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ROLE OF EEG SUGNALS FOR DIAGNOSIS OF NEUROLOGICAL DISORDER

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ABSTRACT:
In this work, we use the same dataset as in previous studies. 14- Normally-sighted humans (7-Females, 7-male). The median age of all women and men taken into account is 26. The participants volunteered their services for the research. This decentralised sensor network consisted of the 32 electrodes on the EEG cap. The 10-20 system recommended by the American encephalographic society was used to determine where to insert the electrodes. These electrodes were separated into two groups, frontal and occipital. 1 kHz frequency was used for recording the data. In order to remove the artifacts, line noise etc. low pass filters were employed and input impedance was kept near 5 kΩ. The images shown to objects were dived into two groups: (i) distracters and (ii) objectives. Out of total 1000 pictures shown to objects, 500 were distracters type and rest 500 were objective type. The testing of blocks started immediately after the training mode. The participants were requested to memorize the pictures.

1. INTRODUCTION
The empirical approach of selecting has a high degree of unpredictability. Using it to obtain a global optimal solution is a complex and demanding endeavour. Grid search is a technique that can enhance the precision of categorization. The time investment and resulting grid expansion are substantial, though. In comparison, the performance accuracy of the SVM parameter combination encoded using the swarm intelligence algorithm fused with the genetic algorithm (GA) is significantly higher. The delayed convergence and heavy computational strain remain, though. The PSO algorithm was used to increase the classification accuracy of SVM by Huang C L & Dun J F, however it was unable to provide a global optimal solution since it frequently became trapped in the local optimal. While differential evolution (DE) can be used to fine-tune the SVM's parameters, the effectiveness of this method is contingent on the mechanism by which trial vectors are generated and the values assigned to those parameters. offers the SVM combined with the ABC, but it loses

efficiency as it gets closer to the optimal answer and provides subpar results in local searches. has created an algorithm (called WOA) based on the habits of humpback whales to optimise performance. When compared to other swarm intelligence systems, it provided superior efficiency, performance, time response, and recognition in a variety of engineering optimization challenges. Yet, it becomes mired in local optima as search agents approach but never quite reach the optimal solution. To find solutions, it employs an optimization exploration tool. Because of this, there is less of a population boom and less stability for exploiting and exploring new areas. The researcher of this dissertation has employed objective function to determine the trauma level using EEG, thereby avoiding the drawbacks of WOA.

2. MEASUREMENT OF EEG SIGNALS

EEG signal is the non-cohesive electrical measurement of neurons activity in the brain. It is low frequency signal from the range of 1Hz to 50 Hz. This signal is picked up using head cap fitted with electrodes, called sensors. Fi. 1 shows the EEG signal picked up at different locations.

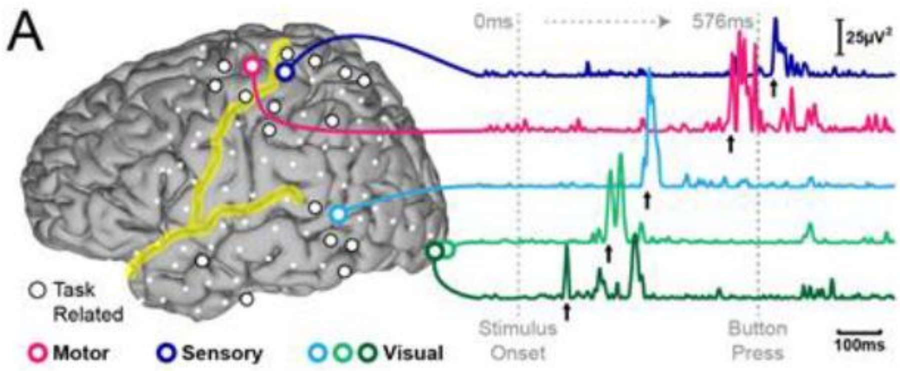

Fig. 1: EEG signal picked up at different locations of brain

The primary task of brain is cortical excitation. This is oscillatory mode activity. Here certain parameter of oscillations covering various area of brain changes the cortical activities which are regulated by brain. Two theories exist that discuss the fast changes in behaviour and consider measurements of phase and power of oscillator.

a. communication-through coherence (CTC)
b. gating-by-inhibition (GBI) hypothesis

Though these theories have explained the significant development and justified the measurements of phase and power of oscillation, these theories are not complete and thus phase and power of oscillation measurements may be sub-optimal.

