A New Method for EEG Signals Classification Based on RBF NN

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Abstract. Automation is necessary since traditional EEG assessments are tedious and time-consuming, particularly the outpatient kind. For this manuscript, the researchers focused on constructing a three-class EEG classifier using FeExt and RBFNN, which stands for Radial Basis Functional Neural Network. If FeExt is finished, RBFnn may be trained to equally recognize the trends. Seizure signals are one of the various anomalies that may be identified using the EEG signal. Stable, interactive, and seizure signals are the three different types of EEG signals. This manuscript's goal is to classify EEG signals using RBFnn. EEG signal data were relied on the CHB-MIT Scalp EEG dataset. There are 55 various FeExt schemes investigated, and a classifier is constructed that is relatively quick and accurate. The 10 morphological features of the literature were not explored or compared with the extraction techniques. According to research, the multilayer perceptron with momentum learning rule is the best classifier topology, and the FeExt algorithms PCA, Bi-gonal 2.2, coif1, DCT, db9, Re-Bi-gonal 1.1, and sym2 perform better than others. The recorded results may be effectively classified for EEG rhythm for quick examination by a neurology professional. Therefore, quick, accurate diagnosis that saves time. Using a similar method, the EEG rhythm categorization for other brain illnesses may be used.

Keywords: Electroencephalogram (EEG), Radial Basis Functional Neural Network (RBFnn), EEG rhythm Classifier.

1 Introduction

EEG analysis forms the basis of brain disease (Neurons disease) diagnosis and is preferred since it is non-invasive, reliable, and less costly than other methods. It utilized to analyze the activity of the brain by cerebral waves recording that setting the head electrodes along the scalp. Diagnoses consistent with EEG are typically performed manually by practitioners of medicine. The key challenge in diagnosing brain failure is to evaluate each EEG rhythm and to correlate the distortions found in different brain diseases [1]**[20].** Due to irregular brain signal can occur spontaneously, monitoring a (24-hour/7 days) EEG signal becomes very repetitive and time-consuming since it can involve massive of EEG signals. It is therefore required to automate the entire EEG signals classification process and preferably diagnose these signals accurately [2]**[21].** Each scalp area produces waves that allow reflecting the cerebral-health status. The EEG analysis shows many anomalies in reported signal waves in the case of diseases. In order to facilitate clinical diagnosis, the detection of these anomalies helps the physician to estimate the disorder and its level. This process can be also used in biomedical researches to investigate cerebral disease characteristics. The major problem associated with EEG analysis is the amount of EEG signals available, especially for ambulatory EEG and the inter-patient variation in the morphology of the EEG signals. It becomes a time-consuming task for classifying/ separating the EEG signal and is also prone to errors induced by manual intervention. This manuscript describes the design of an automated EEG classifier [3]**[22].** Three types of EEG signals are considered here, healthy, interictal, and seizure signals. The EEG data were collected from the database of CHB-MIT Scalp EEG database. Generally, the FeExt schemes of Transform and morphological are mostly preferred. The three transformation mechanisms are discussed with three other morphological FeExt in this manuscript: DFT, PCA, and DWT [4]**[23].** Average classification accuracy exceeding 98.2 percent was reached by the classifier. **The methodology of the proposed system begins from The EEG data is collecting from the CHB-MIT Scalp EEG dataset. forty-one different feature extraction schemes are examined, along with a compact set of statistical morphological features and a reasonably accurate and fast classifier is designed. Ten morphological features and these feature extraction methods have not yet been thoroughly examined and compared in the literature. The bipolar EEG channels were selected for analysis. The EEG data used in our study were from different patients (24-h EEG recorded) from both epileptic patients and normal subjects. Digitized data were stored on an optical disc for further processing.**

The manuscript was organized as follows: Section two, The Description of Dataset was introduced. Section Three, Literature of the Related Works. Changing The Features of the Domain was presented in Section Four. Findings and Discussion, are described in Section Five. And finally, in Section Six, The Conclusion was presented.

