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EEG Signals Classification based on mathematical selection and cosine similarity

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ABSTRACT

This paper presents a new electroencephalogram (EEG) signal classification using a fractal-cosine similarity approach for diagnosing epilepsy patients. The proposed system provides two designed models with PSO as an optimization technique and without optimization. A full classification design is achieved, including prepressing data by normalization, Particle Swarm Optimization (PSO) as optimization technique to reduce the features of EEG signals, Fractal metric computations, metric mapping, and cosine similarity for the final decision. This paper used the BONN university EEG dataset, which consists of five categories. The dataset was divided into four groups based on training set size and testing set size. First, we are used to the training and testing ratio of 90/10. The second case is 80/20, the third case is 70/30, and the final case is 60/40 respectively. The proposed model achieves high rates of accuracy up to 100%.

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1. introduction

An Electroencephalogram (EEG) is a test that uses electrodes (small flat metal discs) attached to your scalp to record and evaluate the electrical signals in your brain[1]. The cells of the brain interact together using electrical activity. They are always active and work even during sleep time[2]. 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[3]. 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[4]. When you sleep Delta (1-3 Hz) signal is appear, 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. gamma signal (39 – 42 Hz) becomes clear when high Concentration. These signals are the common names of EEG waves[3][5]. 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 non-

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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 of memory and accidental stroke are all identified using EEG[6]. Furthermore, it is utilized in many fields of research like brain computer interface (BCI), virtual reality, gaming, emotions recognition, robotics and more.

1.1Motivation

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 diagnosis 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 inpersistent results. Technically, it is significantly required to develop a potential classification model that can overcome traditional classification problems and disadvantages.

1.2 Contribution

- The first model was built based on Fractal Metric-Cosine similarity, and the results were great, with the accuracy metric reaching 100% in some classification scenarios.

- 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. According to the accuracy metric, it reached up to 100% in many classification cases.

1.3 paper layout

The structure of this paper is arranged as: Section 2 describe the related works. Section 3 illustrates the dataset which was used in this paper. Section 4 describes machine learning and its types. Next, section 5 describes the Fractal Cosine classifier for EEG Classification. Then, the K-Nearest Neighbor (K-NN) algorithm is described in section 6. Section 7 illustrates the Support Vector Machine (SVM). Section 8 illustrates the Naive Bias machine learning algorithm. Section 9 describes the Decision Tree algorithm. The Random Forest algorithm is described in section 10. Analysis and evaluation are described in section 11. Finally, section 12 presents conclusion and future work.

2. Related works

Many types of research and studies have been introduced into the classification of EEG based on various approaches. Raghu et al.[9] utilizing the matrix determinant method based on support vector machine (SVM), k-Nearest Neighbor (KNN), and multi-layer perceptron MLP. A research papers published in 2015 by Samiee et.al. [10], The feature has been extracted with Discrete Short Time Fourier Transform (DSTFT) and classifying the EEG signals by multi-layer perceptron neural network (MLPNN). Convolution Neural Network (CNN) for EEG Classification have been proposed by Lian et al.[11] that Test both time domain and frequency EEG features and their impact on CNN. Naïve Bayes(NB) classifier and k-Nearest Neighbor (KNN) have been proposed by Sharmila et al.[12] to diagnose the epilepsy patient. Kabir et al.[13] K-means clustering is used to divide each category of EEG data into multiple groups. Then, select some typical features from each cluster and use Support Vector Machine (SVM), Naive Bayes, and Logistic regression to evaluate that feature set and classify it.

3. Dataset

One of the most widely used datasets for classifying EEG signals for epileptic seizures is the Bonn University dataset. 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 1.

Table 1: Describe Bonn EEG 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

4. Machine learning

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.

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. 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.

3.1 Types of Machine learning:

Machine-learning may be classified into four types based on the purpose for which it is used: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. As seen in figure 1.

