Performance Analysis of EEG Signals using Conventional and Hybrid Artificial Neural Network

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Abstract*: *Brain Computer Interface (BCI) using Electrooencephalogram (EEG) is one of the versatile tools to measure the brain thoughts and convert them to operate the external devices in the deficiency of biological controls. These techniques are used to develop the rehabilitative devices for the individual person who affected with locked in syndrome (LIS). The main reason for LIS is due to death of motor neurons. To overcome the real world problem we conduct our experiment with eight normal patients for four tasks using three electrode system and ADI T26 bio amplifier with Lab chart. Four task signals are applied to statistical method to retrieve the twenty two features and trained with the feed forward neural network (FFNN) and feed forward neural network with wolf Grey optimization algorithm (FFNNWGOA) to see network model which was more perfectly supported to identify the tasks. The study showed that statistical features through feed forward neural network with grey wolf optimized algorithm classifier produced maximum performances of 94.06% compared to other feed forward neural network classifier model and also we identified that optimized features demonstrated maximum performances in minimum time duration during training in all the following twenty trials.

***Keywords* : *Brain Computer Interface, Feed Forward Neural Network, Locked in State, Electrooencephalogram, Feed Forward Neural Network with Wolf Grey Optimization algorithm*.**

I. INTRODUCTION

Communication was one of the versatile tool for human being to interact with their neighbors in the environment to share their thoughts. But sometimes the person with motor neuron disease (MND) like ALS, Cerebral palsy, Brainstem lesion , stroke etc attacked individuals were unable to fulfill their basic needs . So they required help from assistive techniques other than that of conventional methods to complete their needs. For such individual's need of rehabilitative devices were increased rapidly. So the research area was also growing fastly. Developing rehabilitative devices with the help of electroencephalogram (EEG) is one of the necessary techniques to measure the brain signals for people with Locked in State (LIS).

LIS is otherwise called pseudocoma which affects the verbal communication and all the voluntary activities in the body but the affected patients was conscious and aware. During this attack remaining cognitive functions are remain unaffected [1]. To overcome such condition some of the remarkable research products developed by using EEG signals were stated here they are, Gaming controller[2], Smart Home Controller[3], TV channel Controller[4], wheelchair [5]-[9], Keyboard controller[10]-[12], Eye tracking Glass [13], Music Player [14]-[15] , Web browser Controller [16], Arm Movement Controller [17]-[19], Mouse Controller[20], Virtual Car Driving System[21]. In this research work we compared and studied the performances of traditional method with hybrid technique using FFNN (with benchmark Levenberg Marquardt back propagation algorithm and hybrid Grey wolf Optimization algorithm).

II. LITERATURE SURVEY

Using modern Electroencephalogram several systems were developed for the exhausted person to overthrown their problems. Some of the relevant reserach carried out in this area were listed down. S.C.Chen et al (2013) proposed remote control system using fast fourier transform and steady state evoked potential trained with common selection training and simulated path test from ten male subjects and two female subjects and obtained the accuracy of 89.51% and 92.31% with information transfer rate of f105 bits per minutes and 41.79 bits per minute[22]. A.Turnip et al (2016) designed four state wheelchair in offline using adaptive network based fuzzy inference system algorithm from four subjects and obtained the accuracy of 90% [23]. N.Akkaya et al(2016) developed EEG based wheelchair using fast Fourier transform features with several classifiers and obtained 100% accuracy for fuzzy neural network classifier [24].

W.Li, et al(2018)., modeled vehicle driving system using Common Spatial Patterns trained with K-nearest neighbors classifier to analyze the performances from six subjects and reached the average accuracy of 91.1% for classification with a bit transfer rate of 85.80 per minute [25]. T.H.Nguyen et al(2018)., developed offline and online EEG based virtual keyboard to select 26 characters and special symbols using

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Power Spectral Density features with Support Vector Machine classifier and obtained the classification accuracy of 93.8% and 92.3% [26]. Y.Jiang et al(2018)., developed two channel wearable semi asynchronous BCI and obtained the accuracy of 77%[27]. T.H.Nguyen and W.Y.Chung (2019)., designed and tested the EEG based Speller for disabled person in offline and online using steady-state visual-evoked potential and convolutional neural network from eight subjects and obtained the classification accuracy of 99.2% and 97.4%[28]. The background study proves that manipulating the BCI for disabled person using ordinary FEATURES or hybrid technique was the Normally the FFNN model used in this study was trained with benchmark Levenberg Marquardt back propagation algorithm with default parameters to obtain the classification accuracy. But in this research we applied the hybrid technique by training the network using Grey wolf Optimization algorithm to analyze the performance between the traditional technique and modern technique to evaluate the result.