A group of neurons say 1000 or more when trigger simultaneously shows post synaptic potential. This produces appreciable electric field. Whereas the output signal of single neuron is so small that it cannot be measured. If the electrical field is not sufficient strong it may not be picked by the sensor electrodes for EEG signals. It is observed that cortical brain is dominated by pyramidal neurons. Their synchronized activities make available the sufficient electrical potential at scalp for the measurement. The body of the cell is pyramidal or triangle in shape, hence the name. These cells can be found throughout the whole cortex, including the occipital, temporal, parietal, and frontal regions, and are always oriented perpendicular to the surface. By virtue of their different orientation, the cells generate a steady electrical field. Cells in the deeper brain regions (such as the brain stem and cerebellum) are aligned differently than those in the cerebral cortex. It's because of this that electricity can travel in all directions within the earth's crust.

3. RESULTS AND DISCUSSION

Predictions of the optimal trauma level were determined with MATLAB. The EEG data is used as input. Pre-processing with the NLMS method was done on data from all 14 patients (a total of 25 files for each subject, 12 from Day 1 and 13 from Day 2). Artifacts caused by blinking eyes are eliminated with an adaptive filter.

Among these 24, 10 top features are chosen for use in both the existing and new algorithms. The MBPSO algorithm is utilised to do this. In Table 1, we see some of the characteristics of the one cba under investigation.

Here it should be emphasised that the algorithm for selecting best characteristics had ran for 100 iterations and the best results after each iterations were noted. Best-performing iterations are chosen for the next stage.

Table-1: Feature selected for the subject *cba* in feature selection step.

Feature selected using SVM+WOA (current algorithm)	Feature selected using SVM+MWOA (proposed algorithm)
Median	Skewness
Frequency value	Mean absolute deviation
Standard deviation	Wilson amplitude
SNR	Spectral centroid
Standard deviation	Zero crossing rate
Waveform length	Zero crossing rate
Spectral flux	Mean
Mean absolute deviation	Mean absolute deviation
Variance	Spectral flux
Skewness	Cross convolution

The parameters of the confusion matrix constitute the basis of the performance analysis. Accuracy, sensitivity, specificity, and the F1score are used to evaluate the outcomes.

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

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{TN}}$$

$$Specificity = TN/(TN/FP)$$

$$\text{F1 score} = 2\text{TP}/(2\text{TP} + \text{FP} + \text{FN})$$

The aggregate results for all subjects are shown in Fig 2. Several methods, including the suggested MPSO MWOA SVM method as well as PSO MWOA SVM, MBPSO WOA SVM, and MBPSO SVM, were put through a battery of tests to measure their performance. Results from the comparison analysis reveal that the proposed method outperforms the alternatives.