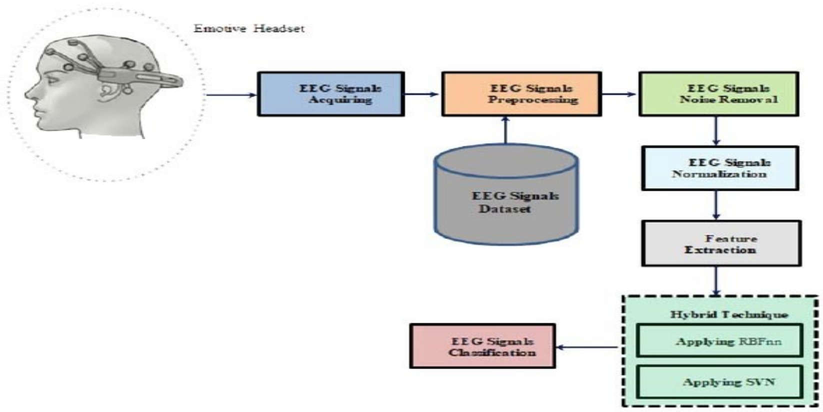
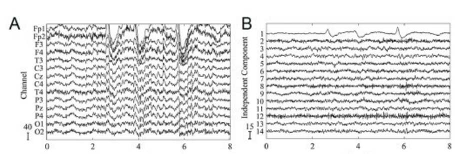


Fig. 1. The Proposed System Structure

2 The Description of Dataset

This manuscript utilized the CHB-MIT Scalp EEG database. The portable wireless headset Emotive is utilized by the Brain-Computer Interfaces (BCI) applied in this work. In total, “16 Sensors”, “2 Reference Signals and 14 Channels” are available: “AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4”[5]. Fig. 1 depicts the Emotive headset showing the proper placement of its electrodes. The sensors are pre-dampened with a saline solution, then applied to the scalp according to the 10-20 international standard as shown in Fig. 2 [6]. The headset’s 14 channels are sampled at a rate of 128 Hz, then digitized with a 14-bit-per-sample resolution before being applied to a built-in fifth-order Butterworth digital filter that cuts-off frequencies above 64 Hz. Furthermore, two notch filters suppress the interference of 50/60 Hz caused by the power lines [7]. All the resulted sensor signals are included in the 0.2 to 64 Hz frequency band and are transmitted wirelessly via a proprietary encoding/modulation on a 2.4 GHz carrier to a USB module on the PC [8]. In Fig. 2, the first two sensor readings are the left front sensor (AF3 and F7) and the right front sensor (AF4 and F4) are the last two sensor readings. Blinks impact the frontal sensors mainly. Two involuntary blinks occur, seen in the signals as sharp rises and falls. Voluntary continuous blinking can easily be detected at the end of the signal [9].



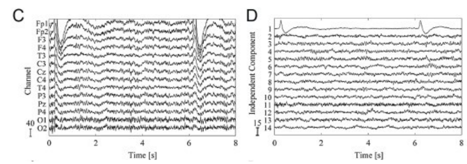


Fig. 2. Separation of EEG Epoch Sample Showing 2- Involuntary Blinks of the Eye Followed by a Voluntary One's Series. (A) An 8-s EEG Signals, (B) 14-Channel of EEG Signals, (C) Calculated Thresholds for the 14 Channels (First and Eighths were Classified as Art factual Components), (D) Extracted Involuntary Eye Blink Features of 14-Channel Signals.

EEG signals utilized in the manuscript was collected from this data set consisting of 5-sets, such as “Group A”, “Group B”, “Group C”, “Group D”, and “Group E”, obtained accord the following: “Group (A)” to “Group (B)”: This consists of a normal EEG signal with eyes open / close, respectively. “Group (C)” to “Group (D)”: During the seizure-free hemisphere formation interval of the brain's hemisphere, EEG is recorded. (i.e. Inter Ictal (in Latin,) (Seizure in English). “Group (E)”: here, EEG during seizure disorder shall be recorded (i.e. Ictal)[10].