III. METHODOLOGY

A. Feature Extraction

Subject selection, Experimental setup, Protocol design and signal collection methods were already prescribed in our preceding study [29]-[32]. An EEG signal gathered from subject2 during data collection was illustrated in the fig.1. Accumulated data from eight subjects are treated with variance method to excavate the different features. Variance is a statistical method to analyze how dataset was spread in larger population as well as in smaller population. It was calculated by subtracting the mean samples from current samples to calculate how much set of observation deviated or diverge from each other [33]-[36]. Variance can be calculated by using below mentioned equation 1.

$$\delta^2 = \sum \frac{(x_i - \bar{X})^2}{n-1} \qquad 1$$

Steps for converting data samples to features

Step1→ Apply the data samples.
Step2→ Analyze the mean samples.
Step3→ Subtract the mean samples from each values of x_i.
Step4→Square the step3 values.
Step5→Determine the sum of the squared values from step4.
Step6→Divide the step5 values by n-1 to compute the variance of the samples.

Were δ^2 indicates the variance of the data samples, x_i represents the items in the dataset, $\bar{X}$ specifies the mean samples ε gives the summation of each values of x_i and n denotes the total number of samples. Twenty-two important features were extracted per trials and trained with FFNN and FFNNWGOA to find the best classification technique to segregate the EEG signals.

(a)

(b)

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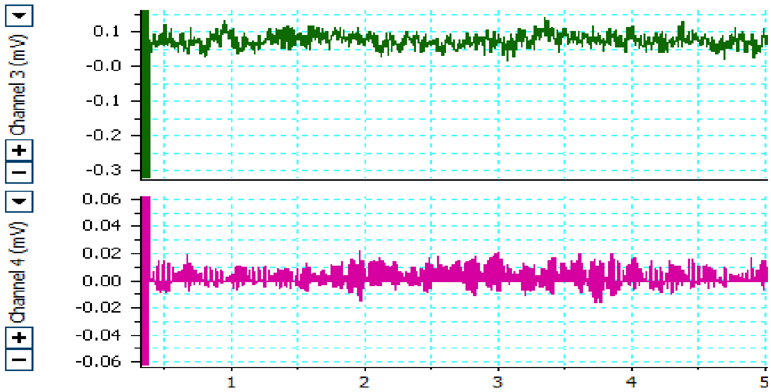

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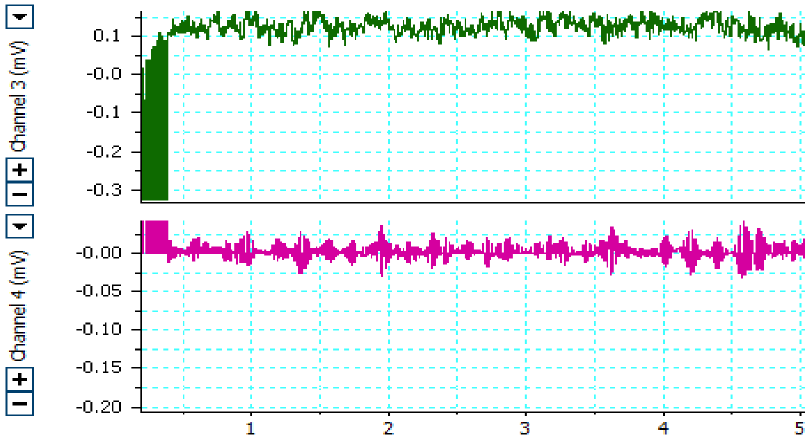

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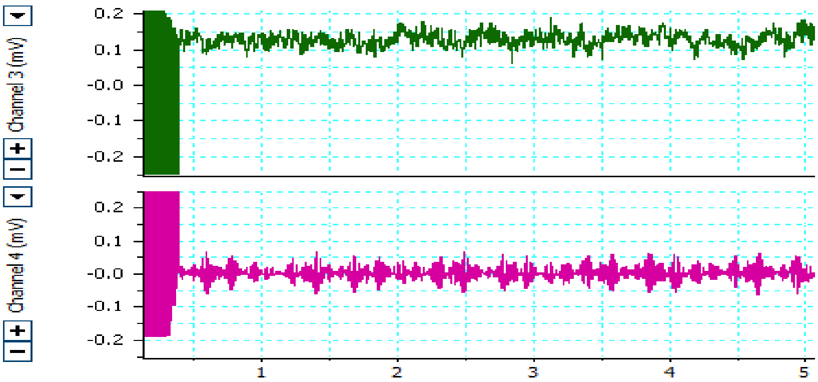

(e)

Fig.1. Raw EEG Signals from the task (a) Forward, (b) Right, (c) Left, (d) Stop and (e) Neutral for Subject2.

IV. CLASSIFICATION TECHNIQUES

Due to simplicity and reliability bio inspired optimization algorithms were commonly used by all the researchers. By hybriding the conventional method with new optimization technique several improved performances were attained by different research groups. In our experiment we prepared to analyze the best classifier for dissimilating the task using FFNN and FFNNWGOA. FFNN classifier with learning algorithm and its default parameter initializations for training the data were discussed in our preceding study [37]-[40].