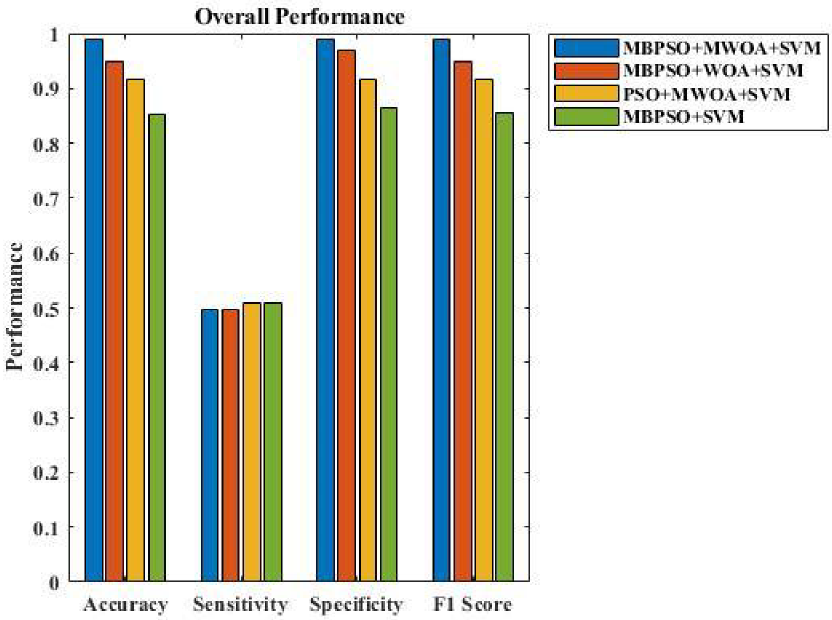

Fig. 2: Graphical representation of table 3.

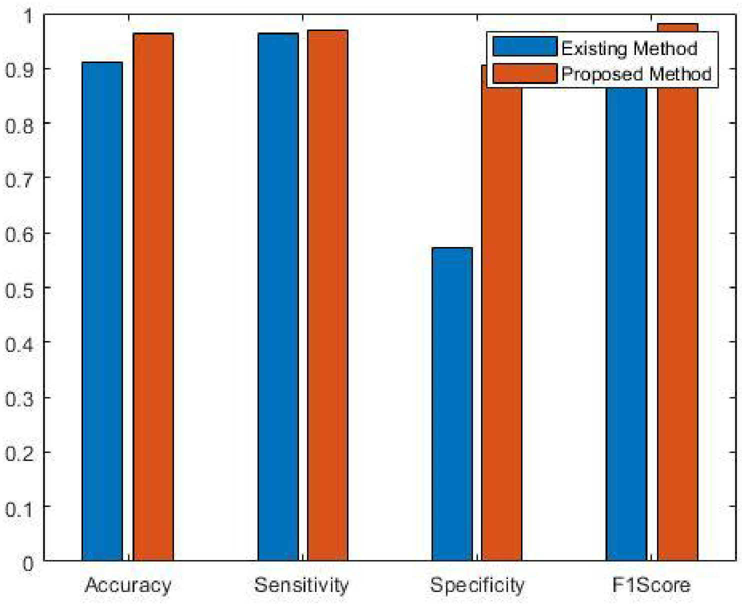

Fig. 3: Average performance comparison of input EEG dataset having 14 subjects.

For each of the 14 subjects, comparison have been studied between current and proposed algorithms and validated on all 4 parameters. It is well explained in fig 3.
The computational time has been reduced to 46 seconds and fig 6.11 shows the accuracy of proposed algorithm to detect the trauma and further table 6.5 categorise trauma for subject *cba* in 3 classes: low, medium and high.
In comparison to state-of-the-art methods, the results show that the suggested trauma level detection improves classification precision.
The results of the tests show how efficient trauma level identification is by determining the proper and precise estimation with the highest accuracy value. The proposed strategy achieves the best possible results with respect to accuracy (96.36%), sensitivity (96.84%), specificity (90.88%), and f1-score (97.96%). Based on these evaluations, we conclude that incorporating a fitness function into WOA may improve the algorithm's performance.

4. CONCLUSION

Further, it is clear from the discussions of the results that the collection of algorithms selected for the research is the best fit for improving the performance of our suggested algorithm. With the help of WOA, an attempt was made to categorise the trauma experienced by each participant. In addition, WOA and a variant of it have been successfully implemented in this context for identifying sources of trauma. A number of additional biological markers, it was thought, along with EEG, may detect levels of trauma more reliably and efficiently.

REFERENCES

[1]. Abiri, Reza, SoheilBorhani, Eric W. Sellers, Yang Jiang, and Xiaopeng Zhao. "A comprehensive review of EEG-based brain–computer interface paradigms." Journal of neural engineering 16, no. 1 (2019): 011001.

