IV RESULTS AND DISCUSSION

Automated detection of seizures using EEG is an area that deeply intensified its roots in the health sector and is becoming a boon to the population where dearth knowledge about the disease and its impact are known to the mass. The treatment of epilepsy highly relies on the decision made by the neurologists. Lack of clinical indication may result in epilepsy being undetected and treated. An effective solution with utmost accuracy is achieved through the system developed in the research work. This research proposed enhanced solutions during each phase of detection. The impacts of these enhanced algorithms were tested with the dataset procured from Sri Rama Krishna hospital and PSG hospitals, Coimbatore. This chapter deals with the assembly of the phases developed in the preceding chapter (i.e. Methodology) with the mechanization of various performance metrics in each of these phases. The results were evaluated for each of the phases which are discussed below. A diagram of the developed system structure is shown in Figure. 4.1.

4.1 Overview of Dataset

Details of dataset used in the training and testing of the proposed system are discussed in this section. A dataset comprising of EEG recordings was collected from the neurology department of Sri Ramakrishna and PSG hospitals, Coimbatore. The database contains EEG recordings from 160 patients admitted for diagnosis of neurology related problems. Out of the 160, 110 patients were positive to epilepsy and 50 turned out to be the normal. Test data does not have any variation from the data set that was collected for the development of the system. From the sample data collected 70% of the data was used for training purposes and the rest 30% was used for testing. The test structure followed in this research work is patient independent pattern, as the hospital did not follow any hierarchy in recording and classifying the dataset based on neonates, children or adults categorized under different age groups. Hence the dataset used for this research work is a conglomeration of patients irrelevant of their age group and sex. The proposed system was developed using MATLAB 2010a and the experiments were conducted on an Intel core i3 machine with 4 GB RAM.

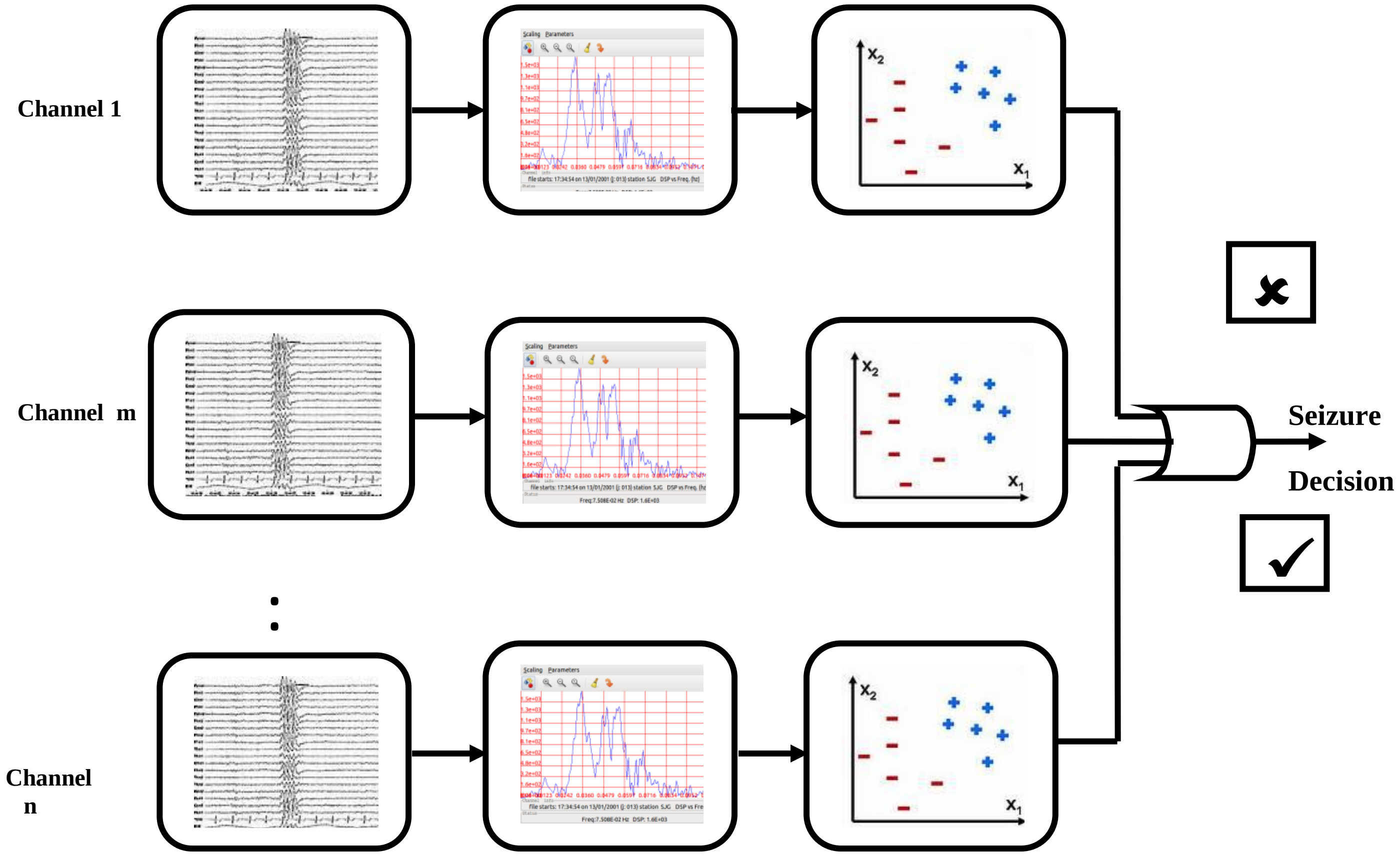

Figure 4.1 Layout of the Developed System

4.2 Performance Parameters

Performance evaluation of the methods adopted, enhanced and developed is the most important step in any research. The proposed ASDEEG system consists of three phases, and each of these phases requires different performance metrics for evaluation. The main objective is to identify methods in each of the phases by comparing it with the methods used as a yardstick. All the phases are then assembled in order to achieve a complete system with better performance. Different researchers regard different parameters for analysis.

Metrics which are used to evaluate the system performance with regard to signals, considered in this research work are outlined in this section.

Mean Square Error (MSE)

Mean Square Error is a measure of signal fidelity and aims at comparing the degree of similarity/fidelity or, conversely, the level of error/distortion between the signals and is based on the assumption that one of the signals is of pristine original, while the other is distorted or contaminated by errors.

$$\textbf{MSE} = \frac{\sum_{M,N}[I_1(m,n) - I_2(m,n)]^2}{M * N} \qquad (4.1)$$

In the above equation M and N represents the number of rows and columns of the given input signal.

Peak Signal to Noise (PSNR)

Peak Signal-to-Noise Ratio abbreviated as PSNR, characterizes the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the conformity of its representation. It is usually expressed in terms of the logarithmic decibel scale. It can be easily computed via MSE.

$$\textbf{PSNR} = 10 \log_{10} \left(\frac{\text{Max}^2}{\text{MSE}} \right) \qquad (4.2)$$

In the previous equation Max denotes the maximum value of the EEG signal. The higher the value of PSNR better is the fidelity of the signal.

Speed of Pre-processing Algorithms

Pre-processing time is a measurement used to estimate the time required to enhance the signals. It depends upon the time taken by each of the algorithms to pre-process the given input signal. The speed basically depends upon the complexity of the algorithm and the performance of the hardware processor. It is a general requirement that an increased speed should suffice any pre-processing algorithm.

Power Spectral Density (PSD)

The PSD is the measurement of power or variance of a time series distributed with respect to frequency**.** It refers to the amount of power per unit frequency. The values of PSD were used to train the network in the Classification phase.

$$\mathrm{PSD} = \frac{1}{\mathrm{k}} \sum_{\mathrm{m}=0}^{\mathrm{K}-1} \mathrm{Px}_{m}, \mathrm{M}(\omega_{\mathrm{K}}) \qquad (4.3)$$

In the above equation Px_{m} denotes the periodogram calculated using Welch estimate of the input signal of length m and ω_{K} is the window size**.**

Specificity

Specificity is a statistical measure used to evaluate the performance of classification. It is also referred to as the true negative rate which measures the proportion of negatives which are correctly identified. It is usually expressed in terms of percentage.

$$\text{Specificity} = \frac{\text{Number of true negative decisions}}{\text{Number of actual negative cases}} \qquad (4.4)$$

Sensitivity

Sensitivity is another statistical measure used to indicate the proportion of positives which are correctly identified. It is also referred to as true positive rate. It is usually expressed in terms of percentage.

$$\text{Sensitivity} = \frac{\text{Number of true positive decisions}}{\text{Number of actual positive cases}} \qquad (4.5)$$

Accuracy

Accuracy is defined as the degree to which a measured value conforms to a true or accepted value. Accuracy is a measure of correctness. The ultimate performance of any classifier is based accuracy. It is usually expressed in terms of percentage.

$$\text{Accuracy}= \frac{\text{Number of correct decisions}}{\text{Total number of cases}} \tag{4.6}$$

Execution time

The total time measurement from the start of the program until its culmination is defined as Execution time. It again depends upon the system configuration, the ability to handle voluminous datasets and of course the complexity of each algorithm. It is the time taken to detect whether the given input signal is epileptic or not.

4.3 Phase I Results : Pre-processing

Performance comparison between analytical results of the different algorithms used in the context of artifact removal is performed in the preprocessing phase. The results of 6 proposed algorithms Spatially Constrained InfomaxICA with Otsu Thresholding, Spatially Constrained InfomaxICA with FuzzyShrink Thresholding, Spatially Constrained Extended InfomaxICA with Otsu Thresholding, Spatially Constrained Extended InfomaxICA with FuzzyShrink Thresholding, Spatially Constrained FastICA with Otsu Thresholding, and Spatially Constrained FastICA with FuzzyShrink Thresholding are compared with a traditional algorithm namely Adaptive filter involving RLS algorithm.

In this section the analytical performance of MSE with an effect on the Seizure detection system is derived. MSE measures the average of the square of the error. It is a ubiquitous estimator seeking optimization in the field of signal processing. It depicts the amount of error mitigated by the estimator from the quantity to be estimated. This deviation is caused due to randomness or because the estimator has not accounted for information that could produce a more accurate estimate. The general observation fact is that lower the value of MSE better is the performance of the algorithm on the signal. Table 4.1 shows the performance of algorithms with respect to Spatially Constrained ICAs in terms of MSE.

TABLE 4.1 Mean Square Error for Spatially Constrained ICAs

Techniques	Electrical Artifact	Eye Ball Movement Artifact	Eye Blink Artifact	Jaw Clenching Artifact	Spit Swallowing Artifact
SC InfomaxICA	10.4790	10.4790	7.1112	14.6513	12.0170
SC Extended InfomaxICA	1.8660	5.8995	1.6601	2.0230	2.0230
SC FastICA	1.0001	1.0007	1.0015	1.0036	1.0015

From the table, out of the proposed Spatially Constrained ICA algorithms, it is evident that the spatially constrained FastICA outperforms the rest, as it has the least MSE values. The next performer with respect to this estimator is spatially constrained Extended InfomaxICA, where the values of MSE are lesser than the values observed for spatially constrained InfomaxICA. Delineating the performance of MSE, it can be observed that SCFastICA outperforms SCExtendedInfomax ICA by a very negligible factor of 1.86 for electrical artifact and SCInfomaxICA by a factor of 10.5. It outperforms SCExtendedInfomax ICA by a factor of 5.89 for Eye Ball movement artifact and SCInfomaxICA by a factor of 10.5. It outperforms SCExtendedInfomax ICA by a very negligible factor of 1.66 for eye blink artifact and SCInfomaxICA by a factor of 7. It outperforms SCExtendedInfomax ICA by a factor of 2 for Jaw Clenching artifact and SCInfomaxICA by a factor of 6. It outperforms SCExtendedInfomax ICA by a factor of 2 for Spit Swallowing artifact and SCInfomaxICA by a factor of 12.

Next a comparative analysis based on the MSE estimator for the proposed spatially constrained algorithms with signal denoising is performed with respect to various artifact interferences. The Table 4.2 depicts the analytical results of spatially constrained InfomaxICA +DWT with Otsu and Fuzzy shrink thresholding. The fuzzy Shrink thresholding performs better than Otsu thresholding. The S shaped curve followed by Sigmoid, B Splines, and Bell shaped curve membership function performs better than Z shaped, triangular and Gaussian curves in fuzzy shrink thresholding.

