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Identification of Fatal Familial Insomnia Sleep Disorder Using Ga Optimization with Svm Classifier

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Abstract: ***Among the genetic disorders in brain Fatal familial insomnia (FFI) is one of the rare disorder. The inability of sleeping is called as FFI which leads to the process of becoming progressively worse mentally and physically. The recordings of brain functioning is known as Electroencephalogram (EEG) and which seeks a vital role in observing and finding the sleep disorders like FFI. The EEG senses the brain functionality. In this paper , genetic optimization based SVM classifier is used to identify the sleep disorder. The proposed technique is used to optimize the features which are obtained from features reduction techniques like PCA, ICA and LDA. For performing the experimental results PhysioNet database is obtained. Preprocessing of the data, performing feature reduction, next feature optimization and then classification using Support vector machine is the process for identifying the FFI. The performance measures such as accuracy, sensitivity, specificity, F1-Score, Recall are computed . The comparison of results obtained using different condition are observed and the ranges are determined for normal class, Bruxism class and FFI class.***

Keywords: EEG signals, Insomnia Sleep Disorder, Genetic Algorithm, SVM Classifier.

I. INTRODUCTION

Fatal Familial Insomnia could be a disorder that causes disturbance in a very traditional sleep pattern ensuing from the difficulties to go to sleep or to remain asleep. The sleep loss in AN insomniac has ensuing a deterioration of cognitive content|activity} function, redoubled rate of accidents and cut daily performance throughout daytime. Current practices in designation FFI square measure through clinical interview by the medical man that square measure subjective and suffer from human error judgement. Bio-signals of shape if measured are affected thanks to these abnormal conditions. Power spectral Analysis of sleep graph in insomniac has shown a discount in delta band and an elevation in beta and alpha bands [1].

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These determined characteristics in sleep disorder square measure related to frequent hyperarousal in central system a nervosum. Studies in cardiovascular variability in sleep disorder patients have incontestible reduction in parasympathetic activity and hyper activation of sympathetic activity [2]. A study in [3] has according that interaction between pulse Variability and graph delta bands of sleep disorder patients square measure altered.

Several studies have applied linear and non-linear measures of graphical record signals along with a sophisticated classifier like Artificial Neural Network (ANN) and Discriminant Analysis in classifying psychological disorders [4]. Manual level diagnosis of the technique is performed and the results are shown in the study. The uses of linear and non-linear options live vital in analyzing biological signals and ones shouldn't deem one measure solely as our biological systems are advanced system and show chaotic behaviour [5]. Subcategory sleep disorder complaints usually embody issue in initiating (sleep onset insomnia) or/and maintaining sleep. They embody extended periods of sleep onset sleep disorder or/and maintaining sleep disorder amounts of already dark sleep [6]. The diagnostic and symptom class of sleep disorder ar best denoted by their subcategory. These subcategories ar represented by totally different combos of perennial sleep issues with sleep period, initiation, quality and impairment throughout the daytime [7]. sleep disorder complaints are often related to the perception of non-restorative or poor quality sleep notwithstanding the number and quality of sleep episodes ar perceived as adequate or regular. The which means of sleep disorder being a criticism of sleep maintenance, sleep initiation, non-restorative sleep or related to daytime impairment [8].

Optimization techniques like GA, PSO, Firefly etc have fewer complicated operations. Some of the parameters need to be summarised and evaluated to overcome. The classification techniques SVM which is used to reduce the risk evolved in structural and empirical for achieving classification of the data.

II. EEG SIGNALS

The activity of brain is measured and recorded with the help of EEG signals from the scalp [9]. It evaluates voltage potentials resulting from the ionic flows of current within the brain neurons. EEG includes multiple electrodes placed on the scalp. Various frequency bands are present in the brain waves which is generated by the EEG system .

The frequency bands are named as delta, alpha, theta and beta wave bands [10,11], the representation is as shown in Figure1.

