World Journal of Advanced Research and Reviews

eISSN: 2581-9615 CODEN (USA): WJARAI

Cross Ref DOI: 10.30574/wjarr

Journal homepage: https://wjarr.com/

(RESEARCH ARTICLE)

Check for updates

EEG workload estimation for simultaneous task using deep learning algorithm

Md. Ariful Islam [1,*], Md. Imran Hossain [2], Md. Tofail Ahmed [3], Md. Humaun Kabir [4] and Sujit Roy [4]

[1] *Department of Electrical and Electronic Engineering, Pabna University of Science and Technology, Pabna-6600, Bangladesh.*

[2] *Department of Electrical, Electronic and Communication Engineering, Pabna University of Science and Technology, Pabna-6600, Bangladesh.*

[3] *Department of Information and Communication Engineering, Pabna University of Science and Technology, Pabna-6600, Bangladesh.*

[4] *Department of Computer Science and Engineering, Bangamata Sheikh Fojilatunnesa Mujib Science & Technology University, Jamalpur-2012, Bangladesh.*

World Journal of Advanced Research and Reviews, 2023, 18(03), 533–542

Publication history: Received on 04 May 2023; revised on 11 June 2023; accepted on 14 June 2023

Article DOI: https://doi.org/10.30574/wjarr.2023.18.3.1142

Abstract

Mental workload plays a vital role in cognitive impairment refers to a person's trouble of remembering, receiving new information, learning new things, concentrating, or making decisions that affect seriously in their everyday life. In this paper, the simultaneous capacity (SIMKAP) experiment-based EEG workload analysis was discussed with 45 subjects for multitasking mental workload estimation using an open access preprocessed EEG dataset. Discrete wavelet transforms (DWT) was used for feature extraction and selection. Scalogram formation was performed for data image conversion form from extracted data. AlexNet classification algorithm was used to classify dataset for low and high workload conditions including some other CNN models to show the comparative study of them. The comparative studies of the used classifier's accuracy along with other performance parameters with the literature expresses the validation for the study which crossed state-of-the art methodologies in the literature by 77.78 percent.

Keywords: Cognitive Impairment; EEG; SIMKAP; 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 usual, such as 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 volume of data [1]. As a result, successful assessment and understanding both low and high mental workload states place a high demand on the ability to retrieve meaningful information from EEG signals. For the purpose of analyzing mental tension, considering a few crucial signal characteristics makes EEG analysis simpler than laborious, time-consuming big data sets. The idea of human mental workload is the cornerstone of research on the functioning of the human brain. The calculation of the cognitive cost of completing a task in a limited amount of time in order to forecast operator, system, or both performances can serve as the broadest definition of mental workload [2], [3]. Mental workload has been identified as a crucial element that significantly affects the human brain task 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]–[9] and educational contexts [10]–[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. From the literature review, some works are found on workload EEG signal analysis. Only a few studies have been conducted in which sufficient and essential features are

* Corresponding author: Ariful Islam

extracted for only workload analysis. Different approaches have been put forth to gauge the workload of the human mind using simultaneous task (SIMKAP). One of them, arithmetic task was introduced to perform mental stress or workload analysis [1]. An approach using ICA with three types of task was also introduced selecting optimal EEG channels for mental tasks classification with only 70% accuracy [13]. Another method for emotion recognition was improved with two types of workload achieving 73.14% classification accuracy [14]. Mental workload recognition of EEG signal using deep learning techniques achieved only 65% classification accuracy [15]. Based on our review of the literature, we identified a clear gap in efficient feature extraction, selection, and classification. We proposed a feature selection technique in this paper to select the most effective features and thus classify low and high workload analysis from EEG data. Our proposed study is organized as follows: 'Materials and Research Methodology' section explains research chronologically, including research design and research procedure, followed by the 'Results and Discussion' section and finally 'Conclusion' section.

2. Material and methods

Descriptive materials and research methodology used in this study will be provided. This will illustrate tasks related to experimentation, a description of a dataset required, a description of discrete wavelet transform (DWT) and statistical data computation for feature extraction, a description of classifiers used and performance metrics for validation.

