Grenze International Journal of Engineering and Technology, June Issue

Forecasting of Mental Workload Index using Higher-Level Features of the EEG Signal

Siti Bealinda Qinthara Rony[1], Sasa Arsovski[2], Tan Wee Chuen[3], Pong Hon Keat[4] and Chai Wen Jia[5]
[1-4]Raffles University Faculty of Artificial Intelligence and Robotics, Iskandar Puteri, Malaysia
Email: sitibealinda.qinthara@raffles.university, arsovskisasa@raffles-university.edu.my, tanweechuen@raffles-university.edu.my, ponghonkeat@raffles-university.edu.my
[5] Raffles University Faculty of Social Sciences, Iskandar Puteri, Malaysia
Email: chaiwenjia@raffles-university.edu.my

***Abstract*— Mental workload can be described as individuals' cognitive exertion during task performance, where an employee may end up being mentally overloaded by the time it is evening. In this paper, we present a technique for forecasting evening mental workload index from the EEG signals recorded in the morning, given a linear relationship between morning and mental workload. The multilayer perceptron neural network is designed to forecast the evening mental workload index using higher-level signal features extracted from alpha and theta EEG signals using Convolutional Neural Network. Methodology for the EEG signal transformation to images for feature extraction are key novelties presented in this paper. We thus effectively established a forecasting relationship capable of determining and predicting an individual's mental workload. During our research we used EEG data recorded from university lecturers and university staff. Findings demonstrate the suitability of our model, as there is no evidence suggesting the existence of a non-linear relationship- we are thus able to use the proposed approaches and model for practical implementation in day-to-day occupations.**

***Index Terms*— forecast, feature extraction, mental workload, EEG, prediction and neural network.**

I. INTRODUCTION

In day-to-day life humans exert cognitive efforts in understanding and processing all kinds of information. These cognitive efforts in which people perform many different tasks are also known as the mental working load [1]. Mental working load is related to a person's performance, and when so when the ability to process information has reached past a certain limit- humans become "overloaded" leading to poor performance [2]. In some occupations and working places, poor performances of employees have little tolerance- such as jobs that include safety hazards for the employees and people around them (drivers, etc.).

Mental working load affects people's efforts in learning, and completing tasks. People in different field of jobs have varying amounts of work and also working hours per day, regardless- in general some days may leave people mentally overloaded by the end of the work day (evening), or even possibly before the day could end. This becomes a problem in any job field where long hours increase the chance of overworking, causing mental overload which then leads to further complications.

Grenze ID: 01.GIJET.10.2.263

Long term, being in a state of constant mental overload cause bad decision-making, fatigue, and stress to accumulate- which not just lead to sub-optimal performance in work, but may also affect general quality of life (i.e. people making terrible decisions that causes irreversible consequences), at times leading to physical complications. As such, it is important for working times to be managed in order to safeguard employees' health. One way to do this is to check if an employee is fit to work for the day by predicting what mental workload index in the evening. If by the evening overload occurs, then employees can be determined as unfit for work on a particular day. Instead of having employees work based on set working hours under sub-optimal conditions, this approach will allow employees to work hours according to their current mental working state. It thus allows employees healthier hours whilst giving better performance- reducing chances of human error made in work.
A person's current mental working state can be analysed through their brain waves [3]. At present, it is widely recognised that neurophysiological measures such as Electroencephalography (EEG) offer the most accurate and reliable outcome as compared to other physiological indicators (skin/respiratory measures, bodily responses, etc.) because it captures brain activities in different wave forms and oscillations which represents a direct measure of mental workload [4, 5, 6]. Mental/cognitive overload has so far been indicated using the mental working load/cognitive load index, which is usually represented through alpha-to-theta and theta-to-alpha signal bands [7]. General methodologies would follow Borghini et al.'s [8] methods, where clusters of power spectral densities from either the frontal EEG signals or the parietal EEG signals are averaged. A ratio of the average power spectral densities will express the mental working index. An example of utilizing the theta-to-alpha ratio as mental working index is written in (1).

$$\frac{\theta}{\alpha} = \frac{avg(\forall e \in c_x - \theta)}{avg(\forall e \in c - \alpha)} \tag{1}$$

This research examines the cognitive state of individuals in the morning relative to the evening based on recorded and analysed EEG signals. By assessing a person's cognitive state in the morning, it aims to predict whether they may experience mental overload later in the day. Multilayer perceptron neural network is designed to forecast the evening mental workload index using high-level features extracted from alpha and theta signals recorded in the morning using CNN (convolutional neural network). This approach enables the identification of days when employees are likely to perform well, reducing the potential risks associated with suboptimal performance and lack of focus.
Hence our research proposes a groundwork that will enable employers to create a healthier work environment for its employees by simply measuring employees' EEG signals in the morning. Furthermore, methodologies presented in this paper can be implemented practically, enabled by the choice of device used for recording the EEG signals: the Muse Headband wearable. It is significant to us that this research not just delves into theoretical frameworks, but also on the tangible and practical usages of EEG technology that is beneficial for the general public and can be implemented to elevate current standards of living and organizational practices.

