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WLnet: towards an approach for robust workload estimation based on shallow neural networks

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ABSTRACT Electroencephalography (EEG) is a non-invasive technology used for the human brain-computer interface. One of its important applications is the evaluation of the mental state of an individual, such as workload estimation. In previous works, common spatial pattern feature extraction methods have been proposed for the EEG-based workload detection. Recently, several novel methods were introduced to detect EEG pattern workloads. However, it is still unknown which one of these methods is the one that offers the best performance for the workload EEG pattern feature detection. In this paper, four methods were used to extract workload EEG features: (a) common spatial pattern feature extraction; (b) temporally constrained sparse group spatial pattern feature extraction; (c) EEGnet; and (d) the new proposed shallow convolutional neural network for workload estimation (WLnet). The classification accuracy of these four methods was compared. Experimental results demonstrate that the proposed WLnet achieved the best detection accuracy in both stress and non-stress conditions. We believe that the proposed methods may be relevant to real-life applications of mental workload estimation.

INDEX TERMS Shallow neural network, electroencephalogram, human computer interface, workload estimation, EEG

I. INTRODUCTION

Mental workload estimation-based brain-computer interface has been widely used in many areas, such as in improving the performance of brain-computer interface (BCI), in educational applications or also in adapting the difficulty of a task [1]–[5]. In previous research works, workload detection has been mainly based on the subjects' behaviour, eye movement, heart rate and brain activity [6]–[10].

Electroencephalography (EEG) signals and near-infrared sensors (NIRS) are usually the technologies used for non-invasive BCI [4], [11]. EEG equipment consists of metal electrodes which are placed directly on the scalp to record electrical signals [12]. The electrodes record the activity of the surrounding neurons [13]. The other BCI system mentioned previously, the NIRS recording system, is generally used to measure hemodynamic signals from target regions of the brain [14].

Although some literature has shown that NIRS signals could be used to estimate the mental workload status ([15]–[17]), in this paper we focus on EEG technology for this task, because it is cheaper and more conveniently portable [18]. EEG signals include a lot of spatio-temporal information of human activity [8]. It is a robust technology which can quantify an individual's mental condition. In 2012, Brouwer et al. introduced a workload estimation system based on EEG spectral power and event-related potentials [3]. The mental workload was mainly quantified using α (8-12 Hz) and β (12-30 Hz) bands of the EEG signal, as previous research revealed that they are highly correlated with mental workload [19]–[21]. Mühl et al. built a novel workload experimental protocol based on EEG signals [8]. All of the subjects were asked to participated in the n-back tasks. The tasks were divided into low and high workload tasks. To classify the low and high-workload EEG signals, they proposed a filter bank common spatial pattern (FBCSP) [8], [22], [23]. The EEG signals were first filtered by specific frequency bands and common spatial pattern (CSP) was used to detect the EEG features. Linear classifiers, such as linear discriminate analysis, or support vector machines were used for the classification. While this method is widely used, it still has some disadvantages. For example, not all the the selected features are useful for the classification, and thus further processing is necessary.

To improve the classification accuracy of motor imagery EEG signals, Zhang et al. proposed a novel algorithm for the EEG feature extraction in 2018 [24]. The algorithm optimized the filter banks and the time window. The results indicated that this algorithm has better feature extraction abilities for motor imagery EEG signals.

In addition, artificial neural network methods have played an important role for EEG signal processing in the last 10 years [25]. Some studies have indicated that deep neural networks can automatically detect EEG patterns [26]–[29]. Many efficient neural networks have been applied for the brain signal processing [30]–[32]. Most of the previous research have been focused on EEG motor imagery dataset classification, steady state visually-evoked potentials detection, event-related potential or P300 experiments [30], [33]–[35]. For example, Event Related Potential Encoder Network was introduced for large-scale dataset processing in [29]. Recurrent neural networks (RNN) and long short term memory (LSTM) networks have been used in many time-series processing and prediction problems [36]–[38]. However, the experiments revealed that the architecture of such types of neural networks cannot detect useful features from raw EEG signals. Many studies have shown that before using LSTM networks, feature detection approaches are necessary [28], [39], [40]. Traditional methods to help the neural network to extract EEG features include using wavelet or Fourier transforms [41]–[46]. In 2010, Phan and Cichocki used tensor decomposition for motion imagery EEG feature extraction and achieved very good results [47]. However, we attempted to implement these methods for estimating the workload using EEG, but the accuracy was lower than when applying FBCSP methods.

It is important to note that training a deep neural network requires a large amount of data samples in order to achieve a satisfactory accuracy, but EEG datasets usually contains a small amount of samples. This is another limitation related to the use of deep neural networks for EEG processing, as having few samples always leads to the overfitting problem [30], [48], [49]. This further leads to less accurate and thus unreliable detection results for many BCI applications. To solve this problem, Dinarès et al. [50] used for the first time empirical mode decomposition to get different components of the original EEG signals, and then, artificially create EEG signals by mixing the obtained components. This strategy was also used by Zhang et al. [30] to increase the dataset size and train a deep-learning network. Another approach to the problem is to use generative adversarial networks to generate artificial EEG signals [51], [52]. However, we tried to use this strategy to train a deep neural network for the workload dataset, but the achieved accuracy was still worst than the one obtained with classical CSP or FBCSP methods.