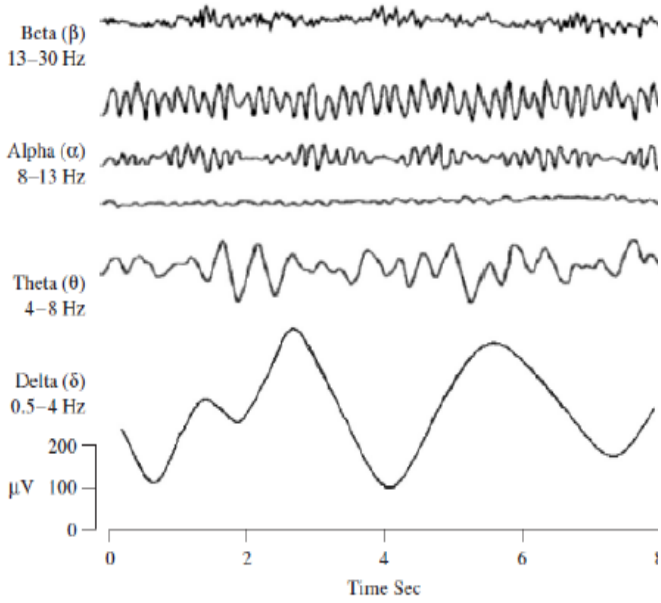

Figure 1. EEG frequency bands, where the y-axis indicates EEG frequency bands and the x-axis indicates time per second (sec) of the brain

Table 1: Normal range and amplitudes

Segment	Normal	Abnormal
Delta waves	0.5Hz -4Hz	>4Hz
Theta Waves	4Hz-7.5Hz	>8Hz
Alpha Waves	8Hz- 13Hz	>13Hz
Beta Waves	14Hz-26Hz	>26Hz
Gamma interval	28Hz- 60Hz	>60Hz

From table 1 the delta wave with said frequency have an amplitude range from 20 to 400 μV , in the presence of low brain activity these ranges are identified, such as medium anaesthetic state and deep sleep [12]. Alpha waves with said frequency have an amplitude range of 2 to 10 μV. These ranges are found when a individual is awake and the eyes are closed, and also when the individual have a physical state of rest. Beta waves are recorded at higher frequencies and their amplitudes range from 1-5 μV [13]. Beta waves are observed at concentrated attentions during the mental working state.

III. METHODOLOGY

A. Database used

The data is collected from PhysioBank (Web: http://www.physionet.org/cgi-bin/atm/ATM)[14]. Among several sleep disorders, in this paper two types are considered and evaluated. One is FFI and Bruxism. The EEG signals are obtained from 393 patients with sleep disorders like FFI and Bruxism. Out of which FFI data of 115 patients, Brux data of 36 patients, normal data of 242 patients. The experimental results are obtained and the parametric values are calculated for various combinations.

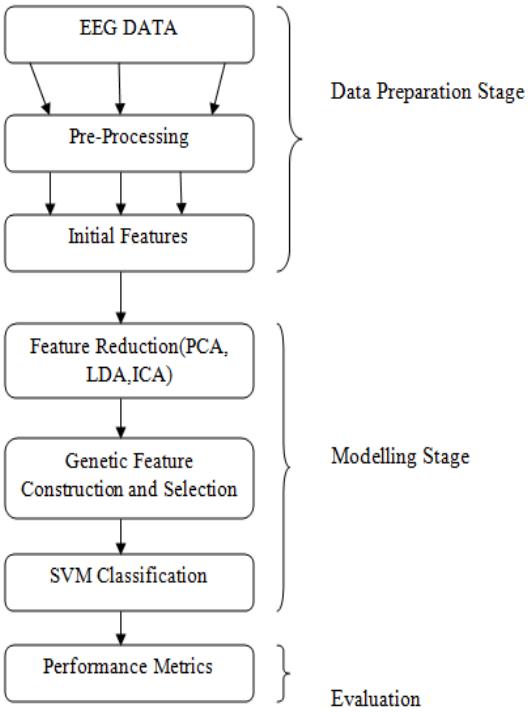

Fig 1. Proposed Flowchart

B. Feature Extraction

EGC signal is considered as input and the noise which is the present in the signal is filtered and divided into five bands of frequency namely delta, theta, alpha, beta and gamma. The division is done using five efficient filters.

