statistical features based on mean, max, median, range, variance and standard deviation values were seen to adhere to the underlying assumptions of this test. However, for the group C against E, the mean, max, median, range variance, standard deviation, skew and kurtosis values representing the features producing a p-value less or equal to 0.05 that were accepted, while those with values exceeding 0.05 were rejected. The cells coloured indicate that there is not enough evidence to reject the null hypothesis with equal medians (no difference between populations) at the 0.05 significance level.

To determine if two datasets differ significantly, the assumptions of Kolmogorov–Smirnov two samples (*K-S*) test H_0 : two samples are from the same continuous distribution vs H_1 : two samples are not from the same continuous distribution. Table 3 reports the results obtained from the *K-S* test indicates that rejects the null hypothesis at the 0.05 significance level. The *K-S* test results presented in Table 3 support the results obtained in Tables 2, by which each group was represented with a different features set.

In accordance with these results, features that passed both tests have been used that means each problem was classified using a different set of features. Table 4 reports the final feature set for each problem based on our investigations in Table 2 and 3. To classify the group {*A, B, C and D*} against group *E*, we combined the two features sets *(i.e., A* vs *E* and *B* vs *E*) to obtain the best representative feature set.

Table 4 shows the final features set used to identify each pair of EEG groups. As a result, to classify any combination of EEG groups such as AB vs CD, we used mathematic operates employing the union and intersection operation to obtain the features set to identify these groups (AB vs CD). We made a thorough investigation in features selection section to select the most effective features set to recognise EEG groups.

4. Experimental results

Next, we evaluate the AB-LS-SVM classifier, coded in MATLab, designed for analysing epileptic EEG signals collected at the Epilepsy Department at the University of Bonn. Several statistical metrics were used to assess the proposed method. A 5-fold cross validation was also applied, and all experiments were performed on a desktop computer with the following capabilities: Intel (R) Core 7 CPU and RAM of 8.0 GB.

4.1. Classification results

The performance of AB-LS-SVM classifier model was assessed in terms of the sensitivity (SE), specificity (SP), accuracy (ACC), positive predict value (PPV) and the negative predict values (NPV). Eleven classification problems were assessed using 5-fold cross-validation approach. Tables 5–9 present the classification results using the proposed AB-LS-SVM model. For the most important classification problem {*A, B, C* & *D* vs *E*}, the model achieved a classification accuracy exceeding 98%. Similarly, an average accuracy of 97%, 99% and 100%, respectively, was obtained for classification problems {*B* vs *E*}, {*C* vs *E*}, and {*D* vs *E*}. It is noteworthy that that most epileptic detection studies have largely conducted their experiments using an unbalanced number of samples. In this study, we resolved this potential problem by using an equal and unequal number of samples for classification of different cases represented by: {*A*}vs{*E*}, {*B*}vs{*E*}, {*C*}vs{*E*}, {*D*}vs{*E*}, {*AB*}vs{*E*}, {*AC*}vs {*E*}, {*AD*}vs{*E*}, {*ACD*}vs{*E*}, {*ABCD*}vs{*E*}, {*A*}vs{*C*}vs{*E*}, and {*AB*}vs {AC}vs {*AD*}vs{*E*}.

The results are presented in Table 5, which show that the highest accuracy of 99% and 100% was achieved from the classification *A* against *E*, and of *C* against *E*, respectively. To investigate this result more closely, a different combination of these groups was also formed and classified against *E*, as follows:

4.1.1. Experiment 1: (AB against CD against E)

In this particular experimental phase, the EEG data from groups *A*, *B*, *C* and *D* were classified against group *E*. Tables 5 and 6 show the 10-fold cross-validation and the resulting confusion matrix results using the proposed AB-LS-SVM method. Notably, the aver-

Table 4
Final feature set.

Problem	Features
A vs *E*	[mean, max, median, range var, standard deviation and kurtosis]
B vs *E*	[mean, max, median, range var, standard deviation]
C vs *E*	[mean, max, median, range var, standard deviation, skewness and kurtosis]
D vs *E*	[mean, max, median, range var, standard deviation, skewness and kurtosis]
{A, B} vs *E*	$\{A\ vs\ E\} \cap \{B\ vs\ E\}$
{A, B, C} vs *E*	$\{A\ vs\ E\} \cup \{B\ vs\ E\} \cup \{C\ vs\ E\}$
{A, B, C, D} vs *E*	$\{A\ vs\ E\} \cup \{B\ vs\ E\} \cup \{C\ vs\ E\} \cup \{D\ vs\ E\}$

Table 5
Classification accuracy for *A-D* vs *E*.

5-Fold cross validation metric	*A* vs *E*	*B* vs *E*	*C* vs *E*	*D* vs *E*
Accuracy	99%	100%	98%	99%
Sensitivity	98%	99%	99%	99%
Specificity	99%	98%	99%	99%

Table 6
Classification accuracy for (*AB* vs *CD* vs *E*).

	Range of 10-fold cross validation metric	Average
Accuracy	97–100%	99%
Sensitivity	97–100%	99%
Specificity	98–100%	99%

Table 7
Confusion matrix for classification (*AB* vs *CD* vs *E*). Note that ictal (*E*) refers to a physiologic state or event such as a seizure, stroke, or headache whereas interictal (CD) refers to the period between seizures, or convulsions, that are characteristic of an epilepsy disorder.

Epileptic Condition	Normal (*AB*)	Interictal (*CD*)	Ictal *E*
Normal (*AB*)	233	5	1
Interictal (*CD*)	23	217	0
Ictal E	0	5	115

Table 8
Classification accuracy for {*AB* vs *C, D, E*}

	Range of 10-fold cross validation metric	Average
Accuracy	97–100%	99%
Sensitivity	97–100%	99%
Specificity	98–100%	99%

Table 9
Classification accuracy for {*A, B*} vs {*C, D*}

	Range of 10-fold cross validation metric	Average
Accuracy	97–100%	99%
Sensitivity	98–100%	99%
Specificity	98–100%	99%

age accuracy and sensitivity were found to be between 99% and 100%.

4.1.2. Experiment 2: normal vs epileptic classification (AB vs CDE and AB vs CD)

In this experiment, different binary classification problems are investigated: normal {*A, B*} against non-seizure epileptic {*C, D*}, normal {*A, B*} against non-seizure and seizure epileptic {*C, D, E*} and 10-fold cross-validation approach was used to assess the performance of the proposed AB-LS-SVM classifier model. Tables 8 and 9 report the classification results. Despite some degree of variation among the different validation results, an average accuracy of 98.2% was obtained for *AB* vs *CD* while for the case {*A, B*} vs {*C, D, E*}the method achieved an average accuracy of 99%, indicating the versatility of proposed classification scheme adopted for epilepsy detection using the EEG signal.

4.2. Comparison with different classification algorithms

To evaluate the robustness in terms of its capability to classify EEG signals in epileptic patients, the objective model (*i.e.,* AB-LS-SVM) performance was compared against some of the well-known classifier systems including support vector machine, *k-means*, *k*-nearest neighbour and Random Forest method. The features extracted by these methods were forwarded to the four classifiers, and the obtained results were recorded.

Table 10 reports the 10-cross validation results in respect to several other competing methods used previously in EEG signal classification problems. Evidently, the AB-LS-SVM classifier system outperformed the other classifiers, while the SVM model (without the AdaBoost algorithm) attained the second highest accuracy level among all of the five-classifier systems. Notably, the weakest performance, with a mean of sensitivity of about 90.5% and a mean accuracy of about 92.8%, was attained by the *k*-nearest classifier method.

4.3. Evaluation of AB-LS-SVM classifier for focal and non-focal EEG signals

In this section, we evaluate the capability of the AB-LS-SVM classifier to extract features from another dataset: the focal and non-focal EEG signals, obtained from the Bern-Barcelona database generated at the Department of Neurology (University of Bonn). It should be mentioned that these data were crosschecked by methodological procedures described in Section 3. Table 11 reports the classification results obtained by AB-LS-SVM classifier system. Importantly, the AB-LS-SVM classifier system applied to focal and non-focal databases attained significantly accurate results, exceeding the performance *k-means*, *k*-nearest neighbour, SVM and Random Forest approaches for all 10-fold validation runs.

Table 10
Comparison of the objective method (*i.e.,* AB-LS-SVM) with the other classifiers used as a validation tool.

Classifier type	Performance evaluation methods	Average of 10 folds
AB-LS-SVM (Objective Classifier)	Acc	99%
	Sen	99%
K-means	Acc	93%
	Sen	91.05%
SVM	Acc	96.5%
	Sen	94.2%
k-nearest neighbour	Acc	92.8%
	Sen	90.5%
Random Forest	Acc	94%
	Sen	93%

4.4. Evaluation of AB-LS-SVM method using receiver operating characteristic (ROC)

Other than checking the computation time required to emulate the AB-LS-SVM classifier, Figs. 5 and 6 also show the ROC and the area under the curve for the proposed AB-LS-SVM against other *k-means*, *k*-nearest and SVM using University of Bonn and focal and non-focal (Bern-Barcelona) dataset. The highest value of the area under the curve was found to be approximately 0.99 with the Bonn University data and approximately 0.98 with focal and non-focal dataset. Moreover, with the University of Bonn dataset, different classification cases were also tested, and all of the results attained were recforded for further analysis. The results demonstrated the improved capability of the proposed AB-LS-SVM classifier used to differentiate the epileptic groups.

4.5. Evaluation of the influence of feature selection on classification results

To assess the efficiency of the feature selection on epileptic seizures detection, the extracted statistical features in Section 3.5 were forwarded at the same time to the proposed method without feature selection phase. The simulation results confirmed that there were big differences in the detection results when the all features used to detect epileptic seizures without elimination the noisy features. Fig. 7 reports the classification results for the eleven groups, including {A}vs{E}, {B}vs{E}, {C}vs{E}, {D}vs{E}, {AB}vs{E}, {AC}vs{E}, (Zahra, Kanwal, ur Rehman, Ehsan, & McDonald-Maier) vs{E}, {ACD} vs{E}, {ABCD}vs{E}, {A}vs{C}vs{E}, and {AB}vs(Zahra et al.) vs {E} with and without using feature selection to classify epileptic EEG data.

5. Comparison with literature investigations and further discussion

To investigate the efficacy of the proposed AB-LS-SVM technique relative to the other benchmark approaches, a comparison of our method to some of the more recently reported approaches in existing literature is now made. Table 10 reports the comparison of various methods against the proposed AB-LS-SVM method. Importantly, the proposed method, by achieving a classification accuracy of 99%, is considered as a significant improvement compared to state of the art approaches in the existing literature. To provide a robust comparison, we present the results from the proposed methods together with twelve other studies. Based on these comparisons, as presented in Table 12, we note that the study of (Martis et al., 2012) classified EEG signals into normal, inter-ictal and ictal subjects based on empirical mode decomposition method where the accuracy obtained was lower than the proposed AB-LS-SVM method.

The studies of Martis et al. (2013), Nigam and Graupe (2004) and Hsu and Yu (2010) also proposed an automatic seizure detection method, but it is evident that our proposed AB-LS-SVM classifier system outperformed their approaches. While the study of Tawfik, Youssef, and Kholief (2016) classified group *A* vs group *E* using weighted permutation entropy combined with an SVM

Table 11
The classification results using the focal and the non-focal dataset.

Classifier	Mean	Standard deviation
AdaBoost-LS-SVM	98.07	0.6405
k-means	93.08	0.534094
SVM	96.02	0.57735
k-nearest neighbour	92.11	0.408248
Random Forest	94.07	0.493548

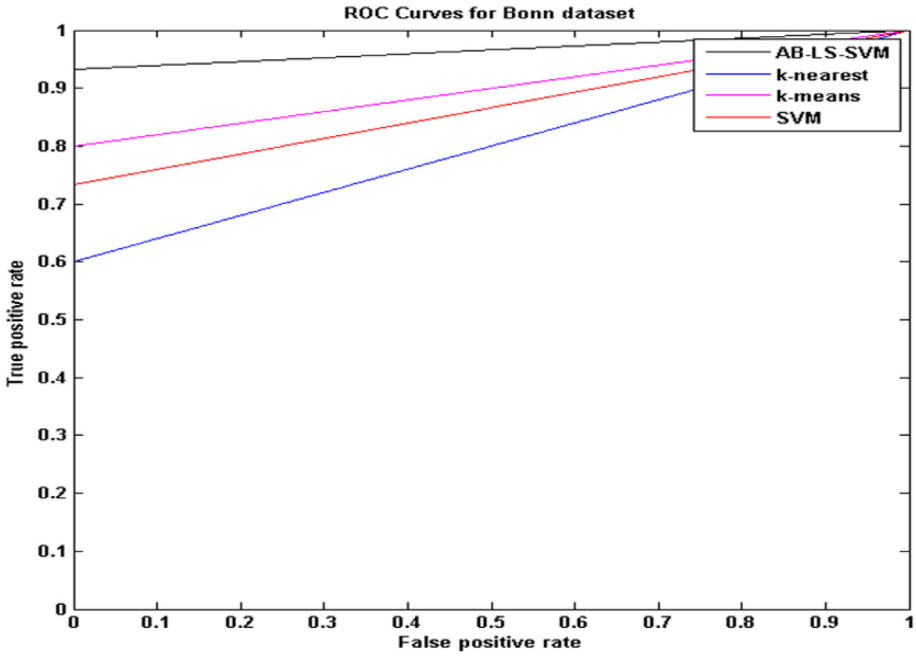

Fig. 5. ROC using University of Bonn dataset.

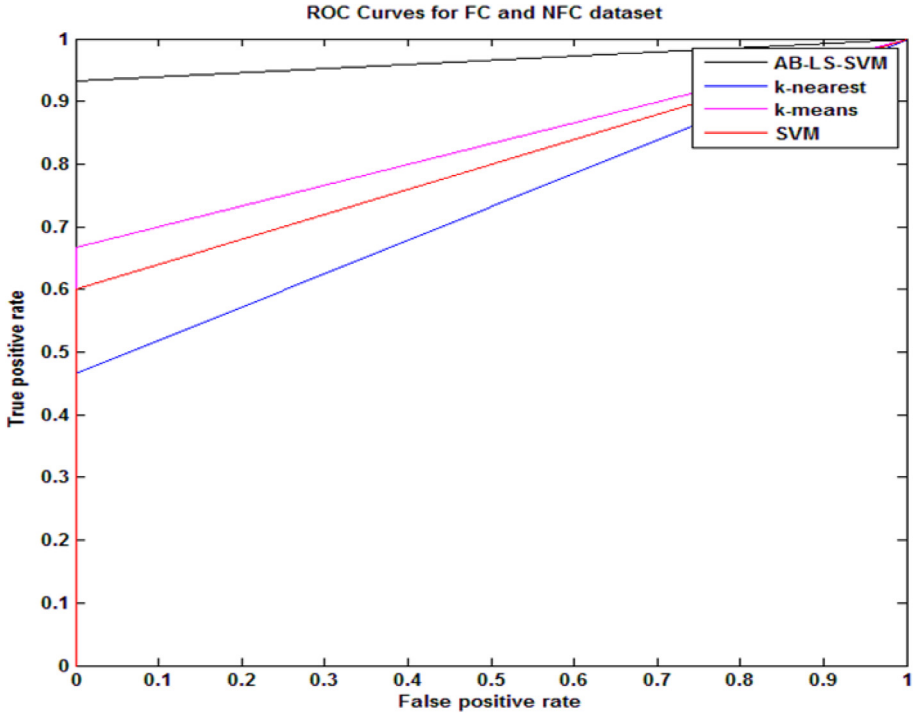

Fig. 6. ROC using the focal and non-focal (Bern-Barcelona) dataset.

model, in that study, only the classification accuracy (and not several other performance metrics used in the present study) was reported. Moreover, Pippa et al. (2016) classified EEG signals into epileptic and non-epileptic segments based on a combination of time and frequency type features with different machine learning methods, but their results were relatively less accurate (in terms of the statistical score metrics stated in Section 3.3) compared to the results obtained by the proposed AB-LS-SVM classifier system.

Further relevance of the AB-LS-SVM method can be gleaned from other studies, such as Martis et al. (2015), who used a nonlinear feature model utilizing Hurst exponent (HE), Higuchi fractal dimension (HFD), largest Lyapunov exponent (LLE) and sample entropy (SE). In the study of (Alam & Bhuiyan, 2013), an empirical mode decomposition combined with neural networks was used, with these authors reporting only the classification accuracy. Another study, Ahammad, Fathima, and Joseph (2014) proposed a

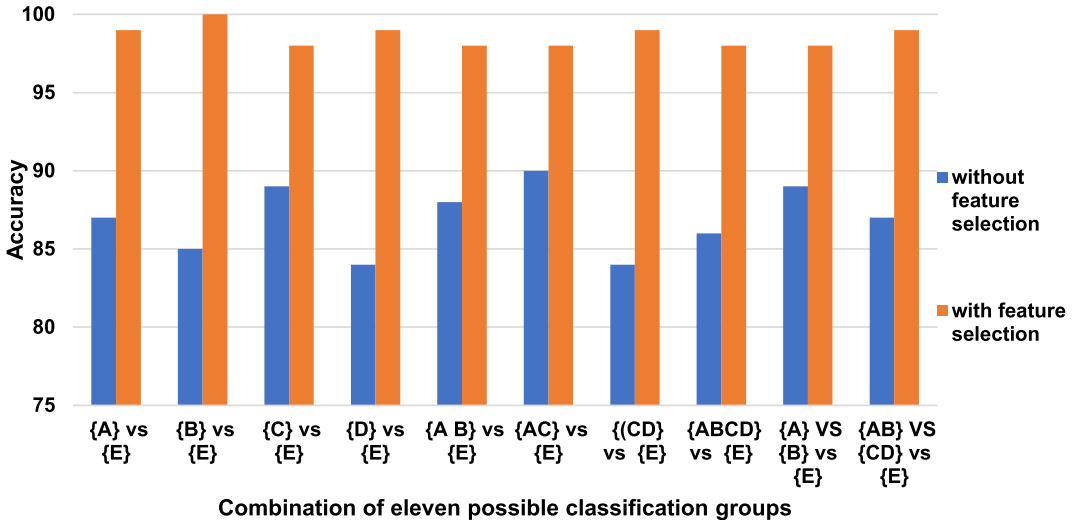

Fig. 7. Shows the differences in results between using feature selection and without using feature selection.

Table 12
Comparison of the proposed method against different epileptic seizures detection approaches with the same datasets.

Study & authors	Approaches	Accuracy	Sensitivity	Specificity
(Martis, Acharya, Tan, Petznick, Yanti, Chua, & Tong, 2012)	Empirical mode decomposition (EMD)	95.33%	98%	97%
(Martis, Acharya, Tan, Petznick, Tong, Chua, & Ng, 2013)	Intrinsic time-scale decomposition (ITD)	95.67%	99%	99.5%
(Nigam & Graupe, 2004)	Multistage nonlinear pre-processing filter in combination with a diagnostic (LAMSTAR)	97.2%	–	–
(Hsu & Yu, 2010)	Genetic algorithm	–	95.8%	–
(Tawfik, Youssef, & Kholief, 2016)	Weighted permutation entropy blended with a SVM	93.75%	–	–
(Pippa et al., 2016)	Time domain and frequency domain features	95%	97%	99%
(Martis, Tan, Chua, Loon, Yeo, & Tong, 2015)	Nonlinear parameters on different frequency bands	98%	99.5%	100%
(Alam & Bhuiyan, 2013)	Empirical mode decomposition	80%	–	–
(Ahammad et al., 2014)	wavelet-based features and certain statistical features	84.2%	–	–
(Riaz et al., 2015)	Empirical mode decomposition (EMD)	96%	–	–
(Bhattacharyya, Gupta, et al., 2017)	Quality factor (Q) based multi-scale entropy measure	99%	–	–
(Kabir & Zhang, 2016)	Optimum allocation technique with logistic model tree	95%	94%	99%
Proposed method	Covariance matrix and AB-LS-SVM	99%	99%	–

new model utilizing wavelet-based features and certain statistical features without wavelet decomposition to detect epileptic seizure events and their onset, yielding a total rate of accuracy of 84.2%.

We also refer to study of Riaz, Hassan, Rehman, Niazi, and Dremstrup (2015), which provided a process for feature extraction using empirical mode decomposition (EMD) applied to the dataset including the identification of epilepsy patients and detection of seizures. However, the results obtained by AB-LS-SVM method were considerably accurate in terms of statistical score metrics, therefore, demonstrating a significant improvement over earlier studies. The present study was also considerably better and achieved 99% classification accuracy compared to Bhattacharyya, Pachori, Upadhyay, and Acharya (2017) that used empirical wavelet transform (EWT) based Hilbert marginal spectrum (HMS) to classify epileptic seizure EEG signals but attained a 50% accuracy of their trained classifier model. The epilepsy detection approach, improved by covariance matrix method, was found to exceed the performance of Kabir and Zhang (2016) that has also utilized datasets identical to the present research study.

By analysing information in Table 13, it is clear that the AB-LS-SVM approach can be considered an optimal data classification method for this database when compared against the most recent works in this field of study. This deduction leads to the following important points as a major contribution of this study:

The 10 statistical features based on the median, maximum, minimum, mean, mode, range, standard deviation, variation, skewness and kurtosis extracted to represent EEG data in this study, were investigated using non-parametric metrics to show that not all EEG cases can be identified using different features set.

However, most epileptic detection studies have conducted experiments using an unbalanced number of samples in both cases. In this study, we resolved this problem by using equal and unequal numbers of samples for classification different cases: {*A*} vs{*E*}, {*B*}vs{*E*}, {*C*}vs{*E*}, {*D*}vs{*E*}, {*AB*}vs{*E*}, {*AC*}vs{*E*}, {*AD*}vs{*E*}, {*ACD*}vs{*E*}, {*ABCD*}vs{*E*}, {*A*}vs{*C*}vs{*E*}, and {*AB*}vs{*AD*}vs{*E*}.

In terms of sensitivity (SE), specificity (SP), accuracy (ACC), positive predictive value (PPV), and negative predictive value (NPV) the performance of the proposed AB-LS-SVM model was assessed. Eleven classification problems were assessed using the 5-fold cross-validation procedure.

Experimental results demonstrated that the proposed method covariance matrix coupled with an AB-LS-SVM method seemed to achieve the most satisfactory results with more than 99% classification accuracy on average for eleven classification issues.

6. Concluding remarks

An accurate detection of epilepsy, by means of capturing persistent neuronal features of this disease with a fast, automated and

robust modelling approach, remains a significant challenge in the field of medical diagnostics and the rapidly advancing health informatics area. In this research, an efficient epileptic detection technique was proposed, together with a robust statistical approach for data dimensionality reduction and feature extraction, to yield a reliable and versatile classification model applied to detect epileptic conditions. To generate a reliable EEG classification model, a covariance matrix was applied to reduce the dimensionality of data to be later employed in the proposed AB-LS-SVM model. To achieve this, the eigenvalues of covariance matrix derived from EEG signals were investigated using a statistical model, and different sets of statistical features arising from these eigenvalues and tested using performance criteria metrics. The AB-LS-SVM method was designed to classify eleven groups of features in the efficient epileptic detection technique, and results compared with state-of-the-art methods in identical databases.

The results of this research demonstrated that the proposed AB-LS-SVM classification method (coupled with covariance matrix method) was able to achieve highly satisfactory results, yielding more than 99% classification accuracy (on average) for eleven classification issues. Moreover, the present findings show that the proposed AB-LS-SVM model has high potential to be used for real-time detection of epileptic seizure as it entailed less of a time complexity factor compared to several other studies in existing literature. While the present study has clearly led to an improved method for the detection of epilepsy, an independent study in future could also apply the proposed technique to detect many other issues, such as signs of sleep spindles and *k*-complexes prevalent in EEG signals. This study therefore avers that the proposed AB-LS-SVM method should be explored further to develop a possible seizure early warning system within a medical diagnostic platform that can potentially assist the practising neurologists to more efficiently diagnose and treat the underlying neurological disorder evident in the EEG signal of such patients.

CRediT authorship contribution statement

Hanan Al-Hadeethi: Conceptualization, Methodology, Software, Validation, Data curation, Formal analysis, Writing - review & editing. **Shahab Abdulla:** Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing - review & editing. **Mohammed Diykh:** Conceptualization, Supervision, Investigation, Writing - review & editing. **Ravinesh C. Deo:** Supervision, Writing - review & editing, Investigation. **Jonathan H Green:** Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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CHAPTER 3

ABNORMAL EVENT DETECTION IN A TIME-SERIES-BASED DETERMINANT OF THE COVARIANCE MATRIX METHOD COUPLED WITH THE HYBRID NEURAL NETWORK: AN EPILEPSY DISEASE DETECTION STUDY

3.1 Foreword

The latest reports indicate that more than 20% of patients are affected by generalized epilepsy which apparent throughout the entire brain, whilst more than 60% of patients suffer from focal epilepsy, localized to a smaller region of the brain. It is not often effective to treat patients with focal epilepsy with medication alone.

In spite of the significant efforts made by the aforementioned researchers, the Federal and Drug Administration has not yet approved formally an approach or system for EEG epileptic seizure detection. This reveals that there is significant scope to improve the methodologies used in previous works. Therefore, in this chapter a new computerized model of epileptic seizure and Focal & Non-Focal detection that is based on the determinant of a covariance matrix (denoted as Cov_Det model) coupled with the AdaBoost Back-Propagation neural network (AB-BP-NN) approach, has been suggested. To the best of the authors' knowledge, this is the first implementation of the Cov_Det model coupled with the AB-BP-NN model for epileptic seizure and Focal & Non-Focal identification. In this study, each EEG signal was partitioned into its respective segments and then each segment was divided into several intervals or clusters, with the Cov_Det model applied to each of the clusters to reduce the dimensionality of the underlying EEG dataset. This was followed by the extraction of a set of statistical features from each interval to generate the final feature vector set, with the noisy features being eliminated using the Kolmogorov–Smirnov Test (KST) and the Mann Whitney U Test (MWUT). After this optimisation process, the final feature set was then fed into the AB-BP-NN algorithm to classify the EEG signal into the normal and the epileptic segments.