A. Grey Wolf Optimization Algorithm

GWO Algorithm was one of the important optimization algorithm which is mainly based on hunting techniques followed by the Grey Wolf based on the predominant hierarchy of hunting wolves to catch the prey. Normally in this method wolves are classified into four categories namely Alpha level (α), Beta level (β), Gamma level (δ) and Omega level (ω). Four levels of the wolves are categorized and fixed as per privileges. Gamma level wolves are divided into three types they are (Scouts, Sentinels and Elder, Hunters and Caretakers). The four wolves levels were shown in the fig.2. Grey wolves are live in hierarchical order from Alpha level (α) to Omega level (ω). Each level of wolves has different style in hunting the prey. The decision was made by Alpha level wolves (α) and followed by Beta level (β) and Gamma level (δ) wolves. According to the movements of three level wolves Omega level (ω) wolves automatically update their position to hunt the prey. For hunting the prey the wolves pack applying the three techniques they are Prey Encircling, Hunting, Attacking and Search for Prey.

In the prey encircling techniques wolves pack encircles the prey according to that location and also individual agent will relocates the place to catch the prey. In the hunting technique wolves are ready to get information from Alpha level wolves (α), Beta level (β) and Gamma level (δ) wolves to attack the prey and also attacking takes place in random order. In the third technique first three level wolves are start to attack the wolves, belong to the prey position, Omega level (ω) automatically update their position to support the remaining wolves [41]-[42]. Working flow of the algorithm was illustrated in Fig.3. 22 features extracted from the variance features was trained and tested with ten hidden neurons using benchmark Levenberg Marquardt back propagation algorithm and hybrid Grey wolf Optimization algorithm based neural network classifier. During the classification the classifier consists of 60% of training data and 40% of testing data with maximum iteration limit of 1000 and also the error tolerance was fixed at 0.1 with a learning rate of 0.0001[43]-[48]. FFNNWGOA architecture model applied in this research was illustrated in the fig.4.