In this process many statistical features or some nonlinear features are been extracted using the EEG signal which is said to be a time series signal. In this study we investigate eight statistical features (mini, max, mean, standard deviation, variance, RMS, skewness, and kurtosis) to be extracted from each DWT output coefficients. These eight features are applied individually on each signal waves to extract the features to identify the range.

C. Feature Reduction

PCA , LDA and ICA techniques are used for performing feature reduction. To reduce the dimensional features two techniques are used. One is Linear Discriminant Analysis (LDA) and other is Principal Component Analysis (PCA) which are linear in transformation. These techniques give good reduction and are used commonly. PCA is known as an unsupervised algorithm in which do not consider class labels and search for better way by which the variance of the data can be maximized. Whereas LDA is known as supervised algorithm which reduce the separations in the class of EEG signals. The third technique is ICA by which the features which are hidden will be reduced. It helps in extracting of sinle term features from the mutli class. Using each individual reduction techniques the features are reduced. The reduced featured obtained using PCA, LDA and ICA are combined together and processed for optimization.

D. Optimisation of Feature using Genetic Algorithm

This step helps in further reducing the features which are obtained using feature reduction technique. The selection of optimal features helps in reducing the level of features which are available originally. The performance level will be increased. The unwanted and the features which are not related which will reduce the rate of accuracy are identified and removed. For doing the such optimization , in this paper genetic algorithm[15] is proposed. The GA has four stages, the first stage is to initialise the population of the individuals which helps in identifying the optimize solution. Next steps are selection process, crossover and mutation. The fitness function is evaluated for every feature. The fitness function will vary every individual population out of which best fitness vales are selected. Considering the cross and mutation some of the features are selected. To obtain the best solution the process of evaluation fitness, crossover , mutation is performed more number of times. The best features are identified to improve the detection rate.