In summary, the acquired outcomes clearly demonstrate the superiority of the proposed Cov_Det model coupled with AB-BP-NN vs the existing state-of-the-art techniques. The proposed technique achieved an average accuracy of 100% and 98.86% for the

two datasets, respectively, which is considered a noteworthy improvement compared to the state of the art methods, conducting comparisons with eleven other studies described in this section. The proposed model can be utilised for aiding neurologists and other medical specialises in the accurate diagnosis of epileptic seizures.

Abnormal Event Classification Utilising the Determinant of Covariance Matrix Method Coupled with a Hybridized AdaBoost Back-Propagation Neural Network: An Epilepsy EEG Signal Classification Study

Hanan Al-Hadeethi[1], Shahab Abdulla[2*], Mohammed Diykh[1, 4*], Ravinesh C Deo[1] and Jonathan H Green[2, 3]

[1]School of Sciences, University of Southern Queensland, QLD 4300, Australia
[2]Open Access College, University of Southern Queensland, Australia
[3]Faculty of the Humanities, University of the Free State, South Africa
[4]University of Thi-Qar, College of Education for Pure Science, Iraq
*corresponding author: Shahab Abdulla & Mohammed Diykh

Abstract

Objective: the present study adds to such growing body of research, proposing an artificial intelligence AI framework tailored for epileptic EEG signals classification based on determinant of a covariance matrix (*Cov–Det*) method coupled with the AdaBoost Back-Propagation neural network (*AB–BP–NN*) algorithm.

Approach: the objective model is constructed by segmenting EEG signal into small, albeit empirically chosen intervals, applying *Cov–Det* to each of these intervals to reduce the dimensionality of input data and extract representative features in EEG. To construct an accurate and reliable *AB–BP–NN* EEG classification methodology the statistical features are extracted from each interval of data time series to construct a feature-based vector for each single EEG channel. To eliminate noisy features that are generally prevalent in EEG signals the Kolmogorov–Smirnov (KST) and Mann Whitney U (MWUT) Tests are integrated so that the extracted features are ranked based on KST and MWUT metrics and arithmetic operators adopted to deduce the most pertinent classified features for each pair of the EEG signal group. The selected features are fed into the newly proposed *AB–BP–NN* model to effectively classify EEG signal into different groups.

Main results: the proposed technique achieved an average accuracy of 100% and 98.86% for the two datasets (epilepsy & focal and non-focal), respectively, which is considered a noteworthy improvement compared to the state of the art methods.

Significance: comparing the studies that obtained an equivalent rate of accuracy to our result, most of the researches has been applied on part of datasets, while we have been applied the proposed model on whole datasets and analysed eight problems,

which clearly showed the superiority of our proposed *Cov–Det* based *AB–BP–NN* model.

Keywords: Electroencephalography, Covariance matrix, Determinant, Focal EEG signals, Non-focal EEG signals, epileptic EEG data, *AB–BP–NN*.

1. Introduction

The human brain is a complex organ with millions of nerve cells called neurons, the command centre of the central nervous system (Kazanis, 2009). These cells produce electrical impulses and messages to produce thoughts, feelings, movement and control body functions (Attwell and Iadecola, 2002). Epilepsy is a disorder of the brain (brain disease) characterized via an enduring readiness to generate epileptic seizures and by the neurobiologic, cognitive, psychological, and social consequences of this condition (Fisher et al., 2005). Socially, it is not easy to receive an individual with this disorder. Furthermore, it could be dangerous if the person is swimming or driving due to loss of consciousness (Arunkumar et al., 2017). Based on the latest UN report on epilepsy, more than 50 million people worldwide have this disease www.who.int/health-topics/epilepsy#tab=tab_1. The number of people with epilepsy is expected to rise further because of increasing life expectancy worldwide and a rising ratio of people surviving insults that often lead to epilepsy, such as birth trauma, traumatic brain injury (TBI), infections of the brain and stroke (Organization, 2019). Thus, it is crucial to diagnose epilepsy correctly and provide the right treatment to the patient.

To record brain activity there are different types of technique can be used such as electroencephalogram (EEG) and Magnetic resonance imaging (MRI). Also, these techniques considered helpful tools in the diagnosis of epilepsy. However, EEG is the preferred data type used for epilepsy diagnosis due to it is low cost (Acharya et al., 2019).

Focal epilepsy is a shape of condition that appears in particular brain areas (Pati and Alexopoulos, 2010); (Acharya et al., 2019). When the first ictal EEG changes are observed, the focal (Foc) EEG signals are gained from this region. While brain regions that do not contribute to seizure onset, the Non-focal (N-Foc) EEG signals are acquired. Reports showed that more than 20% of patients are suffering from generalized epilepsy that appears from the entire brain, whilst greater than 60% of

patients affected by focal (partial) epilepsy, localized to a smaller region of the brain (Pati and Alexopoulos, 2010); (Acharya et al., 2019).

Seizure activities are usually identified visually by inspecting EEG recordings, this way is a manual method requiring significant expertise, time and effort. Moreover, the results of this method can depend very much on the level experience and expertise of medical professionals. Nevertheless, clinical studies have shown that a seizure can leave its signature on a patient's EEG recording, and as such, health informatics researchers employing artificial intelligence methods are nowadays applying EEG signal classification methodologies to classify epileptic EEG recording. However, in most cases, it is quite difficult to classify epileptic using EEG signals, especially if such information are required in a short period for a detailed and quick diagnosis of this disease. Hence, developing an automated epileptic classification model can be considered as an indispensable medical diagnostic tool that can aid doctors in analysing more carefully.

2. Related work

Considering that an EEG recording, together with some of the other records from the patient, can be adopted as a secondary tool in diagnosis of this disease, several clinical studies have attempted to develop predictive models to detect an epileptic seizure from EEG signals. One of the earlier examples was an automatic technique, proposed by Gotman (1982), designed to detect seizures depending on the rhythm of an EEG. The study of Theodore et al. (1985) recommended 1BF-fluorodeoxyglucose with positron emission tomography to study clinical absence and generalized seizures. Placencia et al. (1992) proposed a new approach employing a two-stage process to detect epileptic seizure. Senhadji and Wendling (2002) recommended wavelet transform and time-frequency algorithms to investigate EEG (ictal and inter-ictal) signals. Nigam and Graupe (2004) applied a multistage nonlinear pre-processing filter based on an artificial neural network approach, while Kannathal et al. (2005) compared different entropy estimators to designate normal data from epileptic EEG. Acharya et al. (2011) suggested a new technique based on the recurrence plot for automated identification of epileptic EEG data. These studies clearly advocate the possibility of diagnosing epileptic disease using health informatics systems on EEG signals through artificial intelligence (AI) methods.

Many studies are employing AI methods aimed to improve a baseline model by integrating a set of two or more methods. For example, the study of Fathima et al. (2011) applied a wavelet-based feature selection approach to an AI model for epileptic seizure detection. A new model was also suggested by Acharya et al. (2012) for an automatic detection of normal, pre-ictal, and ictal conditions from recorded EEG signals. The study of Kumar et al. (2014) and Lee et al. (2014) applied wavelet transform techniques to detect epileptic seizures in EEG signals, whereas Sharma et al. (2015a) presented a novel method for the classification of focal and non-focal EEG signals using entropy measures. Their method was able to differentiate focal EEG signal from the non-focal EEG signal, yielding an average classification accuracy of 87%. Diykh et al. (2017) proposed a novel technique to classify epileptic EEG signal based on weighted complex network where a community structure detection algorithm was employed to demonstrate its efficiency in detecting epileptic seizures.

More recently, to improve AI methods, a plethora of research has been focused on using convolutional neural networks (CNN), generalized linear model (GLM), principal component analysis (PCA), global volatility index (GVIX), Tunable-Q wavelet transform (TQWT), neural network model (NNM), fractal dimension (FD), Recurrence Quantification Analysis (RQA), Cross-frequency coupling (CFC), and Discrete Wavelet Transform (DWT) as follows: Lu and Triesch (2019) proposed CNN model with residual connections to detect the onset of seizure trained on raw EEG data. An automatic epileptic EEG detection method based on CNN with two innovative improvements in a data classification problem was proposed by Wei et al. (2019). Türk and Özerdem (2019) adopted CNN to demonstrate its ability to learn the properties of scalogram-based images, whereas the study of Hu et al. (2019) suggested the idea of utilising CNN for feature extraction and support vector machines for epileptic state classification, with their method achieving a high classification accuracy of 86.25%. A time series of epileptic components identified on EEG signals was extracted by Ebrahimzadeh et al. (2019), whereas Capitán et al. (2019) used PCA and distribution of power in different frequency bands to detect epileptic seizures accurately. The GVIX method was employed to measure the holistic signal fluctuation in wavelet coefficients and the original time-series signal studied by Miao et al. (2019), whereas TQWT method was applied by Bhattacharyya et al. (2019) to detect epileptic seizure. San-Segundo et al. (2019) advocated for a deep neural network model to test

the Bern-Barcelona EEG signals and the Epileptic Seizure Recognition data, while a new model was developed by Diykh et al. (2019a) using the fractal dimension (FD) based on a sine cosine driven support vector machine algorithm to identify the focal and the non-focal EEG signals. Gruszczyńska et al. (2019) applied Recurrence Quantification Analysis classified epileptic EEG signals, Yu et al. (2019) investigated frequency bands during an epileptic event in a given patient using cross-frequency coupling, and Tzimourta et al. (2019) used DWT to identify epileptic EEG segments.

In spite of significant efforts made by aforementioned researchers, the Federal and Drug Administration has not yet approved formally an AI approach or a health informatics system to classify epilepsy EEG signals. This reveals that there exists a significant scope to improve the AI methodologies used in previous work. Therefore, this study proposes a new computerized model of epileptic classification that is based on the determinant of a covariance matrix (denoted as *Cov–Det* model) coupled with the AdaBoost Back-Propagation neural network (*AB–BP–NN*) approach. To the best of the authors' knowledge, this is the first implementation of *Cov–Det* model coupled with the *AB–BP–NN* model for epileptic EEG signals identification. Even though many studies have obtained an accuracy rate of 100% and based on the information in the discussion section, the proposed method is considered the best because it was applied to all data sets with eight problems analysed.

3. The EEG datasets

3.1 Focal and Non-Focal database

In this study the Bern-Barcelona dataset collected at The University of Bern Department of Neurology (Andrzejak et al., 2012) was employed to evaluate the proposed *AB–BP–NN* approach. This data comprised of 3750 pairs of focal (FC) and non-focal (NFC) signals containing a relatively large volume of intracranial EEG signals. The number of patients was five, with pharmaco-resistant temporal lobe epilepsy involved in the recording of these signals (labelled *X* & *Y* for FC and NFC data, respectively). Depending on the respective channel and visual identification by two neurologists, the FC recordings from all five subjects were captured. These recordings were utilised to detect the first ictal EEG change. However, NFC recordings were recorded from channels within the neighbourhood of FC channels, whilst all the other channels were categorised as FC EEG channels. The sampling

frequency of all EEG recordings was kept at 512 Hz, and each one contained 10,240 samples. This research aimed to evaluate the proposed approach utilising all 3740 FC signals and 3750 of NFC signals collected. Figurer 1 shows an example of the FC and NFC EEG signals (Raghu and Sriraam, 2018).

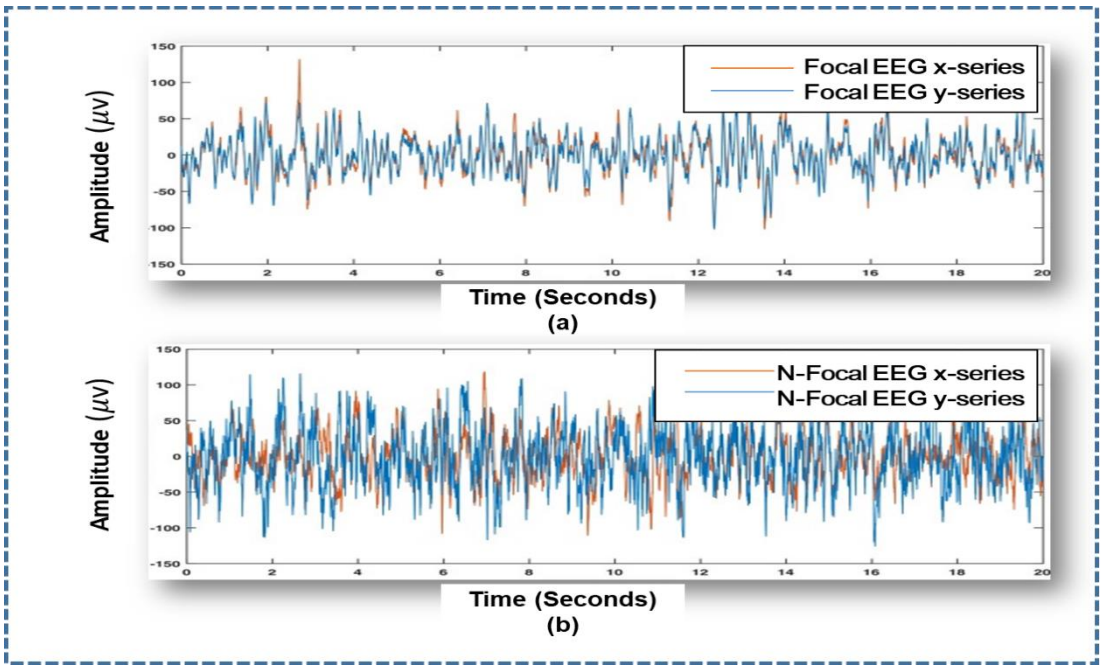

Figure1. An example of the FC and NFC EEG signal.

3.2 The Epileptic EEG database

The epileptic EEG signal database from Department of Epileptology at The University of Bonn located in Germany, is described in previous works (Andrzejak et al., 2001). This database consists of five feature sets, denoted *A–E* with each feature set containing 100 channels running a length of 23.6 s from the five separate classes. Each signal was chosen based on visual inspection for the artefacts, such as the cause of muscle activities or eye movements. With the same 128-channel amplifier system, all EEG recordings were made utilising an average common reference. Utilising the 12-bit resolution all the recorded datasets were digitised at 173.61 samples per second. Figure 2 illustrates the 10–20 system of electrode placement that is used for the recording of the EEG signals (Lagerlund et al., 1993) and Figure 3 reveals the examples of five EEG signals from Set A to Set E. Synopsis of the clinical data from University of Bonn: set (A=Z) from 5 healthy participants with Eyes open; set (B=O) from 5 healthy participants with Eyes closed; set (C=N), set (D=F) and set (E=S) from

5 epileptic patients, set (C & D) with Seizure free (Inter-ictal) while set (E) with Seizure activity (Ictal).

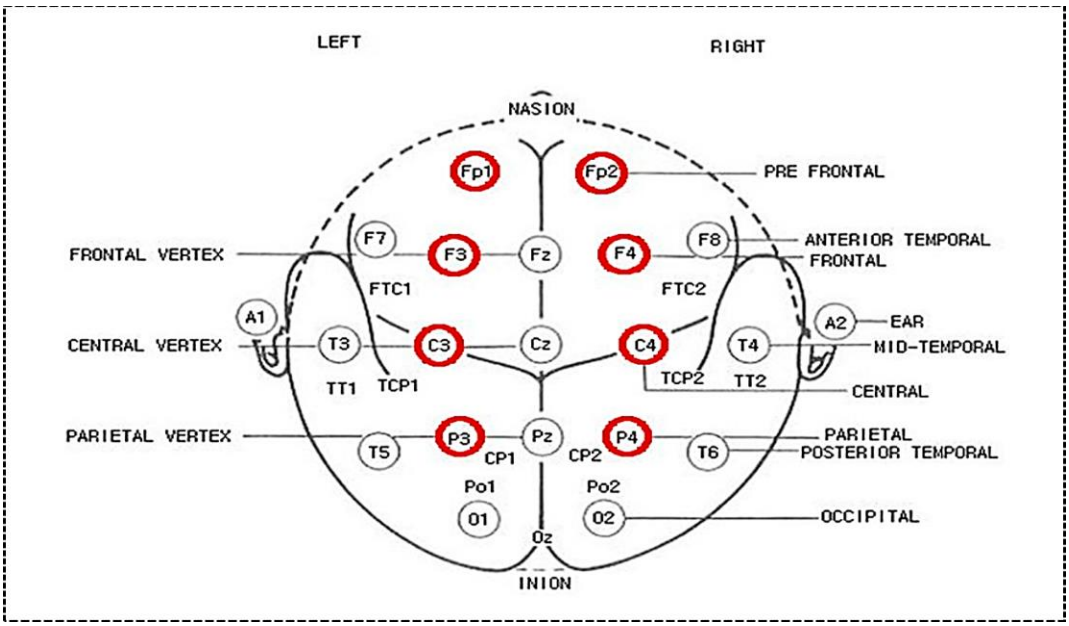

Figure 2. The 10–20 system of electrode placement for the recording of EEG signals.

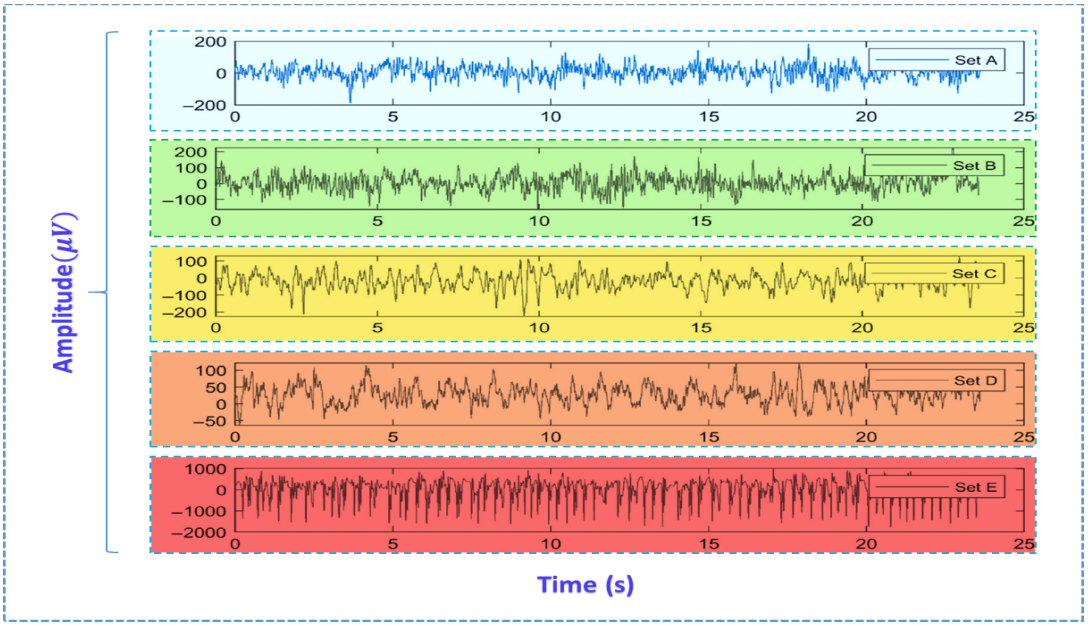

Figure 3. Example of five EEG signals (Sets A to E).

4. Methodology

In this research a new modelling framework utilising the AdaBoost Back-Propagation neural network coupled with covariance and determinant matrix is proposed, reducing time series dimensionality and extracting the most representative

EEG features (Raghu et al., 2019); (Ergezer and Leblebicioğlu, 2018). To assist clinicians in the analysis of EEG signals by reducing the signal dimensionality, eliminating redundant data and subsequently detecting epileptic seizures, this research proposes two kinds of models. Firstly, we propose a model based on the determinant of covariance model (*Cov–Det*) for reduction of data dimensionality and features extraction purposes and secondly, the AdaBoost Back-Propagation neural networks algorithm (*i.e.*, *AB–BP–NN*) is developed for classification of EEG signal that can help identify epileptic disease events.

To implement this process, firstly, each of the EEG signals were partitioned into their respective segments, and, furthermore, each was divided into its respective clusters representing the feature set. Next, the *Cov–Det* model was applied to each EEG cluster to reduce the dimensionality. A set of statistical features, denoted as the *median, maximum, minimum, mean, mode, range, standard deviation, variation, skewness and kurtosis,* was extracted from the EEG signal. To eradicate the noisy components, the extracted features were then investigated using two statistical score metrics based on arithmetic operators (*i.e.*, the Kolmogorov–Smirnov and the Mann Whitney Test). To classify the selected features into their 'normal' and 'abnormal' EEG segments, the hybrid *AB–BP–NN* was designed. Figure 4 shows the general methodology of the proposed hybrid *AB–BP–NN* model tested for the epileptic EEG signal classification. The objectives of this research study can be summarised as follows:

a) To design a feature extraction and dimensionality reduction model by integrating the covariance matrix with the determinant matrix in a single modelling framework to analysis EEG signal datasets;
b) To employ arithmetic operators based the KST and MWUT methods to eliminate the noisy features in EEG signal datasets;
c) To generate a hybrid classification model denoted as the AdaBoost Back-Propagation neural network (*i.e.*, *AB–BP–NN*);
d) To test the performance of the proposed hybrid *AB–BP–NN* model with the other state of the art models to benchmark the overall effectiveness of the newly designed approach for EEG signal and identification of epileptic conditions.

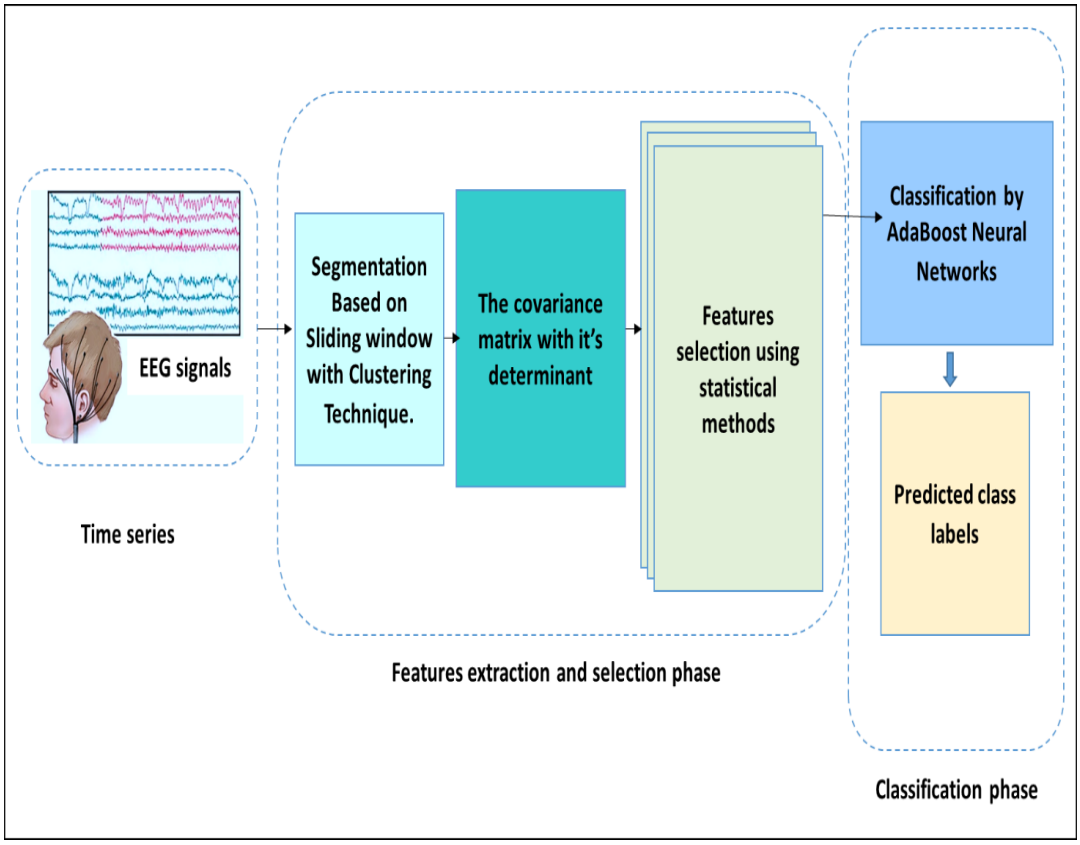

Figure 4. The proposed methodology for EEG signal analysis.

4.1 Segmentation

To ensure validity of the proposed hybrid *AB–BP–NN* model, this study adopted our previous study to segment the EEG signal (Diykh et al., 2017); (Diykh et al., 2018). Evidently, the proposed method generated a highly satisfactory classification accuracy. Mathematically we explain this process as follows: let an EEG signal be denoted as: $X = \{x_1, x_2, \ldots\ldots, x_n\}$ where n is the data point. In this study the EEG signal X was segmented into n segments with each of those segments divided in m clusters. Each segment is divide into 32 clusters to extract the statistical features (Diykh et al., 2019a). During the training session, the number of the clusters was empirically selected. The redundant data in each cluster were reduced by extracting a set of statistical features. Consequently each EEG segment was denoted by a vector of $(f * m)$ features where f was the number of statistical features, and m was the number of clusters. Two EEG databases were used to evaluate the performance of the proposed hybrid *AB–BP–NN* model. For example, the epileptic EEG data contained five groups, *A–E* with each group having 100 single channels containing 4097 data points. Each single channel was divided to four segments (1024, 1024, 1024 and 1025) then each segment was divided into 32 clusters.

4.2 Features extraction

As EEG signals are non-stationary and have no-specific patterns, we have applied *Cov-Det* to be blended with the *AB–BP–NN* model to identify the FC EEG signals and epileptic EEG signal database accurately. This study integrates covariance matrix with its determinant matrix in one model to a design approach that captures relevant features from EEG signals.

4.2.1 Covariance matrix

In a statistical sense, covariance matrix-also known as an auto-covariance matrix, dispersion matrix or a variance matrix-is a matrix whose element in the i, j position is the covariance between the i_{th} and j_{th} elements of a random vector (Anderson, 1962). By using the covariance, the entries of covariance matrix could be calculated, of a random vector $A_{ij} = \sigma(a_i, a_j)$ where $A \in \mathbb{R}^{n \times n}$ with mean vector m represent the dimension or number of random variables of the data (e.g., the number of features). In addition, the covariance matrix is symmetrical since $\sigma(a_i, a_j) = \sigma(a_j, a_i)$, (Carlson, 1988). From the properties of covariance matrix, the diagonal entries are the variances and the other entries are their covariance's (Perlman, 2007). Accordingly sometimes the covariance matrix is called the variance-covariance matrix (MacKinnon and White, 1985). The important properties of the covariance matrix can be summarised as we explained the same scenario as that presented in our earlier study (Al-Hadeethi et al., 2020).