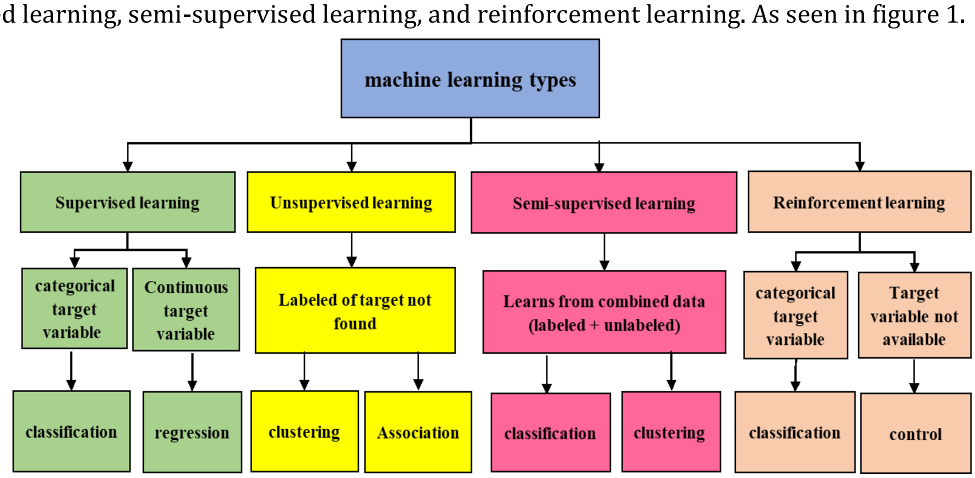

Figure 1: Types of machine learning algorithms

3.1.1 Supervised Learning

Supervised learning algorithms are learning algorithms that utilize training data and related labels (output) with each data sample during the model training process. 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 the 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.

- Classification algorithms are utilized with the aim of predicting output data labels according to the learning of the model during the training phase. 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 the patients who make an exam to cancer, the result has cancer or not have cancer.

- Regression is a type of supervised machine learning task in which the goal is to estimate the value of something. 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 utilizing input data features or characteristics and associated numerical results. For example, predicting house prices or stock prices.

3.1.2 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. This approach of 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 in clusters or arranged data in a method that appears more regular. 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.

3.1.3 Semi-supervised Learning

It is a compound between supervised and unsupervised learning. It utilized both labeled data as well as unlabeled data. Typically, this combination will consist of very little value of labeled data and a very big part of unlabeled data. Which gives the advantages of learning to 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.

3.1.4 Reinforcement Learning

It is a method of learning that interacts with its environment by creating actions and detecting errors or rewards. The most important aspects of reinforcement learning are trial and error search and delayed reward. This approach allows machines and software agents to automatically identify the best behavior in a given situation in order to optimize their efficiency. For the agent to understand which action is optimal, simple reward feedback is required. Nowadays, reinforcement learning applications have become very popular, such as self-driving vacuum cleaners, driverless cars, etc.

5. Fractal Cosine classifier for EEG (proposed methods)

Fractals are the theory of matching self-similarity. It is made up of repeating patterns of self-similar objects with varying sizes and offsets. In fractals, the initial item is known as the range, while a smaller object generated from it is known as a domain. A novel design for an EEG classification system is mainly based on Fractal 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 as a preprocessing step, Particle Swarm Optimization (PSO) is applied to select important EEG features that play an important role in diagnosing Epilepsy seizure, Fractal metric computations, and metric mapping are applied To enhance the categorization process by spreading EEG signals into unambiguous searching space levels, all Fractals metrics are converted to integer values rather than real numbers, and cosine similarity is used for the final decision to predicate the class type. The proposed system provides two designed models with PSO as optimization and without optimization.

6. k-Nearest Neighbor

The algorithm of the k-Nearest Neighbor (k-NN) is easy-to-understand for both classification and regression[14]. It's also a lazy approach that doesn't make any generalizations with the training data points; in other words, it keeps all of the training data during the testing stage[15]. The K-Nearest Neighbor method is a nonparametric supervised pattern classifier that is simple to use but achieves high classification accuracy. It's a strategy for identifying objects based on the feature space's nearest training samples[16]. The k-nearest neighbor algorithm is one of the most basic of all machine learning algorithms: an item is classified by a majority vote of its neighbors, and then allocated to the class in which the majority of its k-nearest neighbors are members.

7. Support Vector Machine (SVM)

SVM is a supervised method for machine learning which are 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 separates 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, sigmoid kernels, and so on.

8. Naive Bias

it is a probabilistic machine learning algorithm depend on the Bayes Theorem[20]. 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[21]. The Nave Bayes model is divided into three kinds. Gaussian naive Bayes, multinomial naive Bayes, and Bernoulli naive Bayes[21][22]. Gaussian Naïve Bayes is the most basic Nave Bayes classifier, assuming that every label's data is obtained from a simple Gaussian distribution. Multinomial Nave Bayes assumes that the features come from a simple Multinomial distribution. This type of Nave Bayes is best proper to features that contain discrete counts. In the Bernoulli Nave Bayes model, features are considered to be Boolean or binary 0s and 1s. Bernoulli Nave Bayes can be used in text classification models. Nave 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.

9. Decision Tree

It is a supervised method that may be used for both classification and regression tasks[23]. As the name suggests, a decision tree is a tree-like structure that the internal nodes correspond to testing on an attribute, each branch reflects the test's result, and each leaf node represents the class label, and the decision should be made after all attributes 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[24]. The determination of the attribute for the root node at each 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 of 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.