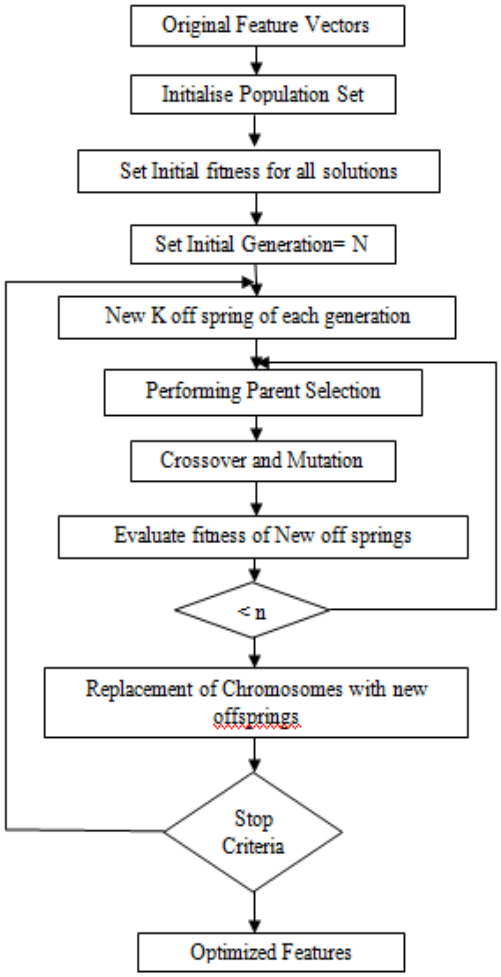

Fig 2. General Flow Diagram of Genetic Algorithm

E. SVM Classification

SVM is one of the most popularly used classification technique for various range of applications. It is a system which process the information depending on the simulation of the particular human process. Most linear classification is performed by producing a hyper-plane. This hyper-plane help is separating the sleep disorder patients with the normal patients depending on the level of class[16]. The data which is obtained based on hyper-plane is called as decision hyper-plane, the distance of the features from the hyper-plane is termed as margins. To find the better solution the training and testing is performed. The distance of the features with respect to hyper-plane plays a critical role in identifying the best solution. Due to the level of efficiency is more in SVM this classifier is mostly used for comparison purpose. The risk involved due to over-fitting is reduced in linear kernels compared to non-linear kernals. and improves the performance for our data and significantly reduces the overall model complexity.

IV. RESULTS AND DISCUSSION

The performance of the classification techniques like SVM and GA based SVM is compared to prove which techniques provides the best results. In proposed method, performance is evaluated on EEG records in that two different sleep disorders and one healthy subject. Training and testing of data is performed. In order to compare the performance of proposed classifiers is evaluated based on the accuracy, sensitivity, specificity, precision and F1 score. The above classification is done with MATLAB software.

The ranges for the features extracted have been evaluated and presented. Here table 2 provides the range of normal patients, range of bruxism patients in table 3 and range of fatal familial insomnia patients shown in table 4

Table 2. Range of Extracted Features for Normal Patients

Parameters	Gamma	Beta	Alpha	Delta	Theta
Max	548.29	1158.6	1958.3	2808.3	14335
Min	-527.01	-1165	-1918.8	-2817.8	-6002
Mean	-0.1185	-0.4061	1.444	3.088	4129.9
STD	64.89	174.87	322.06	552.94	3949.9

SKW	-0.4435	1.1279	-0.2062	-0.2779	0.0993
KRT	160.14	68.31	33.52	22.41	8.43
RMS	64.87	174.81	321.96	552.33	10229
Variance	27573	1.91e+05	4.71e+05	1.15e+06	9.50e+07

Table 3. Range of Extracted Features for Bruxism Patients

Parameters	Gamma	Beta	Alpha	Delta	Theta
Max	5629.4	3688.3	4460.8	5697.9	17433
Min	-3929.8	-3430.3	-4667.1	-6325.9	-11088
Mean	-0.005	-0.4632	-6.7976	-11.846	284.08
STD	227.23	325.85	654.55	1126.9	3369.8
SKW	1.504	0.244	0.2067	0.095	0.711
KRT	361.92	149.7	39.514	16.642	13.197
RMS	227.19	325.71	654.14	1125.6	3417.5
Variance	1.36e+05	2.48e+05	1.09e+06	2.94e+06	1.86e+07

Table 4. Range of Extracted Features for FFI Patients

Parameters	Gamma	Beta	Alpha	Delta	Theta
Max	792.9	1618.8	3261.9	4870.8	10191
Min	-794.13	-1687.5	-3099.5	-5031.1	-20662
Mean	-0.0655	-0.1993	2.4754	-0.1173	-5019.5
STD	78.94	226.73	522.3	994.5	5362.1
SKW	-0.9797	0.2296	0.5119	-0.056	-0.2235
KRT	206.21	80.46	39.48	22.84	10.25
RMS	78.928	226.65	521.95	993.59	20688
Variance	25046	2.31e+05	1.308e+06	5.06e+06	1.22e+08

* STD- Standard Deviation; SKW- Skewness; KRT- Kurtosis; RMS-Root Mean Square

The graphical results obtained by doing feature reduction using different techniques are shown below. The features reduction done for normal patients , brux disorder patients and FFI patients using principal components analysis is shown in fig 3, fig 4, fig 5. The extracted features of 242 normal patients using DWT are reduced using PCA technique. In this 15 principal components are achieved. Figure 3 shows the reduced features for normal patients.