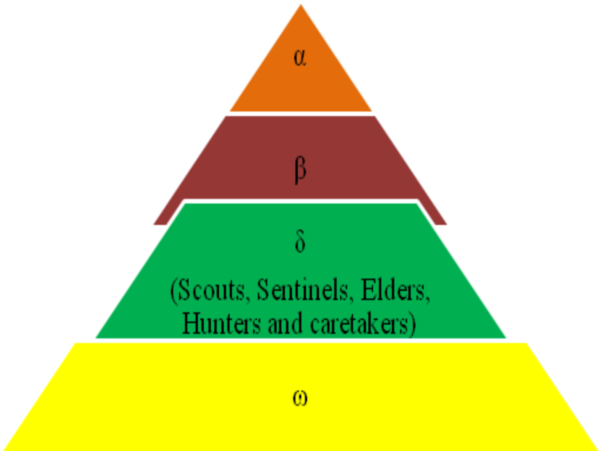

Fig.2.Different Levels of Wolves

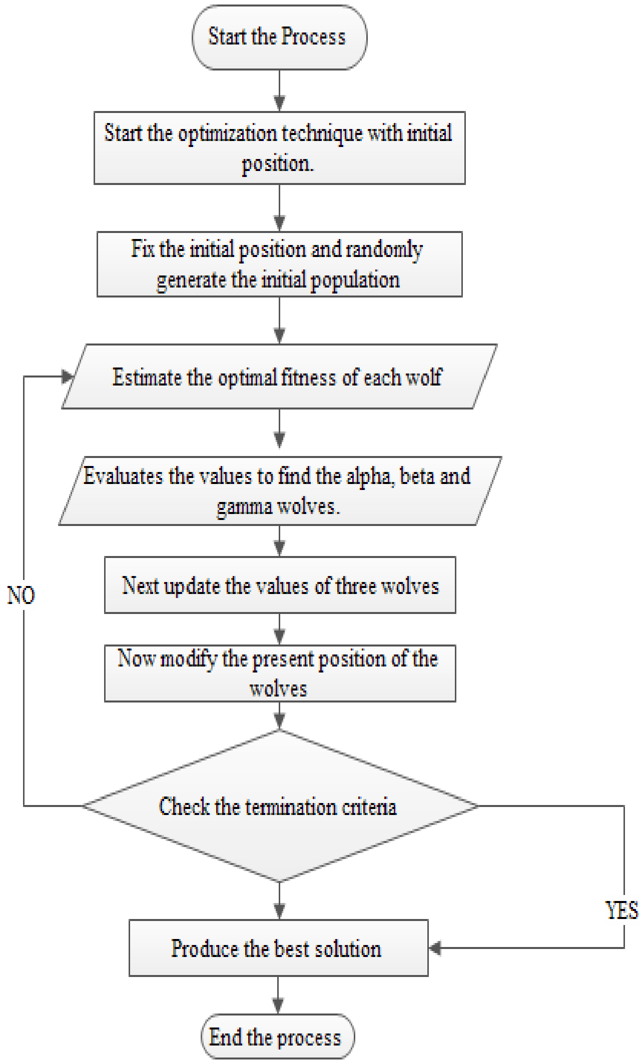

Fig.3.Working Flow of Algorithm

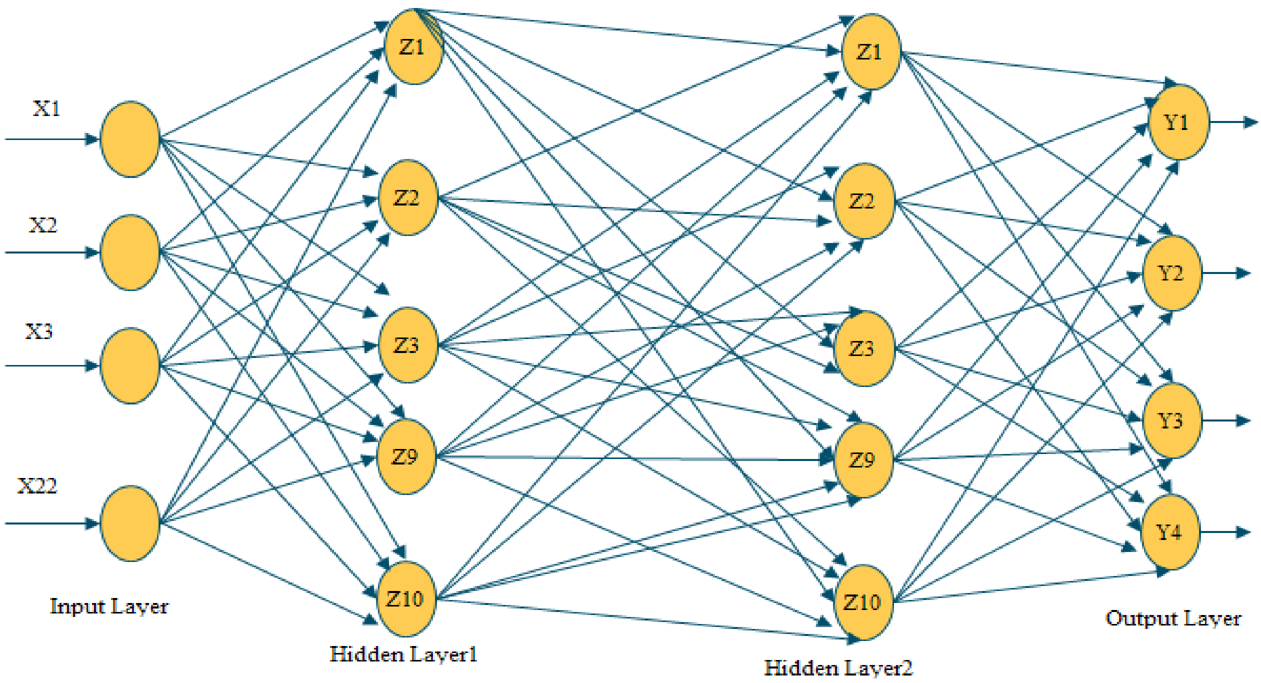

Fig.4. FFNNWGOA architecture model

V. EXPERIMENT RESULT

Experiment was conducted with eight male subjects. Thirty trials per subject were trained with benchmark FFNN and optimized FFNNWGOA to identify the classification accuracy between the two network models. The average performances of the two network models were tabulated in the Table.1 and Table2. From the Table.1 and Table.2 we observed that average performances were varied for subject to subject in terms of all the following parameters. From the Table.1 We interpret that the features trained with feed forward neural network using Levenberg–Marquardt algorithm showed the mean classification accuracy of 91.92% and average maximum classification accuracy of 93.05% and average minimum classification accuracy of 90.20% with testing and training time of 0.91 Second and 40.74 seconds.

From the same Table.1. We determined that maximum classification accuracy of 92.95% for subject S6 and minimum classification accuracy of 90.67% for Subject S2 using the VARIANCE features which was demonstrated in the fig.5 and fig.6.

From the Table.2 We interpret that the features trained with feed forward neural network using Wolf Grey Optimization algorithm showed the mean classification accuracy of 94.06% and average maximum classification accuracy of 95.27% and average minimum classification accuracy of 93.16% with testing and training time of 0.72 Second and 33.02 seconds. From the same Table.2. We determined that maximum classification accuracy of **95.89%** for subject S6 and minimum classification accuracy of 92.98% for Subject S2 using the variance features which was demonstrated in the fig.5 and fig.6.

After the experimental result we finalized that variance features trained using FFNNWGOA network models outperforms the benchmark FFNN network models trained with Levenberg–Marquardt algorithm in terms of accuracy, maximum and minimum performances for all the subjects which was exposed in the fig.7. From all the observation from Table.1 and Table.2 we concluded that features trained with Wolf Grey Optimization algorithm using FFNN was better than Levenberg–Marquardt algorithm using FFNN.