To overcome the above mentioned limitations of existing approaches, in this paper, two new types of neural networks are proposed and evaluated to identify mental workload. The first one is EEGNet, a compact convolutional neural network proposed by Lawhern et al. in 2018 [53]. The second approach is based on a shallow convolutional neural network termed WLnet (WorkLoad network). We used the workload dataset provided by Fabien Lotte research group at INRIA [8] to validate the performance of our neural networks. We also applied CSP and TCSGSP/LDA for this workload classification task. Compared with all of the other methods, WLnet achieved the best accuracy.

This paper is organized as follows: EEG-based workload dataset description, along with an introduction to the methods of CSP, TCSGSP, EEGnet and the proposed WLnet, are included in Section II. EEG-based workload classification results are presented in Section III. The discussion and conclusions are given in Section IV and Section V respectively.

II. METHODS

Our work aims to compare four methods for workload detection. Here, we present a review on CSP, TCSGSP and EEGNet, followed by an introduction of the new proposed WLnet method.

A. COMMON SPATIAL PATTERN

CSP is a classical feature extraction method widely used in motor imagery signal processing. CSP designs a spatial filter where the variance of the filtered time series can be used to reliably discriminate between the two workload conditions. The CSP spatial filter casts the multi-channel EEG signals into more distinctive time series and compresses the channels of EEG signals. The extracted features are usually classified by using a linear discriminant analysis (LDA) classifier. Support Vector Machines (SVM) can provide similar results although it requires to properly tune parameters to ensure good results.

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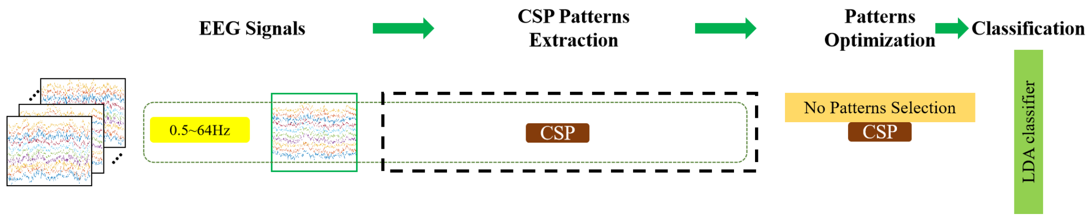
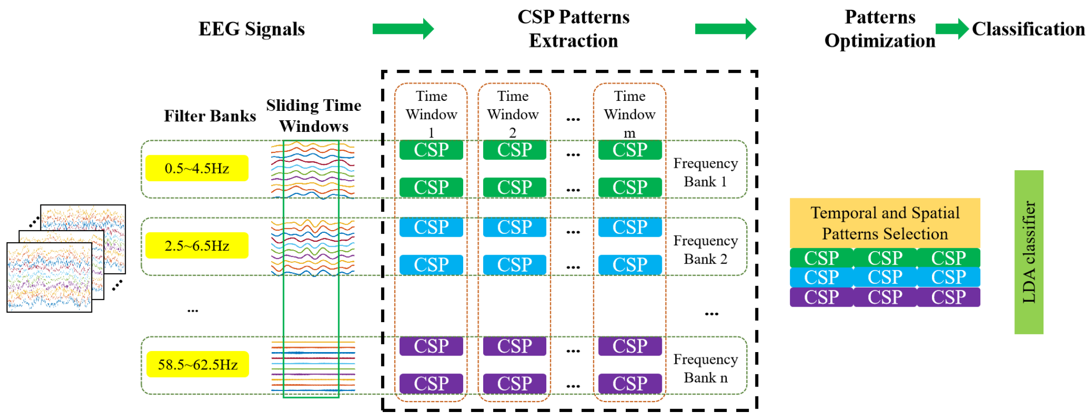


(a) Representation of the CSP method. After a bandpass filter, CSP patterns are extracted from EEG signals. Later, CSP patterns are classified with LDA.



(b) Representation of the TCSGSP method. EEG signals are bandpassed with several filter banks. A time window slides from the start to the end of EEG signals. For each filter bank and time window, CSP patterns are extracted. After extracting the CSP patterns, the Lasso optimization model is used to optimize the CSP patterns. The optimized CSP patterns are classified with LDA.

FIGURE 1: **The illustration of CSP and TCSGSP methods.**

B. TEMPORALLY CONSTRAINED SPARSE GROUP SPATIAL PATTERNS

Temporally Constrained Sparse Group Spatial Patterns (TC-SGSP) is a deep-extension CSP method which was proposed by Zhang et al., 2018 [24]. CSP, from Section.II-A, is applied on the selection of spatial pattern. The features of EEG signals can be represented into both the frequency and time domains. CSP doesn't optimize the features simultaneously from these two domains. To optimize the filter bands, FBCSP extracts CSP features from different filter banks. Moreover, TCSGSP does not only optimize the CSP features from filter banks, but also optimizes them from the time domain. TCSGSP implements bandpass filtering with K overlapping sub-bands on N EEG trials. In each filter band, there are T overlapping time windows. From each time window, M CSP features will be extracted. We can obtain T CSP feature sets $Z^{N\times MK}$. After that, the multitask learning-based feature optimization model, Lasso, is used to filter the features. The Lasso is obtained from the following formula:

$$U = arg\ min_U \frac{1}{2}\sum_{t=1}^{T}\|Z^{(t)}u_t - y\|_2^2 + \beta_1\|U\|_1 + \beta_2\|U\|_{2,1} + \beta_3\sum_{t=1}^{T}\|u_t - u_{t+1}\|_1 \tag{1}$$

where $U = [u_1, \cdots, u_T]$. $\|*\|_1$ and $\|*\|_{2,1}$ denote the l_1-norm and $l_{2,1}$-norm of the matrix, respectively. In our work, the overlapping filter banks used were: 0.5-4.5Hz, 2.5-6.5Hz,$\cdots$,58.5-62.5Hz, 62.5-64Hz. The time windows were 0.5s : 0-0.5s, 0.03125-0.53125s, $\cdots$. In has been previously proved in literature [24] that the classification results are not heavily influenced by the three hyper-parameters, β_1,β_2,β_3. Therefore β_1,β_2,β_3 are all set to a medium value 7.0. Fig. 1 illustrates the CSP and the TCSGSP methods.

C. EEGNET

Considering that the amount of EEG signal data is limited, a shallow neural network termed EEGNet was designed specifically for EEG-based BCIs in [53]. Depthwise convolutional layer and separable convolutional layer are introduced in EEGNet to obtain a simple but effective structure. As a result, three convolution layers are included in the compact architecture, and a dense layer follows in order to classify the trials into the different classes. It has been used not only in motor imagery EEG signals, but also for steady state visually evoked potentials, too [54]. We set part of the hyper-parameters in concordance with the dataset (N=2, fs=32, C=28, T=257) and only tuned the batch size, learning rate and the probability of dropout. Details of the EEGNet are shown in Fig. 2, and the search range of these hyper-parameters are shown in Tab. 1. According to the hyper-parameter search results, $batch\ size = 32$, $lr = 0.0005$ and $p = 0.5$ gave the best accuracy.

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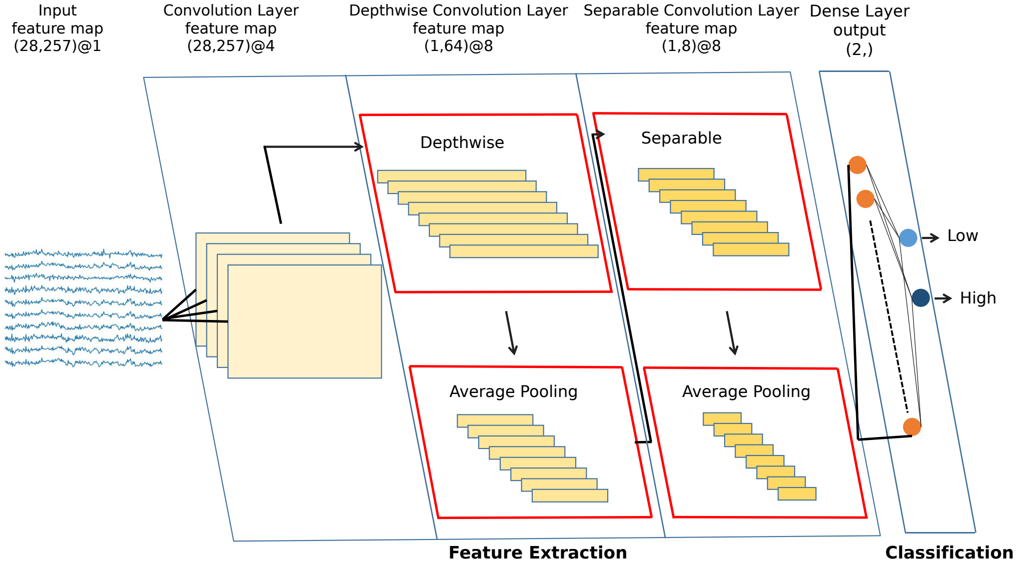

FIGURE 2: **The architecture of the EEGNet.** EEG data is first fed to three convolution layers for feature extraction. This is followed by a dense layer to project features into two units. The trainable variables in EEGNet is 846.

TABLE 1: **Hyper-parameter search range of EEGNet for workload EEG signals**

Hyper-parameters	Search range
batch size	32, 64, 128
lr	$1e^{-4}, 3e^{-4}, 5e^{-4}, 1e^{-3}$
p	0.0, 0.5

D. WLNET

Recently, some one-dimensional convolutional neural networks were also proposed for EEG signals achieving good performance [30]. Similar to separable convolutional layer and depthwise convolutional layer in EEGNet, one-dimensional convolutional layer also has far less learnable parameters as compared to traditional two-dimensional convolutional layer. Inspired by these facts, here we propose the shallow one-dimensional neural network referred to as WLnet for workload detection. Two convolution layers and one dense layer are included in our WLnet. The architecture is shown in Fig. 3 and the hyper-parameters we used are listed in Tab. 2.