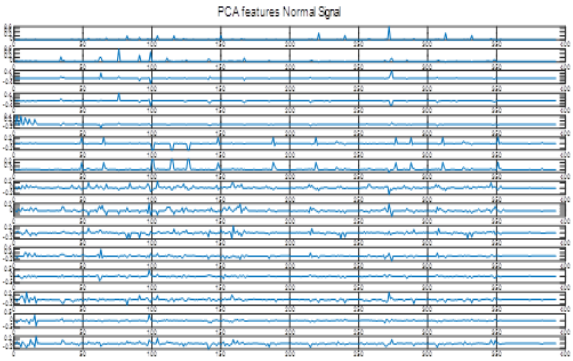

Fig 3. Reduced features for normal patients using PCA

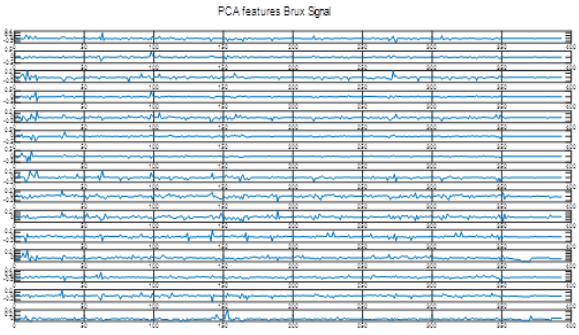

Fig 4. Reduced features for Brux patients using PCA

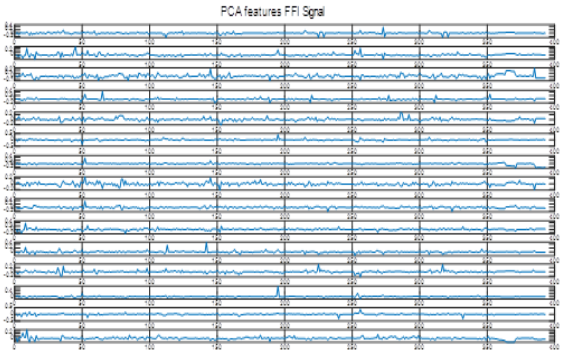

Fig 5. Reduced features for FFI patients using PCA

The extracted features from DWT are reduced using ICA method to reduce the redundancy problem. We have to select the number of independent component levels; here we select seven independent component levels. The Fig. 6 shows the fifteen independent component levels of original feature extracted data for normal patients data. In the same, fig 7 for brux patients data and fig 8 for FFI patients data.

Fig 6. Reduced features for normal patients using ICA

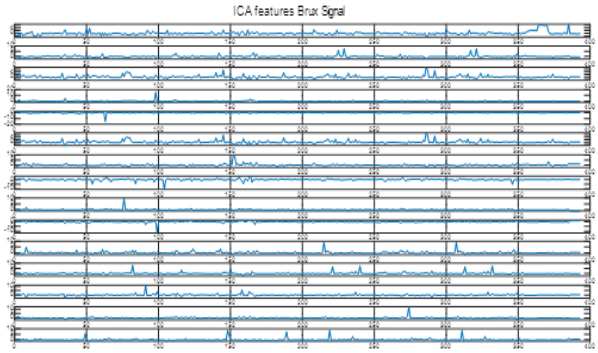

Fig 7. Reduced features for Brux patients using ICA

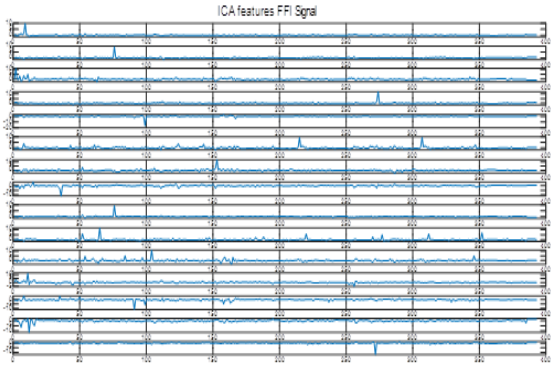

Fig 8. Reduced features for FFI patients using ICA

The extracted features from DWT are reduced using LDA method to reduce the redundancy problem. We have to select the number of linear discriminant levels; here we select fifteen linear discriminant levels. The Fig. 9 shows the fifteen linear discriminant levels of original feature extracted data for normal patients. The features reduction done for brux disorder patients and FFI patients using Independent components analysis is shown in fig 10 and fig 11.