VI. CONCLUSION

Three twenty trials of master dataset obtained from four task signals were applied to statistical method to retrieve the twenty two features and trained with the feed forward neural network (FFNN) and feed forward neural network with wolf Grey optimization algorithm (FFNNWGOA) to see network model which was more perfectly supported to identify the tasks. The study concluded that statistical features through feed forward neural network with grey wolf optimized algorithm classifier produced maximum performances of 94.06% compared to feed forward neural network classifier model and also we identified that optimized features demonstrated maximum performances in minimum time duration during training in all the following twenty trials.

TABLE I. Classification Accuracy for FFNN using variance features

Subjects	Mean Testing Time (sec)	Mean Training Time (sec)	Average Performance (%)			
			MAX	MIN	SD	MEAN
S1	0.9	40.45	93.88	89.54	2.14	**92.23**
S2	0.87	40.98	93.12	88.98	2.11	**90.67**
S3	0.92	40.83	92.4	90.12	1.9	**91.44**
S4	0.93	40.56	92.32	89.9	2.17	**91.85**
S5	0.9	41.52	92.68	90	2.08	**91.56**
S6	**0.9**	**40.2**	**94**	**91.46**	**2.01**	**92.95**
S7	0.94	40.76	93.1	90.66	2.04	**92.31**
S8	0.91	40.64	92.89	90.95	1.94	**92.35**
Average	**0.91**	**40.74**	**93.05**	**90.2**	**2.05**	**91.92**

TABLE II. Classification Accuracy for FFNNWGOA using variance features

Subjects	Mean Testing Time (sec)	Mean Training Time (sec)	Average Performance (%)			
			MAX	MIN	SD	MEAN
S1	0.71	32.89	94.62	92.68	2.01	**93.56**
S2	0.73	32.76	94.67	92.74	1.98	**92.98**
S3	0.76	33.45	95.38	93.1	1.8	**93.23**
S4	0.73	33.58	95.21	92.88	1.92	**93.78**
S5	0.71	33.14	94.84	92.78	1.9	**93.6**
S6	**0.69**	**32.18**	**96.82**	**94.24**	**1.88**	**95.89**
S7	0.72	33.2	95.49	93.56	1.62	**94.67**
S8	0.74	33.02	94.67	93.28	1.56	**94.8**
Average	**0.72**	**33.02**	**95.27**	**93.16**	**1.83**	**94.06**

