

# Prediction of Attention and Short-Term Memory Loss by EEG Workload Estimation

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**How to cite this paper:** Islam, M.A., Sarkar, A.K., Hossain, M.I., Ahmed, M.T. and Ferdous, A.H.M.I. (2023) Prediction of Attention and Short-Term Memory Loss by EEG Workload Estimation. *Journal of Biosciences and Medicines*, 11, 304-318.

<https://doi.org/10.4236/jbm.2023.114022>

**Received:** February 23, 2023

**Accepted:** April 22, 2023

**Published:** April 25, 2023

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## Abstract

Mental workload plays a vital role in cognitive impairment. The impairment refers to a person's difficulty in remembering, receiving new information, learning new things, concentrating, or making decisions that seriously affect everyday life. In this paper, the simultaneous capacity (SIMKAP) experiment-based EEG workload analysis was presented using 45 subjects for multitasking mental workload estimation with subject wise attention loss calculation as well as short term memory loss measurement. Using an open access preprocessed EEG dataset, Discrete wavelet transforms (DWT) was utilized for feature extraction and Minimum redundancy and maximum relevancy (MRMR) technique was used to select most relevance features. Wavelet decomposition technique was also used for decomposing EEG signals into five sub bands. Fourteen statistical features were calculated from each sub band signal to form a  $5 \times 14$  window size. The Neural Network (Narrow) classification algorithm was used to classify dataset for low and high workload conditions and comparison was made using some other machine learning models. The results show the classifier's accuracy of 86.7%, precision of 84.4%, F1 score of 86.33%, and recall of 88.37% that crosses the state-of-the-art methodologies in the literature. This prediction is expected to greatly facilitate the improved way in memory and attention loss impairments assessment.

## Keywords

Attention Loss, Cognitive Impairment, EEG, Feature Selection, SIMKAP, Short Term Memory Loss, Machine Learning, Workload

## 1. Introduction

The electrical activity of brain neurons can be recorded methodically using electroencephalography (EEG). For these recordings, the scalp is used, and numerous electrodes are positioned there in different, specific places. Analyzing recorded EEGs helps describe the status of the brain with deviations from the normal/healthy state, and such deviations engender epileptic seizures, sleep difficulties, attention loss, memory loss, mental stress, and more. Visual examination of the recorded EEG data is not feasible due to the huge volume of data [1]. Successful assessment and understanding of both low and high mental workload states place a high demand on the ability to retrieve meaningful information from EEG signals. Then, considering only a few crucial signal characteristics by using Machine Learning (ML) makes EEG analysis simpler than laborious, time-consuming big data sets for analyzing mental states.

The idea of human mental workload is the cornerstone of research on the assessment of the human brain functions. The broadest definition of mental workload can be stated as the cognitive cost of completing a task in a limited amount of time and its associated prediction is required in order to forecast the operator and system [2] [3]. Mental workload has been identified as a crucial element that significantly affects the human brain's performance [2]. As a concept, it has been widely used in the design and evaluation of complex human-machine systems and environments, including those for operating aircraft [4], operating trains and vehicles [5] [6], different human-computer and brain computer interfaces [7] [8] [9] and educational contexts [10] [11] [12]. Over the past two decades, there has been an increase in interest in studying mental workload due to the emergence of a number of technologies that need users to operate at various levels of cognition and in a variety of environments. The survey of the literature reveals various works on workload EEG analysis to determine attention loss and short-term memory loss. But only a few of them have been conducted for workload analysis where the adequate and useful features are extracted. Different approaches have been put forth to gauge the workload of the human mind using simultaneous tasks (SIMKAP). One of them is an arithmetic task that was introduced to perform mental stress or workload analysis [1]. An approach using (Independent Component Analysis) ICA with three types of task was introduced in [13] for choosing the most suitable EEG channels for classifying mental tasks using power spectrum density (PSD) feature extraction only and it got only 70% accuracy. Simultaneous task EEG workload dataset description with experimental results was proposed with 69.2% accuracy using FFT based PSD features extraction technique only [14]. Another method for emotion recognition was reported by the work in [15] where two types of workload were predicted and it achieved a classification accuracy of 73.14%. Mental workload recognition from EEG signal using deep learning techniques was conducted in [16] and it achieved only 65% classification accuracy. Mental workload estimation using EEG was also introduced by Vishal Pandey *et al.* in 2020 in an international conference

with maximum 72% classification accuracy [17]. Cognitive Workload assessment on simultaneous tasks was proposed by Wonse Jo *et al.* in 2022 with 74.68% [18].

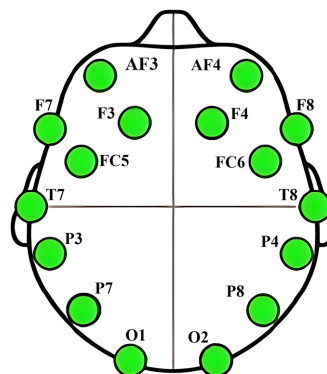
We found a glaring deficit in effective feature extraction and feature selection, along with classification based on our examination of the literature that has been discussed in above. In this study, we proposed a feature selection technique selecting the dominant features after feature extraction with fourteen types of statistical features results high classification accuracy from the literature to fill up the gap of the literature and thus classify low and high workload analysis from EEG data to find out the attention loss and short-term memory loss. This is how the rest of the paper is structured: The “Materials and Research Methods” section provides a chronological explanation of the research, including research design and research procedure. The “Results and Discussion” section is next provided, and lastly the “Conclusion” section.