2.1. Dataset Description and Experimental Design

This paper mainly describes EEG workload estimation technique using simultaneous task or simultaneous capacity (SIMKAP) [16]. The data for each subject follows the naming convention: subno_task.txt. For example, sub01_lo.txt would be filtered EEG data for subject 1 at rest, while sub23_hi.txt would be filtered EEG data for subject 23 during the multitasking test. The rows of each datafile corresponds to the samples in the recording and the columns corresponds to the 14 channels of the EEG device: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4, respectively shown in Figure 2 [16].

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 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

This was done to subjectively confirm 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 did not consider 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[16]. According to a study in [17], the most popular measure in cognitive load studies is the 9-point rating scale [18], which is comparable to the NASA-1 TLX's to 21 scale. Above screenshot of the questionnaire that was used 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 [16].The overall functionality of the system is composed of some parts as depicted in Figure 1 that includes collect the dataset from the IEEE Data Port in .txt format, extracting data based on channels. The processed data is arranged for data corresponding to its label to fit for deep learning, converting EEG data into images according to labels by scalogram and finally classify EEG data during high and low workload.

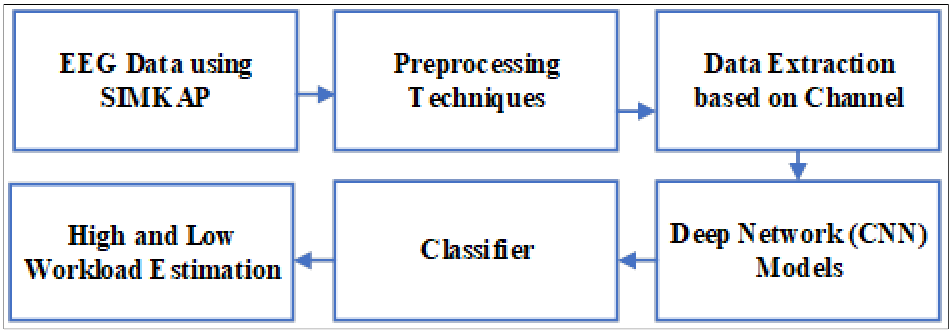

Figure 1 EEG workload estimation and relative power calculation during SIMKAP

The overall scheme of determining the relative power during low and high workload is also depicted in Figure 1.

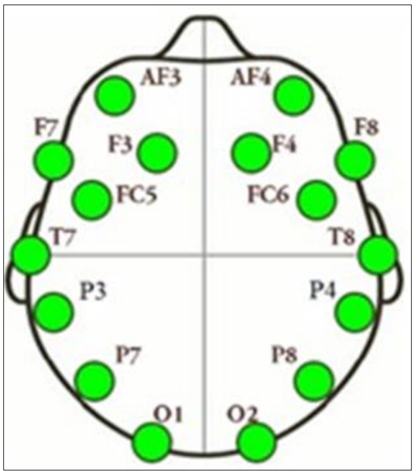

Figure 2 Electrodes positions based on 10-20 international system for EEG recording with The Emotiv EEG Device [16]

2.2. Discrete Wavelet Transform

Discrete wavelet transform (DWT) is utilized in the time–frequency study of biomedical signals [19]. Because of its non-stationary characteristics, this DWT is particularly useful in EEG signal analysis. This transform produces an accurate time-frequency evaluation by using long time frames for low frequencies and short time frames for higher frequencies. Time series high-pass and low-pass filtering, as well as two down samplers by 2, are used in the DWT decomposition of a signal.

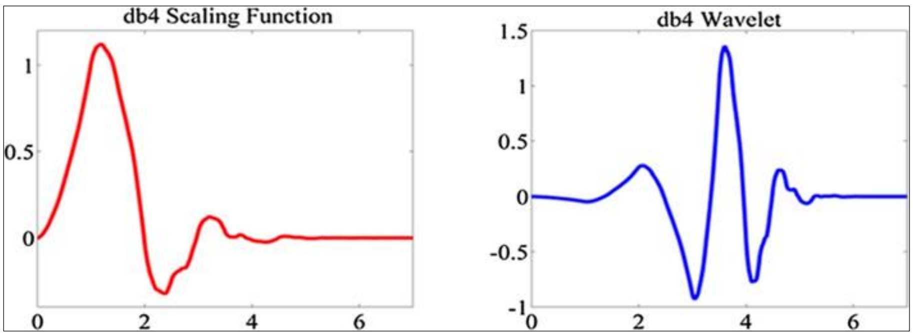

Figure 3 Scaling function and mother wavelet (db4)