3 Literature Related Works

This part includes a thorough discussion with many other machine learning classifiers previous similar studies on functional extraction using linear and nonlinear approaches. Many epileptic seizure identification methods according to linearity and non-linearity of EEG signals [11] have currently been published. Function extraction strategies are crucial to differentiating between non-seizure, seized and normal EEG behavior with machine learning algorithms in the methods that these studies suggest. This includes extraction of the subband frequency, analyzing the entropy, utilize of wavelet degradation, biggest exponent from Lyapunov, fractal estimation, exponent Hurst and cumulative-high-order. Kumar et al. [12] has recently suggested fuzzy approximate entropy (fApEn) and extraction method of EEG dependent WT. Studies have suggested method of overcoming a classic wavelet transformation computational load, as stated by Chen et al. [13] for epileptic seizure behavior classification, RBFnn and logistic regression. In addition, the epileptic seizer events were categorized by the utilize of RBFnn and logistic regression. Kumar et al. [14] and the SVN for functional classification recently reported fApEn method. EEG was breaking up into subbands of discreet wavelet transforms then measured for the disorderly behavior of EEG signals by fApEN of each subband. The authors along with the RBF have recorded highest rating precision with the SVN classifier. The literature review showed that most experiments of signal processing techniques and machine learning strategies for seizure activities were not able to achieve optimal outcomes seizure-free signals of the EEG or from seizure-free EEG activity from stable EEG data. FeExt of EEG is further helpful in classifying, recognizing patterns and detecting events. Hand-designed EEG extraction techniques cause poor analysis. Recurring auto encoders FeExt for EEG are then utilized [15]. Also, the echo-state network FxExt offers better grading and clustering. The classification of motor imaging is based on b and l spatial rhythm distribution. Gradient descent and recursive techniques of classification offer less precision and pace. Consequently, the EEG classification is performed by the Multilayer Perceptron Neural Network (MLP-NN) [16]. The speed and the accuracy of the convergence are measured and matched the metaheuristic algorithm efficiency. Neurocognitive ability is the human's mental/cognitive potential and is utilized for research on neurology. The Neuro-cognitive effect is sleep scoring. The recurring neural network [17] with the utilize of long-term memory-blocks increase the accuracy of the classification involves sleep labeling, non-fast movement of the eyes and phase N1 in sleep, this mean a transition between drowsiness/wakefulness. Deep learning is utilized for the detection of temporal dependency in EEG [18]. For capturing high-level trends in EEG, LSTM [19] will be utilized. LSTM utilizes a fully linked layer for extracting stable, epileptic features and Softmax-layer for the extraction of expected output labels, and it also maintains a high detection efficiency in the detection of devices, such as eyes and muscles movements, and background noises in captured EEG, etc. The transformation between sleep periods in the EEG and extracting its features of the time-invariant are some of the main difficulties. In [20], the authors utilized bidirectional methods CNN and LSTM to pass features accurate and F1 values for different data sets, contrasting their findings and various neural network techniques with statistics.

$$Sample\ Entropy = -\,log \frac{\frac{1}{N-m+1}\sum_{i=1}^{N-m+1} \emptyset^{m}(r,i)}{\frac{1}{N-m}\sum_{i=1}^{N-m} \emptyset^{m+1}(r,i)} \quad (1)$$

$$Fuzzy\ Entropy = \frac{N-m\ \sum_{=1}^{N-m+1}\frac{\sum_{j=1}^{N-m+1} \emptyset^{m}(r,i,j)}{N-m+1}}{N-m+1\ \sum_{i=1}^{N-m}\frac{\sum_{j=1}^{N-m} \emptyset^{m+1}(r,i,j)}{N-m}} \qquad (2)$$

4 Changing The Features of the Domain

In changing domains, signals may be properly represented. There are a number of benefits to representing a signal in morphing domains, including as Frequency domain representation decreases the size of the input vector by removing irrelevant or superfluous information, which is particularly advantageous when using signal neural network architectures, compression for effective data storage, and noise reduction [21]. In the literature, there is a lot of use of transforms such the DFT, DCT, PCA, and DWT in combination with the EEG. Only major transform domain components, such as signal shape, may be maintained without considerable information loss. The parameters used to pick features were 99 percent signal energy retention and percent root mean difference. These components are then used to create the training input vector for the RBFnn [22].

