# EEG-based Mental Workload Level Estimation using Deep Learning Models

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## SUMMARY

Deep learning-based approaches have recently received much attention and managed to accurately capture variance characteristics in the Electroencephalography (EEG) signals. In this paper, we aim to classify the subject's mental workload (MWL) level from EEG signal by using deep learning models named Stacked Gated Recurrent Unit (GRU), Bidirectional GRU (BGRU), BGRU-GRU, Stacked Long-Short Term Memory (LSTM), Bidirectional LSTM (BLSTM), BLSTM-LSTM and Convolutional Neural Network (CNN). The classification was performed on a publicly available mental workload dataset, STEW. Our encouraging results show the potential of deep learning models for MWL level detection.

## KEYWORDS

EEG, Deep Learning, Mental Workload Classification

### Introduction

Mental workload (MWL) has been considered as a crucial factor for underlying human performance, particularly in a complex working environment, since it relates to task performance, vigilance, situation awareness, and human capability to handle emergency events (Fallahi et al., 2016). Therefore, it is essential to capture this phenomenon in real-time. In the Neuroergonomics area, researchers have been tackled this issue by employing neurophysiological metrics to evaluate brain functions in response to work (Mehta and Parasuraman, 2013). EEG is one of the most widely used neurophysiological signals for indicating a subject's brain electrical activity in response to cognitive stimuli and to predict the MWL status effectively (van Erp et al., 2015). However, decoding MWL levels from EEG signals is a difficult task. Recently, machine learning techniques have been received much attention to capture variance characteristics in the EEG signals and classify MWL levels accurately (Jeong et al., 2019).

In this paper, we aim to classify the subject's MWL levels from EEG signals, using an available dataset named STEW (Lim et al., 2018). The EEG signals were collected from 48 subjects (all males) via 14 electrodes, sampled at 128 Hz. The participants were asked to perform the Simultaneous Capacity (SIMKAP) multitasking activity. The signals have been recorded in the resting state and the working state. During resting state, subjects sit on the chair for 3 min with their EEG being recorded. Then, in the testing state, subjects completed a SIMKAP task, and only the final 3 min of the recording was used for analysis. After each segment of the experiment, subjects also estimate their workload status using subjective measures, i.e. self-report questionnaires on a one to nine scale. The nine-point rating scale has been further categorised into three MWL levels; 1-3 as low, 4-6 as moderate and 7-9 as high. To perform classification, we applied several deep learning models as follows: stacked GRU, BGRU, BGRU-GRU, stacked LSTM, BLSTM, BLSTM-LSTM (Nagabushanam et al., 2019) and CNN model (Qayyum et al., 2018).

## Data Preprocessing

Since the EEG signals can be easily contaminated by undesired noise (artefact), an automatic independent component analysis based on ADJUST (ICA-ADJUST) (Mognon et al., 2011) was performed to remove the artefacts components. This algorithm has been proved to provide the most effect on model performance in this dataset (Kingphai and Moshfeghi, 2021a).

## Feature Engineering

In the machine learning area, feature extraction can help us to save a huge amount of time and resource from unnecessary calculation features (Murakami and Kumar, 1982). Therefore, to capture only relevant EEG signal characteristics, we perform feature extraction by computing a set of features that can be broadly classified into four groups: frequency domain, time domain, non-linear domain and linear domain. In the frequency domain, we calculated signal power for each channel at five well-known Power Spectral Density bands, which are Delta (0.5–4 Hz) Theta (4–8 Hz), Alpha (8–12 Hz), Beta (12–30 Hz) and Gamma (30–100 Hz). While Mean, Standard deviation, Skewness and Kurtosis were extracted for time-domain features, the Autoregressive coefficient (AR) with p is set at six (Zhang et al., 2017) was calculated in the linear domain. Finally, an approximate entropy (ApEn) and Hurst exponent (H) is treated as non-linear features. In this study, we took a sliding window with a length of 512 sampling points (4 sec) and a shift of 128 sampling points (1 sec) (Lim et al., 2018). It means that each feature was calculated by using 512 samples, with 384 of them overlapped. For the purpose of extensive usage in the previous study (Chakladar et al., 2020), we then choose PSD alpha, PSD theta, skewness, kurtosis, ApEn, and H features as the optimised feature set of the STEW dataset in this scenario. Eventually, this has led us to have 84 ($14 \times 6$) features extracted from all 14 channels. Additionally, we also performed feature standardisation before further analysis by Fscaled (Buscher et al., 2012).

## Classification and Model evaluation

In this study, we performed the classification in two tasks; Task one: resting vs working state and Task two: low vs moderate vs high MWL level. As the EEG signals have been measured over a period of time so, the signal can be considered as time-series data. Consequently, we trained our deep learning models using a 5-fold time-series cross-validation (Kingphai and Moshfeghi, 2021b).

Table 1: The accuracy of the deep learning models' prediction of MWL level classification

| Task | Stacked GRU | BGRU | BGRU-GRU | Stacked LSTM | BLSTM | BLSTM-LSTM | CNN |
|---|---|---|---|---|---|---|---|
| one | 93.403 | 90.833 | 94.306 | 94.375 | 91.181 | 94.753 | 91.250 |
| two | 82.060 | 79.491 | 82.962 | 83.032 | 79.838 | 77.754 | 79.907 |

## Results and Conclusions

Table 1 shows the accuracy of our models. Our findings reveal that in Task one, BLSTM-LSTM provides the highest accuracy of 94.753%. While in Task two, the BGRU-GRU is the best model providing a classification accuracy of 83.032%. We also observed that the bidirectional model did not contribute much to the classification task; this might be because of the training strategy of the bidirectional model. To train such a model, we have to input data from both the past and future to feed the model in forwarding and backward directions (Schuster and Paliwal, 1997). However, we do not have a future value of time series for the present prediction time in real-life scenarios. Hence, as a future study, we aim to tackle the problem of how to perform a bidirectional model in time-series data. Our positive findings contribute towards better MWL level detection models from EEG signals in real-time and, in turn, enhance human performance in their tasks.

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