II. Literature Review

EEG was originally discovered as a neurologic and psychiatric tool by Hans Berger [9]. The most basic functional unit of the brain and the nervous system is the neuron: an individual nerve cell [10]. Anytime a neuron generates an impulse (which causes change in electric potential) an EEG is able to record this electrical activity produced by our brain; by measuring the difference in local electric potentials between two locations of the brain. EEG recording using BCI is a non-invasive method in examining physiological signals as electrodes are placed on the scalp and acquiesce signals [11].
Stressors impact the way in how our neurons communicate [12], and thus the experience in how we undergo varying workloads can be described by the changes in brain activity. The mental state, as seen with brain waves has five major frequency bands in which EEG results are evaluated [13]: α waves (8-13 Hz), β (13-30 Hz), γ (above 30 Hz), θ (4-8 Hz) and δ (0.5-4 Hz). By decomposing and evaluating the band waves in EEG signals it is thus possible for the BCI to identify and alert people of their current mental state. In this literature review, we try to observe the general processes and/or methods of the evaluation of mental working state, and point out comparisons/contribution done by our proposed system.
A work concerning the classification of working mental states by Hongquan Qu et al. [14] proposed the similarity of the brain signals recorded by the EEG to multi-source mixed signals. Instead of manually analyzing the recorded signals to discern appropriate features for classification, they utilized Independent Component Analysis to

preprocess the mixed signals before performing feature extraction and classification on the EEG's independent components. The energy features (power spectra energy based on frequency bands excluding gamma) for different loads were then tested on several classifiers; ultimately using Support Vector Machine (SVM) for its highest average accuracy. Results both with and without ocular artifacts [15] for the signal's independent components, in comparison to mixed EEG signals prove that classification accuracy is higher for extracted pure signals. This thus can be taken as a depiction of the importance of preprocessing of EEG signals. Despite that, low classification results of the experiment stems from the individuality of participants (internal load) as the measure of external load from given tasks leads to no further change in mental state. From here, the work provided an insight to preprocessing of signals. In the system we propose, signal processing is performed by the MUSE EEG device that is able to perform db10 wavelet transformation. This thus ensures that no artifacts are taken into account- and that sufficient signal preprocessing is carried out during data collection.

On the other hand, Anu Holm et al.'s work highlights both external and internal load on an individual's working state and focused on two specific frequencies which correlate to increasing workload demands [16, 17]: the parietal alpha waves, and frontal theta waves. Using Fourier Transform, their work calculated the EEG signals' power spectra from the frequency of the two bands for data and analyzed the P300 component of event-related potentials (ERPs) as it is related to the brain's processing capacity [18]. Frontal theta waves increased as the external task load and its difficulty increased, while the parietal alpha waves decreased. The work found that utilizing just one particular brain wave as a measure of change in workload was not adequate enough. Thus the power ratio of two brain waves (frontal theta to parietal alpha: theta Fz/alpha Pz) was tested for estimating brain load instead, and proved that the ratio better illustrated the changes in workload in comparison to utilizing individual features. The work also ensured that the theta Fz/alpha Pz ratio is capable of measuring workload changes affected by external or internal stressors. Looking into the ratio's effectiveness as a measure for internal load: lower power/frequency of EEG signals is associated with sleepiness/sleep-deprivation [19]. In the experiment of different sleep protocols, the theta Fz/alpha Pz ratio had increased with sleep restriction than without (which may indicate a decrease in alpha waves than usual due to sleep deprivation [20]). Referencing the observations from Anu Holm et al.'s work, hence our system would utilize this ratio as a quantitative measure of the mental working load, ensuring we take both external/internal loads of an individual into account. If a measure exists to quantify the current mental working state- it is possible to come up with a prediction based on this history. The novelty from our own work is thus to utilize this ratio for feature preparation (dividing extracted feature theta vectors by extracted feature alpha vectors), and for quantifying the forecasted mental working load index.

Another work regarding mental overload that we observed is from Yufeng Ke et al. [21]. Their work showed that an individual's EEG pattern differs from each other due to differing internal load, but also that EEG patterns are temporal and task specific. Classifiers also tend to do poorly when given multi-attribute tasks as training data often focused only on one type of task. Yufeng Ke et al.'s study thus challenges the difficulties of cross-task classification of mental workload by utilizing memory tasks. Our working memory has been shown to be a critical part of our multitasking ability, and this may also be a factor to consider when estimating mental workload as participants may have different capacities [22]. As such efforts of the study was thus mostly focused on generalizing the classifier to work on memory load, and on the mental workload caused by multi-attribute tasks. The model opted for was a regression model (SVM Regressor) was chosen, where signal processing including feature extraction was done with MATLAB. Data containing artifacts were rejected manually, and the power spectral density was calculated from 7 frequency band waves (additional waves include the split of beta waves into $\beta 1$ and $\beta 2$, while gamma waves are also split into two). After feature extraction, Recursive Feature Elimination (RFE) algorithm was also used to select the most salient subset of features, which produced better results than the subset with non-salient features. From this, we determined that feature extraction and selection of EEG signals play an important part in producing good results. An approach that we propose for the method of EEG feature extraction method is by utilizing the CNN. The CNN will not just perform feature extraction- but through training, also extract features are deemed as the best representation of the input data.