In this case, the mother-wavelet is represented by DWT's high-pass filter g(n), and its mirror version is represented by DWT's low-pass filter *h(n)* [19]. Figure 3 depicts the mother wavelet of the Daubechies wavelet (db4) as well as the scaling function. The approximation and detail coefficients, denoted by A1 and D1, are the outcomes of the first high-pass and low-pass filters, correspondingly. The A1 is further disintegrated, and the process is repeated until the appropriate number of breakdown levels has been achieved [19], [20]. The dilation function $\varphi_{j,k}(n)$ is reliant on on the low-pass, and the wavelet function $\psi_{j,k}(n)$ keep on the high-pass filter, which is expressed as follows.

$$\varphi_{j,k}(n) = 2^{j/2} h(2^j n - k) \quad \text{............(4.1)}$$

$$\psi_{j,k}(n) = 2^{j/2} g(2^j n - k) \quad \text{............(4.2)}$$

Where, $n = 0, 1, 2, \ldots, N-1; j = 0, 1, 2, \ldots, J-1; k = 0, 1, 2, \ldots, 2j-1; J = \log2(N)$; and N is called the length of the signal [21]. The maximum decomposed level is obtained by the signal's principle frequency components [22]. The dot product of the original time series and the selected basis functions is referred to as DWT coefficients. The approximation coefficients A_i and the detailed coefficients D_i in the i^{th} level are expressed by (3) and (4) [22].

$$A_i = \frac{1}{\sqrt{M}} \sum_n x(n) \times \varphi_{j,k}(n) \quad \text{............(4.3)}$$

$$D_i = \frac{1}{\sqrt{M}} \sum_n x(n) \times \psi_{j,k}(n) \quad \text{..............(4.4)}$$

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

2.3. Signal Processing, Statistical Features Calculation and Workload Estimation

Computer-based intelligent system for analysis of mental stress is very useful in diagnostics and disease management of human brain. This chapter presents data acquisition, signal processing techniques and finally mental workload classification for human brain workload estimation for low and high workload conditions. The elimination of noise by digital filter enhances the quality of signal and features extraction facilities. The subject wore 10-20 system for EEG recording. The found data was transmitted to wavelet transform for statistical feature selection.

2.3.1. 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:

- Extracting data based on channels.
- The processed data is arranged for data corresponding to its label to fit for deep learning
- Converting EEG data into images according to labels by Scalogram.
- Classify EEG signal using CNN based deep learning algorithm.

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 (O2) data for EEG data preprocessing during SIMKAP process. For this data manipulation process, MATLAB version 2021 was used.

Data processing for corresponding to its label to fit for deep learning

The processed data was arranged for data corresponding to its label to fit for deep learning with the help of information provided in 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.

Converting EEG data into images according to labels by Scalogram.

EEG data signals for low and high workload state are also shown in Figure 4. The found processed EEG data was converted into images according to the data labels (low and high work load) with the help of create time-frequency representations and thus generating scalogram as shown in Figure 5.

