Analysis of Cognitive Abilities in Students using Feature Optimization on EEG Signals

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ABSTRACT:
The characterization of brain activity during cognitive load is a topic of growing interest in the scientific community. The electroencephalography technique has been extensively utilized for this purpose, providing valuable insights into the neural correlates of cognitive processes. In this work, EEG recordsobtained from the Physionet repositoryare analyzed, which are recorded while subjects performed mathematical tasks. The study divides the total 36 signals into two groups: "Good" and "Bad", potentially reflecting different levels of cognitive ability. Various temporal, frequency, and wavelet features were extracted from the EEG data using various signal processing techniques. These features were then classified using a range of machine learning techniques, including Multilayer Perceptron, Support Vector Machines,K-Nearest Neighbors, Linear Discriminant Analysis, and Naive-Bayes. Further the results compared with those obtained after applying feature optimization techniques, such as Particle Swarm Optimization,Genetic Algorithms, Firefly Algorithm, Sequential Floating Forward Selection, and Sequential Forward Selection. The experimental findings suggest that the KNN classifier optimized with FFA is particularly effective in characterizing brain activity under mental cognitive conditions with an accuracy of 95.17%, precision of 95.47%, recall of 91.52%, F1-score of 93.28%, and a False Positive rate of only 4.53%.The outcomes highlight the potential of proposed approach for understanding the neural mechanisms underlying cognitive abilities.

I. Introduction

The human brain is a complex and fascinating organ, capable of a wide range of cognitive functions and information processing. Understanding the neural mechanisms that underlie these cognitive processes has been a long-standing goal in neuroscience. Understanding cognitive load during mental tasks is essential for both cognitive neuroscience and real-world applications. Prolonged task performance can lead to errors in situations requiring sustained attention[1]. Electroencephalography has emerged as a powerful tool for studying brain activity, as it provides a non-invasive and high-temporal resolution measure of electrical signals generated by neuronal activity [2-3].

Numerous studies have utilized EEG to examine the neural correlates of cognitive processes, such as memory, attention,and problem-solving.Recent advancements in machine learning and signal processing have enabled more sophisticated analysis of EEG data, allowing for the identification of relevant features and the development of predictive models of cognitive abilities [4-5].Hema et al. [6] conducted a comprehensive study on the classification of EEG acquired during various imaginary mental tasks, including problem-solving, letter composing, and figure rotation. They employed a multi-step approach, first using Principal Component Analysis for extracting relevant features from the EEG signals, and then applying Artificial Neural Networks for effective classification.

The study [7] delved deeper by exploring four distinct types of motor imagery tasks as the cognitive activities, providing a more diverse set of mental processes to analyze. Additionally, the researchers incorporated feature selection techniques, such as Common Spatial Pattern, to further refine the extracted features and optimize the classification performance.Beyond just cognitive tasks, the study [8] also attempted to measure the attentiveness of subjects while they watched short videos, demonstrating a broader scope in understanding cognitive abilities. To thoroughly analyze the EEG data, the researchers utilized a Six-level Discrete Wavelet Transform with the db1 wavelet, extracting a comprehensive set of features, including power,energy, entropy, median, maximum, andminimum.

Pedro et al. [9] conducted a study using magnetoencephalography to investigate the neural processes involved in solving arithmetic tasks. The researchers recorded MEG signals from 20 subjects as they performed tasks related to solving Python programming problems. Machine learning algorithms, particularly artificial neural networks employed to classify EEG-based data for task identification and mental workload assessment [10-11]. However, a study developed a seven-level load classification system with an artificial neural network model[12]. They extracted wavelet features, such as energy,wavelet entropy, and standard deviation, from the EEG data to characterize the cognitive load associated with the tasks. However, the tasks in their study were relatively simple, involving only single-digit arithmetic additions.

The cognitive tasks employed in previous studies, such as those related to language meaning, video broadcasting, motor imagery, or recognition tasks, generally require less attention and have lower levels of task difficulty compared to more complex problem-solving activities [12]. While this study have explored task classification with up to seven load levels, the actual difficulty of the tasks involved is relatively low.Some studies focused on the assessment of cognitive workload in a naval command and control environment, the Warship Commander Task. It was observed that certain EEG features, such as reduced alpha, elevated theta, and increased beta oscillations, were associated with increased cognitive workload during the naval command and control task [13-15].The study about cognitive work load [16] highlighted the importance of measuring neural correlates of specific cognitive processes to enhance human-computer interaction.