Based on the literature review, we can observe the general process of mental workload classification of: signal preprocessing, feature extraction of signals, quantification of mental working state, and finally classification of the state. With this general pipeline instead of classification, however, we will be performing forecasting of mental workload utilizing our proposed methodologies.

III. MOTIVATION

When the day starts early, by the time afternoon arrives- or after it, it is not uncommon to feel mentally exhausted. At times, no matter what task we try to do after the exhaustion hits we may either be more prone to mistakes, or accomplish these tasks with many errors. And so what if there was a way show that someone was in a mentally overloaded state? Furthermore, what if we can predict the occurrence of mental overload based on an individual's morning condition?

If someone is mentally overloaded by the evening, in workplaces organizations may be able to prevent their employees from accumulating too much stress, and being overworked. This method also has to be practical, without requiring the long setup that traditional EEG devices would use. If it were to succeed, work organizations can be altered to be more performance-based instead of using fixed workhours. This may in turn, lead to not just better efficiency and better results in accomplishing tasks- but also lead to better life conditions for anyone in the working field. Hence these were the thoughts that motivated, and sparked this research.

IV. DATA ANALYSIS

A. Signal Data Collection

Data collection was done by recording the EEG signals at morning and evening intervals. Wavelet transformation (db10) has been used as standard technique for EEG artifact removal. As such no additional signal processing techniques were used to clean the recorded signals. 600 data points recorded by the EEG device is equivalent to 1 minute in real time. Each data row recorded by the EEG has 4 columns, each recording signals (alpha, theta, gamma) at the left parietal, left frontal, right frontal, and right parietal part of the brain respectively.

Data was taken from six participants consisting of university lecturers and university staff. During the morning and the evening participants performed a brief series of psychological tests that increase their mental working load. These tasks include a cueing test (Fig. 1), backward corsi block tapping test (Fig. 2), and a multitask test (Fig. 3) taken and recorded consecutively, back-to-back.

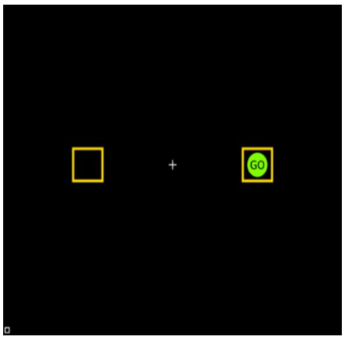

Figure 1. Cueing Test Figure

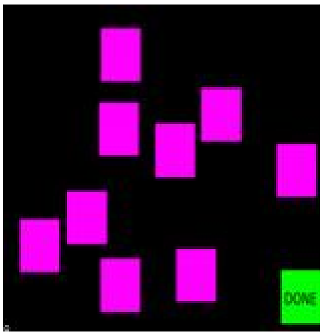

Figure 2. Backward Corsi Tapping Test

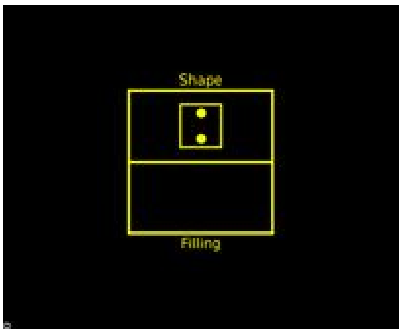

Figure 3. Multitasking Test

B. Signal Data Analysis

Based on the literature review, the left brain's frontal theta average power spectral density against the parietal alpha power spectral density is opted to quantify the mental working load index. The method utilized in this paper calculates working load index by squaring signal values to get the absolute power spectral density. For data analysis per minute interval, 600 theta and alpha absolute power values are then averaged. The mental working index per minute will thus be the average theta power, divided by the average alpha power. The mental working index per minute interval for each patient in the morning and in the evening are shown in Fig. 4 and Fig. 5 (data points are rounded down to the last minute).

These graphs show how the mental working index changes as participants take the test. As data was recorded continuously, it can be observed that there is some increase in mental load during the test for some participants- which may indicate that some participants encountered more difficulty in certain parts of the tests than others. By the last minute of the tests, most participants ended up having a higher mental working load index than the starting minute (participant 1, 2, 3, 6). It can be observed that most workload will cause an increase in the mental working load index.

Calculated index per minute are then averaged, where a line is drawn to see the increase/decrease between average index in the morning and evening. Shown in Fig. 6, out of all 6 participants only 1 has a decrease in average mental working load index value during the evening. This decrease can also be observed in Fig. 4, and Fig. 5, where participant has a higher mental working index in the morning. The rest of the participants, however, have an increase in mental working load index in the evening.

Based on the graph plotted in Fig. 6, it is thereby inferred that there may be a linear relationship between the increase of working load from morning to evening (5 out of 6 people), where the rate of change (line angle) may differ due to personal dependencies- such as the faculty a lecturer is from, stress tolerance, or the amount of classes/work that the lecturer is managing on the day these data were recorded, etc. Hence, tackling it as a regression problem- a neural network model is used to forecast the mental working load index in the evening based on recorded signals in the morning.