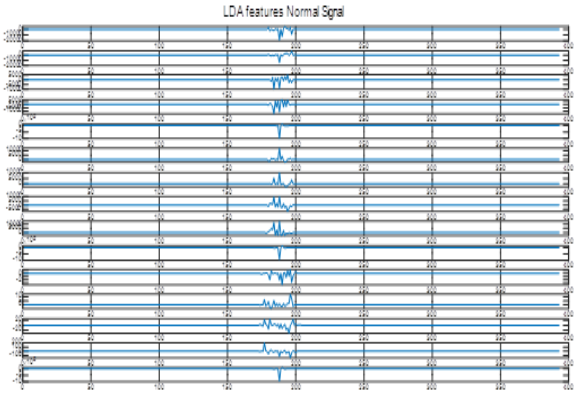

Fig 9. Reduced features for Normal patients using LDA

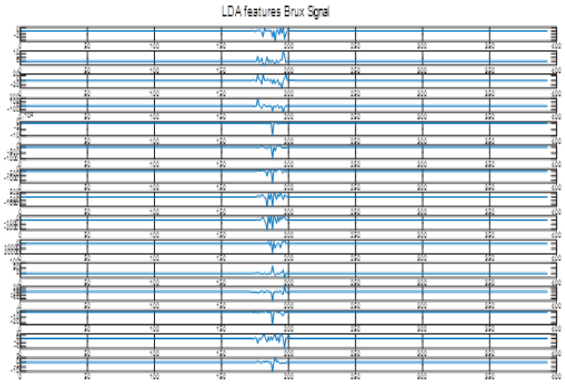

Fig 10. Reduced features for Brux patients using LDA

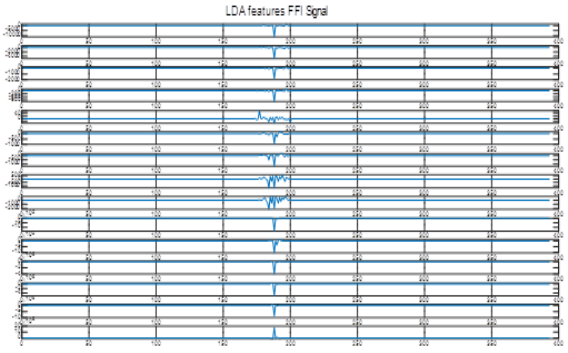

Fig 11. Reduced features for FFI patients using LDA

All the reduced features obtained using different techniques are combined together. Further better unique features are obtained by using one of the optimization technique. The genetic optimization selects best features which are healthy and good to analyze the disorder in the patients. These features helps in achieving good rate of accuracy when given to classifier. The features optimization done for normal patients , brux disorder patients and FFI patients using genetic algorithm is shown in fig 12, fig 13, fig 14.

