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Efficient Health Data Classification for EEG based on fractal – cosine similarity

A Thesis
Submitted to the Council of the College of Computer Science and Information Technology at the University of Al-Qadisiyah in Partial Fulfilment of the Requirements for the Degree of Master in Computer Science

by

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بسم الله الرحمن الرحيم

﴿يَرْفَعِ اللَّهُ الَّذِينَ آمَنُوا مِنْكُمْ وَالَّذِينَ أُوتُوا الْعِلْمَ دَرَجَاتٍ وَاللَّهُ بِمَا

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Abstract

A massive amount of biomedical time series data like Electroencephalograph (EEG) signals are recorded daily to monitor human performance and diagnose different brain diseases. For researchers, efficiently and accurately analyzing these biomedical records is a challenge. Developing new methods to explain and classify these signals can assist in their management, investigation, and diagnosis.

In this thesis, we propose new models for EEG signals classification and analysis based on fractals and cosine similarity. The first proposed model uses fractals and cosine-based classifier without optimization and the second proposed utilizes the fractals and cosine similarity classifier with particle swarm optimization (PSO).

In fact, the two developed models are implemented in order to find out if the proposed classification method requires optimization support or can be independent.

A fractal mathematical model has been derived in this work and new Fractals mathematical equations and factors are obtained. The new Fractals factor is derived intentionally as a ranking factor. The Fractals ranking factors help in groping EEG signals and rank the best group for the new arrival signal. Consequently, the classification task has become significantly easier as the classifier works on only similar records.

The Bonn University EEG dataset has been utilized in this thesis. It is divided into five different files (classes), and each file has 100 samples.

This work has been compared with the most common machine learning algorithms utilized for classification problems, such as support vector machine, K-nearest neighbor, naive Bayes, random forest, and decision tree.

The results show that the proposed solutions outperformed the most of machine learning algorithms in terms of the accuracy metric.

Moreover, the results demonstrated that the categorizing EEG data are effective, where the fractal and cosine similarity models have achieved high accuracy of up to 100% in the case of two-class classification and up to 88% in the case of five-class classification of EEG signals. The findings of this work will assist specialists in related medical fields and reduce the performance of brain disease detection and diagnosis.

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LIST OF ABBREVIATIONS

Abbreviation	Meaning
EEG	Electroencephalogram
SVM	Support Vector Machine
ANN	Artificial Neural Network
KNN	K-Nearest Neighbor
CNN	Convolution Neural Network
LDA	Linear Discriminant Analysis
BCI	Brain Computer Interface
PSO	Particle Swarm Optimization
AI	Artificial Intelligence
RF	Random Forest
DT	Decision Tree
NB	Naive Bayes
TP	True Positives
TN	True Negatives
FP	False Positives
FN	False Negatives
SST	Search Space Threshold
ML	Machine learning
DRDS	dynamic random-dot stereogram
CSP	common spatial pattern
CSG	common spatial group
RBF	radial basis functions
PCA	principal component analysis
ACC	Accuracy
SEN	Sensitivity
SPE	Specificity
ARMA	Auto regressive moving average
KF	kalman filtering
AR	Autoregressive
TQWT	Tunable-Q wavelet transform
DSTFT	Discrete Short Time Fourier Transform
MLP	Multilayer Perceptron
DWT	discrete wavelet transform
MLPNN	Multi-layer perceptron neural network
SNNs	spiking neural networks
FFT	Fast Fourier transform

RBFNN	Radial basis function neural network
MSE	mean square error
SnS	Segmentation and Selection
MAV	Mean absolute value
GHE	Generalized Hurst Exponent
AGMedRep	Automatic generation of medical report
FAWT	Flexible analytic wavelet transform
MDS	Multidimensional scaling
MI	Motor imagery
ANFIS	Adaptive neuro-fuzzy inference system
AUC	Area under curve
MFFVs	multiresolution fractal feature vectors
WPD	Wavelet Packet Decomposition
OPF	Optimum-Path Forest
SD	Standard deviation
CA	Classification accuracy
KELM	Kernel Extreme Learning Machine
FLD	Fisher Linear Discriminant
ELM	Extreme Learning Machine
SGSKM	Structural graph similarity and the K-means
TD	Time-domain
FD	Frequency-domain
Bi-LSTM	bidirectional long short-term memory
HMM	Hidden Markov models
MS	Milliseconds

LIST OF NOTATIONS

symbol	**represent**
$\bar{R}$	approximated range
D	domain value
S	scaling
O	offset
ri	a single value in range
di	a single value in domain
Fmetric	Fractal metric
$\hat{R}$	average for range block

Chapter 1 - Introduction

1.1 Introduction

EEG signals are the core input of many medical systems and applications that have a high interest in decoding, understanding, and encoding human brain activities. Medically, the human brain represents the control center for the nervous system. It is a complex network made up of billions of neurons able to handle information millions of times quick and effective manner[1]. Neurons interact with human organs and generate messages through a complex network of connections[2]. These signals are complicated, noisy, nonlinear, nonstable, and generate a large volume of data. As a result, detecting and finding brain-related information is a difficult function[3].

Several studies and research projects have been performed recently to examine human brain activity using various techniques. However, a popular technique for measuring electrical activity in the brain's cerebral cortex is the electroencephalogram (EEG)[4].

EEG has electrodes (small material disks) put on the scalp[5]. The electrical potentials produced by nerve cells in the brain are read by EEG signals. The EEG signal can discover medical problems like epilepsy, which are uncontrollable movements of a portion of the human body or the whole body[3]. It has an impact on about 50 million people worldwide at different ages[6,2]. The amplitude and wavelength of the brain waves during the epilepsy seizure are unexpectedly greater and quicker than standard brain activity. Clinical studies explained that EEG signals present various patterns of waves depending on the status of a human.

1.2 Research Motivation

EEG classification plays a vital role in several services and applications based on EEG [7]. It represents an important source for medical activities such as diagnosing people with epilepsy, diagnose sleep disorders, depth of anesthesia, coma, encephalopathies, and brain death [8].

- **Time consumption and diagnose availability**: generally, specialist neurologists analyze the records of EEG visually. This is time-consuming and not always available for remote patients therefore machine-learning algorithms have been widely used for automatic detection or prediction of epileptic seizures in raw EEG.
- **EEG classification drawbacks in machine learning algorithms**: Machine-learning algorithms that have been developed for classification suffer from high stagnation probability, stuck with local optimum, high time requirements, and in persistent results. Technically, it is significantly required to develop a potential classification model that can overcome traditional classification problems and disadvantages.

1.3 Research Problem

Despite the fact that the number of studies looking into EEG signals in epilepsy is developing, more work is required to enhance their performance in terms of accuracy and time consumption. The major objective of previous studies is the investigation of EEG signals by separating them into small intervals (partitions). Then, the EEG partitions are classified into different classes or elements, such as healthy and non-healthy.

EEG signals yield a large quantity of data. The visual examination of this data by specialists or neurologists is prone to error and time-consuming.

Visual examination is also a subjective procedure, which implies that a conclusion reached by two EEG signal specialists might differ even from the exact EEG data. In recent decades, there has been an increase in the demand for accurate approaches to EEG signal processing (to reduce the constraints of visual examination). As a result, many EEG analysis techniques have been developed to computerize the processing of EEG data. We focus on analyzing the most essential types of EEG signals in medical applications, such as epileptic seizures.

This work addresses the problem of diagnosing epileptic seizures, which lead to brain health problems.

1.4 Research Questions

This research attempts to answer the following questions:

• How to efficiently classify and detect EEG patient case like epilepsy seizure?

This work discusses and analyzes how to provide an effective model potential to classify EEG signals and detect specific cases like epilepsy?

• Can Fractals similarity measurement be developed to derive new efficient classification factors?

This project discusses if Fractals mathematical concepts can be modeled to provide an efficient classifier for EEG signals.

1.5 Research Contributions

A novel method has been used for diagnosing epilepsy seizures from EEG signals by utilizing mathematical derivation of the fractal concept and the cosine similarity method. The suggested method is capable of detecting and analyzing anomalies in EEG signals, as well as categorizing them. The suggested algorithms will be helpful for detecting brain diseases as well as properly monitoring a patient's situation. The findings of this study will assist doctors and neurologists in diagnosing and brain diseases. This work has proposed two models.

1. The first model is built based on Fractal Metric-Cosine similarity, and the results are significant, with the accuracy metric reaching 100% in some classification scenarios.
2. A second model was created by combining Fractal Metric-Cosine similarity with particle swarm optimization (PSO) as an optimization method. In several classification cases, the results outperformed the first model in many machine learning performance metrics. According to the accuracy metric, it reached up to 100% in many classification cases.

1.6 Thesis Layout

The work in this thesis is organized as follows:

• **Chapter (2):** Explains the literature survey and theoretical background. Many approaches are utilized for EEG signal classifications with special analysis to make the results clearer. The theoretical background for machine learning has been described, as well as the methods of classification algorithms.

• **Chapter (3):** This chapter includes all the details of the designed and implemented EEG classification models and mathematically derived of Fractal equations. All the algorithms used in this work are presented.

• **Chapter (4):** This chapter contains the results of many tests applied for classification EEG signals. The proposed system and many machine learning algorithms results are shown with various comparisons methods.

- **Chapter (5):** includes the conclusions and some suggestions for future work.

Chapter 2 – Literature survey and Theoretical background

2.1 Introduction

This chapter presents a literature survey for electroencephalography (EEG) signal classification approaches and the theoretical background of machine learning algorithms that are utilized in the classification. EEG classification plays a vital role in many health applications using machine-learning algorithms. Mainly, they group and classify patient signals based on learning and developing specific features and metrics. In this chapter, 32 highly reputed research publications are presented focusing on the designed and implemented approach, applied dataset, their obtained results and applied evaluation. Furthermore, a critical analysis and statement is provided for the surveyed papers and an overall analysis in order to have all the papers under an evaluation comparison. SVM, ANN, KNN, CNN, LDA, Multi-classifier and more other classification approaches are analyzed and investigated. All classification approaches have shown potential accuracy in classifying EEG signals. Evidently, ANN has shown higher persistency and performance than all other models with 97.6% average accuracy.

An electroencephalogram (EEG) is an efficient, cheap-cost, non-invasive test applied to examine the electrical activity of the brain [9] . EEG is one of the most techniques used to determine an abnormality of the brain functions [9,10]. EEG signals are computed using electrodes set on the scalp. It is used for diagnosing and monitoring neurological diseases, such as sleep disorders and epilepsy [4]. Furthermore, EEG signals are utilized for several studies and research such as gaming applications, lie detection, augmented reality, neuromarketing and brain computer interface (BCI) and others [4,11].

2.2 Survey Strategy and Evaluation

Potential thirty-two existing approaches are classified into seven groups based on their proposed classification method (Support Vector Machine, Artificial Neural Network, K-Nearest Neighbor, Convolution Neural Network, Linear Discriminant Analysis, Multi-classifier and other classification). Each approach is summarized with their problem statement, proposed solution approach, performance evaluation strategy and results, best achievement. All approaches are analyzed and critical statement is provided. In this survey chapter, performance metrics: accuracy, sensitivity, specificity and processing time are targeted and extracted in order to evaluate previous research. All results of performance measures are depicted and compared. We have concentrated on best achieved results and cross evaluated inside their groups. Finally, average of best accuracy is calculated for all approaches inside the same group and compared with classification groups. ANN group has shown the highest achieved accuracy. Unfortunately, most studies have ignored the measurement of processing time and therefore system performance is not clear for the included studies.

2.3 Support Vector Machine for EEG Classification

Support Vector Machine (SVM) as a successful classification method has been widely applied in machine learning algorithms for EEG signals. Several publications have concentrated on SVM as the core for their proposed solution. L. Zhiwei et al. [12] has addressed the classification of EEG signals for the mental task, which is one of the main issues of the computer brain interface (BCI). This approach has been proposed using wavelet packet entropy and Support Vector Machine. This research has applied seven level wavelet packet decomposition to each channel of EEG. Moreover, four spectrum bands (α, β, θ, ς) are extracted and applied by an entropy algorithm that performed on each band. For evaluation, accuracy is the main metric this research used to investigate the success of the proposed model. The obtained results have shown a persistent success for SVM for two-class classification with average accuracy of 87.5%-93.0% and for three-class classification with average of 91.4%. Colorado State University has been utilized. This approach has provided a high accuracy averaged 93.0%. The provided results and evaluation are considered to be limited which have shown only the accuracy as an evaluation metric.

Lili Shen et al. [13] has addressed the classification of EEG signals. The main goal to find relationship between stereoscopic acuity and EEG signals for the development of 3D technology. A multi-channel selection sparse time window common spatial group (MCS-STWCSG) has been proposed. First, signals based on depth dynamic random-dot stereogram (DRDS) videos are obtained and preprocessed. Second, an improved common spatial pattern (CSP) method applied to select channels. Next, signals segmented by wavelet transform and sliding time window. Then, a common spatial group (CSG) has been applied to extract EEG signal features. Moreover, time-frequency bands and hybrid features have been selected by sparse regression. Finally, Support vector machine (SVM) with RBF kernel has been applied for features classification. Accuracy metric has been computed to evaluate the three proposed methods (3C-STWCSG, CCS-STWCSG, and MCS-STWCSG) to select different channels. The obtained average accuracy values are 50.96% 73.13% 87.50% respectively. EEG signals gathered by international 10–20 systems, embedded 32 lead EEG cap and Neuroscan system. The proposed method has achieved a high performance with accuracy of 94.67%. In fact; this research has failed to show their model performance like processing time. Moreover, accuracy was the only used metric to evaluate the proposed solution.

Another study achieved by Yang Li et al. [14] that have focused on detecting patients with epileptic seizures based on EEG classification with support vector machine (SVM).SVM has been proposed to classify EEG signals. Firstly, multiscale radial basis functions (MRBF) and a modified particle swarm optimization (MPSO) have been applied to the time-frequency feature extraction for epileptic EEG signals. Then, dimensionality of extracted features can be highly reduced via the principal component analysis (PCA) algorithm. Finally, SVM with the radial basis function (RBF) has been applied for classification. This research has provided an analysis of multiple scenarios with different cases for EEG signals. Three metrics such as sensitivity (SEN), specificity (SPE), and accuracy (ACC) have been computed to examine the system's ability. BONN Dataset University of Bonn, Germany's EEG dataset has been utilized. This approach has achieved a high classification accuracy of 100%. Although the proposed model has shown potential classification results, there is no performance analysis in terms of processing time and complexity.

With the aim to early detect seizure cases, ZIXU CHEN et al.[15] Have achieved a significant research that focused on the problem of automatic EEG signals classification. The main goal is for early seizure detection and epilepsy diagnosis for patients. In this paper, a support vector machine (SVM) has been applied. Firstly, Signal intensity has been calculated for each data point of EEG. Secondly, a mathematical model has been proposed to describe the dynamic behavior of EEG signal based on the autoregressive moving average (ARMA). ARMA model has been built and utilized to detect the deviation between the predicted value and the real value. Then, a null hypothesis can be tested for decision-making by detecting the seizure in the continuous monitoring of EEG signals. Finally, suspicious segments can be identified and perform classification based on a pairwise one-class SVMs. Three different metrics have been used such as Accuracy, Sensitivity, and Specificity in order to evaluate the model. Empirically, Bern-Barcelona and CHB-MIT EEG datasets have shown accuracy obtained 93% and 94% respectively. Two public datasets have been used: Bern-Barcelona EEG database and CHBMIT EEG database. This method has achieved a high accuracy of 94%. In fact; the proposed approach has produced high results in comparison with other approaches. However, some earlier studies have achieved higher accuracy. The authors have failed to justify these higher metrics values like P. P. M. Shanir et al.[16] with (99.7% accuracy for the CHB-MIT database and 99% for the Bern-Barcelona database).

In order to remotely diagnose epileptic seizures, L. Chisci et al. [17] have addressed a patient-specific method for the prediction of epileptic seizures performed by an online check of EEG signals. Support vector machine (SVM) and kalman filtering (KF) has been proposed. Initially, a preprocessing step has been achieved to remove noise of frequencies. Then, features extraction has been achieved based on Autoregressive (AR) models. Finally, (SVM) and (KF) have performed the classification for EEG signals. This research has concentrated on the analysis of various scenarios with different cases. Data has been divided into train set and test set and preform10-fold cross-validation technique. Two metrics have been computed such as sensitivity and specificity to investigate system capabilities. EEG Freiburg Database has been utilized. This approach has provided a high sensitivity of 100%. Although they have achieved a good result when applying sensitivity metrics, they have a lack of comparisons with some previous methods.

2.4 Artificial Neural Network (ANN) for EEG Classification

S. Thomas George et al.[1] has focused EEG classification problem and discussed how to automatically identify cases of epilepsy and know the seizures patients. The proposed approach has combined several techniques such as tunable-Q wavelet transform (TQWT), entropies, Particle Swarm Optimization (PSO) and Artificial Neural Network (ANN) to classify epileptic seizures and diagnose its types. Technically, the proposed model starts by transforming EEG signals using Tunable-Q Wavelet, extract features, then feature selection with PSO and finally ANN to classify cases. Three different metrics have been used: Accuracy, Sensitivity and Specificity for different experimental cases of EEG datasets. Two types of dataset have been used, first the Karunya Institute of Technology and Sciences (KITS) EEG database and the second Temple University Hospital (TUH). The proposed method has achieved high accuracy of 94.1%, 97.4%, 96.2% and 88.8% for the four experimental cases (normal-focal, normal-generalized, normal-focal + generalized and normal-focal- generalized). The authors have not analyzed the different performance of the proposed model for the two deployed datasets.

Another study achieved by Kaveh Samiee et al.[18] that had classified EEG signals to detect epileptic seizures. One of the challenges is to distinguish regular discharges from nonstationary patterns occurring when seizures. An artificial neural network (ANN) has been proposed as a potential EEG classifier. Discrete Short Time Fourier Transform (DSTFT) has been applied to feature extraction from EEG. ANN represented by A Multilayer Perceptron (MLP) whose performs the classification to distinguish seizure times from seizure-free times. Experimentally, the dataset has been divided into two groups 50% and 50% for training and testing their proposed system. Three different metrics have been used such as Accuracy, Sensitivity, and Specificity for different experimental cases of EEG datasets. BONN Dataset University of Bonn, Germany's EEG dataset has been used to examine proposal model. This approach has achieved a high classification accuracy of 99.8%. Although the proposed approach provided high results, when compared with other methods, some earlier studies have achieved higher accuracy. The authors have failed to justify these higher metrics value like (Xie and Krishnan et. al[19]) with 100% accuracy.

In order to obtain an automatic epileptic seizure detection, Ling Guo et al.[20] has addressed the classification of EEG signals to detect and diagnose epileptic seizures based on Artificial neural networks. Firstly, EEG signal has been decomposed and used in this research into five sub-signals through discrete wavelet transform (DWT). Each sub-signal represents several frequency bands' information. Then, line length has been applied for feature extraction for every five sub-signals. Finally, Multi-layer perceptron neural network (MLPNN) has been applied to classify EEG signal. This research has concentrated on the analysis of various scenarios with different cases. Three metrics such as accuracy, sensitivity, and specificity have been computed to examine the system capabilities. Dataset has been provided by the University of Bonn dataset, Germany. This approach has achieved a high accuracy of 99.6 %.

In order to identify emotion kinds, Y. Luo et al.[7] Have studied how to classify EEG signals. In this paper, spiking neural networks (SNNs) has been proposed for emotions classification. Three algorithms such as discrete wavelet transform (DWT), variance, and fast Fourier transform (FFT) have been applied to extract EEG signals. This research has focused on the examination of multiple scenarios with various emotion categories. The dataset has been divided into two groups 80% and 20% for training and testing their proposed method. Accuracy metric has been measured to investigate system performance. Empirically, high accuracy can be obtained when the variance data processing method and SNN were applied. On the other hand, FFT and DWT processing methods have produced less accuracy. Moreover, emotion categories of arousal, valence, dominance, and liking can be classified with accuracies of 74%, 78%, 80%, and 86.27% using DEAP dataset, and 96.67% as an average of accuracy for the SEED dataset. Two different datasets have been applied. First, a multimodal dataset using physiological signals for emotion analysis (DEAP). The second was Shanghai Jiao Tong University emotion EEG dataset (SEED). This method has achieved a high classification accuracy reach to 96.67%. Empirically; accuracy was the only used metric to evaluate the proposed solution. They did not show their model performance like processing time.

Another study achieved by Sandeep Kumar Satapathy et al.[21] that have addressed the classification of EEG signal for human brain disorder diseases. Mainly, EEG signal classification to detect patients suffer from an epileptic seizure. In this paper, Radial basis function neural network (RBFNN) and particle swarm optimization (PSO) algorithm have been proposed. First, EEG signal has been preprocessed by discrete wavelet transform (DWT). Then, the proposed model has been trained to optimize mean square error (MSE) by a modified particle swarm optimization (PSO) algorithm. Finally, a radial basis function neural network (RBFNN) has been applied for classifying EEG signals. This research has concentrated on the analysis of multiple scenarios with different cases and various techniques. Four metrics such as precision, specificity, Recall, and F-measure have been computed to investigate the system capabilities. Two types of datasets have been used. First, EEG dataset to detect an epileptic seizure. Second, EEG dataset for Eye state prediction. This approach has achieved a high classification accuracy of 99%. Evidently; obtained results have not been compared with other methods.

With the aim of classification that can assist paralyzed humans by taking the handle of assistive machines, M. H. Bhatti et al.[22] Have addressed EEG signals that interpreted by Brain Computer Interface (BCI) to commands. In this paper, Radial Basis Function Neural Networks have been proposed. Initially, a filter bank has been applied to break up the signals into Sub-band. Then, feature extraction performed based on Linear Discriminant Analysis followed by Common Spatial Pattern. Next, Sequential Backward Floating Selection has been applied to take the best features. Extracted features have been utilized to train radial basis function neural networks (RBFNN). Finally, classification has been performed based on RBFNN. Accuracy metric has been computed to evaluate the proposed model. The proposed method has shown a total accuracy of 93.05% and 84.00% for BCI Dataset and EEG signals acquired by Emotiv Epoc respectively. Two datasets have been used. First, BCI Dataset and the second EEG signals acquired by Emotiv Epoc. This approach has achieved a high classification accuracy of 93.05%. Empirically; accuracy was the only used metric to evaluate the proposed solution. They did not show their model performance like processing time.

2.5 Convolution Neural Network (CNN) for EEG Classification

S. Raghu et al.[23] Have addressed the necessity for recognizing seizure EEG of epileptic patients. In fact, classifying EEG seizure type is a potential requirement for patients' diagnosis and disease control. The main goal is to classify multiple seizure types. Two different approaches have been applied using Convolution neural network (CNN). First approach transfers learning using a pre-trained network. The second approach tries to extract image features using a pre-trained network and classification using the vector support classifier. In this paper, dataset has been divided into two groups 70% and 30% for training and testing their proposed system. Moreover, they have repeated this methodology for 10 times. Temple University Hospital EEG corpus dataset has been utilized for evaluation. The proposed method has achieved high accuracy of 82.85% and 88.30% by using transfer learning and extract image features approach respectively. Although, it is well-known that deep learning model CNN considered to be a time-consuming solution, it is not clear for this paper how good performance can be obtained from the classifier.

S. Ramakrishnan at el.[24] have focused on detecting patients with epileptic seizure based on Convolutional Neural Network (CNN). This paper has tested both time domain and frequency EEG features and their impact on CNN.CNN has been proposed as a significant deep learning model can be used for EEG classification. The authors experimented both time and frequency domain and found out that time domain features may enhance the proposed system performance. This research has concentrated on the analysis of multiple scenarios with different cases. Three metrics like sensitivity and specificity, Classification accuracy are computed to investigate the system capabilities. Two datasets have been used. First, BONN Dataset University of Bonn, Germany's EEG dataset and the second from Boston Children’s Hospital CHB-MIT Dataset. This method has provided a high accuracy, up to 98% overall classification. It has provided a good performance as a very short execution time needed.

Another study in the medical aspect was carried out by the researcher JIAN LIAN et al.[25], that has analyzed EEG signals to identify and diagnose epileptic seizures. It has focused on relationships in spatial and temporal for every pair of EEG signal. In this paper, Convolutional Neural Network (CNN) has been proposed. Firstly, each pair of EEG signals has been utilized to compose a single 2-dimensional matrix which could apply to detect the interactivity between them. Secondly, CNN has been fed by the produced matrices to perform the classification. They have performed10 rounds of experiments for cross-validation. Each round, one record has been taken into the testing set while the other 9 subsets utilized as the training set. Three different metrics have been used such as Accuracy, Sensitivity, and Specificity in order to evaluation the model. University of Bonn, Germany EEG dataset has been utilized. This method has achieved a high average accuracy of 99.3%. In fact; the proposed method has produced high results compared with other methods. However, some previous studies have achieved higher accuracy. The authors have failed to justify these higher metrics values like Das et al. with (100 % accuracy). Furthermore, they have failed to show their model performance like processing time.

In order to detect sleep stages, Mousavi et al.[11] have studied the automatic classification of single-channel EEG signals to detect sleep stages. In this paper, convolutional neural network has been proposed. Data augmentation has been applied as a preprocessing method and to produce balance for the samples of various classes. They have focused on performing the classification without features extraction and feature selection. The proposed approach was composed of 9 convolutional layers followed by 2 fully connected layers. The main goal was to directly classify raw EEG signals into 6-stage by deep convolutional neural network. Experimentally, the dataset has been divided into two groups 50% and 50% for training and testing their proposed system. Two metrics such as accuracy and Kappa Cohen's coefficients have been computed to examine the system capabilities. The proposed model has outperformed several previous models in terms of accuracy metric. The outcomes of the proposed approach for classifying 2 up to 6 classes can give accuracy of 90% and more. Sleep-EDF dataset has been utilized to evaluate the proposed model. This approach has provided a high accuracy of 98.10%. In fact; the proposed method has achieved high classification results compared to some previous methods. However, the proposed model was not the fastest. For example, during training and testing process, this method took 4412 and 4.5 respectively. On the other hand, the MLP method has achieved 600, 2.5, respectively (time in second with100 iterations).

2.6 K-Nearest Neighbor (K-NN) for EEG Classification

Umer I. Awan et al.[26] have discussed the necessity for classification and feature extraction from facial emotions and movements registered using EEG signals. In this paper, the K-Nearest Neighbor Algorithm has been proposed. Initially, a Raw EEG signals Segmentation and Selection (SnS) with Root Mean Square (RMS) were applied to extract feature vector of EEG signals. EEG classification was achieved by using a k-nearest neighbor algorithm. Evidentially, accuracy measures were computed in order to verify their results. They have obtained the best result when SRMS (segmented root mean square) was applied. Furthermore, RMS (root mean square) and MAV (mean absolute value) were applied. KNN was applied on these methods output with accuracy of 80.2%, 80.4%, and 71.3% respectively. EEG signals have been collected from 10 healthy people, aged between 18-45 years. This approach achieved a high accuracy of 96.1%. Empirically; accuracy was the only used metric to evaluate the proposed solution. It would be more useful for both academics and developers to have other evaluation metrics obtained like processing time and complexity.