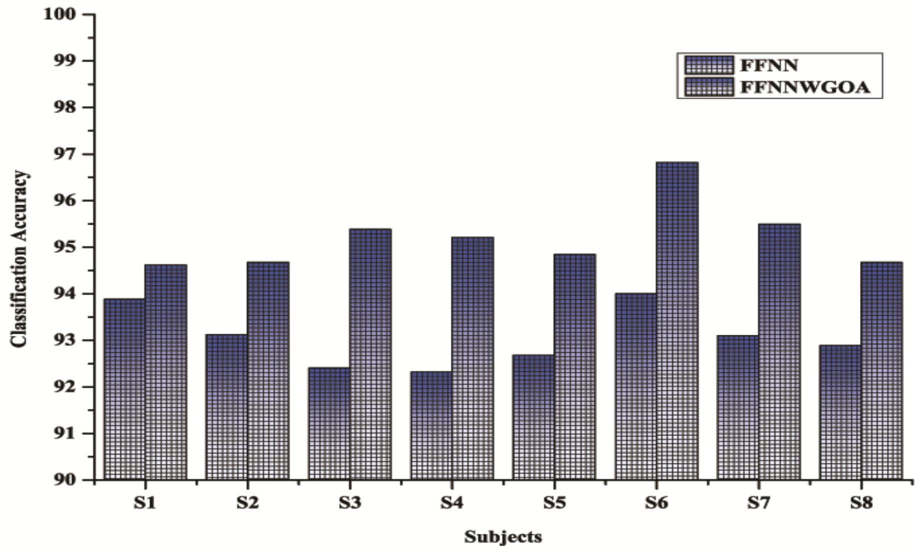

Fig.5. Maximum Accuracy

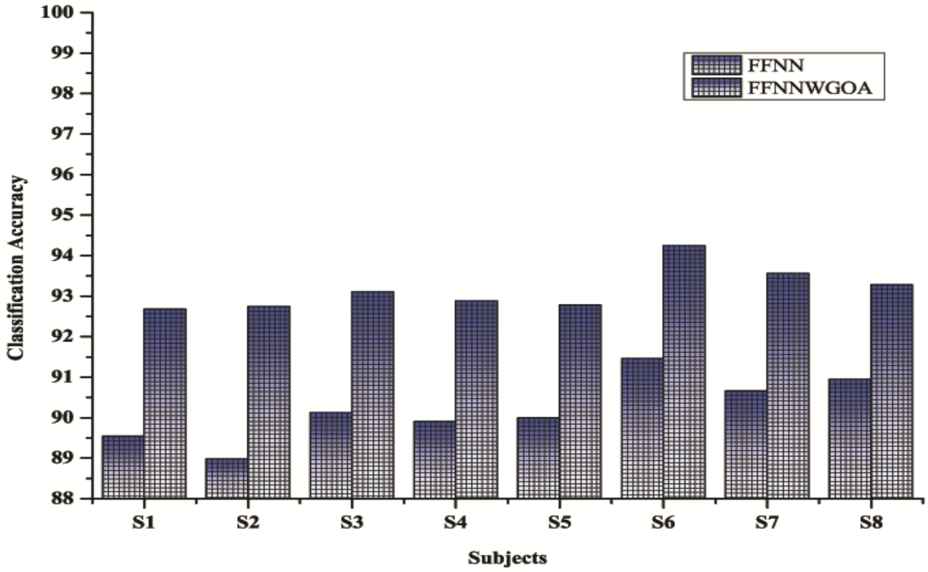

Fig.6. Minimum Accuracy

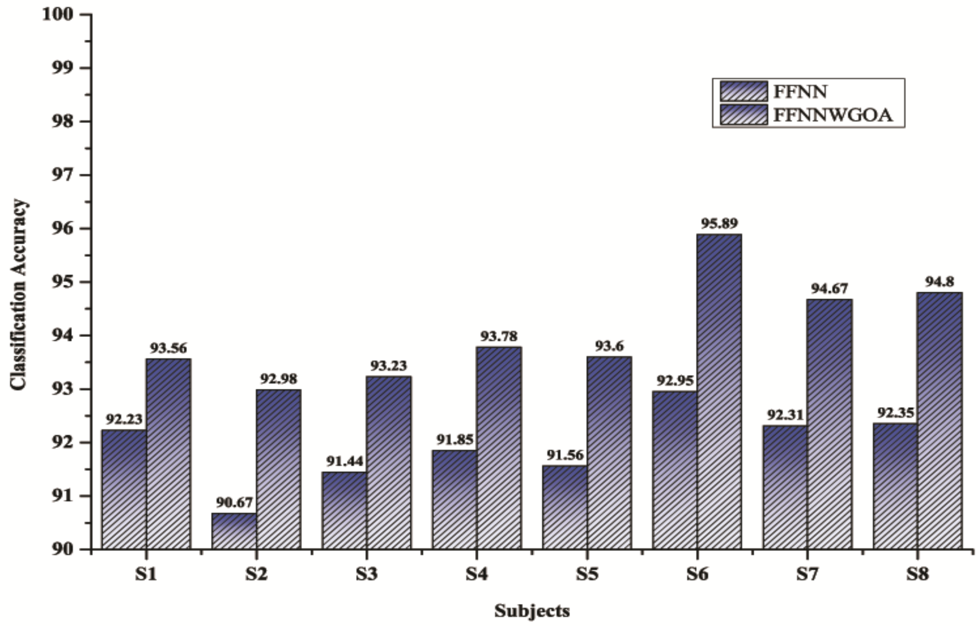

Fig.7.Mean Average Accuracy

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REFERENCES

1. R.Scherer, G.R.Muller, C.Neuper, B.Graimann, G.Pfurtscheller, "An asynchronously controlled EEG-based virtual keyboard: improvement of the spelling rate", IEEE Transactions on Biomedical Engineering, Vol.51(6), pp.979 - 984, 2004.
2. L.D.Liao, C.Y.Chen, S.F.Chen, S.Y.Li, B.W.Chen, J.Y.Chang, C.T.Lin"Gaming control using a wearable and wireless EEG-based brain-computer interface device with novel dry foam-based sensors",Journal of Neuro Engineering and Rehabilitation, Vol.9(5), pp.1-11, 2012.
3. G.Edlinger, C.Guger, "A hybrid Brain-Computer Interface for improving the usability of a smart home control", International Conference on Complex Medical Engineering(ICME), pp.182-185, 2012.
4. K.Miyoung,T.Hwang, "Toward Realistic Implementation of Brain-ComputerInterface for TV Channel Control", IEEE Global Conference on Consumer Electronics (GCCE),PP.394-396, 2013.
5. R.Zhang, Y.Li,Y.Yan, H.Zhang, S.Wu, T.Yu, Z.Gu,"Control of a Wheelchair in an Indoor Environment Based on a Brain–Computer Interface and Automated Navigation", IEEE Transactions on Neural Systems and Rehabilitation Engineering, Vol.24(1), pp.128-139, 2016.
6. P.B.Mendoza, M.A.I.Manzano, E.I.G.Hernandez, D.L.A.Ojeda, C.R.M.Sanjose, R.J.R.Troncoso, H.R.Gonzalez1, "Improving EEG-Based Motor Imagery Classification for Real-Time Applications Using the QSA Method", Computational Intelligence and Neuroscience, Vol.2017, pp.1-16, 2017.
7. H.Wang, A.Bezerianos,"Brain-controlled wheelchair controlled by sustained and brief motor imagery BCIs" Electronics Letters, Vol.53(17), pp.8-17, 2017.
8 K.Tanaka, K.Matsunaga, H.O.Wang, "Electroencephalogram-based control of an electric wheelchair", IEEE Transactions on Robotics, Vol.21(4), pp.762-766, 2005.
9. T.Carlson,J.D.Millan, "Brain–Controlled Wheelchairs:A Robotic Architecture", IEEE Robotics and Automation Magazine, Vol.20(1), pp.65 – 73, 2013.
10. R.H.Aswathy, M.Surekha,"EEG Based Brain Computer-A Virtual Keyboard Control Using Brainwave Sensor for Crippled With IAUI", Journal of Advance Research in Dynamical & Control Systems,Vol.11, 44-50,2017
11. A.B.Usakli and S.Gurkan, "Design of a Novel Efficient Human–Computer Interface: An Electrooculagram Based Virtual Keyboard", IEEE Transactions on Instrumentation and Measurement, Vol.59(8),pp.2099 - 2108, 2010.
12. H.Nisar, H.W.Khow, K.H.Yeap, "Brain–computer interface: controlling a robotic arm using facial expressions", Turkish Journal of Electrical Engineering & Computer Sciences, Vol.26,pp.707-720, 2018.
13. Z.F.Shi, C.Zhou, W.L.Zheng, B.L.Lu, "Attention evaluation with eye tracking glasses for EEG-based emotion recognition", IEEE/EMBS Conference on Neural Engineering (NER), pp.86-89, 2017
14. Z. Li, G. Xuhong, ''EEG control of music player,'' IEEE International Conference on Intelligent Networks and Intelligent Systems, pp.189-192, 2012.
15. B.Arora, T.Choudhury, P.Kumar, Mukherjee, "An intelligent way to play music by brain activity using brain computer interface", International Conference on Next Generation Computing Technologies, pp.223-228, 2016.
16. S.He, T.Yu, Z.Gu ; Y.Li, "A hybrid BCI web browser based on EEG and EOG signals", International Conference of the IEEE Engineering in Medicine and Biology Society, pp.1006 - 1009, 2017.