Some researchers [17-18] utilized the EEG dataset, which included recordings from 25 healthy participants performing a variety of cognitive tasks. The tasks included problem-solving, mental rotation, verbal fluency, and n-back memory tasks, each with varying levels of difficulty to elicit different cognitive demands.Although these studies have made valuable contributions to our understanding of cognitive abilities and their neural correlates, there is still a need for more comprehensive analyses that incorporate a wider range of cognitive tasks and optimize the extraction and classification stages to enhance the accuracy and robustness of the predictions [19-20].

In contrast, the current study aims to offer a comprehensive demonstration of the neural mechanisms underlying complex cognitive process, which likely require greater attention and present higher task difficulty for the participants. We aim to investigate the feasibility of using EEG-based features and machine learning techniques to characterize cognitive abilities in students. The EEG signals of individuals experiencing excessive cognitive load are analyzed. A total of 36 signals are categorized into two groups, "Good" and "Bad," based on the participants' ability to solve arithmetic tasks with ease. Various signal processing techniques are employed to extract features such as minimum, maximum, mean, kurtosis, skewness, peak frequency, median frequency, and wavelet features. These extracted features are then input into classifiers to characterize brain activity. Features are optimized with various algorithms and classified again to compare.

II. MATERIALS AND METHODS

A. *Data acquisition and preprocessing*

This study employed a publicly accessible EEG dataset from Physiobank [21], containing International 10/20 system EEG recordings from 36 participants performing serial subtraction tasks [22]. The participants were categorized into two groups, "Good" and "Bad," based on their task performance. The "Good" group consisted of individuals finished the task with ease, and the "Bad" group required significant effort and time to do so.Figure 1 displayed the EEG signals obtained from a single subject.

The following 19 channels are used while recording the EEG signals: frontal (F3, F4, Fz, F7, F8), anterior frontal (Fp1, Fp2), central (C3, C4, Cz), occipital (O1, O2), parietal (P3, P4, Pz), and temporal (T3, T4, T5, T6). The EEG signals were preprocessed using a combination of low-pass and high-pass filters to retain the frequency components within the range of 0.5-45 Hz. Additionally, a notch filter is used to suppress the power line noise (50 Hz). Each recorded session consisted of two segments: a 180-second resting-state period and a 60-second mental counting task. For the analysis presented in this study, only the 60-second mental counting signal from each subject was utilized and is denoted in Fig 1.

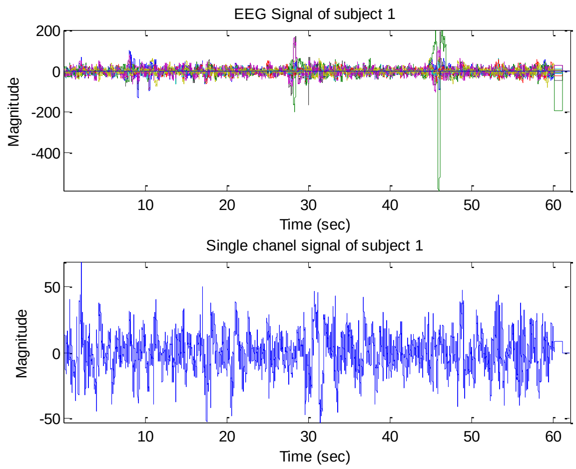

Figure 1: Multichannel EEG signal of a subject (top) and single channel EEG signal (bottom)

B. Feature Engineering

The Feature extraction is the key step in the analysis of EEG for cognitive ability assessment. In the study, we employed a multi-modal approach, extracting a diverse set of features from the preprocessed EEG signals to capture the underlying neural dynamics related to cognitive abilities. To extract a diverse set of relevant features from the preprocessed EEG signals, a multi-pronged approach incorporating time-domain, frequency-domain, and wavelet analyses was employed [23].

In the time-domain, features such as mean, minimum, maximum, kurtosis, and skewness were calculated for each EEG channel. These metrics provide insights into the statistical properties and distribution characteristics of the signal amplitudes. Moving to the frequency-domain, the power spectral density (PSD) was computed for each channel using a Fast Fourier Transform approach. Key frequency-based features, including peak frequency and median frequency, were derived from the power spectrum. These features help capture the underlying rhythmic and oscillatory patterns present in the EEG data.

Furthermore, a wavelet-based feature extraction technique was utilized. Wavelet features like energy, variance, entropy, and standard deviation were computed by decomposing the EEG signals into multiple sub-bands using a 6-level Discrete Wavelet Transform with the coif5 mother wavelet. This wavelet-based analysis allows for the characterization of the EEG signals in both the frequency and time domains, providing a more comprehensive representation of the neural dynamics. All the extracted wavelet features were normalized using a logarithmic function to ensure appropriate scaling and weighting during the subsequent analysis steps.