TABLE 4.2 Mean Square Error for Spatially Constrained InfomaxICA with Signal Denoising Techniques for various artifact interferences

SC InfomaxICA + DWT		Electrical Artifact	Eye Ball Movement Artifact	Eye Blink Artifact	Jaw Clenching Artifact	Spit Swallowing Artifact
Otsu		5.3262	10.5222	7.1130	39.7632	38.9764
Fuzzy Shrink	***S shaped***	4.3878	10.5831	7.1514	28.0242	27.9850
	B splines	4.4687	10.5843	7.1481	27.9904	24.6990
	Z shaped	5.3851	10.4845	7.2475	28.0081	24.8060
	Sigmoid	4.3254	10.5913	7.0138	28.0423	38.9770
	Triangular	5.5099	10.5001	6.9516	28.0193	24.0720
	Bell	4.4753	10.5692	6.9561	27.9814	38.9763
	Gaussian	5.5704	10.5390	7.2572	28.0140	28.9792

Outlining the performance of MSE for SCInfomaxICA, it can be observed that fuzzy shrink outperforms Otsu by a factor of.81 at best for electrical artifact. Again, it outperforms Otsu by a factor of 1.002 at best for Eye Ball movement artifact. It outperforms Otsu by a factor of 1.02 at best for the eye blink artifact. It outperforms Otsu by a factor of 1.42 at best for the Jaw

Clenching artifact. It outperforms Otsu by a factor of 1.61 at best for the Spit Swallowing artifact.

Table 4.3 depicts the analytical results of spatially constrained Extended InfomaxICA +DWT with Otsu and Fuzzy shrink thresholding. The fuzzy Shrink thresholding performs better than Otsu thresholding. Further the membership functions S shaped, Sigmoid, B splines and Bell curve perform a little better than Z-shaped and Gaussian curve in fuzzy shrink thresholding. It can be observed that fuzzy shrink outperforms Otsu by a factor of 1.022 at best for electrical artifact. Again, it outperforms Otsu by a factor of 1.002 at best for Eye Ball movement artifact. It outperforms Otsu by a factor of 1.0008 at best.It outperforms Otsu by a factor of 5.07 at best. It outperforms Otsu by a factor of 4.06 at best for the Spit Swallowing artifact.

TABLE 4.3 Mean Square Error for Spatially Constrained Extended Infomax ICA with Signal Denoising Techniques for various artifact interferences

SC Extended Infomax ICA + DWT		Electrical Artifact	Eye Ball Movement Artifact	Eye Blink Artifact	Jaw Clenching Artifact	Spit Swallowing Artifact
Otsu		1.8753	5.9202	9.8130	10.0490	8.0295
Fuzzy Shrink	S shaped	1.8841	5.9626	9.8208	2.0261	2.0264
	B splines	1.8631	5.8638	9.8698	1.9819	1.9729
	Z shaped	1.8731	5.8967	9.7969	2.0014	2.2414
	Sigmoid	1.8340	5.9182	9.9791	2.0217	2.6212
	Triangular	1.8832	5.9043	9.8126	2.3472	2.3072
	Bell	1.8516	5.9038	9.8045	2.3472	2.0472
	Gaussian	1.8452	5.8737	9.7869	2.3331	2.3031

Table 4.4 depicts the analytical results of spatially constrained fastICA +DWT with Otsu and Fuzzy shrink thresholding. Here again the fuzzy Shrink thresholding performs better than Otsu thresholding. The membership function outperforms the other functions in fuzzy shrink thresholding. From the above tables it can be analyzed that for the MSE estimator out of the 6 proposed

algorithms the spatially constrained fastICA + DWT with fuzzy shrink thresholding performs the best.

TABLE 4.4 Mean Square Error for Spatially Constrained FastICA with Signal Denoising Techniques for various artifact interferences

SCFastICA + DWT		Electrical Artifact	Eye Ball Movement Artifact	Eye Blink Artifact	Jaw Clenching Artifact	Spit Swallowing Artifact
Otsu		0.9996	1.0008	1.0005	1.0002	1.0015
Fuzzy Shrink	***S shaped***	0.0799	0.9931	0.8567	0.9742	0.9699
	B Splines	0.0322	0.0310	0.0437	0.0436	0.0307
	Z shaped	0.0178	0.0054	0.1340	0.0319	0. 6277
	Sigmoid	0.3556	0.4016	0.7122	0.4754	0.4068
	Triangular	0.0318	0.0037	0.4542	0.2106	0.0135
	Bell	0.1337	0.0900	0.2106	0.1172	0.1095
	Gaussian	0.1193	0.0492	0.2520	0.1171	0.0979

From the results of the above table it can be analyzed that best performance is ascertained by using fuzzy shrinkage thresholding**.** Further, it can be observed that fuzzy shrink outperforms Otsu by a factor of 56 at best and a factor of 2.9 at worst, for electrical artifact, a factor of 270 at best and a factor of 2 at worst, for Eye Ball movement artifact, a factor of 22 for eye blink, Jaw Clenching artifact at best and a factor of 1.16 and 1.02 at worst for eye blink, Jaw Clenching artifact and, a factor of 32 at best and 1.03 at worst for the Spit Swallowing artifact.

PSNR is another most important measure in signal processing representing the fidelity of the signal after its persuasion with interferences. It is a general analogy that an algorithm is considered to be good if PSNR is high. Table 4.5 shows the performance of algorithms with respect to Spatially Constrained ICAs in terms of PSNR. Delineating the performance of PSNR for SCICAs from table 4.5 it can be observed that SCFastICA outperforms SCExtendedInfomax ICA by a factor of 1.9 for electrical artifact and SCInfomaxICA by a factor of 2.6.It outperforms SCExtendedInfomax ICA by a factor of 2 and for the Eye Ball movement artifact and SCInfomaxICA by a factor of 2.5. It outperforms SCExtendedInfomax ICA by a very negligible factor of 1.87 for eye blink artifact and SCInfomaxICA by a factor of 3.2. It outperforms SCExtendedInfomax ICA by a factor of 1.97 for Jaw Clenching artifact and SCInfomaxICA by a factor of 3.03. It outperforms SCExtendedInfomax ICA by a factor of 2.14 for Spit Swallowing artifact and SCInfomaxICA by a factor of 3.07.

TABLE 4.5

Peak Signal to Noise Ratio (dB) for Spatially Constrained ICAs

Techniques	Electrical Artifact	Eye Ball Movement Artifact	Eye Blink Artifact	Jaw Clenching Artifact	Spit Swallowing Artifact
SC InfomaxICA	16.1269	17.5039	14.4975	16.3414	16.0232
SC Extended InfomaxICA	22.2000	22.2544	20.5938	25.0250	23.1239
SC FastICA	42.5436	44.6751	46.9401	49.5212	49.6312

From the Table 4.6, it is evident that out of the proposed Spatially Constrained ICA algorithms, the spatially constrained FastICA outperforms the rest, as it has the highest PSNR values. The next best performance was revealed by spatially constrained Extended InfomaxICA, where the values of PSNR are greater than the values observed for spatially constrained InfomaxICA. It can be observed that fuzzy shrink outperforms Otsu by a factor of 1.14 at best for electrical artifact. Further, it outperforms Otsu by a factor of 1.016 at best for Eye Ball movement and 1.013 at best for eye blink artifact, a factor of 1.01 at for Jaw Clenching artifact and a factor of 1.006 for the Spit Swallowing artifact.

Next a comparative performance evaluation based on the PSNR estimator for the proposed spatially constrained algorithms with signal denoising is performed with respect to various artifact interferences. The Table 4.6 depicts the investigative results of spatially constrained InfomaxICA +DWT with Otsu and Fuzzy shrink thresholding. The fuzzy Shrink thresholding performs better than Otsu thresholding. Further the sigmoid membership function outperforms the rest in case of artifact removal fuzzy shrink thresholding.

TABLE 4.6 Peak Signal to Noise Ratio (dB) for Spatially Constrained InfomaxICA with Signal Denoising Techniques for various artifact interferences

SC InfomaxICA + DWT		Electrical Artifact	Eye Ball Movement Artifact	Eye Blink Artifact	Jaw Clenching Artifact	Spit Swallowing Artifact
		16.2576	17.5202	14.5096	27.8120	27.8236
Fuzzy Shrink	*S shaped curve*	18.6950	17.4950	14.5027	27.6995	24.4594
	B Splines	18.6156	17.5060	14.5079	18.0750	19.0750
	Z shaped	16.2098	17.5131	14.5052	16.1420	17.1497
	Sigmoid	17.4463	17.8029	14.6999	27.9612	27.9910
	Triangular	16.1103	17.5067	14.5036	19.2267	18.2267
	Bell curve	18.6092	17.5121	14.5095	27.7964	26.7995
	Gaussian curve	16.0630	17.5018	14.5042	27.8675	27.7978

Performance evaluation based on the PSNR estimator for the proposed spatially constrained Extended InfomaxICA +DWT with Otsu and Fuzzy shrink thresholding is performed with respect to various artifact interferences. The Table 4.7 depicts the investigative results of the above. The fuzzy Shrink thresholding performs better than Otsu thresholding. Further the sigmoid membership function outperforms the rest in fuzzy shrink thresholding. It can be observed that fuzzy shrink outperforms otsu by a factor of 1.05 for electrical artifact, a factor of 1.012 for Eye Ball movement artifact, a factor of 1.184 at best for eye blink artifact, a factor of 1.23 at for Jaw Clenching artifact and factor of 1.048 for Spit Swallowing artifact.

TABLE 4.7 Peak Signal to Noise Ratio (dB) for Spatially Constrained Extended InfomaxICA with Signal Denoising Techniques for various artifact interferences

SC Extended InfomaxICA + DWT		Electrical Artifact	Eye Ball Movement Artifact	Eye Blink Artifact	Jaw Clenching Artifact	Spit Swallowing Artifact
Otsu		22.1796	22.3582	22.2454	20.5047	23.3604
Fuzzy Shrink	***S shaped curve***	22.1593	22.2942	23.2488	25.1995	20.6053
	B Splines	22.2080	22.3393	26.3456	25.2279	20.5837
	Z shaped	22.1846	22.3697	23.5410	25.1853	20.5900
	Sigmoid	22.3254	22.3267	23.2848	25.2088	20.5359
	Triangular	22.1116	22.3913	23.2906	24.3991	20.5831
	Bell curve	22.2839	22.6372	26.3570	24.3911	20.5867
	Gaussian curve	22.2991	22.3046	23.2583	24.4855	24.4855

Performance evaluation based on the PSNR estimator for the proposed spatially constrained fastICA +DWT with Otsu and Fuzzy shrink thresholding is performed with respect to various artifact interferences. The Table 4.8 depicts the exploratory results of the above. The fuzzy Shrink thresholding performs better than Otsu thresholding. Further the triangular membership function outperforms the rest in fuzzy shrink thresholding. It can be observed that fuzzy shrink outperforms Otsu by a factor of 1.05 at the best and a factor of 1.01 at the worst for electrical artifact, a factor of 1.49 at best and a factor of

1.08 at worst for Eye Ball movement artifact , a factor of 1.325 at best and a factor of 1.02 at worst for eye blink artifact, a factor of 1.46 at the best and at worst for 1.09 for Jaw Clenching artifact and factor of 1.32 at best and a factor of 1.15 at worst for Spit Swallowing artifact.

TABLE 4.8 Peak Signal to Noise Ratio (dB) for spatially Constrained Fast ICA with Signal Denoising Techniques for various artifact interferences

SCFastICA DWT		Electrical Artifact	Eye Ball Movement Artifact	Eye Blink Artifact	Jaw Clenching Artifact	Spit Swallowing Artifact
Otsu		41.8702	45.0538	47.3033	44.8261	49.5212
Fuzzy Shrink	***S shaped curve***	41.9567	44.7405	47.0988	49.1803	46.9400
	B splines	57.1300	59.9467	62.2505	62.9732	62.9732
	Z shaped	59.7104	67.5135	62.6926	64.3253	64.3253
	Sigmoid	47.0331	48.9706	50.9111	52.4775	52.4775
	Triangular	60.7999	65.1513	65.8221	65.5235	65.5235
	Bell curve	51.0188	55.3662	56.8389	58.7064	58.7064
	Gaussian curve	51.5807	57.9451	57.3282	58.6816	58.6816

The results while considering speed as the criteria for evaluation reveals that the spatially constrained FastICA performs faster than the spatially constrained Extended InfomaxICA as well as spatially constrained InfomaxICA. Here again spatially constrained Extended InfomaxICA performs faster than spatially constrained InfomaxICA. Table 4.9 portrays the analytical results for time taken to perform the investigations and are specified below. Delineating the performance of time taken for removal of artifact for SCICAs , it can be observed that SCFastICA outperforms SCExtendedInfomax ICA by a factor of 1.27 of for electrical artifact and SCInfomaxICA by a factor of 2.21.It outperforms SCExtendedInfomax ICA by a factor of 3.21 for Eye Ball movement artifact and SCInfomaxICA by a factor of 3.65. It outperforms SCExtendedInfomax ICA by a factor of 3.88 for eye blink artifact and SCInfomaxICA by a factor of 4.78. It outperforms SCExtendedInfomax ICA by a factor of 3.508 for Jaw Clenching artifact and SCInfomaxICA by a factor of 3.86. It outperforms SCExtendedInfomax ICA by a factor of 2.92 for Spit Swallowing artifact and SCInfomaxICA by a factor of 3.85.