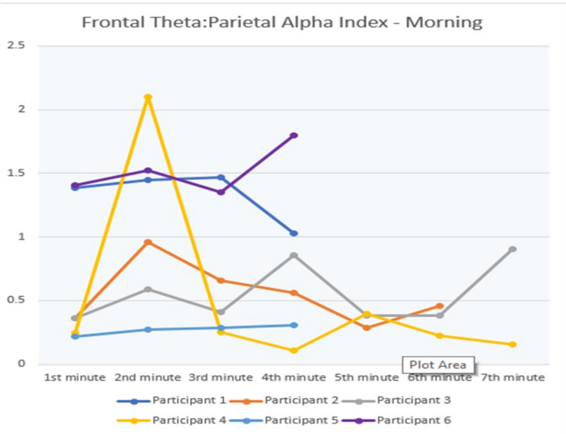

Figure 6. Mental Working Load Index/Minutes in the Morning

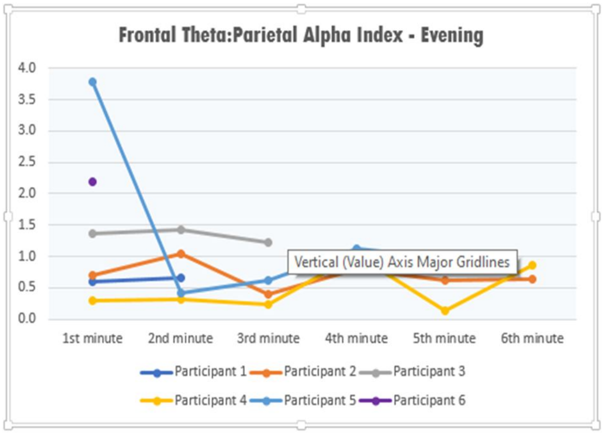

Figure 7. Mental Working Load Index/Minutes in the Evening

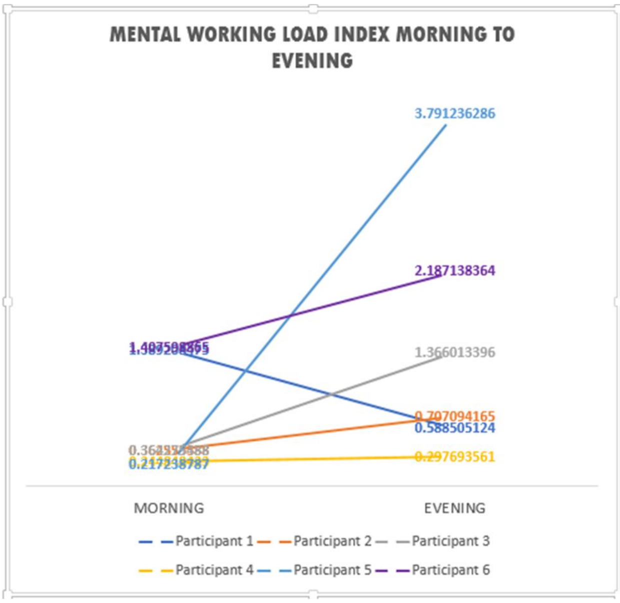

Figure 8. Mental Working Load Index/Minute in the Evening

V. SOLUTION METHODOLOGIES

A. Dataset Creation

The proposed model will predict the evening mental working index based on alpha and theta morning signals in the first minute (600 data points). However, the recorded signals will not directly be fed into the model. Instead, from the EEG signals recorded, numerical signal data points are first transformed into greyscale visual images [30]. Images are generated as a 4 by 4 matrix (represents 4 data rows and the 4 columns for each row). Image conversion is done for alpha and represents of each participant, resulting 150 images each for the alpha and theta signals. This signal-to-image processing is done using the method proposed in [30]. An example of the image created is shown in Fig. 7. The Y output and X features of the dataset of the model will thus center around the created images.

1) Target Output: Each image is created using 4 data point intervals. As such, the target output (Y) of the model will be the morning mental working load index per 4 data point intervals (during the first minute). The Y output mental working load index is calculated using the same steps for index calculation in the data analysis section of this paper (square to get absolute values, average the absolute power spectral densities, then divide theta power density averages by alpha power density averages).

2)Features: A convolutional network (CNN) is then designed for the feature extraction from the produced images. This novel method is proposed to obtain higher-level features of the signals, that cannot be obtained in the original numerical format. The architecture of the designed CNN is shown in Fig. 8.

Alpha and theta signals are trained separately on two identical CNN models (same architecture). For each participant, one model is trained using 150 visual images (first minute) of the alpha signal and the other model using the participant's theta signal data. The output of both CNN (1x4) vectors represents higher- level features of the alpha and theta EEG signals.