S. Lahmiri et al.[8] have discussed Classification for Electroencephalogram (EEG) signals to distinguish between seizure intervals and seizure-free intervals in epileptic patients. In this paper, the K-Nearest Neighbor Algorithm has been proposed. The Generalized Hurst Exponent (GHE) estimated at various scales to characterize the EEG signal by capturing its multiscale long-memory properties. The moment that computed. K-NN has been trained for classification based on GHE estimates. Tenfold cross-validation is utilized and operated 20 times to guarantee more repetitions and randomness. Furthermore, three metrics such as accuracy, sensitivity, and specificity have been used as evaluation metrics. The proposed model has outperformed several previous studies models in terms of accuracy. Dataset have been provided by University of Bonn dataset, Germany. The proposed method has achieved a high accuracy of 100%. In fact, this research has failed to show their model performance like processing time.

In order to generate textual medical reports, Jefferson Tales Oliva et al.[27] Have addressed the classification of EEG signals to detect and diagnose the epileptic seizure. The main goal to generate textual medical reports for epilepsy detection to help Medical personnel in the discovery of events related to epilepsy in EEG signals. The nearest neighbor technique has been proposed. Firstly, cross-correlation with artificial reference, Fourier transform, short-time Fourier transform, and bispectrum have been applied for feature extraction. Secondly, the K-nearest neighbor (KNN) has performed classification. Then, automatic generation of medical report method (AGMedRep) has been developed. Multiclass classifiers have been built depending on signal processing and machine learning techniques that have been applied to produce medical reports through EEG processing. Finally, a predictive model has been built that applied to create textual reports. This research has concentrated on the analysis of multiple scenarios with different cases. The accuracy metric has been computed to investigate system capabilities. BONN Dataset University of Bonn, Germany's EEG dataset has been utilized. This approach has achieved a high accuracy average of 84%. In fact, this research has failed to show their model performance like processing time. Moreover, accuracy was the only used metric to evaluate the proposed solution. Evidently, some earlier studies have achieved higher accuracy. The authors have failed to justify these higher metrics values like D. Sikdar et al.[28] (accuracy 99.60%).

2.7 Linear Discriminant Analysis (LDA) for EEG Classification

Yang You et al.[29] have discussed successful Motor imagery electroencephalogram (MI-EEG) classification model through accurate and efficient classification with quick feature extraction. In this paper, a flexible analytic wavelet transform (FAWT) has been proposed as a classification system for Motor imagery electroencephalogram (MI-EEG). Technically, (MI-EEG) signals get in band filter as a preprocessing step. Furthermore, feature extraction was applied based on (FAWT). Then, features selection was implemented and Multidimensional scaling (MDS) was applied to reduce feature dimensions. Finally, classification was achieved by using linear discriminant analysis (LDA). Experimentally, 50%−50% (train and test) approach have been performed 10 times for each subject and obtained the resultant average. Accuracy and Maximal MaI have been applied as two evaluation metrics. Accuracy values for all subjects is 84.26% as an average of FAWT + MDS. Two public BCI EEG datasets published by BCI Competition II and III have been used. First dataset, BCI Competition II, 2003 http://www.bbci.de/competition/ii. Second dataset, BCI Competition III, 2005 http://www.bbci.de/competition/iii/.This method has achieved a high accuracy of 94.29%.

Another study achieved by Wei-Yen Hsu[30] that has addressed a feature extraction approach by time-series prediction based on the adaptive neuro-fuzzy inference system (ANFIS) for brain-computer interface (BCI) applications. The main goal is for EEG Motor imagery (MI) classification. In this paper, Adaptive neuro-fuzzy inference system (ANFIS) time-series prediction together with multiresolution fractal feature vectors (MFFVs) have been applied for Motor imagery (MI) EEG classification. Finally, classification has been performed based on linear discriminant analysis (LDA). Accuracy (ACC) and area under curve (AUC) metrics have been computed for model evaluation. MFFV features under ANFIS time-series prediction method has obtained 90.3% and 0.88 for accuracy and AUC respectively. Evaluation dataset has been obtained from Graz BCI group. This approach has achieved a high accuracy of 93.7%.

2.8 Multi-classifier approaches for EEG Classification

Several approaches utilized more than one classifier to recognize EEG signals. Jardel das C. Rodrigues et al.[31] Have focused on identifying and diagnosing alcohol addicts based on EEG classification through the application of machine learning techniques. In this paper, machine-learning techniques have been proposed. Take the EEG data and applied the Wavelet Packet Decomposition (WPD) after that feature extraction has been performed. Finally, the classification performed by several machine-learning techniques such as Support Vector Machine (SVM), Optimum-Path Forest (OPF), Naive Bayes, k-Nearest Neighbors (k-NN) and Multi-layer Perceptron (MLP). Experimentally, dataset has been divided into two groups 75% and 25% for training and testing their proposed system. Four metrics: like accuracy, sensitivity, specificity, and positive predictive value (precision) are computed to investigate the system capabilities. The best obtained result from Naive Bayes classifier is about 99.78%. On the other hand, the worse result shown from MLP classifier producing 68.62% for specificity, sensitivity and accuracy, and the precision value was 61.85%.KDD Dataset that has been originated from an examination of a number of subjects with alcoholic and non-alcoholic cases. This method achieves a high classifier accuracy of 99.78%.

Another approach proposed by Alexandra Piryatinska et al.[5] that has discussed how accurate classification for EEG signal based on efficient feature selection and training. It was found that features selection represents the most important step in EEG signals classification. The proposed approach was based on the theory of ϵ-complexity of continuous functions. Firstly, ϵ-complexity coefficients of the original signal and its finite differences have been estimated. Secondly, random forest (RF) and support vector machine (SVM) have been evaluated as classifiers. Accuracy metric was used to evaluate the obtained results. Empirically, the proposed model has achieved an accuracy rate of 84.3% with bootstrap confidence interval (CI). This research has discussed previous studies with an accuracy rate of 79.4% as best obtained results. EEG of healthy adolescents and adolescents with symptoms of schizophrenia dataset are used that is available on ((http://brain.bio.msu.ru/eeg_schizophrenia.htm)). This approach has achieved a high accuracy of 88.1%. Although researchers have achieved potential results in comparison with previous methods using the precision metric, their model has failed to achieve better sensitivity like M. Shim(100%) without any justification for this difference.

In the medical field, Andrius Vytautas Misiukas Misiunas et al.[32] have addressed detecting and classifying epileptic patient type as patients with benign focal childhood epilepsy or patients with structural focal epilepsy based on EEG signals. In this paper, an artificial neural network (ANN) has been proposed. Firstly, spike detection from EEG signals. Then EEG spike parameters have been detected. Finally, ANN has been applied for EEG classification. Several metrics have been applied for evaluation in this research such as accuracy, True negative rate (TNR), and true positive rate (TPR). Evaluation experiments for ANN and SVM as classification methods have shown 0.72 and 0.69 accuracy values respectively. Furthermore, resultant TNR values 0.73 and 0.74 for ANN and SVM respectively. On the other hand, ANN and SVM have TPR values ≈48% and ≈71% respectively. Results have shown that ANN has outperformed SVM based on several metrics. Dataset have been provided by Children’s Hospital, Affiliate of Vilnius University Hospital Santaros Klinikos. This method has achieved a high accuracy up to 75%. In fact; this research has failed to show their model performance like processing time and complexity with lack of comparison with other studies.

Another method based on naïve Bayes (NB) and k-nearest neighbors algorithm(KNN), A. Sharmila et al.[9] have studied how to classify EEG signal to detect and diagnose epileptic seizure patients. In this paper, naïve Bayes (NB) has been proposed. EEG signals have analyzed when performed by discrete wavelet transform (DWT) using linear and nonlinear classifiers.

Statistical features have been computed from DWT (mean absolute value (MAV), Standard deviation (SD) and Average power (AVP)) then utilized for classification based on NB and KNN. Accuracy metric has been computed to investigate system capabilities. It has been discovered that the NB classifier works better than KNN.BONN Dataset University of Bonn, Germany's EEG dataset has been utilized to evaluate their proposal model. This method has achieved a high accuracy of 100%. Accuracy was the only metric been applied to evaluate the proposed solution. Furthermore, this research has failed to show their model performance like processing time.

Based on Artificial neural networks (ANN) and support vector machines (SVM), Atemangoh Bruno Peachap et al. [33] have studied the necessity for recognizing seizure EEG of epileptic patients. EEG seizure classification is a potential requirement for patients' diagnosis and disease control. The main goal is to classify multiple seizure types based on EEG. Artificial neural networks and support vector machines have been proposed. Firstly, features have been extracted by Laguerre polynomial wavelets. Secondly, Principal Component Analysis (PCA) has been utilized for dimensionality reduction. Finally, Both ANN and SVM have been applied for EEG classification in order to detect a seizure or non-seizure signal. This research has concentrated on the analysis of multiple scenarios with several cases. 3-fold, 5-fold, and 10-fold cross-validations have been applied with different ratio of train and test data. Accuracy metric has been computed to investigate the system capabilities. Dataset has been provided by the University of Bonn dataset, Germany. This approach has achieved a high accuracy of 100% and 99% with ANN and SVM respectively. Empirically, accuracy was the only used metric to evaluate the proposed solution. They did not show their model performance like processing time.

Support vector machine (SVM), K-nearest neighbor (KNN), multilayer perceptron (MLP) have been proposed by S Raghu et al.[34] That have addressed the classification of EEG signals to detect and diagnose epileptic seizures. The main goal of this research is to perform an automatic classification for EEG signals that speed up the treatment process for patients. A matrix determinant of EEG has presented an important feature for the identification of epileptic seizures. Initially, arrangement of EEG time series in square matrix form have been applied for feature extraction. The training stage has been performed on two datasets collecting eleven classification problems among epileptic and epileptic-free EEG. The target is to investigate temporal dynamics of brain activity in various categories of the epileptic activity. Finally, classification has been performed by SVM, KNN, and MLP with 10-fold cross-validation. This research has provided an analysis of multiple scenarios with different cases for EEG signals. Five metrics have been applied to evaluate this method such as specificity (SP), sensitivity (SE), and classification accuracy (CA), positive predictive value (PPV), and negative predictive value (NPV). The highest classification accuracy of 99.45% and 97.56% when using the dataset University of Bonn and, RMCH respectively. Two datasets have been utilized. First, University Bonn, Germany, and the second Ramaiah Medical College and Hospital (RMCH). This approach has achieved a high classification accuracy of 99.45%. In fact, the proposed approach has provided great results in comparison with other approaches. However, some earlier researches have achieved higher accuracy. The authors have failed to justify these higher metrics values like Bhattacharyya et al. with (100% accuracy).

Another method achieve by K. Venkatachalam et al. [10] that Have analyzed the Motor Imagery (MI) for Brain-Computer Interfaces (BCIs) based on the classification of EEG signals. The users visualize limb moves to command the system. This significant interest has been due to its potential application in games, prostheses, and medical rehabilitation. Technically, the target was to decode user's ideas for the supposed move. In this paper, Hybrid-KELM (Kernel Extreme Learning Machine) have been proposed. Noises have been removed, and features extracted based on the dimensionality reduction technique through Principal Component Analysis (PCA). Then multi-class data is grouped applying Fisher's Linear Discriminant (FLD). Finally, classification has been achieved based on the hybrid kernel Extreme Learning Machine (H-KELM). Evidentially, two metrics such as accuracy and inventory turnover measures have been computed in order to verify results. The obtained performance accuracy has been compared with other Extreme Learning Machine (ELM) methods. As a result, Hybrid KELM has outperformed other methods with accuracy of 96.54%. Moreover, KHELM has been recognized as the second-best method with an accuracy of 94.54 %.BCI competition III dataset has been utilized for evaluation process. The proposed method has provided a high accuracy of 96.54% as best results in comparison with methods. This paper has missed to compare the proposed method with other methods other than KHELM.

In target of the identification of the sleep stages, M. Diykh et al.[4] have addressed the classification of EEG signals to recognize sleep Stages. In this paper, structural graph similarity and the K-means (SGSKM) have been proposed. Six sleep levels have been identified from single-channel EEG signals based on merge the statistical characteristics in time domain and the (SGSKM). Initially, each EEG segment has been divided into sub-segments. The size of a sub-segment has been specified experimentally. Then, extraction of statistical features and ordering them into different groups of features. Finally, features have been sent to the SGSKM in order to classify EEG sleep stages. Several metrics have been applied such as cross-validation, sensitivity, kappa coefficient and confusion matrix to evaluate the model's performance. Several experiments performed to detect the appropriate number of features. The result of classification based on 12 features set gives a better performance for all sleep stages with high accuracy of 94.93% in comparison with earlier approach with accuracy of 92.3%. Two datasets have been utilized. Datasets have been provided by Sleep-EDF database and Sleep Spindles database. This approach has achieved a high classification accuracy of 94.93 %.

A potential method based on Support vector machines (SVM) and K-Nearest neighbors (KNN) algorithms have been proposed by Marzieh Savadkoohi et al.[35]. They have addressed the classification of EEG signals to detect and predict epileptic seizures. Firstly, raw EEG data have been prepared based on filtered, transformed, and decomposed. Secondly, features extraction has been performed by time-domain (TD), frequency-domain (FD), and Time-Frequency Domain (TFD) (wavelet transform). Then, T-test and Sequential Forward Floating Selection (SFFS) have been used to features selection. Finally, classification has been performed by SVM and KNN. This research has provided analysis of multiple scenarios with different cases for EEG signals. Several metrics have been computed such as Accuracy, Sensitivity, and Specificity to investigate system capabilities. The proposed model has outperformed several previous models in terms accuracy. SVM classifier has outperformed KNN classifier with accuracy of 100% and 99.5% respectively. Empirically, University of Bonn, Germany EEG dataset has been utilized for evaluation. This approach has achieved a high classification accuracy of 100 %. In fact; this research has failed to show their model performance like processing time.

2.9 Other Models for EEG Classification

Rubén San-Segundo et al.[2] have addressed the classification of EEG using deep neural network (DNN). This paper has focused mainly on analyzing DNN efficiency in classifying EEG signals for patients with epilepsy. A significant analysis has been achieved on DNN with architecture made up of two layers for feature selection and three layers for EEG classification. Moreover, several EEG signal transforms are implemented and evaluated in order to investigate best transform for potential DNN efficiency. Furthermore, the proposed analysis is achieved with multiple scenarios and cases using two different epileptic datasets. The research has concentrated on the outcome accuracy. The Bern-Barcelona EEG and the Epileptic Seizure Recognition datasets are used to evaluate the overall analysis. Potential results were obtained with different system accuracy based on the applied dataset. The results have shown high accuracy up to 98.9% with the Bern-Barcelona dataset. At the same time, very high accuracy was obtained when classifying non-seizure and seizure recordings. Finally, this research has failed to investigate system performance in order to estimate and assess how practical to be implemented in real-time scenarios.

Xinmei Hu et al.[36] have addressed the classification of EEG using deep bidirectional long short-term memory (Bi-LSTM) to detect the patients whose suffer from epileptic seizure. In this paper, the (Bi-LSTM) network have been proposed. Raw EEG signals has been initially analyzed by LMD, which suitable for dealing with nonlinear and non-fixed problems. A deep

Bi-LSTM model then designed to classify the seizures and non-seizure EEG classification. This research has concentrated on the analysis of multiple scenarios with different cases. Three metrics like sensitivity, specificity and G-mean are computed to investigate the system capabilities. Children's Hospital Boston CHB-MIT Dataset has been utilized to evaluate the proposed model. The proposed approach has achieved a high mean sensitivity 93.61% and a high mean specificity of 91.85% on the dataset. Although the Authors have shown good results when compared with other approaches of EEG classification, they failed to show their model performance like processing time. Moreover, it is clearly noticed some other models have achieved better results without a detailed clarification

Martin Dobiáš et al.[37] has addressed the classification of forefinger reaching and grasping movement based on EEG. Parallel Hidden Markov models (HMM) has been proposed as a potential EEG classifier. EEG activity of movement is noticeable in two bands (μ and β). Liner Fast Fourier transform (FFT) coefficients have been computed to represent EEG features (feature extraction). Finally, HMM has been applied to classify EEG. In this paper, four methods for decision selection have been applied (Max LogLike, Max Count, Max Sum LogLike and Var Num Max Ele) and investigated their performance with HMM. Study of Stancák et al. dataset has been utilized for evaluation. The proposed method achieves a high classification score of 84.6±0.7%. In fact, this research has failed to show their model performance like processing time. It has a lack of evaluation metrics.

2.10 Analysis and Evaluation

In order to evaluate the results of the classification approaches that achieved by different researchers. With the aim to have an accurate overview about all the included papers, three main criteria are depicted: accuracy, sensitivity, and specificity to be investigated and compared. In fact, most of the research papers concentrated on accuracy metric. Empirically, accuracy metric plays a vital key assessment in classification methods.

We have classified 32 approaches into groups based on their proposed classification method. All results (accuracy, sensitivity, and specificity) are depicted in seven tables. Table 2.1 shows resultant accuracy and sensitivity by Support Vector Machine (SVM) classification for [13, 12, 14, 15, and 17]. Table 2.2 shows resultant accuracy by Artificial Neural Network (ANN) classification for [1, 20, 7, 22, 21, and 18]. Table 2.3 shows resultant accuracy by Convolution Neural Network (CNN) classification for [23, 24, 25 and 11]. Table 2.4 shows resultant accuracy by K-Nearest Neighbor (K-NN) classification for [26, 8, and 27]. Table 2.5 shows resultant accuracy by Linear Discriminant Analysis (LDA) Classification for [29 and 30]. Table 2.6 shows resultant accuracy, sensitivity, and specificity by Other Models for EEG Classification for [36, 2, and 37]. Table 2.7 shows resultant accuracy by Multi-classifier approaches classification for [31, 5, 32, 9, 33, 34, 10, 4, and 35].

Table 2.1: Resultant Accuracy and Sensitivity by Support Vector Machine (SVM) Classification

Authors	**dataset**	**Performance metrics in (%)**	
		Accuracy	**Sensitivity**
Lili Shen et al. [13]	EEG signals gathered by international 10–20 systems	94.67	
L. Zhiwei et al.[12]	Colorado State University	93	
Yang Li et al. [14]	BONN Dataset University of Bonn	100	
ZIXU CHEN et al.[15]	Bern-Barcelona EEG CHBMIT EEG	94	
L. Chisci et al.[17]	EEG Freiburg Database		100

Table 2.2: Resultant Accuracy by Artificial Neural Network (ANN) Classification

Authors	**dataset**	**Performance metrics in (%)**
		Accuracy
S. Thomas George et al.[1]	(KITS), (TUH)	97.4
Ling Guo et al.[20]	BONN Dataset University of Bonn	99.6
Y. Luo et al.[7]	multimodal dataset using physiological signals for emotion analysis (DEAP), Shanghai Jiao Tong University emotion EEG dataset (SEED)	96.67
M. H. Bhatti et al.[22]	BCI Dataset EEG signals acquired by Emotiv Epoc	93.05
Satapathy et al.[21]	EEG dataset to detect an epileptic seizure EEG dataset for Eye state prediction	99
Kaveh Samiee et al.[18]	BONN Dataset University of Bonn	99.8

Table 2.3: Resultant Accuracy by Convolution Neural Network (CNN) Classification

Authors	**dataset**	**Performance metrics in (%)**
		Accuracy
S. Raghu et al.[23]	Temple University Hospital EEG corpus	88.3
S. Ramakrishnan at el.[24]	BONN Dataset University of Bonn, Boston Children’s Hospital CHB-MIT	98
JIAN LIAN et al.[25]	BONN Dataset University of Bonn	99.3
Mousavi et al.[11]	Sleep-EDF dataset	98.1

Table 2.4: Resultant Accuracy by K-Nearest Neighbor (K-NN) Classification

Authors	**dataset**	**Performance metrics in (%)**
		Accuracy
Umer I.Awan et al.[26]	collected from 10 healthy people	96.1
S. Lahmiri et al.[8]	BONN Dataset University of Bonn	100
Tales Oliva et al.[27]	BONN Dataset University of Bonn	84

Table 2.5: Resultant Accuracy by Linear Discriminant Analysis (LDA)

Authors	Dataset	Performance metrics in (%)
		Accuracy
Yang You et al.[29]	BCI Competition II and III	94.29
Wei-Yen Hsu[30]	Graz BCI group	93.7

Table 2.6: Resultant Accuracy, Sensitivity, and Specificity by Other Models for EEG Classification

Authors	Classifier	dataset	Performance metrics in (%)		
			Accuracy	Sensitivity	Specificity
Xinmei Hu et al.[36]	Bi-LSTM	Children's Hospital Boston CHB-MIT		93.61	91.85
Rubén San-Segundo et al.[2]	DNN	The Bern-Barcelona EEG	98.9		
Martin Dobiáš et al.[37]	HMM	study of Stancák et al.	84.6±0.7		

Table 2.7: Resultant Accuracy by Multi-classifier approaches Classification

Authors	Classifier	dataset	Performance metrics in (%)
			Accuracy
Jardel das C. Rodrigues et al.[31]	(SVM), (OPF), Naive Bayes, (*k*-NN) ,(MLP)	KDD Dataset	99.78
Alexandra Piryatinska et al.[5]	SVM, RF	healthy adolescents and adolescents with symptoms of schizophrenia	88.1
Andrius Vytautas Misiukas Misiunas et al.[32]	ANN, SVM	Children's Hospital, Affiliate of Vilnius University Hospital Santaros Klinikos.	75
A. Sharmila et al.[9]	NB, KNN	BONN Dataset University of Bonn	100
Atemangoh Bruno Peachap et al.[33]	ANN, SVM	BONN Dataset University of Bonn	100
S Raghu et al.[34]	SVM, K-NN, MLP	BONN Dataset University of Bonn, Ramaiah Medical College and Hospital (RMCH)	99.45
K. Venkatachalam et al.[10]	PCA and FLD	BCI competition III	96.54
M. Diykh et al. [4]	SGSKM	Sleep-EDF database Sleep Spindles database.	94.93
Marzieh Savadkoohi et al.[35]	SVM, KNN	BONN Dataset University of Bonn	100

Evidently, Support Vector Machine (SVM) has clearly shown significant accuracy range from 93% to 100%. Artificial Neural Network (ANN) has shown high accuracy results as well start from 93.05% to 99.8%. Moreover, Convolution Neural Network (CNN) classification has shown high accuracy start from 88.3% to 99.3%. On the other hand, K-Nearest Neighbor (K-NN) Classification has shown a slightly variable accuracy start from 84% to 100%. Furthermore, Linear Discriminant Analysis (LDA) Classification has shown almost persistent accuracy start from 93.7% to 94.29%. In order to have precise assessment, we have focused on approaches that include multiple classification methods and investigated as they have shown high accuracy start from 75% to 100.

With the aim to have clear visual analysis, all resultant accuracy shown in Tables 2.1 to 2.7 are displayed visually by bar chart figures (Figure 2.1 to 2.6). Figure 2.1 shows resultant accuracy by Support Vector Machine (SVM) classification. Figure 2.2 shows resultant accuracy by Artificial Neural Network (ANN) classification. Figure 2.3 shows resultant accuracy by Convolution Neural Network (CNN) classification. Figure 2.4 shows resultant accuracy by K-Nearest Neighbor (K-NN) classification. Figure 2.5 shows resultant accuracy by Linear Discriminant Analysis (LDA) and some other Classification approaches. Figure 2.6 shows resultant accuracy by Multi-classifier approaches classification.

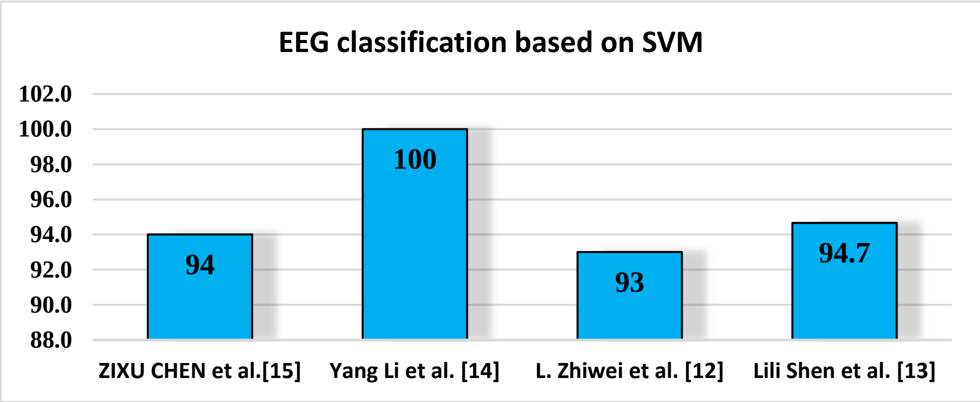

Figure 2.1: Resultant Accuracy by Support Vector Machine (SVM)

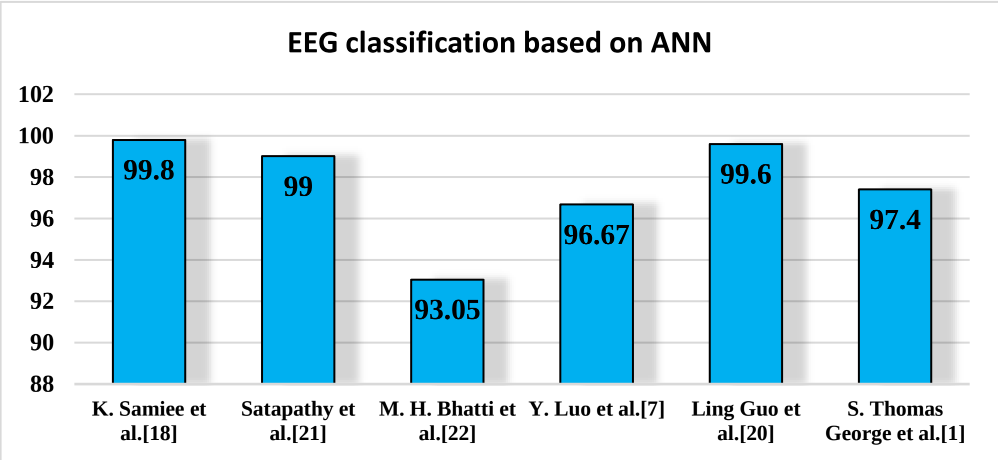

Figure 2.2: Resultant Accuracy by Artificial Neural Network (ANN)

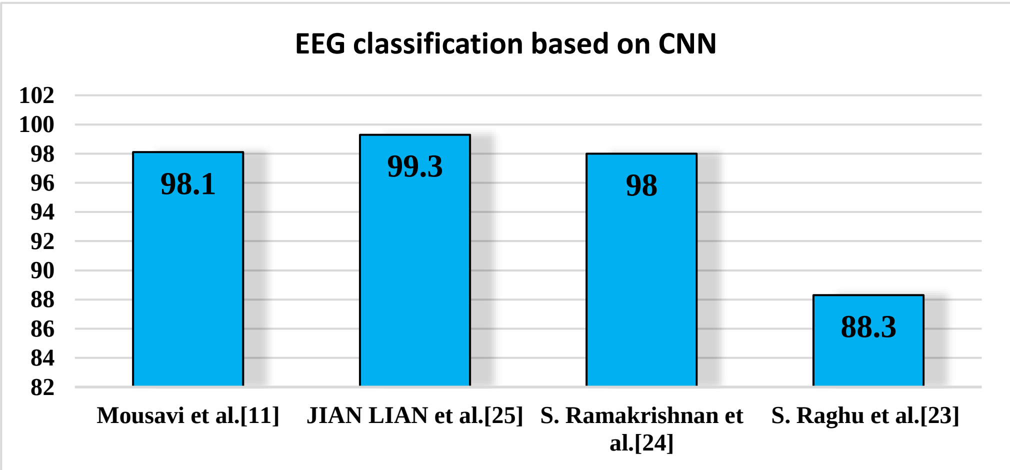

Figure 2.3: Resultant Accuracy by Convolution Neural Network (CNN)