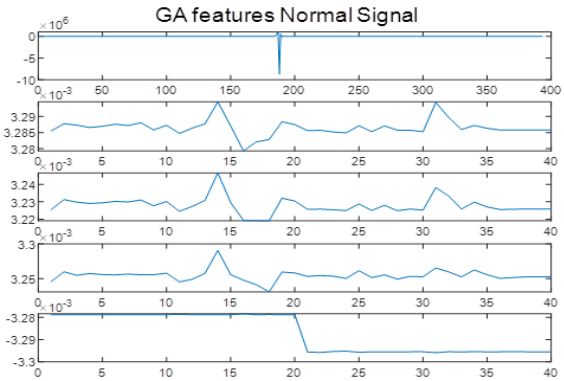

Fig 12. Reduced features for Normal patients using GA

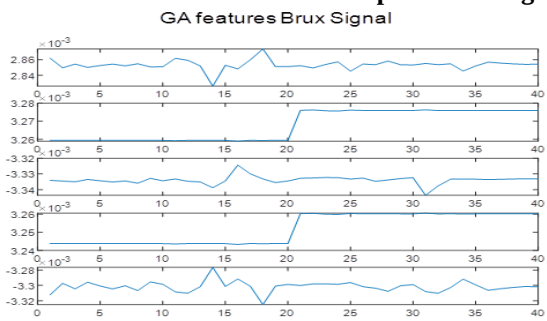

Fig 13. Reduced features for Brux patients using GA

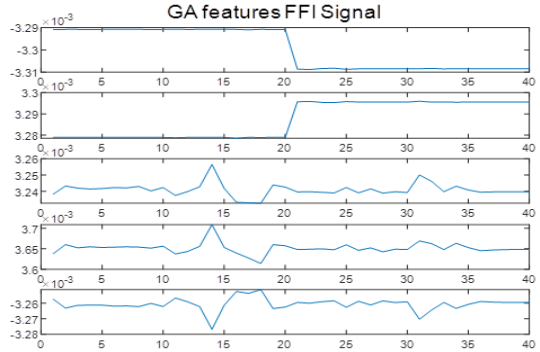

Fig 14. Reduced features for FFI patients using GA

The performance metrics are calculated for different signals. The results obtained using SVM classification and Genetic optimized SVM classification are compared at different SNR values. The feature extracted using genetic and classified using SVM shows better results compared to SVM classifier.

Classification performance is evaluated using Sensitivity(Se), Specificity(Sp) and Accuracy(A).

$$Se = \frac{TP}{TP+FN}$$

$$Sp = \frac{TN}{TN+FP}$$

$$A = \frac{TP+TN}{TP+TN+FP+FN}$$

$$Pr = \frac{TP}{TP+FP}$$

$$F_1 = \frac{2TP}{2TP+FP+FN}$$

Table 5. performance metrics for Normal and FFI using SVM and GA-SVM

Parameters		SVM	GA-SVM
N/B	A	87.1	89.1
	Se	67.5	73.8
	Sp	85.9	88.9
	Pr	84.2	86.2
	F1	0.83	0.89

Table 6. performance metrics for Normal and Bruxism using SVM and GA-SVM

Parameters		SVM	GA-SVM
N/FFI	A	86.3	90.8
	Se	76.3	82.0
	Sp	85.5	89.2
	Pr	83.2	86.4
	F1	0.85	0.90

Table 7. performance metrics for FFI and Bruxism using SVM and GA-SVM

Table 8. performance metrics for Normal, FFI and Bruxism using SVM and GA-SVM

Parameters		SVM	GA-SVM
FFI/B	A	86.7	88.6
	Se	68.5	70.4
	Sp	88.3	89.6
	Pr	83.1	85.6
	F1	0.84	0.88

*N- Normal; FFI- Fatal Familial Insomnia; B- Bruxism

V. CONCLUSION

To study the disorders which occur psychologically EEG signals gives the information that is required. The database of EEG signals are available in Physiobank. To detect the sleep disorders and classifying them needs a continuous evaluation of the patients. The proposed methodology used in this paper in detecting the sleep disorders like FFI and bruxim by considering different combinations and checking the performance of each combination. The features extracted using DWT contains some unnecessary features. To remove these features the feature reduction techniques are used. PCA, ICA and LDA are used for reducing the and optimization of features using genetic algorithm to increase the rate of accuracy. The results prove that GA optimized SVM classifier provides good output compared to simple SVM classifier. In case of considering normal, Brux and FFI the rate of accuracy achieved using GA-SVM is 86.2% and is 1.5% more compared with SVM classification performed using reduction techniques.

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