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Classification of EEG Signals using WPT, MGWO and Rule Based Classifiers

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Abstract: ***The essential intent of the purported work is to develop an accurate automated seizure detection model for the performance evaluation of epileptic patients in an improved manner. Long data sets of EEG signals are recorded for a long duration of time which has taken from PhysioNet CHB-MIT EEG dataset for this experimental work. Six types of elements are excerpted from EEG signals by using WPT method. By using this feature extraction method, variance of monotonic amplitude, Mean of joint instantaneous amplitude and mean monotonic absolute amplitude as features are extracted . These features are inputted to each of the six classifiers for validation of the proposed method. Here, Modified Grey Wolf Optimization technique is used to optimize the parameters of the classifiers. Then, all the features are combinely inputted to the rule based six number of classifiers to detect normal and seizure EEG segments. The developed seizure detection WPT- Naive-Bayes method achieved excellent performance with the average Accuracy, specificity, sensitivity, G-mean, positive predictive value, and Mathews correlation coefficients as 97.24%, 97.34%, 97.13%, 98.1%, 96.99%, 97.66% respectively The average area under curve (AUC) is approximately 1. The proposed method is able to enhance the seizure detection outcomes for proper clinical diagnosis in medical applications.***

Keywords: ***EEG Signal, Epileptic Seizure, WPT, MGWO, Classifiers***

I. INTRODUCTION

A recurrent seizure is used to detect brain disorder in human being. Epilepsy is a common disorder in brain which is found approximately in fifty million people over the world [1]. More than two million people are undergoing treatment in each year [2]. Epilepsy is identified from the recorded brains electrical activity by using EEG signals [3]. An automated detection system is able to distinguish between Epileptic EEG signals and normal signals which is fruitful for diagnoses. In that system , categorization of Electroencephalogram signals are the output and the recorded Electroencephalogram signals is the input.

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Generally first step is the extraction of features and second step is the categorization of the extracted elements for seizure detection in an automated detection system [4] . EEG signals are divided in to different groups to analyze Epilepsy. STFT is utilized in rule-based classification technique to make the signals in to different groups [5]. In [6], N. Rafiuddin et al proposed a method to calculate statistical parameters by using wavelet coefficient. Numerous categorization techniques have been utilized to the automated detection of seizures for effective detection of seizures [7,8] . For two-class categorizations of epilepsy acts, different methods are used : separating Electroencephalogram signals togethered in the ictal and normal stages , a neural network based model [7], an adaptive neuro-fuzzy interference system [9], the Elman network [10], a mixture of model [11,12], a decision tree [13,14], support vector machine (SVM) [14], and a LS-SVM [15] . In [16], author analysed relative values of energy and normalized coefficient of variations. In this work, the accuracy and specificity has been found as 91.8 % and 100% respectively. For three-class categorizations of epilepsy acts : a recurrent neural network [17], support vector machine [18] and the C4.5 algorithm for the decision tree [19] has been proposed. B. Hunya et al calculated sensitivity of 83% by taking 16 number of features extracted in both time domain and frequency domain [20]. In [21], the sensitivity is 100% by using Unsupervised feature learning using Stacked auto encoders method. Features are selected in both time and frequency domain where specificity and sensitivity is found as 94.71% and 89.01% respectively [22]. In [23] author has described how seizure can be detected by using Episcan. Authors have used multivariate textual features extracted from gray level co-occurrence matrix for Epileptic seizure detection [24] . In [25] Authors have presented a method for detecting seizures using seven number of features considering 25% training data initially and then considering 50 % training data.

II. METHODOLOGY

A. CLINICAL DATA SET

Long sets of EEG data are recorded for a specific duration of time for the experimental work taken from PhysioNet [26] CHB-MIT Electroencephalogram dataset [27]. Both male and female epileptic patients are considered for the analysis.

B. Wavelet Packet Decomposition

For this experimental analysis, the EEG signals are processed and decomposed by implementing eight levels Wavelet Packet Decomposition method which is more appropriate than FFT and STFT [28, 29].

For the demultiplexing of EEG signal using wavelet packet decomposition method is also proposed previously in the year 2014 by R.Dhiman et al [30]. The multi resolution analysis using WPD for a signal g(t) is specified [31, 32]:

$$C_0^0 = g(t) \quad (1)$$

$$C_i^{q+1} = \sum_k h_0(k-2t)C_i^q \quad (2)$$

$$C_{2i+1}^{q+1} = \sum_k h_1(k-2t)C_i^q \quad (3)$$

$$i = 0, 1, 2, \ldots\ldots 2^{q-1}$$

C_i^q = Demultiplex coefficient at i^{th} node of q^{th} level

$h_0(n), h_1(n)$ = Orthogonal filters

$h_1(n)$ = Transfer function of HPF

$h_0(n)$= Transfer function of LPF

$$h_1(n) = (-1)^n h_0(n-1) \quad (4)$$

By using this feature extraction method, variance of monotonic amplitude, Mean of joint instantaneous amplitude and mean monotonic absolute amplitude as features are extracted. These features are inputted to each of the six classifiers for validation of the proposed method.