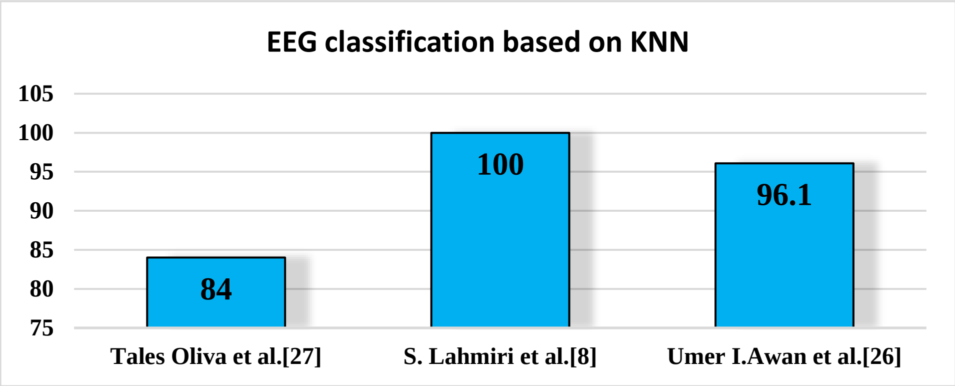

Figure 2.4: Resultant Accuracy by K-Nearest Neighbor (K-NN)

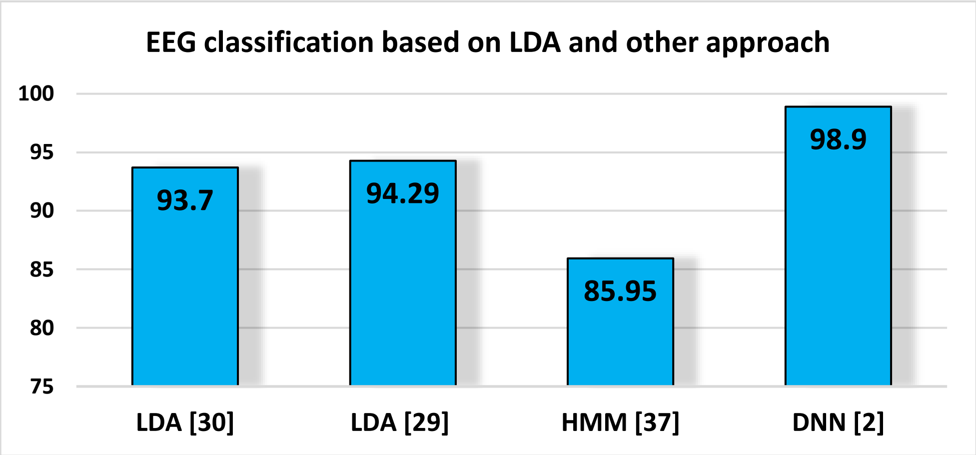

Figure 2.5: Resultant Accuracy by LDA and other approaches

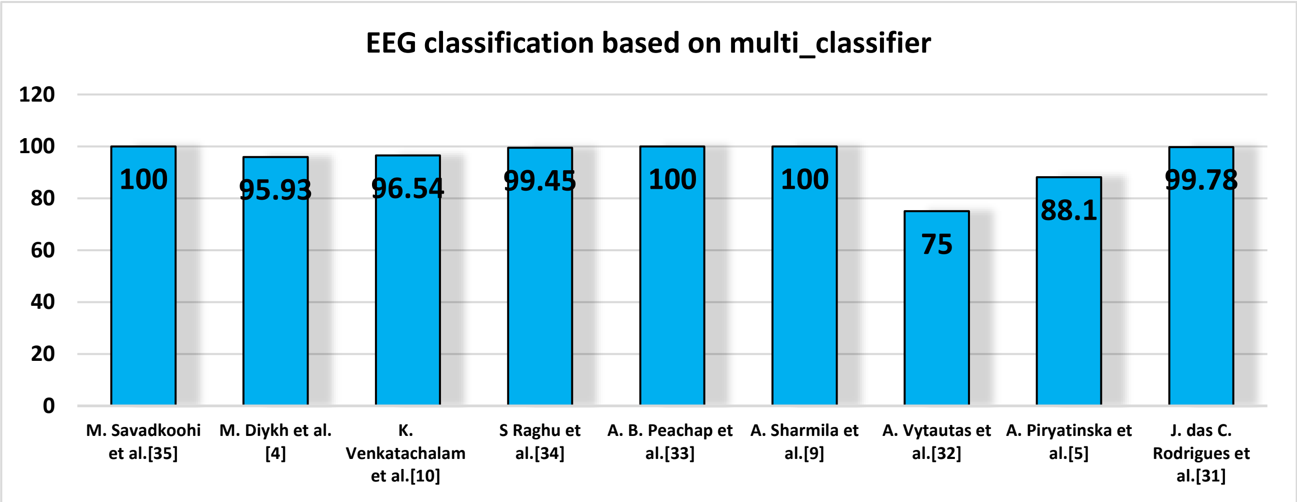

Figure 2.6: Resultant Accuracy by Multi-classifier approach

in order to have a precise overview and assessment for all classification groups and investigate methods performance persistency, average accuracy is calculated for all approaches inside the same group. Figure 7 shows the average accuracy for Multi-Classifier, LDA, SVM, KNN, CNN, and ANN classification groups. Technically, ANN classification has outperformed all other approaches with 97.6% average accuracy. On the other hand, KNN has shown the lowest performance with 93.4% average accuracy. CNN classification has shown the best second performance with 94.9% average accuracy. SVM classification has shown slight difference that CNN with 94.4% average accuracy.

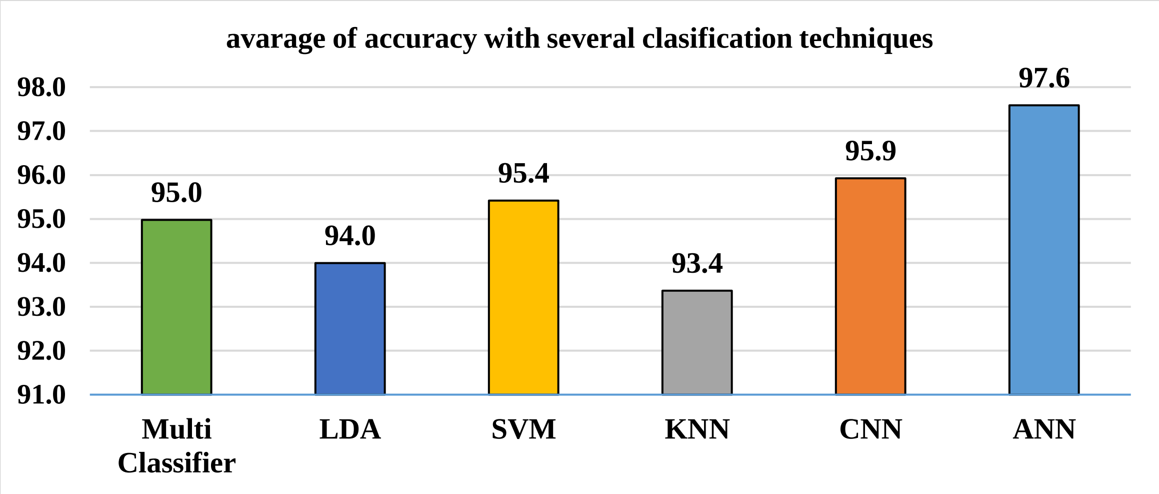

Figure 2.7: Resultant average of Accuracy with several classification techniques

2.11 Theoretical background

These sections provide an explanation of the theoretical background for a variety of machine learning methods. Different kinds of brain waves have been seen in electroencephalograms, which have been described. Seizures are divided into different categories. A short explanation of machine learning and the many kinds of machine learning. Support Vector Machine, k-Nearest Neighbor, Naive Bayes, Decision Trees, and Random Forest are just several of the machine learning techniques covered in this chapter. Particle Swarm Optimization has been presented as a kind of optimization technique.

2.12 Electroencephalogram (EEG):

It is a test that uses electrodes (small flat metal discs) attached to your scalp to record and evaluate the electrical signals in your brain[33]. The cells of the brain interact together using electrical activity. They are always active and work even during sleep time[14]. The electrodes detect short electrical signals that are generated by brain cell activity. Electrical impulses in the brain are known as brainwaves. The actions, emotions, and ideas of an individual are transferred between neurons in our brains[32]. Connected electrical pulses from masses of neurons able to communicate with one another generate all brainwaves. Our brainwaves have different frequencies. Some of them are quick, while others are slow[36]. When you sleep Delta (1-3 Hz) signal appears, theta (4-7 Hz) as a very relaxed state, alpha (8-12 Hz) associated with a state of relaxation, beta (13 – 38 Hz) state of alertness like active and external attention. The gamma signal (39 – 42 Hz) becomes clear when high Concentration. These signals are the common names for EEG waves[32][38]. They are measured in hertz (cycles per second) (Hz). The signals are amplified and become visible as a graph on a screen, or as wavy lines printed out on paper. EEG is a non-surgical, inexpensive test and safe. Seizure diseases, such as epilepsy, brain tumors, brain harm from head injury, brain dysfunction caused by several reasons (encephalopathies), brain inflammation (encephalitis), sleeping issues, problems with memory, and accidental stroke are all identified using EEG[27]. Furthermore, it is utilized in many fields of research, like brain computer interface (BCI), virtual reality, gaming and more.

2.13 Seizure types

Neurologists split seizures into two types based on their symptoms: partial and generalized. A partial seizure, also known as a "focal seizure," affects only a portion of the brain. Simple partial seizures and complicated partial seizures are two types of partial seizures[32].

In the case of simple partial, a patient does not miss consciousness, however cannot communicate correctly. In the complex-partial, a person becomes confused about the surrounding environment and begins behaving abnormally, like chewing and mumbling. This is referred to as a "focal impaired awareness seizure"[39].

In generalized seizures, on the other hand, all areas of the brain suffer and whole-brain networks are affected immediately. Generalized seizures have many types, however in general they are divided into two types: convulsive and non-convulsive[39].

2.14 Machine learning

It is an artificial intelligence (AI) application that allows systems to automatically learn and develop from their experiences, without the need for direct programming on the part of the user. Making computer programs that can access data and utilize it to self-learn is the subject of machine learning research[40].

The goal of machine learning is to extract knowledge from data. It's also referred to as predictive analysis or statistical learning, and it's a field of research that combines statistics, artificial intelligence, and computer science[41]. Machine learning methods have become more common in everyday life in recent years. From automatic suggestions of which movies to watch and which things to buy to personalized internet radio and identifying friends in photographs. The algorithms of machine learning are utilized in a lot of modern websites and products. It's extremely possible that each element of a website like Facebook, Amazon, or Netflix contains various machine learning models when you see it.

2.15 Types of Machine learning:

Machine learning can be classified into four types based on the purpose for which it is used: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning[42].

2.15.1 Supervised Learning

Supervised learning algorithms are learning algorithms that utilize training data and related labels (output) for each data sample during the model training process[41]. The goal of learning from a sample of input data is to uncover equivalent output mappings or relationships between input and output. In the training process, a training model can be used to predict the output of any new collection of input data that hasn't been seen before. In other words, in supervised learning, the machine is given examples of inputs and desired outputs, with the goal of understanding an overall rule that maps inputs to related outputs. The two main techniques for supervised tasks are classification and regression[41].

Classification algorithms are utilized with the aim of predicting output data labels according to the learning of the model during the training phase[40]. Accordingly, every output answer corresponds to a certain discrete class or category. For example, consider spam detection in email messages: there are only two possible outcomes: spam email or no spam email, or patients who take an exam for cancer. The result is either they have cancer or they do not have cancer.

Regression is a type of supervised machine learning task in which the goal is to estimate the value of something[40,41]. In contrast to classification, regression approaches depend on sets of input data and output results that are continuous numerical values, rather than distinct classes or categories. Regression models discover basic relationships and correlations between inputs and their related outputs by utilizing input data features or characteristics and associated numerical results. For example, predicting house prices or stock prices.

2.15.2 Unsupervised learning

In this machine learning, labels are unavailable or the outputs of data are unexplained. The learning algorithm is just shown the input data and finds structure or distribution to derive knowledge from this data[42]. This approach to learning studies the data to distinguish patterns. Correlations or relationships will be determined in the training phase by algorithms of unsupervised learning from analyzing data. The algorithms attempt to order that data in some form to illustrate its structure. The data is grouped into clusters or arranged data in a method that appears more regular[43]. The main goal of the algorithm is to learn more about the available data. Clustering and association problems are two types of unsupervised learning issues.

2.15.3 Semi-supervised Learning

It is a combination of supervised and unsupervised learning. It utilized both labeled and unlabeled data[44]. Typically, this combination will consist of very little value of labeled data and a very big part of unlabeled data[45]. Which gives the advantages of learning for both unsupervised and supervised learning while keeping away from the challenges of finding a large amount of labeled data. This means you can train a machine to identify data with less labeled training data.

2.15.4 Reinforcement Learning

It is a method of learning that communicates with its environment by performing actions and detecting failures or rewards[46]. The most significant aspects of this type of learning are trial and error searches including delayed reward. This method enables machines and software agents to automatically determine the most appropriate behavior in a given situation, allowing them to optimize their efficiency[46,47]. Simple reward feedback is required for the agent, in order to recognize which action is the best. Nowadays, reinforcement learning applications have become very popular, such as self-driving vacuum cleaners, driverless cars, etc.

2.16 Support Vector Machine (SVM)

SVM is a supervised method for machine learning which is used for regression and for classification [17]. However, they are most typically utilized for classification issues. It was originally presented in the 1960s. The primary aim of SVM is to construct a hyperplane that divides the two classes as efficiently as possible while leaving as much space between the hyperplane and the observations as possible [18]. The goal of the SVM is to discover one that has a large margin and can split the data into different categories. The basic SVM can only deal with data that is linearly separable or nearly linearly separable, and it has a hard time dealing with data that is very linearly inseparable. To put it another way, a linear SVM can only be used on datasets that can be divided by a hyperplane with high classification accuracy. Shortly after, a kernel technique is used to improve the SVM's skills, which is called a kernel SVM [19]. There are several kernels to choose from, such as polynomial kernels, Gaussian kernels, also called Radial Basis Function (RBF) kernels and sigmoid kernels.

2.17 k-Nearest Neighbor (KNN)

it is a kind of supervised machine learning algorithm that is utilized to resolve classification (which is the most common) and regression problems. KNN is the most basic of all the machine learning algorithms[48]. The learning strategy of KNN is to remember the training set and then to predict the labels for every new input data depending on the label of its closest neighbors in the training set. It is based on the idea of learning by analogy[49]. To determine the nearest neighbors, this approach employs distance measuring techniques such as the Euclidean distance measure and the Makowski distance measure. There are no clear rules about which distance measurement is the best. It all depends on the implementation that you have. No real learning takes place during the training phase[50]. The KNN is generally referred to as a lazy algorithm. KNN is a lazy algorithm, which means it is speedy at training and slower at prediction. KNN stores all of the training data. It is a computationally costly method. In comparison to other supervised learning algorithms, this approach requires a lot of memory storage.

2.18 Naive Bayes

It is a probabilistic machine learning algorithm dependent on the Bayes Theorem[51]. Naive Bayes considers that the predictors are independent, which means that knowing one attribute's value has no effect on the value of every other attribute. To put it another way, a Naive Bayes classifier assumes that the availability of one feature in a class is independent of the value of any other feature[52]. The Naive Bayes model is divided into three kinds. Gaussian naive Bayes, multinomial naive Bayes, and Bernoulli naive

Bayes[52,53]. Gaussian Naïve Bayes is the most basic Naive Bayes classifier, assuming that every label's data is obtained from a simple Gaussian distribution. Multinomial Naive Bayes assumes that the features come from a simple multinomial distribution. This type of Naive Bayes is best for features that contain discrete counts. In the Bernoulli Naive Bayes model, features are considered to be Boolean or binary 0s and 1s. Bernoulli Naive Bayes can be used in text classification models. Naive Bayes provides many advantages, including being simple to build and fast, using less training data, and being able to handle both continuous and discrete data. Furthermore, the Naive Bayes classification method may be utilized for binary classification and multi-class classification.

2.19 Decision Tree

It is a supervised method that may be used for both classification and regression tasks[54]. As the name indicates, a decision tree is a tree-like structure in which the interior nodes correspond to testing on a characteristic. Every branch reflects the test result, and every leaf node represents the class label. The decision should be taken after every characteristic have been calculated. The classification rules are represented as a path starting from root and ending in leaf. As a result, decision trees are often represented by three different kinds of nodes: root node, branch node, and leaf node[55]. The determination of the attribute for the root node at every level is a key problem in the Decision Tree. Attribute selection is the term for this procedure. The Information Gain and the Gini Index are two of the most frequently utilized techniques for attribute selection. Using a decision tree node to divide the training examples into smaller groups, the entropy of the training instances is modified. Information gain is a measure of the amount of entropy changed. The Gini Index is a statistic that determines how frequently a randomly selected element is wrongly recognized. It indicates that a lower Gini index characteristic should be chosen.

2.20 Random Forest

The Random Forest algorithm is a supervised learning technique which is utilized for classification problems as well as regression tasks. A forest is made up of trees, and having a greater number of trees indicates having a more robust forest[56]. The algorithm of random forest, on the other hand, creates decision trees from data samples, receives predictions from each of them, and then votes on which answer is the most appropriate for the situation that represents the best solution[56]. It is a group collaborative approach that eliminates over-fitting by averaging the results, making it better than a single decision tree[57]. The random forest constructs and combines several decision trees such that a more accurate and reliable prediction is obtained. The random forest method offers many benefits, including the ability to overcome the problem of overfitting by averaging and connecting the outcomes of multiple decision trees, as well as the fact that it does not need large amounts of data. Data accuracy is maintained to a high degree even when data is supplied without scaling. When a large part of the data is missing, the accuracy of the system continues to be excellent. The complexity of Random Forest Algorithms is one of its most significant drawbacks. When compared to other methods, the prediction process takes a long time to complete.

2.21 Particle Swarm Optimization (PSO)

It is an optimization algorithm that was developed by Drs. Eberhart and Kennedy in 1995[58]. PSO is a population-based stochastic optimization method that simulates the social conduct of animals similar to birds congregating or fish schooling. PSO and evolutionary computation approaches such as Genetic Algorithms have a number of similarities. The system starts with a population of stochastic solutions and then iteratively updates generations to discover the best solution[59]. PSO, in contrast to GA, does not include evolutionary operators such as crossover and mutation, among others. Potential solutions are termed particles in PSO, and they search through the problem space by following the best existing particles. Within the problem area, every particle keeps track from the pathway of its coordinates, which is connected to the most suitable solution (fitness) that it has discovered so far. Additionally, the fitness value is stored. pbest is the term given to this particular value. The global version of the particle swarm optimizer, known as gbest, keeps track of the total best value, as well as its position, obtained thus far by each particle in the population using the particle swarm optimization algorithm. The particle swarm optimization concept is based on modifying the velocity (accelerating) of every particle toward its pbest and gbest values at every iteration (global version)[60]. A random term is used to weight acceleration, with separate random values created for acceleration toward pbest and gbest. PSO has been effectively used in a multitude of research and application fields in the last few years. When compared to other approaches, PSO produces better results in a faster and less expensive manner. Another factor that makes PSO interesting is the fact that it has a small number of parameters that may be changed. With very few modifications, a single version may be used in a large range of applications. PSO has been utilized in the development of strategies that may be applied to a wide range of applications.

2.22. Summery

This chapter has surveyed 32 main successful approaches for EEG signal classification. All approaches are distributed into seven groups based on the main proposed classification method (SVM, ANN, KNN, CNN, LDA, Other, Multi-classifier). The proposed analysis in this chapter has targeted the investigation of accuracy, sensitivity, and specificity as main criterion. We have looked for processing time as well and they unfortunately lacking of any system performance analysis including the processing time. Generally, all classification groups have shown high capabilities in terms of accuracy metric. Evidently, ANN has outperformed all other models and KNN has shown the lowest performance. Furthermore, several machine learning algorithms have been explained and different seizure types.

Chapter 3 – Proposed System

3.1 Introduction

This chapter provides a new design for an EEG classification system mainly based on Fractals similarity measures. A new Fractal mathematical metric is derived with the aim of grouping highly similar EEG signals and ignoring other signals. Technically, this process would increase the classification accuracy potentially as the similarity search is achieved among EEG signals with high harmony. Then, a full classification design is achieved including data normalization, Particle Swarm Optimization (PSO), Fractal metric computations, metric mapping and cosine similarity for the final decision. The proposed system has provided two designed models with PSO and without optimization.

3.2 Fractal Classification Mathematical Model

Fractals are the concept of self-similarity matching. It is composed of repeated patterns that are self-similar objects with various scales and offset. Scale and offset factors are the main mathematical measurements in order to measure the proportional objects size and object shifting respectively. Generally, the original object is named range in fractals and usually another smaller object is named domain that is derived from the range object. In the EEG classification system, we have two EEG signals that are considered to be Fractal objects (range and domain), one is the testing EEG signal and the other one is the best similar EEG signal inside the training dataset. Therefore, there is no direct relation between the two EEG objects (e.g, Fractals Objects) – in other words, Range and Domain.

The general equation of the fractal is [61]:

$$(\bar{R}\,) = \mathrm{S} \times \mathrm{D} + \mathrm{O} \quad \ldots (3.1)$$

where $\overline{R}$ is the approximated range value, D is the domain value, S and O are the scaling and shifting (offset) factors respectively. The coefficients S, O can be computed based on equations 3.2 and 3.3 [61]:

And
$$S = \frac{\sum_{i=1}^{n} di \times ri - \sum_{i=1}^{n} di \ \sum_{i=1}^{n} ri}{n \sum_{i=1}^{n} di^2 - \left(\sum_{i=1}^{n} di\right)^2} \text{ ….(3.2)}$$

$$O = \frac{1}{n}\left(\sum_{i=1}^{n} ri - S \sum_{i=1}^{n} di\right) \text{ …. (3.3)}$$

Where n represents the block (object) size, di represents a single value in domain, ri represents a single value in range.

The main target of the mathematical derivation for Fractals is to have a new Fractal metric (F) that can be calculated based on only the values of the given (single) object. In other words, Fractals metric can be calculated using only range object or only domain object. Therefore, Fractals model would be derived to have new mathematical form with only domain or only range objects. This would enable the targeted metric to group the training EEG objects and in indirect link with the testing EEG object.

Let $\widehat{R}$ represents the average for range block

Hypothesis 1:
$$\alpha = \sum_{i=1}^{n} | Ri - \hat{R} | \text{ ... (3.4)}$$

Both Ri and $\widehat{R}$ can be extended into new equations-based Eq. 3.1 to be as:

$$Ri = S \times Di + O \text{ ... (3.5)}$$

$$\hat{R} = S \times \hat{D} + O \text{ …(3.6)}$$

Then, R and $\widehat{R}$ can be substituted with equations 3.5 and 3.6 respectively as this has produced new shape for Eq.3.4 as illustrated in Eq.3.7

$$\alpha = \sum_{i=1}^{n} \left| S \times Di + O - \left(S \times \hat{D} + O\right) \right| \text{ ... (3.7)}$$

Eq.3.7 can be simplified by removing parenthesis to be as:

$$\alpha = \sum_{i=1}^{n} |\mathrm{S} \times Di + \mathrm{O} \; - \mathrm{S} \times \widehat{D} - \mathrm{O})| \ldots (3.8)$$

Then, O (Offset) would be removed as a result of the opposite sign to obtain Eq.3.9:

$$\alpha = \sum_{i=1}^{n} |\mathrm{S} \times Di - \mathrm{S} \times \widehat{D})| \; \ldots (3.9)$$

Now, $|\mathrm{S}|$ can be out the summation as a common parameter to simplify Eq.3.9 as shown in Eq.3.10.

$$\alpha = |\mathrm{S}| \sum_{i=1}^{n} \left|Di - \widehat{D}\right| \ldots (3.10)$$

Hypothesis 2:

$$\beta = \sum_{\mathrm{i}=1}^{\mathrm{n}} (\; Ri - \widehat{R} \;)^{\;2} \ldots \; (3.11)$$

Again, R and $\widehat{\mathrm{R}}$ can be substituted with equations 3.5 and 3.6 to obtain Eq.3.12:

$$\beta = \sum_{i=1}^{n} ((\mathrm{S} \times Di + \mathrm{O}) \; - (\mathrm{S} \times \widehat{D} + \mathrm{O}))^{\;2} \ldots (3.12)$$

Simplify now by removing the inside parenthesis to have Eq.3.13:

$$\beta = \sum_{i=1}^{n} \left(\mathrm{S} \times Di + \mathrm{O} \; - \mathrm{S} \times \widehat{D} - \; \mathrm{O}\right)^{\;2} \ldots \; (3.13)$$

Then, O (Offset) parameters are removed for having opposite signs to produce Eq.3.14.

$$\beta = \sum_{i=1}^{n} (S \times Di - \mathrm{S} \times \widehat{D})^{\;2} \ldots \; (3.14)$$

Now, Scale parameter can be moved outside the summation as a common parameter to produce Eq.3.14.

$$\beta = S^{2} \sum_{i=1}^{n} (D\mathrm{i} - \widehat{D})^{2} \ldots (3.15)$$

In order to have independent domain object metric, consider hypothesis 3 shown in Eq.3.16

Hypothesis 3: $$\mathrm{F} = \frac{\alpha^{2}}{\beta} \ldots (3.16)$$

Now, Fractal metric for domain object can be obtained by replacing α and β parameters in Eq.3.16 by their own mathematical representations in equations 3.10 and 3.15 respectively to produce domain Fractal metric as shown in Eq.3.17.

$$\mathrm{F} = \frac{S^{2}(\sum_{i=1}^{n} |D\mathrm{i} - \widehat{D}|)^{2}}{S^{2} \sum_{i=1}^{n} (D\mathrm{i} - \widehat{D})^{2}} \ldots (3.17)$$

Eq. 3.17 can be simplified by deleting the value of S^{2} in the numerator and in the denominator, to get the Eq. 3.18.

$$\mathrm{F} = \frac{(\sum_{i=1}^{n} |D\mathrm{i} - \widehat{D}|)^{2}}{\sum_{i=1}^{n} (D\mathrm{i} - \widehat{D})^{2}} \ldots (3.18)$$

Finally, Fractal metric for range object can be obtained by replacing α and β parameters in Eq.3.18 by their own mathematical representations in equations 3.4 and 3.11 respectively to produce range Fractal metric as shown in Eq.3.19.

$$\mathrm{F} = \frac{(\sum_{i=1}^{n} |R\mathrm{i} - \hat{R}|)^{2}}{\sum_{i=1}^{n} (R\mathrm{i} - \hat{R})^{2}} \ldots (3.19)$$

Equations 3.18 and 3.19 represent the targeted independent Fractals metric for domain (testing EEG object) and range (training EEG object).