TABLE 4.9 Time taken (seconds) for Spatially Constrained ICAs

Techniques	Electrical Artifact	Eye Ball Movement Artifact	Eye Blink Artifact	Jaw Clenching Artifact	Spit Swallowing Artifact
SC InfomaxICA	5.8883	5.4084	5.5516	5.5293	5.3053
SC Extended InfomaxICA	4.6029	4.7676	6.8360	5.0249	4.0254
SC FastICA	2.6630	1.4815	1.4284	1.4322	1.3747

TABLE 4.10 Time taken (seconds) for Spatially Constrained InfomaxICA with Signal Denoising Techniques for various artifact interferences

SCInfomax ICA + DWT		Electrical Artifact	Eye Ball Movement Artifact	Eye Blink Artifact	Jaw Clenching Artifact	Spit Swallowing Artifact
Otsu		5.3680	5.1037	5.1461	5.2634	5.2701
Fuzzy Shrink	***S shaped***	6.6549	6.1549	7.2585	9.3697	8.5231
	B Splines	22.7487	22.974	11.8048	11.3822	15.0291
	Z shaped	9.4796	5.5426	5.5160	5.1554	5.1729
	Sigmoid	5.1397	5.0338	5.0155	5.0749	5.0141
	Triangular	5.7142	5.6882	5.4513	5.4153	5.2459
	Bell	5.2731	5.0822	5.0798	4.9627	5.0189
	Gaussian	5.0598	4.2611	4.2708	4.4700	4.4838

Analysis on speed of performance was further extended to the proposed spatially constrained InfomaxICA + DWT with Otsu and Fuzzy shrink thresholding with respect to various artifact interferences. The Table 4.10 depicts the performance of speed with respect to the above specified algorithms. The fuzzy Shrink thresholding performs faster than Otsu thresholding. Further the sigmoid membership function is speedily performed than the rest of fuzzy shrink thresholding. It can be further observed that fuzzy shrink outperforms otsu by a factor of 1.06 at best for electrical artifact. Again it outperforms otsu by a factor of 1.19 for Eye Ball movement artifact. It outperforms otsu by a factor of 1.21 for eye blink artifact. It outperforms otsu by a factor of 1.17 for Jaw Clenching artifact and for Spit Swallowing artifact.

TABLE 4.11 Time taken (seconds) for Spatially Constrained Extended InfomaxICA with Signal Denoising Techniques for various artifact interferences

SCExtended Infomax ICA+ **DWT**		**Electrical Artifact**	**Eye Ball Movement Artifact**	**Eye Blink Artifact**	**Jaw Clenching Artifact**	**Spit Swallowing Artifact**
Otsu		4.6570	10.3396	5.0690	4.8128	6.2050
Fuzzy Shrink	***S shaped***	4.8542	4.8096	7.1030	4.5191	4.0548
	B Splines	4.9658	5.0794	6.0177	5.0232	4.1179
	Z shaped	4.8086	4.8173	6.5508	4.9371	3.9814
	Sigmoid	4.7538	4.7425	5.9731	4.4192	4.5535
	Triangular	4.9661	4.7285	6.8099	4.3893	4.5338
	Bell	6.9121	5.0764	6.9123	4.3893	4.1087
	Gaussian	4.4341	4.8893	4.6018	4.6279	4.0051

Table 4.11 depicts the performance of speed with respect to the proposed spatially constrained Extended InfomaxICA + DWT with Otsu and Fuzzy shrink thresholding with respect to various artifact interferences. The fuzzy Shrink thresholding performs faster than Otsu thresholding. The sigmoid membership function is swiftly performed than the rest of fuzzy shrink thresholding and also, it can be observed that fuzzy shrink outperforms otsu by a factor of 1.05 for electrical artifact, a factor of 2 for Eye Ball movement artifact, a factor of 1.07 for eye blink artifact, a factor of 1.09 for Jaw Clenching artifact and factor of 1.55 for Spit Swallowing artifact.

Table 4.12 depicts the performance of speed with respect to the proposed spatially constrained fastICA +DWT with Otsu and Fuzzy shrink thresholding with respect to various artifact interferences. The fuzzy Shrink thresholding performs faster than Otsu thresholding. Further the triangular membership function rapidly performs the artifact removal than the rest of fuzzy shrink thresholding. It can be further observed that fuzzy shrink outperforms otsu by a factor of 56 for electrical artifact, a factor of 27 at for Eye Ball movement artifact , a factor of 2 for eye blink artifact, a factor of 50 for Jaw Clenching artifact and factor of 10 for Spit Swallowing artifact.

TABLE 4.12 Time taken (seconds) for Spatially Constrained FastICA with Signal Denoising Techniques for various artifact interferences

SCFastICA + DWT		**Electrical Artifact**	**Eye Ball Movement Artifact**	**Eye Blink Artifact**	**Jaw Clenching Artifact**	**Spit Swallowing Artifact**
Otsu		0.9996	1.0008	1.380967	1.0002	1.0015
Fuzzy Shrink	***S shaped***	0.9799	0.9931	2.678566	0.9742	0.9699
	B Splines	0.0322	0.0310	2.364757	0.0436	0.0307
	Z shaped	0.0178	0.0054	2.619567	0.0319	0.6277
	Sigmoid	0.3556	0.4016	3.229903	0.4754	0.4068
	Triangular	0.0318	0.0037	0.991317	0.0242	0.0135
	Bell	0.1337	0.0900	5.152736	0.1172	0.1095
	Gaussian	0.1193	0.0492	3.802596	0.1171	0.1095

From the various observations it was delineated that spatially constrained fastICA and signal denoising performed with fuzzy thresholding performed to the maximum in removing the artifacts by retaining the significant information.

To analyze the overall performance of these algorithms against each of the artifacts the results are plotted for MSE, PSNR and execution time. Figure 4.2 shows the plot for overall performance of algorithms with reference to the estimator MSE with respect to Electrical Artifact.

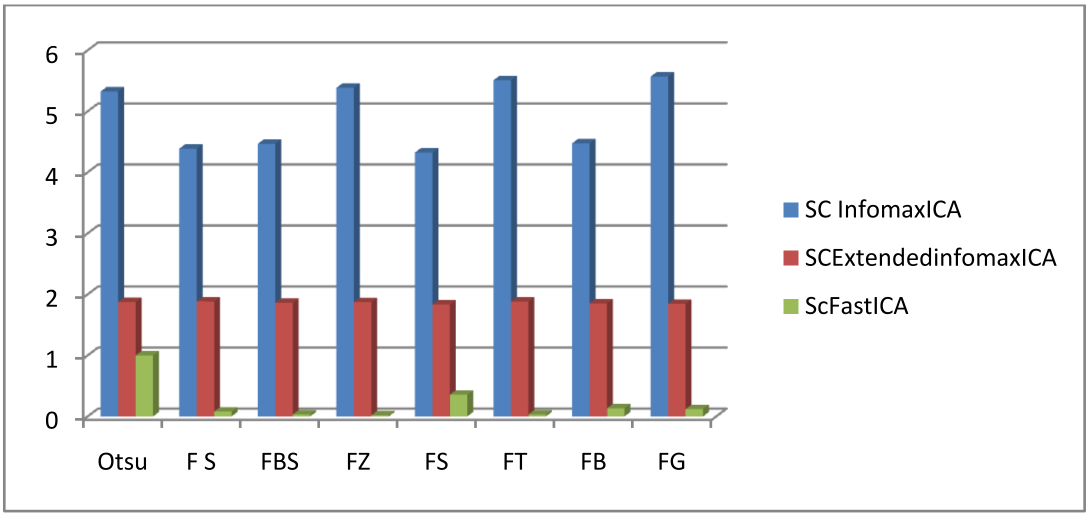

Figure 4.2 MSE of Electrical Artifact

Figure 4.3 shows the plot for overall performance of algorithms based on MSE values with respect to Eyeball Movement Artifact.

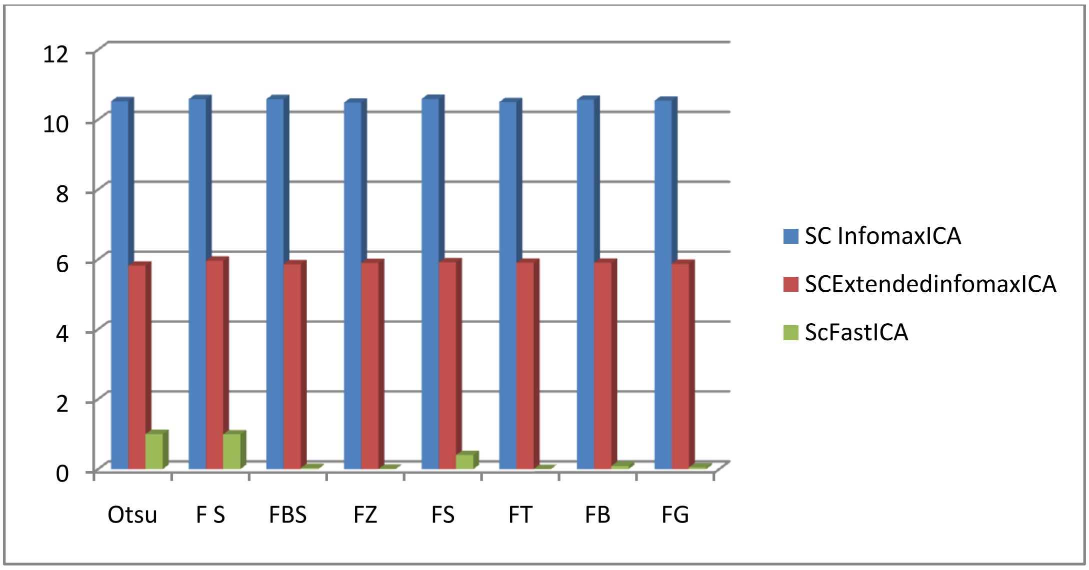

Figure 4.3 MSE of Eye Ball Movement Artifact

Figure 4.4 shows the plot for overall performance of algorithms with reference to MSE with respect to Eye blink Artifact.

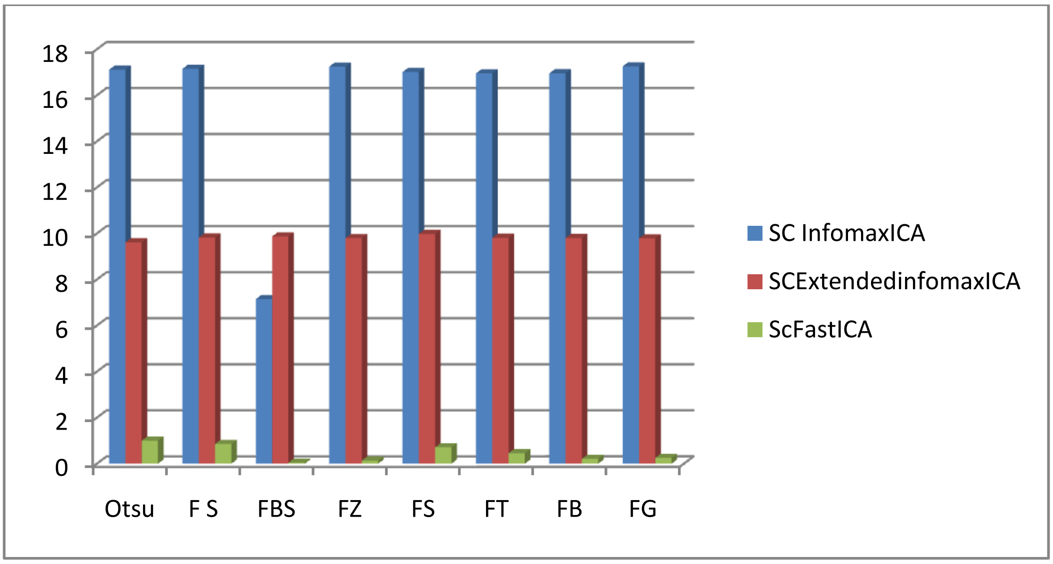

Figure 4.4 MSE of Eye Blink Artifact

Figure 4.5 shows the plot for MSE depicting the overall performance of algorithms with respect to Jaw Clenching Artifact.

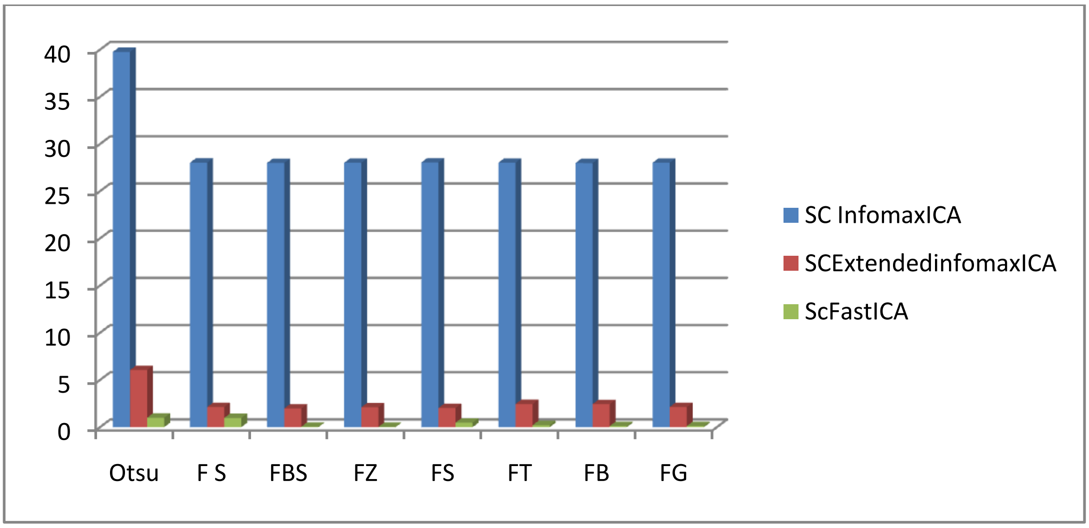

Figure 4.5 MSE of Jaw Clenching Artifact

Figure 4.6 shows the plot for MSE portraying the overall performance of algorithms with respect to Spit Swallowing Artifact.