C. Modified Grey Wolf Optimization (MGWO)

The algorithm used to optimize the parameters of classifiers in this work is

Step 1 : Initialize the parameters as population size, number of features, Grey wolf position, maximum iterations and flag.

Step 2: To arrange initial positions of grey wolves by utilizing the PSO.

Step 3 : Initialize the parameters as $\vec{A} = 2\vec{a}\vec{r}_1 - \vec{a}$ and $\vec{C} = 2\vec{r}_2$.

Step 4 : Decreased the linearity ($\vec{a}$) from 2 to 0.

Step 5 : Compute the fitness value of every search grey wolves with selected features.

Step 6 : Set the positions of alpha, beta and delta with minimum fitness.

Step 7 : If the position of search event >0.5, then flag = 1. If flag = 0, then update a, $\vec{A}$ and $\vec{C}$

Step 8 : Compute the all fitness values of grey wolves and update the positions (k = K+1).

Step 9 : Return the selected features of alpha position till the termination criteria satisfied.

D. Classifiers used

The robustness of the proposed feature extraction method has been evaluated using six well known classifiers namely : Random forest (RF) [26], C4.5 [27], functional tree (FT) [28], Bayes-net [29], Naive-Bayes [30], and K-nearest neighbours (K-NN) [31].

III. PERFORMANCE MATRIX

The research work analyzed the performance of the proposed methods using various statistical parameters [24] Accuracy (Ac), Specificity (Sp), Sensitivity (Se),G-mean(GM), Positive Predictive(PPV), Mathew's Correlation Coefficient(MCC), Area Under Curve(AUC) and also execution time are considered for the validation of the proposed method which are specified from Equation no (11) to Equation no (16).

$$A_c = \frac{TP}{TP+TN+FP+FN} \quad (11)$$

$$S_p = \frac{TN}{TN+FP} \quad (12)$$

$$S_e = \frac{TP}{TP+FN} \quad (13)$$

$$G_M = \sqrt{S_e \times S_p} \quad (14)$$

$$PPV = \frac{TP}{TP+FP} \quad (15)$$

$$MCC = \frac{(TP\times TN)-(FN\times FP)}{T1\times T2} \quad (16)$$

Where, $T1 = \sqrt{(TP+FN)(TP+FP)}$

$T2 = \sqrt{(TN+FN)(TN+FP)}$

TP is True Positive, TN is True Negative

FP is False Positive, FN is False Negative

IV. RESULTS AND DISCUSSION:

The proposed model for the experimental analysis of epileptic seizure detection is shown in form of block diagram represented in "fig .1". The performance evaluation of various classifiers like Random forest (RF) , C4.5 , functional tree (FT) , Bayes-net , Naive-Bayes , and K-nearest neighbours (K-NN) are analyzed by considering the statistical parameters. It is experimented on 23 numbers of epileptic patients. Table-1 represents the outputs of Naive-Bayes classifier, similarly Table-2 to Table-6 represent the outputs of the classifiers K-nearest neighbours (K-NN), Bayes-net, functional tree (FT), C4.5 and Random forest (RF). Comparing the outputs of all the classifiers, Naive-Bayes classifier gives best result in all aspects of performance evaluation for each set of tested works in terms of Accuracy, Specificity, Sensitivity, G-mean, PPV & MCC as 97.24%, 97.34%, 97.13%, 98.1%, 96.99%, 97.66% respectively. Table-7 reflects the comparative analysis of the performance parameters of all the classifiers. The performance evaluation of the proposed method is also analyzed with the existing methods for the seizure detection which is shown in Table-8.

V. CONCLUSION

In this research paper, a novel epileptic seizure detection algorithm has been endorsed for the analysis of multifaceted volatile EEG signals. All the three datasets (DS1, DS2, and DS3) containing scalp EEG data are first of all decomposed by Wavelet Packet Transform (WPT). Variance of monotonic amplitude, Mean of joint instantaneous amplitude and mean monotonic absolute amplitude as features are extracted by using this feature extraction method. These features are inputted to each of the six classifiers for validation of the proposed method.

Then, Correlation-based Feature Selection method is used for the selection of the features. The algorithm used to optimize the parameters of classifiers in this work is Modified Grey wolf Optimization. Finally, all the features are inputted to different rule based Support Vector Machines like Random forest (RF) , C4.5 , functional tree (FT) , Bayes-net , Naive-Bayes , and K-nearest neighbours (K-NN) for the evaluation of statistical parameters. In this tested work, it is observed that, Naive-Bayes outperforms in each aspects compared to other classifiers. The outcomes in terms of Accuracy, Specificity, Sensitivity, G-mean, PPV & MCC are found out as 97.24%, 97.34%, 97.13%, 98.1%, 96.99%, and 97.66% respectively for Naive-Bayes classifier. The future work will be concentrated on short data of EEG signal.