3.3 Fractals Metric – Cosine Classifier without optimization

The first designed model consists of the processes of both training and testing systems for EEG classification. This model starts by normalizing the training EEG dataset in order to support Fractals metric having accurate grouping value. Then, the system calculates Fractals metric for all the EEG training objects and mapping them between the range of (0..100) based on a specific equation. In the testing (classification) phase, the system starts by normalizing the testing EEG object and calculating the Fractals metric. Fractals metric is mapped between 0 and 100. Then, the system is determining the search space size in the EEG dataset by including any training EEG object with a mapped Fractals metric within a search space threshold (SST) in comparison with the mapped Fractals metric of the testing object. Next, the classifier computes the similarity of the testing EEG object with all the training EEG objects included in the search space based on the cosine similarity mechanism to decide the final class based on the best matched EEG object class. Figure 3.1 explains the main component of the first model for EEG classification.

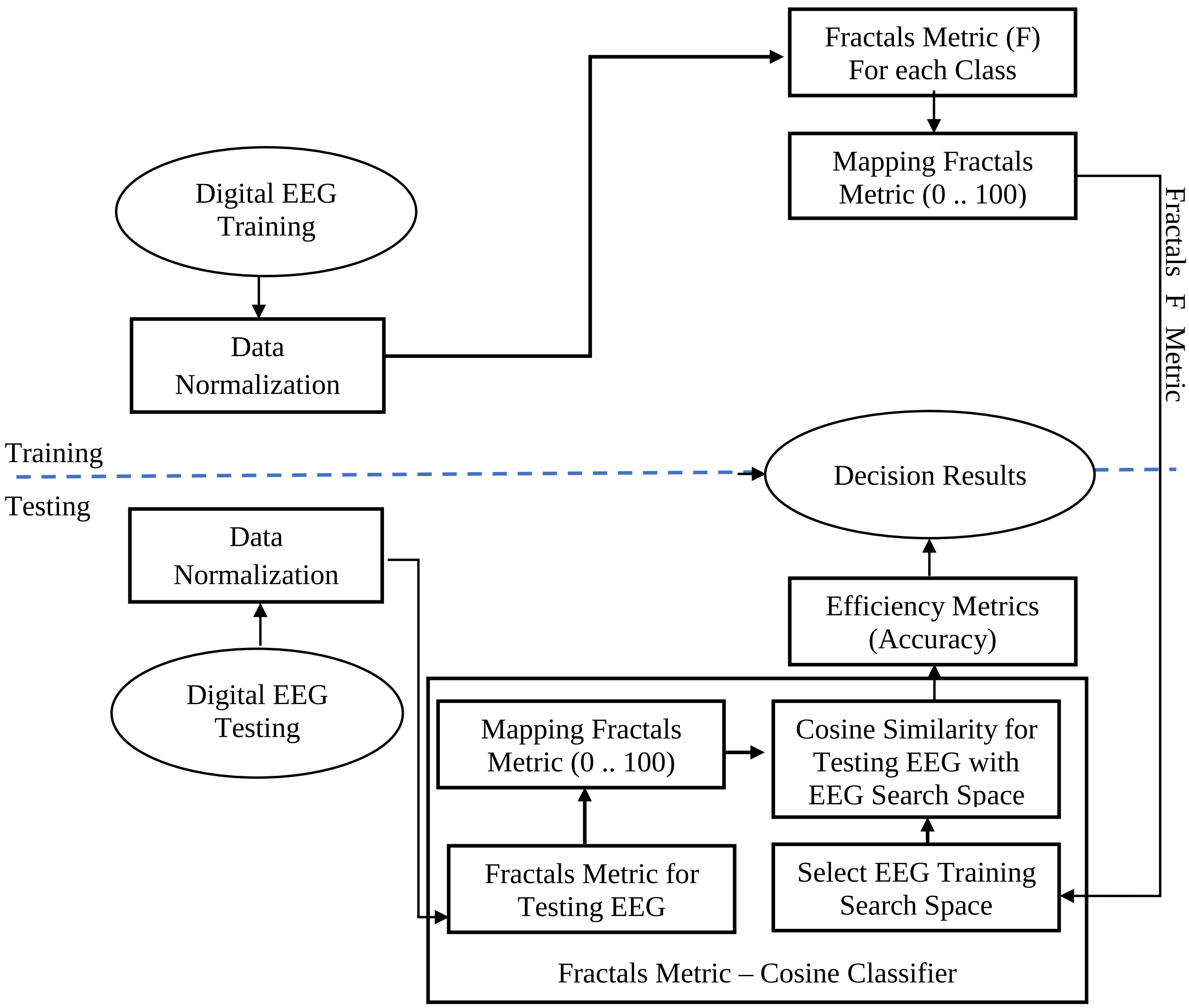

Figure 3.1: Training and Testing Machine Learning for Fractals metric – cosine Classifier without optimization

3.4 Fractals Metric – Cosine Classifier with Optimization

In this model, training starts by normalizing read EEG signals to arrange features in the same scale and weight (significance). Then, features are selected based on particle swarm optimization (PSO) to reduce the depicted features that play an important role in the Fractals classification. Optimization is expected to increase the proposed model accuracy. Fractals metric for all EEG training objects are computed based on the main Fractal Eq. 3.18 and mapping them in the range between 0 and 100 to empower the classification process by distributing EEG signals into clear searching space level. In the testing stage, the system begins by normalizing the testing EEG object and calculate the Fractals metric. Next, Fractals metric is mapped into the same range used in the training system (0..100). Then, search space threshold (SST) is predefined to determine the included training EEG signals. This is achieved based on their mapped Fractals metrics to be within the SST when subtracted from the mapped testing EEG Fractal metric. Next, the classifier computes the cosine similarity of the testing EEG object with all the training EEG objects. Highest Cosine Similarity would decide the final class for the testing EEG object. Figure 3.2 describes the main components of the EEG classification system supported by PSO optimization.

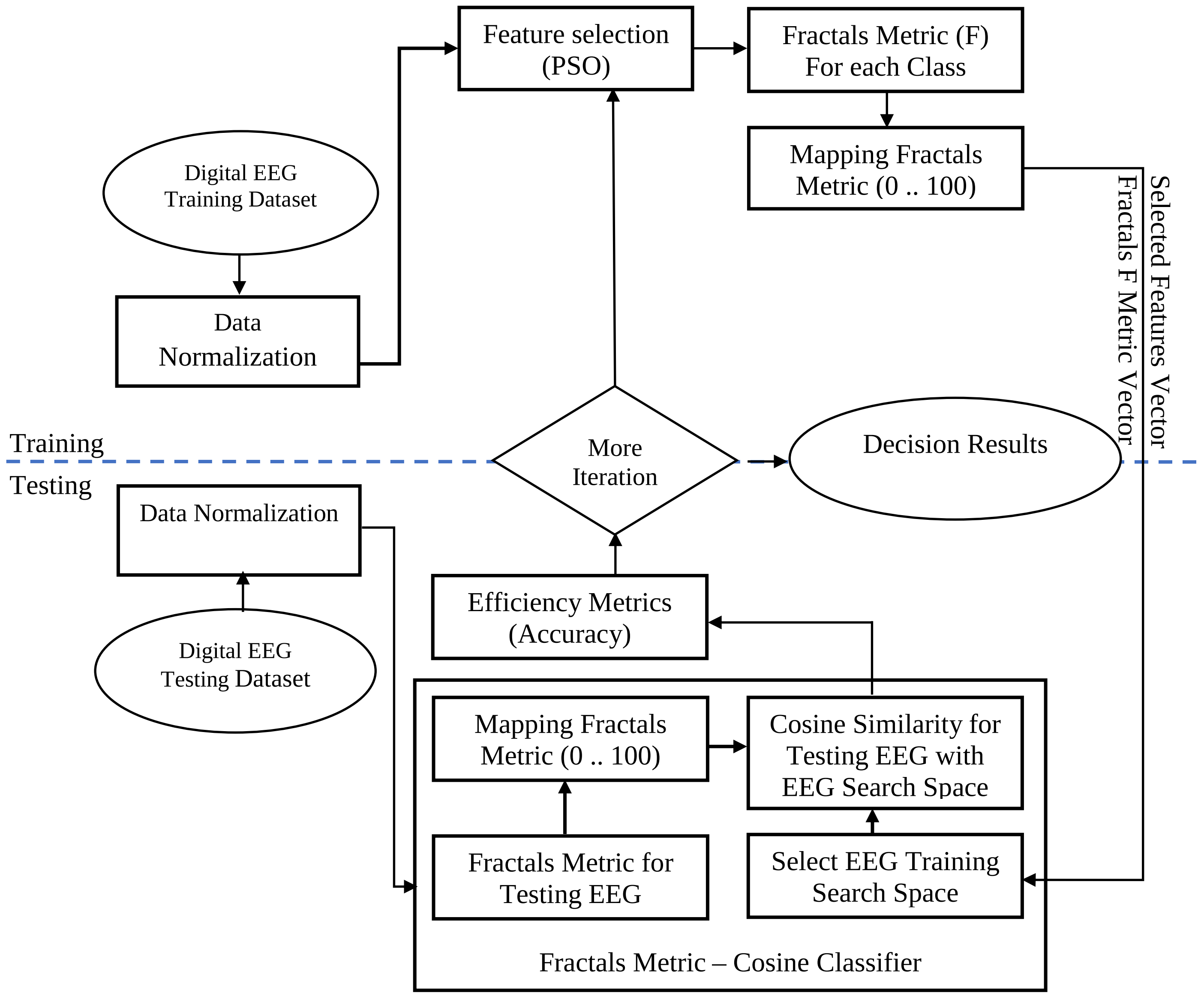

Figure 3.2: Training and Testing Machine Learning for Fractals metric – cosine Classifier with optimization

3.5 Z1_score normalization algorithm

Data normalization, also called preprocessing, is a common process in many machine learning systems. Mainly, it converts the source data into another value level that would boost efficiency for systems and applications. Algorithm 3.1 performs the normalization for EEG signals based on the Z1_score method. As a result, each feature in EEG signals is normalized into another value level located between a predefined range. Basically, it first finds the mean and standard deviation for each feature. Then Z1_score is applied according to Eq.3.20[62].

$$\text{Z1}_{\text{score}} = \frac{x-\mu}{\sigma} \ldots (3.20)$$

Where x represents a single value in a specific feature, μ and σ are the mean and standard deviation, respectively, computed for each feature.

Algorithm 3.1 (Z1_score normalization)

Input:

RowNo, ColNo // Number of rows and columns in EEG dataset
EEGData [RowNo, ColNo] //EEG dataset in two-dimension array excluded data label

```
For i=1 to ColNo
Sum[i] = 0
Count[i] = 0
 For j=1 to RowNo
  Sum[i]=Sum[i] + EEGData [i, j]
  Count[i] =Conut[i]+1
End for
Mean[i]=Sum[i]/Count[i]   //calculate mean for each feature
End for
For i=1 to ColNo
 SumDev[i]=0
  Count[i]=0
For j=1 to RowNo
Deviation[i]= (EEGData [i, j]-Mean[i]) ^ 2
SumDev[i] = SumDev[i] + Deviation[i]
  Count[i] =Conut[i]+1
End for
Standard_Deviation[i]= sqrt root ( SumDev[i] / Count[i] )  // for each feature
End for
For i=1 to ColNo
For j=1 to RowNo
Z1_score[i,j]=(EEG[i,j]-Mean[i]) / Standard_Deviation[i] // for each feature in dataset
End for
End for
```

Output:

Normalized_EEG [RowNo, ColNo] // represent normalized EEG dataset values

3.6 Particle Swarm Optimization algorithm

With the aim to reduce the number of selected features in EEG signals, Particle Swarm Optimization is applied. Algorithm 3.2 starts by selecting a population (swarm) of candidate solutions (particles) randomly. The search for the best solution is achieved by updating generations. First, PSO has initialized all particle's velocity and weight randomly based on parameters. Then, the fitness value is calculated for each particle and updates the global best position that represents the best solution. Next, updating particle velocity and position according to the velocity and position equation. Then, the new iteration is performed with the same steps to optimize the solution until reaching max iteration number. PSO is applied to the normalized data. Several features are randomly assigned according to the parameters of the PSO optimization. This optimizer is implemented approximately 30 times iteratively to obtain the best features and optimize the accuracy. The output of this algorithm is an EEG signal with fewer and best optimal features.

Algorithm 3.2 (Particle Swarm Optimization (PSO))
Input: Normalized_EEG [RowNo,ColNo] // normalized EEG dataset
//initialize position and velocity for all particles 1: Xi = Random (xmin, xmax) //initialize position randomly within allowed range 2: Vi = Random (vmax, vmax) //initialize velocity randomly within allowed range 3: assign (pbest) and (gbest) // based on objective function 4: Loop 5: For t=1:T // Number of iterations 6: For i=1:N // Population size 7: Vi(t) = θ*Vi(t-1) +C1 ∗R1∗ [pbesti −Xi(t-1)] +C2 ∗R2 ∗ [gbesti −Xi(t-1)] // update velocity 8: Xi(t) = Xi(t - 1)+ Vi(t) // update particle's position 9: Evaluate the objective function Fx_i // based on fractal +cosine similarity 10: pbesti=Xi if F(xi) > F(pbest) // update the particle's best position(features) 11: gbest=pbesti if pbesti> gbest // update the global best position 12: if there is no convergence of the current solution and if t < T go to Loop 13: return gbest and pbest // represent best solution and optimal selected features
Output: SelFeature[n] // vector of selected features, n is number of features (column indexes)

3.7 Fractal Metric Raw based Algorithm

The algorithm describes the Fractal implementation. When it is executed without optimization, an average value is calculated for each row of EEG signal features. Then the fractal metric using Eq. 3.19 is applied to be calculated. In the case of applying PSO optimization, the average value of each row would be computed for only the EEG signal features selected by PSO. The output represents a list of Fractals metrics for the training set and produces a single Fractal metric value for the testing signal.

Algorithm 3.3 (Fractal Metric (F) Row based)

Input:

Normalized_EEG [RowNo, ColNo] // Normalized EEG dataset

```
For i=1 to RowNo
 SumRows[ i ] = 0
 CountRow[i]=0
 For j=1 to ColNo
   SumRows[i] = SumRows[i]+ Normalized_EEG [i, j]
   CountRow[i]=CountRow[i] +1
 End for
 SummuryVector[i] = SumRow[i] / CountRow[i] // calculate the average for each row of data
End for
For i=1 to RowNo // length of row
 AlphaSum[i]=0
 For j=1 to ColNo
  AlphaSum[i] = AlphaSum[i] + abs (Normalized_EEG [i,j]-SummuryVector[i])
  AlphaSum[i]= AlphaSum[i]^2 // sqrt of Summation
 End for
End for
For i=1 to RowNo
 BetaSum[i]=0
 For j=1 to ColNo
  BetaSum[i] = BetaSum[i] + (Normalized_EEG [i, j]- SummuryVector[i]) ^ 2
 End for
End for
For i=1 to RowNo
Fmetric[i] = AlphaSum[i] / BetaSum[i] // vector of fractal metric for each row (represent Eq. 3.19)
End for
```

Output:

Fmetric[n]// Fractal metric for each row

3.8 Mapping Fractals Metrics Algorithm

The Fractal metric is mapping in the range between 0 and 100 based on the parameters set (max-map,min-map) in Eq. 3.21. All Fractals metric convert into integer number instead of a real number to reinforcement the classification process with distributing EEG signals into clear searching space level. This mapping would rank similar signals by the same integer Fractal metric or close Fractal metric.

$$\mathrm{Map}_{\mathrm{Fmetric}} = integer\left(\frac{Fmetric - F_{Min}}{\Delta F}\right) \times \Delta Map + Min_{Map} \; \ldots \; (3.21)$$

Where *Fmetric* represents Fractal metric, ΔF is the difference between maximum and minimum *Fmrteics* in the training set. ΔMap represents mapping range between 0-100 (in our case). F_{Min} is a minimum value of the Fractal metrics. Min_{Map} represents minimum value of the mapping range.

Algorithm 3.4 (Mapping of Fractals metrics)

Input:

Fmetric for the training dataset[N]
Fmetric for the testing EEG signal

```
1: F_Max=maximum_value in Fmetrics [Train]
2: F_Min=minimum_value in Fmetrics [Train]
3: Max_Map =100        // max value of mapping
4: Min_Map = 0         // min value of mapping
5: ΔF=F_Max– F_Min      // The difference between maximum and minimum Fmrteics
6: ΔMap= Max_Map - Min_Map   //The difference between maximum and minimum values of map range
7: For i=1 to datalength
6: Map_Fmetric[i] = integer((Fmetric[i] - F_Min / ΔF) * ΔMap + Min_Map)
7: End For
```

Output:

Map_Fmetric[N] // mapping Fmetrics between [0-100]

3.9 Select EEG search space algorithm

To find the nearest values for the new EEG signal, instead of making a comparison and searching for all the mapping Fractal metrics in the training dataset, we reduce the search space size based on the absolute value of the difference between mapping the new EEG signal and all the mapping training dataset by comparing the result with a specific parameter. Several tests have been made for several numbers to detect the best parameter. The most appropriate value is 60, which selects the best groups of extremely similar signals. As a result, we have a list with a search space size for each new EEG signal.

Algorithm 3.5 (Selection of EEG search space (SST))
Input: Mapped_Fmetric[N] // for all training EEG data Mapped_EEG [M] // mapped Fmetric testing EEG signal
1: set value to SetSpace // parameter set the size of search space 2: For i=1 to length(M) 3: For j=1 to length (N) 4: if abs(Mapped_EEG[i] - Mapped_Fmetric[j]) < SetSpace 5: Nearest_EEG[i]= Mapped_Fmetric[j] 6: End for
Output: Nearest_EEG[n] // list of Selected EEG Training Search Space

3.10 Cosine similarity algorithm

In this algorithm, the input is the testing EEG signal and a set of ranked training signals allocated by the search space threshold. Cosine similarity is computed for all the training dataset together with the test EEG signal. For each testing signal, a list of cosine similarity values is computed that represent the similarity of the testing signal with each ranked training signal. Then we determine the largest (best) value in this list, which represents the predicted class of the testing EEG signal. The general equation of cosine similiratiy is shown in Eq 3.22[63].

$$similarity(A,B) = \frac{\sum_{i=1}^{n} Ai \times Bi}{\sqrt{\sum_{i=1}^{n} Ai^2} \times \sqrt{\sum_{i=1}^{n} Bi^2}} \quad \ldots (3.22)$$

Where A represent the values in training set, B represent the value in testing set and n is number of selected EEG search space.

Algorithm 3.6 (Cosine similarity)
Input: Nearest_EEG[n] //represent search space for specific signal Map_Fmetric // for testing EEG signal (Testing EEG signal)
1: For i=1 to N // N represent the size of search space 2: Num[i] = Map_Fmetric* Nearest_EEG[i] // calculate numerator in cosine 3: Den[i]= sqrt (Map_Fmetric) ^2 * sqrt (Map_Fmetric) ^ 2) // calculate denominator 4: Cosine_similarity[i]= Num[i] /Den[i] 5: End For 6: For i=1 to N 7: ClassIndex=Maximun_value(cosine_similarity[i]) 8: End For
Output: ClassIndex// predicate class type of test EEG signal

Chapter 4 – Experiments and Results

4.1 Introduction

This chapter explains the experiments and results obtained from the proposed system. The results were examined and presented based on the proposed model without optimization and with optimization using the PSO algorithm. The experiments that have been presented are based on different lengths of EEG signals. Also, experiments and tests were conducted on several sizes of training and testing. The comparison was made under the same conditions with several popular machine learning algorithms utilized for classification tasks. Comparisons with many similar previous works and on the same available dataset. We have made many illustrative charts in order to present the results in a clear view.

4.2 The performance metrics for classification in machine learning.

Evaluation of machine learning algorithms is the main part of each project in machine learning. Several metrics for evaluating the performance of machine learning models in various applications are presented. The most commonly used metric in classification is accuracy as a predicting metric. To offer a clear evaluation of our method, many metrics like accuracy, precision, recall, and F1-score are utilized.

A confusion matrix is a relation between the predicted class labels of a proposed model and the actual class labels of the data utilized as shown in Figure 4.1.

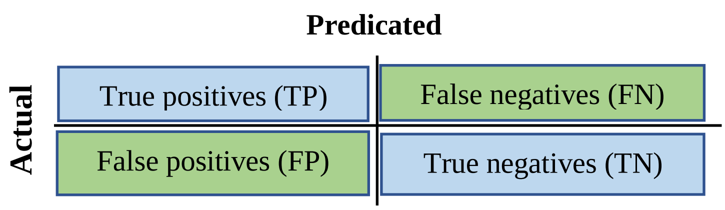

Figure 4.1: Describe the confusion matrix

True Positives (TP): The predicate is true and true in the actual.

True negatives (TN): The predicate is false and false in the actual.

False positives (FP): The predicate is true and false in the actual.

False negatives (FN): The predicate is false and true in the actual.

4.2.1 Accuracy metric:

This is the most widely used performance metric for classification algorithms. It can be computed as the number of correct predictions divided by the total number of calculated results. To calculate the accuracy based on the confusion matrix, using Eq 4.1[21]:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FN + FP} \ldots (4.1)$$

4.2.2 Precision:

Precision is a metric that detects the count of correct positive predictions made. It is calculated as the rate of correctly predicted positive examples divided by the total account of positive examples that were predicted. Mathematically, it is measured by applying Eq 4.2[21]:

$$\text{Precision} = \frac{TP}{TP + FP} \ldots (4.2)$$

4.2.3 Recall or sensitivity:

The recall is a measure that counts how many right positive predictions have been made. It shows missed positive predictions. It was calculated mathematically utilizing Eq 4.3[21]:

$$\text{Sensitivity} = \frac{TP}{TP + FN} \ldots (4.3)$$

4.2.4 F-Measure(F1_score):

F-Measure is a technique for combining precision and recall into a single measurement. A high F1 score indicates a low number of false positives and false negatives. When the F1 score is 1, the method is regarded as perfect, and when it is 0, the model is considered a complete failure. It is determined using Eq 4.4[21]:

$$\mathrm{F-Measure} = 2 * \frac{\mathrm{Precision} * \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}} \ldots (4.4)$$

4.3 EEG Bonn dataset

One of the most widely used datasets for classifying EEG signals for epileptic seizures is the Bonn university dataset[64].

It consists of five distinct folders. Each one has 100 files, each of which contains information about a particular case. Every file comprises the brain activity captured for 23.6 seconds. The related time sequence is sampled using 4096 data points. As a result, we have a total of 500 people, each with 4096 data points gathered over a 23.6-second period. There is a ZIP file with 100 TXT files for each set (A-E). Each TXT file contains 4096 ASCII code samples of one EEG time sequence. All of the sets are clearly explained in table 4.1.

Table 4.1: Describe Bonn university dataset

Set name	File name	Number of samples	Patient type	Patient situation
A	Z	100	Healthy/open eyes	Normal
B	O	100	Healthy/closed eyes	Normal
C	N	100	Seizure free	Pre-ictal
D	F	100	Seizure free	Post-ictal
E	S	100	Seizure activity	Epileptic

Figure 4.2 illustrates an example of drawing the first EEG signal from each set in the dataset.

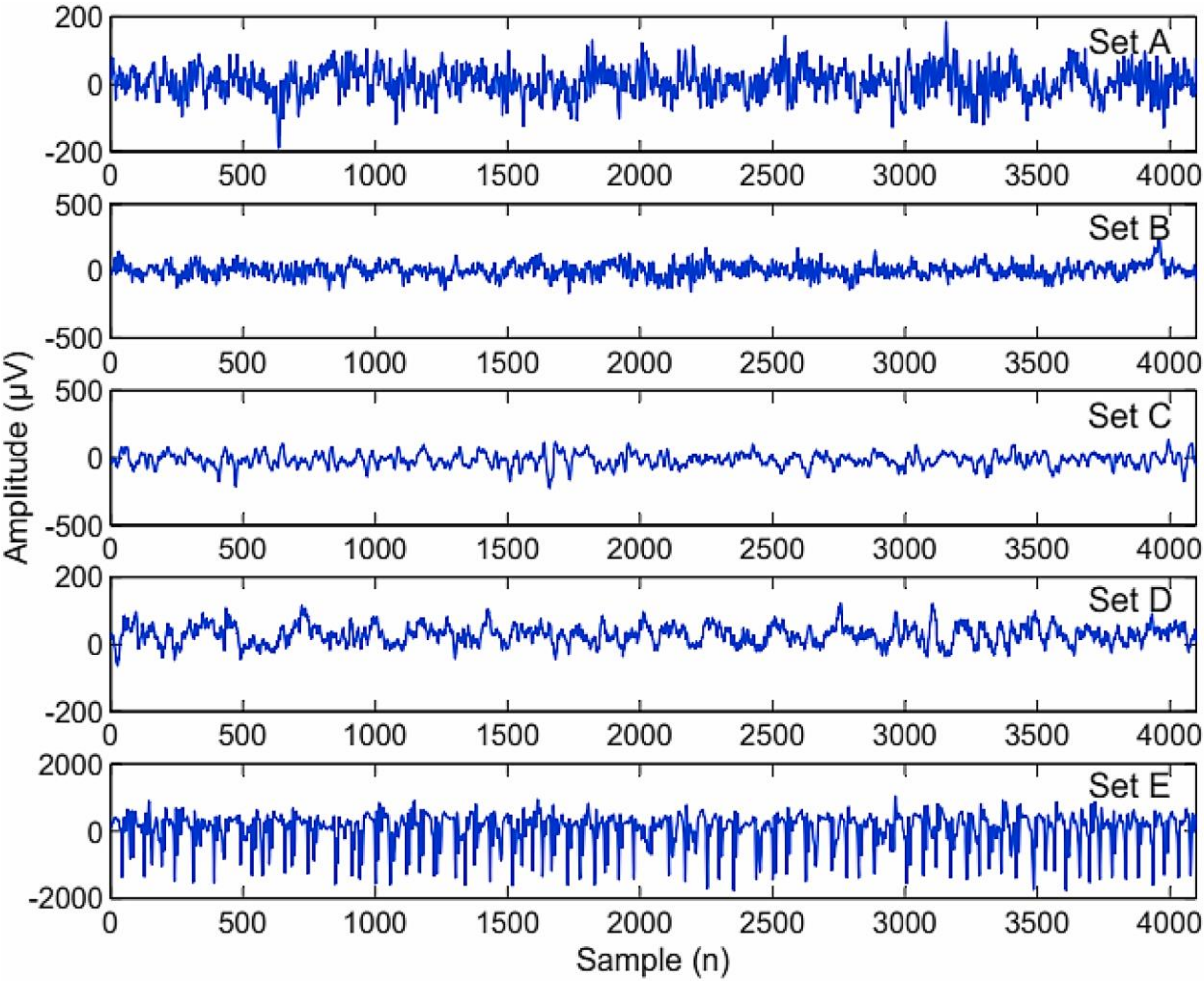

Figure 4.2: First EEG signal from each set

4.4 Evaluation Strategy

The dataset from the University of Bonn consisted of five types of classes. We focused on the class that represents the state of epilepsy as shown in table 4.2. The process of examination and comparisons were made along the entire wavelength of EEG signals and with parts of them. The results of the test are compared with classification algorithms of machine learning such as K-nearest neighbor (KNN) with k=3, support vector machine (SVM), random forest (RF), decision tree (DT), and naive bias (NB).