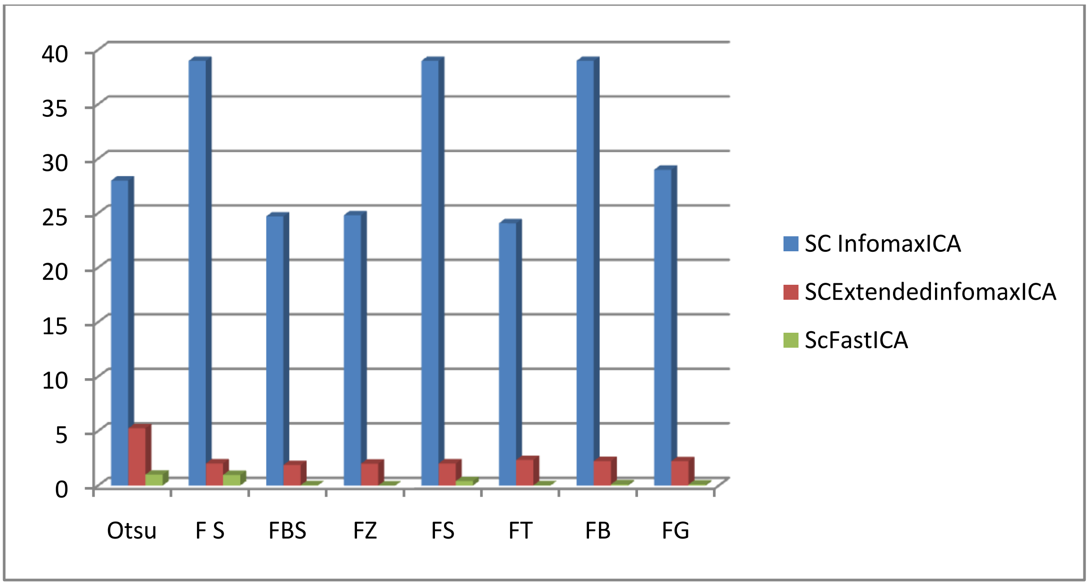

Figure 4.6 MSE of Spit Swallowing Artifact

Performance analyses of algorithms with respect to the PSNR estimator for each of the artifacts are plotted. Figure 4.7 shows the plot for overall performance of algorithms with reference to the estimator PSNR with respect to Electrical Artifact.

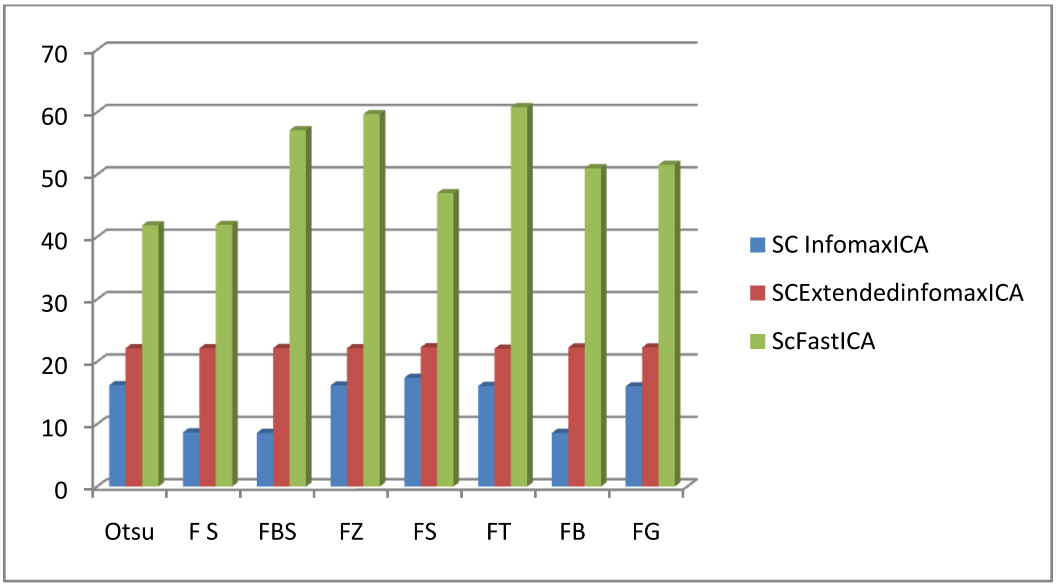

Figure 4.7 PSNR of Electrical Artifact

Figure 4.8 shows the plot for overall performance of algorithms based on PSNR with respect to Electrical Artifact.

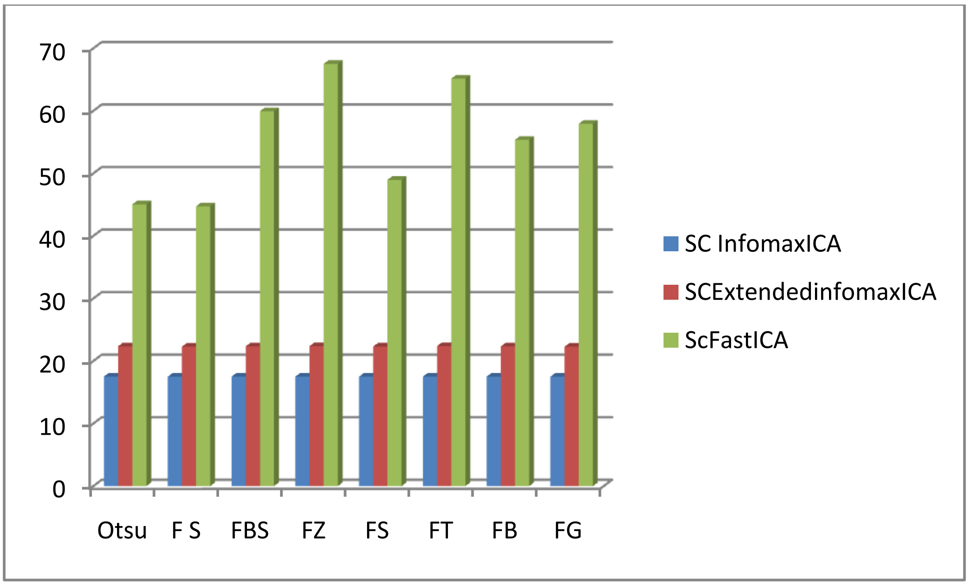

Figure 4.8 PSNR of Eye Ball Movement Artifact

Figure 4.9 shows the plot for overall performance of algorithms with reference to PSNR for Eye blink Artifact.

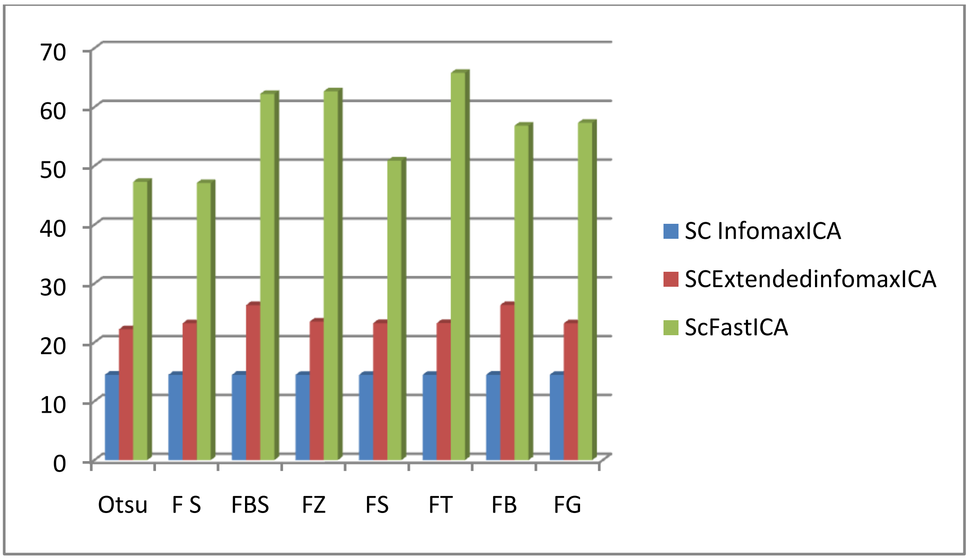

Figure 4.9 PSNR of Eye Blink Artifact

Figure 4.10 shows the plot for PSNR depicting the overall performance of algorithms with respect to Jaw Clenching Artifact.

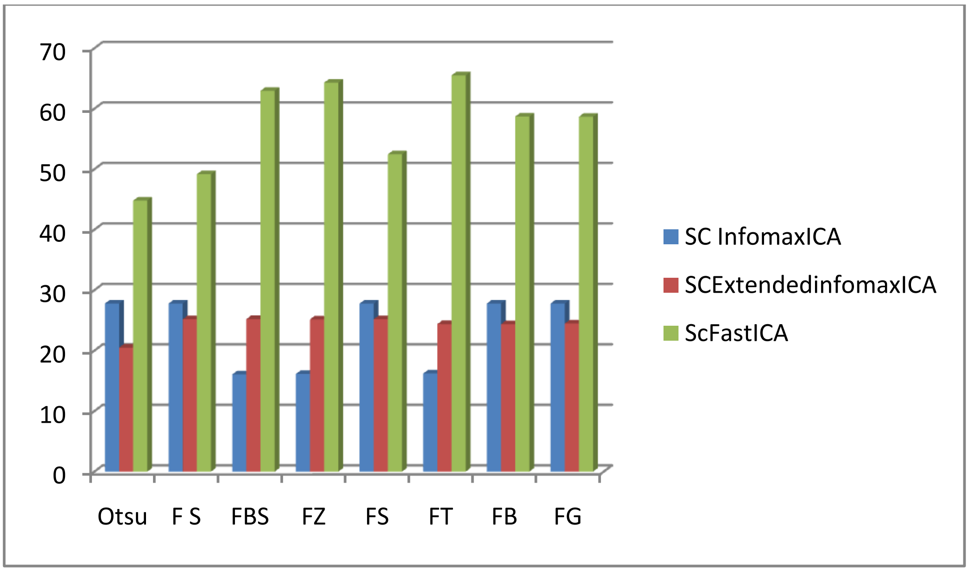

Figure 4.10 PSNR of Jaw Clenching Artifact

Figure 4.11 shows the plot for PSNR portraying the overall performance of algorithms with respect to Spit Swallowing Artifact.

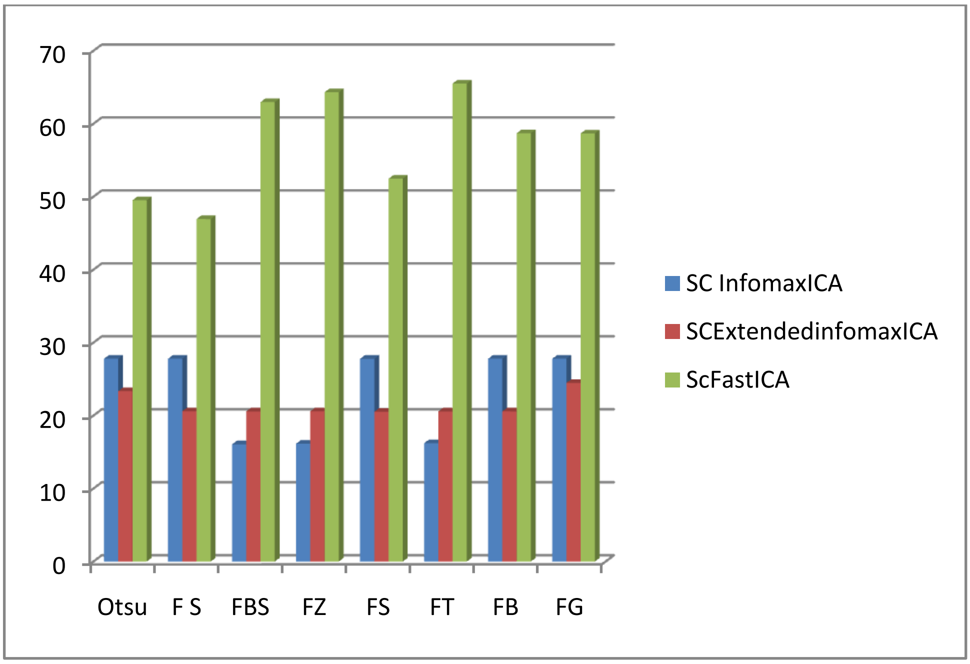

Figure 4.11 PSNR of Spit Swallowing Artifact

Execution time for performing artifact removal is plotted. Figure 4.12 shows the plot for time taken to perform Electrical artifact removal.