4.2.2 Determinant

The determinant of a matrix is a number (scalar), gained from elements of a matrix by specified, operations, which is an attribute (Lütkepohl, 1996). The determinants are defined just for square matrices (Searle and Khuri, 2017). A determinant is denoted by (Det) or | | for a square matrix. The determinant in which each element in any row, or column, consists of two terms, then the determinant can be expressed as the sum of two other determinants.

4.2.3 Determinants of Covariance matrix Determinants (*Cov–Det*)

Based on basic linear algebra, the determinant could capture how linear transformation changes area or volume, and changes variables in integrals. That led to a process of eliminating the repetition and similarity in computing the high

dimensionality of the database, which was our main target behind the integration of these two approaches: covariance matrix and determinant.

In this study, the matrix elements of EEG time series, with each point having its own characteristic (*e.g.*, time index, magnitude, slope, distance to mean, etc) contained fundamental information that could potentially be used in the present disease classification problem. The primary reason for the utilization of *Cov–Det* as a data shrinking method was to reduce the dimensionality of the EEG signal and eliminate redundant features, while improving the accuracy of the classification model. Initially, a time series can be described as a sequential combination of F points or more formally, written as a vector of length $F([x_1, \dots, x_F])$. The feature candidates, therefore, can be combined in a feature vector set for a point in the EEG time series. Let $\{v_i\}$ be the number of features, defined for a point K. The feature vector for N^{th} point of the subsequence is:

$$a_n = [v_{N1}, \dots, v_{Nk}] \tag{3.1}$$

when feature vectors are merged for all points, this end up with a feature matrix A,

$$A = \begin{bmatrix} v_{11} & \cdots & v_{1k} \\ \vdots & \ddots & \vdots \\ v_{\mu 1} & \dots & v_{\mu k} \end{bmatrix} \tag{3.2}$$

The covariance of the feature matrix is

$$(H_A) = \frac{1}{F-1} \sum_{i=1}^{F-1} (A_i - m)(A_i - m)^T \tag{3.3}$$

where μ is the mean vector of feature vectors $\{a_1, \dots, a_M\}$.

To improve the extraction process, this study aimed to compute the determinant of covariance matrix. Based on essential properties of this covariance matrix, the H_A can be symmetric (*i.e.*, self-adjoint) with the usual inner output its eigenvalues that are all real and positive, and the eigenvectors that belong to distinct eigenvalues orthogonal,

$$H_A = \vee \wedge \vee^T \tag{3.4}$$

Consequently, the determinant of the H_A is:

$$|H_A| = |\vee \wedge \vee^T| = |\vee||\wedge||\vee^T| = |\wedge||\vee||\vee^T| = |\wedge||\vee^T \vee| = |\wedge||I| = \prod_{i=1}^{F} \gamma_i \tag{3.5}$$

In the proposed technique the matrix elements are chosen to be EEG time series which are one dimensional (Raghu et al., 2019). Initially, EEG time series were arranged sequentially to form a square matrix based on covariance matrix with the usual inner output its eigenvalues that are all real and positive, and the eigenvectors that belong to distinct eigenvalues orthogonal, and its determinant was estimated. EEG time series were arranged sequentially to form a square matrix of order 32 cluster. The total elements in the square matrix represent a segmentation length. Then, *Cov-Det* was applied to get a vector (1 × 32), a total of 10 statistical characteristics were extracted. Hence, the dimensionality of each segment was decreased from 1024 to 320 (32 × 10) data points. Therefore, the dimension of each single-channel supplying the optimum EEG features was decreased from 4097 to 1280 data points to build the proposed *AB–BP–NN* classification technique.

4.3 Feature Selection Methods and Outcomes

The idea behind feature selection process is to reduce the probability of model overfitting (Diykh et al., 2019a, Abdulla et al., 2019). By removing irrelevant data, this ensures a classification model is trained only on the most important features (Jović et al., 2015). In addition, removing irrelevant information is expected to increase the accuracy of a predictive model (Chandrashekar and Sahin, 2014) and reduce the computation time involved (Diykh et al., 2019b). Based on statistics applied to measure the similarity and dissimilarity of the means in two independent samples, the study also employed a nonparametric test that was deemed appropriate for comparing two independent samples. Generally, to compare the outcomes between independent samples, there are two popular nonparametric tests: the Kolmogorov–Smirnov test (KST) and the Mann Whitney U test (MWUT). To reduce the dimensionality of input data used in the classifier algorithm, the EEG features extracted from the signal were subjected to these two non-parametric tests. Figure 5 shows the process of obtaining EEG features according to the statistical theory by which the most distinguishing features are extracted from the EEG dataset.

Tables 1 and 2 below show the different sets of input features in EEG signal that pass the prescribed two-stage non-parametric test. It is noteworthy that compound events in a given EEG signal can be captured from diverse sample points, but these could belong to various events. The set theory and its operators, with the most basic

operators being the union and the intersection of the EEG features, can describe these operations. Based on the set theory and its operators, the features selected were those where each event was classified using a diverse set of features. Table 3 shows the final features identified for each event based on our investigation in as shown in Table 1 and 2.

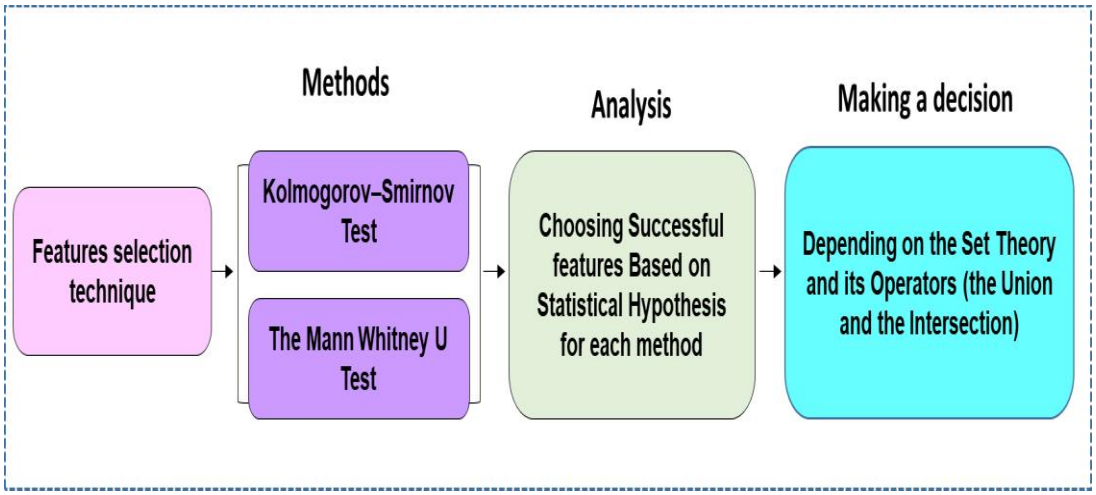

Figure 5. Two-stage feature selection method. Note: Stage 1 was attained by Kolmogorov-Simonov and Stage 2 was attained by Mann Whitney test.

The ability to quantify the (dis)similarity between two different samples is an essential step in the feature selection process of the EEG signal. This study has applied two different ways of achieving this. Dissimilarity measures are based on non-parametric hypothesis tests such as the Kolmogorov–Smirnov test (KST) Mann Whitney U test. These are designed to objectively decide whether two samples are derived from a common population.

4.3.1 Stage One: Kolmogorov–Smirnov test (KST)

Kolmogorov–Smirnov test (KST), a widely-used nonparametric method to test the equivalence of continuous or discontinuous, utilising one-dimensional probability distributions to compare a sample with a reference probability distribution (*i.e.*, one-sample KST), or comparing two samples (*i.e.*, two-sample KST) (Justel et al., 1997). The two-sample KST test is a useful nonparametric method for comparing two groups, as it is sensitive to differences in both location and shape of the empirical cumulative distribution functions of the two samples (Friedman and Rafsky, 1979), (Lilliefors, 1967). The method can be summarised as we explained the same scenario as that presented in our earlier study (Al-Hadeethi et al., 2020).

Table 1. Stage 1 of the features selection process (among the key features denoted as *A, B, C, D & E*) based on Kolmogorov–Smirnov metric

Feature Statistics	A vs E(1)	B vs E(2)	C vs E (3)	D vs E (4)
Mean	3.6964×10^{-12}	1.4660×10^{-09}	4.2607×10^{-13}	5.6969×10^{-10}
Maximum	9.4812×10^{-44}	2.9582×10^{-32}	9.4812×10^{-44}	2.3304×10^{-35}
Minimum	1.2251×10^{-44}	1.9582×10^{-32}	2.7628×10^{-40}	1.6754×10^{-31}
Mode	5.6969×10^{-10}	2.9582×10^{-32}	9.4812×10^{-44}	2.3304×10^{-35}
Median	3.6951×10^{-09}	1.2116×10^{-07}	$5.2233\times^{-08}$	1.4670×10^{-09}
Range	1.2251×10^{-44}	5.1128×10^{-33}	7.1865×10^{-43}	8.6551×10^{-34}
Variance	1.2251×10^{-44}	5.1128×10^{-33}	9.500×10^{-44}	8.6551×10^{-34}
Standard	1.5506×10^{-45}	8.8103×10^{-38}	1.9277×10^{-39}	5.1128×10^{-33}
Skewness	0.14	0.7942	0.0994	0.9610
Kurtosis	0.8938	0.4431	0.3439	0.0470

Table 1 show the results obtained using Stage 1 (KST) feature selection. Evidently, not all EEG groups appear to have the same features. This depends on the hypothesis, test H_0: two samples are from the same continuous distribution *vs* H_1: two samples are not from the same continuous distribution with a level of significance $\alpha = 0.05$. Depending on KST to distinguish between groups *B* against *E*, the features [*max, min, Mode, range, var. and standard deviation*] were seen to meet the assumption. However, for group *C* against *E*, the features based on [*max, min, Mode, range, var., standard deviation and kurtosis*] with the values less or equal to 0.05 were accepted while those with values of more than 0.05 were rejected "green shading".

4.3.2 Stage Two: The Mann Whitney U Test (MWUT)

The Mann Whitney U test (MWUT), referred to as the Mann Whitney Wilcoxon Test or the Wilcoxon Rank Sum Test, is applied to test whether two samples are derived from the same population (Smith-McCune and Weidner, 1994). This test is carried out as a two-sided test and, consequently, the research hypothesis indicates that the populations are not equal, as opposed to specifying directionality (Rosner and Grove, 1999), (McKnight and Najab, 2010). The method can be summarised as we explained the same scenario as that presented in our earlier study (Al-Hadeethi et al., 2020).

Table 2. Stage 2 of the feature selection process (among the key features denoted as *A, B, C, D & E*) based on Mann Whitney U metric.

Feature Statistics	**A vs E(1)**	**B vs E(2)**	**C vs E (3)**	**D vs E (4)**
Mean	0.14364	0.84789	0.13836	0.26889
Maximum	0.00001	0	0	0.00001
Minimum	0.00001	0	0.00001	0.00001
Mode	0	0.00001	0.00001	0
Median	0.22789	0.18177	0.39448	0.20432
Range	0	0	0.00001	0.00001
Variance	0.00001	0.00001	0	0.00001
Standard	0.00001	0.00001	0	0
Skewness	0.067418	0.79658	0.21952	0.076688
Kurtosis	0.73874	0.7871	0.0099791	0.023436

At the second stage, a further investigation of the input features using the (KST) result (*i.e.*, Table 2) through another evaluation test based on MWUT was performed to select the most appropriate features that represented the EEG dataset. Following the hypothesis of MWUT to test the null hypothesis that two samples are from continuous distributions with equal medians, against the alternative that they are not, test values of less than or equal to 0.05 were accepted, whilst those exceeding this threshold were not significant "green shading".

4.3.3 Stage Three: Selected Features

Based on the set theory and its operators, the features selected were those where each event was classified using a diverse set of features, Table 3 has been obtained.

Table 3. The final features data set

Problem	**Features**
A vs *E*	[*max, min, Mode, range, var. and standard deviation*]
B vs *E*	[*max, min, Mode, range, var. and standard deviation*]
C vs *E*	[*max, min, Mode, range, var., standard deviation and kurtosis*]
D vs *E*	[*max, min, Mode, range, var., standard deviation and kurtosis*]
{A, B vs *E}*	$\{A\ vs\ E\} \cap \{B\ vs\ E\}$
{A, C vs *E}*	$\{A\ vs\ E\} \cap \{C\ vs\ E\}$
{A, B, C} vs *E*	$\{A\ vs\ E\} \cup \{B\ vs\ E\} \cup \{C\ vs\ E\}$
{A, B, C, D} vs *E*	$\{A\ vs\ E\} \cup \{B\ vs\ E\} \cup \{C\ vs\ E\} \cup \{D\ vs\ E\}$

Table 3 shows the final features identified for each event based on our investigation in as shown in Table 1 and 2. To classify the group {*A*, *B* and *C*} into group *E*, this research has merged the two feature sets (i.e., *A*, *E* and *B* vs *E*) to attain a superior representative feature dataset.

5. AdaBoost Back-Propagation Neural Network (*AB–BP–NN*)

This study develops the *AB–BP–NN* method based on successful implementation of a back-propagation neural network in an EEG classification problem for abnormal event detection (Owusu et al., 2014). To enhance the performance of traditional neural network models, the AdaBoost technique, resulting in the hybrid *AB–BP–NN*, is proposed where the AdaBoost neural network could be less vulnerable to the issues of data over-fitting compared to some of the other machine-learning algorithms. To resolve this problem, in this study about 15% of the data from the training set are subsequently used to validate each of the neural networks. Figure 6 shows the architectural structure of the proposed hybrid *AB–BP–NN* model. The procedure of implementing AdaBoost Back-Propagation neural network model is as follows:

Let *N* be a set of the weak classifiers or the Back propagation network. This study has trained the i^{th} neural network on the $x_i\ and\ y_i$ sets and then evaluated the classification output of the testing set y_i^{class}, where the distribution *D* is used to calculate the evaluation error for the i^{th} neural network defined as:

$$D_{i+1,j} = D_{i,j} X \left(1 + \delta . I\left(y_j - y_{i,j}^{class}\right)\right) with \begin{cases} i = 1, \dots, L \\ j = 1, \dots, M \end{cases} \quad (3.6)$$

Here, δ is multiplication factor, and $D_{i,j}$ is the ith in D vector.

$$I(x) = \begin{cases} 1 \; if \; x > 0.2 \\ 0 \; otherwise \end{cases} \tag{3.7}$$

The i^{th} neural network assessment error E with the equivalent distribution error D is:

$$E = \sum_{j=1}^{M} |D_{i,j} \, XI\left(y_j - y_{i,j}^{class}\right)| \tag{3.8}$$

Here, I is a binary function:

A weight, w was assigned for the i^{th} neural network based on its error, E. Then, the i^{th} neural network classified p based on the input f. For each neural network, the weights and biases were initialized and the error threshold for I was set to 0.2. To convert the error of each neural network into its respective weight and to provide each neural network with low error and high weight, a covert function was utilised so that w for each neural network was:

$$w_i = \frac{1}{E_i} \tag{3.9}$$

Here, w_i is the weight of i^{th} neural network. The overall classification score was given by the weighted sum:

$$Q = \sum_{i=1}^{m} w_i \, Xp \tag{3.10}$$

The classification score was bounded by [0, 1] with a better score being close to a trivial value. The AdaBoost neural network was employed, therefore, to classify the FC and the NFC EEG signal with the input of the AdaBoost neural network being the extracted features in the EEG signal. In this study, a total of nine input cells were applied based on the number of the input features: two hidden layers with nine cells each. As used in most deep learning algorithms, two transfer functions denoted by the tangent sigmoid (*tansig*) and the rectified linear unit (*ReLU*) function were selected for the first and the second hidden layer, respectively, whereas a pure linear transfer function $(x) = x$ was used for the single node output layer. In the hidden layers, several tests were performed using various activation functions with *tansig* and *ReLU* used to select the best performance. In Figure 6, we show the proposed algorithm hybrid *AB–BP–NN* model.

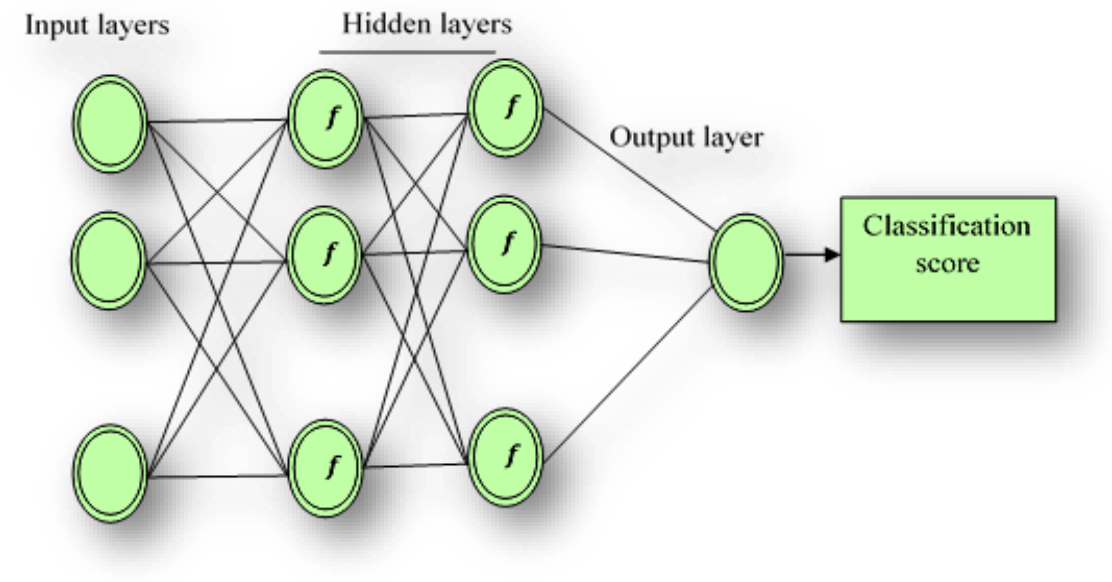

Figure 6. The structure of the newly proposed AdaBoost Back-Propagation neural network (*AB–BP–NN*) model applied for EEG signal classification purposes, and subsequent epileptic disease identification.

6. Performance Evaluation Metrics

To test the performance of the proposed *AB–BP–NN* model, several metrics, used with classification models, were employed: accuracy (*ACC*); sensitivity (*Sen*); specificity (*Spec*); Negative Predictive value (*NPV*); f-scor (*FSCOR*); informedness (*INFO*); negative likelihood ratio (*NLR*); false negative rate (*FNR*); positive likelihood ratio (*PLR*); diagnostic odds ratio (*DOR*); false positive rate (*FPR*); and Mathews-correlation coefficients (*MCC*) (Altman and Bland, 1994), (Baldi et al., 2000), (Youden, 1950). Based on the confusion matrix, the metrics of terminologies based on true positives (*TP*), false negatives (*FN*), true negatives (*TN*), and false-positives (*FP*) were also calculated. Table 4 shows a short description of the score metrics used to evaluate the proposed *AB–BP–NN* model.

Table 4: Summary description of score metrics used to evaluate the proposed *AB–BP–NN* model.

No.	Score Metric	Formula	No.	Metric	Formula
1	*Acc.*	$(TP + TN)/(TP + TN + FP + FN)$	7	*NLR*	*FNR/Spec.*
2	*Sen.*	$TP/(TP + FN)$	8	*DOR*	*(TP/FN)/(FP/TN)*
3	*Spec.*	$TN/(TN + FP)$	9	*INFO.*	*Sen.+Spec.-1*
4	*NPV*	$TN/(TN + FN)$	10	*FNR*	*1-Sen.*
5	*FSCOR*	$2 \times \frac{PPV \times Sen.}{PPV + Sen.}$	11	*PLR*	*Sen./FPR*
6	*MCC.*	*((TP×TN)-(FP×FN))/√((TP+FP)(TP+FN)(TN+FP)(TN+FN))*	12	*FPR*	*FP/(FP+TN)*

7. Results

To evaluate the proposed *AB–BP–NN* model utilising the *Cov–Det* method, two different EEG datasets collected from Bern-Barcelona and Born University were used to detect abnormal events in EEG signals. Specifically, the FC and the NFC EEG datasets included a sufficiently long EEG series of 3750 pairs of FC and the NFC EEG signals, with the epileptic EEG dataset containing five feature subsets, denoted as *A–E*, and each subset collected from 100 single channels.

7.1 Classification results for epileptic EEG data

In this section, the proposed *Cov–Det* based *AB–BP–NN* model is assessed using epileptic EEG data. Eight experiments were conducted to obtain a clear picture of the efficiency of the proposed *Cov–Det* based *AB–BP–NN* model. In each experiment, different pairs of EEG cases were considered as follows.

$\Rightarrow$ Exp.1: $\{A\ vs\ E\}$

$\Rightarrow$ Exp.2: $\{B\ vs\ E\}$

$\Rightarrow$ Exp.3: $\{C\ vs\ E\}$

$\Rightarrow$ Exp.4: $\{D\ vs\ E\}$

$\Rightarrow$ Exp.5: $\{(A, B)\ vs\ E\}$

$\Rightarrow$ Exp.6: $\{(C, D)\ vs\ E\}$

$\Rightarrow$ Exp.7: $\{(A, C, D)\ vs\ E\}$

$\Rightarrow$ Exp.8 $\{(A, B, C, D)\ vs\ E\}$

The EEG data were divided into two equal groups for training and testing, respectively. Table 5 shows the performance of the proposed *AB–BP–NN* model for different EEG cases. The features in Table 5 were considered for each pair of EEG cases. Thirteen different metrics were used to evaluate the performance of the model with classification accuracies of eight cases as: 100%; 100%; 99%; 98%; 100%; 98%; 99%; and 98.5%, respectively. The average of classification accuracy of the proposed *AB–BP–NN* model was 98%, with an average sensitivity and specificity of 99% and 98%, respectively. In addition, the proposed *AB–BP–NN* model also gained high scores for the other performance metrics as showed in Table 5.

Table 5. Classification accuracy under feature selection

Case	*Sen*	*Spec*	*ACC*	*NPV*	*FNR*	*FPR*	*FSCOR*	*INFO*	*NLR*	*DOR*	*PLR*	*MCC*
{*A vs E*}	99%	98%	100%	97%	87%	97%	97%	99%	97%	98%	98%	97%
{*B vs E*}	98%	99%	100%	98%	85%	98%	98%	98%	97%	98%	98%	99%
{*C vs E*}	99%	99%	99%	99%	87%	97%	99%	97%	96%	97%	98%	99%
{*D vs E*}	98%	100%	100%	99%	86%	99%	99%	99%	99%	99%	99%	100%
{*(A, B) vs E*}	99%	98%	99%	97%	85%	98%	97%	97%	98%	97%	97%	97%
{*(C, D) vs E*}	98%	97%	98%	98%	85%	99%	98%	96%	98%	98%	98%	98%
{*(A, C, D) vs E*}	98%	99%	99%	99%	84%	98%	99%	99%	99%	99%	98%	99%
{*(A, B, C, D) vs E*}	99%	98%	98%	98%	86%	98%	97%	97%	98%	97%	98%	97%

To further investigate the findings in Table 5, all features including the [*Mean, max, min, mode, median, range, variance, standard division, Skewness and kurtosis*] were adopted to classify all of the EEG cases, and these were ported to the proposed *AB–BP–NN* classification model without the feature selection phase. The results demonstrated that using the same features set to classify all EEG cases appeared to degrade the classification accuracy. Table 6 and Figure 7 reports the classification accuracy of the proposed *Cov–Det* based *AB–BP–NN* model without feature selection methods and with feature selection.