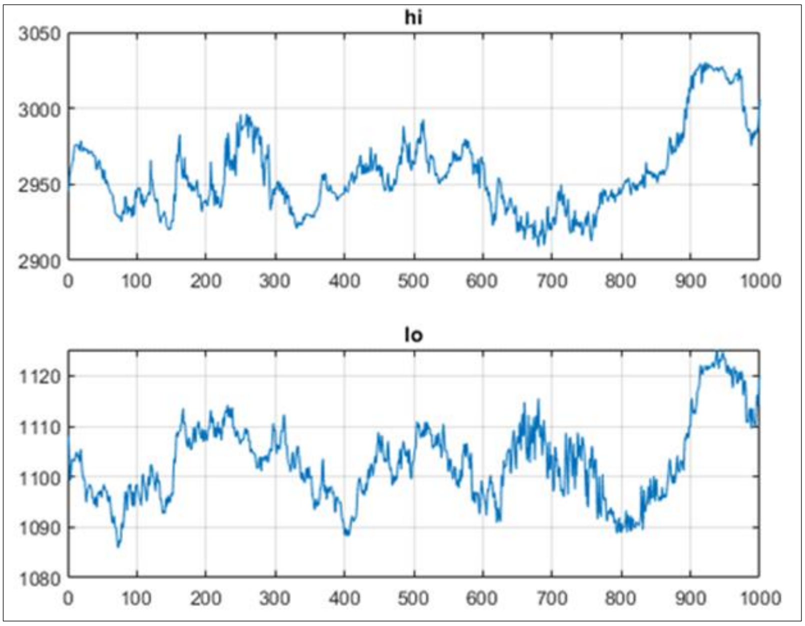

Figure 4 Plotting of a representative of each EEG category

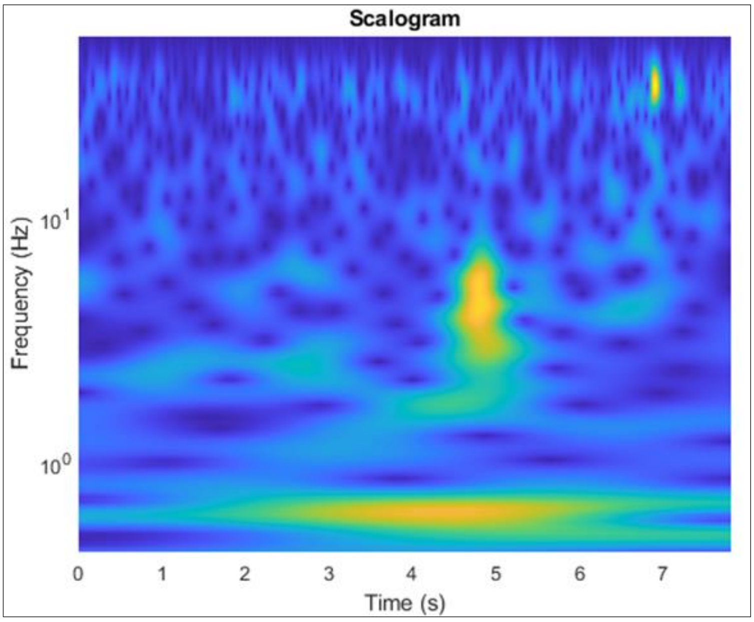

Figure 5 Creating Time-Frequency Representations for Scalogram

Classification

The most challenging ImageNet visual object identification task, known as the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), was won in 2012 by Alex Krizhevesky and colleagues who provided a deeper and wider CNN model in comparison to LeNet [23]. In comparison to all existing machine learning and computer vision techniques, AlexNet achieved state-of-the-art recognition accuracy. For visual recognition and classification tasks, it was a big advancement in machine learning and computer vision, and it was at this time in history that interest in deep learning skyrocketed. 96 distinct receptive filters, each measuring 11 by 11, are employed in the first convolutional layer to perform convolution and max pooling with Local Response Normalization (LRN). With 33 filters and a stride size of 2, the max pooling operations are carried out. With 55 filters, the identical operations are carried out in the Figure layer. With 384, 384, and 296 feature maps, the third, fourth, and fifth convolutional layers all employ 33 filters. Use is made of two fully connected (FC) layers with dropout, followed by a Softmax layer. For this model, two parallel networks with comparable structural similarities and equal numbers of feature maps are trained. This network introduces two novel ideas: dropout and local response normalization (LRN). LRN can be implemented in two different ways: first, on single channel or feature maps, where a NN patch is chosen from the same feature map and normalized based on the neighborhood values. Second, LRN can be used with channels or feature maps (neighborhood along the third dimension but a single pixel or location).