10. Random Forest

The Random Forest algorithm is a supervised learning technique which utilized for classification problem as well as a regression task. A forest is made up of trees, and having a greater number of trees indicates having a more robust forest[25]. 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[25]. It is a group of collaborative approach that eliminates over-fitting by averaging the results, making it better than a single decision tree[26]. 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 at 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.

Algorithm 1 (Normalization)
Input: RowNo, ColNo // Number of rows and columns in EEG dataset EEGData [RowNo, ColNo] //EEG dataset in two-dimension array excluded data label
1: CurrentMax=maximum_value in EEGData [RowNo, ColNo] 2: CurrentMin=minimum_value in EEGData [RowNo, ColNo] 3: TargetMax=1 4: TargetMin=0 5: for i=1 to RowNo 6: for j=1 to ColNo 7: Normalized_EEG[i,j]= ((EEGData [i,j]-CurrentMin)/(CurrentMax- CurrentMin))*(TargetMax-TargetMin)+TargetMin 8: end for 9: end for
Output: Normalized_EEG [RowNo, ColNo] // represent normalized EEG dataset values between [1,0]

```
Algorithm: 2 (Fractal metric (F) for each class)

Input:
    SummuryVector[n] //average for five classes based on selected features
    Totaverage      // total average overall label
    Normalized_EEG [RowNo, ColNo]    // Normalized EEG dataset

1: For i=1 to n// number of labels
2: AlphaSum=0
3: AlphaSum[i] = AlphaSum[i] + abs (SummuryVector[i] - Totaverage)
3: End for
4: AlphaSum[i]= AlphaSum[i]^2 // sqrt of summation
5: BetaSum=0 //
6: For i=1 to n
7: BetaSum[i] = BetaSum[i] + (SummuryVector[i] - Totaverage) ^ 2
8: End for
9: For i=1 to n
10: Fmetric[i] = AlphaSum[i] / BetaSum[i]// five fractal metrics
11: End for

Output:
    Fmetric[n]// Fractal metric for each class, n is number of classes
```

```
Algorithm: 3(classifier)

Input:
    SlctedPsoCol[n] // vector of selected features by pso, n is number of features
    Fmetric[n]// fractal metric for n classes
    Input signal (D) // is a vector represent EEG signal

// calculate DAverage
1: Dsum=0
2: For i=1 to SlctedPsoCol[n]
3: Dsum =Dsum+EEG[i] // summation column that have selected feature
4: End for
5: DAvarege= Dsum/n
6: AlphaSum=0 // Initial value of the numerator in the fractal equation (domain)
7: for i=1 to n
8: AlphaSum = AlphaSum + abs (D[SlctedPsoCol[i]] - DAvarege)
9: end for
10: AlphaSum= AlphaSum^2 // Squared the sum
11: BetaSum=0 // The initial value of the denominator in the fractal equation (domain)
12: for i=1 to n
13: BetaSum = BetaSum + (D[SlctedPsoCol[i]] - DAvarege) ^2
14: end for
15: EEGFmetric= AlphaSum / BetaSum // represent fractal metric for new EEG signal
// search for smallest difference to find predicate class
16: CurrentSmallest=Abs (Fmetric[1]-EEGFmetric) //
17: ClassIndex=1
18: for i=2 to ClassTot //number of fractal metrics
13: if Abs (Fmetric[i]-EEGFmetric) <CurrentSmallest then
  CurrentSmallest= Abs (Fmetric[i]-EEGFmetric)
  ClassIndex=i
14: End if

Output:
    ClassIndex// represent class (decision of pattern explains the status of EEG signal)
```

11. Experiments and Results

There are several techniques developed for detecting epileptic seizures. The University of Bonn dataset had five types of classes. We concentrated on the Seizure activity class. We used a binary classification to compare the epilepsy cases to the other four cases that were available in the dataset. 90% of the total dataset was used for training and 10% for testing. To show the effect of train set size on the patterns formed, 20%, 30%, and 40% of the test dataset were applied to show the changes in results. All computations used a normalization method based on the Z1-score and the EEG signal length (time) within 23.6 s. Furthermore, accuracy metrics are applied to compare the proposed approach with the previously existing approaches. Only approaches that were tested within the same dataset (classes) are included in this comparison, allowing for results to be compared between sets with the same classes.