Table 6. Classification accuracy without feature selection

Case	*Sen*	*Spec*	*ACC*	*NPV*	*FNR*	*FPR*	*FSCOR*	*INFO*	*NLR*	*DOR*	*PLR*	*MCC*
{*A vs E*}	88%	87%	89%	83%	82%	81%	83%	81%	82%	83%	83%	85%
{*B vs E*}	86%	88%	86%	82%	83%	81%	82%	85%	81%	81%	83%	84%
{*C vs E*}	87%	85%	87%	81%	82%	83%	81%	84%	83%	82%	99%	83%
{*D vs E*}	85%	84%	87%	80%	83%	81%	82%	83%	80%	81%	100%	83%
{*(A, B) vs E*}	87%	83%	89%	82%	83%	81%	84%	82%	83%	83%	99%	85%
{*(C, D) vs E*}	88%	85%	85%	83%	82%	83%	83%	84%	81%	81%	98%	83%
{*(A, C, D) vs E*}	86%	86%	84%	82%	84%	84%	82%	82%	83%	83%	82%	82%
{*(A, B, C, D) vs E*}	85%	84%	83%	81%	83%	82%	81%	82%	81%	81%	83%	83%

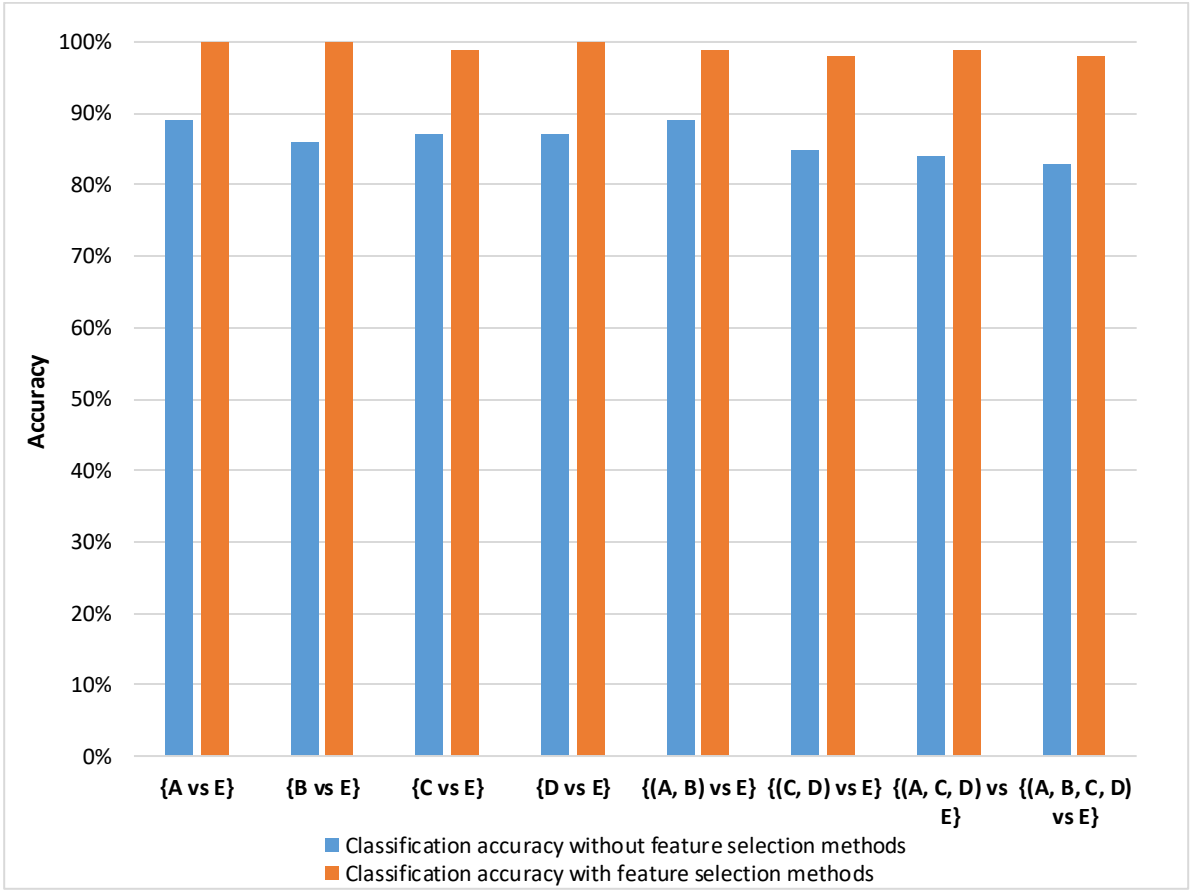

Figure 7. The classification accuracy of the proposed *Cov–Det* based *AB–BP–NN* model without feature selection methods and with feature selection.

As most of the epileptic EEG data are non-ictal, a new experiment that reflected the actual situation of EEG data was designed to test the proposed *Cov–Det* based *AB–BP–NN* model. In this experiment, the epileptic EEG signals were separated into two different sets. The first set comprised of all ictal EEG data while the second set represented the 25% of the non-ictal EEG data for the four non-ictal sets A– D. The experiment was repeated several times, with each of the 25% non-ictal sets of A–D considered. Based on the results, the proposed *Cov–Det* based *AB–BP–NN* model attained a satisfactory performance in all of the experiments with an average accuracy of 97%. Table 7 shows the performance of the proposed *Cov–Det* based *AB–BP–NN* model through a 10-cross-validation process for each EEG case. An overall classification accuracy of 99% was obtained. From the results in Table 7, it can be observed that the classification accuracy is considered to be satisfactory, and it is able to reflect the efficiency of the proposed *Cov–Det* based *AB–BP–NN* model. In addition, we can notice that the performance of the proposed model is stable and there are no high fluctuations in the obtained results among the 10 crosses.

Table 7. Classification accuracy for each EEG Case.

EEG cases	Accuracy based on 10 cross validation
{*A vs E*}	100%
{*B vs E*}	100%
{*C vs E*}	98.5%
{*D vs E*}	99%
{*(A, B) vs E*}	98%
{*(C, D) vs E*}	98.2%
{*(A, C, D) vs E*}	98%
{*(A, B, C, D) vs E*}	98.5%

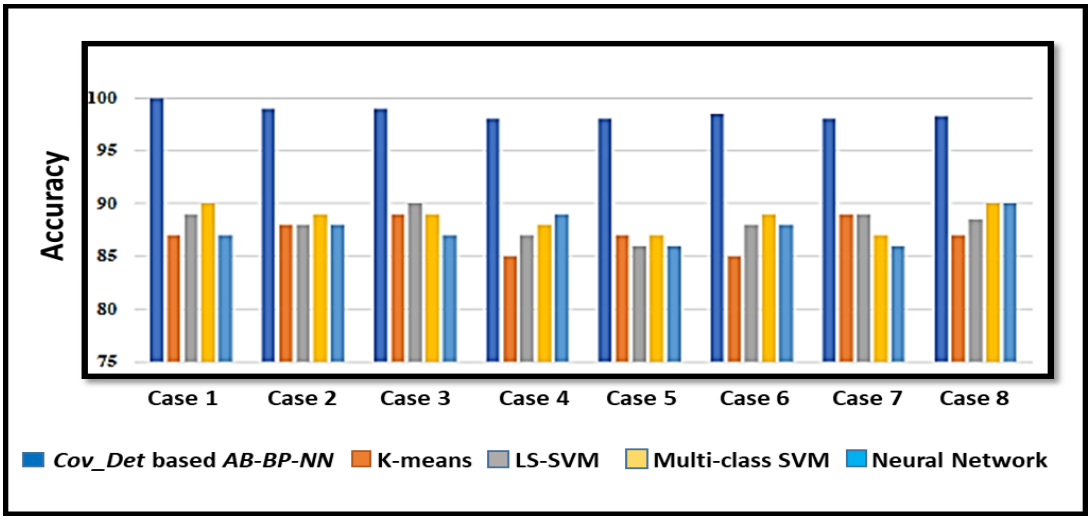

Figure 8. The classification results using different classification algorithms.

To further demonstrate its accuracy, this study has compared the newly proposed *Cov–Det* based *AB–BP–NN* model with a number of other classification algorithms such as *k*-means, LS-SVM and the multi-class SVM, including a neural network model. Figure 8 shows the performance of the proposed *Cov–Det* based *AB–BP–NN* model against that of the *k*-means, LS-SVM and multi-class SVM and neural network method. From these results, there is no doubt that the proposed *AB–BP–NN* model outperforms the *k*-means, LS-SVM and multi-class SVM and neural networks model, evidenced by the highest classification accuracy among all pairs of EEG cases.

7.2 Classification results for the FC and the NFC EEG data

This section discusses the classification results of the proposed *Cov–Det* based *AB–BP–NN* model for the FC and the NFC EEG signal. The same scenario for the epileptic EEG data was applied to segment the FC and the NFC EEG signal and to extract the most influential features in the EEG signal. In Table 8, we show the performance of the proposed *Cov–Det* based *AB–BP–NN* model based on the sensitivity, specificity and classification accuracy against the other classification models (*i.e.*, *k*-means, LS-SVM and multi-class SVM, & neural networks). Evidently, the classification accuracy of the proposed *Cov–Det* based *AB–BP–NN* model for almost all subjects was considerably higher than that of the *k*-mean, LS-SVM and multi-class SVM and neural network models. The average sensitivity and specificity for the proposed model was 98.7% and 99.37%, respectively, while the LS-SVM scored the second highest classification accuracy with 90%, ascertaining the efficacy of the *Cov–Det* based *AB–BP–NN* model.

Table 8. Comparison of the objective model (i.e., *Cov–Det* based *AB–BP–NN*) relative to the other classifiers.

Methods	Subject 1			Subject 2			Subject 3			Subject 4			Subject 5		
	Acc	*Spec*	*Sen*	*Acc*	*Spec*	*Sen*	*Acc*	*Spec*	*Sen*	*Acc*	*Spec*	*Sen*	*Acc*	*Spec*	*Sen*
The proposed [*Cov–Det* based *AB–BP–NN*] model	99	98.4	99	98.7	98	98	99	98.4	97.9	98.6	97.8	97.6	99	97.5	97.5
k-means	86	85	83	89	88	86	87	83	85	88	87,3	86.5	90	88	87
NN	90	89	88	87	88	86	89	87.5	88.4	89.5	87.9	87.6	91	89	88.9
LS-SVM	92	91	90	89	90	88	91	90	89	92	91	89	93	91	89
Multi-class-SVM	90	89	88	88	86	89	90	90	89	91	90	90	89	87	88

To further explore the utility of the *Cov–Det* based *AB–BP–NN* model, another experiment was conducted using the 10-cross-validation procedure, with its results shown in Figure 9. It is unambiguous that the performance of the proposed *Cov–Det* based *AB–BP–NN* model was relatively stable, and that there were no high fluctuations in the attained results among all of the 10-fold cross validations.

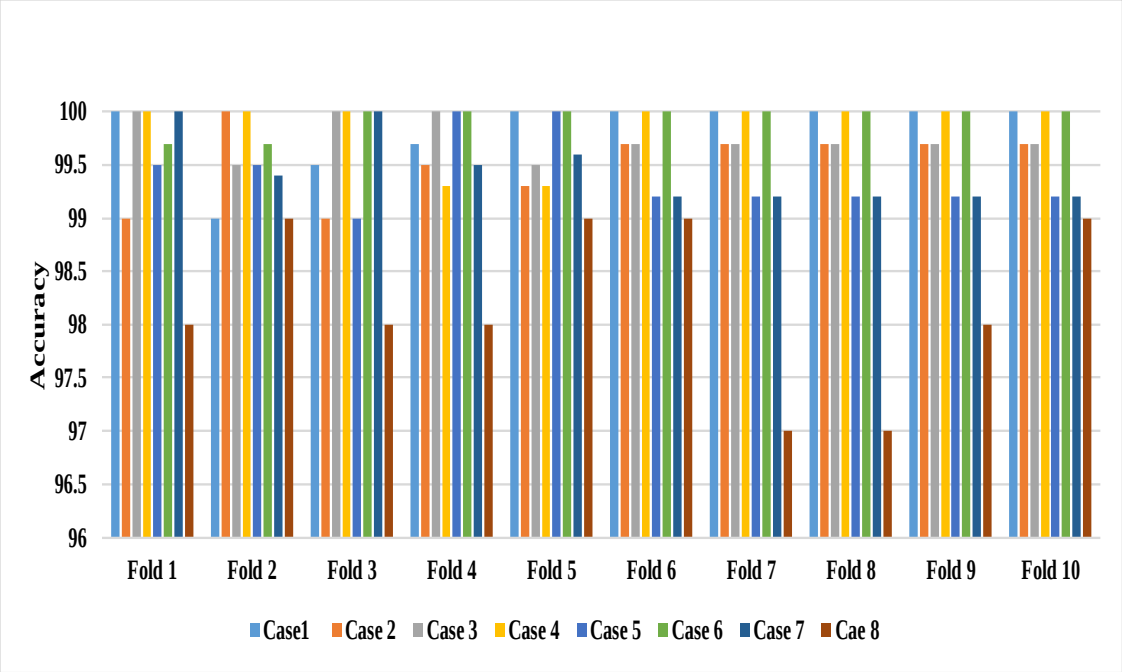

Figure 9. The performance of the proposed *Cov–Det* based *AB–BP–NN* model using 10-cross validation procedure.

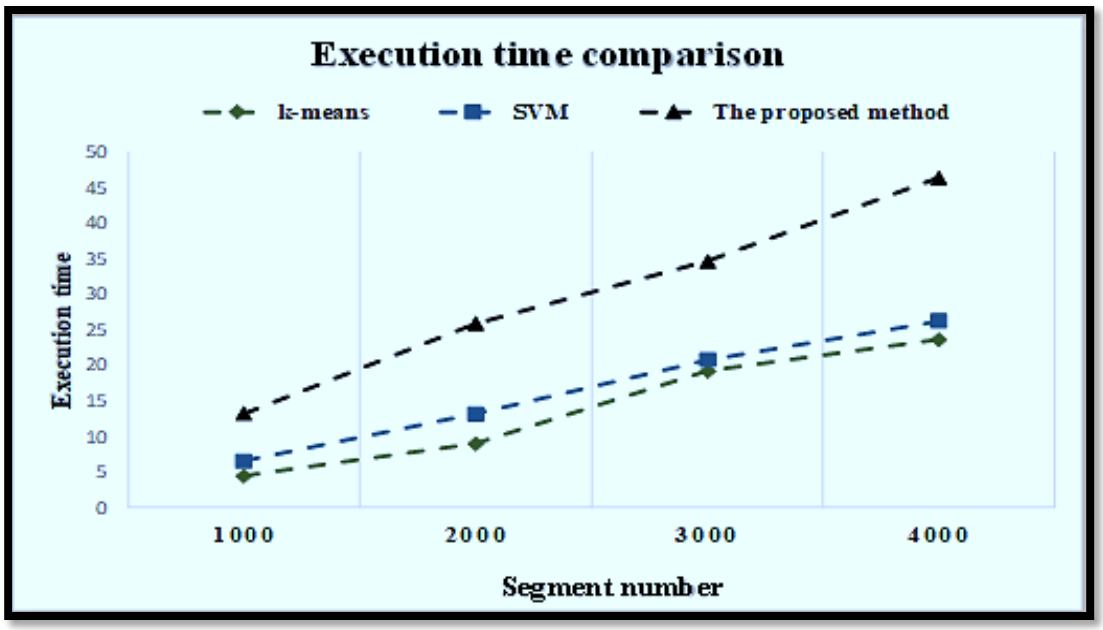

Figure 10. The Execution time in second of the proposed *Cov–Det* based *AB–BP–NN* model for different numbers of samples with FC and NFC EEG signals.

Figure 10 depicts the execution time in seconds of the proposed *Cov–Det* based *AB–BP–NN* model for different numbers of samples with FC and NFC EEG signals. The total number of samples for FC and NFC EEG is represented on the *x*-axis and the total execution time on the *y*-axis. Figure 10 shows that the proposed *AB–BP–NN* classification model recorded higher execution time than BPNN. However, the increase in the execution time is acceptable given the increase in the classification accuracy shown in Table 5.

8. Discussion

To scrutinize the advantage of the proposed *Cov–Det* based *AB–BP–NN* model relative to the other benchmark techniques, a comparison of our model against those existing in the literature was made. Table 9 reports the comparison results among the proposed *Cov–Det* based *AB–BP–NN* model with the existing methods. The proposed technique achieved an average accuracy of 100% and 98.86% for the two datasets, respectively, which is considered a noteworthy improvement compared to the state of the art methods, conducting comparisons with 36 other studies described in this section.

Based on the obtained comparisons presented in Table 9, it can be noted that the study of Zhu et al. (2013) used delay permutation entropy (DPE) feature with SVM to distinguish 50 pairs of focal and 50 non-focal epileptic signals, obtaining an average accuracy of 84%. Das and Bhuiyan (2016) suggested empirical mode decomposition (EMD), discrete wavelet transform (DWT) with K-nearest neighbour classifier to discriminate focal and non-focal signals. The studies of Bhattacharyya et al. (2017), Sharma et al. (2015c) and Sharma et al. (2015b) also proposed an automatic classification technique, but it is evident that our proposed AB-BP-NN model system outperformed their methods. Sharma et al. (2017) applied a wavelet filter bank with LS–SVM to classify 50 pairs of focal and 50 non-focal epileptic signals, gaining an average accuracy, sensitivity and specificity of 94.25%, 91.95% and 96.56% respectively. Arunkumar et al. (2017) utilised three entropies, such as approximate entropy (ApEn), Sample Entropy (SampEn) and Reyni's entropy as features with six classifiers: Naïve Bayes (NBC); Radial Basis Function (RBF); SVM, KNN classifier; Non-Nested Generalized Exemplars classifier (NNge); and Best First Decision Tree (BFDT) classifier to classify Focal and Non Focal EEG. Sharma et al. (2014) applied the sample entropies and variances of the intrinsic mode functions (IMFs) gained by

empirical mode decomposition (EMD) of EEG signals for classification of focal and non-focal EEG signals when radial basis function (RBF) has been employed as a kernel with LS-SVM classifier.

Sriraam and Raghu (2017) and Gupta et al. (2017) classified EEG signals into focal and non-focal segments based on several feature extraction methods with different machine learning methods. While the study of Bhattacharyya et al. (2018) proposed an automatic seizure classification method based on empirical wavelet transform technique with LS-SVM classifier to classify the 50 pairs of focal and non-focal EEG signals. Another study, Acharya et al. (2019) applied a new model utilizing Detrended fluctuation analysis (DFA), Entropies, Fractal dimension (FD), Hjorth, Hurst exponent, Kolmogorov complexity and Largest Lyapunov exponent (LLE) to classify focal and non-focal epilepsy signals, yielding a total rate of accuracy of 87.93%. Deivasigamani et al. (2016) obtained an equivalent rate of accuracy to our result, however, it has been applied on 50 pairs of focal and non-focal EEG signals while we have been applied the proposed model on 3750 pairs of focal and non-focal EEG signals, which produced more accurate and reliable outcomes. However, despite the promising results of those studies, their classification accuracy was lower than our proposed *Cov–Det* based *AB–BP–NN* model.

The studies of Nicolaou and Georgiou (2012) suggested Permutation Entropy (PE) as a feature for automated epileptic seizure detection with SVM to classify segments of normal and epileptic EEG based on PE values, an average of sensitivity 94.38% and specificity 93.23% was gained. The performance of the model in that study was lower than the *Cov–Det* based *AB–BP–NN* model. Another group of studies Srinivasan et al. (2007), Lee et al. (2014), Ahmedt-Aristizabal et al. (2018), Lu and Triesch (2019) and Siuly et al. (2018) achieved more than 95% rates of accuracy based on several epilepsy classification techniques such as Neural Network Classifier (ANNs), Neural Network with Weighted Fuzzy Membership functions (NEWFM), Recurrent Neural Networks (RNNs) via the use of LongShort Term Memory (LSTM) networks, Deep Convolutional Neural Network Architecture and SVM. Kabir and Zhang (2016) proposed an optimum allocation technique with a logistic model tree to detect epileptic seizure events, yielding a total rate accuracy of 95% and 94% of sensitivity. Tawfik et al. (2016) detected two EEG groups, Group A vs Group E, based on weighted

permutation entropy merged with an SVM model; in that study, only a classification accuracy was reported.

Moreover, Şengür et al. (2016), Guler and Ubeyli (2007), Khan and Farooq (2015), Ahammad et al. (2014), Tzallas et al. (2007) and Das et al. (2016) gained a rate of accuracy 99-100% based on Wavelet Transform, Discrete Wavelet Transform (DWT), Lyapunov Exponents, Time-Frequency and Dual-Tree Complex (WT) with different types of machine learning classifiers. However, regardless of the promising results of those studies, their classification accuracy was gained based on three or two datasets while our proposed Cov–Det based AB–BP–NN model is applied on whole datasets. The works of Liang et al. (2010), Nigam and Graupe (2004), Polat and Güneş (2007), Kannathal et al. (2005), Ghosh-Dastidar et al. (2008), Tzallas et al. (2009) and Madhu et al. (2012) proposed an automatic classification model based on diverse machine learning classifiers such as Artificial Neural Network, SVM, Decision tree classifier, Adaptive neuro-fuzzy Inference System (ANFIS) and Probabilistic Neural Network, obtaining an average accuracy of 89-98%, but their results were relatively less accurate compared to the results obtained by the proposed AB-LS-SVM classifier system. Patidar and Panigrahi (2017) proposed Kraskov Entropy based Tunable-Q wavelet with LS-SVM for analysis of epileptic EEG signals, obtaining an average accuracy and sensitivity of 97.75% and 97%, respectively. Subasi et al. (2019) proposed a genetic algorithm and particle swarm optimization with SVM to automatically detect an epileptic seizure, obtaining an average of accuracy 99.38%. Even though the studies described above provided advanced results, the high classification accuracy of the *Cov–Det* model coupled with *AB–BP–NN* outperformed all of them.

Comparing the studies that obtained an equivalent rate of accuracy to our result, most of the researches has been applied on part of datasets, while we have been applied the proposed model on whole datasets and analysed eight problems, which clearly showed the superiority of our proposed Cov–Det based AB–BP–NN model. Through analysing and investigating the information presented in Table 9, it is clear that the *Cov–Det* based *AB–BP–NN* model can be considered an optimum technique for these databases (against the recent works).

Table 9. Comparison of the proposed method vs different epileptic seizures and focal and non-focal detection approaches with the same datasets.

FC and NFC EEG dataset						
Authors	**Methods**	**Classifiers**	**Cases**	**Acc.**	**Sen.**	**Spe.**
Zhu et al. (2013)	Delay permutation entropy (DPE) feature	SVM	50 pairs of focal and 50 non-focal	84%	-	-
Das and Bhuiyan (2016)	Empirical mode decomposition (EMD), Discrete wavelet transform (DWT)	K-nearest neighbour	Entire Dataset	89.4%	-	-
Bhattacharyya et al. (2017)	Tunable-Q Wavelet Transform (TQWT)	LS-SVM	3750 pairs of focal and non-focal	84.67%	-	-
Sharma et al. (2015c)	Discrete Wavelet Transform (DWT)	LS-SVM	50 pairs of focal and non-focal	84%	84%	84%
Sharma et al. (2015b)	Entropy features	LS-SVM	50 pairs of focal and non-focal	87%	-	-
Sharma et al. (2017)	Wavelet filter bank	LS–SVM	50 pairs of focal and 50 non-focal	94.25%	91.95%	96.56%
Arunkumar et al. (2017)	Approximate entropy (ApEn), Sample entropy (SampEn) and Reyni's entropy	Naïve Bayes (NBC), Radial Basis Function (RBF), (SVM), KNN classifier, Non-Nested Generalized Exemplars classifier (NNge) and Best First Decision Tree (BFDT) classifier	50 pairs of focal and non-focal signals	98%	100%	96%
Sharma et al. (2014)	Empirical mode decomposition (EMD)	LS-SVM	50 pairs of focal and 50 non-focal	85%	-	-
Sriraam and Raghu (2017)	Multi-Features	SVM	3750 pairs of focal and 3750 non-focal	92.15%	94.56%	89.74%
Gupta et al. (2017)	Flexible Analytic wavelet Transform (FAWT)	LS-SVM	3750 pairs of focal and 3750 non-focal	94.41%	93.255	95.57%
Deivasigamani et al. (2016)	Dual Tree Complex Wavelet Transform (DT-CWT)	Adaptive Neuro Fuzzy Inference System (ANFIS) classifier	50 pairs of focal and 50 non-focal	99%	98%	100%
Bhattacharyya et al. (2018)	Empirical wavelet transform technique with reconstructed phase space	LS-SVM	50 pairs of focal and 50 non-focal	90%	88%	92%

Acharya et al. (2019)	Detrended fluctuation analysis (DFA), Entropies, Fractal dimension (FD), Hjorth, Hurst exponent , Kolmogorov complexity and Largest Lyapunov exponent (LLE)	LS-SVM	3750 pairs of focal and 3750 non-focal	87.93%	89.97%	85.89%
Proposed Method	***Cov–Det***	***AB–BP–NN* model**	**3750 pairs of focal and 3750 non-focal**	**98.86%**	**98.7%**	**99.37%**
Epileptic EEG dataset						
Authors	**Methods**	**Classifiers**	**Cases**	**Acc.**	**Sen.**	**Spe.**
Nicolaou and Georgiou (2012)	Permutation Entropy (PE)	SVM	Five sets *A*, *B*, *C*, *D*, and *E*	-	94.38%	93.23%
Srinivasan et al. (2007)	Approximate entropy (ApEn)	Neural Network Classifier (ANNs)	Two sets of EEG data (normal and epileptic subjects)	100%	-	-
Lee et al. (2014)	Wavelet transform (WT), phase-space reconstruction (PSR) and Euclidean distance (ED)	Neural Network with Weighted Fuzzy Membership functions (NEWFM)	Five sets A, B, C, D, and E	98.17%	96.33%	100%
Ahmedt-Aristizabal et al. (2018)	End-to-end Training Scheme	Recurrent Neural Networks (RNNs) via the use of LongShort Term Memory (LSTM) networks	Five sets A, B, C, D, and E	95.54%	91.83%	90.50%
Lu and Triesch (2019)	Modern Deep Learning Methods	Deep Convolutional Neural Network Architecture	Five sets A, B, C, D, and E	99%	96.15%	100%
Siuly et al. (2018)	Hermite Transform	SVM	Two sets A and E	99.55	100%	99%
Kabir and Zhang (2016)	Optimum allocation technique	Logistic Model Trees (LMT)	Two sets *A* and *E*	95%	94%	-
Tawfik et al. (2016)	Weighted permutation entropy blended	SVM	Five sets *A*, *B*, *C*, *D*, and *E*	93.75%	-	-
Şengür et al. (2016)	Gray-level Co-occurrence Matrix (GLCM), Texture Feature Coding Method (TFCM), and Local Binary Pattern (LBP)	SVM	Two sets A and E	100%	100%	100%
Guler and Ubeyli (2007)	Wavelet Transform, Lyapunov Exponents	SVM	Five sets A, B, C, D, and E	99.28%	99.25%	99.65%

Khan and Farooq (2015)	Wavelet Transform	Linear	Two sets A and E	100%	100%	100%
Ahammad et al. (2014)	Discrete Wavelet Transform (DWT)	Linear	Three sets A, D and E	100%	100%	100%
Tzallas et al. (2007)	Time-Frequency	Artificial Neural Network (ANN)	Two sets A and E	99%	-	-
Das et al. (2016)	Dual Tree Complex (WT)	SVM	Three sets A, D and E	100%	100%	-
Liang et al. (2010)	Principle component analysis (PCA) and genetic algorithms (GAs)	linear least squares, linear discriminate analysis, a backpropagation (BP) neural network, and the support vector machine with either the linear (LISVM)	Three sets A, D and E	96.83%	-	-
Nigam and Graupe (2004)	Nonlinear pre-processing filter	Artificial Neural Network (ANN)	Two sets A and E	97.2%	-	-
Polat and Güneş (2007)	Fast Fourier transform (FFT), Decision Tree (DT)	Decision tree classifier	Two sets A and E	98.72%	99.40%	99.31%
Kannathal et al. (2005)	Entropy Measures	Adaptive neurofuzzy Inference System (ANFIS)	Two sets A and E	92.22%	-	-
Ghosh-Dastidar et al. (2008)	Chaos theory and wavelet analysis, Principle component analysis (PCA)	Radical Basis Function Neural Network	Three sets A, D and E	96.73%	-	-
Tzallas et al. (2009)	Time-Frequency Analysis	Artificial Neural Network (ANN)	Five sets A, B, C, D, and E	89%	-	-
Madhu et al. (2012)	Time domain methods, frequency domain methods, and time frequency methods	Probabilistic Neural Network (PNN)	Five sets A, B, C, D, and E	92.75%	72.5%	98%
Patidar and Panigrahi (2017)	Entropy based Tunable-Q wavelet	LS-SVM	Two sets *A* and *E*	97.75%	97%	-
Subasi et al. (2019)	genetic algorithm (GA) and particle swarm optimization (PSO)	SVM	Five sets *A*, *B*, *C*, *D*, and *E*	99.38%	-	-
Proposed Method	***Cov–Det***	***AB–BP–NN* model**	**Five sets A, B, C, D, and E with Eight cases (8 problems)**	**100%**	**99%**	**98%**

9. Limitation

To the best of the author's knowledge, no prior studies have been conducted using our proposed model. In spite of this success, it might be possible to explore some limitations of the proposed model:

- An average accuracy of 100% was achieved for two relatively small databases. The proposed method should be tested with larger clinical databases; we believe the proposed method may or may not yield perfect classification accuracy. The proposed model could be modified by testing other feature selection methods. Second, the proposed model could be computationally costly, especially when it is used in real time applications. However, this study will try to apply big data technology and use some parallel processing techniques to reduce time complexity of the prosed model by which the feature numbers would not be a problem.
- The proposed model was trained and tested based on leave-one-out-cross-validation (LOOCV) for avoiding the overfitting issue. The performance of proposed models is assessed in terms of accuracy, f-measure, and precision sensitivity, specificity, and Matthews Correlation Coefficient (MCC). All results are reported in Table 10.