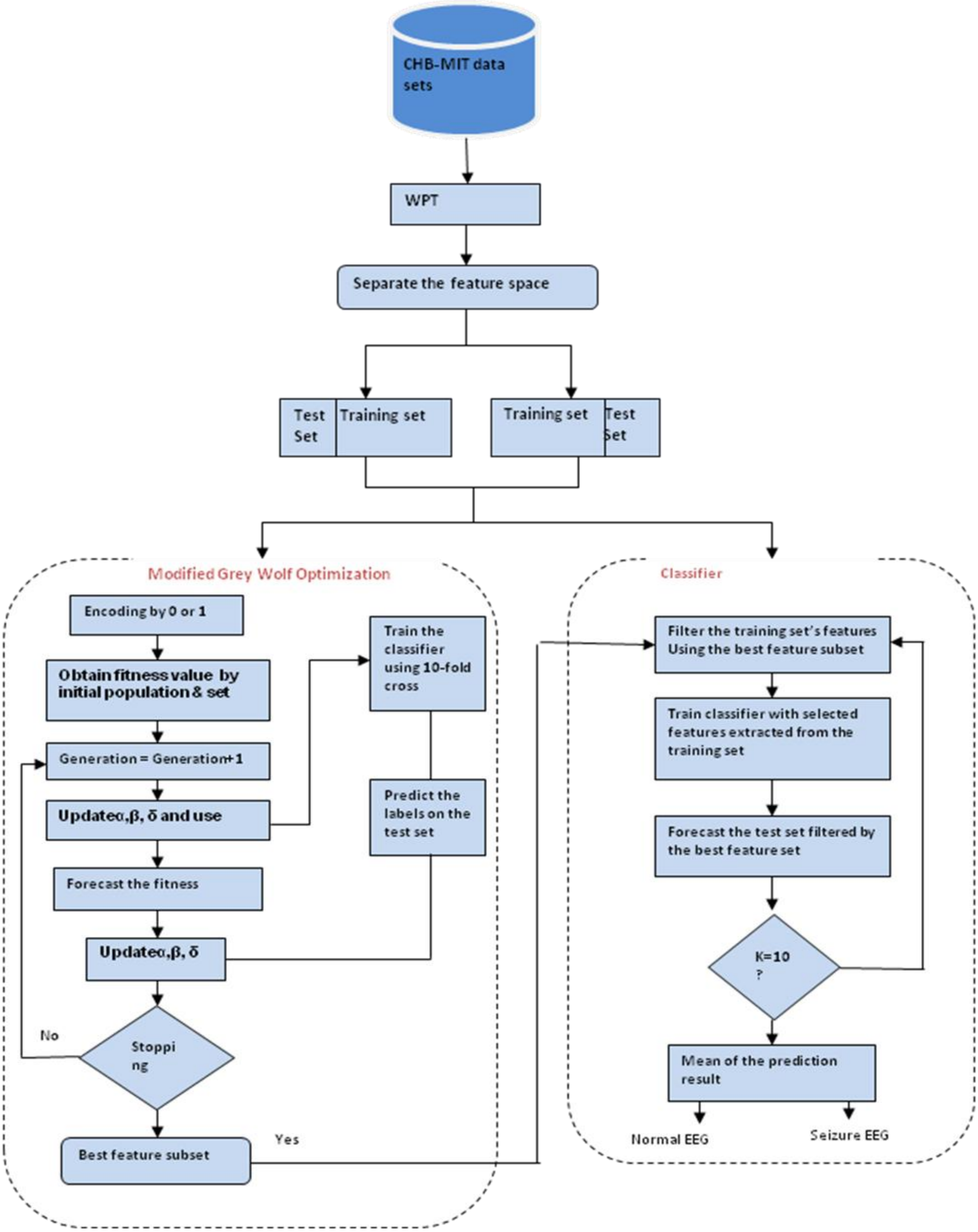

Fig.1. Block Diagram of the proposed method

Table- I:Evaluated performance parameters using NAIVE-BAYES classifier

METHOD	NAÏVE-BAYES CLASSIFIER					
PATIENT INDEX	A_C	S_P	S_e	G_M	*PPV*	*MCC*
1	94.9±1.02	95.9±1.02	95.8±1.17	96.9±1.28	97.6±1.42	96.7±1.32
2	96.5±1.09	96.4±1.42	94.8±1.30	97.2±1.33	95.5±1.53	97.2±1.35
3	96.7±1.21	96.8±1.32	96.3±1.12	97.8±1.63	91.9±1.55	93.8±1.76
4	97.3±1.02	98.6±1.61	96.4±1.67	97.9±1.54	94.3±1.21	95.3±1.18
5	98.1±1.27	98.2±1.72	98.7±1.52	99.1±1.74	95.4±1.22	96.7±1.12
6	99.1±1.53	99.4±1.22	97.4±1.20	95.8±1.73	96.9±1.75	95.6±1.35
7	98.4±1.97	96.2±1.30	98.2±1.45	98.7±1.69	98.9±1.82	94.0±1.26
8	95.8±1.32	97.5±1.24	94.9±1.75	98.1±1.20	98.6±1.63	94.5±1.51
9	93.7±1.65	98.0±1.45	99.9±1.50	92.9±1.67	99.4±1.50	96.8±1.40
10	95.8±1.73	96.9±1.75	95.7±1.35	99.7±1.49	98.0±1.55	95.8±1.37
11	99.7±1.69	98.9±1.82	94.0±1.26	98.8±1.70	97.9±1.25	98.6±1.59
12	99.9±1.20	98.8±1.63	93.5±1.51	93.8±1.05	97.0±1.92	96.8±1.55
13	97.8±1.50	99.3±1.35	98.8±1.48	94.5±1.64	98.5±1.09	95.9±1.75
14	91.9±1.35	99.9±1.52	99.5±1.38	98.9±1.55	92.9±1.02	95.9±1.65
15	98.0±1.72	95.7±1.80	98.9±1.47	98.7±1.90	93.0±1.43	97.5±1.50
16	96.5±1.45	97.8±1.12	97.4±1.82	96.7±1.24	96.9±1.40	94.7±1.30
17	93.9±1.67	99.2±1.50	96.8±1.40	96.9±1.27	96.8±1.53	97.3±1.37
18	99.7±1.49	98.1±1.55	95.8±1.37	97.5±1.45	98.4±1.65	96.1±1.67
19	98.9±1.92	97.9±1.25	98.6±1.59	98.9±1.29	99.5±1.60	95.5±1.55
20	97.9±1.65	93.9±1.12	95.9±1.65	97.8±1.65	99.4±1.39	98.1±1.40
21	99.7±1.90	95.2±1.33	96.5±1.40	98.9±1.24	98.3±1.36	94.1±1.14
22	98.3±1.45	98.8±1.85	99.6±1.23	99.2±1.54	98.8±1.09	99.2±1.35
23	98.6±1.70	99.1±1.75	98.6±1.27	97.9±1.08	97.6±1.47	94.6±1.95
Average	97.24	97.34	97.13	98.1	96.99	97.66