Two fully linked layers and three convolutional layers make up AlexNet. For processing the ImageNet dataset, the total number of parameters for AlexNet can be determined as follows: the input images size should be 227×227×3, filters (kernels or masks) or a receptive field with a size of 11, the stride is 4, and the output of the first convolution layer is 555596. This first layer has 290400 (555596) neurons and 364 (11113 = 363 + 1 bias) weights, as determined by the formulae in section 3.1.4. The first convolution layer's parameters are 290400364 = 105,705,600. For the entire network, there are 61M weights and 724M MACs.

A convolutional neural network of 22 layers deep is called GoogleNet. The network can be loaded in a pretrained state that has been trained on either the Places365 [24] or ImageNet [25] data sets. The network that was trained on ImageNet divides images into 1000 different object categories, including several animals, a keyboard, a mouse, and a pencil. Similar to networks trained on ImageNet, Places365 networks classify photos into 365 distinct place types, such as field, park, runway, and lobby. For a variety of images, these networks have learned several feature representations. The input picture size for both of the pretrained networks is 224 by 224.

SqueezeNet is an 18-layer convolutional neural network. A network that has been pretrained using more than a million photos can be loaded from the ImageNet database [25]. The trained network is able to categorize photos into 1000 different object categories, including several different animals, a mouse, a keyboard, and a pencil. Consequently, the network has picked up detailed feature representations for a variety of images. The SqueezeNet v1.1 network that this function produces has a similar accuracy to SqueezeNet v1.0 but uses less floating-point computation per prediction [26]. The network may accept images up to 227 by 227 in size.

Convolutional neural network Inception-ResNet-v2 was developed using training data from the ImageNet collection, which contains more than one million images [25]. The network has 164 layers and can categorize photos into 1000 object types, including keyboard, mouse, pencil, and numerous animals. This has led to the network learning detailed feature representations for a variety of images. A 299 by 299-input size image can be fed to the network.

The convolutional neural networks with 18, 50, and 101 layers, respectively, are called ResNet-18, ResNet-50, and ResNet-101. From the ImageNet database, you can load a pretrained version of the network [25] that was trained on more than a million photos. The pretrained network is capable of classifying photos into 1000 different object categories, including keyboard, mouse, pencil, and numerous animal images. This has led to the network learning detailed feature representations for a variety of images. A 224 by 224 input size image can be entered into the network.

During the classification process, the ratio of Images Training: Images Validation: Images Test was 60% (54 images):20% (18 images):20% (18 images) respectively.

2.4. Numerical Analysis

The proposed EEG signal classification for low and high mental workload estimation during simultaneous capacity (SIMKAP) task is validated in this chapter. The test was performed to determine workload estimation of human brain during low workload and high workload state in case of SIMKAP task. Discrete wavelet analysis for both cases are presented graphically and statistical parameters with classification results as well as performance parameters are extracted numerically for the comparison with the existing methods.

3. Results and discussion

In this section, result has been presented of the proposed scheme for validation and discuss them chronologically. The only accuracy is not sufficient to take step for the reliability of a method. Other measures needed to support the performance of a technique included sensitivity, specificity, accuracy, F1-score, negative projected value, and so on. Sensitivity detects positive EEG signal during arithmetic task, Specificity detects actually EEG signal before arithmetic task. The performances of the used classifiers were calculated using the most often utilized characteristics stated above, for example, accuracy, sensitivity, and specificity, precision, F1-score, negative predicted value and kappa statistics is defined as below [28].

$$Accuracy = \frac{(TP + TN)}{TP + TN + FP + FN} \qquad \text{……………(5.1)}$$

$$Sensitivity = \frac{TP}{(TP + FN)} \qquad \text{………………(5.2)}$$

$$Specificity = \frac{TN}{(TN + FP)} \qquad \text{………………(5.3)}$$

$$Precision = \frac{TP}{TP + FP} \qquad \text{……………(5.4)}$$

$$F1score = 2 \times \frac{PPV \times TPR}{PPV + TPR} \qquad \text{………………(5.5)}$$