Sequential feature selection (SFS) is a fundamental method for feature selection. This is a wrapper feature selection method, where the criterion function is evaluated with a classifier [24]. The algorithm starts with empty set and continuously updates the feature space by including a feature f that gives the maximum criterion value in each step. The final feature space is selected when the criterion function reaches its maximum value.Sequential Floating Forward Selection (SFFS)is also a wrapper feature selection for classification [25]. The criterion function is evaluated using k-nearest neighbor (KNN) discrimination on a feature subset. The final result is the unweighted average recall, which is the average correct classification rate across all classes. The class label for each test data point is determined using the Euclidean distance metric.

The genetic algorithm was used for feature selection, where individuals were represented as binary vectors, with each bit corresponding to the inclusion or exclusion of a particular feature [26]. The GA is based on the survival of fittest theory, where individuals with high fitness are selected as parents for to generation. Selection, crossover and mutation operators were used to create the new population in each iteration.

Particle swarm optimization is a meta-heuristic algorithm inspired by the collective social behavior observed in bird flocks or fish schools [27]. The particles in the swarm represent potential solutions, and their movements are guided by their own personal best position and the global best position achieved by any particle in the swarm. The firefly algorithm is a meta-heuristic optimization method inspired by the bioluminescent flashing patterns of fireflies [28]. The algorithm builds upon the idea that each firefly is attracted towards brighter fireflies, regardless of their sex.

The selected features were then used as inputs to a variety of machine learning classifiers, including Support Vector Machines (SVM), K-nearest neighbors (KNN), Multilayer perceptron (MLP) and Naïve-Bayes classifiers (NB), to evaluate their performance in discriminating between the "Good" and "Bad" cognitive ability groups.

C. Classification

The optimal subset of features identified through feature selection was then used to train and evaluate different machine learning classifiers for distinguishing between the "Good" and "Bad" cognitive ability groups. Five widely used algorithms - LDA, MLP, KNN, SVM, and NB - were employed for this classification task.

The artificial neural network (ANN) with a multilayer perceptron (MLP) structure was utilized for classifying features extracted from EEG signals recorded during mathematical tasks. ANNs are recognized as versatile classifiers and, with an appropriately designed architecture, are well-suited for classifying noisy and nonstationary data like EEG signals [29]. The MLP structure employed in this study incorporates hidden layers, enabling it to model complex and nonlinear input-output relationships effectively.

Linear discriminant analysis is a statistical classification method designed to identify the linear combination of features that optimally distinguishes between two or more classes [30]. The LDA classifier was used here due to its simplicity and efficiency, as well as its ability to handle high dimensional feature spaces. Support Vector Machine (SVM) is a supervised machine learning algorithm that constructs one or more hyperplanes in a high-dimensional space, which can be utilized for classification, regression, and other tasks [31]. SVM was included due to its strong theoretical foundations and effectiveness in handling complex, high-dimensional data.

The k-Nearest Neighbors (kNN) classifier was also utilized, as it is a simple yet powerful method that classifies a new instance based on the class labels of its k-nearest neighboring instances [32]. Finally, the Naive Bayes classifier, which applies Bayes' theorem to classify instances based on the assumption of independence between features, was included to provide a baseline performance comparison [33].The seven sub-bands generated by the Discrete Wavelet Transform (DWT) each provide five features. When combined with the previously mentioned temporal and frequency features, this results in a feature vector of size 42 for each channel. The feature space is then divided into training and testing sets, with 30% of the feature space used for testing against the trained classifier.

III. RESULTS AND DISCUSSION

The following parameters are used to evaluate the classifier's performance. Accuracy is defined as the ratio of correctly predicted instances to the total number of predictions.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \qquad (1)$$

Precisionis the ratio of true positive to the total predicted positive

$$Precision = \frac{TP}{TP + FP} \qquad (2)$$

Recallis the ratio of true positive to the total actual value (TP+FN) and also known as sensitivity.

$$Recall = \frac{TP}{TP + FN} \qquad (3)$$

F1-scoreis defined as the harmonic mean of the recall and precision and defined as follows

$$F1\_score = \frac{2 * TP}{2 * TP + FP + FN} \qquad (4)$$

The false positive rate (FPrate) is calculated as the ratio of incorrectly classified signals to the total number of signals that do not belong to the actual class.

$$FPrate = \frac{FP}{TN + FP} \qquad (5)$$

The values of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) are derived from the confusion matrix of the classifier. The performance parameters calculated from these values are summarized in Table 1.