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Table- II: Evaluated performance parameters using KNN classifier

METHOD	KNN CLASSIFIER					
PATIENT INDEX	A_C	S_P	S_e	G_M	*PPV*	*MCC*
1	93.9±1.12	95.8±1.32	96.8±1.07	97.9±1.38	97.4±1.52	92.7±1.12
2	96.4±1.19	96.7±1.32	95.8±1.31	94.2±1.23	96.5±1.43	96.2±1.35
3	97.7±1.31	97.8±1.02	96.4±1.02	93.8±1.53	92.9±1.35	94.8±1.76
4	98.3±1.02	93.1±1.51	97.4±1.77	92.9±1.64	95.3±1.31	96.3±1.18
5	92.2±1.37	92.2±1.62	98.7±1.62	92.3±1.64	95.5±1.22	90.7±1.12
6	95.0±1.43	93.5±1.32	97.4±1.24	91.8±1.63	95.9±1.35	91.6±1.45
7	90.2±1.98	94.2±1.35	97.2±1.95	98.9±1.39	98.9±1.72	94.3±1.26
8	95.8±1.32	91.5±1.24	94.9±1.75	94.1±1.20	98.6±1.63	91.5±1.51
9	93.7±1.65	90.0±1.45	91.9±1.50	92.9±1.67	98.4±1.50	92.8±1.40
10	95.8±1.73	96.9±1.75	95.7±1.35	93.7±1.49	98.0±1.55	90.8±1.37
11	97.7±1.69	98.9±1.82	94.0±1.26	94.8±1.70	97.9±1.25	98.6±1.59
12	96.9±1.20	98.8±1.63	93.5±1.51	93.8±1.05	97.0±1.92	96.8±1.55
13	97.8±1.50	96.3±1.35	92.8±1.48	94.5±1.64	98.5±1.09	94.9±1.75
14	91.9±1.35	96.9±1.52	91.5±1.38	95.9±1.55	92.9±1.02	95.9±1.65
15	98.0±1.72	95.7±1.80	93.9±1.47	96.7±1.90	93.0±1.43	95.5±1.50
16	96.5±1.45	93.8±1.12	96.4±1.82	94.7±1.24	96.9±1.40	92.7±1.30
17	93.9±1.67	98.2±1.50	96.8±1.40	96.9±1.27	96.8±1.53	91.3±1.37
18	99.7±1.49	94.2±1.65	96.2±1.34	93.5±1.35	94.4±1.25	90.1±1.67
19	98.6±1.82	92.9±1.35	98.4±1.49	97.9±1.39	94.5±1.60	95.6±1.65
20	97.8±1.95	91.9±1.02	96.9±1.25	94.8±1.65	93.3±1.29	92.3±1.40
21	99.6±1.90	93.2±1.31	96.3±1.43	95.6±1.23	92.3±1.36	93.1±1.16
22	98.4±1.45	95.32±1.45	90.4±1.33	97.3±1.44	98.7±1.18	94.2±1.35
23	97.6±1.05	97.3±1.45	91.6±1.07	97.6±1.18	97.9±1.37	91.6±1.85
Average	97.24	96.35	95.32	96.34	95.76	93.83