Table 10. Results of the proposed model based on leave-one-out-cross-validation.

FC and NFC EEG dataset					
Subject No.	Acc	Sen.	Spec.	F-S	precision
Subject 1	99%	98%	96%	98%	99%
Subject 2	98%	96%	98%	97.5%	98.2%
Subject 3	100%	98%	98%	99%	98.7%
Subject 4	98%	98.5%	99%	97%	98%
Subject 5	99%	97%	98%	98.5%	99%
Epileptic EEG dataset					
Subject 1	99%	98%	99%	99%	98.5%
Subject 2	98%	99%	98%	97.8%	97.7%
Subject 3	100%	98%	99%	98.5%	99%
Subject 4	98%	99%	97.5%	99%	99.2%
Subject 5	100%	98.5%	99%	99%	99%

In spite of these limitations, there are significant advantages in applying the covariance matrix and determinant method. When the population contains higher dimensions, such as that found in medical datasets, a matrix could be utilised to describe the relationship between various dimensions. To clarify this, the present study has applied a covariance matrix to define the relationship in the entire dimensions as the relationships between every two random variables. In addition, based on basic information in linear algebra, the determinant can capture how linear transformation changes area or volume and changes variables in integrals. Thus, integrating the covariance matrix with its determinant matrix into one model as a design approach can capture the relevant features from EEG signals.

10. Conclusion

A neurological disorder may be caused by recurring seizures such as epilepsy. The EEG signals that are used to classify epilepsy are periodical, non-stationary and contain a massive amount of data. Consequently, automated classification of abnormal events in the EEG signals can be beneficial in the monitoring and treatment of epilepsy diseases. In this study, an efficacious automated classification model of abnormal events in the EEG signals, named the *Cov–Det* based *AB–BP–NN* model, was proposed and its efficacy was evaluated using two separate medical datasets.

The proposed model was evaluated by using several metrics to test the performance, including the accuracy (ACC), sensitivity (Sen), specificity (Spec), Negative Predictive Value (NPV), f-scor (FSCOR), informedness (INFO), negative likelihood ratio (NLR), false-negative rate (FNR), positive likelihood ratio (PLR), diagnostic odds ratio (DOR), false-positive rate (FPR), and Mathews-correlation coefficients (MCC). Compared to the previous studies in Table 10, the results of the proposed *Cov–Det* based *AB–BP–NN* model demonstrated the robustness of the method to detect an epileptic event in EEG signals. Two datasets were employed to assess the *Cov–Det* based *AB–BP–NN* model. The proposed *Cov–Det* based *AB–BP–NN* model in this paper can be designed as a real-time system to support patients with epilepsy by a warning message. Therefore, the *Cov–Det* based *AB–BP–NN* model can be used in clinical studies as a real-time expert diagnostic system due to its automated nature.

Comparing the studies that obtained an equivalent rate of accuracy to our result, most of the researches has been applied on part of datasets, while we have been applied the proposed model on whole datasets and analysed eight problems, which clearly showed the superiority of our proposed *Cov–Det* based *AB–BP–NN* model. The proposed model can be utilised for aiding neurologists and other medical specialists in the accurate diagnosis of epileptic seizures. A follow-up study may investigate the improvement of the performance of the proposed model by reducing the number of features used in this initial study. Moreover, due to the scarce number of studies focused on designing a feature extraction, as well as detection model for the accurate diagnosis of epileptic seizures, there is a need for further research in this area.

CHAPTER 4

AN EIGENVALUE-BASED COVARIANCE MATRIX BOOTSTRAP MODEL WITH SUPPORT VECTOR MACHINES FOR MULTI-CHANNELS EEG SIGNALS ANALYSIS

4.1 Foreword

Alcoholism is a common neurological disorder caused by excessive and repetitive drinking of alcoholic beverages; the harmful effects of alcoholic beverages could be physical and psychological as well as social, legal and economic. The heavy consumption of alcohol disturbs the functioning of the entire nervous system, especially the brain: it not only weakens the brain neurons but also leads to cognitive and mobility weakness. Based on the latest reports issued by the World Health Organization (WHO) https://www.who.int/health-topics/alcohol#tab=tab_1 , three million deaths every year are caused by the harmful use of alcohol. In addition, more than 200 disease- and injury-related conditions are caused by the excessive use of alcohol. An effective method of recognising alcoholics from non-alcoholics could decrease unnecessary economic losses and social problems as well as expedite diagnosis in clinical settings. Thus, in chapter 3, a new mechanism for classification of alcoholism from multi-channel EEG signals was proposed. A new machine learning model for the reduction of data prior to the classification process by integrating the clustering and bootstrapping CT-BS technique in one phase of model design was developed. To detect and further analyse the abnormalities in the EEG signal, the eigenvalues of the covariance matrix, determined from EEG signals, were investigated using a statistical method by extracting ten statistical features from the eigenvalues of the covariance matrix. These features are represented by the mean, median, maximum, minimum, mode, range, standard deviation, variation, skewness and kurtosis commonly used in EEG classification problems. In order to improve the automated detection system, a combination-based approach using the F-SVM and FOA fruit fly optimization algorithm, i.e., FOA-F-SVM, has been proposed to correctly classify alcoholism from multi-channel EEG signals.

Based on an extensive literature search, the CT-BS-Cov-Eig-based FOA-F-SVM model is proposed here for the first time to analyse and detect alcoholism from EEG

signals. With respect to the results, compared with the other algorithms, the proposed model, CT-BS-Cov-Eig-based FOA-F-SVM, has shown promising performance, and can, therefore, be adopted as a classification technique for alcoholism- detection in EEG signals.

An Eigenvalue-based Covariance Matrix Bootstrap Model Integrated with Support Vector Machines for Multi-Channel EEG Signals Analysis

Hanan Al-Hadeethi[a], Shahab Abdulla[b], Mohammed Diykh[1a, d], Ravinesh C Deo[a,*] and Jonathan H Green[b, c]

[a]*School of Sciences, University of Southern Queensland, QLD 4300, Australia*
[b]*USQ College, University of Southern Queensland, QLD 4300, Australia*
[c]*Faculty of the Humanities, University of the Free State, South Africa*
[d]*University of Thi-Qar, College of Education for Pure Science, Iraq*

Abstract

Identification of alcoholism is clinically important because of the way it affects the operation of the brain. Alcoholics are more vulnerable to health issues, such as immune disorders, high blood pressure, brain anomalies, and heart problems. These health issues are also a significant cost to national health systems. To help health professionals diagnose the disease with high rate of accuracy, there is an urgent need to create accurate and automated diagnosis systems capable of classifying human bio-signals. In this study, an automatic system, denoted as (CT-BS- Cov-Eig based FOA-F-SVM), has been proposed to detect prevalence and health effects of alcoholism from multi-channel EEG signals. The EEG signals are segmented into small intervals, with each segment passed to a clustering technique-based bootstrap (CT-BS) for selection of modelling samples. A covariance matrix method with its eigenvalues (Cov-Eig) is integrated with the CT-BS system and applied for useful feature extraction related to alcoholism. To select most relevant features, a non-parametric approach is adopted, and to classify the extracted features, a radius-margin-based support vector machine (F-SVM) with a fruit fly optimisation algorithm (FOA), (i.e., FOA-F-SVM) is utilised. To assess the performance of the proposed CT-BS model, different types of evaluation methods are employed, and the proposed model is compared with state-of-the-art models to benchmark the overall effectiveness of the newly designed system for EEG signals. The results in this study show that the proposed CT-BS model is more effective than the other commonly-used methods, and yields a high accuracy rate of 99%.

[1]Corresponding author: Mohammed Diykh, School of Sciences, University of Southern Queensland, QLD 4300, Australia, mohammed.diykh@usq.edu.au

In comparison with state-of-the-art algorithms (i.e., KNN, k-means and SVM) tested on identical databases describing the capability of the newly proposed FOA-F-SVM method, the study ascertains the CT-BS model as a promising medical diagnostic tool with potential implementation in automated alcoholism detection systems used by clinicians and other health practitioners. The proposed model, adopted as an expert system where EEG data could be classified through advanced pattern recognition techniques, can assist neurologists and other health professionals in accurate and reliable diagnosis and treatment decisions related to alcoholism.

Key words: Alcoholism, Electroencephalogram, Covariance matrix, Support Vector Machine (SVM), Eigenvalues and Fruit fly optimisation

1. Introduction

The human brain, as an integral part of the central nervous system (CNS), operates normally by receiving signals from the body's organs and providing information to the muscles (Pelvig et al., 2008). The effects of alcohol on the CNS can lead to long- and short-term issues such as impaired vision, impaired hearing, dementia and depression (Deiner and Silverstein, 2009). Alcoholism is a common neurological disorder caused by excessive and repetitive drinking of alcoholic beverages; the harmful effects of alcoholic beverages could be physical and mental as well as social, legal and economic (Volkow et al., 2017) (Lieber, 1995). The heavy consumptions of alcohol disturbs the functioning of the entire nervous system, especially the brain: it not only weakens the brain neurons but also leads to cognitive and mobility weakness (Knight and Longmore, 1994) (Oscar-Berman et al., 1997). Based on the latest reports issued by the World Health Organization (WHO) https://www.who.int/health-topics/alcohol#tab=tab_1, three million deaths every year are caused by the harmful use of alcohol. In addition, more than 200 disease- and injury-related conditions are caused by the excessive use of alcohol. An effective method of recognising alcoholics from non-alcoholics could decrease unnecessary economic losses and social problems as well as expedite diagnosis in clinical settings.

Figure 1 shows the difference in the shape of a brain between alcoholics and non-alcoholics, and Figure 2 showing a manifestation of the shape of the (alcoholic/non-alcoholic) brain analyse these two signals (Bavkar et al., 2019). Electroencephalogram (EEG) technology is becoming increasingly important in the identification, diagnosis

and treatment of mental and neurodegenerative diseases and abnormalities (Isaksson et al., 1981). The function of the EEG assists physicians in establishing an accurate diagnosis. Thus, it can be utilised as a diagnostic tool to discern alcoholic from non-alcoholic subjects based on the variation in the signals.

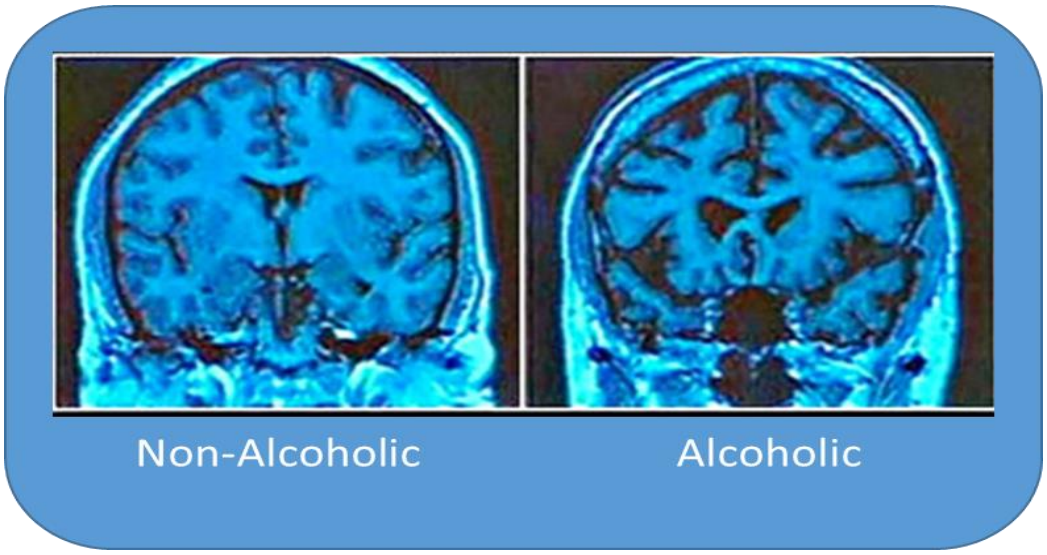

Figure 1: A depiction of the shape of the human brain for an alcoholic and a non-alcoholic person (Myilsamy, 2016). https://www.webmd.com/mental-health/addiction/ss/slideshow-alcohol-body-effects

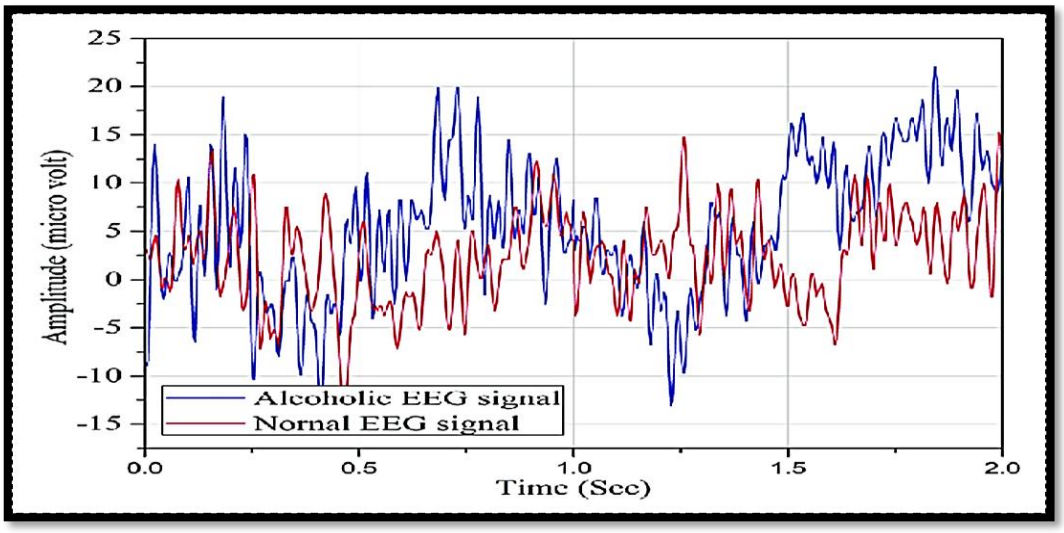

Figure 2: The EEG signal recorded from an alcoholic and a normal person (Acharya et al., 2012).

Much effort has been expended in deducing the preferred classification method in analysing EEG signals for alcoholism. For instance, Fast Fourier transform (FFT),

autoregressive modelling (AR) techniques, Tunable-Q Wavelet Transform (TQWT), Principal Component Analysis (PCA), Synchronization Likelihood Hilbert-Huang Transformation, and Wavelet transforms have been applied to detect EEG signals indicating alcoholism. For example, Faust et al. (2008) analysed normal, epileptic and alcoholic EEG signals utilising FF, and AR techniques. Their results showed that the power spectral density (PSDs) of these signals was varied. Patidar et al. (2017) applied TQWT to decompose EEG rhythms into different bands. The PCA was utilised for feature extraction then fed to a least-squares-support-vector machine. Cao et al. (2017) utilised a synchronization likelihood to measure synchronization variations among 28 alcoholics and 28 control subjects. The study showed that the synchronization for the control group reflected the complexity levels of the cognitive tasks, while the alcoholics only displayed erratic changes. Lin et al. (2009) analysed the clinical alcoholic and normal control FP1 EEG signals based on a Hilbert-Huang Transformation. PCA and WT were also applied to analyse EEG data by Sun et al. (2006), and other studies have used power spectrum of Haar mother wavelet, approximate entropy, sample entropy and empirical mode decomposition: Kousarrizi et al. (2009) applied power spectrum of the Haar mother wavelet to extract the features with PCA . The extracted features were fed to a support vectors machine and neural networks. The simulation results showed that their method achieved a higher rate of classification accuracy than other methods. Shooshtari and Setarehdan (2010) proposed a reduction method to select an optimum subset of EEG channels based on spectral analysis and correlation matrices: their technique was successful in selecting an optimal number of channels. Kumar et al. (2012) employed approximate entropy and sample entropy to extract entropy features from EEG time series: they illustrated that the average value of ApEn and SampEn for an epileptic time series was less than that of a non-epileptic time series. The study of Priya et al. (2018) has used mode decomposition (EMD) for features extraction.

Time-frequency (T–F) image information, high pass IIR filter with zero phase distortion, Separability and Correlation analysis, computer-aided diagnosis, and EEG rhythms based features were utilised in many studies that follow. Bajaj et al. (2017) proposed a new hybrid method to classify automatically an alcoholic and a control EEG signal based on time-frequency (T–F) image information and found it useful in conveying key characteristics in EEG signals. The results of this study were

promising. Fattah et al. (2015) proposed a new method based on a high pass IIR filter with zero phase distortion, which aimed to preserve the Gamma band and all higher frequencies with K-nearest neighbor (KNN) classifier and leave-one-out cross-validation technique. Their proposed scheme also classified alcoholic and non-alcoholic subjects with a higher rate of accuracy than did existing methods. To select an optimal feature subset automatically and to obtain a minimum correlation between selected channels and maximum class separation, a statistical feature selection technique based on Separability and Correlation analysis (SEPCOR) was proposed by Shri and Sriraam (2016); a significant improvement in the classification accuracy based on the SEPCOR method was noted in that study compared with feature selection methods used in previous studies. The study of Acharya et al. (2014) presented a review of the known features of EEGs gained from people with alcoholism. EEG-rhythms-based features for automatic identification of alcohol EEG signals were also proposed by the study of Taran and Bajaj (2017)—in this study, an extreme learning machine (ELM) and a least squares support vector machine classifiers was used to detect non-alcoholic and alcoholic EEG signals, with the investigators' techniques showing an accuracy of 97.92%.

As demonstrated in previous studies, finding new techniques for detection of alcoholism can help in further clinical applications and research. The present study provides a new mechanism for classification of alcoholism from multi-channel EEG signals. This study has developed a new machine learning model for the reduction of data prior to the classification process by integrating the clustering and bootstrapping CT-BS technique in one phase of model design. To detect and further analyse the abnormalities in the EEG signal, the eigenvalues of the covariance matrix, determined from EEG signals, are investigated using a statistical method by extracting ten statistical features from the eigenvalues of the covariance matrix. These features are represented by the *mean, median, maximum, minimum, mode, range, standard deviation, variation, skewness* and *kurtosis* commonly used in EEG classification problems. In order to improve the automated detection system, a combination-based approach using the F-SVM and FOA fruit fly optimization algorithm, i.e., FOA-F-SVM, has been proposed to correctly classify alcoholism from multi-channel EEG signals. Based on an extensive literature search, the CT-BS-Cov-Eig-based FOA-F-SVM model is proposed here for the first time to analyse and detect alcoholism from

EEG signals. In respect to the results, compared with the other algorithms, the proposed model, CT-BS-Cov-Eig-based FOA-F-SVM, has promising performance, and can, therefore, be adopted as a classification technique for alcoholism- detection in EEG signals.

This research paper is divided into several sections: Section 2 presents the methodology; Section 3 contains a description and explanation of the datasets, Segmentation, Sampling, Feature Extraction and feature selection; Section 4 contains performance evaluation methods; in Section 5 includes Radius-Margin-Based Support Vector Machine (F-SVM), fruit fly optimization algorithm (FOR) and the proposed classification model FOR-F-SVM; Section 6 includes experimental results, evaluation of the performance of the proposed FOA-F-SVM model, channels selection based on classification accuracy, comparison of classification accuracy of the proposed model FOA-F-SVM with KNN, k-means and SVM, and comparison the proposed model, FOA-F-SVM, with previous Studies and discussion; and Section 7 presents the conclusions.

2. Methodology

This paper describes the design a new technique trained to classify alcoholism from multi-channel EEG signals. A hybrid method by integrating clustering technique and bootstrapping, i.e., CT-BS has been developed to improve the performance of the sampling stage to reduce the dimensions of the data. Then, the covariance matrix with its Eigen-values, coupled with the FOA-F-SVM, is proposed to predict alcoholism in patients' recordings. Knowledge Discovery in Databases (KDD) recorded at the University of California, Department of Information and Computer Science (Hettich and Bay, 1999) is used for the evaluation of the proposed model. Figure 3 demonstrates the essential proceedings in this study. The EEG signals are divided into four segments; after that each segment is sent into CT-BS method for sampling phase. To extract EEG features, the covariance matrix with its eigenvalues suggested in our previous work (Al-Hadeethi et al., 2020) is applied. Following this, to detect and analysis abnormalities in the EEG signal, the eigenvalues of the covariance matrix are investigated utilising a statistical method to extract ten statistical features from eigenvalues of the covariance matrix. These features are *mean*, *median*, *maximum*, *minimum*, *mode*, *range*, *standard deviation*, *variation*, *skewness* and *kurtosis*,

posteriorly employing a non-parametric method, the Kolmogorov–Smirnov test (KST), for selecting relevant features. Then, to estimate the performance of the proposed model, different types of assessment methods, such as accuracy, sensitivity and specificity are used. In addition, we compare the proposed model with the other state of the art models to benchmark the overall effectiveness of the newly designed approach for EEG signal classification.

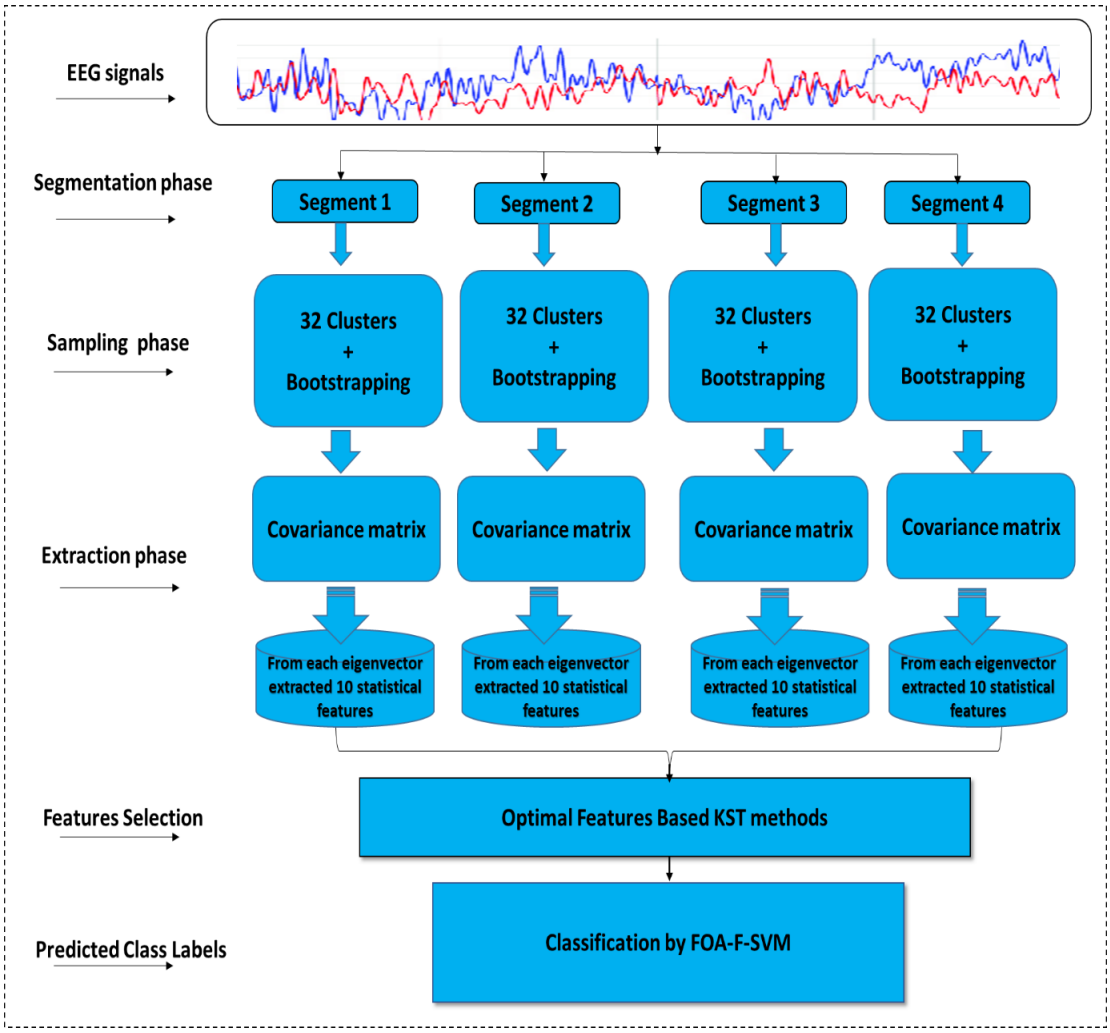

Figure 3: A flow diagram representation of the algorithm developed for detection and classification of alcoholism-based EEG signals.