## 2. Materials and Research Methodology

Materials and required methodology used in this research is provided in this section descriptively. The tasks related to experiment, a description of a dataset used, wavelet transform (DWT), statistical data computation for feature extraction, and a detailed description of classifiers used along with the performance metrics for validation are illustrated in the following subsections.

### 2.1. Dataset Description and Experimental Design

This paper mainly describes EEG workload estimation technique using simultaneous task or simultaneous capacity (SIMKAP) [14]. The data for each subject follows the naming convention as subno\_task.txt. For example, sub01\_lo.txt is filtered EEG data for subject 1 at rest, while sub23\_hi.txt is filtered EEG data for subject 23 during the multitasking test. The rows of each datafile correspond to the samples in the recording and the columns correspond to the 14 channels of the EEG device, those are AF3, F7, F3, FC5, T7, P7, O1, P3, P7, O1, O2, P8, T8, FC6, F4, F8, AF4, respectively depicted in **Figure 1** [14].



**Figure 1.** Electrodes positions based on 10 - 20 international system for EEG recording with The Emotiv EEG Device [14].

In order to minimize the impact of any between-task activity, the start and last 15 seconds of data from each recording were removed, yielding recordings that lasted 2.5 minutes. After each trial section, subjects were asked to assess their perceived mental workload (MWL) on a scale from 1 to 9.

Defining cognitive workload as the amount of mental effort, on the scale (1-9) below, rate the cognitive challenge involved in the task of this segment with 1 being the lowest and 9 being the highest.								
1	2	3	4	5	6	7	8	9

Questionnaire on a 1 - 9 scale for rating of mental workload, which subjects were required to fill after completion of each segment of the experiment has been shown in above screenshot [14]. This was done subjectively confirming that the subject actually felt more work during the test than they did while they were resting. A rating of 1 - 3 can be interpreted as low (lo) workload, (4 - 6 as medium workload was not considered in this study) and 7 - 9 as high (hi) workload. In both low and high workload states, 128 Hz sampling frequency was used with 2.5 minutes of EEG recordings utilizing the Emotiv EPOC EEG headset [14]. According to a study in [19], the most popular measure in cognitive load studies is the 9-point rating scale [20], which is comparable to the NASA-1 TLX's to 21 scale.

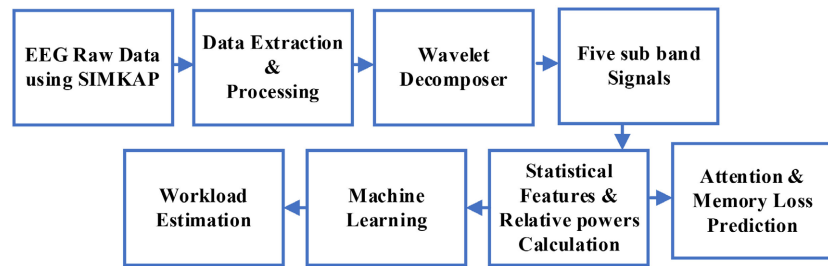
The overall functionality of the system is composed of several parts as depicted in **Figure 2**. Those parts include collecting the dataset from the IEEE Data Port in text format, extracting data based on channels, arranging the processed data corresponding to its label to fit for classification and finally classifying EEG data during high and low workload.

To determine the attention loss as well as the short-term memory loss in brain wavelet decompose technique was applied to decompose EEG signal into its sub band signals, and the relative power of those signals, namely, theta, alpha and beta signals, was determined using percentage of five signals, preparing area and radar plot in excel during high workload.

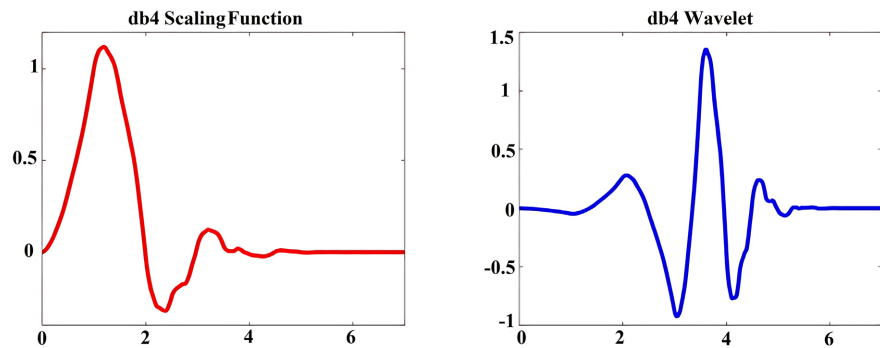
## 2.2. Discrete Wavelet Transform

In order to analyze the time-frequency relationship of biomedical signals, discrete wavelet transform (DWT) is used [21]. This DWT is especially helpful in EEG signal processing because of its non-stationary properties. By using long time frames for low frequencies and short time frames for higher frequencies, this transform generates an accurate time-frequency evaluation. The DWT decomposition of a signal uses two down samplers by 2, time series high-pass and low-pass filtering, and time series high-pass and low-pass filtering.

In this case, the mother-wavelet is indicated by DWT's high-pass filter  $g(n)$ , and its mirror version is expressed by DWT's low-pass filter  $h(n)$  [21]. **Figure 3** depicts the mother wavelet of the Daubechies wavelet (db4) and the scaling function associated to it. The approximation and detail coefficients, marked by A1 and D1, are the outcomes of the first high-pass and low-pass filters respectively.