Table- III: Evaluated performance parameters using Bayes-net classifier

METHOD	BAYES-NET CLASSIFIER					
PATIENT INDEX	A_C	S_P	S_e	G_M	*PPV*	*MCC*
1	93.8±1.02	95.8±1.32	96.8±1.07	97.1±1.08	97.4±1.52	91.7±1.12
2	96.4±1.09	96.7±1.32	95.8±1.31	94.2±1.13	96.5±1.43	92.2±1.35
3	90.7±1.11	97.8±1.02	96.4±1.02	91.8±1.23	92.9±1.35	84.8±1.76
4	92.3±1.02	93.1±1.51	97.4±1.77	93.9±1.64	85.3±1.31	86.3±1.98
5	91.2±1.35	92.2±1.62	98.7±1.62	93.3±1.64	85.5±1.22	91.4±1.32
6	95.0±1.43	93.5±1.32	97.4±1.24	92.8±1.63	95.9±1.35	83.7±1.45
7	92.2±1.98	94.2±1.35	96.2±1.95	94.9±1.29	88.9±1.72	84.3±1.26
8	95.8±1.31	95.5±1.24	94.9±1.75	95.1±1.23	88.6±1.63	91.5±1.51
9	93.7±1.62	93.0±1.45	91.9±1.50	93.9±1.67	90.4±1.50	92.8±1.40
10	94.8±1.73	96.9±1.75	93.7±1.35	94.7±1.49	91.0±1.55	90.8±1.37
11	97.7±1.69	97.9±1.80	94.0±1.26	93.8±1.70	92.9±1.25	92.6±1.59
12	90.9±1.20	96.8±1.23	93.5±1.51	91.8±1.05	91.0±1.92	91.8±1.55
13	87.8±1.50	97.3±1.35	924±1.38	94.5±1.64	92.5±1.12	92.9±1.75
14	90.9±1.35	95.9±1.02	91.5±1.38	95.9±1.55	92.9±1.02	93.9±1.65
15	91.8±1.72	95.7±1.80	93.9±1.37	92.7±1.90	87.2±1.13	91.5±1.50
16	92.5±1.45	93.8±1.12	94.4±1.62	91.7±1.24	93.9±1.30	90.7±1.30
17	93.9±1.67	98.2±1.50	96.8±1.40	92.9±1.26	91.8±1.53	91.3±1.37
18	99.7±1.49	94.2±1.65	92.2±1.34	93.5±1.37	87.4±1.25	90.1±1.67
19	98.6±1.82	92.9±1.35	91.4±1.49	94.9±1.39	89.5±1.60	85.6±1.65
20	97.8±1.95	91.9±1.02	92.9±1.25	95.8±1.65	90.3±1.29	87.3±1.40
21	98.0±1.90	93.2±1.31	93.3±1.43	95.4±1.33	92.3±1.36	93.1±1.16
22	98.4±1.45	95.32±1.45	94.4±1.33	93.3±1.54	91.7±1.18	94.2±1.35
23	97.6±1.05	97.3±1.45	92.6±1.07	97.5±1.28	90.9±1.37	91.6±1.85
Average	94.48	95.35	94.62	94.43	92.99	91.73

Table IV: Evaluated performance parameters using Functional tree classifier

METHOD	FUNCTIONAL TREE CLASSIFIER					
PATIENT INDEX	A_C	S_P	S_e	G_M	*PPV*	*MCC*
1	93.8±1.72	92.3±1.32	91.8±1.17	90.1±1.08	87.4±1.52	81.7±1.12
2	92.4±1.29	94.3±1.25	92.8±1.31	91.2±1.13	86.5±1.43	86.2±1.36
3	90.7±1.11	97.8±1.02	86.4±1.02	92.8±1.43	92.5±1.35	84.7±1.76
4	92.3±1.02	93.1±1.51	87.4±1.77	90.9±1.64	85.9±1.41	86.3±1.98
5	91.2±1.35	92.2±1.62	89.7±1.62	90.3±1.64	85.5±1.22	91.4±1.32
6	93.0±1.13	91.5±1.02	91.4±1.24	89.8±1.63	90.9±1.35	83.7±1.45
7	91.2±1.98	90.2±1.35	91.2±1.25	86.9±1.39	87.9±1.72	84.3±1.26
8	92.8±1.31	91.5±1.24	90.9±1.35	84.1±1.23	88.6±1.63	91.5±1.51
9	90.7±1.02	93.1±1.15	88.9±1.50	91.9±1.67	90.4±1.50	83.8±1.40
10	92.8±1.33	92.9±1.75	93.7±1.35	92.7±1.49	91.0±1.55	90.8±1.37
11	91.7±1.69	84.9±1.80	94.0±1.26	86.8±1.70	92.9±1.25	80.72±1.59
12	91.9±1.20	87.8±1.23	91.5±1.51	90.8±1.15	91.0±1.92	91.8±1.55
13	87.8±1.50	92.3±1.35	91.4±1.38	91.5±1.64	92.5±1.12	90.8±1.75
14	90.9±1.35	91.9±1.02	91.5±1.38	90.9±1.55	92.1±1.02	90.9±1.65
15	91.8±1.72	85.7±1.81	93.9±1.37	91.7±1.90	87.9±1.13	91.5±1.50
16	90.5±1.45	93.8±1.02	90.4±1.62	89.7±1.24	90.9±1.30	84.7±1.30
17	90.9±1.67	91.2±1.50	91.8±1.32	92.9±1.26	91.8±1.53	91.3±1.37
18	91.7±1.49	90.2±1.65	90.2±1.34	93.5±1.37	87.4±1.25	90.1±1.67
19	88.6±1.72	91.5±1.25	87.4±1.49	94.9±1.39	89.5±1.60	85.6±1.65
20	89.8±1.95	91.9±1.02	82.9±1.05	95.8±1.65	90.3±1.29	87.3±1.40
21	87.2±1.85	93.2±1.31	91.3±1.13	95.4±1.33	92.3±1.36	83.1±1.16
22	90.4±1.45	92.32±1.25	91.4±1.33	93.3±1.54	90.7±1.18	84.2±1.35
23	93.6±1.05	94.3±1.25	90.6±1.07	97.5±1.28	90.9±1.37	81.6±1.65
Average	92.51	92.67	91.34	91.30	90.72	87.59