3. Database

In the work described here, we have utilised a public database known as the UCI Knowledge Discovery in Databases (KDD) Archive www.kdd.ics.usi.edu from Irvine, CA: the University of California, Department of Information and Computer Science (Hettich and Bay, 1999). Data were collected from 122 participants; for each

participant, there were 120 trials with three kinds of stimuli (Zhang et al., 1997). The EEG signals were recorded from 64 channels, two Electrooculography (EOG) channels and one reference electrode. The duration of each trial was one second and the sampling rate of all channel data was 256 Hz. UCI KDD contains three types of datasets, which are SMNI CMI TEST, SMNI CMI TRAIN and FULL, respectively. FULL datasets contain a few all-zero recordings (Zhu et al., 2011); therefore, the first two databases were utilised. There are 600 recorded files in SMNI CMI TEST and the same number in the SMNI CMI TRAIN which equals 1200 recorded files, and for each recording there are signals from 64 electrode caps. Figure 4 shows how data are divided into classes with 64 channels. In this study, EOG signals and *nd* reference electrodes were excluded. Figure 5 illustrates the 61 channels.

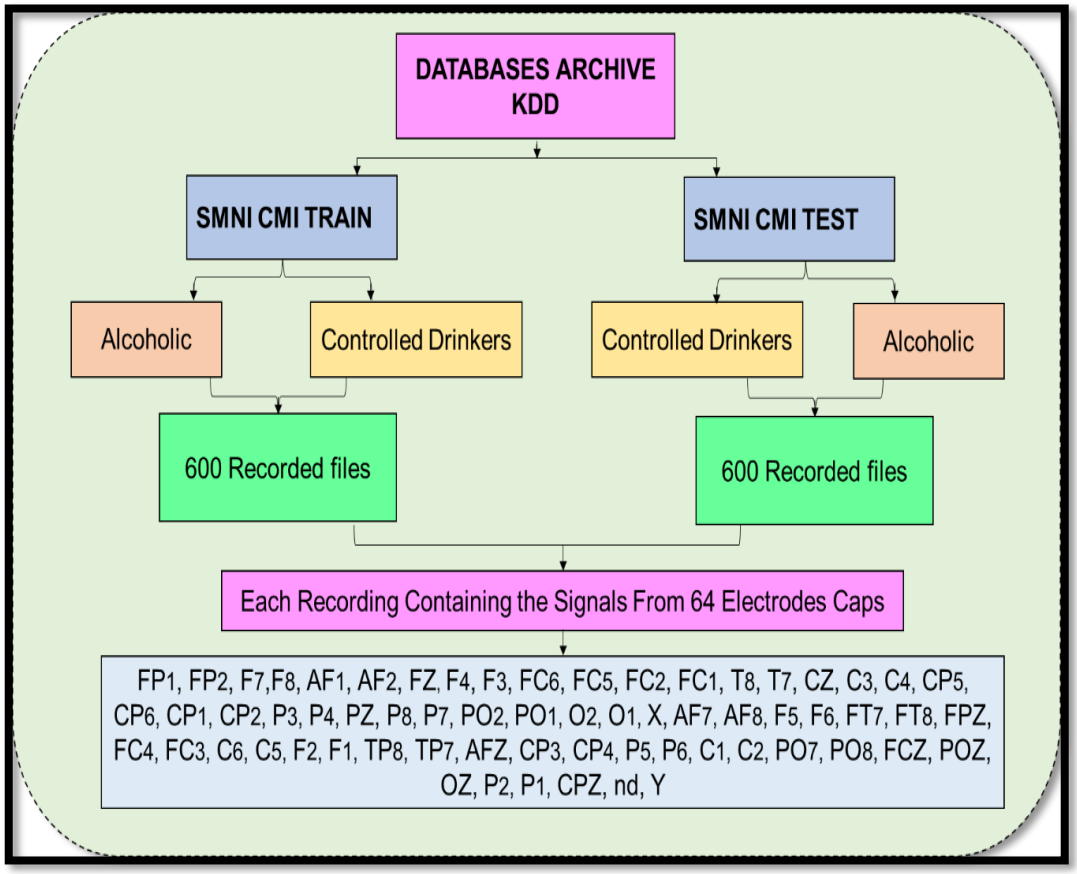

Figure 4: The UCI Knowledge Discovery in Databases (KDD) Archive www.kdd.ics.usi.edu from Irvine, CA: the University of California, Department of Information and Computer Science.

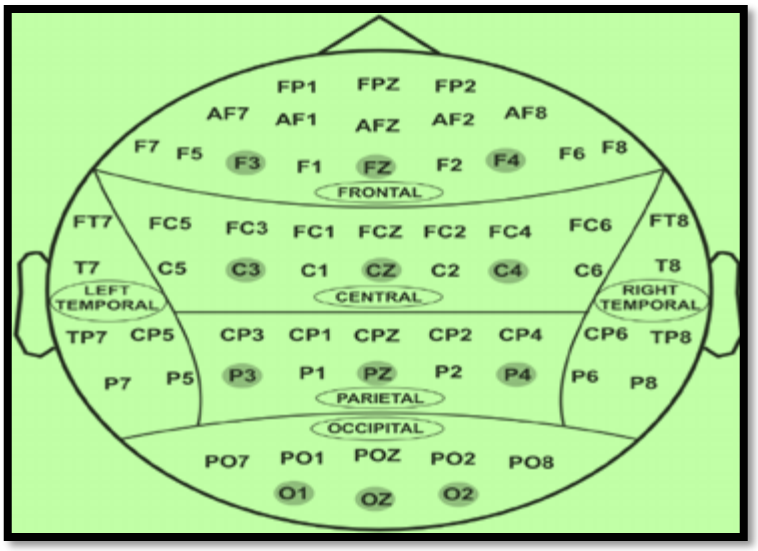

Figure 5: Sixty-one electrodes from which signals were taken and used in this research (Zheng and Lu, 2015).

3.1 Segmentation

To understand some of the fundamental concepts of statistical analysis, it is very important to be aware of the significance of the distribution of data points in the sample that is drawn to represent the population (Sheats and Pankratz, 2002). To be clear, it is very important to know the type of distribution in order to build a reliable analysis system. First of all, the data was tested to show the distributions of both alcohol and controlled EEG signals: normal probability plots (a special case of the Q–Q probability plot for a normal distribution) were used to test whether the data were normally distributed (Box and Draper, 2007). Figure 6 and 7 shows that the EEG signals did not follow normal distributions. The frequency range of the recordings from a subject that includes 61 channel EEG signals is 256 Hz. The typical length of those waveforms is one second. Based on previous work (Diykh et al., 2017); (Diykh et al., 2018), this project has applied the sliding window technique (SWT) to split the EEG signals into their respective periods. It was found that the proposed method generated highly satisfactory classification accuracy. Mathematically, let an EEG signal be denoted as: $X = \{x_1, x_2, \ldots\ldots, x_k\}$ with n being the data points. In this study, the EEG signal X was segmented into n segments (Diykh et al., 2019b).

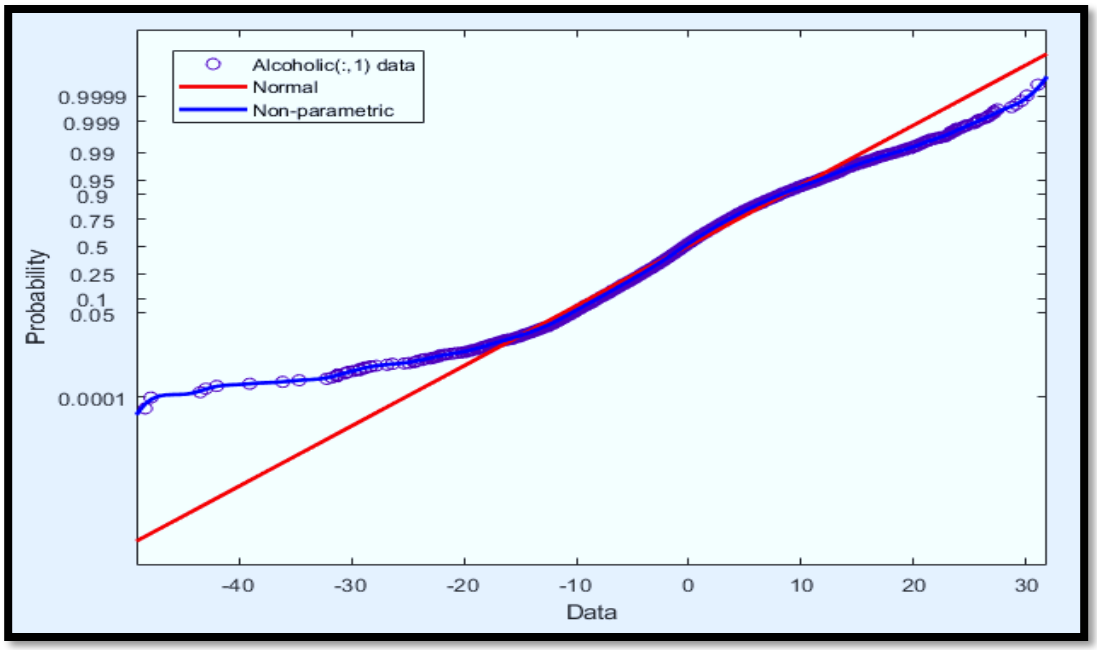

Figure 6: The distribution of an alcoholic's EEG signal.

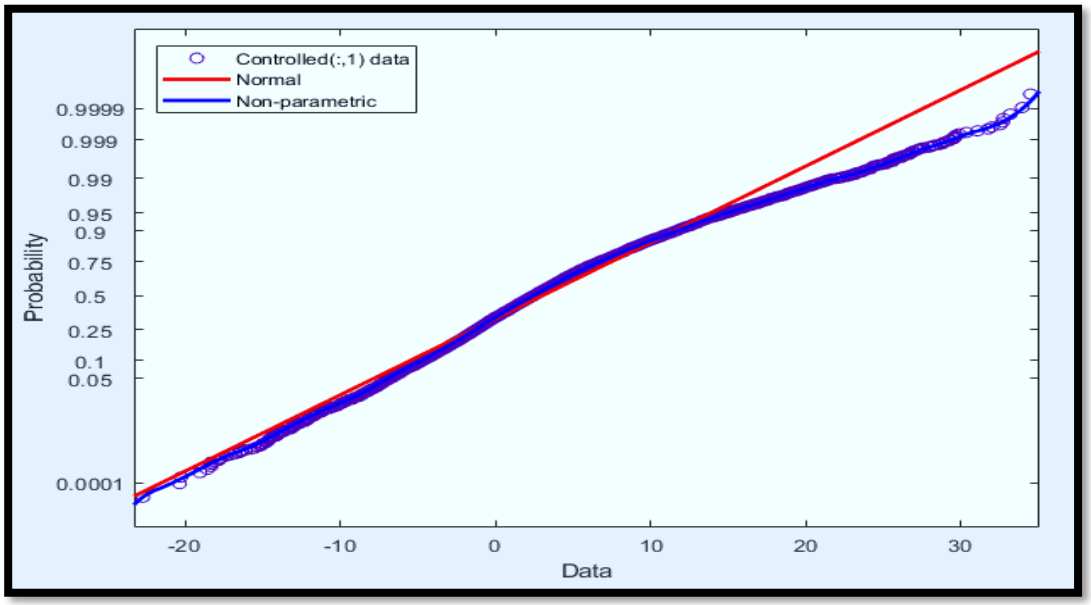

Figure 7: The distribution of a controlled EEG signal.

3.2 Sampling: Clustering Technique Coupled with Bootstrapping

To design a powerful sampling technique, a hybrid method that integrates the clustering technique and bootstrapping, (i.e., CT-BS) is proposed in this study for reducing the dimensionality of EEG signals. This also prevents problems such as bias and variation that may occur when applying a clustering technique. Not only is bootstrapping a method that depends on random sampling with replacement, but it also estimates properties of an estimator. Adapting standard errors for clustering can be a

very important part of any statistical analysis (Elkomy et al., 2016, Cameron et al., 2008); further, in terms of statistical modelling, validation is extremely important in cluster analysis because clustering techniques resort to generate clustering even for completely homogeneous data groups. Most clustering techniques suppose a certain paradigm for clusters, and this could be adequate for some portions of data, but not for others. The issue of stability in cluster analysis is complex, but it is considered an important part of the cluster validity (García-Escudero and Gordaliza, 1999). We propose to use the bootstrap method to reduce the error rate, which leads to reducing the bias and variation. The main concept behind utilising the non-parametric bootstrap for the estimation of cluster constancy or stability is the following: suppose that there is a mixture distribution $K = \sum_{i=1}^{z} \varepsilon_i K_i$ where *i=1, 2, 3, …, z,* are the distributions generating *z* 'true' clusters, and ε_i is the probability that a point from K_i is drawn (Ben-Hur et al., 2001, Hennig, 2004, Hennig, 2007). For a given dataset with *n* points, the 'true' clustering would then be composed of *z* clusters, each of which includes precisely the points generated by K_i, $i = 1, 2, 3, \ldots, z$. The dataset, when generated from *K*, is clustered; the found clusters vary from the 'true' clusters because the clustering approach introduces an assured bias and variation.

The concept of bias and variation can be expressed via the maximum *Jaccard* coefficient (compares members for two sets to see which members are shared and which are distinct. It's a measure of similarity for the two sets of data, with a range from 0% to 100%. The higher the percentage, the more similar the two populations) between the group of all the points generated via K_i and the most identical cluster in the actually gained clustering. The bootstrap is habitually utilised to grant an idea of bias and variation caused via a certain statistical approach because, in reality, no true clustering is known and there is no true underlying distribution. To simulate *K*, the empirical distribution of the observed dataset is taken. The originally found clusters can be treated as the 'true' ones, and the points can be drawn from the dataset. The mean maximal *Jaccard* coefficient can be explained as denoting the stability of the authentic clusters. Given a number *b* of bootstrap replications and a cluster *C* from the original clustering $E_n(y)$, the schema works as below:

Reiterate for *i = 1, 2, 3, …, b*:

- For n points draw a bootstrap sample y_n^i with replacement from the original dataset y_n.
- Calculate the clustering $E_n(y_n^i)$.
- Suppose $y_*^i = y_n \cap y_n^i$ be the points of the original dataset that are also in the bootstrap sample. Suppose $C_*^i = C \cap y_n^i, \Delta = E_n(y_n^i) \cap y_*^i$.
- If $C_*^i \neq \emptyset$, calculate the maximum *Jaccard* similarity between the induced cluster C_*^i and the induced new clustering Δ on y_*^i: $\tau_{C,i} = max_{D \in \Delta} \tau(C_*^i, D)$ (i.e., D is the maximizer of $\tau(C_*^i, D)$; else $\tau_{C,i} = 0$).

  where *Jaccard* coefficient (Jaccard, 1901): $\tau(C, D) = \frac{|C \cap D|}{|C \cup D|}, C, D \subseteq y_n$.

This generates a sequence $\tau_{C,i}$, *i=1, 2, 3, ...,b*. Based on Hennig (2007) suggested the mean: $\bar{\tau}_C = \frac{1}{b^*} \sum_{i=1}^{b} \tau_{C,i}$ as stability measure (b^* being the number of bootstrap replications for which $C_*^i \neq \emptyset$ and is utilised here because in all other cases $\tau_{C,i} = 0$).

3.3 Features Extraction

In machine learning, with huge dimensions of data, the necessity to provide a reliable analysis grows exponentially (Hira and Gillies, 2015, Alonso et al., 2007). There are diverse types of mental and neurological conditions where the EEG data size is huge and requires observation by the clinician over an extended period. Alcoholism EEG signals may contain valuable and useful information about the different states of the brain. Since the biological signal is highly random in both time and frequency domain, computerised analysis is indispensable. Due to the signals being non-stationary, appropriate analysis is fundamental for EEG to differentiate the alcoholic/control EEG signals. A covariance matrix method that was used in previous work (Al-Hadeethi et al., 2020) is proposed to reduce the EEG signal (and data) dimensionality while extracting most important features for better classification accuracy.

Time series (EEG signals) can be defined as a vector of length $W([x_1, x_2, \ldots, x_W])$. Feature nominees can be integrated into a feature vector for a point in time series. Let $\{P_i\}$ the number of features, defined for a point be Q. The feature vector for the Nth point of the subsequence can be manifest as (Ergezer and Leblebicioğlu, 2018, Ergezer and Leblebicioğlu, 2016):

$$h_N = [P_{N1}, P_{N2}, \ldots, P_{NQ}] \quad (4.1)$$

After combined the feature vectors for all points, this study gets a feature matrix *H*,

$$H = \begin{bmatrix} P_{11} & \cdots & P_{1Q} \\ & \vdots & \\ P_{W1} & \cdots & P_{WQ} \end{bmatrix} \tag{4.2}$$

It can be calculated the covariance of the feature matrix as follow:

$$COV = \frac{1}{W-1} \sum_{i=1}^{W-1} (H_i - \mu)\ (H_i - \mu)^T \tag{4.3}$$

where μ is the mean vector of feature vectors $\{h_1, h_2, \ldots, h_W\}$.

Based on separating the time series into *L* overlapping subsequences with each having a length *W*, the general representation was adapted for time series classification problem. In this study, to decrease the dimensionality of data which leads to enhance detection of possible abnormalities in the prescribed EEG signal. Based on the 10 different statistical features the eigenvalues of the covariance matrix are investigated by extracted these features from each eigenvector.

In this research, the data were derived from multi-channel EEG signals, where each channel consists of (256×30). For more clarification, we will explain using the following example: an experiment of 61channels that consists of a matrix (15616×30) is used; the time-series was divided into four segments (n=4), each segment containing (3904×30) data points, which was then divided into 32 clusters (m=32) to obtain (122×30); next, from each cluster samples were randomly selected and replaced through 100 rows-based bootstrapping to get a matrix (100×32). After that, a matrix of (32×32) was obtained from the covariance matrix; next, from each eigenvector, a matrix of (32×1) was gained and ten statistical features extracted from that matrix. As a result, the dimensionality was reduced for each segment from 3904 to 1200 (40×30) data points. Thus, the dimensionality of 61 channels providing the optimal EEG features was decreased from 15616 to 4800 data points to construct the proposed FOA-F-SVM classification system.

3.4 Feature Selection

In the work described here, one of the primary objectives of conducting many experiments was to find the optimal features that improved results (Diykh et al., 2020). The features briefly summarise the most important information in the data, thus this is used in cases where there is a large number of dimensions (Diykh et al., 2019a,

Abdulla et al., 2019). Selecting the optimal features could lead to a high rate of classification accuracy. Therefore, six experiments were conducted on EEG channels to determine the feature set using Kolmogorov–Smirnov test (KST). Below is a summary of the results obtained:

A. In the first experiment, 11 channels were tested ($AF_1, AF_2, AF_7, AF_8, AFZ, C_1, C_2, C_3, C_4, C_5$ and C_6) to determine whether these channels were adequate to analysis the alcoholism signals (Table 1). Based on statistical analysis, the results showed that using these channels could explain 60% of the data.

Table 1: feature set outcome of Experiment No. 1

Features	Testing	Training	Compared with the p-values
	Controlled vs Alcohol	Controlled vs Alcohol	
Mean	0.1088	0.2003	Rejected
Max	0.46	0.342	Rejected
Med	0.0017	2.9480×10^{-09}	Accepted
Min	0.011	0.02	Accepted
Mod	0.011	0.02	Accepted
Range	1.7552×10^{-05}	0.034	Accepted
Skew	0.1088	0.94	Rejected
Kur	0.1	0.93	Rejected
Std.	2.0212×10^{-04}	0.01088	Accepted
Var.	1.7552×10^{-05}	0.02003	Accepted

B. The channels ($AF_8, C_1, C_2, C_3, C_4, CP_1, CP_5, CP_6, FC_5, FT_7, P_8, PO_8$ and P) were utilised in the second experiment below. The outcomes indicate that the acceptance rate was high, reaching 90%, which means that the signal in these channels was suitable for detecting the EEG signals (Table2).

Table 2: feature set outcome of Experiment No. 2

Features	Testing	Training	Compared with
	Controlled vs Alcohol	Controlled vs Alcohol	the p-values
Mean	5.5870×10^{-08}	0.02585	Accepted
Max	2.0480×10^{-09}	0.00455	Accepted
Med	1.7973×10^{-14}	3.5202×10^{-10}	Accepted
Min	1.4977×10^{-13}	0.00165	Accepted
Mod	1.4977×10^{-13}	0.00165	Accepted
Range	2.0480×10^{-09}	2.6199×10^{-07}	Accepted
Skew	0.10875	0.935	Rejected
Kur	0.045	6.1578×10^{-04}	Accepted
Std.	0.00465	0.045	Accepted
Var.	1.1088×10^{-08}	0.00165	Accepted

C. The number of channels in the experiment below was 23, with a success rate of 70%. The channels were (CP_1, CP_2, CP_3, CP_4, CP_5, CP_6, CPZ, CZ, F_1, F_2, F_3, F_4, F_5, F_6, F_7, F_8, FC_1, FC_2, FC_3, FC_4, FC_5, FC_6 and FCZ) (Table 3).

Table 3: feature set outcome of Experiment No. 3

Features	Testing	Training	Compared with
	Controlled vs Alcohol	Controlled vs Alcohol	the p-values
Mean	0.055	0.3420	Rejected
Max	0.0259	0.0017	Accepted
Med	0.0113	1.7552×10^{-05}	Accepted
Min	1.1615×10^{-12}	5.6313×10^{-11}	Accepted
Mod	1.1615×10^{-12}	5.6313×10^{-11}	Accepted
Range	0.05	0.0113	Accepted
Skew	0.2003	0.76	Rejected
Kur	0.5372	0.9360	Rejected
Std.	6.1578×10^{-04}	0.011	Accepted
Var.	0.0113	0.002	Accepted

D. With an acceptance rate of 50%, twenty-eight channels passed the test in this experiment. The channels used in this experiment were (FP_1, FP_2, FPZ, FT_7, FT_8, FZ, O_1, O_2, OZ, P_1, P_2, P_3, P_4, P_5, P_6, P_7, P_8, PO_1, PO_2, PO_7, PO_8, POZ, PZ, S_1, T_7, T_8, TP_7 and TP_8) (Table 4).

Table 4: feature set outcome of Experiment No. 4

Features	Testing	Training	Compared with
	Controlled vs Alcohol	Controlled vs Alcohol	the p-values
Mean	0.34	0.2	Rejected
Max	0.53	0.20	Rejected
Med	0.002	0.005	Accepted
Min	0.06	0.2003	Rejected
Mod	0.06	0.2003	Rejected
Range	0.012	0.0017	Accepted
Skew	0.8	0.54	Rejected
Kur	0.026	0.0259	Accepted
Std.	0.005	0.0046	Accepted
Var.	6.1578×10^{-04}	0.005	Accepted

E. The channels ($AF_1, AF_2, AF_7, AF_8, AFZ, FP_1, FP_2, FPZ, FT_7, FT_8, P_1, P_2, P_3, P_4, P_5, P_6, P_6, P_7, P_8, PO_1, PO_2, PO_7, PO_8, POZ, F_1, F_2, F_3, F_4, F_5, F_6, F_7, F_8, T_7, T_8, TP_7$ and TP_8) were used in this experiment. At 40%; the acceptance rate was very low; this indicates that the signals used were not valid for classification (Table 5).

Table 5: feature set outcome of Experiment No. 5

Features	Testing	Training	Compared with
	Controlled vs Alcohol	Controlled vs Alcohol	the p-values
Mean	6.1740×10^{-05}	0.012	Accepted
Max	2.0212×10^{-04}	0.109	Accepted
Med	1.7973×10^{-14}	0.03	Accepted
Min	0.34	0.9	Rejected
Mod	0.34	0.9	Rejected
Range	2.0212×10^{-04}	0.005	Accepted
Skew	0.55	0.54	Rejected
Kur	0.93	0.4	Rejected
Std.	0.76	0.46	Rejected
Var.	0.1088	0.01	Rejected

F. Results obtained from Experiment No. 6 indicate that the use of 61 channels was efficient in the analysis; they could, thus, be used to classify EEG signals.

The 61 channels were as follows: $FC_4, FC_3, C_6, C_5, F_2, F_1, TP_8, TP_7, AFZ, CP_3, CP_4, P_5, P_6, C_1, C_2, PO_7, FP_1, FP_2, F_7, F_8, AF_1, AF_2, FZ, F_4, F_3, FC_6, FC_5, FC_2, FC_1, T_8, T_7, CZ, C_3, C_4, CP_5, CP_6, CP_1, CP_2, P_3, P_4, PZ, P_8, P_7, PO_2, PO_1, O_2, O_1, AF_7, AF_8, F_5, F_6, FT_7, FT_8, FPZ, PO_8, FCZ, POZ, OZ, P_2, P_1, CPZ$ (Table 6).

Table 6: feature set outcome of Experiment No. 6

Features	Testing	Training	Compared with the p-values
	Controlled vs Alcohol	Controlled vs Alcohol	
Mean	0.045	0.0446	Accepted
Max	0.3420	0.1088	Rejected
Med	6.1740×10^{-05}	1.7973×10^{-14}	Accepted
Min	1.4977×10^{-13}	0.026	Accepted
Mod	1.4977×10^{-13}	0.026	Accepted
Range	0.011	0.03	Accepted
Skew	0.1	0.76	Rejected
Kur	0.046	0.034	Accepted
Std.	0.00238	0.01	Accepted
Var.	0.0476	0.02	Accepted

As a result, with the highest acceptance rates, the second and sixth experiments performed the best. The last group of features utilised to identify each pair of EEG groups (Controlled vs Alcoholic) were *[Mean, Med, Min, Mod, Range, Kur, Std., and Var.]*. Therefore, by conducting a number of experiments, we were able to thoroughly investigate feature selection in order to select the most effective feature set to recognise EEG groups.