Table 4.2: Evaluation Strategy for classification EEG dataset

Test number	classes	Classification cases
Test 1	S-Z	Elliptic seizures and health/open eyes
Test 2	S-O	Elliptic seizures and health/closed eyes
Test 3	S-F	Elliptic seizures and post-ictal
Test 4	S-N	Elliptic seizures and pre-ictal
Test 5	S-Z-O	Active epilepsy seizures against two cases of healthy people
Test 6	S-F-N	Active epilepsy seizures against epilepsy patients
Test 7	S-Z-O-F	Active epilepsy seizures, two cases of healthy people and one case of epilepsy patients
Test 8	S-Z-O-N	Active epilepsy seizures, two cases of healthy people and one case of epilepsy patients
Test 9	S-F-N-O	two cases for patients with epilepsy, one case for healthy people and active epilepsy
Test 10	S-F-N-Z	two cases for patients with epilepsy, one case for healthy people and active epilepsy
Test 11	S-O-Z-N-F	All classes

4.5 Results and Analysis

In machine learning, the dataset is divided into two parts: training set and testing set. A training set is used to train the machine and develop the proposed model, while a testing set is used to measure the model's performance and efficiency based on many efficiency metrics of the machine learning algorithms. The proposed system has been examined with different training sets and test sets sizes to measure the efficiency of the proposed model.

4.5.1 Results and Analysis with different test size

Training and testing sizes were determined by using 90 percent and 10 percent of the total dataset, respectively. 20 percent, 30 percent, and 40 percent of the test dataset have been used to obtain the varied results and to illustrate the effect of the size of the train set on the patterns that have been generated. All calculations were performed using a normalization approach based on the Z1-score and the length of the EEG signal (time) within 23.6 s. All the obtained results were evaluated using more than one metric in order to obtain the analysis and evaluation of the performance in full. The accuracy, precision, recall, and F1-score metrics were utilized to give a clear view of the proposed models.

Table 4.3: Explains the accuracy metric results of the Fractal + Cosine similarity model with and without PSO and machine learning algorithms for 10% testing size

dataset	Normalization	EEG signal length	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	Z1 score	23.6 s	**10%**	**100**	**100**	60	100	100	80	100
S-O	Z1 score	23.6 s	**10%**	**100**	**100**	60	95	100	85	100
S-F	Z1 score	23.6 s	**10%**	**100**	**100**	60	100	100	85	100
S-N	Z1 score	23.6 s	**10%**	**100**	**100**	60	100	100	75	100
S-Z-O	Z1 score	23.6 s	**10%**	**93.33**	**93.33**	40	83.33	83.3	63.33	83.33
S-F-N	Z1 score	23.6 s	**10%**	**83.33**	**90**	43.33	73.33	90	60	70
S-Z-O-F	Z1 score	23.6 s	**10%**	**70**	**75**	30	62.5	82.5	40	65
S-Z-O-N	Z1 score	23.6 s	**10%**	**72.5**	**75**	25	45	77.5	47.5	70
S-F-N-O	Z1 score	23.6 s	**10%**	**87.5**	**92.5**	50	55	82.5	42.5	52.5
S-F-N-Z	Z1 score	23.6 s	**10%**	**82.5**	**90**	45	47.5	85	57.49	45
S-O-Z-N-F	Z1 score	23.6 s	**10%**	**86**	**88**	40	48	74	56	52

Table 4.4: Explains the precision metric results of the Fractal + Cosine similarity model with and without PSO and machine learning algorithms for 10% testing size

dataset	Normalization	EEG signal length	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	Z1 score	23.6 s	**10%**	**100**	**100**	77.77	100	100	84.35	100
S-O	Z1 score	23.6 s	**10%**	**100**	**100**	77.77	94.45	100	84.35	100
S-F	Z1 score	23.6 s	**10%**	**100**	**100**	77.77	94.45	100	94.45	94.45
S-N	Z1 score	23.6 s	**10%**	**100**	**100**	77.77	94.45	100	94.45	100
S-Z-O	Z1 score	23.6 s	**10%**	**91.66**	**91.66**	46.91	80	79.04	59.68	78.97
S-F-N	Z1 score	23.6 s	**10%**	**81.85**	**87.44**	59.09	79.48	87.77	53.38	67.46
S-Z-O-F	Z1 score	23.6 s	**10%**	**74.8**	**82.69**	41.96	76.04	84.84	47.03	62.45
S-Z-O-N	Z1 score	23.6 s	**10%**	**72.61**	**74.48**	37.08	67.63	79.16	47.96	72.72
S-F-N-O	Z1 score	23.6 s	**10%**	**87.5**	**92.77**	73.17	70.62	82.38	42.99	53
S-F-N-Z	Z1 score	23.6 s	**10%**	**83.64**	**89.24**	47.47	66.37	84.16	57.33	49.65
S-O-Z-N-F	Z1 score	23.6 s	**10%**	**87.66**	**88.89**	34.84	66	77	50.51	47.07

Table 4.5: Explains the recall metric results of the Fractal + Cosine similarity model with and without PSO and machine learning algorithms for 10% testing size

dataset	Normalization	EEG signal length	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	Z1 score	23.6 s	**10%**	**100**	**100**	60	100	100	85	100
S-O	Z1 score	23.6 s	**10%**	**100**	**100**	60	95	100	85	100
S-F	Z1 score	23.6 s	**10%**	**100**	**100**	60	95	100	95	95
S-N	Z1 score	23.6 s	**10%**	**100**	**100**	60	95	100	95	100
S-Z-O	Z1 score	23.6 s	**10%**	**91.88**	**91.88**	34.89	74.21	79.79	60.06	77.73
S-F-N	Z1 score	23.6 s	**10%**	**83.25**	**88.85**	46.5	76.22	84.85	52.87	70.66
S-Z-O-F	Z1 score	23.6 s	**10%**	**71.59**	**79.16**	32.77	56.73	88.33	44.76	61.31
S-Z-O-N	Z1 score	23.6 s	**10%**	**74.37**	**76.04**	27.98	52.36	79.51	49.79	70.48
S-F-N-O	Z1 score	23.6 s	**10%**	**86.18**	**92.08**	46.11	63.4	81.73	41.87	61.73
S-F-N-Z	Z1 score	23.6 s	**10%**	**81.38**	**84.83**	39.86	52.56	84.51	50.55	47.98
S-O-Z-N-F	Z1 score	23.6 s	**10%**	**84.91**	**87.73**	37.57	48.68	73.61	46.14	53.97

Table 4.6: Explains the F-Measure metric results of the Fractal + Cosine similarity model with and without PSO and machine learning algorithms for 10% testing size

dataset	Normalization	EEG signal length	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	Z1 score	23.6 s	**10%**	**100**	**100**	67.74	100	100	84.17	100
S-O	Z1 score	23.6 s	**10%**	**100**	**100**	67.74	94.22	100	84.17	100
S-F	Z1 score	23.6 s	**10%**	**100**	**100**	67.74	94.22	100	94.22	94.22
S-N	Z1 score	23.6 s	**10%**	**100**	**100**	67.74	94.22	100	94.22	100
S-Z-O	Z1 score	23.6 s	**10%**	**91.77**	**91.77**	40.67	77.53	79.42	59.87	78.35
S-F-N	Z1 score	23.6 s	**10%**	**82.54**	**88.14**	52.04	77.82	86.8	53.12	69.02
S-Z-O-F	Z1 score	23.6 s	**10%**	**73.16**	**80.89**	36.8	64.98	86.55	46.39	61.88
S-Z-O-N	Z1 score	23.6 s	**10%**	**73.48**	**74.76**	31.89	59.025	79.33	48.86	71.58
S-F-N-O	Z1 score	23.6 s	**10%**	**86.83**	**92.42**	56.57	66.81	82.05	42.42	57.03
S-F-N-Z	Z1 score	23.6 s	**10%**	**82.5**	**87.5**	43.33	58.67	84.33	53.73	48.8
S-O-Z-N-F	Z1 score	23.6 s	**10%**	**86.78**	**88.31**	36.16	56.03	74.27	48.22	50.29

Table 4.7: Explains the accuracy metric results of the Fractal + Cosine similarity model with and without PSO and machine learning algorithms for 20% testing size

dataset	Normalization	EEG signal length	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	Z1 score	23.6 s	**20%**	**100**	**100**	57.49	100	100	70	100
S-O	Z1 score	23.6 s	**20%**	**100**	**100**	57.49	95	100	70	97.5
S-F	Z1 score	23.6 s	**20%**	**100**	**100**	57.49	92.5	92.5	92.5	95
S-N	Z1 score	23.6 s	**20%**	**100**	**100**	57.49	95	100	77.5	100
S-Z-O	Z1 score	23.6 s	**20%**	**90**	**91.6**	43.33	71.6	83.3	58.3	85
S-F-N	Z1 score	23.6 s	**20%**	**86.66**	**90**	56.66	78.33	86.66	66.66	73.33
S-Z-O-F	Z1 score	23.6 s	**20%**	**78.75**	**82.5**	32.5	62.5	77.5	57.49	65
S-Z-O-N	Z1 score	23.6 s	**20%**	**80**	**82.5**	28.74	66.25	71.25	45	73.75
S-F-N-O	Z1 score	23.6 s	**20%**	**90**	**92.5**	42.5	56.25	78.75	48.75	57.49
S-F-N-Z	Z1 score	23.6 s	**20%**	**85**	**88.75**	40	60	76.25	51.24	55
S-O-Z-N-F	Z1 score	23.6 s	**20%**	**79**	**82**	38	44	73	41	49

Table 4.8: Explains the Precision metric results of the Fractal + Cosine similarity model with and without PSO and machine learning algorithms for 20% testing size

dataset	Normalization	EEG signal length	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	Z1 score	23.6 s	**20%**	**100**	**100**	78.2	100	100	77.36	100
S-O	Z1 score	23.6 s	**20%**	**100**	**100**	78.2	94.83	100	69.79	97.82
S-F	Z1 score	23.6 s	**20%**	**100**	**100**	78.2	92.71	92.85	88.66	95
S-N	Z1 score	23.6 s	**20%**	**100**	**100**	78.2	94.83	100	88.66	94.83
S-Z-O	Z1 score	23.6 s	**20%**	**90.49**	**93.8**	54.24	74.77	84.02	66.23	84.78
S-F-N	Z1 score	23.6 s	**20%**	**87.42**	**90.43**	69.82	80.87	86.59	67.65	74.18
S-Z-O-F	Z1 score	23.6 s	**20%**	**79.94**	**81.58**	66.01	64.24	77.69	61.25	61.26
S-Z-O-N	Z1 score	23.6 s	**20%**	**78.59**	**81.73**	61.35	66.81	72.12	47.85	72.08
S-F-N-O	Z1 score	23.6 s	**20%**	**89.67**	**94.79**	69.55	67.29	8.15	53.39	57.03
S-F-N-Z	Z1 score	23.6 s	**20%**	**84.52**	**89.72**	49.42	68.99	74.17	56.44	56.22
S-O-Z-N-F	Z1 score	23.6 s	**20%**	**80.07**	**82.13**	34.6	69.29	74.22	43.78	62.7

Table 4.9: Explains the recall metric results of the Fractal + Cosine similarity model with and without PSO and machine learning algorithms for 20% testing size

dataset	Normalization	EEG signal length	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	Z1 score	23.6 s	**20%**	**100**	**100**	52.77	100	100	77.02	100
S-O	Z1 score	23.6 s	**20%**	**100**	**100**	52.77	94.44	100	69.19	97.22
S-F	Z1 score	23.6 s	**20%**	**100**	**100**	52.77	92.17	93.18	86.61	94.45
S-N	Z1 score	23.6 s	**20%**	**100**	**100**	52.77	94.44	100	86.61	94.44
S-Z-O	Z1 score	23.6 s	**20%**	**90**	**93.33**	40	71.66	83.33	63.33	85
S-F-N	Z1 score	23.6 s	**20%**	**86.66**	**90**	56.66	78.33	86.66	66.66	73.33
S-Z-O-F	Z1 score	23.6 s	**20%**	**77.89**	**80.54**	34.17	58.88	77.15	60	62.18
S-Z-O-N	Z1 score	23.6 s	**20%**	**79.15**	**81.32**	30.3	64.16	71.76	43.01	72.59
S-F-N-O	Z1 score	23.6 s	**20%**	**89.14**	**94.27**	43.74	58.63	78.1	50.78	59.5
S-F-N-Z	Z1 score	23.6 s	**20%**	**84.66**	**89.31**	41.26	60.63	74.2	56.25	54.08
S-O-Z-N-F	Z1 score	23.6 s	**20%**	**78.32**	**80.61**	34.87	48.31	73.76	43.49	52.74

Table 4.10: Explains the F1_measure metric results of the Fractal + Cosine similarity model with and without PSO and machine learning algorithms for 20% testing size

dataset	Normalization	EEG signal length	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	Z1 score	23.6 s	**20%**	**100**	**100**	63.02	100	100	77.19	100
S-O	Z1 score	23.6 s	**20%**	**100**	**100**	63.02	94.13	100	69.49	97.52
S-F	Z1 score	23.6 s	**20%**	**100**	**100**	63.02	92.44	93.01	87.62	94.22
S-N	Z1 score	23.6 s	**20%**	**100**	**100**	63.02	94.13	100	87.62	94.13
S-Z-O	Z1 score	23.6 s	**20%**	**90.24**	**93.56**	46.04	73.66	83.67	64.75	84.39
S-F-N	Z1 score	23.6 s	**20%**	**87.04**	**90.21**	62.55	79.58	86.63	67.15	73.75
S-Z-O-F	Z1 score	23.6 s	**20%**	**78.9**	**81.05**	44.03	61.9	77.42	60.65	61.72
S-Z-O-N	Z1 score	23.6 s	**20%**	**78.87**	**81.52**	40.57	64.97	71.94	44.3	72.33
S-F-N-O	Z1 score	23.6 s	**20%**	**89.4**	**94.53**	53.7	62.66	78.13	52.05	58.24
S-F-N-Z	Z1 score	23.6 s	**20%**	**84.59**	**89.52**	44.97	64.54	74.18	56.35	54.64
S-O-Z-N-F	Z1 score	23.6 s	**20%**	**79.19**	**81.36**	34.73	56.93	73.99	43.64	57.29

Table 4.11: Explains the accuracy metric results of the Fractal + Cosine similarity model with and without PSO and machine learning algorithms for 30% testing size

dataset	Normalization	EEG signal length	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	Z1 score	23.6 s	**30%**	**98.33**	**100**	60	100	100	76.66	100
S-O	Z1 score	23.6 s	**30%**	**98.33**	**100**	60	96.6	100	86.66	100
S-F	Z1 score	23.6 s	**30%**	**98.33**	**100**	60	93.3	98.33	88.33	96.6
S-N	Z1 score	23.6 s	**30%**	**100**	**100**	60	96.66	98.33	81.66	100
S-Z-O	Z1 score	23.6 s	**30%**	**84.55**	**87.77**	38.88	73.33	83.33	56.66	84.44
S-F-N	Z1 score	23.6 s	**30%**	**84.55**	**88.88**	53.33	70	77.77	64.55	72.22
S-Z-O-F	Z1 score	23.6 s	**30%**	**82.5**	**84.16**	34.16	57.49	78.33	60.83	60
S-Z-O-N	Z1 score	23.6 s	**30%**	**80**	**82.5**	33.33	59.16	73.33	48.33	70.83
S-F-N-O	Z1 score	23.6 s	**30%**	**85**	**87.5**	37.5	50.83	82.5	47.5	59.16
S-F-N-Z	Z1 score	23.6 s	**30%**	**81.66**	**85**	39.16	52.5	80	49.16	65
S-O-Z-N-F	Z1 score	23.6 s	**30%**	**78.6**	**80.66**	34.33	58.66	74.33	41.33	56

Table 4.12: Explains the Precision results of the Fractal + Cosine similarity model with and without PSO and machine learning algorithms for 30% testing size

dataset	Normalization	EEG signal length	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	Z1 score	23.6 s	**30%**	**98.43**	**100**	78.18	100	100	83.42	100
S-O	Z1 score	23.6 s	**30%**	**98.43**	**100**	78.18	96.96	100	90.57	100
S-F	Z1 score	23.6 s	**30%**	**98.43**	**100**	78.18	98.33	98.33	83.5	96.77
S-N	Z1 score	23.6 s	**30%**	**100**	**100**	78.18	96.96	98.33	86.65	100
S-Z-O	Z1 score	23.6 s	**30%**	**87.12**	**89.6**	52.08	73.41	83.41	59.11	84.13
S-F-N	Z1 score	23.6 s	**30%**	**91.76**	**92.75**	73.22	68.12	88.29	68.14	64.15
S-Z-O-F	Z1 score	23.6 s	**30%**	**82.67**	**84.78**	66.04	64.26	78.25	57.04	57.15
S-Z-O-N	Z1 score	23.6 s	**30%**	**79.65**	**82.98**	64.21	72.27	74.17	51.05	70.78
S-F-N-O	Z1 score	23.6 s	**30%**	**86.16**	**88.46**	54.03	64.74	82.15	50.62	58.34
S-F-N-Z	Z1 score	23.6 s	**30%**	**82.01**	**84.89**	54.93	56.46	79.51	54.36	66.16
S-O-Z-N-F	Z1 score	23.6 s	**30%**	**80.08**	**82.21**	57.97	68.68	77.14	42.57	57.78

Table 4.13: Explains the recall metric results of the Fractal + Cosine similarity model with and without PSO and machine learning algorithms for 30% testing size

dataset	Normalization	EEG signal length	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	Z1 score	23.6 s	**30%**	**98.27**	**100**	58.62	100	100	83.42	100
S-O	Z1 score	23.6 s	**30%**	**98.27**	**100**	58.62	96.55	100	90.21	100
S-F	Z1 score	23.6 s	**30%**	**98.27**	**100**	58.62	98.38	98.38	83.2	96.77
S-N	Z1 score	23.6 s	**30%**	**100**	**100**	58.62	96.55	98.38	86.65	100
S-Z-O	Z1 score	23.6 s	**30%**	**84.45**	**86.67**	39.46	71.3	82.84	57.63	83.9
S-F-N	Z1 score	23.6 s	**30%**	**91.31**	**92.29**	59.07	62.45	88.2	66.82	66.85
S-Z-O-F	Z1 score	23.6 s	**30%**	**81.86**	**83.5**	33.21	56.68	77.67	54.09	59.74
S-Z-O-N	Z1 score	23.6 s	**30%**	**79**	**82.59**	32.37	58.19	73.31	49.16	71.03
S-F-N-O	Z1 score	23.6 s	**30%**	**84.19**	**87.71**	39.6	51.94	82.02	48.53	58.69
S-F-N-Z	Z1 score	23.6 s	**30%**	**82.03**	**84.24**	41.21	53.56	79.73	52.23	63.9
S-O-Z-N-F	Z1 score	23.6 s	**30%**	**78.51**	**80.56**	34.49	58.42	76.05	39.35	56.33

Table 4.14: Explains the F1_measure metric results of the Fractal + Cosine similarity model with and without PSO and machine learning algorithms for 30% testing size

dataset	Normalization	EEG signal length	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	Z1 score	23.6 s	**30%**	**98.35**	**100**	67.002	100	100	83.42	100
S-O	Z1 score	23.6 s	**30%**	**98.35**	**100**	67.002	96.76	100	90.39	100
S-F	Z1 score	23.6 s	**30%**	**98.35**	**100**	67.002	98.36	98.36	83.35	96.77
S-N	Z1 score	23.6 s	**30%**	**100**	**100**	67.002	96.76	98.36	86.65	100
S-Z-O	Z1 score	23.6 s	**30%**	**84.77**	**88.11**	44.9	72.34	83.12	58.36	84.02
S-F-N	Z1 score	23.6 s	**30%**	**91.53**	**92.52**	64.39	64.16	88.24	67.48	64.99
S-Z-O-F	Z1 score	23.6 s	**30%**	**82.26**	**84.14**	44.19	60.67	77.96	54.52	58.42
S-Z-O-N	Z1 score	23.6 s	**30%**	**79.32**	**82.78**	43.05	64.47	74.23	50.09	70.9
S-F-N-O	Z1 score	23.6 s	**30%**	**84.67**	**88.08**	46.06	57.64	82.08	49.55	58.51
S-F-N-Z	Z1 score	23.6 s	**30%**	**82.02**	**84.06**	47.46	54.97	79.62	53.75	64.01
S-O-Z-N-F	Z1 score	23.6 s	**30%**	**79.29**	**81.38**	43.25	63.13	76.59	40.9	57.04

Table 4.15: Explains the accuracy results of the Fractal + Cosine similarity model with and without PSO and machine learning algorithms for 40% testing size

dataset	Normalization	EEG signal length	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	Z1 score	23.6 s	**40%**	**96.25**	**98.75**	58.75	100	98.75	75	100
S-O	Z1 score	23.6 s	**40%**	**97.5**	**100**	58.75	96.25	100	78.75	100
S-F	Z1 score	23.6 s	**40%**	**96.25**	**98.75**	58.75	93.75	97.5	77.5	95
S-N	Z1 score	23.6 s	**40%**	**97.5**	**98.75**	58.75	96.25	98.75	77.5	100
S-Z-O	Z1 score	23.6 s	**40%**	**82.5**	**83.33**	38.33	71.66	81.66	53.33	83.33
S-F-N	Z1 score	23.6 s	**40%**	**82.5**	**84.83**	49.16	64.16	84.83	58.33	70
S-Z-O-F	Z1 score	23.6 s	**40%**	**79.37**	**81.87**	31.87	50.62	77.5	49.37	61.25
S-Z-O-N	Z1 score	23.6 s	**40%**	**79.37**	**81.25**	29.37	46.25	75	46.25	71.87
S-F-N-O	Z1 score	23.6 s	**40%**	**78.75**	**80.62**	38.12	51.87	73.12	44.62	54.62
S-F-N-Z	Z1 score	23.6 s	**40%**	**78.12**	**80.62**	37.5	50.62	79.37	43.75	64.37
S-O-Z-N-F	Z1 score	23.6 s	**40%**	**73**	**75**	31.5	43	69	43.5	56.49

Table 4.16: Explains the Precision results of the Fractal + Cosine similarity model with and without PSO and machine learning algorithms for 40% testing size

dataset	Normalization	EEG signal length	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	Z1 score	23.6 s	**40%**	**96.59**	**98.8**	77.7	100	98.75	67.82	100
S-O	Z1 score	23.6 s	**40%**	**97.67**	**98.8**	77.7	96.59	100	76.66	100
S-F	Z1 score	23.6 s	**40%**	**96.59**	**98.8**	77.7	94.06	97.56	82.77	94.34
S-N	Z1 score	23.6 s	**40%**	**97.67**	**98.8**	77.7	96.59	98.75	81.51	100
S-Z-O	Z1 score	23.6 s	**40%**	**84.1**	**89.26**	54.08	72.003	82.07	58.39	83.23
S-F-N	Z1 score	23.6 s	**40%**	**83.25**	**86.14**	64.12	80.3	84.35	63.87	69.35
S-Z-O-F	Z1 score	23.6 s	**40%**	**81.94**	**83.32**	42.21	47.75	77.7	54.76	58.73
S-Z-O-N	Z1 score	23.6 s	**40%**	**80.87**	**82.87**	38.17	57.66	74.79	51.38	72.72
S-F-N-O	Z1 score	23.6 s	**40%**	**81.01**	**82.95**	51.65	69.25	74.37	49.35	54.55
S-F-N-Z	Z1 score	23.6 s	**40%**	**79.76**	**81.39**	50.31	66.43	79.62	52.13	68.89
S-O-Z-N-F	Z1 score	23.6 s	**40%**	**73.7**	**74.63**	56.88	59.6	69.95	41.56	56.79

Table 4.17: Explains the recall metric results of the Fractal + Cosine similarity model with and without PSO and machine learning algorithms for 40% testing size

dataset	Normalization	EEG signal length	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	Z1 score	23.6 s	**40%**	**96.15**	**98.71**	57.69	100	98.78	67.29	100
S-O	Z1 score	23.6 s	**40%**	**97.43**	**98.71**	57.69	96.15	100	76.07	100
S-F	Z1 score	23.6 s	**40%**	**96.15**	**98.71**	57.69	93.65	97.56	82.61	94.12
S-N	Z1 score	23.6 s	**40%**	**97.43**	**98.71**	57.69	96.15	98.78	74.42	100
S-Z-O	Z1 score	23.6 s	**40%**	**81.05**	**82.75**	38.2	70.38	81.33	57.89	82.84
S-F-N	Z1 score	23.6 s	**40%**	**82.64**	**84.91**	52.01	64.9	84.39	59.03	70.1
S-Z-O-F	Z1 score	23.6 s	**40%**	**79.63**	**81.5**	32.42	52.71	78.24	54.2	60.31
S-Z-O-N	Z1 score	23.6 s	**40%**	**79.58**	**81.33**	30.2	48.66	74.47	49.79	71.53
S-F-N-O	Z1 score	23.6 s	**40%**	**78.62**	**80.47**	36.7	54.16	73.63	46.3	57.39
S-F-N-Z	Z1 score	23.6 s	**40%**	**78.15**	**80.02**	36.08	52.55	79.87	49.34	66.01
S-O-Z-N-F	Z1 score	23.6 s	**40%**	**72.78**	**74.69**	31.26	46.1	69.43	39.4	54.76

Table 4.18: Explains the F1_measure metric result of the Fractal + Cosine similarity model with and without PSO and machine learning algorithms for 40% testing size

dataset	Normalization	EEG signal length	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	Z1 score	23.6 s	**40%**	**96.37**	**98.76**	66.21	100	98.76	67.55	100
S-O	Z1 score	23.6 s	**40%**	**97.55**	**98.76**	66.21	96.37	100	76.36	100
S-F	Z1 score	23.6 s	**40%**	**96.37**	**98.76**	66.21	93.85	97.56	82.69	94.23
S-N	Z1 score	23.6 s	**40%**	**97.55**	**98.76**	66.21	96.37	98.76	77.8	100
S-Z-O	Z1 score	23.6 s	**40%**	**83.03**	**84.88**	44.11	71.18	81.7	58.14	83.04
S-F-N	Z1 score	23.6 s	**40%**	**82.94**	**86.02**	57.83	71.79	84.37	61.35	69.72
S-Z-O-F	Z1 score	23.6 s	**40%**	**80.77**	**82.4**	36.67	50.11	77.97	54.97	59.51
S-Z-O-N	Z1 score	23.6 s	**40%**	**80.22**	**82.09**	33.72	52.78	74.13	50.57	72.12
S-F-N-O	Z1 score	23.6 s	**40%**	**79.8**	**81.69**	42.91	60.78	74.001	47.77	54.94
S-F-N-Z	Z1 score	23.6 s	**40%**	**78.95**	**80.7**	42.02	58.68	79.74	50.7	67.42
S-O-Z-N-F	Z1 score	23.6 s	**40%**	**73.24**	**74.16**	40.35	51.98	69.69	40.45	56.27

With the aim to have clear visual analysis, all resultant accuracy shown in Tables 4.3, 4.7, 4.11 and 4.15 are displayed visually by bar chart figures (Figure 4.3 to 4.12) Figure 4.3 shows resultant accuracy by (S-Z) classes for our proposed classifier with and without optimization and the accuracy for various machine learning algorithms. Figure 4.4 shows resultant accuracy by (S-O) classes for our proposed classifier with and without optimization and the accuracy for various machine learning algorithms. Figure 4.5 shows resultant accuracy by (S-F) classes for our proposed classifier with and without optimization and the accuracy for various machine learning algorithms. Figure 4.6 shows resultant accuracy by (S-N) classes for our proposed classifier with and without optimization and the accuracy for various machine learning algorithms. Figure 4.7 shows resultant accuracy by (S-F-N) classes for our proposed classifier with and without optimization and the accuracy for various machine learning algorithms. Figure 4.8 shows resultant accuracy by (S-Z-O) classes for our proposed classifier with and without optimization and the accuracy for various machine learning algorithms. Figure 4.9 shows resultant accuracy by (S-Z-O-F) classes for our proposed classifier with and without optimization and the accuracy for various machine learning algorithms. Figure 4.10 shows resultant accuracy by (S-Z-O-N) classes for our proposed classifier with and without optimization and the accuracy for various machine learning algorithms. Figure 4.11 shows resultant accuracy by (S-F-N-Z) classes for our proposed classifier with and without optimization and the accuracy for various machine learning algorithms. Figure 4.12 shows resultant accuracy by (S-F-N-O) classes for our proposed classifier with and without optimization and the accuracy for several machine learning algorithms. Figure 4.13 shows resultant accuracy by (S-O-F-N-Z) classes for our proposed classifier with and without optimization and the accuracy for various machine learning algorithms.