In the first convolution layer, we use filters with a kernel size of 3 to downsample the signals into 128 time-points with a stride of 2. Note that the padding mode we used is 'Valid' so we set the padding to 0 because there are no time-points left after the convolution. Batch normalization and the ReLU function are then applied to make the network easier to train and obtain a better performance. Max pooling is then used to downsample and get a smaller amount of parameters. This structure is repeated in the second convolution layer, and in the end 1024 features are obtained after flattening. Here we set the padding to 1, since one time point is left after the convolution or pooling. A dense layer is added at the end to project features into two classes: high workload level and low workload level. In the end, we set $batch\ size = 64$ and $lr = 0.0003$.

III. EXPERIMENTS AND RESULTS

A. WORKLOAD DATASET

The dataset used in this work was provided by Fabien Lotte research group at INRIA [8], which includes 22 subjects. In that study, each subject was asked to participate in the n-back tasks under two affective contexts: stressful and non-stressful (relax). High-workload signals (2-back task) and low-workload signals (0-back task) were used, and each workload level contained signals recorded under both affective contexts (stress and non-stress). One subject was discarded because the data only included one condition. Moreover, as the trials in the non-stress setting for 4 subjects were less than 720, they were also eliminated from the experiments to ensure a fair comparison of results. Therefore, only 18 subjects were used to validate the methods.

For the rest of the subjects, 1440 EEG trials were recorded in total, of which 720 are high-workload (360 stressful and 360 non-stressful) and 720 are low-workload (360 stressful and 360 non-stressful as well). As shown in Fig. 4, 28 channels were used according to the 10/20 system except for T7, T8, Fp1 and Fp2, and 257 time-points were recorded for each trial. All signals were filtered through a bandpass of frequency between 0.5 and 64 Hz and downsampled to 128Hz (see [8] for details).

B. EXPERIMENT SETTINGS

In our work, we apply the test and record the binary accuracy on stressful and non-stressful workload data with four meth-

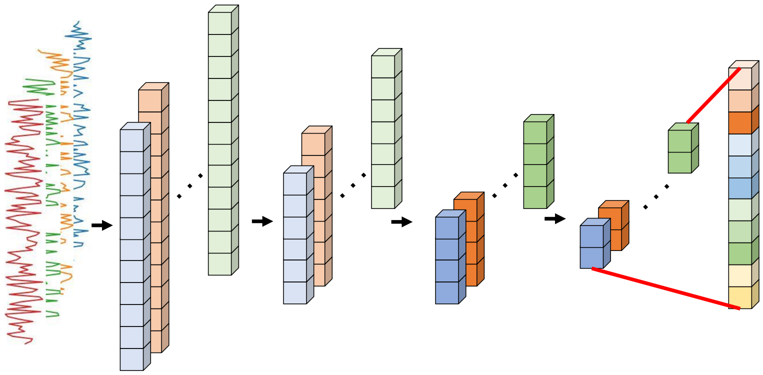

FIGURE 3: **The architecture of the WLnet.** Two one-dimensional convolution layers are used for extraction, and a dense layer is used for classification as the output layer. The trainable variables in WLnet is 3834.

TABLE 2: **Hyper-parameters for WLnet**

Layers	Hyper-parameters	Activation	Output
Input	\	\	$(B, 28, 257)$
Conv1D	$k = 3, s = 2, C = 32, padding = 0$	\	$(B, 32, 128)$
BatchNormalization1D	\	$ReLU$	$(B, 32, 128)$
MaxPooling1D	$k = 3, s = 2, padding = 1$	\	$(B, 32, 64)$
Conv1D	$k = 3, s = 2, C = 64, padding = 1$	\	$(B, 64, 32)$
BatchNormalization1D	\	$ReLU$	$(B, 64, 32)$
MaxPooling1D	$k = 3, s = 2, padding = 1$	\	$(B, 64, 16)$
Flatten	\	\	$(B, 1024)$
Linear	$out\_feature = 2$	$Softmax$	$(B, 2)$

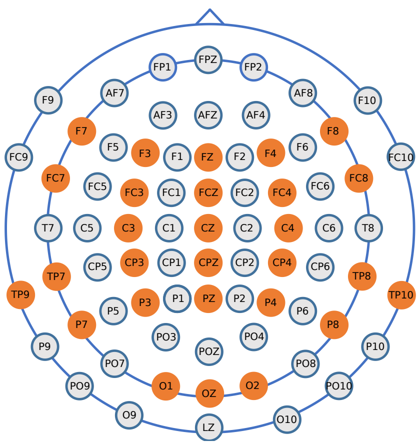

FIGURE 4: **The EEG electrodes' location used in the workload experiment**. A 10/20 EEG recording system was used for the data collection.

ods mentioned above. Two scenes are designed as reported in [8]. (1) For within-context, 720 trials from stressful or non-stressful context are applied for training and testing. Results were calculated by conducting a 6-fold cross validation, following the same criteria used in [8] to ensure a fair comparison of the results. (2) For cross-context, 720 trials from stressful or non-stressful context are applied for training and the rest from another context for testing. Results were obtained by taking the mean value of 5 repeated experiments. We used the results reported in [8] as the baseline, which were obtained using filter bank common spatial patterns (FBCSP) with the event related potentials (ERP). Note that all experiments in our paper used the Adam algorithm to optimize networks with cross-entropy as the loss function, and all the results of the neural networks were obtained by early stopping when the value of the loss function in the validation data did not change for 20 consecutive iterations using $epoch = 200$.