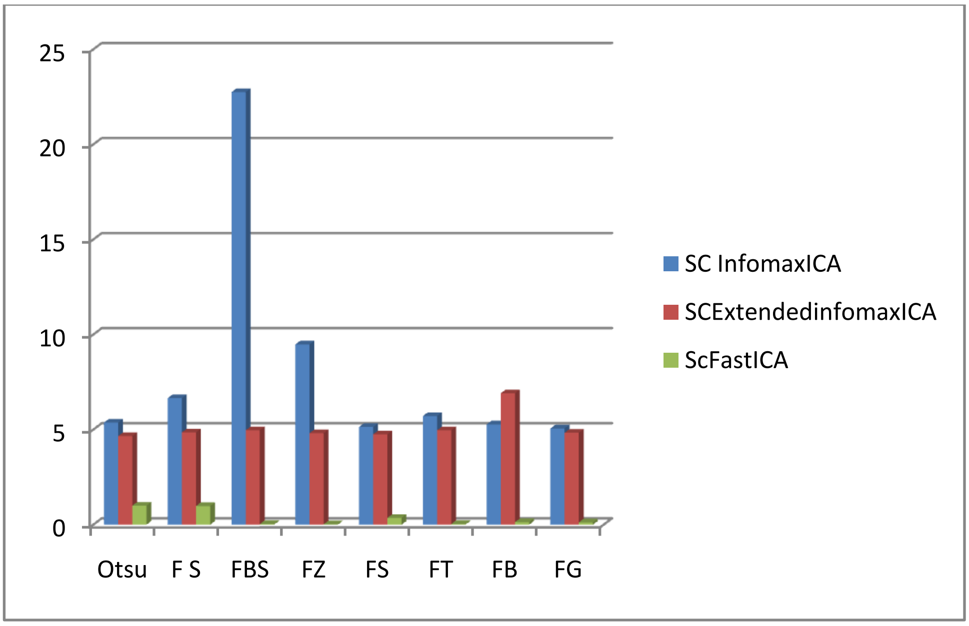

Figure 4.12 Time taken for Electrical artifact removal

Figure 4.13 shows the plot for execution time to perform Eye ball movement artifact removal.

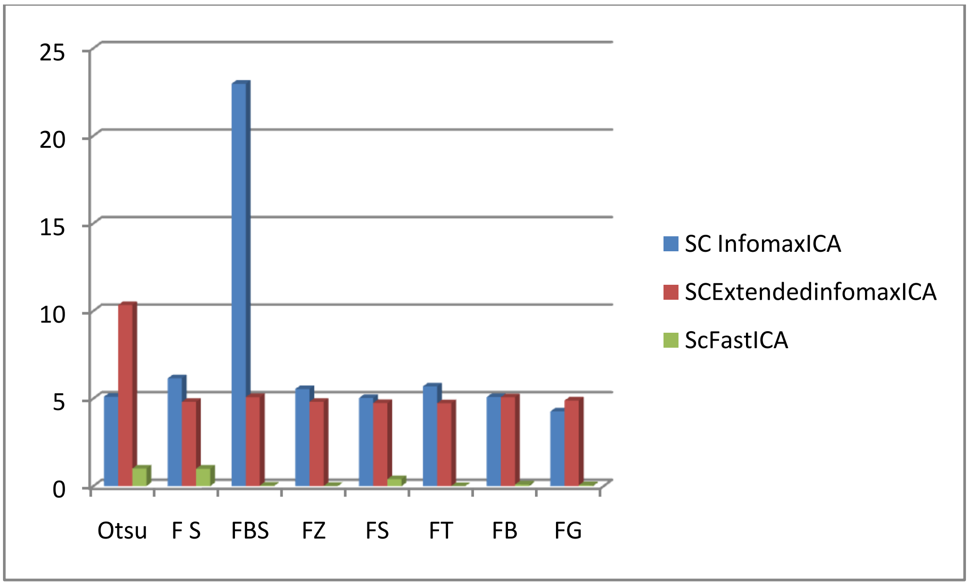

Figure 4.13 Time taken for Eye Ball Movement artifact removal

Figure 4.14 shows the time taken plot for removing Eye blink artifact from the EEG input signal.

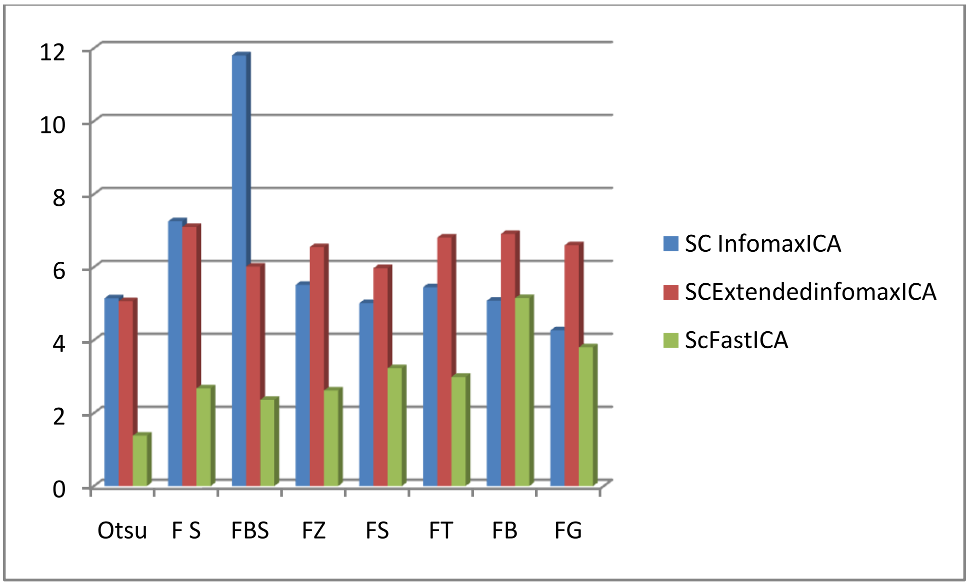

Figure 4.14 Time taken for Eye Blink artifact removal

Figure 4.15 shows the plot for execution time to perform Jaw Clenching artifact removal.

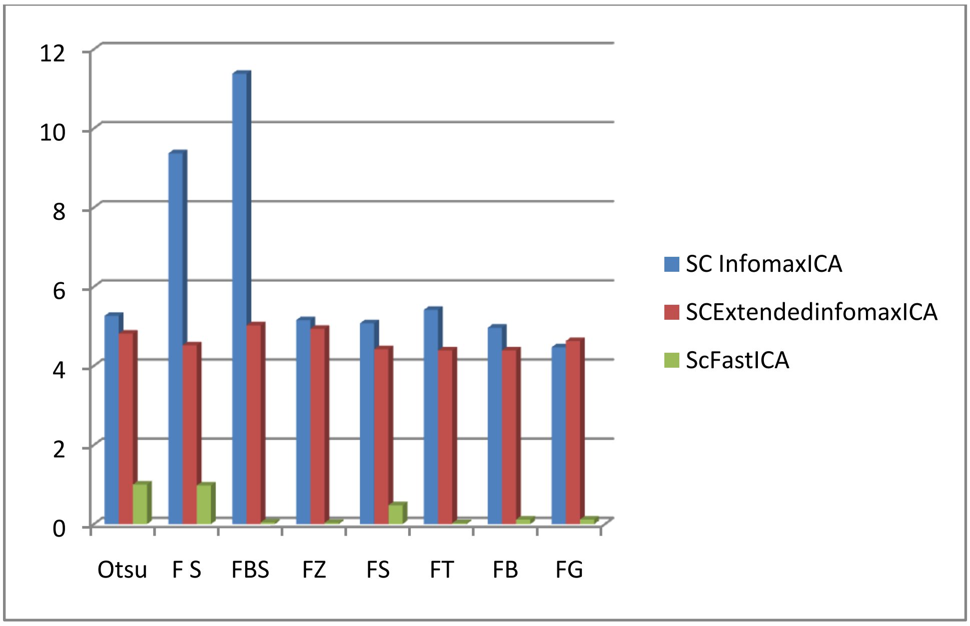

Figure 4.15 Time taken for Jaw clenching artifact removal

Figure 4.16 shows the plot for execution time to perform Spit swallowing artifact removal.

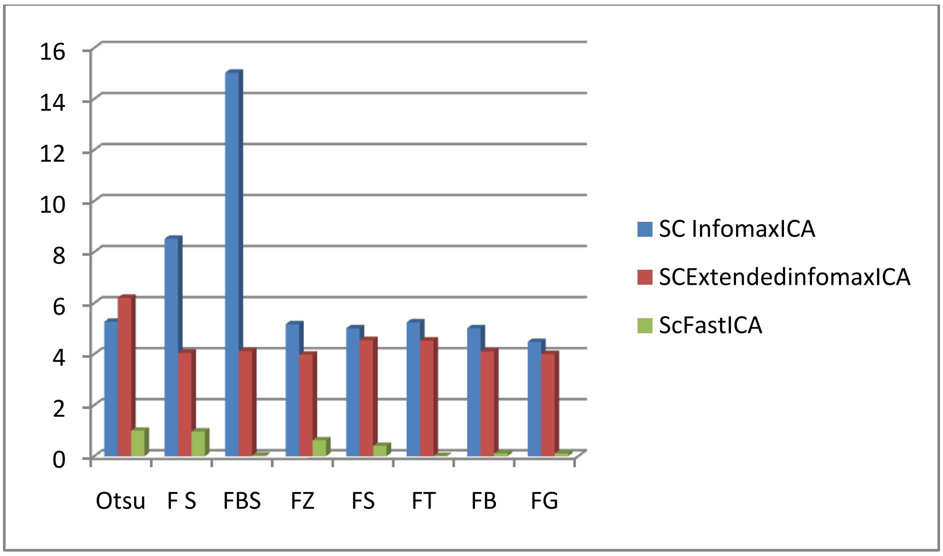

Figure 4.16 Time taken for Spit swallowing artifact removal

Visual representation of various artifacts obtained from the hospital and their equivalent results after preprocessing in MATLAB are portrayed from figure 4.17-4.26 which are depicted below.

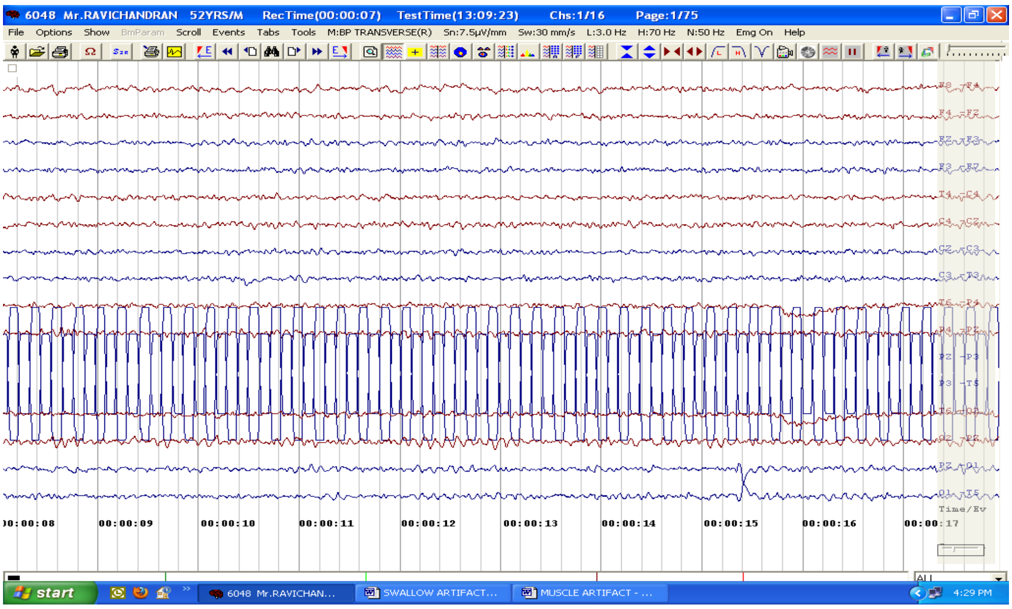

Figure 4.17 Electrical disturbances arising due to popping up of electrodes

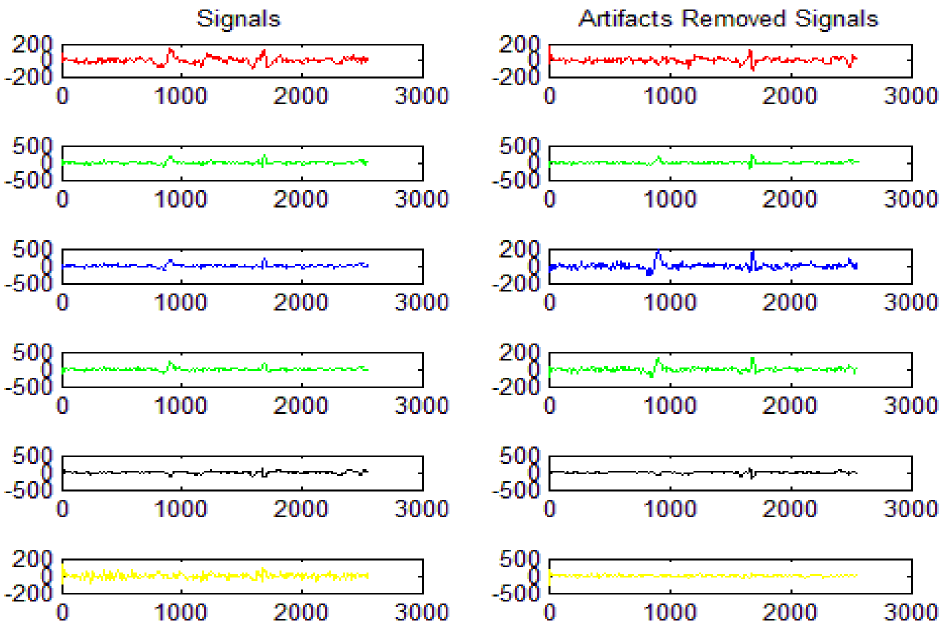

Figure 4.18 Pre processing of signals using spatially constrained InfomaxICA with fuzzy thresholding