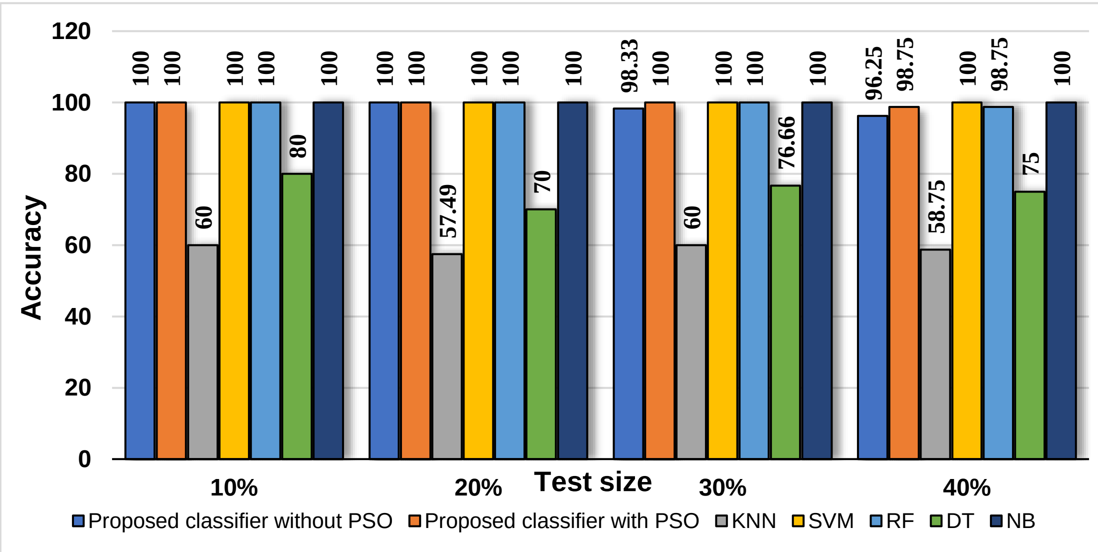

Figure 4.3: Shows classification accuracy for (S-Z) classes of the fractal + cosine model with and without optimization compared to machine learning algorithms for different test sizes.

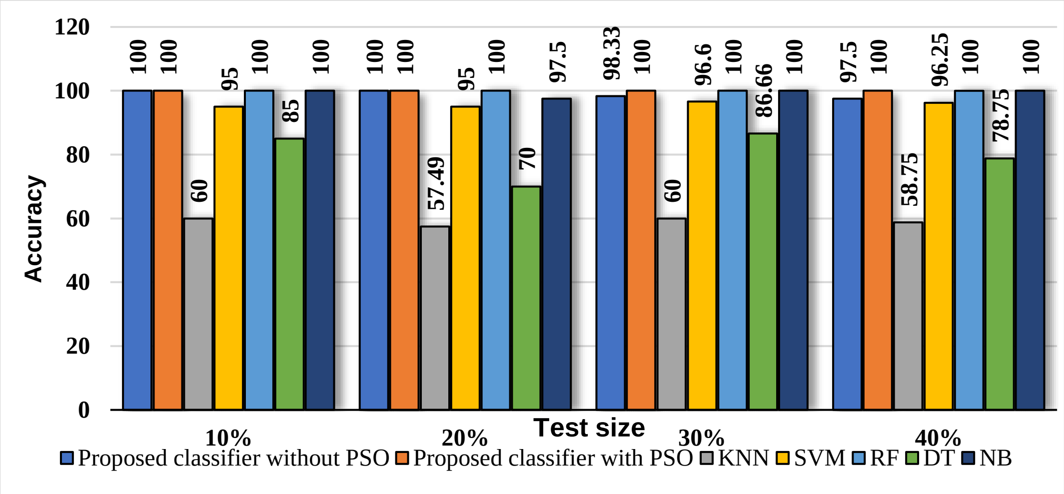

Figure 4.4: Shows classification accuracy for (S- O) classes of the fractal + cosine model with and without optimization compared to machine learning algorithms for different test sizes.

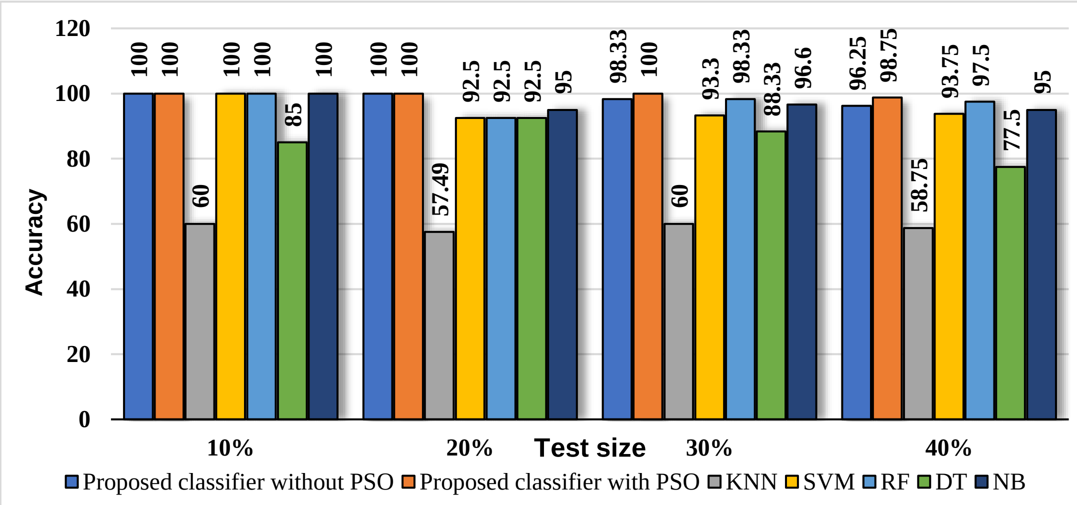

Figure4.5: Shows classification accuracy for (S- F) classes of the fractal + cosine model with and without optimization compared to machine learning algorithms for different test sizes

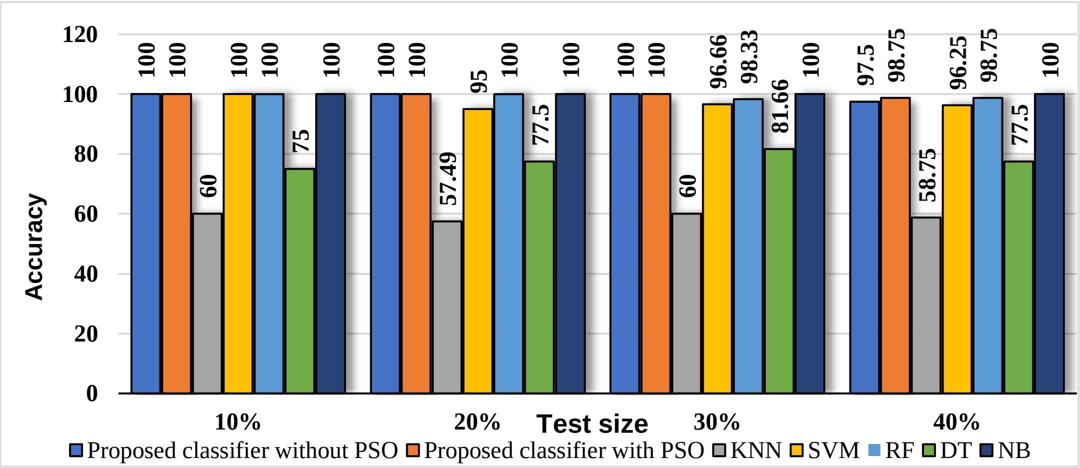

Figure 4.6: Shows classification accuracy for (S- N) classes of the fractal + cosine model with and without optimization compared to machine learning algorithms for different test sizes

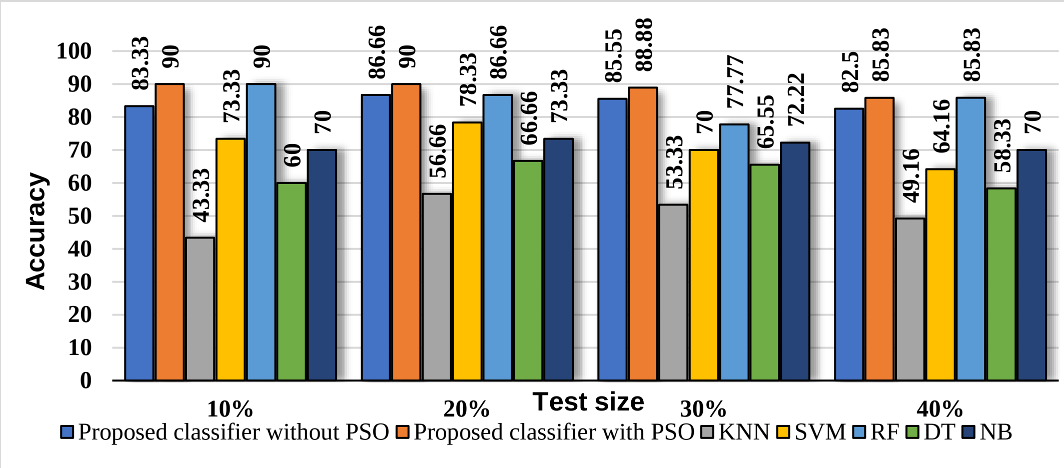

Figure 4.7: Shows classification accuracy for (S-F-N) classes of the fractal + cosine model with and without optimization compared to machine learning algorithms for different test sizes

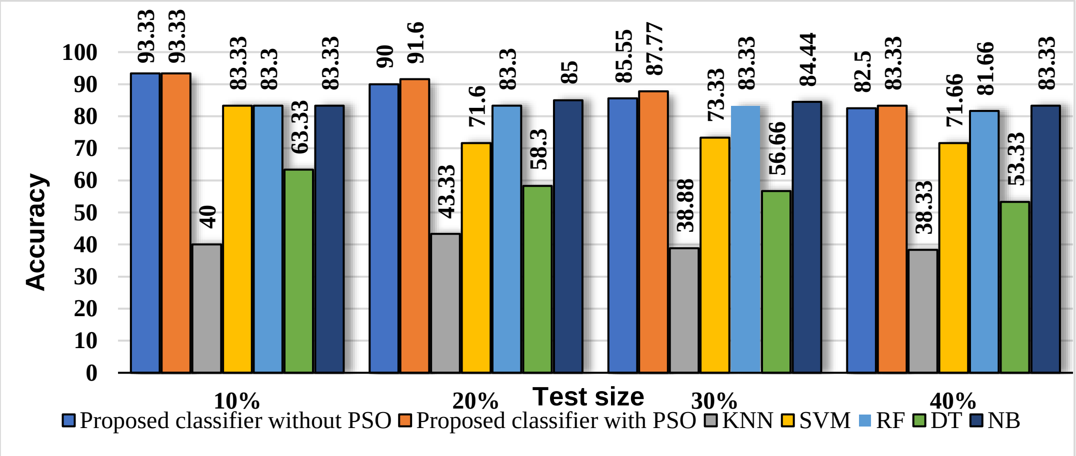

Figure 4.8: Shows classification accuracy for (S-Z-O) classes of the fractal + cosine model with and without optimization compared to machine learning algorithms for different test sizes

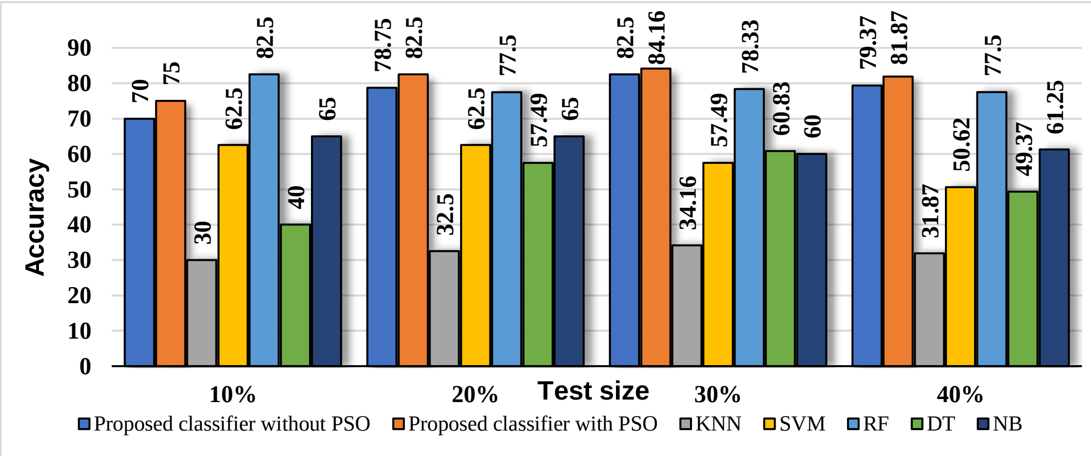

Figure 4.9: Shows classification accuracy for (S-Z-O-F) classes of the fractal + cosine model with and without optimization compared to machine learning algorithms for different test sizes

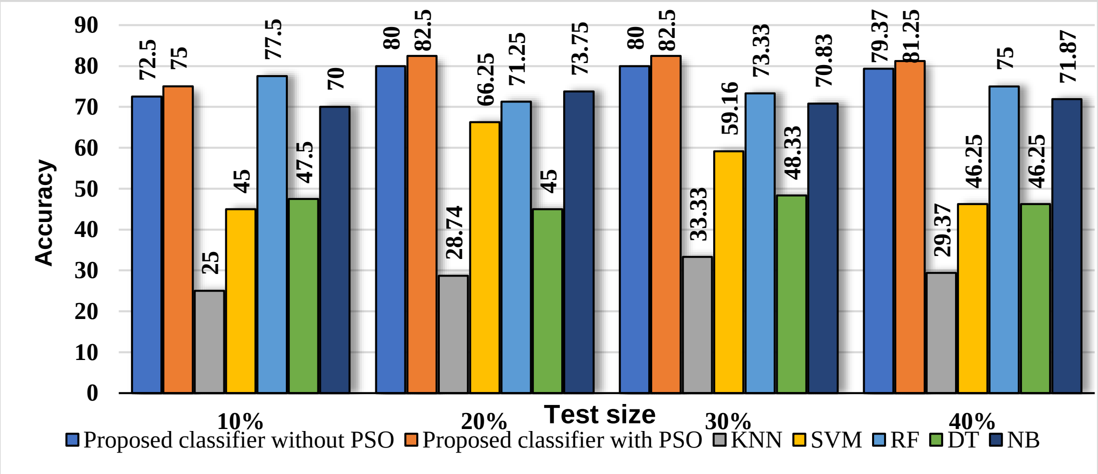

Figure 4.10: Shows classification accuracy for (S-Z-O-N) classes of the fractal + cosine model with and without optimization compared to machine learning algorithms for different test sizes

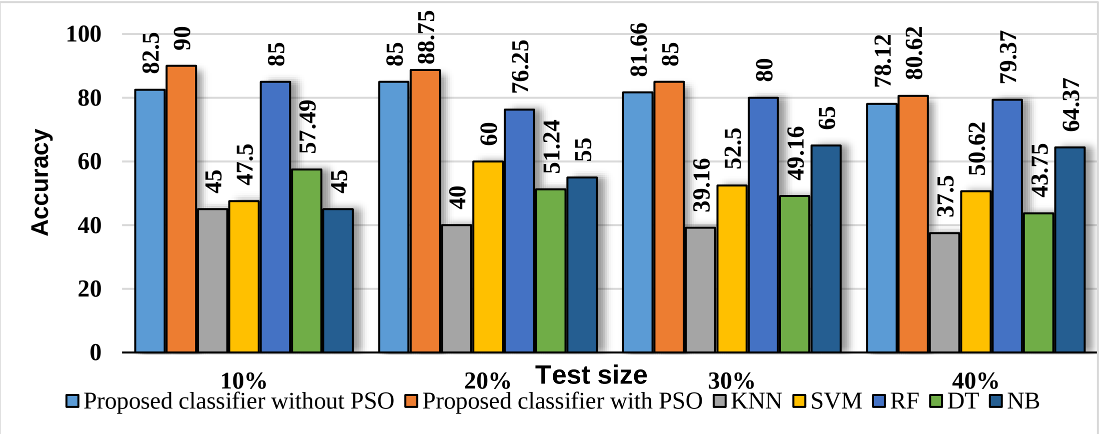

Figure 4.11: Shows classification accuracy for (S-F-N-Z) classes of the fractal + cosine model with and without optimization compared to machine learning algorithms for different test sizes

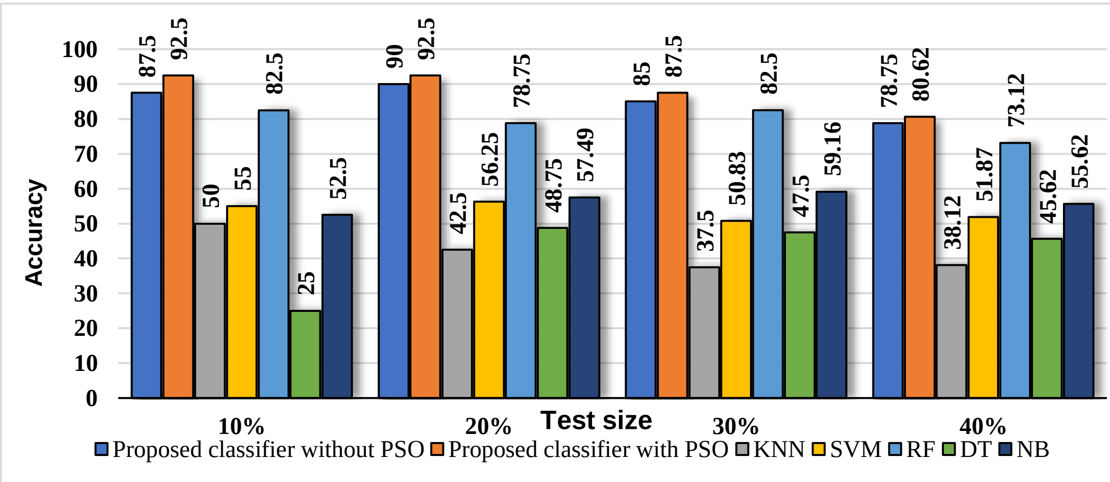

Figure 4.12: Shows classification accuracy for (S-F-N-O) classes of the fractal + cosine model with and without optimization compared to machine learning algorithms for different test sizes

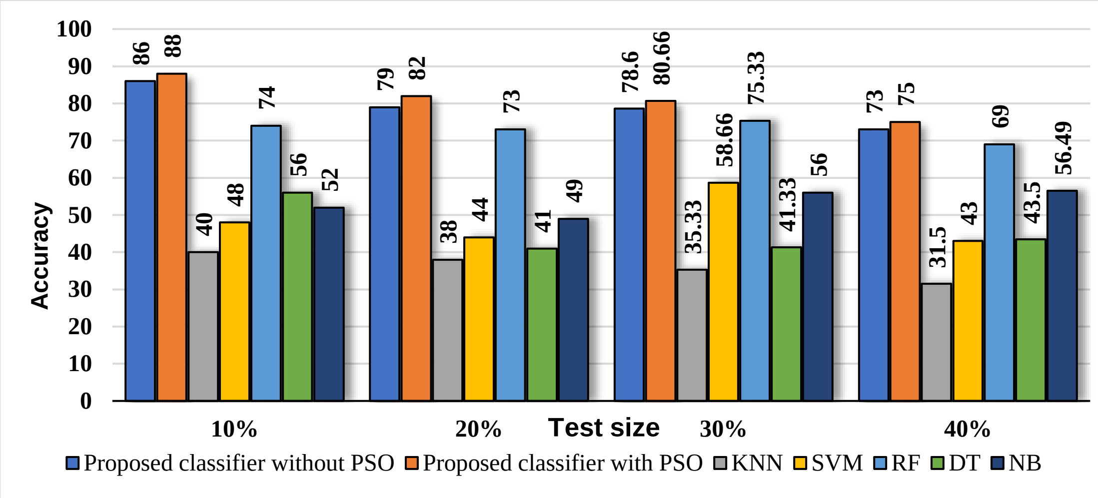

Figure 4.13: Shows classification accuracy for (S-O-F-N-Z) classes of the fractal + cosine model with and without optimization compared to machine learning algorithms for different test sizes

Clearly, the larger the training size, the more accurate the results. This resulted in a large variety of patterns that assist the system in determining the types of classes for EEG signals. by applying a 10% training set size and Without applying optimization, the proposed model obtains high rates of the accuracy of up to 100 percent in the case of two-class classification and up to 86 percent in the case of five-class classification of EEG data. When the suggested method was combined with an optimizer, the accuracy of the two classes was up to 100 percent and 88 percent for the five classes of EEG signals. The lowest efficiency was obtained by using 60% of the EEG dataset for training and 40% for testing. The lowest accuracy was obtained in the case of two classes, with 96.25 percent without optimization and 98.75 percent with optimization. In the case of the five classes of electroencephalogram signals, the accuracy reached up to 73 percent without optimization and 75 percent with optimization, respectively.

4.5.2 Results and Analysis with different testing signal lengths

The University of Bonn dataset provides EEG signals with a time length of up to 23.6 seconds. Our proposed model was evaluated with a variety of signal lengths to examine how the results of predictions changed. Signal lengths of 1 sec, 5 sec, 10 sec, 15 sec, and 20 sec were used in the test. Furthermore, the performance test is performed on the electroencephalogram for the total signal length that shown in tables 4.11 to 4.14. Several metrics are applied, such as Accuracy, Precision, Recall, and F1-measure to examine the performance of fractal and cosine similarity models. All the results have been compared with the most popular algorithms for machine learning that are utilized for classification, like K-Nearest Neighbor, Support Vector Machine, Decision tree, Random forest, and naive bias. The following tables show all of the results obtained for various signal lengths. All results are based on a training size of 70% and a testing size of 30%.

Table 4.19: Results of accuracy metric for testing signal length during 1 sec for fractal +cosine similarity model with and without optimization compared with ML algorithms.

dataset	Normalization	EEG signal length	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	Z1 score	**1 s**	30%	**95**	**96.66**	85	95	95	85	100
S-O	Z1 score	**1 s**	30%	**96.66**	**100**	81.66	91.66	95	85	98.33
S-F	Z1 score	**1 s**	30%	**86.66**	**95**	81.66	88.33	93.33	86.66	91.66
S-N	Z1 score	**1 s**	30%	**90**	**95**	80	91.66	96.66	88.33	98.33
S-Z-O	Z1 score	**1 s**	30%	**67.77**	**74.44**	52.22	73.33	73.33	56.66	82.22
S-F-N	Z1 score	**1 s**	30%	**76.66**	**82.22**	57.77	71.11	81.11	67.77	72.22
S-Z-O-F	Z1 score	**1 s**	30%	**73.33**	**77.5**	52.5	58.33	73.33	45	55
S-Z-O-N	Z1 score	**1 s**	30%	**70.83**	**74.16**	52.5	62.5	72.5	50.83	64.16
S-F-N-O	Z1 score	**1 s**	30%	**74.83**	**79.16**	50	51.66	75	42.5	55
S-F-N-Z	Z1 score	**1 s**	30%	**67.5**	**73.33**	50	58.33	71.66	50	60
S-O-F-N-Z	Z1 score	**1 s**	30%	**62.6**	**64.33**	44.66	56.66	64.66	44	52

Table 4.20: Results of precision metric for testing signal length during 1 sec for fractal +cosine similarity model with and without optimization compared with ML algorithms.

dataset	Normalization	EEG signal length	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	Z1 score	**1 s**	30%	**94.58**	**96.96**	88.75	94.58	95	91.74	100
S-O	Z1 score	**1 s**	30%	**96.96**	**100**	86.9	93.05	94.08	89.58	98.43
S-F	Z1 score	**1 s**	30%	**87.42**	**94.58**	85	88.8	93.43	83.5	91.66
S-N	Z1 score	**1 s**	30%	**90.85**	**94.58**	86.04	93.05	96.66	80.08	98.43
S-Z-O	Z1 score	**1 s**	30%	**68.95**	**74.05**	61.52	73.21	73.14	59.27	81.87
S-F-N	Z1 score	**1 s**	30%	**77.92**	**82.68**	68.12	70.19	84.31	62.65	66.09
S-Z-O-F	Z1 score	**1 s**	30%	**74.56**	**78.34**	68.52	67.5	73.37	44.33	53.72
S-Z-O-N	Z1 score	**1 s**	30%	**73.69**	**74.75**	67.26	69.67	72.73	53.52	64.51
S-F-N-O	Z1 score	**1 s**	30%	**79.44**	**81.89**	67.09	60.19	74.02	47.28	53.06
S-F-N-Z	Z1 score	**1 s**	30%	**71.35**	**74.11**	60.6	58.28	71.43	57.39	59.31
S-O-F-N-Z	Z1 score	**1 s**	30%	**66.65**	**67.72**	59.74	62.8	64.89	46.15	54.53

Table 4.21: Results of recall metric for testing signal length during 1 sec for fractal +cosine similarity model with and without optimization compared with ML algorithms.

dataset	Normalization	EEG signal length	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	Z1 score	**1 s**	30%	**94.82**	**96.55**	84.48	94.82	94.05	91.6	100
S-O	Z1 score	**1 s**	30%	**96.55**	**100**	81.03	91.37	94.93	88.04	98.27
S-F	Z1 score	**1 s**	30%	**86.42**	**94.82**	81.14	88.15	93.43	83.2	91.71
S-N	Z1 score	**1 s**	30%	**89.76**	**94.82**	79.31	91.37	96.66	80.08	98.27
S-Z-O	Z1 score	**1 s**	30%	**66.82**	**73.3**	52.67	71.98	72.15	57.63	81.52
S-F-N	Z1 score	**1 s**	30%	**76.95**	**82.45**	59.61	67.59	84.15	60.01	67.08
S-Z-O-F	Z1 score	**1 s**	30%	**73.27**	**77.42**	52.02	57.38	73.24	39.11	54.51
S-Z-O-N	Z1 score	**1 s**	30%	**70.41**	**73.88**	52.07	61.36	72.35	50.77	63.44
S-F-N-O	Z1 score	**1 s**	30%	**76.19**	**79.5**	51.13	52.46	73.82	44.54	54.88
S-F-N-Z	Z1 score	**1 s**	30%	**68.07**	**73.78**	51.21	57.49	70.77	54.07	59.94
S-O-F-N-Z	Z1 score	**1 s**	30%	**63.12**	**64.78**	46.46	56.36	64.53	44.87	51.83