C. RESULTS

For the within-context experiments, we first trained and tested the model using the data from the stress context, and then repeated the process using the data from the non-stress context. On the other hand, for the cross-context experiments, we first trained our models using all the data from the stress context and then tested them on all the non-stress context data and vice versa in another similar experiment. Results of the average accuracy of all 18 subjects are shown in Fig. 5.

Compared to traditional machine learning methods, such as CSP/LDA, TCSGSP/LDA and FB/ERP, convolutional layers in EEGNet and WLnet can extract feature automatically

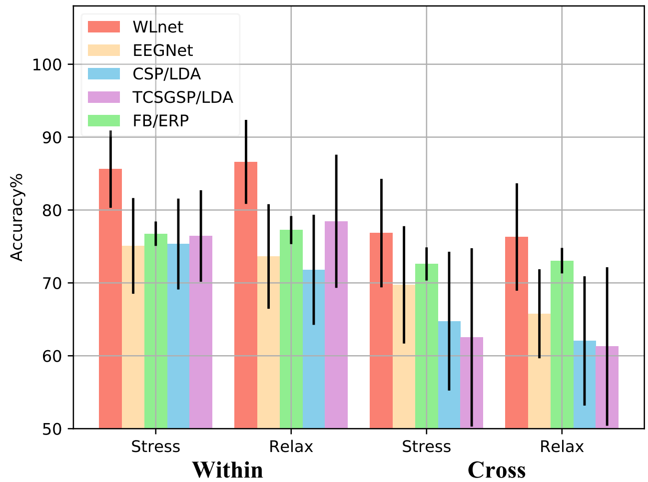

FIGURE 5: **The results on within-context classification and cross-context classification.** Bars denote average values of the accuracy, black lines indicate the standard deviation. Results of within-context accuracy are on the left,and the cross-context accuracy results are on the right. Labels on the x-axis represent the trials for training; for example, $Stress$ means the model is trained using trials from the stress context. The y-label represents the binary accuracy.

rather than manually. Results in Fig. 5 show that WLnet achieves higher binary accuracy in within-context task. Overall, the model works best in a cross-context task as well. In other words, the proposed WLnet is more powerful in both tasks. We applied Kolmogorov-Smirnov test for the results and it confirmed that the accuracy was normally distributed at a significance level of 0.01. To compare the accuracy between two neural networks, we used two-sample t-Test. The null hypothesis was rejected at the significance level of 1%, indicating that the accuracy values of the two networks had statistically significant differences for within-context task and cross-context tasks. We would also like to point out that the WLnet is a lightweight network similar to the EEGNet, which allows it to be accessed, for example, by mobile devices.

IV. DISCUSSION

Even though some literature indicates that deep neural network could achieve good performance for EEG processing, we tried all of the deep neural network architectures known to us, and some of them had overfitting issues whilst others showed unreliable results. For real life applications, a robust and stable method is necessary, so we selected shallow neural networks instead.

In the experiment of within-context and cross-context classification, it can be seen that all three models could achieve higher accuracy score in within-context tasks compared to the cross-context tasks, which means that a different affective context does influence the workload level, leading to a different distribution on data.

To provide more details of the experiments, the loss curve of WLnet is depicted in Fig. 6. Besides, the ROC curves of both WLnet and EEGNet for Subject 1 are shown in Fig. 7. In both cases the data used to plot them is from the within-context task of stressful context. The loss curve is obtained from one of the six folds cross validation, which demonstrates how WLnet avoids overfitting with the early stop strategy. The ROC curve in Fig. 7 is calculated averaging the curves of the 6 folds. One-dimensional linear interpolation is applied in each fold to obtain 100 points. Results also show the superiority of WLnet, which has higher AUC value than EEGNet. Note that in our experiments, the size of neural networks is different. EEGNet has 846 trainable variables and WLnet has 3834 trainable variables.

V. CONCLUSION

EEG has been used to estimate the human workload status by means of experimental protocols. For these workload estimations, we have tried several approaches, including (a) common spatial pattern feature extraction; (b) temporally constrained sparse group spatial patterns feature extraction; (c)EEGnet; (d) the proposed WLnet, based on shallow convolutional neural networks. Experimental results demonstrate that WLnet achieved the best detection accuracy in both stress and non-stress conditions. We also analysed the detection accuracy for each individual subject. The WLnet was robust enough to overcome the overfitting problem. For the workload dataset, it achieved the best classification accuracy. Our research not only proposes several methods to process the workload EEG signals, but also provides the comparison for different subjects, methods and conditions. All of this information is critical for the development of workload estimation BCI applications.

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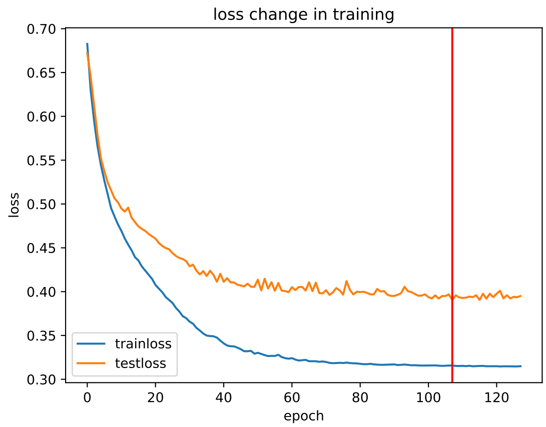

FIGURE 6: **Loss curve of WLnet.** The cross entropy loss of WLnet is recorded while training on Subject1. The red line is the stopping epoch with early stop strategy.