**Figure 2.** EEG workload estimation and relative power calculation during SIMKAP.



**Figure 3.** Scaling function and mother wavelet (db4).

The A1 is additionally disintegrated, and procedure is carried out again and again until the desired number of breakdown levels is reached [21] [22]. The dilation function  $\phi_{j,k}(n)$  is reliant on the low-pass, and the wavelet function  $\psi_{j,k}(n)$  keeps on the high-pass filter, which is represented as follows.

$$\phi_{j,k}(n) = 2^{j/2} h(2^j n - k) \tag{1}$$

$$\psi_{j,k}(n) = 2^{j/2} g(2^j n - k) \tag{2}$$

where,  $n = 0, 1, 2, \dots, N - 1$ ;  $j = 0, 1, 2, \dots, J - 1$ ;  $k = 0, 1, 2, \dots, 2^j - 1$ ;  $J = \log_2(N)$ ; and  $N$  represents the length of the signal [23]. The primary frequency components of the signal are used to determine the highest decomposition level [24]. DWT coefficients are the dot products of the original time series and the chosen basis functions. The term approximation coefficients  $A_i$  and the another term detailed coefficients  $D_i$  in the  $i^{\text{th}}$  level are expressed by (3) and (4) [24].

$$A_i = \frac{1}{\sqrt{M}} \sum x(n) \times \phi_{j,k}(n) \tag{3}$$

$$D_i = \frac{1}{\sqrt{M}} \sum x(n) \times \psi_{j,k}(n) \tag{4}$$

where,  $k = 0, 1, 2, \dots, 2^j - 1$  and  $M$  is the length of the EEG time-series in the discrete points.

### 3. Signal Processing, Statistical Features Calculation and Workload Estimation

Computer-based intelligent systems for analysis of mental stress are very useful in diagnostics and disease management. This part presents data acquisition, sig-

nal processing techniques and finally mental workload classification for human brain workload estimation. The elimination of noise by digital filter enhances the quality of signal and features extraction facilities. The subject wore a 10 - 20 system for EEG recording. The found data was transmitted to wavelet transform for feature selection for statistical analysis.

### **3.1. Major Steps Involved for Processing of EEG Signal to Estimate Workload during SIMKAP Task**

Below steps are considered for processing EEG signal to estimate workload during SIMKAP task:

#### **3.1.1. Extracting Data Based on Channels**

The data are extracted from the dataset and information files found in IEEE data port according to the number of channels. This paper discussed single channel (O<sub>2</sub>) data for EEG data preprocessing during the SIMKAP process. For this data manipulation process, MATLAB version 2021 was used.

#### **3.1.2. Data Processing for Corresponding to Its Label to Fit for Classification**

The processed data was arranged for data corresponding to its label to fit for machine learning with the help of information provided in the rating file in IEEE Data port. A separate file called ratings.txt contains the ratings for each subject. Subject number, rating at rest, and rating for test were provided in comma separated value format. As an illustration, 1, 2, 8 would be subject 1, with a rating of 2 for “at rest”, and 8 for “test”. It was awarded that subjects 5, 24, and 42 did not have available ratings.

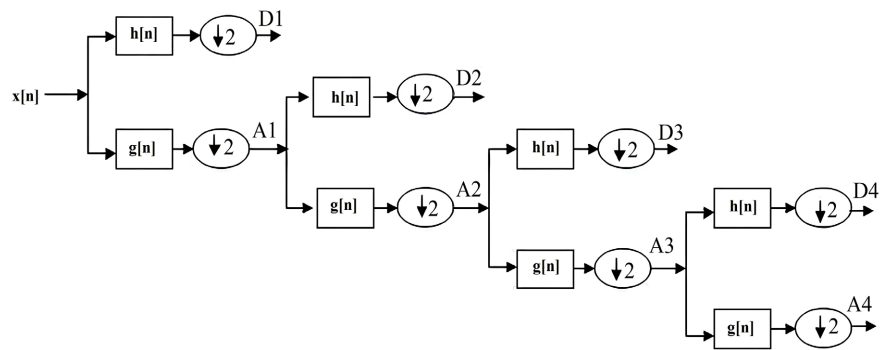
#### **3.1.3. Wavelet Decomposition Technique**

Wavelet decomposer was used to decompose the EEG signal into its five signals. These are (D5-D8, and A8) gamma, theta, delta, beta and alpha (respectively). After calculating individual power of each signal or level relative power in percentage of the signals are easily calculated.

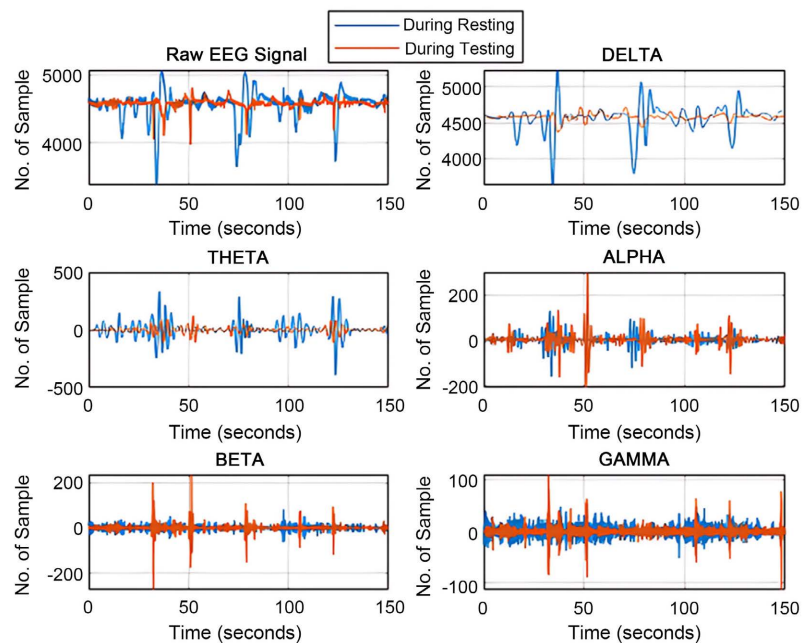
The overall repeated procedure of the decomposition of EEG signals is been given in **Figure 4**.