Table1: Performance metrics of different Classifiers (%)

Classifier	Accuracy	Precision	Recall	F1-score	FP Rate
NB	67.98	55.76	52.97	55.43	47.03
MLP	78.51	76.89	59.36	60.04	23.11
LDA	75.88	66.28	66.28	59.49	33.72
KNN	82.46	78.22	71.34	73.61	21.77
SVM	83.33	90.91	66.67	70.00	9.09

The metrics showed the classification metrics without optimization. It should be noted that that the SVMattained the highest overall classification accuracy of 83.33%, with very high precision (90.91%) but relatively lower recall (66.67%).The KNN algorithm demonstrated strong performance, achieving an accuracy of 82.46% along with well-balanced precision and recall scores. The MLP neural network had an accuracy of 78.51%, demonstrating the potential of deep learning approaches for this task.

The LDA classifier achieved an accuracy of 75.88%, which is respectable but lower than the top-performing algorithms.The Naive Bayes classifier had the lowest performance, with an accuracy of only 67.98%.In our previous work [24], the random subspace classifier was found to deliver the best performance, achieving an accuracy of 89.91%, a precision of 99.4%, a recall of 92.88%, and an F1 score of 84.47%.This indicates that ensemble techniques may be able to improve the classification results compared to individual classifiers. Table 2 compares the classification results obtained with and with out optimization algorithms.

The feature selection in Table 2 represents without optimization and SFS, SFFS, GA, PSO and FFA resembles corresponding feature optimization algorithm. The outcomesindicates that the feature selection methods have a substantial impact on the performance of the classifiers. For the Naive Bayes and Multilayer Perceptron classifiers, the feature selection techniques did not consistently improve the performance metrics.For the Naive Bayes classifier, the feature selection techniques had mixed effects on its performance. The Sequential Floating Forward Selection and Sequential Forward Selection methods led to a slight increase in the accuracy, while the Genetic Algorithm resulted in a decrease. However, the more advanced feature selection algorithms, namely Particle Swarm Optimization and Firefly Algorithm, were able to enhance the NB classifier's accuracy by around 3 to 4 percentage points.

Table 2: Comparison of metricsfordifferent classifiers with and without feature selection (%)

Classifier	**Feature Selection**	**Accuracy**	**Precision**	**Recall**	**F1-score**	**FP Rate**
NB	Direct	67.98	55.76	52.97	55.43	47.03
	SFS	68.86	60.82	58.33	61.26	41.67
	SFFS	68.42	59.41	56.83	59.71	43.17
	GA	63.16	56.46	57.89	56.36	43.97
	PSO	70.61	58.45	55.87	57.39	44.13
	FFA	71.05	54.73	52.16	51.84	47.84
MLP	Direct	78.51	76.89	59.36	60.04	23.11
	SFS	72.81	51.19	50.29	46.42	48.81
	SFFS	71.49	59.86	58.19	58.67	40.14
	GA	74.12	59.51	52.92	50.79	40.49
	PSO	74.56	60.74	52.63	49.88	32.22
	FFA	75.00	50.00	37.50	42.86	31.67
LDA	Direct	75.88	66.28	66.28	59.49	33.72
	SFS	75.00	50.00	37.50	42.86	12.50
	SFFS	75.00	50.00	37.50	42.86	12.50
	GA	77.19	68.95	64.33	65.69	31.05
	PSO	79.39	74.43	64.03	66.02	25.57

	FFA	81.14	76.39	68.71	70.96	23.61
KNN	Direct	82.46	78.22	71.34	73.61	21.77
	SFS	88.60	86.52	81.87	83.81	13.48
	SFFS	88.16	84.11	84.50	84.30	15.89
	GA	88.16	85.22	82.16	83.51	14.77
	PSO	90.79	88.22	86.84	87.50	11.78
	FFA	95.17	95.47	91.52	93.28	4.53
SVM	Direct	83.33	90.91	66.67	70.00	9.09
	SFS	87.72	92.96	75.44	79.94	7.03
	SFFS	85.09	91.71	70.17	74.23	8.29
	GA	85.53	91.91	71.05	75.23	8.09
	PSO	91.67	95.00	83.33	87.37	5.00
	FFA	93.86	90.14	95.91	92.40	9.86

In contrast, the Multilayer Perceptron neural network demonstrated a decrease in performance when the feature selection methods were applied. This suggests that the MLP was able to effectively learn the relevant features from the raw data, and the additional feature engineering steps may have actually degraded the model's learning capability.However, for the Linear Discriminant Analysis, Support Vector Machine classifiers, and k-Nearest Neighbors, the feature selection methods, especially Particle Swarm Optimization and Firefly Algorithm, were able to substantially enhance the classification accuracy, precision, Frate, recall, and F1-score.