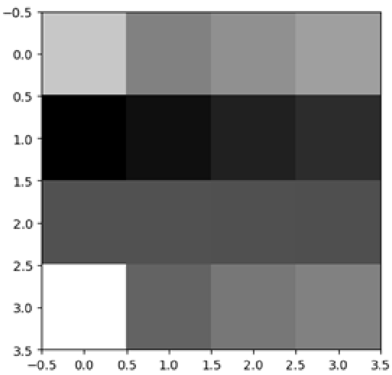

Figure 7. A Generated Visual Image for Alpha Signal (Representing 4 Data Points)

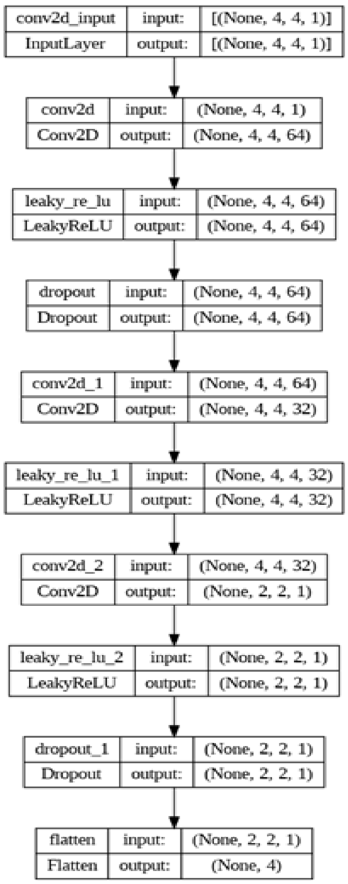

Figure 8. CNN (Feature Extractor) Architecture

	X1	X2	X3	X4	0
0	-0.012774	-0.024059	-0.044045	-0.030288	0.099145
1	0.080998	0.037797	0.075770	0.050234	0.099145
2	0.015725	0.009150	0.000616	0.004494	0.099145
3	0.010466	0.001967	-0.011205	0.000451	0.099145
4	-0.000488	-0.006619	-0.018012	-0.005441	0.099145
...	...	...	...	...	...
895	0.269790	0.258637	0.175288	0.266010	-0.360362
896	0.242184	0.498559	0.169837	0.281601	-0.360362
897	0.220664	0.946472	0.112982	0.150587	-0.360362
898	0.143460	0.168826	0.033462	0.085206	-0.360362
899	0.222031	0.457170	0.107062	0.172781	-0.360362

Figure 9. Compiled Created Dataset

After feature extraction by CNNs, the extracted feature vectors of morning theta signal are divided by the corresponding vectors of the morning alpha signal to get 4 processed features (X1, X2, X3, X4). These new feature vectors thus quantifies the mental working index for the 4 columns of the morning recorded signals. The newly created features for all 6 participants are compiled together (Fig. 9) with the corresponding evening mental working index values (calculated from recorded alpha and theta signals of participants in the evening) for the forecasting dataset with a total of 900 data points. A distinction we would like to note is that the CNN’s target output are based on the morning signals, while the desired target output for the neural network for forecasting are based on the evening signals (prediction of evening mental working load index).

B. Standardization

After creation of the initial dataset, data is standardized before model training (since this dataset consists of data from different participants). The features of the dataset and the output mental working index is standardized respectively. The features are standardized to remove personal dependencies of the data between the participants, meanwhile the output is chosen to be scaled as there is an extreme outlier with a value of 1004, which causes a huge range in output values (histogram plot as seen in Fig. 10). This huge range may cause a problem during training of the model. However, it is impossible to take out these outliers as in any data regarding human behavior, these outliers may just represent an extreme case (it may represent that a person is under extreme working load in comparison to the average) [23].

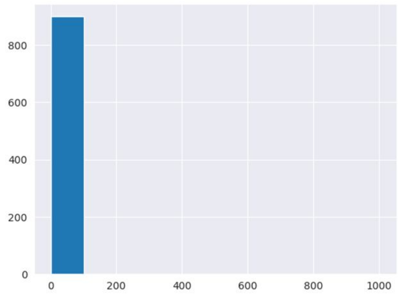

Figure 10. Histogram of Y Output Values

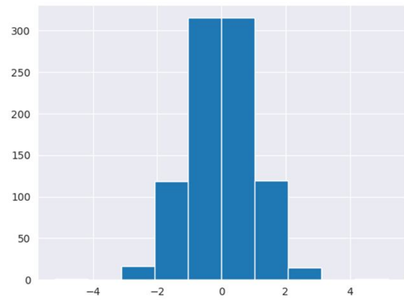

Figure 11. Histogram of Scaled Y Output Values

	X1	X2	X3	X4	0
0	-0.012774	-0.024059	-0.044045	-0.030288	0.099145
1	0.080998	0.037797	0.075770	0.050234	0.099145
2	0.015725	0.009150	0.000616	0.004494	0.099145
3	0.010466	0.001967	-0.011205	0.000451	0.099145
4	-0.000488	-0.006619	-0.018012	-0.005441	0.099145
...	...	...	...	...	...
895	0.269790	0.258637	0.175288	0.266010	-0.360362
896	0.242184	0.498559	0.169837	0.281601	-0.360362
897	0.220664	0.946472	0.112982	0.150587	-0.360362
898	0.143460	0.168826	0.033462	0.085206	-0.360362
899	0.222031	0.457170	0.107062	0.172781	-0.360362

Figure 12. Standardized Dataset

The X features of our dataset was standardized using the Yeo-Johnson scaler [24], whereas our output (Y) was scaled using the Quantile Transformer [25]. The quantile transformer is utilized as to not just deal with the presence of outliers, but also to transform the distribution into a gaussian one.