4. Performance Evaluation Methods

It is important to evaluate the performance of any classification or detection system. A set of methods was used to assess the performance of the alcoholism classification and detection system based on the proposed FOA-F-SVM technique, as described below:

a) Accuracy (Acc.) is a degree of proximity of a measured or calculated quantity to its actual (true) value. The term accuracy is utilised to assess the performance of the SVM method depending on the formula as below:

$$\text{Acc.} = (TP + TN)/(TP + TN + FP + FN) \tag{4.4}$$

b) Sensitivity (Sen.) is a statistical measure of the performance of a binary classification test used to measure the rate of the real positive predication. This is defined as follows:

$$Sen. = TP/(TP + FN) \tag{4.5}$$

c) Specificity (Spe.) is utilized to measure the proportion of the real negative predication and is defined as follows:

$$Spe. = TN/(TN + FP) \tag{4.6}$$

d) Predictive Positive Value (PPV.) is defined as the rate of positives that correspond to the presence of the condition described via the formula as below:

$$PPV. = TP/(TP + FP) \tag{4.7}$$

e) Predictive Negative Value (PNV.) is the ratio of negatives that correspond to the absence of the condition and is defined as follows:

$$PNV. = TN/(TN + FN) \tag{4.8}$$

5. Classification approach based on SVM

5.1 Radius-Margin-Based Support Vector Machine (F-SVM)

Given the training set $q = \{(x_1, y_1), \ldots (x_n, y_n)\}$, the fundamental SVM paradigm is displayed below. The paradigm only deems the maximisation of margin. However, an accurate description can explain that the generalisation error bounds of SVM are the function of radius and margin (Hedges et al., 1999).

$$\begin{aligned} &\min_{d,b,\delta} \tfrac{1}{2} \|(n)\|_2^2 + Z \sum_i \delta_i \\ &s.t.\ \ y_i(n^T x_i + b) \geq 1 - \delta_i \forall_i \\ &\delta_i \geq 0, \qquad i = 1, 2, 3, \ldots, \end{aligned} \tag{4.9}$$

Given the radius, a group of researchers, (Wu et al., 2018), have proposed a novel formula $\frac{1}{2}\bar{R} \leq R \leq \bar{R}$. Let the matrix $K = A^T A$ where A is denoted to transform matrix, the slack variables $\delta_i (i = 1, 2, 3, \ldots, n)$. The paradigm of linear F-SVM is represented in (2):

$$\min_{w,b,\delta,K} \ \frac{1}{2}(w^T K^{-1} w) + Z\sum_{i=1}^{n}\delta_i + \rho tr(KS)$$

$$s.t. \ \ y_i(w^T x_i + b) \geq 1 - \delta_i \forall_i \qquad (4.10)$$

$$\delta_i \geq 0, \qquad i = 1, 2, 3, \ldots,$$

$$K \succ 0$$

Wu et al. solved the nonlinear classification problems by incorporated kernel principal component analysis into linear F-SVM. The proportion of cumulative eigenvalues to the sum of all eigenvalues is set as 0.9 in the dimension selection of kernel principal component analysis. The paradigm can be formulated as follows:

$$\min \ \frac{1}{2}(w^T K^{-1} w) + Z\sum_{i=1}^{n}\delta_i + \rho tr(KNq)$$

$$s.t. \ \ y_i(w^T f_i + b) \geq 1 - \delta_i \forall_i \qquad (4.11)$$

$$\delta_i \geq 0, \qquad i = 1, 2, 3, \ldots,$$

$$K \succ 0$$

where $N_q = \sum_{i=1}^{n} w_i q_i q_i^T$, $q_i = Q^T \Phi(x_i)$, $Q = [q_1, q_2, q_3, \ldots, q_{Go}]$ is indicated to the eigenvectors corresponding to the first G eigenvalues. The mapping function of kernel F-SVM that is always utilised is Radial-Basis-Function (RBF), i.e., $(x_i, x_j) = \exp\left(-\gamma \|x_i - x_j\|^2\right)$, where γ is the specified parameter to limit the width of the RBF (ling Chen et al., 2014). Between the minimization of training error and maximization of the classification margin in the paradigm, factor Z controls the trade-off (Tharwat and Hassanien, 2018). The classification accuracy differs between these two parameters. Therefore, defining the values of the parameters is essential to the performance of the SVM classifier.

5.2 Fruit fly Optimization Algorithm (FOA)

The fruit fly optimization algorithm is based on the foraging behaviour of the insect after which it is named (Pan, 2012). The main concept of the algorithm is that the insect primarily flies towards food via utilising its olfactory sensory neurons: one of the groups of neurons will emit a pheromone when it is near to food. Thereafter, the fruit flies change its direction and flies to meet its peers. Through continually updating its status and flying direction, the fruit fly will finally get nearer to the food, the position of which is the optimum solution. The algorithm will be completed if the iteration reaches maximization or the outcome is to archive the permissible accuracy. The algorithm can be split into a number of steps:

1) The position of fruit fly is random initialization (*InitX*, *InitY*).
2) For each fruit fly, give a random direction and distance to hunt for food via its olfactory sensory neurons:
   $X_i = X + Random\ value$
   $Y_i = Y + Random\ value$
3) Due to unknowing exact location of food, the distance will be computing from the location of fly to the origin; thereafter, computing the mutual distance. As a result, the value will be defined as a smell concentration judgment value (d):
   $Dist_i = (X_i^2 + Y_i^2)^{1/2}$
   $d1_i = \frac{1}{Dist_i}$
4) to detect a better smell concentration, set the above smell concentricity judgment value into smell concentricity judgment function:
   $Smell_i = Function\ (n_i)$
5) discover individuals with the raised concentricity in the population:
   $[bestSmell, bestIndex] = \max(Smell)$
6) preservation the most appropriate concentricity and an assortment of the fruit fly, and other fruit flies to that coordinates utilising vision:
   $X = X(bestindex)$
   $Y = Y(bestindex)$
7) In Steps 2-5, the iterative optimization was performed. Thereafter, judge whether the concentricity is higher than that of the former level. If so, perform Step 6.

5.3 Classification based on FOA-F-SVM model

This section introduces the main idea used in developing the newly proposed FOA-F-SVM system. In order to improve and further develop the performance accuracy of the traditional SVM model, the radius-margin-based SVM, i.e., F-SVM, for joint learning of the feature transformation and SVM classifier integrated with fruit fly optimization algorithm were proposed for the analysis of alcoholism through multi-channel EEG signals. As shown in Figure 8, the proposed model consists of different stages. The first five steps represent internal parameter optimization and the next five steps display the external evaluation of the classification performance. The path of the proposed model is this: tune parameters depending on the FOA, after that gain an optimum classifier. Eventually, by testing the dataset through external assessment, the performance of the classifier was measured.

The FOA was utilised to set the parameters in the section of parameter optimisation. Depending on the RBF kernel of the SVM classifier, the fruit fly's solution was used to represent the classifier parameters Z and γ. To direct the updating of the fruit fly location, the rate of classification accuracy of the structure SVM classifier was used. The optimum solution was gained via the iterative optimisation procedure, depending on the location. The SVM classifier was built up with the optimum parameters gained above in the external assessment section; thereafter, the eventual classification outcomes were gained on the test set via this classifier.

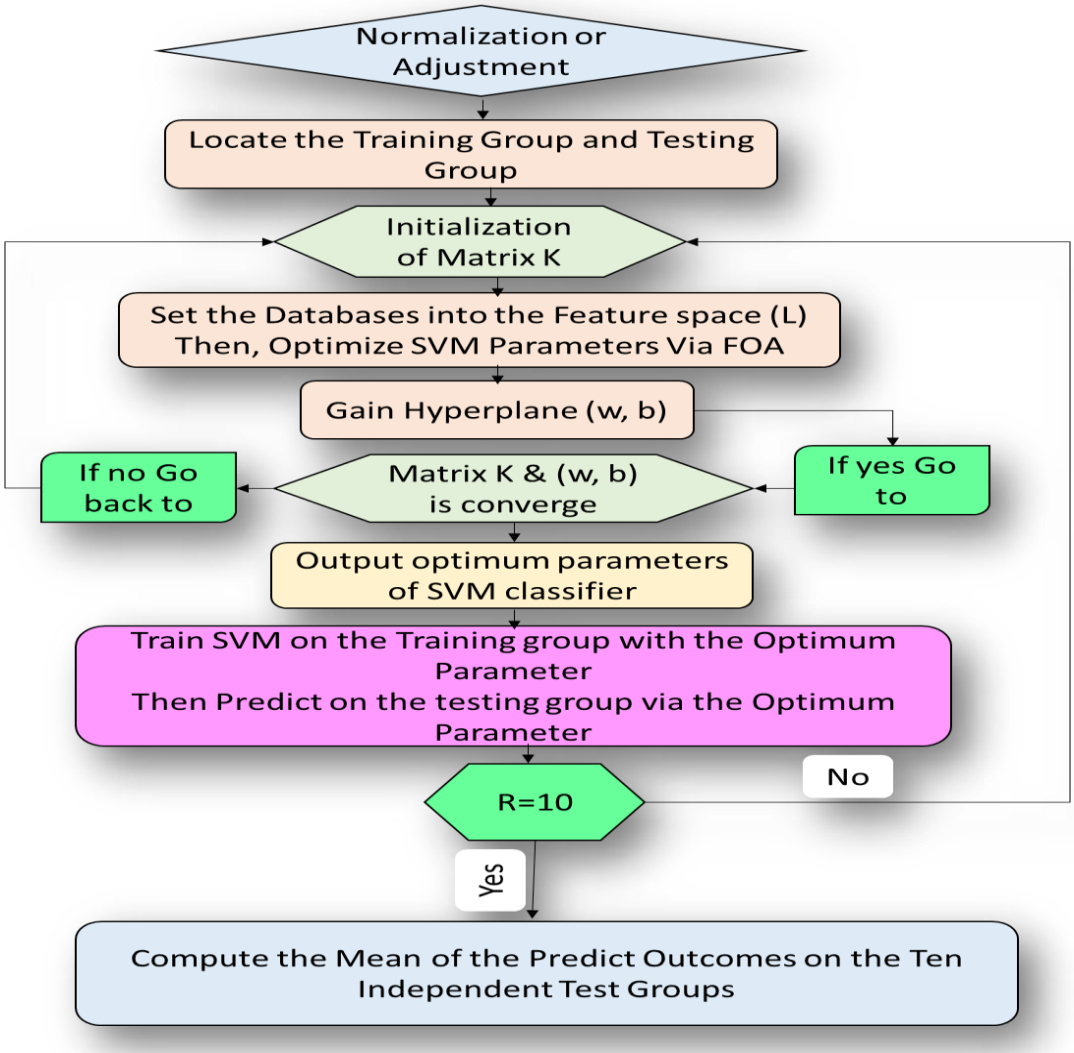

Figure 8: flow diagram representation Algorithm the proposed FOA-F-SVM model

5.4 Optimisation Algorithm

In the FOA-F-SVM model, there are many unknown variables, such as in the formula (11). To solve obscure variables (matrix K and hyperplane (w, b)) of the FOA-F-SVM model, there are three main steps:

i. **Initiating *K***

Suppose the weighted covariance N_q performs eigenvalue decomposition, i.e. $N_q = D\Lambda D^T$, where $\Lambda = Diag\{\lambda_1, _{2...}, \lambda_n\}$ and λ is arranged in order from highest to lowest. After algebraic computation, matrix K_0 can be denoted as $K_0 = D \wedge^{-(1/2)} D^T$. Due to $K = A^T A$, the transformation matrix A can be written as

$A_0 = \Lambda^{-(1/4)} D^T$. Therefore, the samples are transformed into $z = dataset * A_0$.

ii. ***Resolve hyperplane (w, b)***

This step consists of an explanation of how the FOA model is adopted to gain an optimum SVM classifier. The particular operation is that: the range of each parameter is given; thereafter various values are randomly allocated within this range for every fruit fly. In the meantime, the fruit fly is represented every group solution. Subsequently, find the preferable of these solutions. The finding operation includes two portions: via a smell search procedure, every fruit fly adjusts its position; based on the preferable fruit fly through the vision-based search procedure, the worst fruit fly in the population will be encouraged. This will then lead to obtaining a solution of the parameters via the iteration. Eventually, the test samples from z and gained optimum parameters are fed to the F-SVM prediction model.

iii. ***Resolve matrix K***

Now, having gained the SVM classifier, formula (11) can be formulated again as follows:

$$\min_K f(K) = \frac{1}{2}(w^T K^{-1} w) + Z\sum_{i=1}^{n}\delta_i + \rho tr(KN)$$

$$s.t. K \succ 0 \tag{4.12}$$

The function is cambered and able to be differentiated for K, thus, to solve K the gradient-projection method was chosen. The derived function for this term is below. Thereafter, update K *via* $K_{h+1} = PN + (K_h - t_1 \nabla f(K_h))$ until K converge.

$$\nabla f(K) = -\frac{1}{2} K^{-1} w w^T K^{-1} + \rho N \tag{4.13}$$

i. From all the illustration and explanation above, it is clear that the matrix K is a significant parameter in the FOA-F-SVM. Only via initialising K, it can transform the dataset into a new feature space. Thereafter, an SVM classifier is gained via optimising parameters through FOA. Eventually, an optimal classifier is gained by constantly updating K.

6. Experimental Results

To conduct the simulation effectively, the same number of iterations and the same population size were set for PSO, GA, and FOA. According to our preliminary experiment, when the number of maximum iteration and population size are respectively set as 100 and 20, the methods involved result in satisfactory classification performance. Furthermore, in the experiment, parameter Z is in range $Z \in \{2^{-10,1,20}\}$, parameter g is set $g \in \{2^{-20,1,10}\}$. The parameters of each model are as follows: for FOA-F-SVM, the x and y are denoted to initialize the location of fruit fly and the search direction $ax, bx, ay\ and\ by$ respectively set as 10, 20, 20, 10 in the distance function. For PSO-SVM, the maximum velocity is 0.5 times the maximum parameter Z. The learning factor $Z1, Z2$ were set 1.6, 1.5, and the intermediate variable w was set 1 in the updating velocity function and updating location function. All experiments were carried out on a desktop computer with CPU (2.30 GHz) and 8.00 GB RAM under the MATLAB 2020 a programming environment.

The experimental EEG data used to assist the proposed model were obtained from the University of California, Irvine Knowledge Discovery in Databases Archive UCI KDD. The EEG signals were collected from 122 participants, and each subject performed 120 trials with three types of stimuli (Zhang et al., 1997). The recordings were obtained from 61 channel EEG signals, two EOG channels and one reference electrode. There are three datasets, named SMNI_CMI_- TRAIN, SMNI_CMI_TEST and FULL, respectively. In this study, only the first two databases were utilised because the full datasets contain a few all-zero recordings. There were 600 recorded files in SMNI_CMI_TRAIN, with each recording containing the signals from 64 electrodes caps. The 64 electrodes are $FC_4, FC_3, C_6, C_5, F_2, F_1, TP_8, TP_7, AFZ, CP_3, CP_4, P_5, P_6, C_1, C_2, PO_7, FP_1, FP_2, F_7, F_8, AF_1, AF_2, FZ, F_4, F_3, FC_6, FC_5, FC_2, FC_1, T_8, T_7, CZ, C_3, C_4, CP_5, CP_6, CP_1, CP_2, P_3, P_4, PZ, P_8, P_7, PO_2, PO_1, O_2, O_1, X, AF_7, AF_8, F_5, F_6, FT_7, FT_8, FPZ, PO_8, FCZ, POZ, OZ, P_2, P_1, CPZ, nd$ and Y. The electrodes X and Y are EOG signals, and nd are reference electrodes. The EOG and nd were removed in our analysis. However, features were extracted from 61 channels.

6.1 The influence of Bootstrap on classification results

The development of the sampling stage is the optimal solution to obtain segmented data that contain all the information. It thus leads to increased reliability of the results.

In this study, the bootstrap technique was utilised to evaluate variation and bias in the estimated model reliability (clustering technique). By using the bootstrap method, most of the problems associated with the clustering technique have been eliminated, which leads to developing the sampling strategy. When integrated with clustering methods, bootstrapping has been shown to be more robust in quantifying statistical error than other approaches, since this method provides large samples of random realisations of statistical estimates. Obtaining segmentation methods free from problems leads to an improved detection system; this was achieved in this research.

6.2 Evaluating the performance of the proposed FOA-F-SVM model

To evaluate the performance of the FOA-F-SVM in alcoholic EEG signals, a comparison was made with SVM, PSO-SVM, GA-SVM, and F-SVM. Table 7 shows the average results of the comparison among the FOA-F-SVM, PSO-SVM, GA-SVM, F-SVM and SVM. Based on the results, the performance of the FOA-F-SVM attains higher classification accuracy than other approaches. However, the PSO-SVM and GA-SVM scored the second highest results and they outperformed the basic SVM. This research findings indicate that tuning parameters was important in improving classification accuracy of EEG signals. In addition, the classification accuracy obtained by the F-SVM is higher than the basic SVM.

Table 7: Classification accuracy of the comparison among the FOA-F-SV, PSO-SVM, GA-SVM, F-SVM and SVM.

Approach	Accuracy	Sensitivity	Specificity
FOA-F-SVM	99%	98%	98.5%
PSO-SVM	95%	94%	95%
GA-SVM	96.5%	95%	95%
F-SVM	92.5%	91%	92%
SVM	85.5%	86%	84%

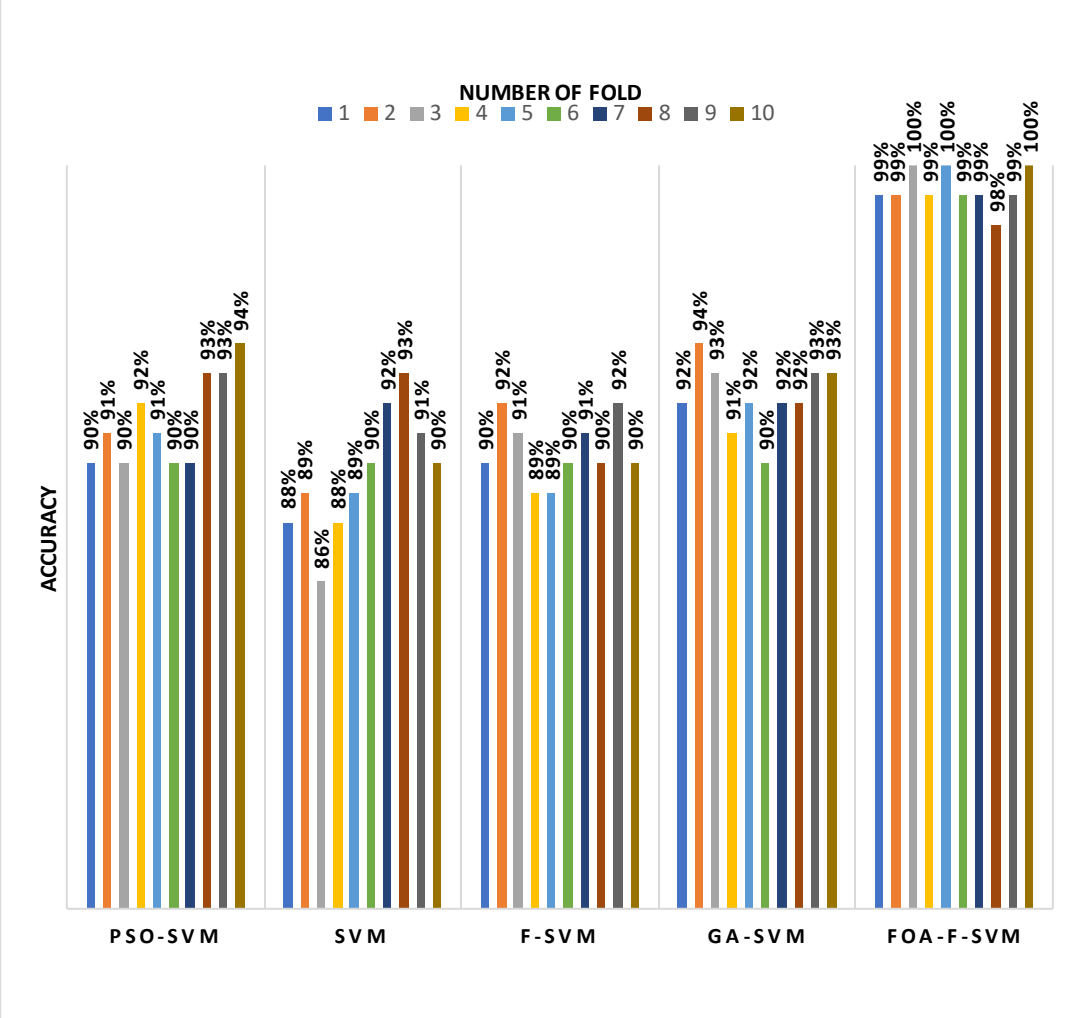

Figure 9: The detailed classification accuracy of 10 folds.

Figure 9 shows the detailed classification accuracy of 10 runs, as well the results of FOA-F-SVM, which are up to 98%, while the results of PSO-SVM and GA-SVM are distributed in the range from 90% to 94%. While the F-SVM and SVM gained a rate of accuracy from 86% to 93%. As a result, it can be observed that the FOA-F-SVM obtained the highest accuracy on each run and the best value is 100%. However, because of the robustness of the proposed method, the average result is the highest with 99.2%.

6.3 Channel selection based on classification accuracy

The accuracy of the proposed model based on 61-channel EEG signals is shown in Figure 10. In this experiment, the features were extracted from each channel and forwarded to the proposed model. The results show that not all channels yielded high classification accuracy. As a result, 13 optimal channels including $AF_8, C_1, C_2, C_3, C_4,$

$CP_1, CP_5, CP_6, FC_5, FT_7, P_8, PO_8, P$ were selected and used to classify EEG signals as shown in Figure 10.

The results in Figure 10 are compatible with the results obtained by statistical metrics in the section of feature selection and enhanced the results (not all channels gave high classification accuracy). The present study thus demonstrates the ability of the proposed model to assess alcoholic EEG signals from multi-channel EEG signals. The extracted features from electrodes C1, C3 and FC5 were found to be significantly effective in classifying EEG signals: an accuracy of 87.6 % was achieved. In addition, it was found that when the 13 channels were used to extract the features, the classification accuracy was close to the whole 61-channel performance. Table 8 presents the classification accuracy based on the number of channels. In addition, Figure 11 presents the three cases of chosen channels based on accuracy, sensitivity and specificity respectively.

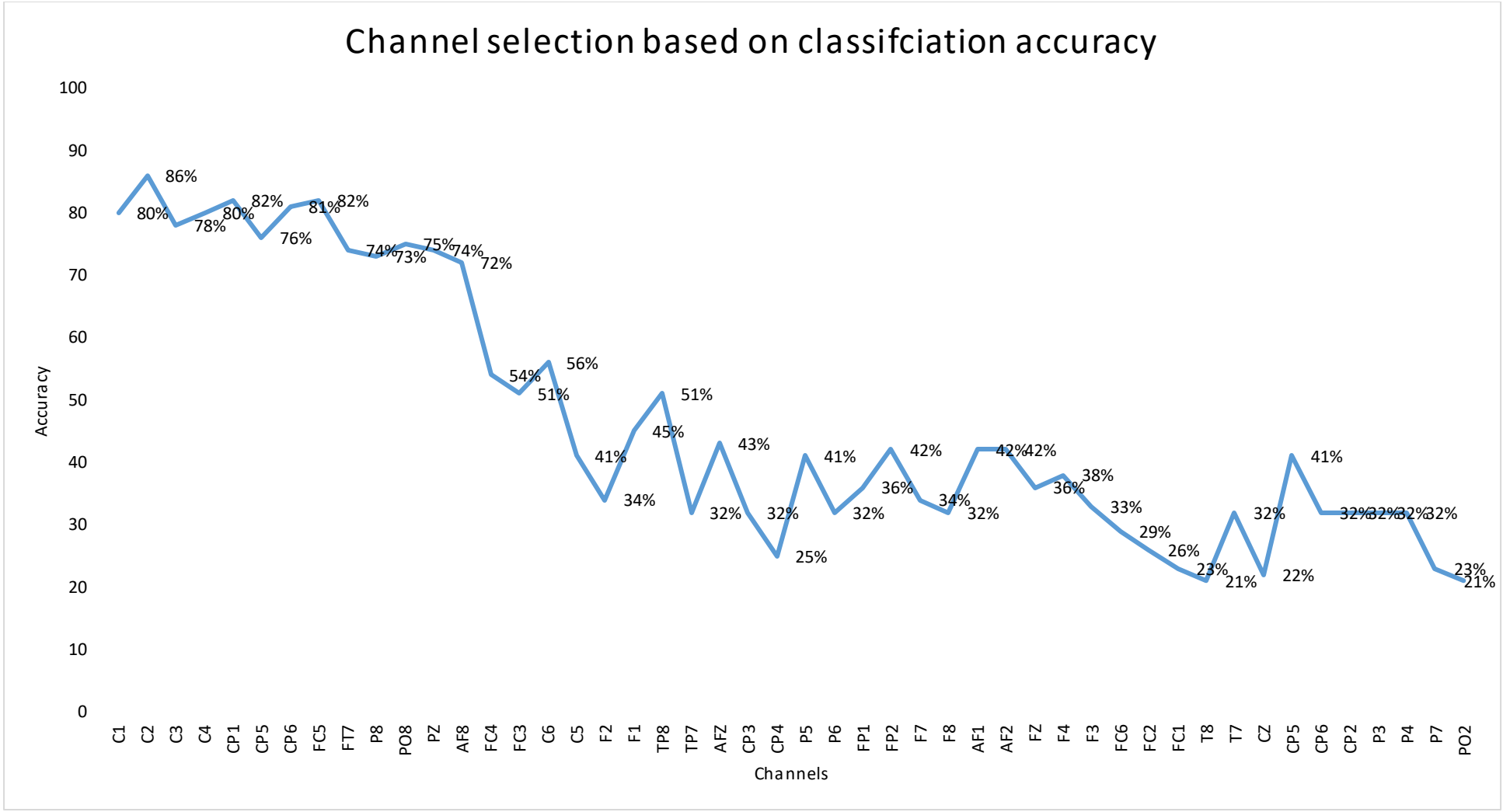

Figure 10: The accuracy of the proposed model based on 61-channel EEG signals.