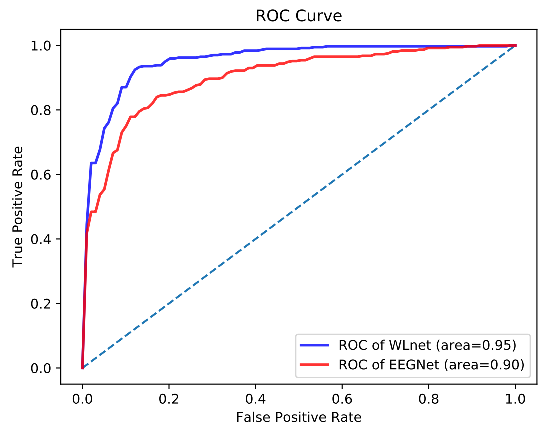

FIGURE 7: **Mean ROC of EEGNet and WLnet.** Mean ROC curve is calculated by six curves of cross validation. AUC value is also marked in the figure.

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A. REFERENCES

REFERENCES

[1] A. Riccio, E. M. Holz, P. Aricò, F. Leotta, F. Aloise, L. Desideri, M. Rimondini, A. Kübler, D. Mattia, and F. Cincotti, "Hybrid P300-based brain-computer interface to improve usability for people with severe motor disability: electromyographic signals for error correction during a spelling task," Archives of physical medicine and rehabilitation, vol. 96, no. 3, pp. S54–S61, 2015.

[2] M. Spüler, T. Krumpe, C. Walter, C. Scharinger, W. Rosenstiel, and P. Gerjets, "Brain-computer interfaces for educational applications," in Informational Environments, pp. 177–201, Springer, 2017.

[3] A.-M. Brouwer, M. A. Hogervorst, J. B. Van Erp, T. Heffelaar, P. H. Zimmerman, and R. Oostenveld, "Estimating workload using EEG spectral power and ERPs in the n-back task," Journal of neural engineering, vol. 9, no. 4, p. 045008, 2012.

[4] S. Lei and M. Roetting, "Influence of task combination on EEG spectrum modulation for driver workload estimation," Human factors, vol. 53, no. 2, pp. 168–179, 2011.

[5] F. C. Galán and C. R. Beal, "Eeg estimates of engagement and cognitive workload predict math problem solving outcomes," in International Conference on User Modeling, Adaptation, and Personalization, pp. 51–62, Springer, 2012.

[6] Y. Yu, H. Li, W. Umer, C. Dong, X. Yang, M. Skitmore, and A. Y. Wong, "Automatic biomechanical workload estimation for construction workers by computer vision and smart insoles," Journal of Computing in Civil Engineering, vol. 33, no. 3, p. 04019010, 2019.

[7] N. Moray, Mental workload: Its theory and measurement, vol. 8. Springer Science & Business Media, 2013.

[8] C. Mühl, C. Jeunet, and F. Lotte, "EEG-based workload estimation across affective contexts," Frontiers in neuroscience, vol. 8, p. 114, 2014.

[9] L. Yang, K. Lu, M. Forsman, K. Lindecrantz, F. Seoane, Ö. Ekblom, and J. Eklund, "Evaluation of physiological workload assessment methods using heart rate and accelerometry for a smart wearable system," Ergonomics, vol. 62, no. 5, pp. 694–705, 2019.

[10] C. M. Schulz, E. Schneider, L. Fritz, J. Vockeroth, A. Hapfelmeier, M. Wasmaier, E. Kochs, and G. Schneider, "Eye tracking for assessment of workload: a pilot study in an anaesthesia simulator environment," British journal of anaesthesia, vol. 106, no. 1, pp. 44–50, 2011.

[11] L. M. Hirshfield, K. Chauncey, R. Gulotta, A. Girouard, E. T. Solovey, R. J. Jacob, A. Sassaroli, and S. Fantini, "Combining electroencephalograph and functional near infrared spectroscopy to explore users' mental workload," in International Conference on Foundations of Augmented Cognition, pp. 239–247, Springer, 2009.

[12] Y. Zheng, Y. Peng, G. Xu, L. Li, and J. Wang, "Using corticomuscular coherence to reflect function recovery of paretic upper limb after stroke: a case study," Frontiers in neurology, vol. 8, p. 728, 2018.

[13] Q. G. Ma, Q. Shang, H. J. Fu, and F. Z. Chen, "Mental workload analysis during the production process: EEG and GSR activity," in Applied Mechanics and Materials, vol. 220, pp. 193–197, Trans Tech Publ, 2012.

[14] B. Koo, H.-G. Lee, Y. Nam, H. Kang, C. S. Koh, H.-C. Shin, and S. Choi, "A hybrid NIRS-EEG system for self-paced brain computer interface with online motor imagery," Journal of neuroscience methods, vol. 244, pp. 26–32, 2015.