The Quantile Transformer will thus scale the output to present a gaussian distribution in order to increase performance the regression model built (as to aid in the assumption/learning the model has towards the data) [26]. The histogram of the scaled outputs are as seen in Fig. 11. After standardization, the final dataset for forecast model training is as shown in Fig. 12.

C. Neural Network (Forecasting) and System Architecture

For forecasting, we chose a multilayer perceptron neural network as our model. The architecture of the network is shown in Fig. 13. All dense layers before the output layer utilizes the ReLU activation function, mean squared error loss and an AdaMax [27] optimizer with a learning rate of 0.2 are used. The training and test set of the standardized dataset is created, with an 8:2 data split- where data points for the split are shuffled. The model is thus trained for around 4000 epochs, with a batch size of 30.

With the network model for forecasting defined, we then define the entire proposed system's structure. For day-to-day implementation, the entire system will perform as described by firstly recording participant EEG signal for the first minute (600 data points)- where task tests may be provided accordingly. It is then followed by the conversion of alpha and theta EEG signals to 4 by 4 greyscale images to produce 150 alpha and 150 theta images. Calculation of recorded morning mental working load index per 4 data point intervals is then done for the alpha and theta signal each, which will be the Y output for the CNN feature extractor. Meanwhile, the X features for the CNNs are the created greyscale images. Then, separate feature extraction of alpha and theta images by two identical CNNs is done. A new dataset is then created by dividing the extracted theta feature vectors with alpha feature vectors of the CNN (here we note that after calculation, the outputs of the CNN will become the feature inputs for the prediction model). This new dataset will then be standardized, before finally passing it through the trained forecasting neural network to obtain the mental working load index prediction.

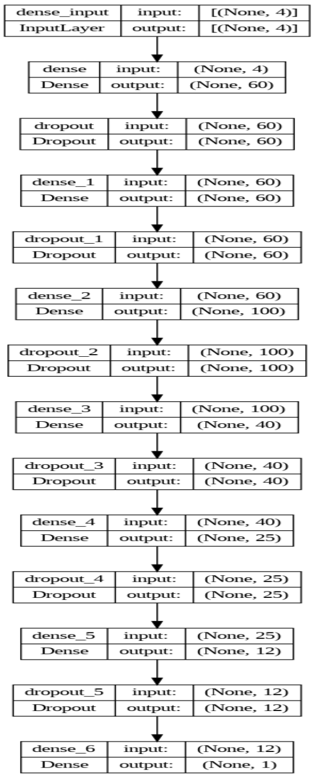

Figure 13. Regression Model Architecture

VI. RESULTS DISCUSSION

Few methods including the K-fold cross validation model to calculate the R^2 score are used for the model validation. 6 folds were chosen for cross validation as the data originally came from 6 participants. From cross validation, an R^2 squared score of approximately 27% is obtained. The lower variance may be caused by the presence of outliers/unpredictability in recording human behavior- in this case the mental working load index [28]. Due to this, results of the model's goodness of fit are also measured by plotting scatter plots of the predicted points and the actual target output together (x axis is just index of the data). This is done to see the difference between predicted and actual output. There are two models predicting test data: the non-cross validated model, and the cross-validated model. The real (non-scaled) forecasting results for the two models are shown in Fig. 14. The scaled results for the non-cross validated and the cross validated model are shown in Fig. 15 and Fig. 16 respectively., while the real (non-scaled) value results of the non-cross validated model and the cross-validated model are shown in Fig. 17 and Fig. 18 respectively.

The cross validated model is able to predict a wider range of values (higher maximum mental working load index and also lower minimum mental working load index) than the non-cross validated model (seen in Fig. 14 and Fig. 16). Moreover, the cross validated model also appear to predict more values that are closer to the actual target output. From this it can be concluded that the cross-validated model performs better than the non-cross validated model. However, it can be seen that for both models, there is still difficulty in accurately predicting indexes- where some predicted values go far below/above the target output.

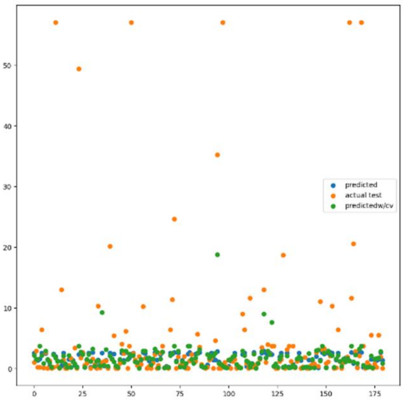

Figure 14. Models output (non-scaled data)