17. A.Úbeda, E.Hortal, E.Ianez, D.Planelles, J.M. Azorín, "Passive robot assistance in arm movement decoding from EEG signals", IEEE/EMBS Conference on Neural Engineering (NER), pp.895 - 898, 2013
18. H.Nisar, H.W.Khow, K.H.Yeap, "Brain–computer interface: controlling a robotic arm using facial expressions", Turkish Journal of Electrical Engineering & Computer Sciences, Vol.26,pp.707-720, 2018.
19. J.Meng, S.Zhang, A.Bekyo, J.Olsoe, B.Baxter and B.He, "Noninvasive Electroencephalogram Based Control of a Robotic Arm for Reach and Grasp Tasks", Scientific Reports, Vol.6(38565), pp.1-15, 2016.
20. M.Spüler, "A Brain-Computer Interface (BCI) system to use arbitrary Windows applications by directly controlling mouse and keyboard", IEEE- International Conference on Engineering in Medicine and Biology Society (EMBC), pp.1087-1090, 2015.
21. X.Pan, Z.Zhang, J.Qu, C.Zhao, Y.Li, "Enjoy driving from thought in a virtual city", IEEE Chinese Control Conference (CCC),pp.11034 - 11040, 2017.
22. S.C.Chen, A.R.See, Y.J. Chen,C.H.Yeng, C.K.Liang, "The Use of a Brain Computer Interface Remote Control to Navigate a Recreational Device", Mathematical Problems in Engineering, Vol.2013, pp.1-8,2013.
23. A.Turnip, D.Soetraprawata, M.Turnip, E.Joelianto,"EEG-Based Brain-Controlled Wheelchair with Four Different Stimuli Frequencies",Internetworking Indonesia Journal, Vol.8(1), pp.65-69, 2016.
24. R.H.Abiyev, N.Akkaya, E.Aytac, I.Günsel, A.Çagman,"Brain-Computer Interface for Control of Wheelchair Using Fuzzy Neural Networks", Biomed Research International, 2016(9359868), 2016.
25. W.Li, F.Duan, S.Sheng, C.Xu, R.Liu, Z.Zhang, X.Jiang, "A Human-Vehicle Collaborative Simulated Driving System Based on Hybrid Brain–Computer Interfaces and Computer Vision", IEEE Transactions on Cognitive and Developmental Systems, Vol.10(3), pp.810-822, 2018.
26. T.H.Nguyen, D.L.Yang, W.Y.Chung, "A high-rate BCI speller based on eye-closed EEG signal", IEEE Access, vol. 6, pp. 33995-34003,2018.
27. Y.Jiang ; N.T.Hau, W.Y.Chung, "Semiasynchronous BCI Using Wearable Two-Channel EEG", IEEE Transactions on Cognitive and Developmental Systems", Vol.10(3), pp.681-686, 2018.
28. T.H.Nguyen, W.Y.Chung, "A Single-Channel SSVEP-Based BCI Speller Using Deep Learning", IEEE Access, Vol.7, pp.1752 - 1763, 2019.
29. Xin Wan, Kezhong Zhang, S.Ramkumar, J.Deny, G.Emayavaramban, M.Siva Ramkumar, Ahmed Faeq Hussein, "A Review On Electroencephalogram Based Brain Computer Interface For Elderly Disabled",IEEE Access, Vol.7, pp. 36380-36387, April 2019.
30. Li Junwei, S.Ramkumar, G.Emayavaramban, D.Franklin vinod, M.Thilagaraj, V.Muneeswaran , M.Pallikonda Rajasekaran, V.Venkatraman, Ahmed Faeq Hussein "Brain Computer Interface For Neurodegenerative Person Using Electroencephalogram, IEEE Access, Vol.7, pp. 2439-2452, Jan 2019.
31. Shao Fang, Ahmed Faeq Hussein, S.Ramkumar, K. S. Dhanalakshm, G.Emayavaramban, "Prospects of Electrooculography in Human-Computer Interface Based Neural Rehabilitation for Neural Repair Patients", IEEE Access, Vol.7, pp. 25506-25515.
32. Gu Jialu, S. Ramkumar, G. Emayavaramban, M. Thilagaraj, V. Muneeswaran, M. Pallikonda Rajasekaran, Ahmed Faeq Hussein, "Offline Analysis for Designing Electrooculogram Based Human Computer Interface Control for Paralyzed Patients", IEEE Access, Vol.6, pp. 79151-79161, Dec 2018,
33. S.C.Machavarapu, M.K.Mukul, D.Kumar, "EEG classification based on variance, International Conference on Green Computing Communication and Electrical Engineering, pp.1-4, 2014.