#### **3.1.4. Statistical Features Calculation and Dominant Features Selection from Decomposition Levels (D5-D8, and A8)**

There are five decomposed signals or levels found in EEG signals. To find the statistical features from EEG signal wavelet decomposition technique was used to decompose the signal into five sub bands. These are delta, theta, alpha, beta, gamma and **Figure 5** depicts the decomposed sample versus time signals. Fourteen statistical features viz. minimum, maximum, mean, mode, median, inter quartile range, standard deviation, variance, root mean square (rms), entropy, kurtosis, peak2rms, peak2peak, Root-sum-of-squares level were calculated for each sub band signal for O<sub>2</sub> channel. In this process, 5 × 14 features widow size was found for each number of samples.



**Figure 4.** EEG signal sub-band decomposition using DWT.



**Figure 5.** Decomposed EEG signals for  $60 \times 2.5$  seconds (2.5 minutes) (No. of sample VS time curve) duration low and high state.

Maximum relevance, minimum redundancy analysis (MRMR) model was used to select dominant features among 70 features. Selecting only five statistical features by this feature selection model provided (denoted by bar diagram) from 70 features (along features index) which results in the same classification accuracy with a wide neural network. The features selection model and confusion matrix found by applying MRMR are depicted by **Figure 6** and **Figure 7(b)** respectively.

### 3.1.5. Classification

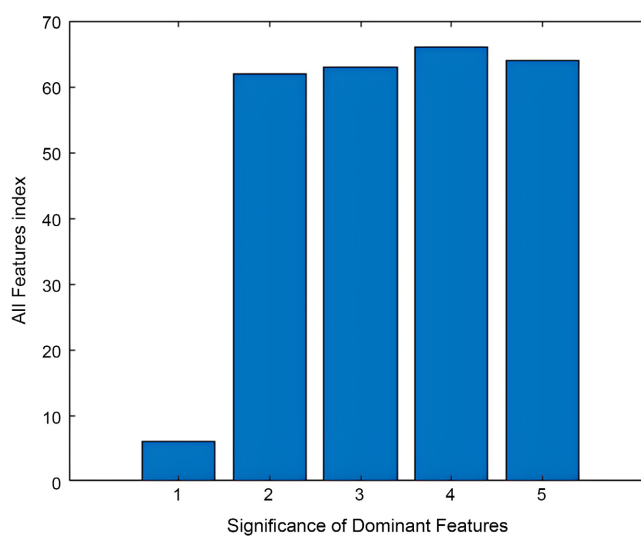
The most rapidly used classification technique is machine learning. We used various machine learning algorithms for classification purposes to classify low and high states that have been discussed in below.

Among all classifiers used in this study, neural networks algorithm helps us in second position to improve machine learning the results of classification per-

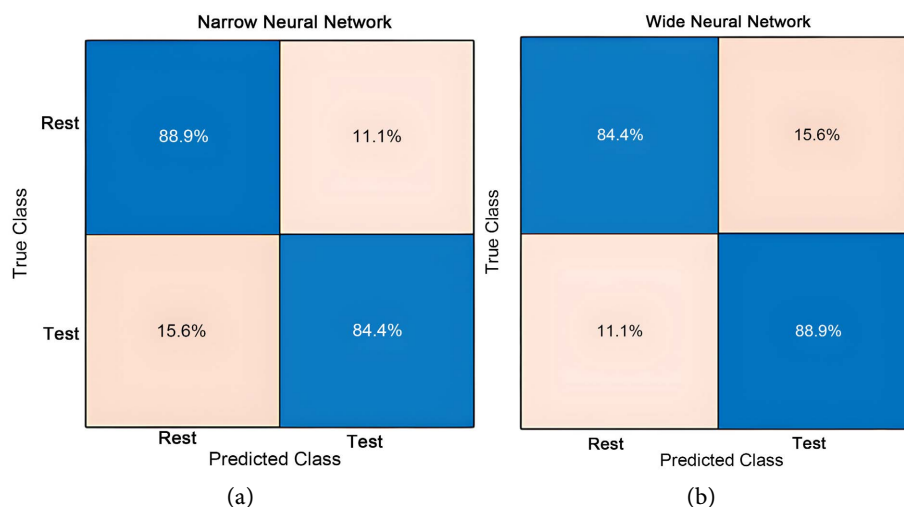


formance parameters by combining several models. Neural networks, which are a subset of machine learning and the core of deep learning algorithms, which are also known as artificial neural networks (ANNs) or simulated neural networks (SNNs). In order to mirror the way that organic neurons communicate with one another, their name and structure are both derived from the human brain. Input, one or more hidden layers, and an output layer are the layers that make up a node layer in artificial neural networks (ANNs). There are connections between each node, or artificial neuron, and each one has a threshold and weight that go along with it [25].