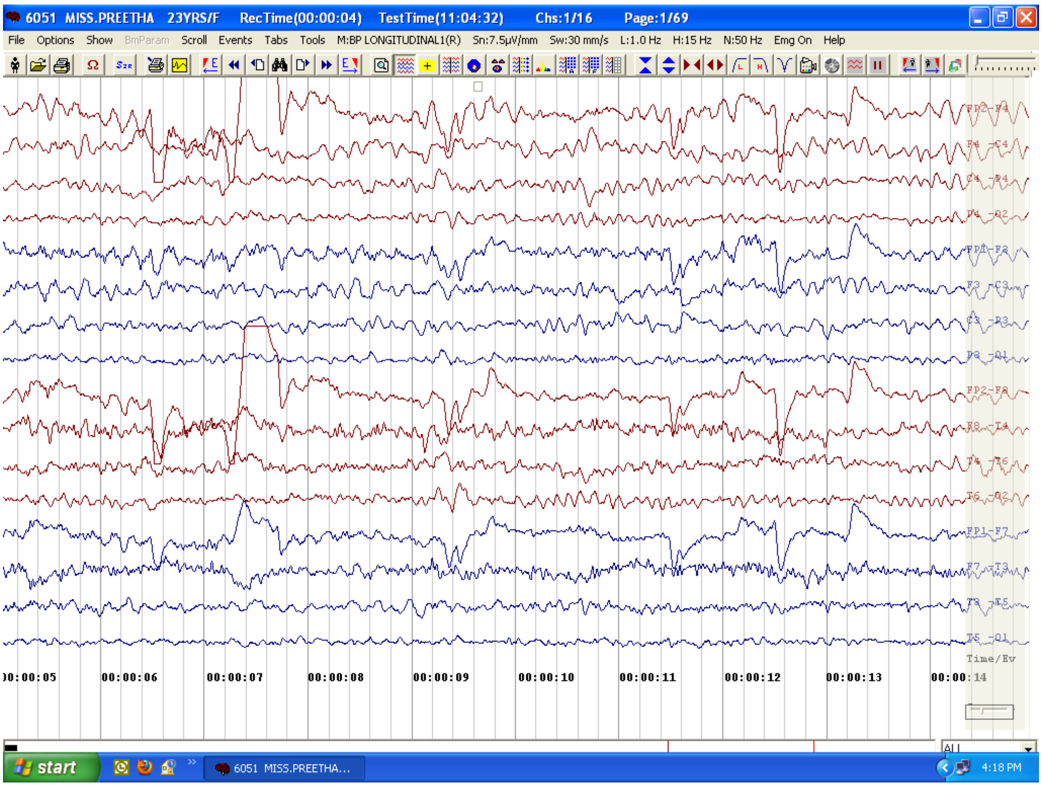

Figure 4.19 Eye Ball Movement artifact

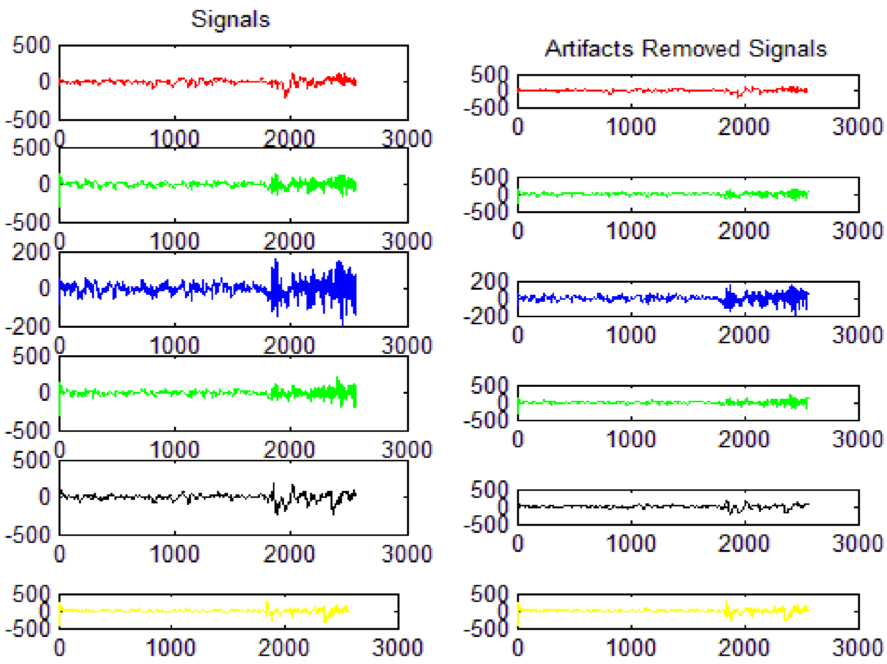

Figure 4.20 Pre processing of Eye ball movement signal using spatially constrained InfomaxICA with fuzzy thresholding

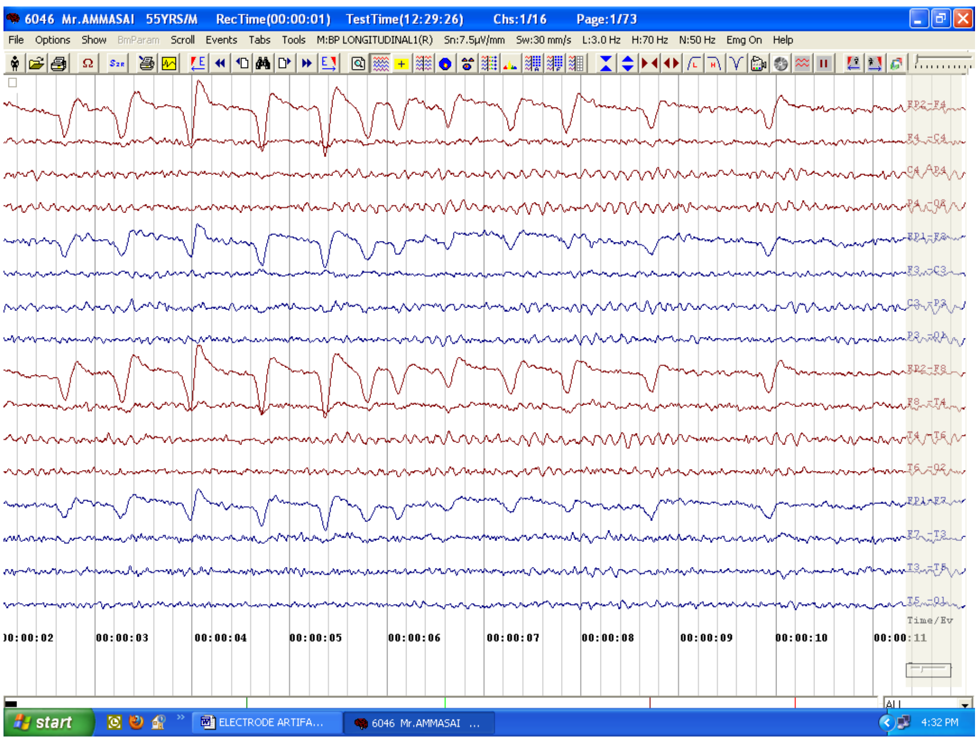

Figure 4.21 Eye Blink artifact

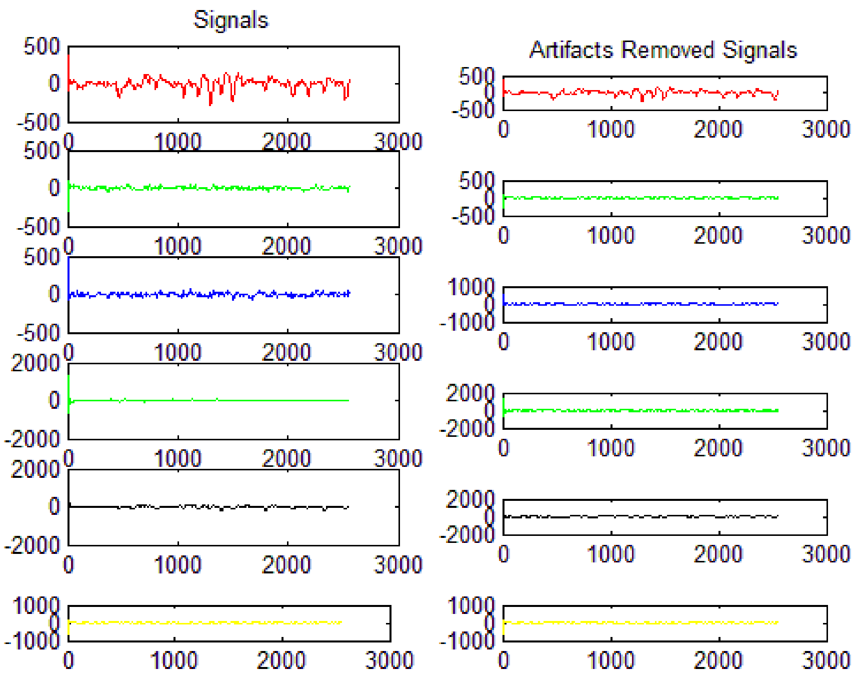

Figure 4.22 Artifact removal of Eye Blink signal using spatially constrained fastICA with Otsu thresholding

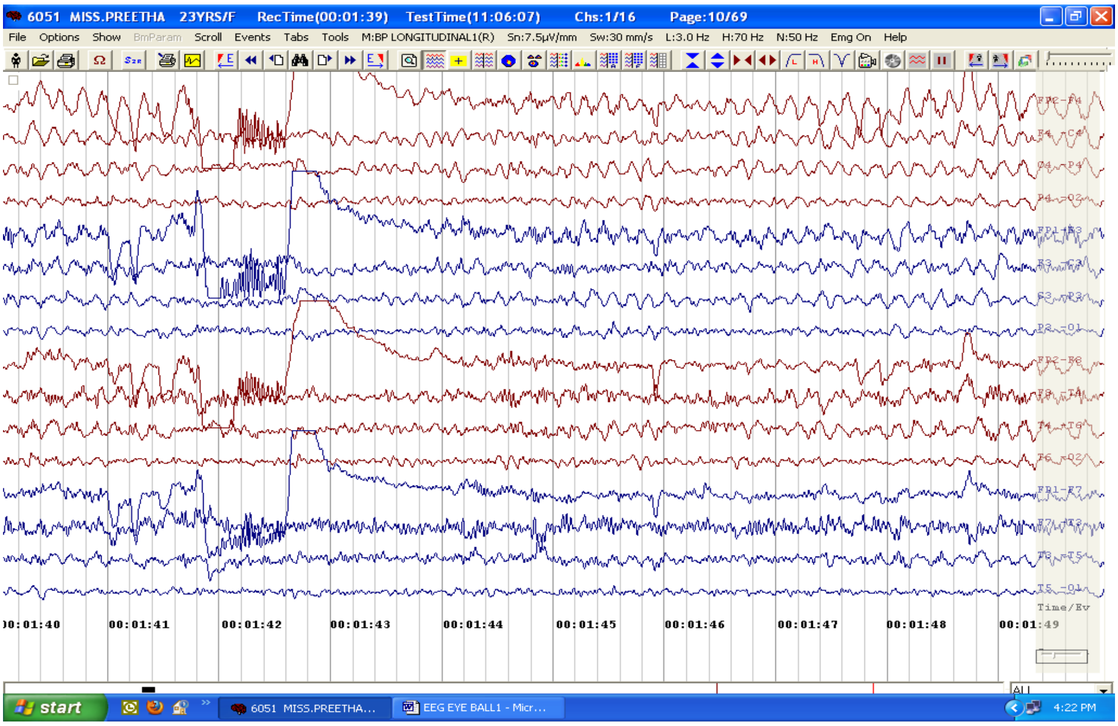

Figure 4.23 Spit Swallowing Artifact

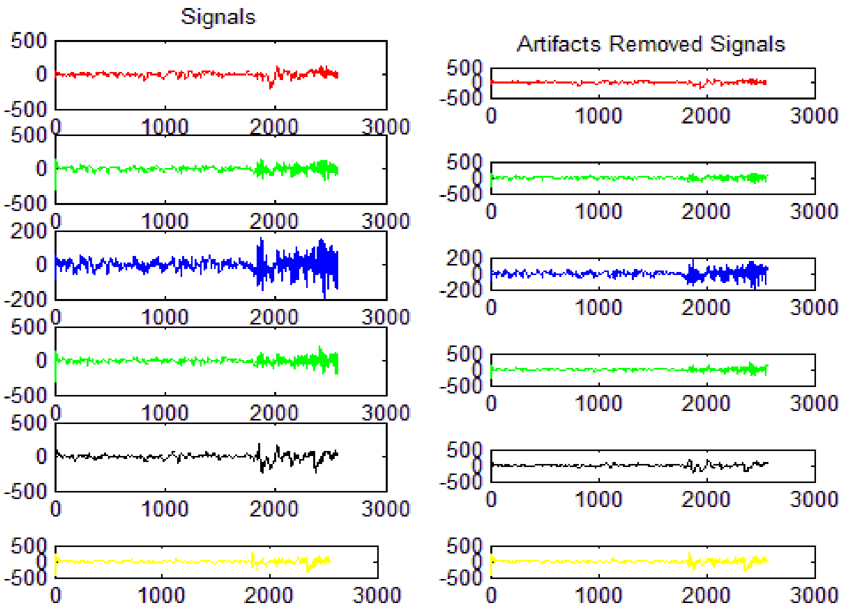

Figure 4.24 Artifact removal of spit swallowing signal using spatially constrained fastICA with Otsu thresholding