[15] S. Keshmiri, H. Sumioka, R. Yamazaki, and H. Ishiguro, "A non-parametric approach to the overall estimate of cognitive load using NIRS time series," Frontiers in human neuroscience, vol. 11, p. 15, 2017.

[16] E. B. Coffey, A.-M. Brouwer, and J. B. van Erp, "Measuring workload using a combination of electroencephalography and near infrared spectroscopy," in Proceedings of the Human Factors and Ergonomics Society Annual Meeting, vol. 56, pp. 1822–1826, Sage Publications Sage CA: Los Angeles, CA, 2012.

[17] N. Dzung, "Multifractality in NIRS data of brain activity," in The Third International Conference on the Development of Biomedical Engineering in Vietnam, pp. 80–83, Springer, 2010.

[18] P. Sawangjai, S. Hompoonsup, P. Leelaarporn, S. Kongwudhikunakorn, and T. Wilaiprasitporn, "Consumer grade eeg measuring sensors as research tools: A review," IEEE Sensors Journal, vol. 20, no. 8, pp. 3996–4024, 2019.

[19] G. Pfurtscheller, A. Stancak Jr, and C. Neuper, "Event-related synchronization (ERS) in the alpha band—an electrophysiological correlate of cortical idling: a review," International journal of psychophysiology, vol. 24, no. 1-2, pp. 39–46, 1996.

[20] K. Jann, T. Dierks, C. Boesch, M. Kottlow, W. Strik, and T. Koenig, "Bold correlates of EEG alpha phase-locking and the fMRI default mode network," Neuroimage, vol. 45, no. 3, pp. 903–916, 2009.

[21] A.-M. Brouwer, M. A. Hogervorst, P. Herman, and F. Kooi, "Are you really looking? finding the answer through fixation patterns and EEG," in International Conference on Foundations of Augmented Cognition, pp. 329–338, Springer, 2009.

[22] H. Sun, L. Bi, B. Chen, and Y. Guo, "EEG-based safety driving performance estimation and alertness using support vector machine," Int. J. Secur. Appl, vol. 9, no. 6, pp. 125–134, 2015.

[23] K. K. Ang, Z. Y. Chin, C. Wang, C. Guan, and H. Zhang, "Filter bank common spatial pattern algorithm on BCI competition iv datasets 2a and 2b," Frontiers in neuroscience, vol. 6, p. 39, 2012.

[24] Y. Zhang, C. S. Nam, G. Zhou, J. Jin, X. Wang, and A. Cichocki, "Temporally constrained sparse group spatial patterns for motor imagery BCI," IEEE transactions on cybernetics, vol. 49, no. 9, pp. 3322–3332, 2018.

[25] A. Appriou, A. Cichocki, and F. Lotte, "Modern machine learning algorithms to classify cognitive and affective states from electroencephalography signals," IEEE Systems, Man and Cybernetics Magazine, 2020.

[26] S. L. Oh, Y. Hagiwara, U. Raghavendra, R. Yuvaraj, N. Arunkumar, M. Murugappan, and U. R. Acharya, "A deep learning approach for Parkinson's disease diagnosis from EEG signals," Neural Computing and Applications, pp. 1–7, 2018.

[27] X. Jia, K. Li, X. Li, and A. Zhang, "A novel semi-supervised deep learning framework for affective state recognition on EEG signals," in 2014 IEEE international conference on bioinformatics and bioengineering, pp. 30–37, IEEE, 2014.

[28] K. M. Tsiouris, V. C. Pezoulas, M. Zervakis, S. Konitsiotis, D. D. Koutsouris, and D. I. Fotiadis, "A long short-term memory deep learning network for the prediction of epileptic seizures using EEG signals," Computers in biology and medicine, vol. 99, pp. 24–37, 2018.

[29] A. Ditthapron, N. Banluesombatkul, S. Ketrat, E. Chuangsuwanich, and T. Wilaiprasitporn, "Universal joint feature extraction for p300 eeg classification using multi-task autoencoder," IEEE Access, vol. 7, pp. 68415–68428, 2019.

[30] Z. Zhang, F. Duan, J. Solé-Casals, J. Dinarès-Ferran, A. Cichocki, Z. Yang, and Z. Sun, "A novel deep learning approach with data augmentation to classify motor imagery signals," IEEE Access, vol. 7, pp. 15945–15954, 2019.

[31] G. Xu, X. Shen, S. Chen, Y. Zong, C. Zhang, H. Yue, M. Liu, F. Chen, and W. Che, "A deep transfer convolutional neural network framework for EEG signal classification," IEEE Access, vol. 7, pp. 112767–112776, 2019.

[32] T. Wilaiprasitporn, A. Ditthapron, K. Matchaparn, T. Tongbuasirilai, N. Banluesombatkul, and E. Chuangsuwanich, "Affective eeg-based person identification using the deep learning approach," IEEE Transactions on Cognitive and Developmental Systems, 2019.

[33] Y. Zhang, G. Zhou, J. Jin, X. Wang, and A. Cichocki, "Frequency recognition in SSVEP-based BCI using multiset canonical correlation analysis," International journal of neural systems, vol. 24, no. 04, p. 1450013, 2014.

[34] T.-H. Nguyen and W.-Y. Chung, "A single-channel SSVEP-based BCI speller using deep learning," IEEE Access, vol. 7, pp. 1752–1763, 2018.