Table 8: Presents the classification accuracy based on the number channels.

Channel No.	Accuracy	Sensitivity	Specificity
C_1, C_3 and FC_5	85%	83%	82%
AF_8, C_1, C_2, C_3, C_4, CP_1, CP_5, CP_6, FC_5, FT_7, P_8, PO_8, P	99%	98%	99%
All 61 channels	99.5%	98%	99%

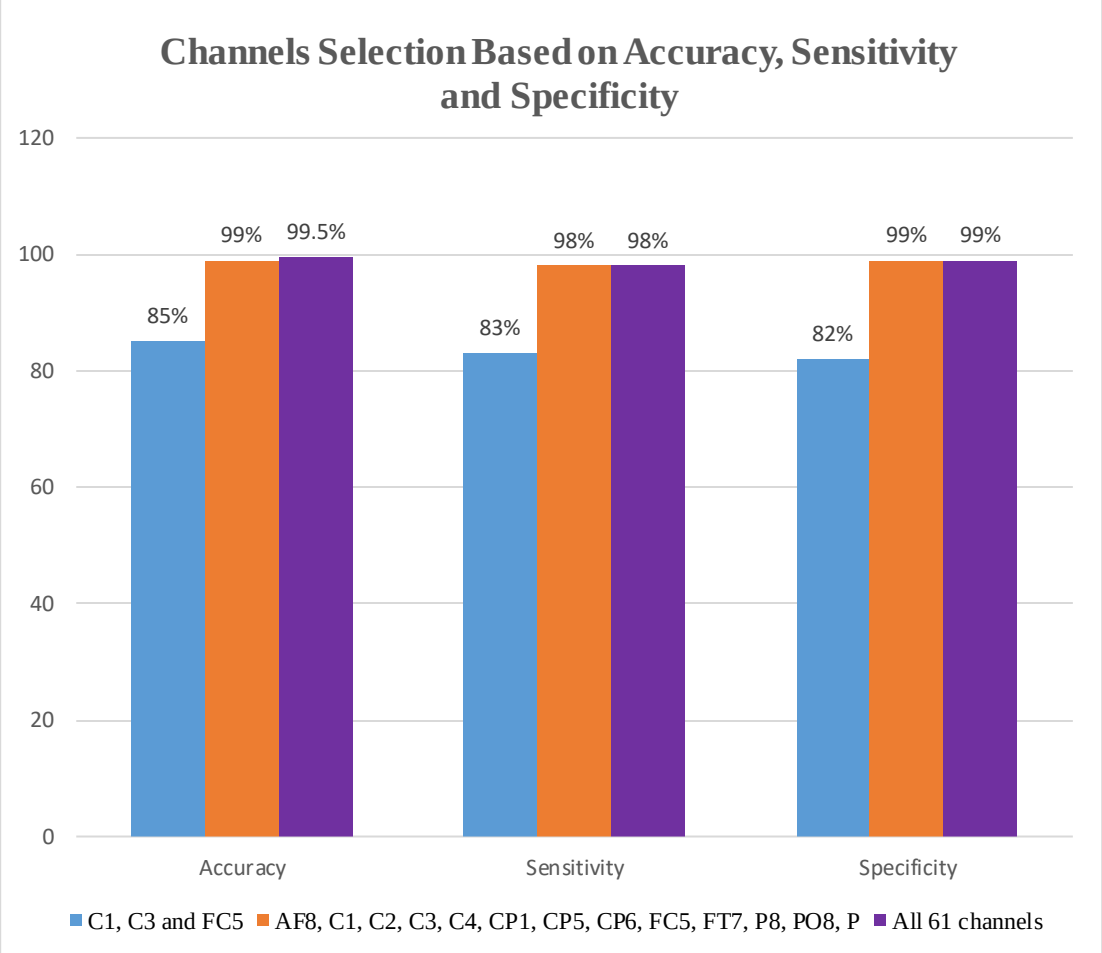

Figure 11: The three cases of channels chosen based on accuracy, sensitivity and specificity respectively.

6.4 Comparison of classification accuracy of the proposed model FOA-F-SVM with KNN, k-means and SVM

This section reports on the performance of the proposed model FOA-F-SVM based on 13 EEG channels. For further verification and to reach the highest level of reliability, the results were compared with KNN, k-means and SVM. To the best of our knowledge after extensive research, this is the first time the FOA-F-SVM model has been proposed and applied to the analysis and detection of alcoholism EEG signals. The results showed that compared to other algorithms, the proposed model FOA-F-SVM has promising performance that can be adopted as a classification technique of alcoholism EEG signals. The database SMNI_CMI_TRAIN was used for the training, and the database SMNI_CMI_TEST was utilised for the testing set. To show clearly the classification results based on 13 selected channels, Figure 12 depicts the accuracy of the proposed model FOA-F-SVM with KNN, k-means and SVM. It can be seen that the proposed model outperformed KNN, k-means and SVM over all 13 channels. In addition, the proposed model achieves 99% when all channels are used for the classification of EEG signals.

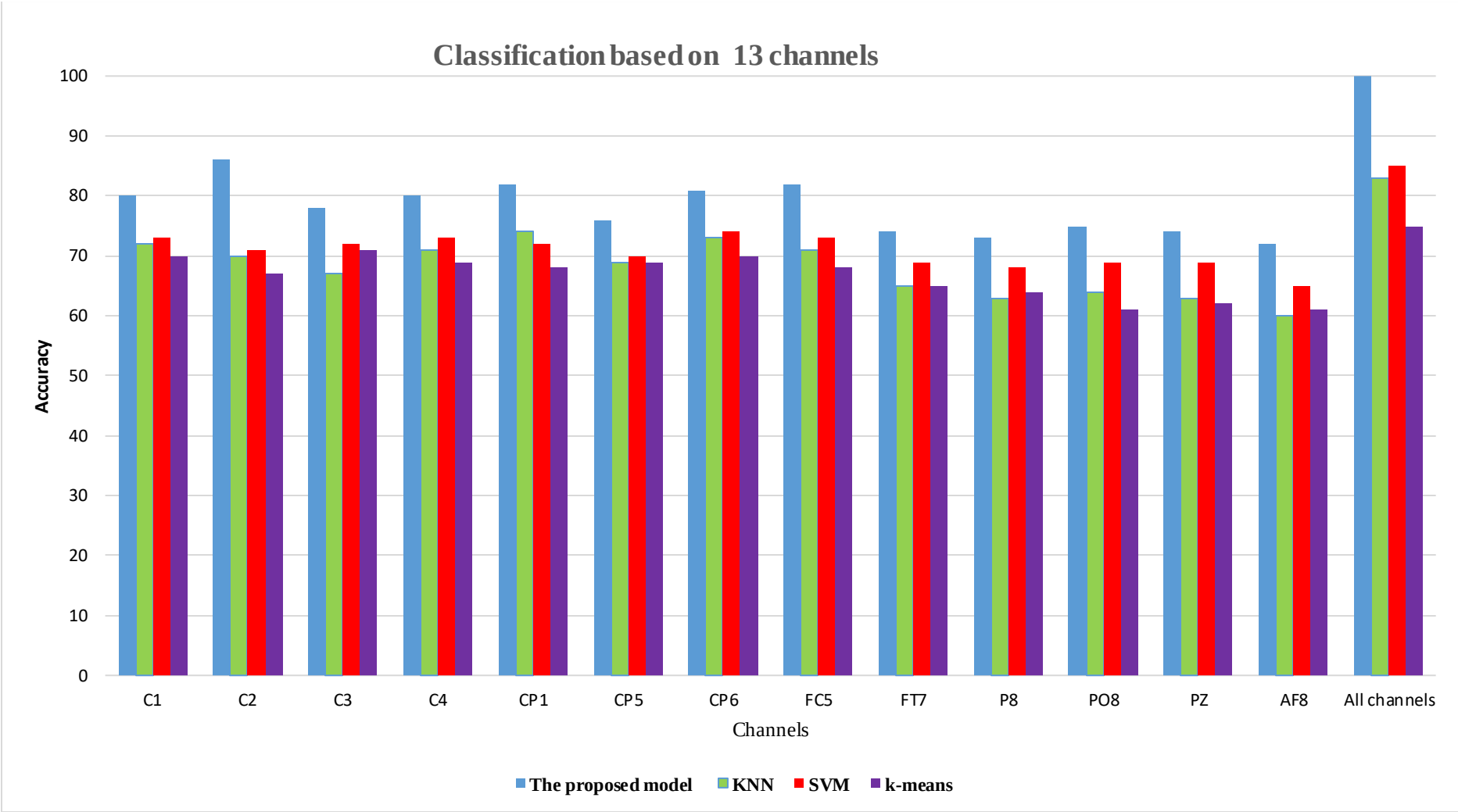

Figure 12: The accuracy of the proposed model FOA-F-SVM with KNN, k-means and SVM.

6.5 Discussion: Benchmarking the proposed model FOA-F-SVM with previous studies

Many studies were focused on finding a system that could be utilised for the automated detection of alcoholism EEG signals to estimate the effect of treatment and help significantly with clinical diagnosis. In this section, we shall review some of the previous studies that used the same data as did this work; for each, we shall provide a comparison of results.

The identification of non-linear features such as SAMENT, APPENT, LLE and HOS with LS-SVM classifier were used by (Acharya et al., 2012), who obtained an average classification accuracy of 91.7%. However, the classification accuracy that is achieved by the proposed model is significantly higher than that of (Acharya et al., 2012). Another group of researchers, (Faust et al., 2013b) has improved an automated system utilising wavelet packet based energy measures with the k-nearest neighbour (KNN) classifier; the method achieved a classification accuracy of 95.8% which is less than the rate obtained by the proposed model. A study by (Patidar et al., 2017) suggested an automated system for the diagnosis of alcoholism. This study utilised Tunable Q-wavelet transform (TQWT); then extracted CE of SBs gained from TQWT. Compared to the results obtained by the proposed method, the model of (Patidar et al., 2017) obtained a classification accuracy of 97.02%, which is, again, less than our classification accuracy of 99%. For the detection of alcoholic-related changes in EEG signals, (Faust et al., 2013a) have proposed the use of higher Order Spectra (HOS) cumulants-based features. Based on Fuzzy Sugeno Classifier (FSC), the investigators achieved a classification accuracy of 92.4%--considerably less than the 99% obtained in the present work. Finally, largest Lyapunov exponent (LLE), entropies, correlation dimension (CD), and Hurst exponent (H) were proposed by (Kannathal et al., 2005) to obtain the features for detecting of alcoholism from EEG signals: the rate of accuracy was 90%, which is considerably less than the classification accuracy achieved by the model proposed here.

The results in Table 9 show that the method proposed was superior to other studies and obtained a higher level of accuracy. After conducting many experiments and various types of comparisons, it has become clear that the proposed CT-BS-OFA-F-SVM model has a promising future in analysing and classifying EEG signals with a

high rate of accuracy. It was also noted that most of the previous studies were working on developing one part of the analysis, whereas in this study the focus was on most of the analysis steps.

The major advantages of this study are given below:

- Improving the sampling technique and dimensionality reduction model by integrating the clustering technique with bootstrapping CT-BS then applying the covariance matrix with eigenvalues in a single modelling framework to analysis EEG signal datasets;
- Utilizing arithmetic operators based on the KST technique to remove the noisy features in EEG signal datasets.
- Proposing the CT-BS-Cov-Eig technique coupled with FOA-F-SVM, (i.e., CT-BS-FOA-F-SVM) to detect multi-channels EEG signals;
- Proposing applying the OFA-F-SVM model to analyse and classify alcoholism EEG signals;
- Evaluating the performance of the FOA-F-SV in alcoholic EEG signals, comparing this with different methods such as SVM, PSO-SVM, GA-SVM, and F-SVM;
- Comparing the performance of the proposed hybrid OFA-F-SVM model to other state- of-the-art models to benchmark the overall effectiveness of the newly-designed approach for EEG signal classification and the identification of alcoholism;
- Investigating the performance of the proposed model FOA-F-SVM based on 13 EEG channels, three EEG channels and all 61 EEG channels;
- Comparing the results of FOA-F-SVM with KNN, k-means and SVM for further verification and to reach the highest level of reliability.

Table 9: Comparison with existing methods using the same database

Authors	Features/ techniques	Analysis	Accuracy
Acharya et al. (2012)	APPENT, SAMENT, LLE	SVM	91.7%
Faust et al. (2013b)	WPT, energy measures	KNN	95.8%
Patidar et al. (2017)	TQWT, CE	LS-SVM	97.02%
Faust et al. (2013a)	HOS cumulants	FSC	92.4%
Kannathal et al. (2005)	CD, LLE, entropy, H	Unique ranges	90%
The proposed model	**CT-BS-Cov-Eig**	**FOA-F-SVM**	**99%**

7. Conclusion

Accurate detection algorithms can be used effectively to help clinical research as a fast, reliable and easy-to-use tool in the diagnosis and monitoring of neurological disorders and in alcoholism. The EEG signals that are utilised to detect alcoholism are periodical, non-stationary and include a huge amount of data. In this study, there are two unique contributions to these efforts. First, we developed an effective method that was designed for sampling by integrating clustering technique and bootstrapping CT-BS in one phase. To detect and analyse abnormalities in the EEG signal, the eigenvalues of the covariance matrix were investigated utilising a statistical method that extracted ten statistical features from the eigenvalues of the covariance matrix. This research adopted the non-parametric method of KST as an effective statistical and mathematical tool for selecting and obtaining the optimum features. Thereafter, the proposed model was evaluated based on various metrics to test performance, including accuracy (ACC), sensitivity (Sen), specificity (Spec) and Negative Predictive Value (NPV). The second contribution was to integrate the CT-BS with FOA-F-SVM, (i.e., CT-BS-FOA-F-SVM) to detect and analyse multi-channel EEG signals.

To assess the performance of the FOA-F-SVM in alcoholic EEG signals, comparisons were made to different algorithms, for example SVM, PSO-SVM, GA-SVM, and F-SVM. Additionally, we investigated the performance of the proposed model, FOA-F-

SVM, based on 13 & 61 EEG channels, and, for further verification to reach the highest level of reliability, the results were compared with various methods, such as KNN, k-means and SVM. Furthermore, the model was compared to previous studies: the results showed that the proposed CT-BS-OFA-F-SVM model was superior, with a high accuracy rate of 99%.

To sum up, this study avers that the acquired results clearly illustrate the superior performance of the proposed CT-BS-Cov-Eig model coupled with FOA-F-SVM to existing state-of-the-art methods. The proposed model can be used to assist neurologists and other medical specialists in the precise diagnosis of alcoholism EEG signals. Future studies may investigate the improvement of the performance of the proposed model by decreasing the number of features used in this initial study. Also, because there is a great similarity between the results of feature selection and the results of channel selection, the possibility of proposing and implementing feature selection methods will be studied to find the optimal channels. Furthermore, with regard to the few numbers of studies focused on designing feature extraction, as well as a detection model for the reliable diagnosis of alcoholism EEG signals, there is a need for further research in this area.

Declaration of Competing Interest

The authors declare there is no conflict of interest.

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CHAPTER 5

Discussion, Conclusions, and Future work Suggestions

EEGs signals are considered a fundamental artefact of electrical activity created by a brain. They record signals utilising electrodes placed on the scalp with a conductive gel. The human brain consists of millions of neurons, each one creating a small electrical domain which form an electrical map on the scalp which can be revealed and recorded.

An assortment of techniques were created to explore the composition of EEG signals. This dissertation exhibits the design and development of robust techniques that detect and analyse abnormality in different EEG signals. In this dissertation three techniques, considered to be its essential objectives, were developed:

1. Design of a robust features extraction technique to reduce the dimensionality of EEG signals, thus improving classification accuracy. As well as, Design a powerful sampling technique, a hybrid method by integrating clustering technique and bootstrapping, (i.e., CT-BS) is proposed for improving the sampling technique and reducing the dimensionality of EEG signals.
2. Development of methods to select appropriate features using parametric and non-parametric methods.
3. Introduction of new models to detect epileptic seizures, Focal and Non-Focal and alcoholism in EEG signals.

To achieve these objectives, different methods based on the covariance matrix, eigenvalue, determinant, clustering, bootstrapping, Kolmogorov Smirnov, Mann Whitney U, Wilcoxon, AdaBoost Back-Propagation neural networks, Adaptive Boost Least Square Support Vector Machines and radius-margin-based support vector machine (F-SVM) with a fruit fly optimisation algorithm (FOA), (i.e., FOA-F-SVM), were developed and used. A summary of the developed method is provided in the following sections:

5.1 Features Extraction Technique to Reduce the Dimensionality of EEG Signals

To design a powerful technique for extract features, a method to reduce the dimensionality of EEG signals based on covariance matrix integrate with different methods, was introduced (see Chapters 2, 3 and 4).

In Chapter 2; to detect abnormalities in the EEG signal; a covariance matrix, with eigenvalues, was applied to reduce dimensionality, employing different sets of statistical features extracted and then evaluated with statistical score metrics. The eigenvalues of the covariance matrix are investigated using a statistical method by extracting ten statistical features from eigenvalues of the covariance matrix. These features, based on the mean, median, maximum, minimum, mode, range, standard deviation, variation, skewness and kurtosis, are the key attributes normally used to represent any EEG time-series data. The contribution of the covariance matrix approach to reduce the dimensionality of data, leading to improved classification accuracy in the problem of detecting epileptic disease in EEG signals.

In Chapter 3 the covariance matrix was integrated with its determinant matrix in one model to a design an approach that captures the relevant features from EEG signals. Based on basic information in linear algebra, the determinant could capture how linear transformation changes area or volume, and changes variables in integrals. That led to a process of eliminating the repetition and similarity in computing the high dimensionality of the database, which was our main target behind the integration of these two approaches: covariance matrix and determinant. Thus, the statistical features are extracted from each interval to construct a feature-based vector for each single EEG channel. The experimental outcomes demonstrate that the Cov_Det method is efficacious for extracting features to represent the EEG signals.

In Chapter 4 a covariance matrix method with its eigenvalues (Cov-Eig) were integrated with the clustering technique with bootstrapping CT-BS system applied for useful feature extraction related to alcoholism. To avert the problems that may occur when using a clustering technique such as bias and variation, bootstrapping is a method that depends on random sampling with replacement as well as it is estimating properties of an estimator. Further, in terms of statistical modelling, validation is

extremely important in cluster analysis because clustering techniques resort to generate clustering even for completely homogeneous data groups. The issue of stability in cluster analysis is complex but it is considered an important part of the cluster validity. The bootstrap method was proposed to reduce the error rate, which leads to reducing bias and variation.

Chapters 2, 3 and 4 clearly manifested that utilising a covariance matrix with eigenvalues, covariance matrix with its determinant matrix Cov-Det and covariance matrix with eigenvalues Cov-Eig unified with CT-BS could improve the classification accuracy of detecting epileptic disease in EEG signals.

5.2 Optimal Features Based Non-Parametric Methods.

In Chapters 2, 3, and 4 the primary idea behind the feature selection process was reducing the probability of model overfitting. By removing irrelevant data, this step ensures a classification model that is trained only on the most important features of the EEG data. In addition, removing irrelevant information also increases the accuracy of the prediction model and reduces the computation time involved. Based on the statistics applied to measure the similarity and the dissimilarity of the means in two independent samples, all papers also employed a nonparametric test that was appropriate for comparing two independent samples. Generally, to compare the outcomes between independent samples, there are three popular nonparametric tests: the Kolmogorov–Smirnov test (KST), Wilcoxon and the Mann Whitney U test (MWUT).

To assess the efficiency of the feature selection on epileptic seizures, Focal & Non-Focal and alcoholism detection, the extracted statistical features were forwarded at the same time to the proposed classifiers without feature selection phase. The simulation results confirmed that there were big differences in the detection results when all features used to detect epileptic seizures, Focal & Non-Focal and alcoholism without elimination the noisy features.

5.3 A new Models to Detect Epileptic Seizures, Focal and Non-Focal and Alcoholism in EEG Signals.

Three models were developed in this thesis:

5.3.1 AdaBoost based LS-SVM technique (AB-LS-SVM classifier)

Chapter 2, aimed to improve current epileptic warning devices that can be used to identify the onset of such events in the absence of a clinical symptom. Generally, the presence of non-epileptic segments and its features in any real-world EEG data is higher than that of the epileptic-based segments. To differentiate the relatively smaller quantity of non-epileptic segments from the epileptic type segments and also to balance the EEG data (as a requirement for machine learning algorithm), the newly proposed hybrid technique denoted as AB-LS-SVM classifier was proposed. Firstly, the EEG data were partitioned into the training and the testing sub-sets from the full dataset. Next, the important features related to epileptic conditions were extracted based on the covariance matrix, with eigenvalues. Within the proposed AB-LS-SVM algorithm, the AdaBoost technique was used for training purposes to attain a robust classifier system that was able to discern the epileptic events from the non-epileptic events. The LS-SVM classification method was employed to discriminate the features for non-epileptic events, to classify them into different classes. If one EEG segment was recognised as a non-epileptic event using the AdaBoost classifier, the LS-SVM was employed thereafter to identify the specific category of the predictive non-epileptic segments.

The results of Chapter 2 demonstrated that the proposed AB-LS-SVM classification method (coupled with covariance matrix method) was able to achieve highly satisfactory results, yielding more than 99% classification accuracy (on average) for eleven classification issues. Moreover, the present findings show that the proposed AB-LS-SVM model has high potential to be used for real-time detection of epileptic seizure as it entailed less of a time complexity factor compared to several other studies in the existing literature.

5.3.2 AdaBoost Back-Propagation neural networks

Chapter 3, adopted the AB-BP-NN method based on the successful implementation of the back-propagation neural network in EEG classification for abnormal event detection. To enhance the performance of a traditional neural network model, the AdaBoost technique, resulting in the hybrid AB-BP-NN, was proposed where the AdaBoost neural network could be less vulnerable to the issues of data over-fitting compared to some of the other machine-learning algorithms. To resolve this problem, in this chapter about 15% of the data from the training set are subsequently used to validate each of the neural networks. The classification score was bounded by [0, 1] with a better score being close to a trivial value. The AdaBoost neural network was employed, therefore, to classify the FC and the NFC EEG signal with the input of the AdaBoost neural network being the extracted features in the EEG signal.

The proposed technique achieved an average accuracy of 100% and 98.86% for the two datasets, respectively, which is considered a noteworthy improvement compared to the state of the art methods.

5.3.3 FOA-F-SVM Model

In Chapter 4 to improve and evolve the performance of SVM, the radius-margin-based SVM, i.e., F-SVM, for joint learning of the feature transformation and SVM classifier integrated with fruit fly optimization algorithm were proposed to analysis alcoholism multi-channels EEG signals. The proposed model consists of different stages. The first five steps content represent internal parameter optimization and the second five steps of this figure display the external evaluation of classification performance. The path of the proposed model is that: tune parameters depending on the FOA, after that gain an optimum classifier. Eventually, via testing the dataset through external assessment the performance of the classifier was measured.

The results show that the proposed model FOA-F-SVM was superior to and obtained the highest rating of 99% accuracy compared with previous studies. After conducting many experiments and various types of comparisons, it became clear that the proposed OFA-F-SVM model has a promising future in analysing and classify the EEG signals via achieved a high rate of accuracy.

5.4 Future work Suggestions

Through the works reviewed in this thesis, there are many ideas formed that can improve detection methods in analysing brain signals such as apply AB-LS-SVM on signs of sleep spindles and *k*-complexes prevalent in EEG signals, investigate the improvement of the performance of the proposed the *Cov–Det* based *AB–BP–NN* model by reducing the number of features used in the chapter 3 and apply the CT-BS-FOA-F-SVM) to detect and analyse epileptic and Focal & Non-Focal EEG signals. Furthermore, this thesis advocates that:

- The segmentation stage depending on the third work showed that there is a clear improvement when merging clustering sampling with bootstraps, where the error is reduced by a high rate. For this in the future, this stage will be expanded upon by combining sampling methods with other approaches to obtain good samples and reduce the error rate as much as possible.
- The covariance matrix after its use in all three works clearly demonstrated the ability to extract features with a superior advantage compared with conventional methods. Thus, the covariance matrix can be developed by combining it with many other approaches to design an effective feature extraction tool.
    - Blending covariance matrix with a highly structured estimator to reduce the estimation error.
    - Rousseeuw's Minimum Covariance Determinant as a robust estimator to recording errors.
    - The sandwich estimator, also known as robust covariance matrix estimator, heteroscedasticity-consistent covariance matrix estimate, or empirical covariance matrix estimator.
- Expanding the number of statistical features, as there are many statistical features that have not been used in this field (EEG signals). The following figure shows the most important statistical features that will be used in the future such as: Winsorized mean, Weighted mean, Geometric mean, Harmonic mean, Relative Standard Deviation, Average Deviation, absolute Deviation, Mean Difference, Count, Sum, Coefficient of Variation, Omega Ratio, Trimean, Truncated mean, Interquartile mean, Midrange and Midhinge.

- The development and expansion of the feature selection stage based on the use of the largest number of non-parametric methods such as:
    - Anderson–Darling test
    - Cochran's Q tests
    - Cohen's kappa
    - Friedman two-way analysis of variance by ranks
    - Kaplan–Meier
    - Kendall's tau
    - Kendall's W
    - Kolmogorov–Smirnov test
    - Kruskal–Wallis one-way analysis of variance by ranks
    - Kuiper's test
    - Log-rank test
    - Mann–Whitney U or Wilcoxon rank-sum test
    - McNemar's test
    - Median test
    - Pitman's permutation test
    - Rank products
    - Siegel–Tukey test
    - Sign test
    - Spearman's rank correlation coefficient
    - Tukey–Duckworth test
    - Wald–Wolfowitz runs test
    - Wilcoxon signed-rank test
- A review research paper under the processes, this work consists of several stages, which will be focused on as follows:
    - Sampling methods.
    - Filters
    - Wavelets.

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