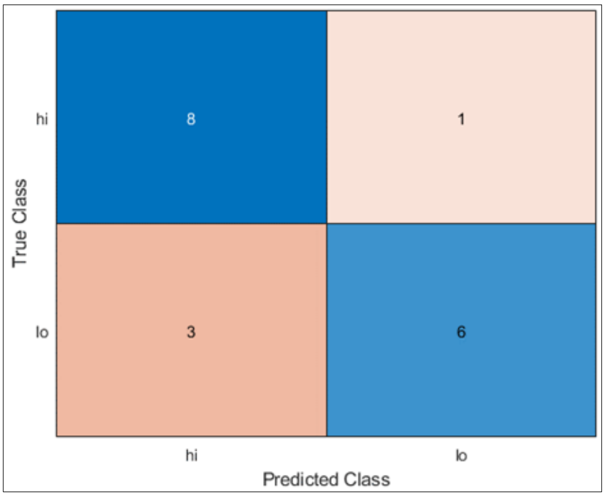

Figure 6 Confusion matrix found by deep learning during SIMKAP task

Table 1 Classification Result of The Extracted Features Using different Classifier

Classifier Type	Accuracy (%)	Precision (%)	F1 score (%)	Recall (%)
GoogleNet	61.11	61.25	61.18	61.11
SqueezeNet	55.56	76.47	64.36	55.56
InceptionresNet-v2	55.56	76.47	64.36	55.56
ResNet-50	55.56	76.47	64.36	55.56
ResNet-101	55.56	76.47	64.36	55.56
AlexNet (Proposed)	77.78	79.22	78.49	77.78

Table 2 Performance Comparison with Existing Methods

Methods' Ref.	Data Preprocessing Techniques	Task Type	Used Classifier	Accuracy (%)
[13]	High-pass filter the raw data at 1Hz with Artifact Independent Component Analysis (ICA)	Three	Support Vector Machine (SVM)	70
[29]	High-pass filter the raw data at 1Hz with Artifact Subspace Reconstruction (ASR)	Two	Support Vector Regression (SVR)	73.14

[30]	-	Three	subject independent deep learning classification	69
Proposed Method	CWT Filter	Two	CNN based Deep Learning (AlexNet)	77.78

3.1. Classification results

In case of SIMKAP task during high and low workload CNN based AlexNet deep learning model was used to classify EEG data. During the classification process using AlexNet, 60% (54 images) images were used as training, 20% (18 images) images for validation and 20% (18 images) images for testing purpose. The confusion matrix generated from AlexNet algorithm is depicted in Figure 6 having training result with 77.78% accuracy (Validation) with two tasks (low and high workload). GoogleNet, SqueezeNet and InceptionresNet-v2 CNN, ResNET-50 and ResNet-101 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.

3.2. Performance evaluation

For SIMKAP task, the classification results are presented in Table 2 with accuracy 77.8% including two tasks (low and high workload) resulting comparative studies among various classifiers model. The comparative study with literature is shown in Table 5.4 which crossed state-of-the-art methodologies in the literature by 77.8 percent.

4. Conclusion

The proposed method examines EEG signals from the occipital (O2) section of the brain. The proposed technique produced the best results for the proposed classifier, with 77.78% accuracy (Validation), 79.22% precision, 78.49% F1 score and 77.78% 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; this conclusion can be reached.

Future Work

This analysis can be used as a foundation for further research into the human brain short term memory loss problem associated with various memory loss or mild cognitive impairment large data set to do further research on Alzheimer's disease with Parkinson.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest.

References

[1] A. Islam, A. K. Sarkar, and T. Ghosh, EEG signal classification for mental stress during arithmetic task using wavelet transformation and statistical features, 2021 Int. Conf. Autom. Control Mechatronics Ind. 4.0, ACMI 2021, Jul. 2021, doi: 10.1109/ACMI53878.2021.9528230.

[2] L. Rizzo and L. Longo, Inferential Models of Mental Workload with Defeasible Argumentation and Non-monotonic Fuzzy Reasoning: a Comparative Study, Conf. Pap., Jan. 2019, Accessed: Feb. 03, 2023. [Online]. Available: https://arrow.tudublin.ie/scschcomcon/248

[3] G. M. Hancock, L. Longo, M. S. Young, and P. A. Hancock, MENTAL WORKLOAD, Handb. Hum. FACTORS Ergon., pp. 203–226, Sep. 2021, doi: 10.1002/9781119636113.CH7.