Table-V : Evaluated performance parameters using C4.5 classifier

METHOD	C4.5 CLASSIFIER					
PATIENT INDEX	A_C	S_P	S_e	G_M	*PPV*	*MCC*
1	85.8±1.72	82.3±1.32	91.8±1.17	90.1±1.08	80.4±1.62	81.7±1.32
2	90.4±1.29	84.3±1.75	92.8±1.31	89.2±1.13	81.5±1.23	80.2±1.06
3	90.7±1.11	90.8±1.12	86.4±1.02	83.8±1.43	82.5±1.35	80.7±1.76
4	87.3±1.02	89.1±1.51	87.4±1.77	85.9±1.64	85.9±1.41	81.3±1.98
5	89.2±1.35	82.2±1.62	89.7±1.62	81.3±1.64	80.5±1.92	80.4±1.32
6	90.0±1.13	90.5±1.32	91.4±1.24	89.8±1.24	83.9±1.35	83.7±1.34
7	91.2±1.98	91.2±1.35	91.2±1.25	86.1±1.29	81.9±1.72	81.3±1.26
8	87.8±1.21	81.5±1.24	90.9±1.35	84.1±1.23	80.6±1.03	83.5±1.51
9	90.7±1.02	83.1±1.05	88.9±1.50	81.9±1.67	84.4±1.50	81.2±1.40
10	90.8±1.03	85.9±1.75	93.7±1.35	82.7±1.49	83.0±1.55	80.8±1.37
11	90.7±1.69	84.9±1.80	94.0±1.26	86.8±1.70	80.9±1.25	81.7±1.59
12	89.9±1.20	87.8±1.23	91.5±1.51	90.8±1.15	80.0±1.92	80.8±1.55
13	87.8±1.50	86.3±1.15	91.4±1.38	91.5±1.64	85.5±1.12	82.8±1.75
14	90.9±1.35	90.9±1.02	91.5±1.38	90.9±1.55	82.2±1.02	82.9±1.65
15	91.8±1.72	85.7±1.81	93.9±1.37	89.7±1.90	81.1±1.23	78.5±1.50
16	90.5±1.15	83.8±1.02	90.4±1.62	89.7±1.24	90.1±1.20	79.7±1.30
17	90.9±1.37	86.2±1.50	91.8±1.32	82.9±1.26	81.8±1.23	81.3±1.32
18	91.7±1.49	83.2±1.65	90.2±1.34	83.5±1.37	82.4±1.05	82.1±1.45
19	88.6±1.72	87.5±1.25	87.4±1.49	89.1±1.09	84.5±1.60	83.6±1.65
20	89.1±1.35	84.9±1.12	82.9±1.05	87.1±1.65	80.3±1.21	77.3±1.40
21	87.2±1.85	83.2±1.31	91.3±1.13	82.4±1.43	90.3±1.36	73.1±1.16
22	90.1±1.05	90.32±1.25	91.4±1.33	84.3±1.34	8.7±1.18	80.2±1.50
23	90.6±1.15	88.3±1.25	90.6±1.07	87.5±1.28	80.9±1.37	80.6±1.25
Average	89.93	86.56	86.4	85.15	83.5	82.76