The Ensemble classification algorithm provided 2<sup>nd</sup> height classification accuracy and other performance parameters. Bagged, Random Forest is some types of Ensemble classification [26].



**Figure 6.** First five features (6, 62, 63, 66, 64) selected by maximum relevance, minimum redundancy analysis (MRMR) model.



**Figure 7.** Confusion matrix found by Neural Network classifier, (a) without MRMR and (b) with MRMR.



A group of supervised learning techniques called support vector machines (SVMs) are employed in the identification of outliers, regression, and classification. Support vector machines have some benefits including high-dimensional spaces effectively. Even when there are more dimensions than samples, the method is still effective [27]. It is a revolutionary small-sample learning method that also outperforms existing methods in many ways since it is based on the structural risk reduction principle rather than the conventional empirical risk minimization concept. The optimal surface that resulted from the linearly separable instance is described in two dimensions by the support vector machine [28].

The Support Vector Machine (SVM) algorithm employs quantum rules to carry out calculations in the Quantum Support Vector Machine (QSVM) quantum version. Classical SVM algorithms that run on traditional machines with CPUs or GPUs can perform better thanks to QSVM, which harnesses the power of quantum technology and software. The first significant stage in quantum machine learning is the conversion of classical data into quantum data using calculations on a quantum computer. The second key step is the conversion of the quantum result back into classical data using the same computer [29].

#### **4. Finding Attention Loss and Short-Term Memory Loss**

To fulfill the demand of the study, after performing the classification process using a complete set of data with more features with machine learning it is needed to find the memory loss in the brain. The relative power of decomposed EEG sub band signals, as mentioned, Alpha, Beta and Theta signals, were investigated with respect to high and low EEG workload (High alpha and low beta power = high retention capacity) [30]. In this work, estimation of the short-term memory loss in the brain during high workload is introduced graphically by radar plot and area chart in excel after following some steps.

##### **4.1. Major Steps Involved for Finding Attention Loss and Memory Loss in Brain**

The following steps are involved for finding attention loss and short-term memory loss in brain during high workload:

##### **Relative Power Calculation from Decomposition Levels (D5-D8, and A8)**

Five decomposed signals or levels found applying wavelet decomposition technique of EEG signals are labeled by A8, D8, D7, D6 and D5 depicted by **Figure 5**. The power of each signal was calculated and finally the relative power of them was measured. Finding attention loss and memory loss (short term) in the brain has been discussed in upcoming section 5.

#### **5. Numerical Analysis**

The proposed EEG signal classification for low and high mental workload esti-

mation during simultaneous capacity (SIMKAP) tasks is validated in this section. Discrete wavelet analysis for both cases (low and high mental workload) is presented graphically, and statistical parameters with classification results as well as performance parameters are extracted numerically. Finally, the attention loss and short-term memory loss in brain is predicted from the Radar plot and Area curve by using Excel.

### 5.1. Results and Discussions

In this section, the results from this work and its validation are discussed chronologically. The reliability of a procedure cannot be improved by acting based just on accuracy. Sensitivity, specificity, F1-score, negative projected value, and other metrics are also necessary to support a technique's performance. In states of high workload, sensitivity identifies a positive EEG signal; in states of low workload, specificity recognizes a real EEG signal. By assessing accuracy, sensitivity, and specificity, precision, F1-score, and negative predicted value as specified below, the performances of the employed classifiers were calculated [31]. Several classification models with the proposed model is shown in **Table 1** and comparative of performance of the proposed method with existing methods is also summarized in **Table 2**.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (5)$$

**Table 1.** High and low Workload Classification Result using different Classifiers algorithms.

Classifier Type	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1 score (%)	NPV (%)	AUC
SVM	80	80	80	80	80	80	0.84
Neural Network (Bilayered)	82.2	85.4	79.61	77.8	81.42	86.7	0.85
Ensemble Subspace	78.9	79.55	78.27	77.8	78.66	80	0.88
Ensemble Bagged Trees	83.3	87.51	80	77.8	82.36	88.9	0.88
Neural Network (Narrow)	86.7	88.37	85.07	84.4	86.33	88.9	0.91

**Table 2.** Performance comparison with existing methods.

Methods' Ref.	Data Preprocessing Techniques	Task Type	Used Classifier	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)
[17]	High-pass filter ( $f_c = 1$ Hz), Notch filter (50 Hz) with Artifact Independent Component Analysis (ICA)	Two	K-Nearest Neighbors (KNN)	72.4	66.12	49.54	59.39
[32]	High-pass filter at 1 Hz with Artifact Subspace Reconstruction (ASR)	Two	Support Vector Regression (SVR)	73.14	-	-	-
Proposed Method	Raw	Two	Neural Network (Narrow)	86.7	88.37	85.07	84.4

$$\text{Sensitivity} = \text{Recall} = \frac{TP}{TP + FN} \tag{6}$$

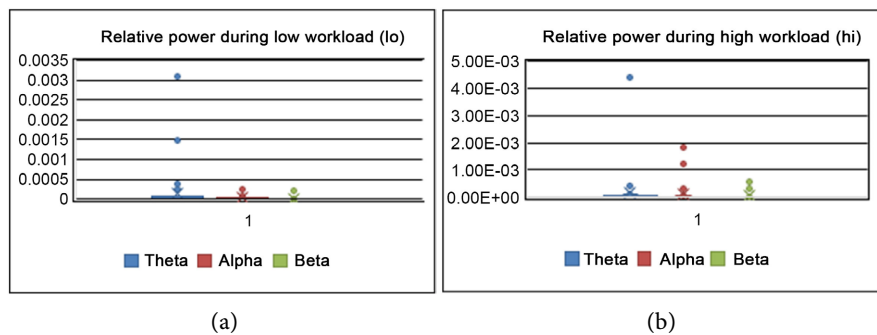
$$\text{Specificity} = \frac{TN}{TN + FP} \tag{7}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{8}$$