Table 1. Examining the performance of several RBFnn models

RBFnn Model	Best Configuration	Fusibility Accuracy (%)	Standard Accuracy (%)	Stroke Accuracy (%)	Average Accuracy (%)	Time/standard/1000Epochs seconds)
MLP	Single hidden layer, 10 Hidden Layer neurons, Momentum learning	90.33	90.88	93.55	91.173336	25.981
SOFM	8 x 8 size of the Mapping	89	94.98	88.87	89.3445545	305.119
RBF	50 clusters, kernel adatron	89.33	91.18	88.66	95.522251	371.223
SVN	Null	91	93.27	91	98.246346	610

5 Findings and Discussion

Table 2 lists the results of all the schemes' performance. The performances of each transform category are assessed in terms of percent average accuracy, percent stroke accuracy, and optimum data pre-processing time in order to narrow the search for the best strategy. Bi gonal 2.2, coif1, db9, Re_ Bi gonal 1.1, sym2, DCT, and PCA are the schemes that perform better. In the case of FFT, however, the data pre-processing time for various transformations is shown in Fig. 3. Transforms like FFT, DCT, PCA, and DWT may be used to FeExt for RBFnn-based pattern categorization of EEG signals. EEG signal amplitude, Mean Power Spectral Density (MPSD), Peaks distance, Energy of the Signal, Peaks area, Singular Decomposition Value (SVD), Area under the auto-correlation curve, and signal interval are just a few of the statistical morphological features that can be used with RBFnn-based EEG classification. This collection of statistical characteristics is small, and the results are represented in a feature vector with a decreased dimension.

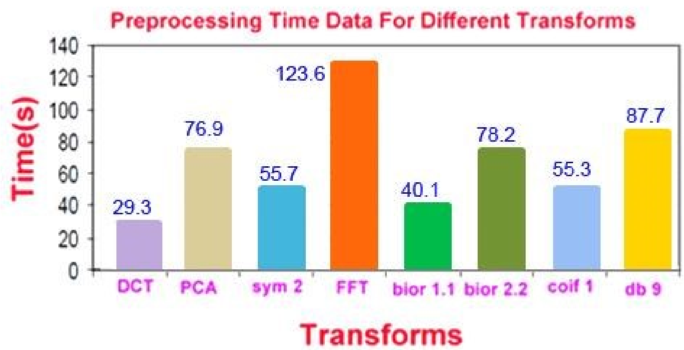


Fig. 3. Pre-processing Time consumed by best-performing schemes.

Table 2. The identifications of the Patients (P_ID) in the Health Status (H_St) may be 0=Healthy, or 1 Non-Healthy.

P_ID	H_St	P_ID	H_St	P_ID	H_St	P_ID	H_St	P_ID	H_St	P_ID	H_St
1	1	11	1	21	1	31	0	41	0	51	0
2	1	12	1	22	1	32	0	42	0	52	0
3	1	13	1	23	1	33	0	43	0	53	0
4	1	14	1	24	1	34	0	44	0	54	0
5	1	15	1	25	1	35	0	45	0	55	0
6	1	16	1	26	1	36	0	46	0	-	-
7	1	17	1	27	1	37	0	47	0	-	-
8	1	18	1	28	1	38	0	48	0	-	-
9	1	19	1	29	1	39	0	49	0	-	-
10	1	20	1	30	1	40	0	50	0	-	-