Table-VI: Evaluated performance parameters using Random Forest classifier

METHOD	RANDOM FOREST CLASSIFIER					
PATIENT INDEX	A_C	S_P	S_e	G_M	*PPV*	*MCC*
1	75.8±1.62	72.3±1.42	81.8±1.17	80.1±1.25	80.5±1.62	76.7±1.32
2	76.4±1.09	74.3±1.65	80.8±1.21	77.2±1.23	81.2±1.43	80.2±1.06
3	82.7±1.31	70.8±1.12	80.4±1.22	80.8±1.63	72.5±1.65	75.7±1.76
4	77.3±1.22	79.1±1.01	81.4±1.07	81.9±1.64	75.9±1.41	71.3±1.28
5	71.2±1.35	72.2±1.92	79.7±1.22	71.3±1.64	80.5±1.92	80.4±1.32
6	73.0±1.13	70.5±1.32	71.4±1.24	73.8±1.24	74.9±1.35	80.7±1.04
7	81.2±1.98	71.2±1.46	81.2±1.45	74.1±1.29	76.9±1.72	81.3±1.26
8	82.8±1.32	71.5±1.32	80.9±1.25	80.1±1.23	70.6±1.03	73.5±1.51
9	74.3±1.25	73.1±1.05	81.9±1.50	81.9±1.37	78.4±1.43	71.2±1.40
10	76.8±1.03	75.9±1.45	73.7±1.35	72.7±1.79	79.0±1.55	76.8±1.37
11	72.7±1.39	74.9±1.70	80.0±1.26	76.8±1.70	80.9±1.25	77.7±1.59
12	76.9±1.20	70.8±1.23	81.5±1.51	80.8±1.15	80.0±1.92	80.1±1.55
13	71.8±1.50	71.3±1.15	80.4±1.38	81.5±1.64	76.5±1.12	80.8±1.75
14	76.9±1.45	72.9±1.02	81.5±1.38	80.9±1.55	80.2±1.02	72.9±1.65
15	78.8±1.67	74.7±1.81	73.9±1.37	78.7±1.70	81.1±1.23	76.5±1.50
16	79.5±1.15	70.8±1.22	80.4±1.62	80.7±1.74	76.1±1.20	77.7±1.30
17	72.9±1.37	72.2±1.30	81.8±1.32	72.9±1.26	77.8±1.23	71.3±1.32
18	81.7±1.49	73.2±1.65	79.2±1.34	73.5±1.27	72.4±1.05	72.1±1.45
19	76.6±1.72	70.5±1.05	77.4±1.49	80.1±1.19	82.5±1.60	73.6±1.25
20	77.1±1.35	71.9±1.02	82.9±1.05	81.1±1.65	80.3±1.21	77.3±1.44
21	77.2±1.45	70.2±1.31	81.3±1.13	78.4±1.63	80.3±1.36	73.1±1.19
22	78.1±1.35	70.3±1.25	81.4±1.56	74.3±1.94	80.7±1.18	72.2±1.62
23	74.6±1.65	71.3±1.25	80.6±1.37	77.5±1.28	75.9±1.47	70.6±1.25
Average	77.77	73.98	81.5	79.33	79.21	76.45

Table-VII: Summary of experimental analysis using various classifiers

Statistical Parameters (%)	Naive-Bayes	K-NN	Bayes-net	FT	C4.5	RF
Accuracy	97.24	94.98	94.48	92.51	89.93	77.77
Specificity	97.34	96.35	95.35	92.67	86.56	73.98
Sensitivity	97.13	95.32	94.62	91.34	86.40	81.50
G-mean	98.1	96.34	94.43	91.30	85.15	79.33
PPV	96.99	95.76	92.99	90.72	83.50	79.21
MCC	97.66	93.83	91.73	87.59	82.76	76.45

Table-VIII: Comparative Analysis of existing methods and the proposed method

Serial No.	Reference Paper	Ac (%)	Sp (%)	Se (%)	GM (%)	PVV (%)	MCC (%)
1	S.Kiranyaz et al [6]	80.16	NA	NA	NA	NA	NA
2	S. Mallat [16]	91.8	100	83.6	NA	NA	NA
3	B. Hunyadi et al [20]	NA	NA	83	NA	NA	NA
4	A. Supratak et al [21]	NA	NA	100	NA	NA	NA
5	S. Kiranyaz et al [22]	NA	94.71	89.01	NA	NA	NA
6	F.Fiirbas et al [23]	NA	NA	67	NA	NA	NA
7	K. Samiee et al [24]	NA	97.74	70.19	NA	NA	NA
8	M. Zabihi et al [25]	93.11	93.21	88.27	NA	NA	NA
9	M. Zabihi et al [25]	94.69	94.80	89.10	NA	NA	NA
10	Proposed method	97.24	97.34	97.13	98.1	96.99	97.66