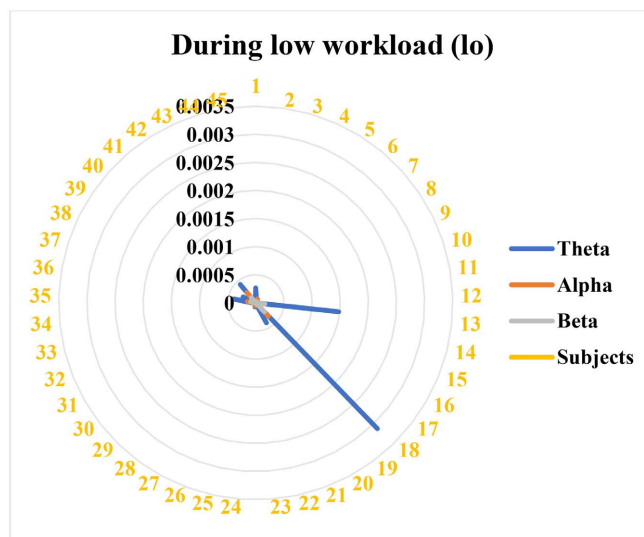
$$\text{F1 score} = 2 \times \frac{PPV \times TPR}{PPV + TPR} = 2 \times \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \tag{9}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{10}$$

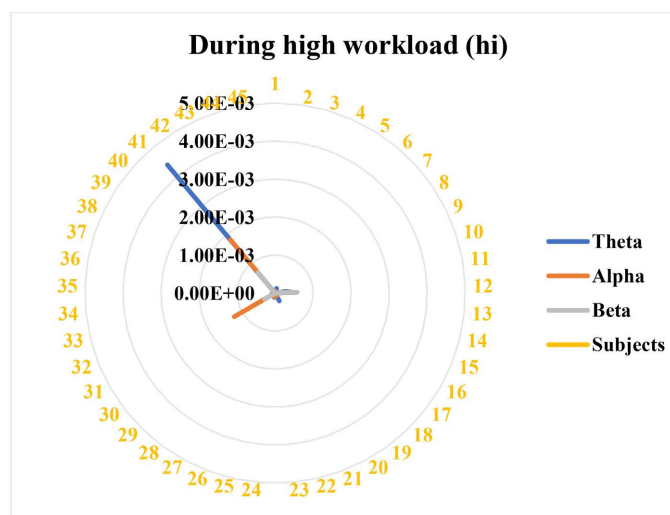
The relative power levels of theta, alpha and beta signals during low and high workload are shown from **Figure 8**. The area plot shows the graphical representation of them. Radar plot of **Figure 9** and **Figure 10** show the graphical representation of the overall case according to the number of subjects. From these figures it is seen that, theta and alpha powers go higher from low to high workload. Literature showed that an increase in the alpha band is associated with a decrease in attention, and alertness [33].



**Figure 8.** Area plot of sub bands signals.



**Figure 9.** Radar plot of sub bands signals during low workload.



**Figure 10.** Radar plot of sub bands signals during low workload.

Moreover, a higher power spectrum in theta band indicates a decrease in vigilance and alertness [33]. In this study, alpha and theta bands increase from low to high workload as depicted in **Figure 8** resulting in subjects decreasing or losing their attention during SIMKAP tasks going from low to high workload level. After analysis of **Figure 9** and **Figure 10** it is concluded that, subjects 41 and 31 lost their attention going from low to high workload. Literature also showed that beta band is inversely associated with short term memory tasks [34]. As this study does not start with short term memory loss data, that is why beta power increases from low high workload condition resulting no short-term memory loss in this study.

### 5.1.1. Classification Results

In case of SIMKAP task during low and high (workload) Neural Network (Narrow) machine learning model was used to classify EEG data. The confusion matrix generated from the Neural Network (Narrow) algorithm is depicted in **Figure 7(a)** having training results with 86.7% accuracy (max.) with two labels (low and high). **Figure 7(b)** is depicted for the confusion matrix of the same classification algorithm using MRMR feature selection technique with 86.65% accuracy (max.). SVM, QSVM, Neural Network (Wide) and Ensemble Subspace models were also used to compare the performance parameters with the proposed model shown in **Table 1**. Performance comparison with existing methods of the proposed method is also shown in **Table 2**.

### 5.1.2. Performance Evaluation

For SIMKAP tasks, the classification results are presented in **Table 2** with accuracy 86.7% including two labels tasks (low and high) resulting from comparative studies among various classifiers models. The comparative study with literature is shown in **Table 2** which outperformed cutting-edge techniques described in the literature by 86.7%.