[2]. Alkawadri, Rafeed. "Brain–Computer Interface (BCI) Applications in Mapping of Epileptic Brain Networks Based on Intracranial-EEG: An Update." Frontiers in Neuroscience 13 (2019): 191.
[3]. Arvaneh, Mahnaz, Ian H. Robertson, and Tomas E. Ward. "A p300-based brain-computer interface for improving attention." Frontiers in human neuroscience 12 (2019): 524.
[4]. Baek, Hyun Jae, Min Hye Chang, JeongHeo, and Kwang Suk Park. "Enhancing the usability of brain-computer interface systems." Computational intelligence and neuroscience 2019 (2019).
[5]. Bozinovski, Stevo, and LiljanaBozinovska. "Brain–Computer Interface in Europe: the thirtieth anniversary." Automatika 60, no. 1 (2019): 36-47.
[6]. Carino-Escobar, Ruben I., Paul Carrillo-Mora, Raquel Valdés-Cristerna, Marlene A. Rodriguez-Barragan, Claudia Hernandez-Arenas, JimenaQuinzaños-Fresnedo, Marlene A. Galicia-Alvarado, and Jessica Cantillo-Negrete. "Longitudinal analysis of stroke patients' brain rhythms during an intervention with a brain-computer interface." Neural plasticity 2019 (2019).
[7]. Khalaf, Aya, Ervin Sejdic, and Murat Akcakaya. "Common spatial pattern and wavelet decomposition for motor imagery EEG-fTCD brain-computer interface." Journal of Neuroscience Methods 320 (2019): 98-106.
[8]. Corsi, Marie-Constance, Mario Chavez, Denis Schwartz, Laurent Hugueville, Ankit N. Khambhati, Danielle S. Bassett, and Fabrizio de VicoFallani. "Integrating EEG and MEG signals to improve motor imagery classification in brain–computer interface." International journal of neural systems 29, no. 01 (2019): 1850014.
[9]. Degenhart, Alan D., William E. Bishop, Emily R. Oby, Elizabeth C. Tyler-Kabara, Steven M. Chase, Aaron P. Batista, and M. Yu Byron. "Stabilization of a brain–computer interface via the alignment of low-dimensional spaces of neural activity." Nature Biomedical Engineering (2020): 1-14.
[10]. Di Flumeri, Gianluca, Francesca De Crescenzio, Bruno Berberian, Oliver Ohneiser, Jan Kramer, PietroAricò, GianlucaBorghini, Fabio Babiloni, Sara Bagassi, and Sergio Piastra. "Brain–computer interface-based adaptive automation to prevent out-of-the-loop phenomenon in air traffic controllers dealing with highly automated systems." Frontiers in human neuroscience 13 (2019).
[11]. Eloy, Joana, Ana Rita Teixeira, Anabela Gomes, and António José Mendes. "Using brain computer interaction in programming problem solving." In 2019 IEEE Global Engineering Education Conference (EDUCON), pp. 510-518. IEEE, 2019.
[12]. Hoffmann, Ulrich, Jean-Marc Vesin, and TouradjEbrahimi. "Recent advances in brain-computer interfaces." In IEEE International Workshop on Multimedia Signal Processing (MMSP07), no. CONF. 2007.
[13]. Gaur, Pramod, Ram BilasPachori, Hui Wang, and Girijesh Prasad. "An Automatic Subject Specific Intrinsic Mode Function Selection for Enhancing Two-Class EEG-Based Motor Imagery-Brain Computer Interface." IEEE Sensors Journal 19, no. 16 (2019): 6938-6947.
[14]. Georgiadis, Kostas, Nikos Laskaris, SpirosNikolopoulos, Dimitrios A. Adamos, and

IoannisKompatsiaris. "Using Discriminative Lasso to Detect a Graph Fourier Transform (GFT) Subspace for robust decoding in Motor Imagery BCI." In 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 6167-6171. IEEE, 2019.