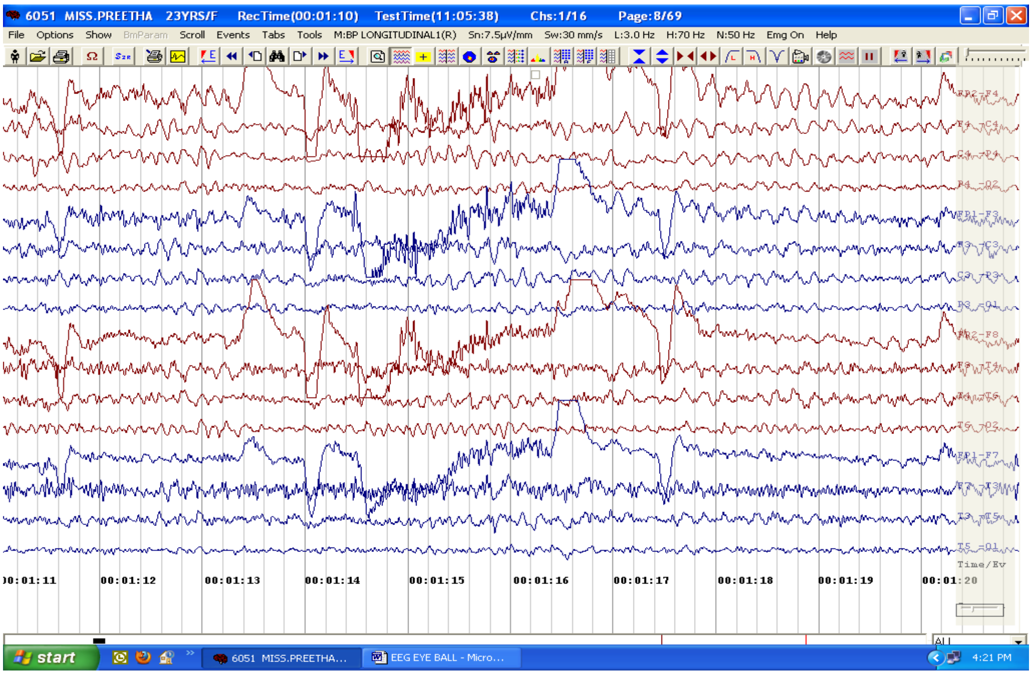

Figure 4.25 Jaw Clenching Artifact embedded with Eye Ball movement artifact

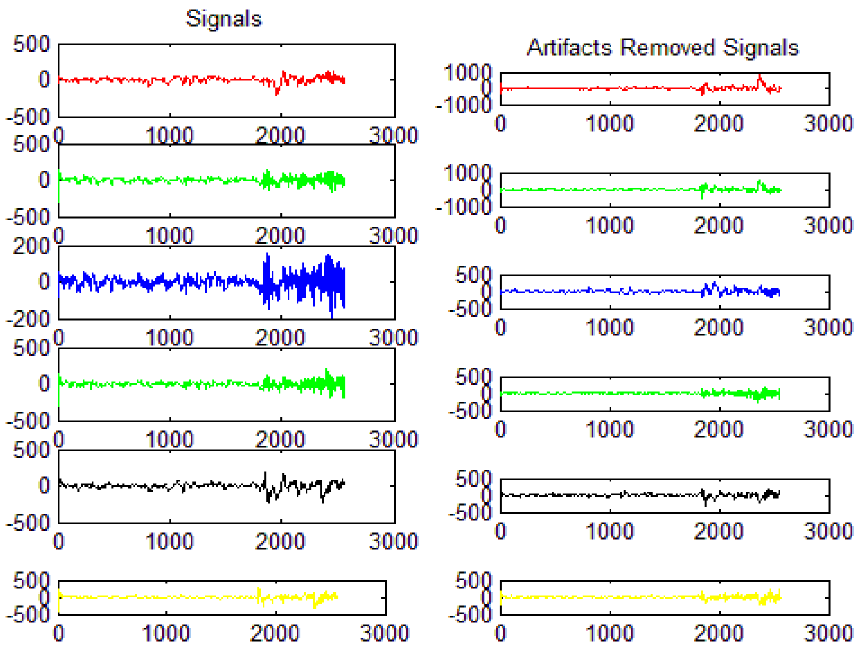

Figure 4.26 Removal of Jaw Clenching Artifact embedded with Eye Ball movement artifact using SCInfomaxICA

From the various results discussed it is clearly revealed that, spatially constrained fastICA with fuzzy thresholding performed well throughout the whole process of artifact removal. This was approved from the estimators MSE, PSNR, and time taken.

4.4 Phase II Results - Feature Extraction

Artifact free EEG signals evolved from Phase-I are fed as input to the second Phase for extracting the vital features. The Fast Walsh Hadamard transform was performed after windowing the 10 second data set into 2 second slices by employing a Hanning window. The features extracted by FWHT were delta, alpha, beta, theta and gamma bands. The reason behind windowing the signals and then extracting the features was to reduce the spectral leakage and computational complexity. This window was slid throughout the signal. A simple periodogram was performed over the entire 2-second sliced window using the Welch method, to calculate the PSD. The statistical features were incorporated over the power levels of PSD. Following are the statistical features used in reducing the dimensionality of the extracted features in each of the sub-band signifying the signals under study:

1. Minimum of the PSD in each of the sub-bands Delta, Theta, Alpha and Beta.
2. Maximum of the PSD in each of the sub-bands Delta, Theta, Alpha and Beta.
3. Mean value of the PSD in each of the sub-bands Delta, Theta, Alpha and Beta.
4. Standard Deviation of the PSD in each of the sub-bands Delta, Theta, Alpha and Beta.

Table 4.13 Extracted Features of 4 Sub-bands

Sub-Bands	Minimum Value of PSD	Maximum Value of PSD	Mean of PSD	Standard Deviation of PSD
Delta	-0.10	46	23.12	9.12
Theta	0	42	22.01	9.26
Alpha	-0.18	49	23.89	10.25
Beta	-0.12	41	22.02	09.12

The feature vectors for each of the sub-bands are depicted in Table 4.13. The power levels of PSD with respect to the following statistical values (minimum value, maximum value, mean and Standard deviation are tabulated and analyzed in each of the bands. These extracted features are then used for training the classifier.

4.5 Phase III Results - Classification

After performing artifact removal and feature extraction, the final phase relies on the decisive information about the signal, if it is epileptic or not.

Classification algorithms are trained to perform correct classification resulting in an automated decision making. There are many ways to measure the performance of classification. The significant ones as discussed in section 4.2 are Sensitivity, Specificity, Accuracy and Execution time of classification. Results of two proposed algorithms Hybrid Extreme Learning Machine (HELM) and Fast Adaptive Neuro Fuzzy Inference System (FANFIS) are compared with the existing algorithms SVM, ANFIS and ELM.

Performance evaluation based on Sensitivity for the proposed algorithms FANFIS and HELM is compared with the conventional algorithms SVM, ANFIS and ELM. The performance of feature extraction is analysed at this stage along with the classification results. Table 4.14 depicts the comparative study based on the performance of classifiers with respect to sensitivity based on the existing feature extraction method using sample entropy and proposed Fast Walsh Hadamard Transform. It is portrayed that the Sensitivity percentage of HELM is larger by 5% when using FWHT for feature extraction when compared to Sample Entropy.

Table 4.14 Sensitivity (%)

Classification Algorithms / Feature Extraction (FE)	**SVM**	**ANFIS**	**FANFIS**	**ELM**	**HELM**
Sample entropy	72.50	75.38	76.67	74.85	79.64
FWHT	75.62	80.26	83.64	78.34	84.68

Table 4.15 depicts the comparative study based on the performance of classifiers with respect to specificity and feature extraction (FE) method using sample entropy and Fast Walsh Hadamard Transform. It is depicted that the

Specificity percentage of HELM is larger by 6% when using FWHT when compared to Sample Entropy.

Table 4.15 Specificity (%)

Classification Algorithms / FE	SVM	ANFIS	FANFIS	ELM	HELM
Sample entropy	75.68	83.23	85.14	89.25	92.14
FWHT	78.64	88.31	94.14	90.43	98.26

Table 4.16 depicts the comparative study based on the performance of classifiers with respect to accuracy and feature extraction methods using Sample Entropy and Fast Walsh Hadamard Transform. The Accuracy percentage of HELM is larger by 3% when using FWHT for feature extraction when compared to Sample Entropy.

Table 4.16 Accuracy (%)

Classification Algorithms / FE	SVM	ANFIS	FANFIS	ELM	HELM
Sample entropy	88.89	92.30	94.64	93.42	95.24
FWHT	92.86	95.24	96.62	94.69	98.68

Table 4.17 depicts the comparative study based on the performance of classifiers with respect to execution time. This is the time taken to perform feature extraction along with classification. It can be further observed that HELM is faster by 1.14 times when using FWHT, when compared to Sample Entropy.

Table 4.17 Execution time (seconds)

Classification Algorithms / FE	**SVM**	**ANFIS**	**FANFIS**	**ELM**	**HELM**
Sample entropy	0.604	0.971	0.162	0.044	0.024
FWHT	0.289	0.783	0.089	0.025	0.021

From the analytical results tabulated above from Tables (4.13 - 4.16) it is can be annotated that

i) When the feature extraction is considered as FWHT, it always shows a better performance when compared to the existing method Sample Entropy.

ii) The proposed algorithms HELM and FANFIS show an enhanced performance when compared to the existing methods SVM, ANFIS and ELM.

The performance of Hybrid ELM for the proposed feature extraction FWHT with respect to specificity, sensitivity, accuracy and time taken are plotted. Fig 4.27 depicts the HELM's performance based on Sensitivity.