For the LDA classifier, the feature selection techniques of Sequential Floating Forward Selection and Sequential Forward Selection resulted in a reduction of the performance metrics compared to the direct use of the raw features. However, a lower False Positive rate was observed in both of these cases (12.5%), which is desirable. The Genetic Algorithm increased the accuracy from 75.88% to 77.19%, the Particle Swarm Optimization method achieved an accuracy of 79.39%, and the Firefly Algorithm was able to further enhance the accuracy to 81.14%. This represents an approximately 6 percentage point increase in accuracy when using the Firefly Algorithm-based feature selection.Figure 2 dislays the LDA performance for different feature optimization methods.

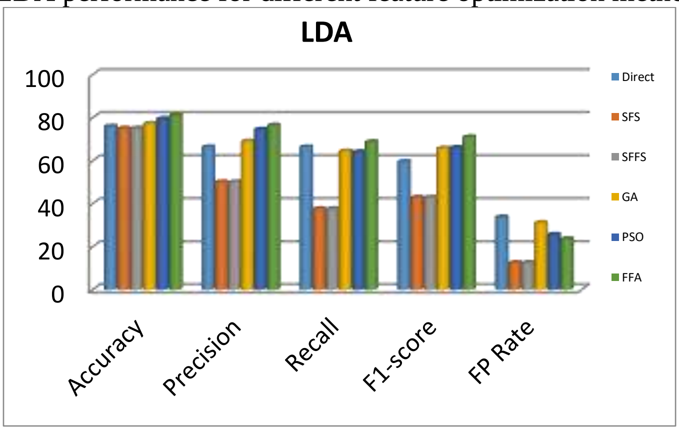

Figure 2: The performance metric of LDA classifier for various optimization techniques

The k-Nearest Neighbors classifier demonstrated the most substantial improvements from the feature selection techniques. The Firefly Algorithm-based feature selection achieved the best overall performance when applied to the KNN classifier, resulting in an accuracy of 95.17%, recall of 91.52%, precision of 95.47%, F1-score of 93.28%, and a False Positive rate of only 4.53%. This represents a remarkable enhancement in the KNN classifier's ability to accurately classify cognitive abilities based on the EEG signals.

The other feature selection techniques, such as Sequential Floating Forward Selection, Sequential Forward Selection, and Genetic Algorithm, also had a positive impact on the KNN classifier's performance, with similar accuracy levels around 88%. This consistent improvement across multiple feature selection techniques highlights the KNN classifier's ability to leverage the most informative features for the cognitive ability classification task.The observed trends were not limited to the accuracy metric alone, but rather extended to other important performance indicators, such as precision, recall, and F1-score. This suggests that the feature selection methods are able to optimize the most discriminative features, allowing the KNN classifier to make more reliable and robust predictions on the cognitive ability of the students based on their EEG signals. Figure 3 and 4 reiterates the KNN and SVM outperformance for different methods used in the study.

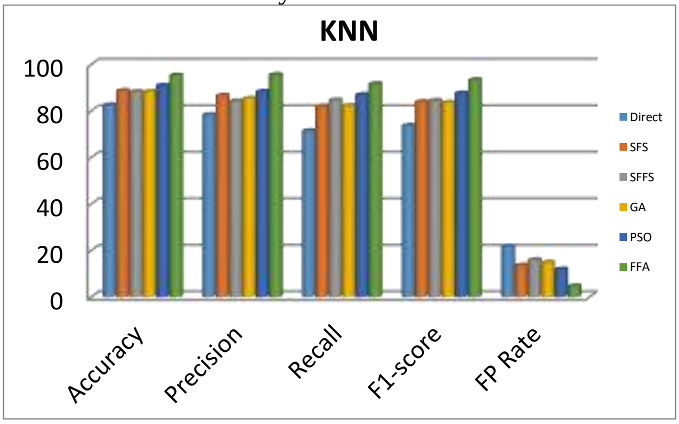

Figure 3: The performance of KNN classifier for different feature selection techniques

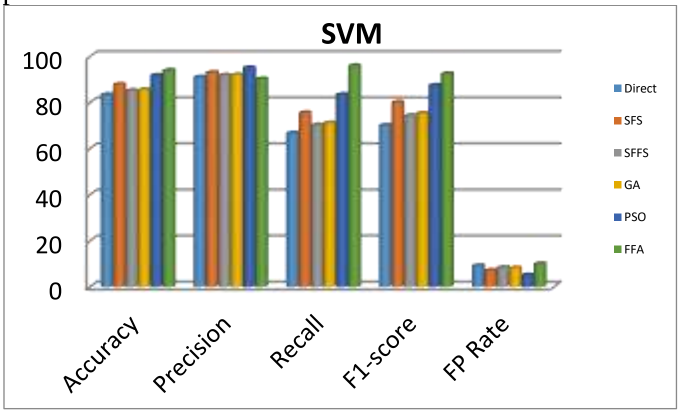

Figure 4: The performance metrics of SVM classifier for different feature selection techniques