## 6. Conclusion and Future Work

### 6.1. Conclusion

The suggested method analyzes EEG data from the occipital (O<sub>2</sub>) region of the brain. The proposed classifier responded most favorably to the proposed approach with 86.7% accuracy (max.), 84.4% precision, 86.33% F1 score and 88.37% recall including two tasks (low and high workload). This method is more efficient and performs better than existing equivalent methods in terms of sensitivity, accuracy, precision and F1 Score. Moreover, a furnished and well decorated easy procedure is introduced to find out the short-term memory loss in the human brain with a large number of datasets by using only relative power considerations of the sub band signals. It is envisaged that this work will help further in short term memory loss analysis using EEG data.

### 6.2. Future Work

The analysis in this study can be used as a gateway for further research on human brain short term memory loss associated with mild cognitive impairment using a large data set.

### Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

### References

- [1] Islam, A., Sarkar, A.K. and Ghosh, T. (2021) EEG Signal Classification for Mental Stress during Arithmetic Task Using Wavelet Transformation and Statistical Features. *International Conference on Automation, Control and Mechatronics for Industry 4.0 (ACMI)*, Rajshahi, 8-9 July 2021, 1-6. <https://doi.org/10.1109/ACMI53878.2021.9528230>
- [2] Longo, L., Rizzo, L. and Dondio, P. (2021) Examining the Modelling Capabilities of Defeasible Argumentation and Non-Monotonic Fuzzy Reasoning. *Knowledge-Based Systems*, **211**, Article ID: 106514. <https://doi.org/10.1016/j.knosys.2020.106514>
- [3] Hancock, G.M., Longo, L., Young, M.S. and Hancock, P.A. (2021) Mental Workload. In: Salvendy, G. and Karwowski, W., Eds., *Handbook of Human Factors and Ergonomics*, John Wiley & Sons, Inc., Hoboken, 203-226. <https://doi.org/10.1002/9781119636113.ch7>
- [4] Yu, D., Antonik, C.W., Watz, F.W.E. and Bennett, W. (2021) Correction to: Multi-Modal Physiological Sensing Approach for Distinguishing High Workload Events in Remotely Piloted Aircraft Simulation. *Human-Intelligent Systems Integration*, **3**, 201-211. <https://doi.org/10.1007/s42454-021-00033-3>
- [5] Wang, P., Fang, W. and Guo, B. (2019) Mental Workload Evaluation and Its Application in Train Driving Multitasking Scheduling: A Timed Petri Net-Based Model. *Cognition, Technology & Work*, **23**, 299-313. <https://doi.org/10.1007/s10111-019-00608-w>
- [6] Li, X., Vaezipour, A., Rakotonirainy, A., Demmel, S. and Oviedo-Trespalacios, O. (2020) Exploring Drivers' Mental Workload and Visual Demand While Using an

- In-Vehicle HMI for Eco-Safe Driving. *Accident Analysis & Prevention*, **146**, Article 105756. <https://doi.org/10.1016/j.aap.2020.105756>
- [7] Asgher, U., *et al.* (2020) Enhanced Accuracy for Multiclass Mental Workload Detection Using Long Short-Term Memory for Brain-Computer Interface. *Frontiers in Neuroscience*, **14**, Article 584. <https://doi.org/10.3389/fnins.2020.00584>
- [8] Bagheri, M. and Power, S.D. (2021) Investigating Hierarchical and Ensemble Classification Approaches to Mitigate the Negative Effect of Varying Stress State on EEG-Based Detection of Mental Workload Level—And Vice Versa. *Brain-Computer Interfaces*, **8**, 26-37. <https://doi.org/10.1080/2326263X.2021.1948756>
- [9] Putze, F., *et al.* (2020) Editorial: Brain-Computer Interfaces and Augmented/Virtual Reality. *Frontiers in Human Neuroscience*, **14**, Article 144. <https://doi.org/10.3389/fnhum.2020.00144>
- [10] Moustafa, K. and Longo, L. (2019) Analysing the Impact of Machine Learning to Model Subjective Mental Workload: A Case Study in Third-Level Education. In: Longo, L. and Leva, M., Eds., *Communications in Computer and Information Science*, Springer, Cham, 92-111. [https://doi.org/10.1007/978-3-030-14273-5\\_6](https://doi.org/10.1007/978-3-030-14273-5_6)
- [11] Longo, L. and Orrú, G. (2022) Evaluating Instructional Designs with Mental Workload Assessments in University Classrooms. *Behaviour & Information Technology*, **41**, 1199-1229.
- [12] Longo, L. and Rajendran, M. (2021) A Novel Parabolic Model of Instructional Efficiency Grounded on Ideal Mental Workload and Performance. In: Longo, L. and Leva, M.C., Eds., *Communications in Computer and Information Science*, Vol. 1493, Springer, Cham, 11-36. [https://doi.org/10.1007/978-3-030-91408-0\\_2](https://doi.org/10.1007/978-3-030-91408-0_2)
- [13] Chai, R., Naik, G.R., Nguyen, T.N., Ling, S.H., Tran, Y. and Nguyen, H.T. (2016) Selecting Optimal EEG Channels for Mental Tasks Classification: An Approach Using ICA. 2016 *IEEE Congress on Evolutionary Computation*, Vancouver, BC, 24-29 July 2016, 1331-1335. <https://doi.org/10.1109/CEC.2016.7743942>
- [14] Lim, W.L., Sourina, O. and Wang, L.P. (2018) STEW: Simultaneous Task EEG Workload Data Set. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, **26**, 2106-2114. <https://doi.org/10.1109/TNSRE.2018.2872924>
- [15] Atkinson, J. and Campos, D. (2016) Improving BCI-Based Emotion Recognition by Combining EEG Feature Selection and Kernel Classifiers. *Expert Systems with Applications*, **47**, 35-41. <https://doi.org/10.1016/j.eswa.2015.10.049>
- [16] Zeng, C. (2020) EEG-Based Mental Workload Recognition Using Deep Learning Techniques. Nanyang Technological University, Singapore. <https://dr.ntu.edu.sg/handle/10356/140005>
- [17] Pandey, V., Choudhary, D.K., Verma, V., Sharma, G., Singh, R. and Chandra, S. (2020) Mental Workload Estimation Using EEG. 2020 *Fifth International Conference on Research in Computational Intelligence and Communication Networks*, Bangalore, 26-27 November 2020, 83-86. <https://doi.org/10.1109/ICRCICN50933.2020.9296150>
- [18] Jo, W., Wang, R., Sun, S., Senthilkumaran, K., Foti, D. and Min, B.C. (2022) MOCAS: A Multimodal Dataset for Objective Cognitive Workload Assessment on Simultaneous Tasks. <https://arxiv.org/abs/2210.03065>
- [19] de Jong, T. (2010) Cognitive Load Theory, Educational Research, and Instructional Design: Some Food for Thought. *Instructional Science*, **38**, 105-134. <https://doi.org/10.1007/s11251-009-9110-0>
- [20] Paas, F.G.W.C. (1992) Training Strategies for Attaining Transfer of Problem-Solving Skill in Statistics: A Cognitive-Load Approach. *Journal of Educational Psychology*,