Table 2: Explain the accuracy result of our model with and without PSO and machine learning algorithms for 10% testing size

dataset	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	10%	100	100	60	100	100	80	100
S-O	10%	100	100	60	95	100	85	100
S-F	10%	100	100	60	100	100	85	100
S-N	10%	100	100	60	100	100	75	100

Table 3: Explain the accuracy result of our model with and without PSO and machine learning algorithms for 20% testing size

dataset	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	20%	100	100	57.49	100	100	70	100
S-O	20%	100	100	57.49	95	100	70	97.5
S-F	20%	100	100	57.49	92.5	92.5	92.5	95
S-N	20%	100	100	57.49	95	100	77.5	100

Table 4: Explain the accuracy result of our model with and without PSO and machine learning algorithms for 30% testing size

dataset	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	30%	98.33	100	60	100	100	76.66	100
S-O	30%	98.33	100	60	96.6	100	86.66	100
S-F	30%	98.33	100	60	93.3	98.33	88.33	96.6
S-N	30%	100	100	60	96.66	98.33	81.66	100

Table 5: Explain the accuracy result of our model with and without PSO and machine learning algorithms for 40% testing size

dataset	Test size	Proposed classifier without PSO	Proposed classifier with PSO	KNN	SVM	RF	DT	NB
S-Z	40%	96.25	98.75	58.75	100	98.75	75	100
S-O	40%	97.5	100	58.75	96.25	100	78.75	100
S-F	40%	96.25	98.75	58.75	93.75	97.5	77.5	95
S-N	40%	97.5	98.75	58.75	96.25	98.75	77.5	100

Table 6: Explain the comparison of proposed model with the previously existing approaches

Author	Method	Datasets	Best Accuracy
Raghu et al. [1]	Matrix determinant and MLP	A-E	99.45
A. Sharmila et al.[2]	Naïve Bayes	A-E	100
A. Sharmila et al.[2]	k-Nearest Neighbor	A-E	100
Kaveh Samiee et al[5]	Discrete Short Time Fourier Transform (DSTFT) + MLP	A-E	99.8
JIAN LIAN et al[7]	Pairwise matching of EEG signal and CNN	A- E	99.84
Enamul Kabir et al.[8]	Support Vector Machine	A- E	98.13
Enamul Kabir et al.[8]	Naïve Bayes	A- E	98.50
Proposed Method	**Fractals metric – cosine Classifier without optimizer**	**A-E**	**98.48**
Proposed Method	**Fractals metric – cosine Classifier with PSO**	**A-E**	**100**
Raghu et al.[1]	Matrix determinant and MLP	B-E	99.76
A. Sharmila et al.[2]	Naïve Bayes	B-E	99.25
A. Sharmila et al.[2]	k-Nearest Neighbor	B-E	98.25
Kaveh Samiee et al[5]	Discrete Short Time Fourier Transform (DSTFT) + MLP	B-E	99.3
Enamul Kabir et al.[8]	Support Vector Machine	B-E	97.75
Enamul Kabir et al.[8]	Naïve Bayes	B-E	98.38
Proposed Method	**Fractals metric – cosine Classifier without optimizer**	**B-E**	**98.48**
Proposed Method	**Fractals metric – cosine Classifier with PSO**	**B-E**	**100**
Raghu et al.[1]	Matrix determinant and MLP	C-E	97.6
A. Sharmila et al.[2]	NB	C-E	99.62
A. Sharmila et al.[2]	k-Nearest Neighbor	C-E	97.25
Kaveh Samiee et al[5]	Discrete Short Time Fourier Transform (DSTFT) + MLP	C-E	98.5
Enamul Kabir et al.[8]	Support Vector Machine	C-E	100
Enamul Kabir et al.[8]	Naïve Bayes	C-E	99.63
Proposed Method	**Fractals metric – cosine Classifier without optimizer**	**C-E**	**100**
Proposed Method	**Fractals metric – cosine Classifier with PSO**	**C-E**	**100**
Raghu et al.[1]	Matrix determinant and MLP	D-E	97.6
A. Sharmila et al.[2]	Naïve Bayes	D-E	95.12
A. Sharmila et al.[2]	k-Nearest Neighbor	D-E	95.62
Kaveh Samiee et al[5]	Discrete Short Time Fourier Transform (DSTFT) + MLP	D-E	95
Enamul Kabir et al.[8]	Support Vector Machine	D-E	75.38
Enamul Kabir et al.[8]	Naïve Bayes	D-E	88.25
Proposed Method	**Fractals metric – cosine Classifier without optimizer**	**D-E**	**98.48**
Proposed Method	**Fractals metric – cosine Classifier with PSO**	**D-E**	**100**

12. Conclusion

In this paper, we have introduced a novel method for classification of EEG signals by utilizing Fractal Metric-Cosine similarity to diagnose epileptic seizures from EEG signals. The proposed analysis in this paper targeted the investigation of the accuracy of our proposed method and made a comparison with the most popular machine learning algorithm that is used for classification. In total, the overall classification problems were formed using the University of Bonn database. Technically, our models in many classification cases overcame the machine learning algorithm and achieved a high accuracy up to 100%. Furthermore, the proposed models Outperformed many previously existing approaches.

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