The Support Vector Machine classifier also benefited significantly from the feature selection techniques. The Particle Swarm Optimization and Firefly Algorithm-based feature selection led to the best performance, with accuracy levels exceeding 90%. Specifically, the Firefly Algorithm feature selection achieved an accuracy of 93.86%, precision of 90.14%, F1-score of 92.40%, recall of 95.91%, and a False Positive rate of only 9.86%. The other feature selection methods, such as Sequential Forward Selection and Genetic Algorithm, also improved the SVM classifier's performance, but to a lesser extent compared to the Particle Swarm Optimization and Firefly Algorithm.

The feature set used in this study consists of a combination of temporal, frequency, and wavelet features extracted from the electroencephalography signals. These features were selected based on a review of the existing literature, which has demonstrated their effectiveness in classifying EEG signals for various applications, such as the prediction of mental stress,epilepsy, driver attention, and vigilance. The choice of classifiers, including Naive Bayes, Multilayer Perceptron, Linear Discriminant Analysis, Support Vector Machines, and k-Nearest Neighbors was guided by their proven track record in cognitive load or mental task classification tasks.

While the individual features may have been capable of providing efficient classification performance, the study aimed to investigate the impact of combining these diverse feature types. The rationale behind this approach was to leverage the complementary information captured by the temporal, frequency, and wavelet features, potentially enhancing the overall classification accuracy.

Increasing task difficulty leads to heightened brain activity in the frontal lobe. Future research could focus on analyzing mental activity across other brain lobes, which were not the focus of this study. While previous studies primarily explored simple motor imagery tasks, this research emphasizes the challenges associated with complex arithmetic tasks.The key findings of this study are:

- The performance of the machine learning models is heavily affected by the feature selection techniques employed.
- NB and MLP classifiers did not consistently benefit from the feature selection methods, suggesting they were able to effectively learn the relevant features from the raw data.

- LDA, KNN, and SVM classifiers demonstrated significant improvements in their performance metrics when advanced feature selection algorithms, such as PSO and FFA, were applied.
- The FFA-based feature selection achieved the best overall performance when applied to the KNN classifier, resulting in an accuracy of 95.17%, of 95.47%, recall of 91.52%, a False Positive rate of only 4.53%, and F1-score of 93.28%.

These findings hold significant potential for advancing reliable and accurate systems to assess cognitive abilities, laying a robust groundwork for future research in this field.

IV. CONCLUSION

The study presents a comprehensive analysis of various machine learning techniques, including Naive Bayes, Multilayer Perceptron, Linear Discriminant Analysis, Support Vector Machines, and k-Nearest Neighbors, for classifying cognitive ability in students based on electroencephalography signals. It demonstrates the capability of different features selection techniques in discerning the cognitive levels load levied in an arithmetictask.The Firefly Algorithm-based feature selection achieved the best overall performance when applied to the KNN classifier, resulting in an accuracy of 95.17%, precision of 95.47%, recall of 91.52%, F1-score of 93.28%, and a False Positive rate of only 4.53%.

Future work may include exploring deep learning architectures and investigating transfer learning or data augmentation techniques to address the challenge of limited EEG data availability. There is scope for incorporating additional modalities, such as demographic information or behavioral data, to further enhance the classification performance.Thesimulation results have important implications for the development of reliable and accurate systems for assessing cognitive ability in educational and clinical settings, as well as for further research in this area.

REFERENCES

[1] G. Borghini, L. Astolfi, G. Vecchiato, D. Mattia, and F. Babiloni,"Measuring neurophysiological signals in aircraft pilots and car driversfor the assessment of mental workload, fatigue and drowsiness,"Neurosci. Biobehav. Rev., vol. 44, pp. 58–75, Jul. 2014.

[2] G. Sammer et al., "Relationship between regional hemodynamicactivity and simultaneously recorded EEG-theta associated with mental arithmetic-induced workload," Hum. Brain Mapp., vol. 28, no. 8, pp. 793–803, Aug. 2007.

[3] P. Sauseng, B. Griesmayr, R. Freunberger, and W. Klimesch, "Controlmechanisms in working memory: A possible function of EEG theta oscillations," Neurosci. Biobehav. Rev., vol. 34, no. 7, pp. 1015–1022, Jun. 2010.