Table 3. The effectiveness of different FeExt systems

Sr. No.	Structure of FeExt	Number of Nuron in Hidden Layer	Accuracy of the Average (%)	Number of Nuron in Hidden Layer	Stroke Accuracy (%)	Preprocessing-Data Time
1	Bi_gonal	31	94.25667	27.85	94.75	27.68604
2	Bi_gonal	22	94.02333	23.85	94.45	28.41851
3	Bi_gonal	38	94.12333	38.85	94.35	29.08835
4	**Bi_gonal**	**46**	**94.42333**	**13.85**	**94.55**	**29.11511**
5	Bi_gonal	22	94.05667	30.85	94.55	29.49316
6	Bi_gonal	23	93.99	14.85	94.25	30.15026

7	Bi_gonal	30	94.22333	15.85	94.45	30.84684
8	Bi_gonal	15	94.32333	18.85	94.35	30.6519
9	Bi_gonal	43	94.02333	18.85	94.25	31.26219
10	Bi_gonal	29	94.29	29.85	94.45	31.87712
11	Bi_gonal	29	94.35667	20.85	94.65	32.5647
12	Bi_gonal	25	93.99	34.85	94.35	33.17013
13	Bi_gonal	34	94.02333	34.85	94.55	33.47596
14	Bi_gonal	13	93.95667	13.85	94.25	34.04615
15	Bi_gonal	23	94.05667	1.85	94.25	35.06008
16	**coif1**	**29**	**94.15667**	**7.85**	**94.55**	**22.83888**
17	coif2	5	93.99	18.85	94.15	23.55712
18	coif3	23	94.05667	23.85	94.35	24.37332
19	coif4	38	93.95667	38.85	94.25	25.27603
20	coif5	19	93.95667	18.85	94.25	26.30116
21	db1	24	94.25667	11.85	94.75	22.03059
22	db2	37	94.15667	37.85	94.65	22.57694
23	db3	20	94.22333	28.85	94.75	23.09459
24	db4	23	94.22333	17.85	94.75	23.52142
25	db5	14	94.15667	15.85	94.65	24.12922
26	db6	16	94.22333	2.85	94.55	24.59219
27	db7	7	94.12333	11.85	94.55	25.08093
28	db8	41	94.05667	35.85	94.45	25.55431
29	**db9**	**19**	**94.35667**	**19.85**	**94.65**	**27.41787**
30	db10	46	93.50111	46.85	93.08	26.94038
31	**Re_**	**6**	**94.29**	**17.85**	**94.75**	**27.68604**
32	Re_	32	94.09	24.85	94.45	29.72013
42	Re_	2	93.82333	8.85	94.05	34.3755
43	Re	18	93.99	22.85	94.55	34.22256
44	Re_	4	93.95667	4.85	94.45	34.818
45	Re_	3	93.99	34.85	94.35	35.81682
46	**sym2**	**27**	**94.22333**	**27.85**	**94.55**	**23.02003**
7	sym3	26	94.15667	20.85	94.75	23.45988
48	sym4	21	94.09	22.85	94.65	23.80114
54	FFT	17	94.59	17.85	94.85	129.2217
55	**PCA**	**20**	**94.12333**	**17.85**	**94.15**	**6.036395**

6 Conclusion

RBFnn model consisting of single-layer MLP with momentum learning was found to perform best concerning average accuracy, stroke accuracy, and training time. It was confirmed that a minimum of 200 rhythm/class is sufficient to train the classifier. This

experimentation is important since it highlights the power of the RBFnn model to learn from a comparatively small amount of data. This is a welcome result that entails the possibility of a patient, adaptable (customizable) diagnostic system.
Upon experimenting with 55 different combinations of feature vector formation for the three-class problem, it was found that the best-performing schemes in terms of percentage average accuracy, percentage stroke accuracy, and low data pre-processing time are: DCT, Bi_gonal 2.2, coif1, PCA, Re_ Bi_gonal 1.1, sym2, and db9 with the combinations often statistical morphological features each. PCA is a good candidate for FeExt since it offers good accuracy as well as a compact feature set.

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