[35] M. Liu, W. Wu, Z. Gu, Z. Yu, F. Qi, and Y. Li, "Deep learning based on batch normalization for P300 signal detection," Neurocomputing, vol. 275, pp. 288–297, 2018.

[36] F. A. Gers, D. Eck, and J. Schmidhuber, "Applying LSTM to time series predictable through time-window approaches," in Neural Nets WIRN Vietri-01, pp. 193–200, Springer, 2002.

[37] P. Malhotra, L. Vig, G. Shroff, and P. Agarwal, "Long short term memory networks for anomaly detection in time series," in Proceedings, vol. 89, Presses universitaires de Louvain, 2015.

[38] Y. Xing, J. Yue, C. Chen, K. Cong, S. Zhu, and Y. Bian, "Dynamic displacement forecasting of dashuitian landslide in china using variational mode decomposition and stack long short-term memory network," Applied Sciences, vol. 9, no. 15, p. 2951, 2019.

[39] R. T. Schirrmeister, J. T. Springenberg, L. D. J. Fiederer, M. Glasstetter, K. Eggensperger, M. Tangermann, F. Hutter, W. Burgard, and T. Ball, "Deep learning with convolutional neural networks for EEG decoding and visualization," Human brain mapping, vol. 38, no. 11, pp. 5391–5420, 2017.

[40] S. Roy, I. Kiral-Kornek, and S. Harrer, "Chrononet: a deep recurrent neural network for abnormal EEG identification," in Conference on Artificial Intelligence in Medicine in Europe, pp. 47–56, Springer, 2019.

[41] H. Adeli, Z. Zhou, and N. Dadmehr, "Analysis of EEG records in an epileptic patient using wavelet transform," Journal of neuroscience methods, vol. 123, no. 1, pp. 69–87, 2003.

[42] H. Adeli, S. Ghosh-Dastidar, and N. Dadmehr, "A wavelet-chaos methodology for analysis of EEGs and EEG subbands to detect seizure and epilepsy," IEEE Transactions on Biomedical Engineering, vol. 54, no. 2, pp. 205–211, 2007.

[43] N. Hazarika, J. Z. Chen, A. C. Tsoi, and A. Sergejew, "Classification of EEG signals using the wavelet transform," Signal processing, vol. 59, no. 1, pp. 61–72, 1997.

[44] K. Polat and S. Güneş, "Classification of epileptiform EEG using a hybrid system based on decision tree classifier and fast fourier transform," Applied Mathematics and Computation, vol. 187, no. 2, pp. 1017–1026, 2007.

[45] A. Sharmila and P. Geethanjali, "DWT based detection of epileptic seizure from EEG signals using naive bayes and k-NN classifiers," Ieee Access, vol. 4, pp. 7716–7727, 2016.

[46] M. Murugappan and S. Murugappan, "Human emotion recognition through short time electroencephalogram (EEG) signals using fast fourier transform (FFT)," in 2013 IEEE 9th International Colloquium on Signal Processing and its Applications, pp. 289–294, IEEE, 2013.

[47] A. H. Phan and A. Cichocki, "Tensor decompositions for feature extraction and classification of high dimensional datasets," Nonlinear theory and its applications, IEICE, vol. 1, no. 1, pp. 37–68, 2010.

[48] X.-R. Zhang, M.-Y. Lei, and Y. Li, "An amplitudes-perturbation data augmentation method in convolutional neural networks for EEG decoding," in 2018 5th International Conference on Information, Cybernetics, and Computational Social Systems (ICCSS), pp. 231–235, IEEE, 2018.

[49] D. Freer and G.-Z. Yang, "Data augmentation for self-paced motor imagery classification with C-LSTM," Journal of neural engineering, vol. 17, no. 1, p. 016041, 2020.

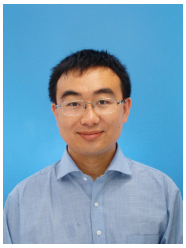
[50] J. Dinarès-Ferran, R. Ortner, C. Guger, and J. Solé-Casals, "A New Method to Generate Artificial Frames Using the Empirical Mode Decomposition for an EEG-Based Motor Imagery BCI," Frontiers in Neuroscience, vol. 12, pp. 1–9, May 2018.

[51] S. M. Abdelfattah, G. M. Abdelrahman, and M. Wang, "Augmenting the size of EEG datasets using generative adversarial networks," in 2018 International Joint Conference on Neural Networks (IJCNN), pp. 1–6, IEEE, 2018.

[52] Z. Wang, G. Healy, A. F. Smeaton, and T. E. Ward, "Use of neural signals to evaluate the quality of generative adversarial network performance in facial image generation," Cognitive Computation, vol. 12, no. 1, pp. 13–24, 2020.

[53] V. Lawhern, A. Solon, N. Waytowich, S. Gordon, C. Hung, and B. Lance, "EEGnet: A compact convolutional network for EEG-based brain-computer interfaces. arxiv 2016," arXiv preprint arXiv:1611.08024.

[54] N. K. N. Aznan, S. Bonner, J. Connolly, N. Al Moubayed, and T. Breckon, "On the classification of SSVEP-based dry-EEG signals via convolutional neural networks," in 2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC), pp. 3726–3731, IEEE, 2018.



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