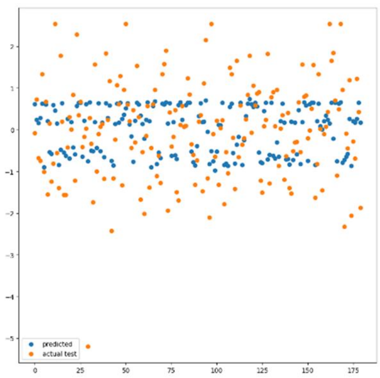

Figure 15. Scaled non-Cross Validated Model Output

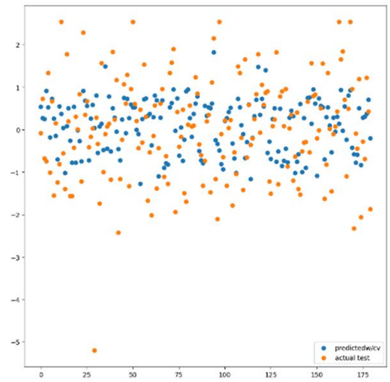

Figure 16. Scaled Cross Validated Model Output

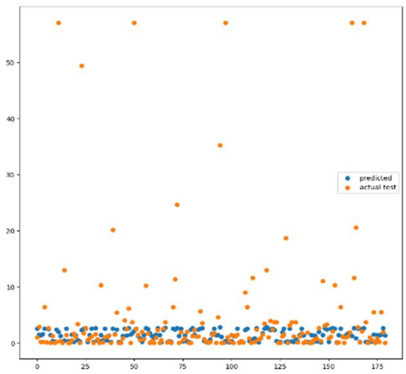

Figure 17. non-Cross Validated Model

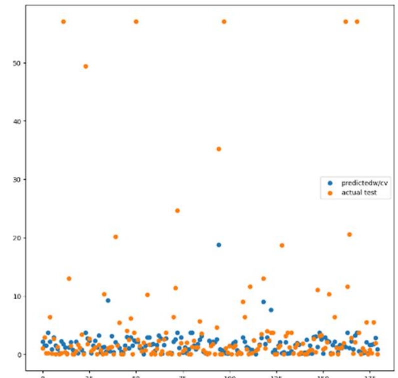

Figure 18. Cross Validated Model

Residual plots are also used to further observe the goodness of fit of the model created. The residual plot (Fig. 19) is plotted for the cross validated model, as it has been determined to produce better results, and is the final model selected for predictions. From the residual plot we can observe: model does not exhibit heteroscedasticity, has no clear patterns/shape, distributed quite symmetrically, and has a clear outlier.

Having no clear patterns indicate that our model is suitable as it does not indicate the presence of a non-linear relationship [29]. The observations indicate that the goodness of fit of the regression model with the data is acceptable. However, the outlier may become a point of discussion. This outlier can indicate that the created model is still not as accurate as desired, but it can also be argued that since the model is used to predict mental working load index (part of human behavior), outliers can be deemed as valid data and not an error. Thereby although improvements may still be made, observations on the scatter and residual plots of the model indicate that the built model using extracted higher-level features of EEG signals is viable.

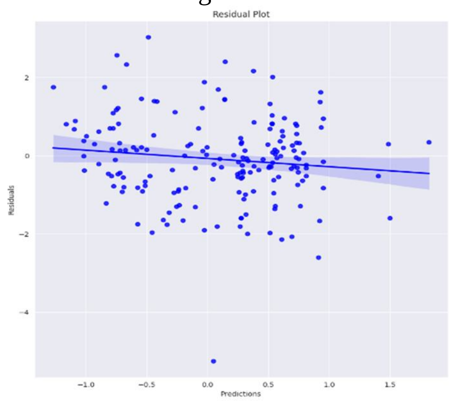

Figure 19. Residual Plot (Cross Validated Model)

VI. CONCLUSION

A practical implementation of the forecasting of mental workload index is thus proposed. Utilizing EEG measuring wearables, a multilayer perceptron neural network with linear activation function in output layer is used to forecast evening mental working load index as a linear relationship between morning and evening mental working load index is presumed. Model features are designed by extracting higher-level features from images that represents recorded EEG signals. Our research presents the methodologies utilized, and its implementation as key novelties. Further improvements to the model can be attributed to the amount of data used. Future works require more participants to increase the model's goodness of fit and predictive ability data.

In order to determine whether the predicted mental working load index by the model indicates if a person will be mentally overloaded by the evening, a psychological analysis may be conducted to determine an index threshold that indicates whether a person is mentally overloaded or not. With the establishment of an appropriate threshold through psychological tests, this approach to forecast mental workload index can effectively determine an individual's readiness for the day, thereby averting instances of overworking among employees. Although this paper utilizes data from university lecturers/staff, this proposed method still serves as a baseline for a multitude of occupations. Nevertheless, the threshold indicating mental overload may differ from job to job, and various factors should also be considered when creating the threshold for the predictions.

REFERENCES

[1] T. B. Sheridan and H. G. Stassen, "Definitions, Models and Measures of Human Workload," Mental Workload, pp. 219–233, 1979.

[2] C. D. Wickens, "Multiple Resources and Mental Workload," Human Factors: The Journal of the Human Factors and Ergonomics Society, vol. 50, no. 3, pp. 449–455, 2008.

[3] P. A. Abhang, B. W. Gawali, and S. C. Mehrotra, Introduction to EEG- and Speech-Based Emotion Recognition. Amsterdam: Elsevier, 2016.

[4] H. Ayaz et al., "Optical Brain Monitoring for Operator Training and Mental Workload Assessment," NeuroImage, vol. 59, no. 1, pp. 36–47, January 2012.

[5] B. Cheng et al., "Measuring and Computing Cognitive Statuses of Construction Workers based on Electroencephalogram: A Critical Review," IEEE Transactions on Computational Social Systems, vol. 9, no. 6, pp. 1644–1659, 2022.