[4] D. Yu, • Chantale, W. Antonik, • Frederick Webber, E. Watz, and W. Bennett, Correction to: Multi-modal physiological sensing ap-proach for distinguishing high workload events in remotely piloted aircraft simulation, Human-Intelligent Syst. Integr. 2021 32, vol. 3, no. 2, pp. 201–211, Jul. 2021, doi: 10.1007/S42454-021-00033-3.

[5] P. Wang, W. Fang, and B. Guo, Mental workload evaluation and its application in train driving multitasking scheduling: a Timed Petri Net-based model, Cogn. Technol. Work, vol. 23, no. 2, pp. 299–313, Oct. 2019, doi: 10.1007/S10111-019-00608-W.

[6] X. Li, A. Vaezipour, A. Rakotonirainy, S. Demmel, and O. Oviedo-Trespalacios, Exploring drivers' mental workload and visual demand while using an in-vehicle HMI for eco-safe driving, Accid. Anal. Prev., vol. 146, Oct. 2020, doi: 10.1016/J.AAP.2020.105756.

[7] U. Asgher et al., Enhanced Accuracy for Multiclass Mental Workload Detection Using Long Short-Term Memory for Brain–Computer Interface, Front. Neurosci., vol. 14, p. 584, Jun. 2020, doi: 10.3389/FNINS.2020.00584/BIBTEX.

[8] M. Bagheri and S. D. Power, 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, https://doi.org/10.1080/2326263X.2021.1948756, vol. 8, no. 1–2, pp. 26–37, 2021, doi: 10.1080/2326263X.2021.1948756.

[9] F. Putze et al., Editorial: Brain-Computer Interfaces and Augmented/Virtual Reality, Front. Hum. Neurosci., vol. 14, May 2020, doi: 10.3389/FNHUM.2020.00144.

[10] K. Moustafa and L. Longo, Analysing the Impact of Machine Learning to Model Subjective Mental Workload: A Case Study in Third-Level Education, Commun. Comput. Inf. Sci., vol. 1012, pp. 92–111, 2019, doi: 10.1007/978-3-030-14273-5_6.

[11] L. Longo and G. Orrú, Evaluating instructional designs with mental workload assessments in university classrooms, https://doi.org/10.1080/0144929X.2020.1864019, vol. 41, no. 6, pp. 1199–1229, 2020, doi: 10.1080/0144929X.2020.1864019.

[12] L. Longo and M. Rajendran, A Novel Parabolic Model of Instructional Efficiency Grounded on Ideal Mental Workload and Perfor-mance, Commun. Comput. Inf. Sci., vol. 1493 CCIS, pp. 11–36, 2021, doi: 10.1007/978-3-030-91408-0_2/COVER.

[13] R. Chai, G. R. Naik, T. N. Nguyen, S. H. Ling, Y. Tran, and H. T. Nguyen, Selecting optimal EEG channels for mental tasks classifica-tion: An approach using ICA, 2016 IEEE Congr. Evol. Comput. CEC 2016, pp. 1331–1335, Nov. 2016, doi: 10.1109/CEC.2016.7743942.

[14] J. Atkinson and D. Campos, Improving BCI-based emotion recognition by combining EEG feature selection and kernel classifiers, Expert Syst. Appl., vol. 47, pp. 35–41, Apr. 2016, doi: 10.1016/J.ESWA.2015.10.049.

[15] C. Zeng, EEG-based mental workload recognition using deep learning techniques, 2020, Accessed: Feb. 03, 2023. [Online]. Available: https://dr.ntu.edu.sg/handle/10356/140005

[16] W. L. Lim, O. Sourina, and L. P. Wang, STEW: Simultaneous task EEG workload data set, IEEE Trans. Neural Syst. Rehabil. Eng., vol. 26, no. 11, pp. 2106–2114, Nov. 2018, doi: 10.1109/TNSRE.2018.2872924.