Table 4.22: Results of F1-measure metric for testing signal length during 1 sec for fractal +cosine similarity model with and without optimization compared with ML

dataset	Normalization	EEG signal length	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	Z1 score	**1 s**	30%	**94.20**	**96.76**	86.56	94.20	94.02	91.67	100
S-O	Z1 score	**1 s**	30%	**96.76**	**100**	83.86	92.20	94.01	88.80	98.35
S-F	Z1 score	**1 s**	30%	**86.92**	**94.20**	83.02	88.47	93.43	83.35	91.68
S-N	Z1 score	**1 s**	30%	**90.30**	**94.20**	82.54	92.20	96.66	80.08	98.35
S-Z-O	Z1 score	**1 s**	30%	**67.87**	**74.16**	56.75	72.59	72.64	58.44	81.69
S-F-N	Z1 score	**1 s**	30%	**77.44**	**82.56**	63.58	68.86	84.23	61.30	66.58
S-Z-O-F	Z1 score	**1 s**	30%	**74.40**	**77.88**	59.14	62.03	73.30	41.56	54.11
S-Z-O-N	Z1 score	**1 s**	30%	**72.02**	**74.80**	58.70	64.25	72.54	52.11	63.97
S-F-N-O	Z1 score	**1 s**	30%	**77.78**	**80.67**	58.03	56.06	74.41	46.40	53.96
S-F-N-Z	Z1 score	**1 s**	30%	**69.67**	**74.44**	54.51	57.88	71.10	54.68	59.62
S-O-F-N-Z	Z1 score	**1 s**	30%	**64.84**	**66.73**	52.27	59.40	64.71	44.50	53.15

Table 4.23: Results of accuracy metric for testing signal length during 5 sec for fractal +cosine similarity model with and without optimization compared with ML algorithms.

dataset	Normalization	EEG signal length	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	Z1 score	**5 s**	30%	**98.33**	**100**	70	100	100	83.33	100
S-O	Z1 score	**5 s**	30%	**98.33**	**100**	73.33	93.33	96.66	83.33	98
S-F	Z1 score	**5 s**	30%	**96.66**	**98.33**	71.66	90	98.33	83.33	96.66
S-N	Z1 score	**5 s**	30%	**98.33**	**98.33**	70	96.66	98.33	81.66	98.33
S-Z-O	Z1 score	**5 s**	30%	**81.11**	**83.33**	41.11	73.33	74.44	57.77	84.44
S-F-N	Z1 score	**5 s**	30%	**74.55**	**83.33**	54.44	68.88	80	68.88	71.11
S-Z-O-F	Z1 score	**5 s**	30%	**74.83**	**80.83**	44.16	60	79.16	40	61.66
S-Z-O-N	Z1 score	**5 s**	30%	**74.16**	**76.66**	40.83	62.5	78.33	54.16	67.5
S-F-N-O	Z1 score	**5 s**	30%	**83.33**	**85**	41.66	54.16	81.66	43.33	54.83
S-F-N-Z	Z1 score	**5 s**	30%	**76.66**	**80**	42.5	58.33	80.83	44.83	61.66
S-O-F-N-Z	Z1 score	**5 s**	30%	**74**	**76**	44.66	59.33	72.66	40	52.66

Table 4.24: Results of precision metric for testing signal length during 5 sec for fractal +cosine similarity with and without optimization model compared with ML algorithms.

dataset	Normalization	EEG signal length	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	Z1 score	**5 s**	30%	**98.43**	**100**	81.63	100	100	81.69	100
S-O	Z1 score	**5 s**	30%	**98.33**	**100**	82.97	94.28	96.96	83.31	98.43
S-F	Z1 score	**5 s**	30%	**96.96**	**98.43**	82.29	90.85	98.33	73.71	96.66
S-N	Z1 score	**5 s**	30%	**98.43**	**98.43**	81.63	96.96	98.33	88.75	98.33
S-Z-O	Z1 score	**5 s**	30%	**81.53**	**86.29**	68.06	74.7	74.14	59.68	84.13
S-F-N	Z1 score	**5 s**	30%	**77.46**	**83.87**	68.06	72.59	79.26	70.58	70.59
S-Z-O-F	Z1 score	**5 s**	30%	**74.78**	**78.96**	53.45	68.4	79.07	44.15	59.6
S-Z-O-N	Z1 score	**5 s**	30%	**74.94**	**78.53**	53.72	71.15	77.94	53.66	66.89
S-F-N-O	Z1 score	**5 s**	30%	**84.51**	**87.38**	56.64	64.48	81.67	43.46	54.55
S-F-N-Z	Z1 score	**5 s**	30%	**80.01**	**84.23**	58.37	64.79	80.95	46.65	61.05
S-O-F-N-Z	Z1 score	**5 s**	30%	**76.39**	**78.18**	57.42	67.02	71.59	34.87	53.16

Table 4.25: Results of recall metric for testing signal length during 5 sec for fractal +cosine similarity model with and without optimization compared with ML algorithms.

dataset	Normalization	EEG signal length	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	Z1 score	**5 s**	30%	**98.27**	**100**	68.96	100	100	81.59	100
S-O	Z1 score	**5 s**	30%	**98.38**	**100**	72.41	93.1	96.55	83.31	98.27
S-F	Z1 score	**5 s**	30%	**96.55**	**98.27**	70.68	89.76	98.38	73.08	96.66
S-N	Z1 score	**5 s**	30%	**98.27**	**98.27**	68.96	96.55	98.38	84.48	98.38
S-Z-O	Z1 score	**5 s**	30%	**80.03**	**83.3**	57.26	71.3	73.72	57.41	83.9
S-F-N	Z1 score	**5 s**	30%	**74.89**	**83.43**	57.26	68.32	79.3	68.57	70.28
S-Z-O-F	Z1 score	**5 s**	30%	**74.13**	**77.99**	43.269	58.92	78.87	42.32	61.46
S-Z-O-N	Z1 score	**5 s**	30%	**73.67**	**76.12**	39.82	61.42	78.01	52.13	67.11
S-F-N-O	Z1 score	**5 s**	30%	**83.92**	**84.44**	43.72	54.96	81.36	41.25	54.2
S-F-N-Z	Z1 score	**5 s**	30%	**77.21**	**81.98**	44.24	58.99	80.15	44.46	60.18
S-O-F-N-Z	Z1 score	**5 s**	30%	**74**	**74.35**	41.51	58.58	72.14	34.83	52.51

Table 4.26: Results of F1-measure metric for testing signal length during 5 sec for fractal +cosine similarity model with and without optimization compared with ML algorithms.

dataset	Normalization	EEG signal length	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	Z1 score	**5 s**	30%	**98.35**	**100**	74.76	100	100	81.64	100
S-O	Z1 score	**5 s**	30%	**98.36**	**100**	77.33	93.69	96.76	83.31	98.35
S-F	Z1 score	**5 s**	30%	**96.76**	**98.35**	76.05	90.30	98.36	73.39	96.66
S-N	Z1 score	**5 s**	30%	**98.35**	**98.35**	74.76	96.76	98.36	86.56	98.36
S-Z-O	Z1 score	**5 s**	30%	**80.77**	**84.77**	62.20	72.96	74.42	58.52	84.02
S-F-N	Z1 score	**5 s**	30%	**74.89**	**83.65**	62.20	70.39	79.28	69.56	70.43
S-Z-O-F	Z1 score	**5 s**	30%	**74.45**	**78.47**	47.82	63.31	78.97	43.22	60.51
S-Z-O-N	Z1 score	**5 s**	30%	**74.79**	**77.30**	44.74	64.92	77.97	52.88	67.00
S-F-N-O	Z1 score	**5 s**	30%	**84.71**	**86.40**	49.35	59.76	81.51	42.33	54.37
S-F-N-Z	Z1 score	**5 s**	30%	**78.59**	**83.09**	50.33	61.76	80.54	46.05	60.61
S-O-F-N-Z	Z1 score	**5 s**	30%	**74.18**	**76.74**	48.19	62.51	71.86	34.34	52.83

Table 4.27: Results of accuracy metric for testing signal length during 10 sec for fractal +cosine similarity model with and without optimization compared with ML algorithms.

dataset	Normalization	EEG signal length	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	Z1 score	**10 s**	30%	**98.33**	**100**	63.33	98.3	100	90	100
S-O	Z1 score	**10 s**	30%	**95**	**98.33**	63.33	96.66	98.33	88.33	98.33
S-F	Z1 score	**10 s**	30%	**100**	**100**	63.33	90	98.33	83.33	95
S-N	Z1 score	**10 s**	30%	**98.33**	**100**	63.33	96.66	100	80	100
S-Z-O	Z1 score	**10 s**	30%	**82.22**	**84.55**	38.88	74.44	83.33	64.44	84.44
S-F-N	Z1 score	**10 s**	30%	**84.55**	**88.88**	56.66	68.88	81.11	63.33	71.11
S-Z-O-F	Z1 score	**10 s**	30%	**74.83**	**79.16**	40	57.49	77.5	53.33	62.5
S-Z-O-N	Z1 score	**10 s**	30%	**79.16**	**80.83**	40	58.33	80	46.66	70
S-F-N-O	Z1 score	**10 s**	30%	**85**	**87.5**	40	49.16	77.5	44.83	61.66
S-F-N-Z	Z1 score	**10 s**	30%	**82.5**	**84.83**	41.66	50.83	79.16	51.66	60.83
S-O-F-N-Z	Z1 score	**10 s**	30%	**76**	**78**	44	54.33	70.66	34.33	54.33

Table 4.28: Results of precision metric for testing signal length during 10 sec for fractal +cosine similarity with and without optimization model compared with ML algorithms.

dataset	Normalization	EEG signal length	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	Z1 score	**10 s**	30%	**98.43**	**100**	79.24	98.43	100	90.1	100
S-O	Z1 score	**10 s**	30%	**94.08**	**98.43**	79.24	96.96	98.43	90.57	98.43
S-F	Z1 score	**10 s**	30%	**100**	**100**	79.24	90.85	98.33	86.76	95
S-N	Z1 score	**10 s**	30%	**98.43**	**100**	79.24	96.96	100	86.86	100
S-Z-O	Z1 score	**10 s**	30%	**83.61**	**84.99**	53.6	74.76	83.41	62.25	84.13
S-F-N	Z1 score	**10 s**	30%	**84.77**	**88.69**	70.26	77.01	80.34	67.11	70.89
S-Z-O-F	Z1 score	**10 s**	30%	**77.38**	**79.63**	44.65	63.24	78.25	54.98	60.41
S-Z-O-N	Z1 score	**10 s**	30%	**79.22**	**81.27**	44.81	71.74	80.21	46.7	69.84
S-F-N-O	Z1 score	**10 s**	30%	**84.65**	**87.02**	54.94	46.98	77.12	42.61	61.55
S-F-N-Z	Z1 score	**10 s**	30%	**83.94**	**86.97**	56.82	70.45	81.16	54.08	60.39
S-O-F-N-Z	Z1 score	**10 s**	30%	**78.34**	**79.07**	60.57	71.21	70.53	43.9	57.8

Table 4.29: Results of recall metric for testing signal length during 10 sec for fractal +cosine similarity model with and without optimization compared with ML algorithms

dataset	Normalization	EEG signal length	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	Z1 score	**10 s**	30%	**98.27**	**100**	62.06	98.27	100	90.1	100
S-O	Z1 score	**10 s**	30%	**94.93**	**98.27**	62.06	96.55	98.27	90.21	98.27
S-F	Z1 score	**10 s**	30%	**100**	**100**	62.06	89.76	98.38	86.76	94.05
S-N	Z1 score	**10 s**	30%	**98.27**	**100**	62.068	96.55	100	86.54	100
S-Z-O	Z1 score	**10 s**	30%	**80.92**	**84.37**	39.46	72.53	82.84	60.6	83.9
S-F-N	Z1 score	**10 s**	30%	**84.73**	**88.84**	59.56	68.49	80.28	63.24	70.36
S-Z-O-F	Z1 score	**10 s**	30%	**74.09**	**77.69**	38.94	56.55	77.48	50.86	62.19
S-Z-O-N	Z1 score	**10 s**	30%	**78.14**	**80.94**	38.79	57.26	80.16	44.46	69.99
S-F-N-O	Z1 score	**10 s**	30%	**84.41**	**86.22**	42	50.37	77.02	41.99	61.16
S-F-N-Z	Z1 score	**10 s**	30%	**83.09**	**86.3**	43.64	51.99	79.33	52.16	59.37
S-O-F-N-Z	Z1 score	**10 s**	30%	**76.2**	**77.48**	43.11	54.17	71.02	37.8	54.57

Table 4.30: Results of F1-measure metric for testing signal length during 10 sec for fractal +cosine similarity model with and without optimization compared with ML

dataset	Normalization	EEG signal length	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	Z1 score	**10 s**	30%	**98.35**	**100**	69.61	98.35	100	90.10	100
S-O	Z1 score	**10 s**	30%	**94.01**	**98.35**	69.61	96.76	98.35	90.39	98.35
S-F	Z1 score	**10 s**	30%	**100**	**100**	69.61	90.30	98.36	86.76	94.02
S-N	Z1 score	**10 s**	30%	**98.35**	**100**	69.61	96.76	100	86.70	100
S-Z-O	Z1 score	**10 s**	30%	**82.24**	**84.17**	44.46	73.63	83.12	61.42	84.02
S-F-N	Z1 score	**10 s**	30%	**84.75**	**88.76**	64.47	72.50	80.31	64.12	70.63
S-Z-O-F	Z1 score	**10 s**	30%	**76.21**	**78.65**	41.60	59.71	7.86	52.84	61.29
S-Z-O-N	Z1 score	**10 s**	30%	**78.68**	**81.11**	42.01	63.69	80.19	44.56	69.91
S-F-N-O	Z1 score	**10 s**	30%	**84.53**	**86.62**	47.98	48.62	77.07	42.30	61.35
S-F-N-Z	Z1 score	**10 s**	30%	**83.52**	**86.63**	49.36	59.82	80.23	53.10	59.88
S-O-F-N-Z	Z1 score	**10 s**	30%	**77.26**	**78.27**	50.37	62.17	70.78	40.62	56.66

Table 4.31: Results of accuracy metric for testing signal length during 15 sec for fractal +cosine similarity model with and without optimization compared with ML algorithms.

dataset	Normalization	EEG signal length	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	Z1 score	**15 s**	30%	**100**	**100**	61.66	98.33	100	85	100
S-O	Z1 score	**15 s**	30%	**98.33**	**100**	61.66	96.66	100	86.66	98.33
S-F	Z1 score	**15 s**	30%	**100**	**100**	61.66	93.33	98.33	78.33	95
S-N	Z1 score	**15 s**	30%	**100**	**100**	61.66	96.66	98.33	88.33	100
S-Z-O	Z1 score	**15 s**	30%	**84.44**	**86.66**	38.88	73.33	83.33	58.88	84.44
S-F-N	Z1 score	**15 s**	30%	**88.88**	**90**	53.33	72.22	86.66	60	72.22
S-Z-O-F	Z1 score	**15 s**	30%	**74.83**	**80**	37.5	56.66	78.33	55	60.83
S-Z-O-N	Z1 score	**15 s**	30%	**74.83**	**80.83**	34.83	56.66	75	55	69.16
S-F-N-O	Z1 score	**15 s**	30%	**83.33**	**84.83**	39.16	51.66	80	42.5	61.66
S-F-N-Z	Z1 score	**15 s**	30%	**83.33**	**85**	41.66	51.66	77.5	54.83	63.33
S-O-F-N-Z	Z1 score	**15 s**	30%	**74**	**77**	39.33	57.33	71.33	38	56

Table 4.32: Results of precision metric for testing signal length during 15 sec for fractal +cosine similarity with and without optimization model compared with ML algorithms.

dataset	Normalization	EEG signal length	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	Z1 score	**15 s**	30%	**100**	**100**	78.7	98.43	100	82.01	100
S-O	Z1 score	**15 s**	30%	**98.43**	**100**	78.7	96.96	100	90.57	98.43
S-F	Z1 score	**15 s**	30%	**100**	**100**	78.7	93.6	98.33	81.69	95
S-N	Z1 score	**15 s**	30%	**100**	**100**	78.7	96.96	98.33	88.36	100
S-Z-O	Z1 score	**15 s**	30%	**87.47**	**90.24**	51.12	73.41	83.1	66.9	84.13
S-F-N	Z1 score	**15 s**	30%	**89.14**	**89.7**	67.49	79.6	86.26	64.17	72.17
S-Z-O-F	Z1 score	**15 s**	30%	**76.42**	**77.78**	55	60.5	79.77	58.03	58.68
S-Z-O-N	Z1 score	**15 s**	30%	**74.44**	**79.3**	49.98	70.57	74.26	54.39	69.72
S-F-N-O	Z1 score	**15 s**	30%	**84.63**	**89.39**	54.36	50.95	81.43	43.16	62.24
S-F-N-Z	Z1 score	**15 s**	30%	**84.05**	**84.68**	52.91	49.11	77.47	54.92	63.73
S-O-F-N-Z	Z1 score	**15 s**	30%	**76.58**	**79.46**	46.46	71.47	72.02	41.51	58.37

Table 4.33: Results of recall metric for testing signal length during 15 sec for fractal +cosine similarity model with and without optimization compared with ML algorithms.

dataset	Normalization	EEG signal length	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	Z1 score	**15 s**	30%	**100**	**100**	60.34	98.27	100	81.47	100
S-O	Z1 score	**15 s**	30%	**98.27**	**100**	60.34	96.55	100	90.21	98.27
S-F	Z1 score	**15 s**	30%	**100**	**100**	60.34	93.21	98.38	81.59	94.05
S-N	Z1 score	**15 s**	30%	**100**	**100**	60.34	96.55	98.38	86.31	100
S-Z-O	Z1 score	**15 s**	30%	**83.3**	**84.69**	39.46	71.3	82.75	64.95	83.9
S-F-N	Z1 score	**15 s**	30%	**88.5**	**89.65**	56.03	71.68	86.2	59.96	71.51
S-Z-O-F	Z1 score	**15 s**	30%	**74.11**	**76.68**	36.47	54.67	78.46	54.06	60.55
S-Z-O-N	Z1 score	**15 s**	30%	**74.06**	**79.07**	34.75	54.57	74.77	52.59	69.31
S-F-N-O	Z1 score	**15 s**	30%	**83.62**	**87.81**	41.24	52.8	79.8	40.71	61.16
S-F-N-Z	Z1 score	**15 s**	30%	**83.57**	**84.33**	43.69	52.80	77.38	54.42	62.23
S-O-F-N-Z	Z1 score	**15 s**	30%	**74.06**	**78.02**	38.45	57.17	71.71	34.28	56.33

Table 4.34: Results of F1-measure metric for testing signal length during 15 sec for fractal +cosine similarity model with and without optimization compared with ML

dataset	Normalization	EEG signal length	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	Z1 score	**15 s**	30%	**100**	**100**	68.31	98.35	100	81.74	100
S-O	Z1 score	**15 s**	30%	**98.35**	**100**	68.31	96.76	100	90.39	98.35
S-F	Z1 score	**15 s**	30%	**100**	**100**	68.31	93.40	98.36	81.64	94.02
S-N	Z1 score	**15 s**	30%	**100**	**100**	68.31	96.76	98.36	87.33	100
S-Z-O	Z1 score	**15 s**	30%	**84.33**	**87.90**	44.54	72.34	82.92	64.91	84.02
S-F-N	Z1 score	**15 s**	30%	**88.82**	**89.67**	61.23	74.43	86.23	61.99	71.84
S-Z-O-F	Z1 score	**15 s**	30%	**74.76**	**77.22**	43.86	57.98	79.11	56.50	59.60
S-Z-O-N	Z1 score	**15 s**	30%	**74.25**	**79.18**	41	62.18	74.01	53.48	69.52
S-F-N-O	Z1 score	**15 s**	30%	**84.61**	**88.59**	47.27	51.86	80.61	41.90	61.69
S-F-N-Z	Z1 score	**15 s**	30%	**83.81**	**84.50**	47.86	50.89	77.43	54.16	62.97
S-O-F-N-Z	Z1 score	**15 s**	30%	**74.30**	**78.74**	42.08	63.53	71.86	38.14	57.33

Table 4.35: Results of accuracy metric for testing signal length during 20 sec for fractal +cosine similarity model with and without optimization compared with ML algorithms.

dataset	Normalization	EEG signal length	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	Z1 score	**20 s**	30%	**98.33**	**100**	61.66	98.33	100	83.33	100
S-O	Z1 score	**20 s**	30%	**100**	**100**	61.66	96.66	100	73.33	98.33
S-F	Z1 score	**20 s**	30%	**98.33**	**100**	61.66	93.33	96.66	83.33	95
S-N	Z1 score	**20 s**	30%	**98.33**	**100**	61.66	96.66	98.33	85	100
S-Z-O	Z1 score	**20 s**	30%	**81.11**	**84.44**	38.88	73.33	80	54.55	84.44
S-F-N	Z1 score	**20 s**	30%	**84.44**	**87.77**	52.22	72.22	83.33	70	74.44
S-Z-O-F	Z1 score	**20 s**	30%	**79.16**	**82.5**	33.33	58.33	78.33	55	60.83
S-Z-O-N	Z1 score	**20 s**	30%	**79.16**	**82.5**	35	59.16	80	50.83	68.33
S-F-N-O	Z1 score	**20 s**	30%	**84.83**	**88.33**	39.16	50.83	50.83	50	60.83
S-F-N-Z	Z1 score	**20 s**	30%	**78.33**	**80**	30	51.66	74.83	54.16	66.66
S-O-F-N-Z	Z1 score	**20 s**	30%	**78.66**	**80**	34.33	58.66	71.33	41.33	56

Table 4.36: Results of precision metric for testing signal length during 20 sec for fractal +cosine similarity with and without optimization model compared with ML algorithms

dataset	Normalization	EEG signal length	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	Z1 score	**20 s**	30%	**98.43**	**100**	78.7	98.43	100	84.04	100
S-O	Z1 score	**20 s**	30%	**100**	**100**	78.7	96.96	100	70	98.43
S-F	Z1 score	**20 s**	30%	**98.43**	**100**	78.7	93.6	96.77	84	95
S-N	Z1 score	**20 s**	30%	**98.43**	**100**	78.7	96.96	98.33	84.04	100
S-Z-O	Z1 score	**20 s**	30%	**84.66**	**86.29**	52.08	73.41	79.83	61.45	84.13
S-F-N	Z1 score	**20 s**	30%	**84.25**	**87.82**	66.29	83.27	82.57	71.18	74.51
S-Z-O-F	Z1 score	**20 s**	30%	**80.44**	**83.07**	52.18	66.1	79.64	54.85	58.68
S-Z-O-N	Z1 score	**20 s**	30%	**78.98**	**81.14**	64.64	71.94	79.91	51.93	68.25
S-F-N-O	Z1 score	**20 s**	30%	**86.85**	**88.88**	59.82	49.06	76.45	52.49	61.69
S-F-N-Z	Z1 score	**20 s**	30%	**82**	**84.06**	54.28	48.95	82.96	52.55	66.16
S-O-F-N-Z	Z1 score	**20 s**	30%	**80.96**	**82.02**	57.42	69.43	71.9	46.14	57.52

Table 4.37: Results of recall metric for testing signal length during 20 sec for fractal +cosine similarity model with and without optimization compared with ML algorithms.

dataset	Normalization	EEG signal length	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	Z1 score	**20 s**	30%	**98.27**	**100**	60.34	98.27	100	84.92	100
S-O	Z1 score	**20 s**	30%	**100**	**100**	60.34	96.55	100	67.79	98.27
S-F	Z1 score	**20 s**	30%	**98.27**	**100**	60.34	93.21	96.77	83.09	94.05
S-N	Z1 score	**20 s**	30%	**98.27**	**100**	60.34	96.55	98.38	84.92	100
S-Z-O	Z1 score	**20 s**	30%	**80.36**	**83.30**	39.46	71.3	79.22	60.27	83.9
S-F-N	Z1 score	**20 s**	30%	**84.49**	**87.43**	54.88	71.77	82.50	69.46	73.81
S-Z-O-F	Z1 score	**20 s**	30%	**78.50**	**81.81**	32.40	57.48	77.98	54.33	60.55
S-Z-O-N	Z1 score	**20 s**	30%	**78.32**	**80.79**	34.04	58.19	80.16	49.34	68.48
S-F-N-O	Z1 score	**20 s**	30%	**86.12**	**87.68**	41.37	52.04	76.24	51.01	60.51
S-F-N-Z	Z1 score	**20 s**	30%	**82.08**	**84.34**	41.21	52.04	82.67	49.78	63.90
S-O-F-N-Z	Z1 score	**20 s**	30%	**78.58**	**79.92**	34.59	58.56	72.03	43.49	56.43

Table 4.38: Results of F1-measure metric for testing signal length during 20 sec for fractal +cosine similarity model with and without optimization compared with ML

dataset	Normalization	EEG signal length	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	Z1 score	**20 s**	30%	**98.35**	**100**	68.31	98.35	100	84.98	100
S-O	Z1 score	**20 s**	30%	**100**	**100**	68.31	96.76	100	68.88	98.35
S-F	Z1 score	**20 s**	30%	**98.35**	**100**	68.31	93.40	96.77	83.54	94.02
S-N	Z1 score	**20 s**	30%	**98.35**	**100**	68.31	96.76	98.36	84.98	100
S-Z-O	Z1 score	**20 s**	30%	**82.46**	**84.77**	44.90	72.34	79.52	60.85	84.02
S-F-N	Z1 score	**20 s**	30%	**84.87**	**87.62**	60.05	77.09	82.53	70.31	74.16
S-Z-O-F	Z1 score	**20 s**	30%	**79.46**	**82.44**	39.98	61.49	78.80	54.08	59.60
S-Z-O-N	Z1 score	**20 s**	30%	**78.65**	**80.97**	44.83	64.34	80.03	51.82	68.37
S-F-N-O	Z1 score	**20 s**	30%	**86.48**	**88.28**	48.91	50.50	76.34	51.20	61.09
S-F-N-Z	Z1 score	**20 s**	30%	**82.04**	**84.20**	46.85	50.45	82.81	51.13	64.01
S-O-F-N-Z	Z1 score	**20 s**	30%	**79.75**	**80.96**	43.17	63.53	71.97	44.78	56.97

To have a clear visual analysis, all the resultant accuracy shown in Tables 4.11,4.19,4.23,4.27,4.31 and 4.35 are displayed visually by bar chart figures (Figure 4.14 to 4.19). The result shows the fractal and cosine similarity model with particle swarm optimization (PSO) achieved a higher result compared to the results without optimization.

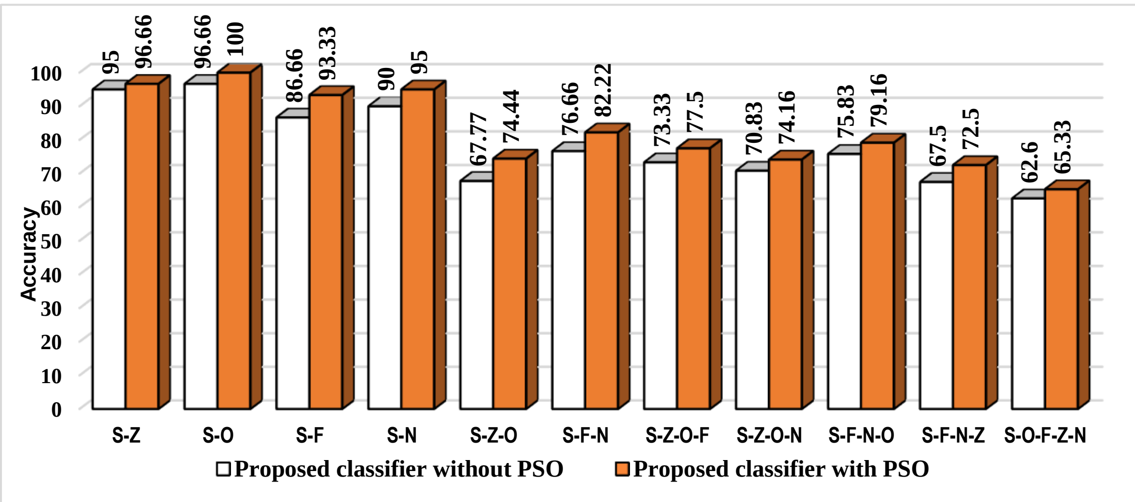

Figure 4.14: Describes the resultant accuracy of fractal+cosine similarity models with and without optimization with a 1-second signal length for all classes.