34. https://www.sciencebuddies.org/science-fair-projects/science-fair/variance-and-standard-deviation
35. https://www.wikihow.com/Calculate-Variance
36. https://en.wikipedia.org/wiki/Variance
37. S.Ramkumar, K.Sathesh Kumar G.Emayavaramban," EOG Signal Classification Using Neural Network For Human Computer Interaction" International Journal of Control Theory and Applications, Vol. 9(24), pp. 223-231, Sep-2016.
38. G.Emayavaramban, S.Ramkumar, A.Amudha and K.Sathesh Kumar, "Classification Of Hand Gestures Using FFNN And TDNN Networks", International Journal of Pure and Applied Mathematics, Vol.118(8) Pp. 27-32, Jan 2018.
39.Hema.C.R, Paulraj.M.P & Ramkumar.S," Classification of Eye Movements Using Electrooculography and Neural Networks", International Journal of Human Computer Interaction, Vol.5 (3), pp.51-63, Aug 2014,
40. Hema.C.R, Ramkumar.S Paulraj.M.P," Identifying Eye Movements Using Neural Networks for Human Computer Interaction", International Journal of Computer Application, Vol.105 (8), pp.18-26, Nov 2014.
41.W.Gai, C.Qu, J.Liu, J.Zhang, "An improved grey wolf algorithm for global optimization", IEEE Conferences on Chinese Control And Decision Conference (CCDC),pp.2494 - 2498, 2018.
42. D.Jitkongchuen, P.Phaidang,P.Pongtawevirat, "An adaptive elitism-based immigration for grey wolf optimization algorithm", IEEE-International Conference on Digital Arts, Media and Technology (ICDAMT), pp.222 - 225, 2017.
43. S.Ramkumar, K.Sathesh Kumar G.Emayavaramban," Nine states HCI using Electrooculogram and Neural Networks", International Journal of Engineering and Technology, Vol. 8(6), pp. 3056-3064, Jan-2017.
44. S.Ramkumar, K.Sathesh Kumar, K.Maheswari and P.Packia Amutha Priya, "Offline Study For Implementing Human Computer Interface For Elderly Paralyzed Patients Using Electrooculography and Neural Networks"International Journal of Intelligent Enterprise, 2019.
45. LiKai, S.Ramkumar, J.Thimmiaraja, S.Diwakaran, "Optimized artificial neural network based performance analysis of wheelchair movement for ALS patients", Artificial Intelligence in Medicine, Vol.101, pp.101754, 2019.
46. WenpingTang, AiqunWang, S.Ramkumar, Radeep Krishna RadhakrishnanNair,"Signal identification system for developing Rehabilittive device using deep learning algorithms", Artificial Intelligence in Medicine, Vol.101, pp.101755, 2019.
47. S.Ramkumar, G.Emayavaramban, K. Sathesh Kumar, J.MacklinAbraham Navamani, K.Maheswari, P.Packia Amutha Priya, "Task Identification System for Elderly Paralyzed Patients Using Electrooculography and Neural Networks", EAI International Conference on Big Data Innovation for Sustainable Cognitive Computing, pp. 151-161, 2020.
48. S.Ramkumar,G.Emayavaramban, J.MacklinAbraham Navamani, R.Renuga Devi, A.Prema, B.Booba " Human Computer Interface for Neurodegenerative Patients Using Machine Learning Algorithms", Advances in Computerized Analysis in Clinical and Medical Imaging , 2019.

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