[6] M. A. Hogervorst, A.-M. Brouwer, and J. B. van Erp, "Combining and Comparing EEG, Peripheral Physiology and Eye-related Measures for the Assessment of Mental Workload," Frontiers in Neuroscience, vol. 8, 2014.

[7] B. Raufi and L. Longo, "An Evaluation of the EEG Alpha-to-Theta and Theta-to-Alpha Band Ratios as Indexes of Mental WorkloadAn evaluation of the EEG alpha-to-theta and theta-to-alpha band ratios as indexes of mental workload," Frontiers in Neuroinformatics, vol. 16, May 2022.

[8] G. Borghini et al., “Avionic Technology Testing by Using a Cognitive Neurometric Index: A study with Professional Helicopter Pilots,” 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2015.

[9] M. Tudor, L. Tudor, and K. I. Tudor, “Hans Berger (1873-1941)—the history of electroencephalography,” Acta Med Croatica, vol. 59, no. 4, pp. 307-313, February, 2005.

[10] M. F. Bear, B. W. Connors, and M. A. Paradiso, Neuroscience: Exploring The Brain. USA: Wolters Kluwer, 2016.

[11] Brunner, C, et al., “BNCI Horizon 2020: Towards a roadmap for the BCI community,” Brain-Comput. Interfaces, vol. 2, pp. 1–10, 2015.

[12] A. Caldwell, “The Neuroscience of Stress,” brainfacts.org, Jun. 19, 2018. [Online]. Available: https://www.brainfacts.org/thinking-sensing-and-behaving/emotions-stress-and-anxiety/2018/the-neuroscience-of-stress-061918. [Accessed: Nov. 29, 2023].

[13] Z. Koudelková and M. Strmiska, “Introduction to the identification of brain waves based on their frequency,” MATEC Web of Conferences, vol. 210, 2018.

[14] H. Qu, et al., “Mental Workload Classification Method Based on EEG Independent Component Features,” Applied Sciences, vol.10, April 2020.

[15] M. Sazgar and M. G. Young, Absolute Epilepsy and EEG Rotation Review. Switzerland: Springer, 2019.

[16] Holm, A., Lukander, K., Korpela, J., Sallinen, M., and Müller, K.M.I., “Estimating brain load from the EEG”, TheScientificWorldJOURNAL vol. 9, pp. 639–651, 2009.

[17] Brookings, J.B., Wilson, G.F., and Swain, C.R., “Psychophysiological Responses to Changes in Workload During Simulated Air Traffic control,” Biol. Psychol. vol. 42, pp. 361–377, 1996.

[18] Kok, A, “On the utility of P3 amplitude as a measure of processing capacity,” Psychophysiology, vol. 38, pp. 557–577, 2001.

[19] H. Landolt et al., “Zolpidem and Sleep Deprivation: Different Effect on EEG Power Spectra,” Journal of Sleep Research, vol. 9, no. 2, pp. 175–183, June 2000.

[20] “NIOSH Training for Nurses on Shift Work and Long Work Hours,” cdc.gov, 2022. [Online]. Available: https://www.cdc.gov/niosh/work-hour-training-for-nurses/longhours/mod2/11.html. [Accessed: Nov. 29, 2023].

[21] Y. Ke, “An EEG-based mental workload estimator trained on working memory task can work well under simulated multi-attribute task,” Frontiers in Human Neuroscience, vol. 8, no. 703, September 2014.

[22] T. S. Redick, “On the Relation of Working Memory and Multitasking: Memory Span and Synthetic Work Performance,” Journal of Applied Research in Memory and Cognition, vol. 5, no. 4, pp. 401-409, December 2016.

[23] R. Parasuraman and P. A. Hancock, “Adaptive Control of Mental Workload,” Stress, Workload, and Fatigue, pp. 305–320, 2000.

[24] K. Yeo and R. A. Johnson, “A New Family of Power Transformations to Improve Normality or Symmetry,” Biometrika, vol. 87, no. 4, pp. 954–959, December 2000.

[25] Dancker, “A brief introduction to Feature Scaling,” Medium, Oct. 4, 2022. [Online]. Available: https://medium.com/@jodancker/a-brief-introduction-to-feature-scaling-e396356937b8. [Accessed: Nov. 29, 2023].

[26] A. Barai, “Normal Distribution and Machine Learning,” Medium, Nov. 20, 2020. [Online]. Available: https://medium.com/analytics-vidhya/normal-distribution-and-machine-learning-ec9d3ca05070. [Accessed: Nov. 29, 2023).

[27] D. P. Kingma, and J. L. Ba, “Adam: A Method for Stochastic Optimization,” Proceedings of the 3rd International Conference on Learning Representations, 2015.

[28] A. Gulati, “How to Interpret R Squared and Goodness of Fit in Regression Analysis,” knowledgehut, Sep. 14, 2023. [Online]. Available: https://www.knowledgehut.com/blog/data-science/interpret-r-squared-and-goodness-fit-regression-analysis. [Accessed: Nov. 29, 2023].

[29] “Interpreting Residual Plots to Improve Your Regression,” Qualtrics. [Online]. Available: https://www.qualtrics.com/support/stats-iq/analyses/regression-guides/interpreting-residual-plots-improve-regression/. [Accessed: Nov. 29, 2023].