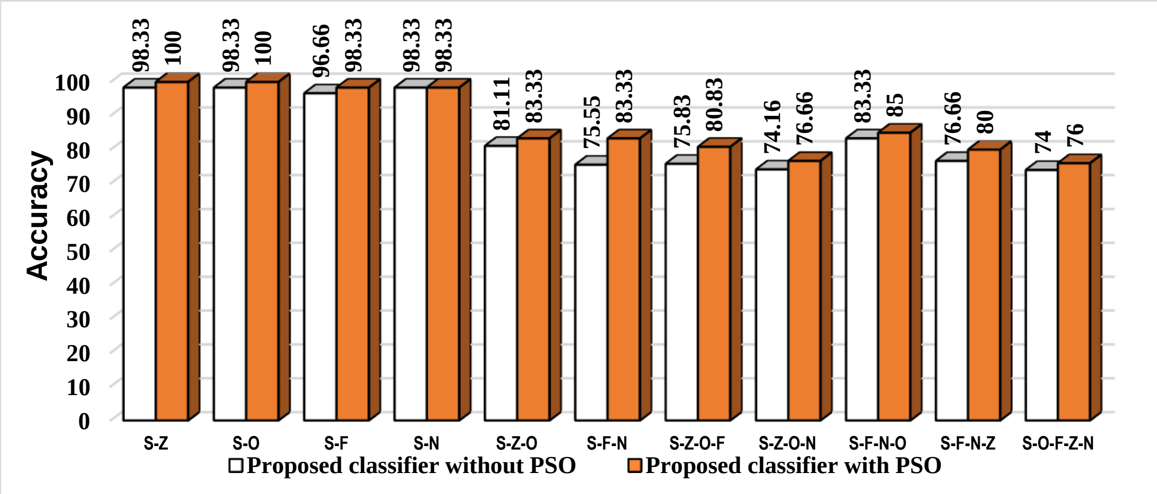

Figure 4.15: Describes the resultant accuracy of fractal+cosine similarity models with and without optimization with a 5-second signal length for all classes.

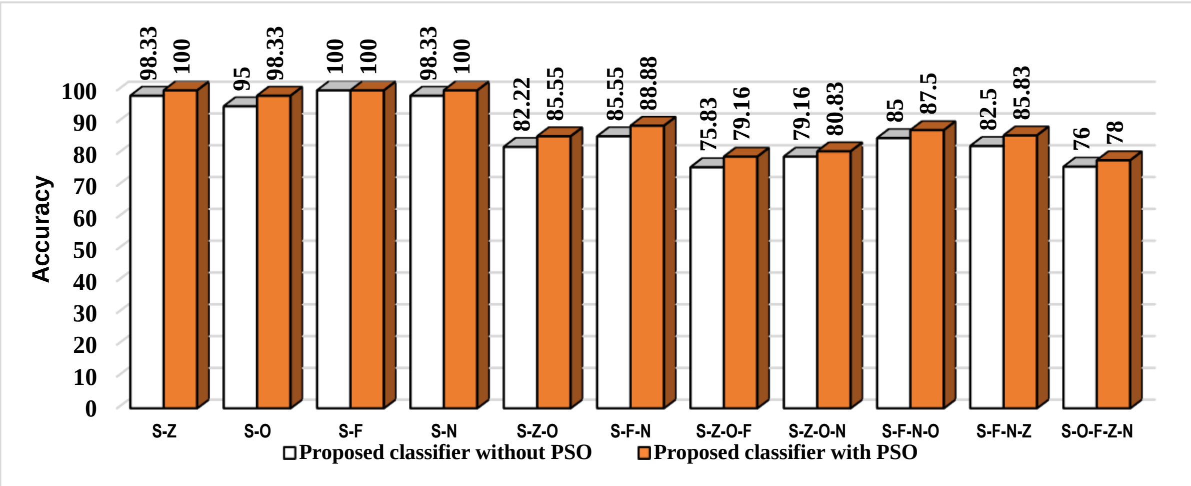

Figure 4.16: Describes the resultant accuracy of fractal+cosine similarity models with and without optimization with a 10-second signal length for all classes.

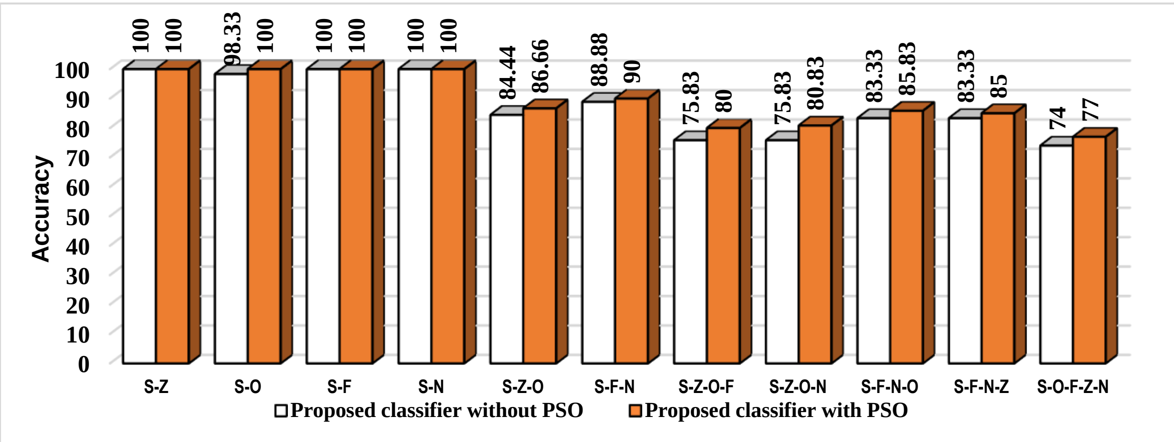

Figure 4.17: Describes the resultant accuracy of fractal+cosine similarity models with and without optimization with a 15-second signal length for all classes

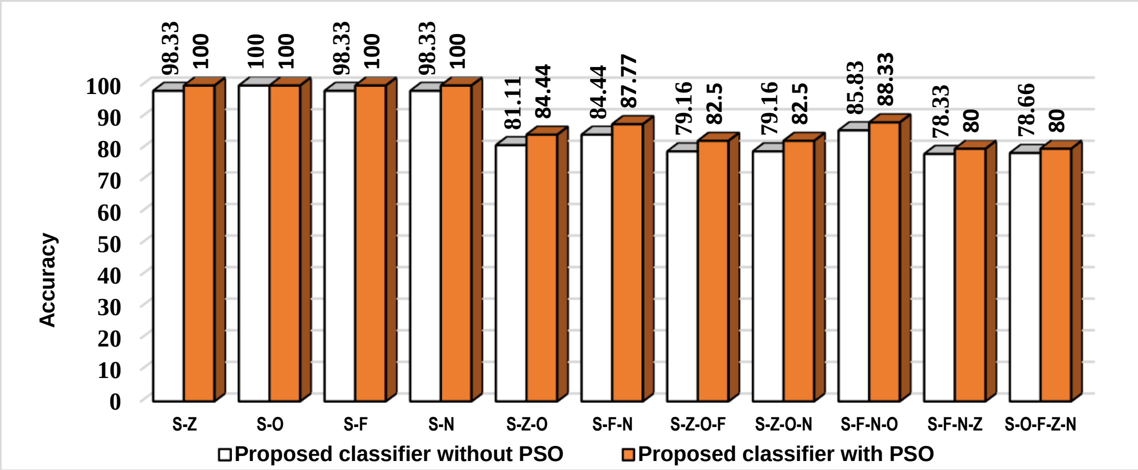

Figure 4.18: Describes the resultant accuracy of fractal+cosine similarity models with and without optimization with a 20-second signal length for all classes

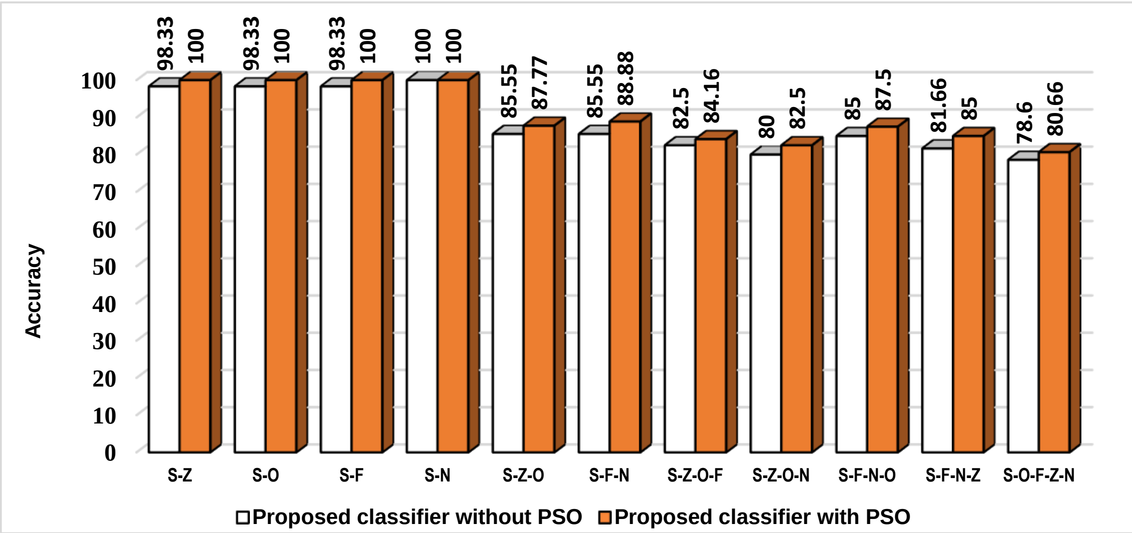

Figure 4.19: Describes the resultant accuracy of fractal+cosine similarity models with and without optimization with a 23.6-second signal length for all classes

in utilization of an EEG signal with a length of one second, Fractal and cosine similarity model achieved a high accuracy of 96.66% without optimization and up to 100 % with optimization. Classification has been applied to the total EEG signal length of 23.6 seconds. The proposed models have shown better results with an accuracy up to 100 % with and without optimization by PSO.

The minimum accuracy result has been obtained by utilizing five classes at a 1-second signal length that have only 177 features of EEG signals. It has reached 62.6 % without optimization and 64.33% with optimization. The results of our models have still outperformed the machine learning algorithms.

In order to show the results and performance in such an accurate presentation, the average of accuracy metric for 1 sec, 5 sec, 10 sec, 15 sec, 20 sec and the total EEG signal length have been calculated. Table 4.39 shows the average results of fractal and cosine similarity models, as well as machine learning techniques, for all categorization classes.

Table 4.39: Results of the average accuracy metric of different time lengths for fractal +cosine similarity models with and without optimization compared with ML algorithms.

dataset	Normalization	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	Z1 score	30%	**98.05**	**99.44**	66.94	98.33	99.17	83.89	100
S-O	Z1 score	30%	**97.78**	**99.72**	66.94	94.26	98.33	83.89	98.55
S-F	Z1 score	30%	**96.66**	**98.61**	66.66	91.38	97.22	83.89	94.99
S-N	Z1 score	30%	**97.50**	**98.89**	66.11	94.83	98.33	84.16	99.44
S-Z-O	Z1 score	30%	**80.37**	**84.63**	41.48	73.52	79.63	58.33	84.07
S-F-N	Z1 score	30%	**82.77**	**87.03**	54.63	70.55	81.66	64.92	72.22
S-Z-O-F	Z1 score	30%	**77.08**	**79.17**	40.28	58.05	77.50	51.53	60.14
S-Z-O-N	Z1 score	30%	**76.52**	**78.33**	39.58	59.72	76.53	50.97	68.33
S-F-N-O	Z1 score	30%	**83.05**	**86.39**	41.25	51.38	74.58	44.28	59.02
S-F-N-Z	Z1 score	30%	**78.33**	**82.22**	40.83	53.89	77.50	51.11	62.91
S-O-F-N-Z	Z1 score	30%	**73.98**	**77.39**	40.55	57.66	71	40	54.67

All the results have been illustrated by the bar chart in figure 4.20.

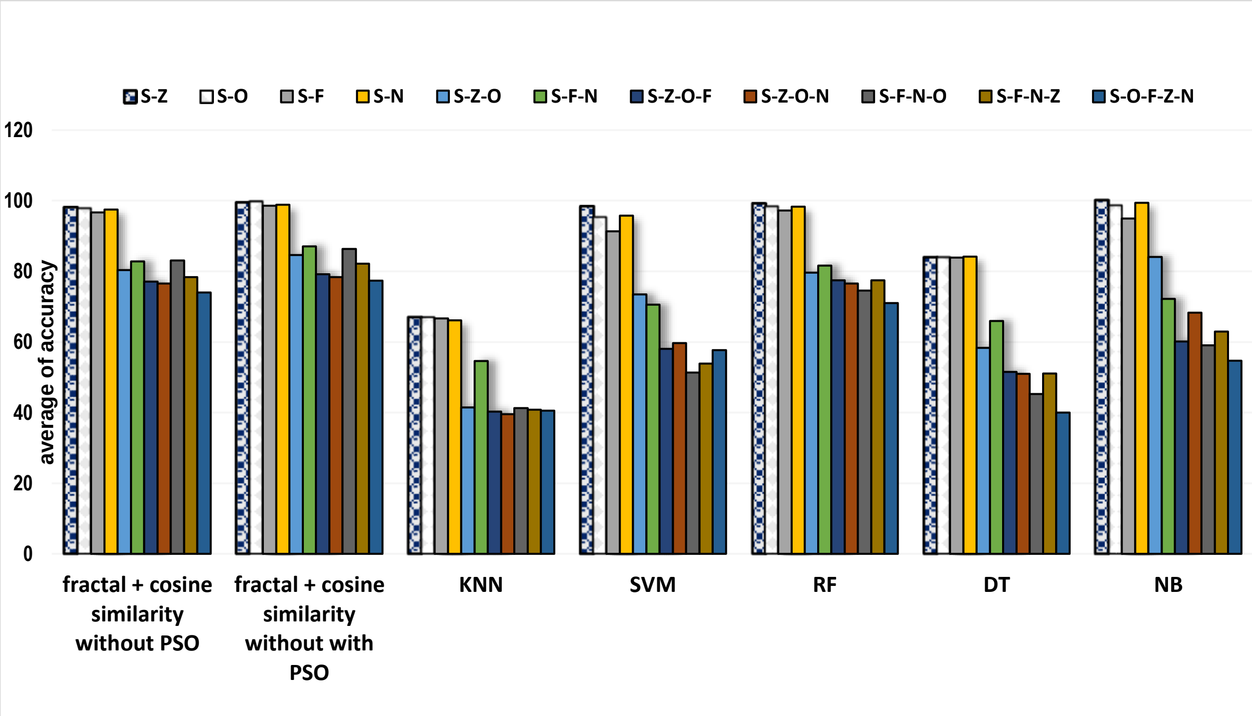

Figure 4.20 Results of the average accuracy metric of different time lengths for fractal +cosine similarity models with and without optimization compared with ML algorithms.

The fractal and cosine similarity models have outperformed most machine learning algorithms for several classification classes.

The Windows 10 operating system is used to implement our models that have been designed in the Python programming language (version 3.9). The systems are executed on a personal computer with an Intel (R) Core (TM) i7-10750H processor speed of 2.60 GHz and 16 Gigabytes of memory.

The proposed model has a minimum execution time without optimization of 0.032416 MS and a maximum execution time of 0.082479 MS, with an average processing time of 0.052097 MS. The minimum execution time with

PSO as optimization 0.027092 MS and the maximum execution time of 0.053358 MS, with an average processing time of 0.039356 MS.

Figure 4.21 shows the execution time of proposed models for several classes with PSO as optimization and without optimization.

Figure 4.21 Execution time of fractals + cosine similarity models for several classes with and without optimization.

4.6 Comparison with other models

There have been a wide variety of different approaches developed for identifying epileptic seizures. Accuracy measures are used to compare the proposed approach to other approaches that have been developed previously. Only approaches that were tested within the same dataset are included in this comparison, allowing for results to be compared between sets with the same classes.

Table 4.40: A comparison of Fractal+Cosine similarity models with other previous methods based on best accuracy metric.

Author	Method	Datasets	Best accuracy
Raghu et al. [34]	Matrix determinant and MLP	A-E	99.45
A. Sharmila et al.[9]	NB	A-E	100
A. Sharmila et al.[9]	k-NN	A-E	100
Yang Li et al[14]	MRBF-MPSO, PCA, SVM	S- Z	100
Ling Guo et al.[20]	ANN	S- Z	99.6
Kaveh et al[18]	Discrete Short Time Fourier Transform (DSTFT) and MLP	A-E	99.8
A.B.Peachap et al[33]	ANN + SVM	A-E	100
JIAN LIAN et al[25]	Pairwise matching of EEG signal and CNN	A- E	99.84
Enamul Kabir et al.[3]	SVM	A- E	98.13
Enamul Kabir et al.[3]	Naïve Bayes	A- E	98.50
Enamul Kabir et al.[3]	Logistic regression	A- E	99.00
Proposed Method	**Fractal + Cosine similarity**	**S-Z**	**100**
Raghu et al.[34]	Matrix determinant and MLP	B-E	99.76
A. Sharmila et al.[9]	NB	B-E	99.25
A. Sharmila et al.[9]	k-NN	B-E	98.25
Kaveh et al[18]	Discrete Short Time Fourier Transform (DSTFT) and MLP	B-E	99.3
A.B.Peachap et al[33]	ANN + SVM	B-E	100
Enamul Kabir et al.[3]	SVM	B-E	97.75
Enamul Kabir et al.[3]	Naïve Bayes	B-E	98.38
Enamul Kabir et al.[3]	Logistic regression	B-E	99.25
Proposed Method	**Fractal + Cosine similarity**	**O-S**	**100**
Raghu et al.[34]	Matrix determinant and MLP	C-E	97.6
A. Sharmila et al.[9]	NB	C-E	99.62
A. Sharmila et al.[9]	k-NN	C-E	97.25
Yang Li et al[14]	MRBF-MPSO, PSD, PCA, SVM	S-N	99.8
Kaveh et al[18]	Discrete Short Time Fourier Transform (DSTFT) and MLP	C-E	98.5
Enamul Kabir et al.[3]	SVM	C-E	100
Enamul Kabir et al.[3]	Naïve Bayes	C-E	99.63
Enamul Kabir et al.[3]	Logistic regression	C-E	99.38
Proposed Method	**Fractal + Cosine similarity**	**S-N**	**100**
Raghu et al.[34]	Matrix determinant and MLP	D-E	97.6
A. Sharmila et al.[9]	NB	D-E	94.12
A. Sharmila et al.[9]	k-NN	D-E	94.62
Yang Li et al[14]	MRBF-MPSO, PSD, PCA, SVM	S- F	97.6
Kaveh et al[18]	Discrete Short Time Fourier Transform (DSTFT) and MLP	D-E	95
Enamul Kabir et al.[3]	SVM	D-E	74.38
Enamul Kabir et al.[3]	Naïve Bayes	D-E	88.25
Enamul Kabir et al.[3]	Logistic regression	D-E	93.13
Proposed Method	**Fractal + Cosine similarity**	**S- F**	**100**

The results of the comparison in Table 4.40 show that fractal and cosine similarity models outperform most of the previous methods. Most of the other approaches to classification of EEG signals have not used more than two classifiers to examine and evaluate the performance of their classifier. In contrast to our method, we have classified different EEG signals and identified different states through those signals.

Chapter 5 – Conclusions and Future Work

5.1 introduction

This chapter addressed conclusions and future works related to the research work discussed in the thesis.

5.2 Conclusion

Electroencephalography (EEG) is a test that uses electrodes (small flat metal discs) attached to your scalp to record and evaluate the electrical signals in the human brain. Electrical impulses in the brain are known as brainwaves. Many medical diagnoses can be detected utilizing EEG signals. The most common one is seizure epilepsy.

The Bonn university dataset is one of the most commonly used datasets for detecting EEG signals for epileptic seizures. It is divided into five different files and any file has 100 samples. Each of which provides information on a specific instance. As a consequence, we have 500 persons with data points collected over a 23-second period.

A novel method has been proposed based on fractal metric and cosine similarity. A new Fractal mathematical measure is derived in order to group extremely related EEG data while disregarding other signals. Technically, this approach has improved classification accuracy by measuring similarity searches among EEG signals. The proposed system provides two designed models with PSO as optimization and without optimization. Results and experiments are explained which were obtained from the proposed system. The results were examined and performed without optimization and with optimization using the PSO algorithm. Several metrics are applied, such as accuracy, precision, recall, and F1-measure to examine the performance of proposed models. The experiments that have been shown were based on different time lengths of EEG signals. Furthermore, experiments and tests were conducted on a split dataset into several training and testing sizes. Training and testing sizes were determined by using 90% and 10% of the total dataset, respectively. 20%, 30%, and 40% of the test dataset have been used to get the varied results and to illustrate the effect of the training set's size on the patterns generated.

The fractal and cosine similarity models have achieved high accuracy of up to 100% in the case of two-class classification and up to 86 % in the case of five-class classification of EEG data while using a 90 % training set size and without optimization. The optimization by pso is applied with our proposed method and the accuracy metric is increasing. It reaches 100% for the two classes and 88% for the five classes of EEG signals. The lowest efficiency metric was obtained by using 60% of the EEG dataset for training and 40% for testing. The lowest accuracy of the two classes is 96.25 % without optimization and 98.75 % with optimization. In the case of the five classes, the accuracy reached up to 73% without optimization and 75% with optimization.

Our suggested models have been tested with different signal durations to see how the result of the predictions changed. The test has been implemented on signal durations of 1 second, 5 seconds, 10 seconds, 15 seconds, 20 seconds, and the total signal length at 23.6 seconds. All achieved results were based on 70% of the training set and 30% of the testing set.

The accuracy metric for binary classification is achieved up to 96.66 % without optimization and 100 % with optimization using an EEG signal with a length of one second. The result was obtained in five classification classes without PSO 62.6 % and with optimization up to 64.33%. The best result has been obtained with the total signal length. It reaches according to the accuracy, up to 100% with and without optimization in some cases. However, the optimization by PSO still achieves higher accuracy. 78.6% accuracy for the classification of five classes and it was optimized by PSO to reach up to 80.66%.

The proposed models have been compared with the most common machine learning algorithms utilized for classification problems. Our models outperformed these algorithms in many situations. In comparison with other previous works, we outperformed or equal the binary classification problems. On the other hand, most of the other approaches to classification of EEG signals have not used more than two classifiers to examine and evaluate the performance of their classifier.

5.3 Future works

- Processing EEG data using a variety of techniques, such as the Fourier transform, wavelet transform, and peak detection, and others.
- Applying the proposed system with many methods of features selection and extraction to increase efficiency, reduce classification time, and reduce memory size usage.
- The possibility of developing the proposed models by classifying patients' EEG signals online and giving the diagnosis result to the health center or the specialist doctor to save time and effort reading EEG signals.
- Developing the classifier of fractal metric and cosine similarity and making it a general classifier.
- A user interface for the proposed system will be built to make it an easier application for the users.

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الخلاصة

يتم تسجيل كمية هائلة من بيانات السلاسل الزمنية الطبية الحيوية مثل إشارات مخطط كهربائية الدماغ (EEG) يوميًا لمراقبة أداء الإنسان وتشخيص أمراض الدماغ المختلفة. بالنسبة للباحثين، فإن تحليل هذه السجلات الطبية الحيوية بكفاءة ودقة يمثل تحديًا. يمكن أن يساعد تطوير طرق جديدة لشرح وتصنيف هذه الإشارات في إدارتها والتحقيق فيها وتشخيصها.

في هذه الرسالة، نقترح نماذج جديدة لتصنيف إشارات EEG وتحليلها بناءً على تشابه الجزيئي وجيب التمام. يستخدم النموذج الأول المقترح تشابه الجزيئيات والمصنف المستند إلى جيب التمام دون تحسين، بينما يستخدم النموذج الثاني المُقترَح مُصنِّف تشابه الجزيئيات وجيب التمام مع خوارزمية تحسين سرب الجسيمات(PSO) .

في الواقع، يتم تنفيذ النموذجين المطورين من أجل معرفة ما إذا كانت طريقة التصنيف المقترحة تتطلب دعم التحسين أو يمكن أن تكون مستقلة.

تم اشتقاق نموذج رياضي كسوري في هذا العمل وتم الحصول على معادلات وعوامل رياضية جديدة للجزيئيات. يتم اشتقاق عامل تشابه الجزيئيات الجديد عن قصد كعامل ترتيب. تساعد عوامل ترتيب الجزيئيات في ملامسة إشارات مخطط كهربائية الدماغ وترتيب أفضل مجموعة لإشارة الوصول الجديدة. وبالتالي، أصبحت مهمة التصنيف أسهل بكثير حيث يعمل المصنف على سجلات مماثلة فقط.

تم استخدام مجموعة بيانات جامعة بون لمخطط كهربائية الدماغ (EEG) في هذه الرسالة. وهي مقسمة إلى خمسة ملفات (فئات) مختلفة، ويحتوي كل ملف على ١٠٠ عينة.

تمت مقارنة هذا العمل مع خوارزميات التعلم الآلي الأكثر شيوعًا المستخدمة في مشاكل التصنيف، مثل آلة متجه الدعم، وأقرب جار منK ، ونايف بايز، والغابة العشوائية، وشجرة القرار. أظهرت النتائج أن الحلول المقترحة تفوقت على معظم خوارزميات التعلم الآلي من حيث مقياس الدقة.

علاوة على ذلك، أظهرت النتائج أن النماذج المقترحة فعاله في تصنيف اشارات مخطط كهربائية الدماغ، حيث حققت نماذج التشابه الجزيئي وجيب التمام دقة عالية تصل إلى ١٠٠٪ في حالة التصنيف بفئتين وما يصل إلى ٨٨٪ في حالة التصنيف لخمس فئات من إشارات EEG .ستساعد نتائج هذا العمل المتخصصين في المجالات الطبية ذات الصلة وتقليل الجهد في اكتشاف أمراض الدماغ وتشخيصها.

جمهورية العراق
وزارة التعليم العالي والبحث العلمي
جامعة القادسية
كلية علوم الحاسوب وتكنولوجيا المعلومات

التصنيف الالكتروني الصحي للنبضة الدماغية بناءً على التشابه الجزيئي وجيب التمام

رسالة ماجستير
مقدمة إلى مجلس كلية علوم الحاسوب وتكنولوجيا المعلومات في جامعة القادسية كجزء من متطلبات نيل شهادة الماجستير في تخصص علوم الحاسوب

من قبل

صفاء شبرم علي

بإشراف:

أ.م.د. ضياء عيدان جبر الشمري

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