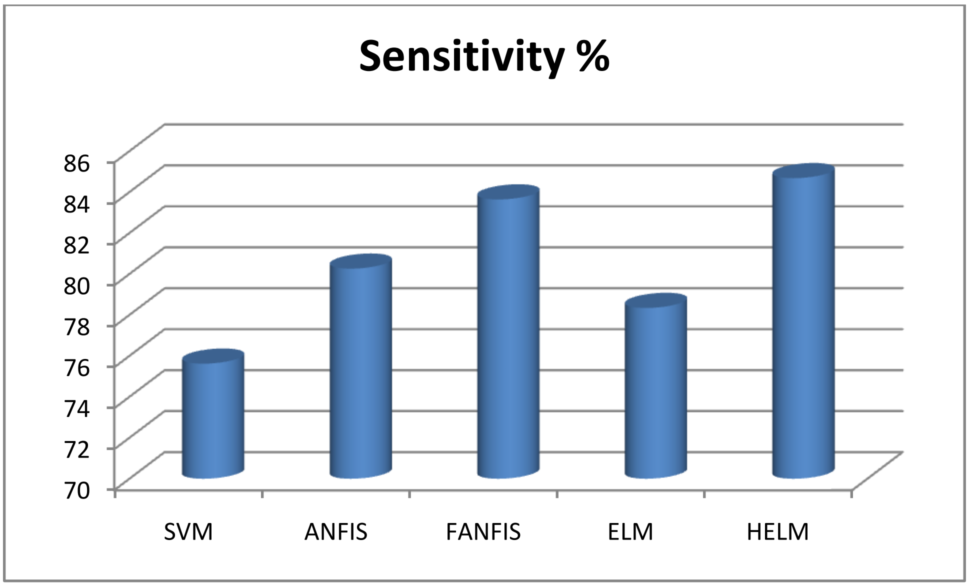

Figure 4.27 Sensitivity based evaluation of classifiers using FWHT

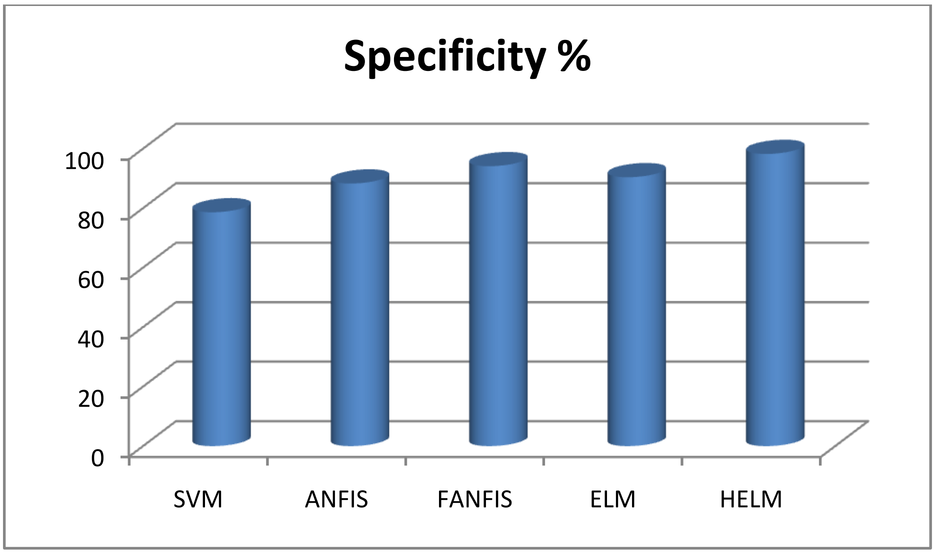

Figure 4.28 Specificity based evaluation of classifiers using FWHT

Performance evaluation of HELM based on specificity and sensitivity are depicted in figures 4.27 and 4.28. Fig 4.29 depicts the performance based on accuracy.

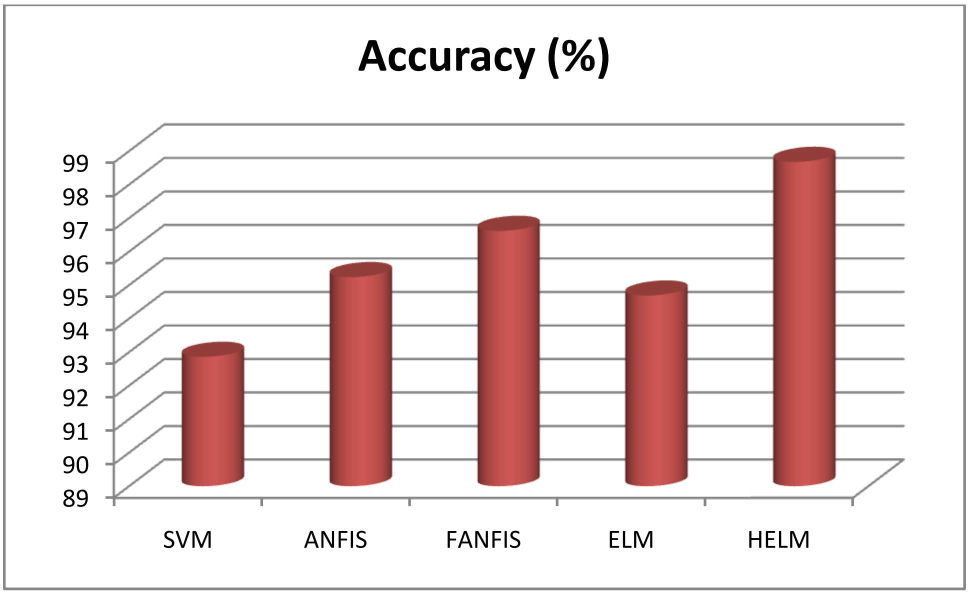

Figure 4.29 Accuracy based evaluation of classifiers using FWHT

The rapidness of algorithms are depicted in figure 4.30

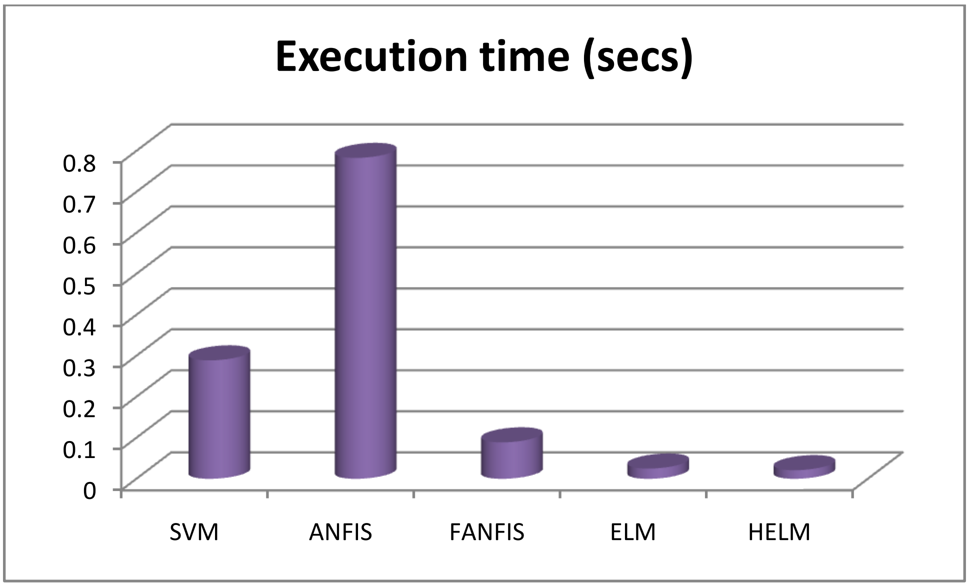

Figure 4.30 Execution time of classifiers using FWHT

The above experimentations were carried out using 70% data samples for training and 30% samples for testing purposes. It is apparent that increasing the training set improves the robustness of classification and is exhibited in terms of accuracy and significant estimates of time taken for training and testing. An investigation was performed by varying the testing and training samples for each of the classifier used in our study. Table 4.18 depicts the training set and testing set ratio with their obtained accuracy percentage, training duration and testing duration for the SVM classifier.

Table 4.18 SVM classifier Training and Test set ratio evaluation

Training set (%)	Testing set (%)	Accuracy (%)	Training time(sec)	Testing time(sec)
60	40	91.12	0.95	0.54
70	30	92.86	0.97	0.51
80	20	92.97	0.98	0.49
90	10	91.12	0.98	0.45

Table 4.19 ANFIS classifier training and Test set ratio evaluation

Training set (%)	Testing set (%)	Accuracy (%)	Training time(sec)	Testing time(sec)
60	40	95.01	0.85	0.51
70	30	95.24	0.86	0.46
80	20	95.47	0.87	0.43
90	10	96.01	0.89	0.41

Table 4.19 depicts the training set and testing set ratio with their obtained accuracy, percentage, training duration and testing duration for ANFIS classifier.

Table 4.20 depicts the training set and testing set ratio with their obtained accuracy, percentage, training duration and testing duration for FANFIS classifier.

Table 4.20 FANFIS classifier Training and Test set ratio evaluation

Training set (%)	Testing set (%)	Accuracy (%)	Training time(sec)	Testing time(sec)
60	40	93.12	0.58	0.36
70	30	96.62	0.58	0.31
80	20	96.82	0.59	0.28
90	10	97.12	0.60	0.27

Table 4.21 depicts the training set and testing set ratio with their obtained accuracy, percentage, training duration and testing duration for ELM classifier.

Table 4.21 ELM classifier Training and Test set ratio evaluation

Training set (%)	Testing set (%)	Accuracy (%)	Training time(sec)	Testing time(sec)
60	40	94.08	0.55	0.19
70	30	94.69	0.56	0.18
80	20	96.55	0.57	0.16
90	10	97.08	0.60	0.15

Table 4.22 depicts the training set and testing set ratio with their obtained accuracy, percentage, training duration and testing duration for HELM classifier.

Table 4.22 HELM classifier Training and Test set ratio evaluation

Training set (%)	Testing set (%)	Accuracy (%)	Training time(sec)	Testing time(sec)
60	40	98.54	0.55	0.18
70	30	98.68	0.57	0.17
80	20	98.81	0.58	0.15s
90	10	98.94	0.59	0.14

Evidences prove that increasing the training set improves the robustness of classification in terms of accuracy and estimates of time taken for training and testing. Overtraining is a scenario when there is an excessive tuning to the training set, which can lead to poor generalization of classification, whereas under training occurs when the classifier has analyzed only very few samples and is complex enough to detect a pattern in a complicated data set resulting in an inadequacy to accurately represent the solution. If the number of parameters of classifiers is excessive, overtraining results in overfitting. The likelihood towards overfitting subsists as the criterion used for training the model is not the same as the criterion used to judge the efficacy of a model. The effectiveness of any model is enhanced by maximizing its performance based on training. The real efficiency of any classification model lies not by its performance on the training data but by its ability to perform well on unseen data. Overfitting occurs when a model begins to memorize training data rather than learning to generalize from trend. Cross-validation is a technique to generalize the independent data set of partitioning the available dataset into complementary subsets. The set which is used for performing the analysis is the training set and the one which validates the analysis is called the testing set. Though multiple rounds of cross validations are performed by using different partitions, based on the common rule of thumb feasible solution is achieved with 70% training data and 30% testing data (Charles Elkan,2002). Hence the final results are concluded such that a generalized classifier is obtained by reducing variability with the consistency procured through 70-30 data set.

Table 4.23 Accuracy based evaluation of classifiers using FWHT with PSD (in %)

Classification Algorithms	**SVM**	**ANFIS**	**FANFIS**	**ELM**	**HELM**
Feature Extraction and Selection -FWHT with PSD	93.78	96.52	97.54	95.82	99.56

Table 4.23 depicts the comparative study based on the performance of classifiers and feature extraction method Fast Walsh Hadamard Transform with and without the statistical features of PSD with respect to accuracy.

Table 4.24 Sensitivity based evaluation of classifiers using FWHT with PSD (in %)

Classification Algorithms	**SVM**	**ANFIS**	**FANFIS**	**ELM**	**HELM**
FWHT with PSD	78.56	84.26	87.24	85.54	89.68

Table 4.24 depicts the Sensitivity of classifiers for FWHT with statistical features of PSD.

Table 4.25 Specificity based evaluation of classifiers using FWHT with PSD (in %)

Classification Algorithms	**SVM**	**ANFIS**	**FANFIS**	**ELM**	**HELM**
FWHT with PSD	80.23	90.53	95.18	92.43	99.26

Table 4.25 depicts the Specificity of classifiers for FWHT with statistical features of PSD.

Table 4.26 Execution time evaluation of classifiers using FWHT with PSD (in seconds)

Classification Algorithms	**SVM**	**ANFIS**	**FANFIS**	**ELM**	**HELM**
FWHT with PSD	0.265	0.742	0.062	0.020	0.018

Table 4.26 depicts the Execution time of classifiers for FWHT with statistical features of PSD

4.6 Discussion on Previous works

This work was motivated by Yedong Song (2010) who had projected an Epileptic Seizure Detection system based on a new statistical parameter Sample entropy for feature extraction. This was the only input feature vector fed as input to the classifiers BPNN and ELM. The data set used by Song is a benchmark dataset and the one adopted in this research work is a real time dataset obtained from local hospitals of Coimbatore. The EEG recording adopted by Song comprised of only 5 volunteers using a single channel of electrode, but the one used in this research work comprised of 160 subjects with 16 electrode channels. A classification accuracy of 95.67% was achieved in an assimilation of Sample entropy and ELM. This proposed system aimed in further improving the performance of the above work by making several alterations over the system proposed by Song. Adopting techniques for artifact removal was the first alteration made to the system implemented by Song et al, which had an impact in augmenting the accuracy rate of the proposed system. The FWHT + PSD based feature values also attributed to the performance of the proposed winning classifier, the HELM. This compendium of algorithm which makes up the winning classifier has achieved an accuracy of 99.56%.

4.7 Chapter Summary

Upon experimentation, it was found that all the proposed deviations of methodology implemented in ASDEEG performed satisfactorily and was able to accomplish an accuracy of 98.68% while using FWHT without PSD and 99.56% accuracy while using FWHT with PSD. The experimental results of the artifact removal phase comprising of a collection of methodologies with its foundation as spatially constrained ICA proves that SCFastICA outperforms the SCInfomaxICA and SCExtendedInfomaxICA. The observations from the feature extraction phase suggest that it is highly acceptable to select just a single feature i.e. PSD. The third phase highlights that the proposed Hybrid ELM has a paramount contribution to ASDEEG. The research work is concluded with future research directions in the next chapter, Summary and Conclusion.