[4] Bosl, W. J., Tager-Flusberg, H., & Nelson, C. A. (2018). EEG Analytics for Early Detection of Autism Spectrum Disorder: A data-driven approach. In Scientific Reports (Vol. 8, Issue 1). Nature Portfolio. https://doi.org/10.1038/s41598-018-24318-x.

[5] Craik, A., He, Y., & Contreras-Vidal, J. L. (2019). Deep learning for electroencephalogram (EEG) classification tasks: a review. Journal of Neural Engineering, 16(3), 31001. IOP Publishing. https://doi.org/10.1088/1741-2552/ab0ab5

[6] C.R. Hema, M.P.Paulraj, R. Nagarajan,S. Yaacob, A.H. Adom, "Application of Particle Swarm Optimization for EEGSignal Classification", Biomedical Soft Computing and Human Sciences, Vol.13, No.1, pp.79-84 (2008).

[7] Aiming Liu, Kun Chen, Quan Liu, Qingsong Ai, Yi Xie, Anqi Chen, "Feature Selection for Motor Imagery EEGClassification Based on Firefly Algorithm and Learning Automata" ,Sensors 2017, 17, 2576; doi:10.3390/s17112576.

[8] Paul Alton Nussbaum and Rosalyn Hobson Hargraves, "Pilot Study: The Use of Electroencephalogram to Measure Attentiveness towards Short Training Videos", (IJACSA) International Journal of Advanced Computer Science and Applications,Vol. 4, No.3, 2013.

[9] Pinheiro-Chagas, P., et al., Decoding the processing stages of mental arithmetic with magnetoencephalography,Cortex (2018), https://doi.org/10.1016/j.cortex.2018.07.018.

[10] A. Gevins et al., "Monitoring working memory load during computerbasedtasks with EEG pattern recognition methods," Hum. Factors,vol. 40, no. 1, pp. 79–91, 1998.

[11] C. L. Baldwin and B. N. Penaranda, "Adaptive training using an artificialneural network and EEG metrics for within- and cross-task workloadclassification," NeuroImage, vol. 59, no. 1, pp. 48–56, Jan. 2012.

[12] Pega Zarjam, Julien Epps, and Nigel H. Lovell, "Beyond Subjective Self-Rating: EEG SignalClassification of Cognitive Workload", IEEE Transactions On Autonomous Mental Development, Vol. 7, No. 4, December 2015.

[13] Yichuan Liu, Hasan Ayaz, Patricia A Shewokis, shewokis@drexel.edu. (2017). Mental workload classification with concurrent electroencephalography and functional near-infrared spectroscopy. https://www.tandfonline.com/doi/full/10.1080/2326263X.2017.1304020.

[14] Grootjen, M., Neerincx, M. A., & Veltman, J. A. (2006). Cognitive task load in a naval ship control centre: from identification to prediction. In Ergonomics (Vol. 49, Issue 12, p. 1238). Taylor & Francis. https://doi.org/10.1080/00140130600612705

[15] Tjerk De Greef, Delft University of Technology, Henryk Arciszewski. (n.d.). Triggering Adaptive Automation in Naval Command and Control. Retrieved January 18, 2025, from https://www.intechopen.com/chapters/5928

[16] Walter, C., Rosenstiel, W., Bogdan, M., Gerjets, P., & Spüler, M. (2017). Online EEG-Based Workload Adaptation of an Arithmetic Learning Environment. In Frontiers in Human Neuroscience (Vol. 11). Frontiers Media. https://doi.org/10.3389/fnhum.2017.00286.

[17] Liu, Y., Ayaz, H., & Shewokis, P. A. (2017). Multisubject "Learning" for Mental Workload Classification Using Concurrent EEG, fNIRS, and Physiological Measures. In Frontiers in Human Neuroscience (Vol. 11). Frontiers Media. https://doi.org/10.3389/fnhum.2017.00389

[18] Miklody, D., Uitterhoeve, W., Heel, D. van, Klinkenberg, K., & Blankertz, B. (2017). Maritime Cognitive Workload Assessment. In Lecture notes in computer science (p. 102). Springer Science+Business Media. https://doi.org/10.1007/978-3-319-57753-1_9.

[19] Faust, O., Hagiwara, Y., Hong, T. J., Lih, O. S., & Acharya, U. R. (2018). Deep learning for healthcare applications based on physiological signals: A review. Computer Methods and Programs in Biomedicine, 161, 1. Elsevier BV. https://doi.org/10.1016/j.cmpb.2018.04.005.