[17] T. de Jong, Cognitive load theory, educational research, and instructional design: Some food for thought, Instr. Sci., vol. 38, no. 2, pp. 105–134, Aug. 2010, doi: 10.1007/S11251-009-9110-0/METRICS.

[18] F. G. W. C. Paas, Training Strategies for Attaining Transfer of Problem-Solving Skill in Statistics: A Cognitive-Load Approach, J. Educ. Psychol., vol. 84, no. 4, pp. 429–434, 1992, doi: 10.1037/0022-0663.84.4.429.

[19] A. Subasi, EEG signal classification using wavelet feature extraction and a mixture of expert model, Expert Syst. Appl., vol. 32, no. 4, pp. 1084–1093, May 2007, doi: 10.1016/j.eswa.2006.02.005.

[20] P. Jahankhani, V. Kodogiannis, and K. Revett, EEG signal classification using wavelet feature extraction and neural networks, in Pro-ceedings - IEEE John Vincent Atanasoff 2006 International Symposium on Modern Computing, JVA 2006, 2006, pp. 120–124. doi: 10.1109/JVA.2006.17.

[21] Digital Image Processing (2nd Edition) by Rafael C. Gonzalez, Richard E. Woods: New Hardcover (2002) 2nd. | Ergodebooks.

[22] U. Orhan, M. Hekim, and M. Ozer, EEG signals classification using the K-means clustering and a multilayer perceptron neural network model, Expert Syst. Appl., vol. 38, no. 10, pp. 13475–13481, Sep. 2011, doi: 10.1016/j.eswa.2011.04.149.

[23] A. Krizhevsky, I. Sutskever, and G. E. Hinton, ImageNet Classification with Deep Convolutional Neural Networks, Adv. Neural Inf. Process. Syst., vol. 25, 2012.

[24] B. Zhou, A. Khosla, A. Lapedriza, A. Torralba, and A. Oliva, Places: An Image Database for Deep Scene Understanding, Oct. 2016, Accessed: Feb. 09, 2023. [Online]. Available: http://arxiv.org/abs/1610.02055

[25] T. Ridnik, E. Ben-Baruch, A. Noy, and L. Zelnik-Manor, ImageNet-21K Pretraining for the Masses, Apr. 2021, doi: 10.48550/arxiv.2104.10972.

[26] F. N. Iandola, S. Han, M. W. Moskewicz, K. Ashraf, W. J. Dally, and K. Keutzer, SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and <0.5MB model size, Feb. 2016, Accessed: Feb. 09, 2023. [Online]. Available: https://github.com/forresti/SqueezeNet

[27] Y. G. Pavlov and B. Kotchoubey, Temporally distinct oscillatory codes of retention and manipulation of verbal working memory, Eur. J. Neurosci., vol. 54, no. 7, pp. 6497–6511, Oct. 2021, doi: 10.1111/EJN.15457.

[28] A. Subasi and M. I. Gursoy, EEG signal classification using PCA, ICA, LDA and support vector machines, Expert Syst. Appl., vol. 37, no. 12, pp. 8659–8666, 2010, doi: 10.1016/j.eswa.2010.06.065.

[29] J. Atkinson and D. Campos, Improving BCI-based emotion recognition by combining EEG feature selection and kernel classifiers, Expert Syst. Appl., vol. 47, pp. 35–41, Apr. 2016, doi: 10.1016/J.ESWA.2015.10.049.

[30] C. Zeng, EEG-based mental workload recognition using deep learning techniques, 2020, Accessed: Feb. 02, 2023. [Online]. Available: https://dr.ntu.edu.sg/handle/10356/140005

[31] A. T. Kamzanova, A. M. Kustubayeva, and G. Matthews, Use of EEG workload indices for diagnostic monitoring of vigilance decre-ment, Hum. Factors, vol. 56, no. 6, pp. 1136–1149, 2014, doi: 10.1177/0018720814526617.

[32] S. Palva, S. Kulashekhar, M. Hämäläinen, and J. M. Palva, Localization of cortical phase and amplitude dynamics during visual working memory encoding and retention, J. Neurosci., vol. 31, no. 13, pp. 5013–5025, Mar. 2011, doi: 10.1523/JNEUROSCI.5592-10.2011.