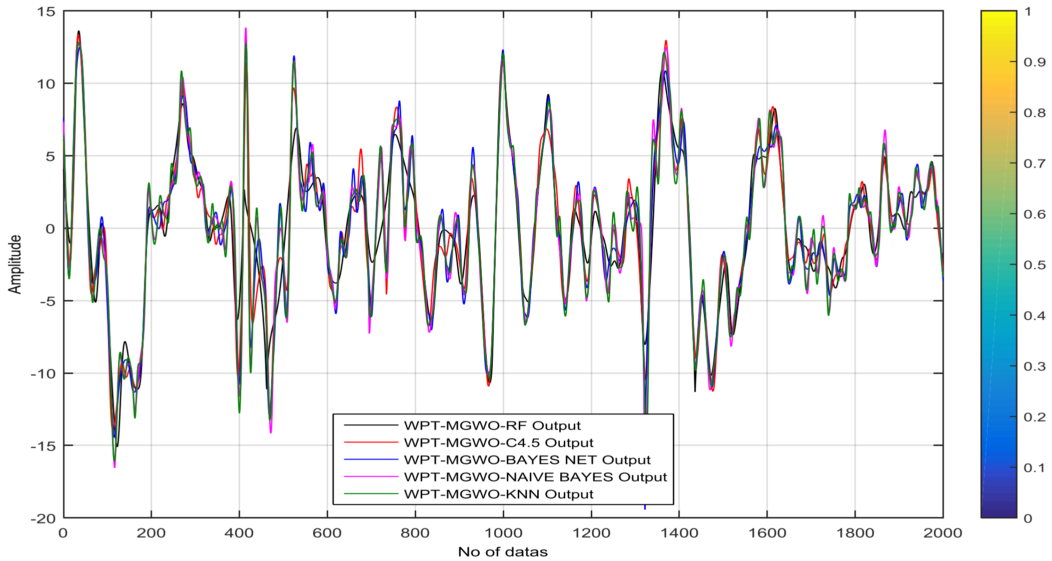


Fig 2. Plot show the comparative outputs of different methods

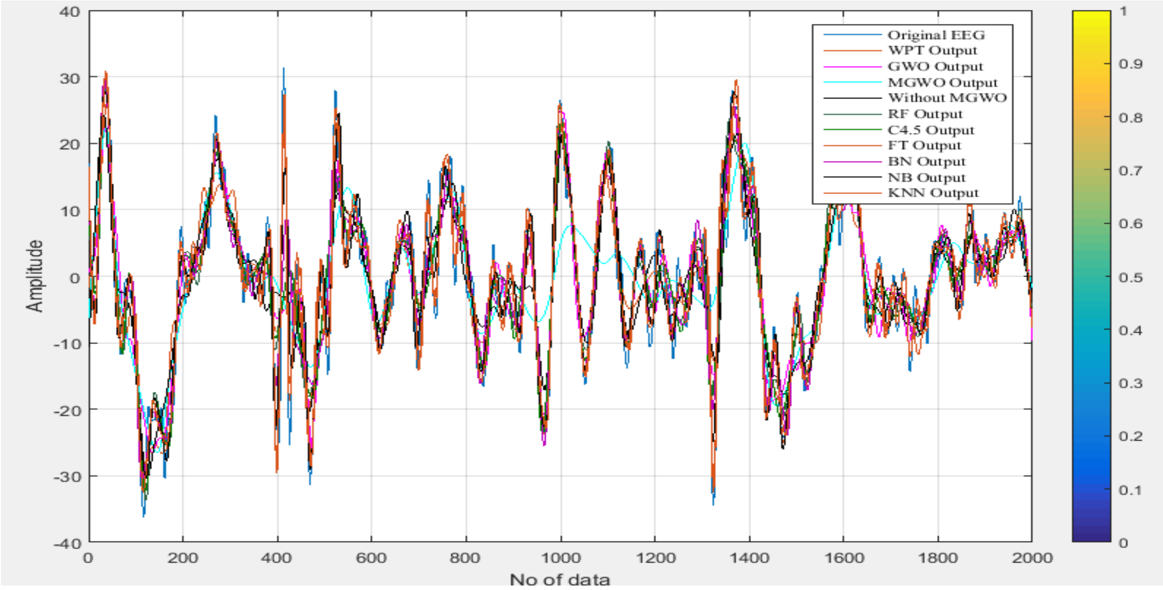
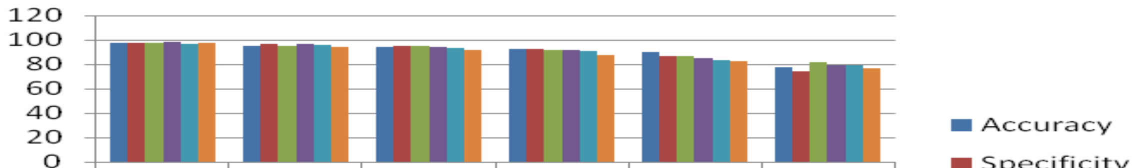
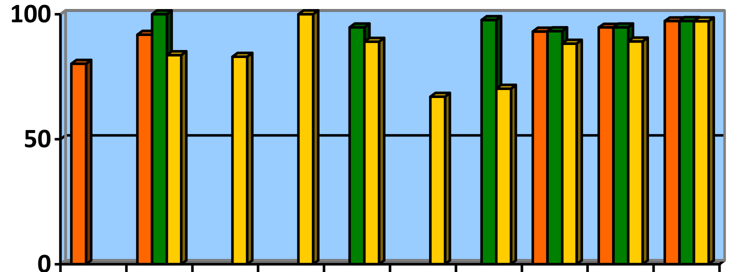


Fig-3. Comparative outputs of different classifiers



	Naïve-Bayes	KNN	Bayes-net	FT	C4.5	RF
Accuracy	97.24	94.98	94.48	92.51	89.93	77.77
Specificity	97.34	96.35	95.35	92.67	86.56	73.98
Sensitivity	97.13	95.32	94.62	91.34	86.4	81.5
G-mean	98.1	96.34	94.43	91.3	85.15	79.33
PVV	96.99	95.76	92.99	90.72	83.5	79.21
MCC	97.66	93.83	91.73	87.59	82.76	76.45

Fig.4. Comparative analysis of outputs of various classifiers



	SN 1	SN2	SN 3	SN 4	SN 5	SN 6	SN 7	SN 8	SN 9	SN 10
Accuracy	80.16	91.8	NA	NA	NA	NA	NA	93.11	94.69	97.24
Specificity	NA	100	NA	NA	94.71	NA	97.74	93.21	94.8	97.34
Sensitivity	NA	83.6	83	100	89.01	67	70.19	88.27	89.1	97.13

Fig.5. Comparative analysis of previous methods with existing method

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