[20] Yu, K., Prasad, I., Mir, H., Thakor, N. V., & Al-Nashash, H. (2015). Cognitive workload modulation through degraded visual stimuli: a single-trial EEG study. In Journal of Neural Engineering (Vol. 12, Issue 4, p. 46020). IOP Publishing. https://doi.org/10.1088/1741-2560/12/4/046020.

[21] A.L. Goldberger, Glass L. Amaral LAN, J.M. Hausdorff, Mark R.G. Ivanov PCh, J.E.Mietus, G.B. Moody, C.-K. Peng, H.E. Stanley, PhysioBank, PhysioToolkit, andPhysioNet: components of a new research resource for complex physiologicsignals, Circulation 101 (23) (2000) e215–e220 [Circulation Electronic Pages;http://circ.ahajournals.org/cgi/content/full/101/23/e215].

[22] Zyma I, Tukaev S, Seleznov I, Kiyono K, Popov A,Chernykh M, Shpenkov O, "Electroencephalograms during Mental ArithmeticTask Performance", Data 2019, Vol. 4, Issue 14; doi:10.3390/data4010014.

[23] T. A. Babu, S. Gadde, S. Ravi, K. V. V. Rao, Y. Mamillu and D. Krishna, "Analysis of Mental Task Ability in Students based on Electroencephalography Signals," 2022 IEEE International Conference on Signal Processing, Informatics, Communication and Energy Systems (SPICES), Thiruvananthapuram, India, 2022, pp. 274-278, doi: 10.1109/SPICES52834.2022.9774092.

[24] Pohjajalainena J, Rasanen O, Kadioglub S, "Feature Selection Methods and Their Combinations in High-Dimensional Classification of Speaker Likability, Intelligibility and Personality Traits", *Computer Speech & Language*, November 2013, DOI: 10.1016/j.csl.2013.11.004.

[25] Pudil P, Novovicova J, Kittler J,"Floating search methods in feature selection", Pattern Recognition Letters, vol. 15, pp. 1119-1125,November 1994.

[26] Yang J, Singh H, Hines EL, Schlaghecken F, Iliescu DD, Leeson MS, Stocks NG. "Channel selection and classification of electroencephalogram signals: an artificial neural network and genetic algorithm-based approach". Artif Intell Med. 2012 Jun;55(2):117-26. doi: 10.1016/j.artmed.2012.02.001. Epub 2012 Apr 12. PMID: 22503644.

[27] A. Atyabi, M. Luerssen, S. Fitzgibbon and D. M. W. Powers, "Dimension reduction in EEG data using Particle Swarm Optimization," 2012 IEEE Congress on Evolutionary Computation, Brisbane, QLD, Australia, 2012, pp. 1-8, doi: 10.1109/CEC.2012.6256487.

[28] Ananda Babu T., Rajesh Kumar P., "Optimized feature selection for the classification of uterine magnetomyography signals for the detection of term delivery", Biomedical Signal Processing and Control, Volume 58, 2020, 101880, ISSN 1746-8094, doi.org/10.1016/j.bspc.2020.101880

[29] F. Lotte, M. Congedo, A. Léuyer, and B. Arnaldi, "A review of classificationalgorithms for EEG-based brain–computer interfaces," J. Neural Eng., vol. 4, pp. R1–R13, 2007.

[30] M. Bhatnagar, G. S. Gupta and R. K. Sinha, "Linear Discriminant Analysis Classifies the EEG Spectral Features Obtained from Three Class Motor Imagination," 2018 2nd International Conference on Power, Energy and Environment: Towards Smart Technology (ICEPE), Shillong, India, 2018, pp. 1-6, doi: 10.1109/EPETSG.2018.8659292.

[31] Ma Y, Ding X, She Q, Luo Z, Potter T, Zhang Y. Classification of Motor Imagery EEG Signals with Support Vector Machines and Particle Swarm Optimization. Comput Math Methods Med. 2016;2016:4941235. doi: 10.1155/2016/4941235. Epub 2016 May 30. PMID: 27313656; PMCID: PMC4904086.

[32] Sha'abani, M.N.A.H., Fuad, N., Jamal, N., Ismail, M.F. (2020). kNN and SVM Classification for EEG: A Review. In: Kasruddin Nasir, A.N., et al. InECCE2019. Lecture Notes in Electrical Engineering, vol 632. Springer, Singapore. https://doi.org/10.1007/978-981-15-2317-5_47.

[33] Machado J, Balbinot A. Executed Movement Using EEG Signals through a Naive Bayes Classifier. Micromachines. 2014; 5(4):1082-1105. https://doi.org/10.3390/mi5041082.