- 84**, 429-434. <https://doi.org/10.1037/0022-0663.84.4.429>
- [21] Subasi, A. (2007) EEG Signal Classification Using Wavelet Feature Extraction and a Mixture of Expert Model. *Expert Systems with Applications*, **32**, 1084-1093. <https://doi.org/10.1016/j.eswa.2006.02.005>
- [22] Jahankhani, P., Kodogiannis, V. and Revett, K. (2006) EEG Signal Classification Using Wavelet Feature Extraction and Neural Networks. *IEEE John Vincent Atanasoff 2006 International Symposium on Modern Computing*, Sofia, 3-6 October 2006, 120-124. <https://doi.org/10.1109/IVM.2006.17>
- [23] Gonzalez, R.C. and Woods, R.E. (2002) Digital Image Processing. 2nd Edition, Prentice Hall, Hoboken.
- [24] Orhan, U., Hekim, M. and Ozer, M. (2011) EEG Signals Classification Using the K-Means Clustering and a Multilayer Perceptron Neural Network Model. *Expert Systems with Applications*, **38**, 13475-13481. <https://doi.org/10.1016/j.eswa.2011.04.149>
- [25] Novak, R., Bahri, Y., Abolafia, D.A., Pennington, J. and Sohl-Dickstein, J. (2018) Sensitivity and Generalization in Neural Networks: An Empirical Study. <https://arxiv.org/abs/1802.08760>
- [26] Gomes, H.M., Barddal, J.P., Enembreck, A.F. and Bifet, A. (2017) A Survey on Ensemble Learning for Data Stream Classification. *ACM Computing Surveys*, **50**, 1-36. <https://doi.org/10.1145/3054925>
- [27] Smola, A.J. and Schölkopf, B. (2004) A Tutorial on Support Vector Regression. *Statistics and Computing*, **14**, 199-222. <https://doi.org/10.1023/B:STCO.0000035301.49549.88>
- [28] Zhang, Y. (2012) Support Vector Machine Classification Algorithm and Its Application. In: Liu, C., Wang, L., Yang, A., Eds., *Communications in Computer and Information Science*, Springer, Berlin, 179-186. [https://doi.org/10.1007/978-3-642-34041-3\\_27](https://doi.org/10.1007/978-3-642-34041-3_27)
- [29] Saini, S., Khosla, P., Kaur, M. and Singh, G. (2020) Quantum Driven Machine Learning. *International Journal of Theoretical Physics*, **59**, 4013-4024. <https://doi.org/10.1007/s10773-020-04656-1>
- [30] Pavlov, Y.G. and Kotchoubey, B. (2021) Temporally Distinct Oscillatory Codes of Retention and Manipulation of Verbal Working Memory. *European Journal of Neuroscience*, **54**, 6497-6511. <https://doi.org/10.1111/ejn.15457>
- [31] Subasi, A. and Gursoy, M.I. (2010) EEG Signal Classification Using PCA, ICA, LDA and Support Vector Machines. *Expert Systems with Applications*, **37**, 8659-8666. <https://doi.org/10.1016/j.eswa.2010.06.065>
- [32] Atkinson, J. and Campos, D. (2016) Improving BCI-Based Emotion Recognition by Combining EEG Feature Selection and Kernel Classifiers. *Expert Systems with Applications*, **47**, 35-41. <https://doi.org/10.1016/j.eswa.2015.10.049>
- [33] Kamzanova, A.T., Kustubayeva, A.M. and Matthews, G. (2014) Use of EEG Workload Indices for Diagnostic Monitoring of Vigilance Decrement. *Human Factors*, **56**, 1136-1149. <https://doi.org/10.1177/0018720814526617>
- [34] Palva, S., Kulashekhar, S., Hämäläinen, M. and Palva, J.M. (2011) Localization of Cortical Phase and Amplitude Dynamics during Visual Working Memory Encoding and Retention. *Journal of Neuroscience*, **31**, 5013-5025. <https://doi.org/10.1523/JNEUROSCI.5592-10.2011>