Deep Learning-based Method for Jointly Identifying Human Emotions and Concentration Levels using mEEG

Mona Chen*
yuec9@illinois.edu
University of Illinois, Uraban-Champaign

Jiayun Yan*
jiayuny3@illinois.edu
University of Illinois, Uraban-Champaign

Abstract

Our work aims to identify a mechanism for detecting human emotions and concentration levels using EEG signals. We utilized a commercial and portable Muse 2 headband with four EEG channels (TP9, AF7, AF8, TP10) as opposed to the research-grade headset that is typically used for EEG data acquisition. Using mobile EEG (mEEG) inputs, we present a deep learning strategy for concurrently detecting emotions and concentration levels. With an experiment on eight participants, we were able to achieve an accuracy of over 90%.

ACM Reference Format:
Mona Chen and Jiayun Yan. 2023. Deep Learning-based Method for Jointly Identifying Human Emotions and Concentration Levels using mEEG.

1 Introduction

With the continuous development of the times, the pace of people's life and work is accelerating. Maintaining relatively decent work/study efficiency is critical, but sustained attention or long-term cognitive activity can lead to mental fatigue and reduced concentration levels[6]. Any cognitive-motor task, including switching [8], flanker compatibility [16], and visual attention [6], can result in a gradual lowering of reaction times with time. A straightforward illustration is long-distance auto driving; Saroj and Ashley [14] note that mental weariness is a substantial danger in the transportation sector and considerably affects traffic fatalities. Nevertheless, a severe issue is that it is difficult to assess cognitive states [13] appropriately. It is challenging for individuals to recognize when they are losing attention since it is a lengthy and slow cumulative process, which makes self-reporting particularly troublesome [21].

Consequently, a portable, systematic method for detecting human concentration levels in a timely manner is required. In an effort to address this issue, researchers attempt to utilize electroencephalogram (EEG) signals. EEG is a spontaneous physiological signal that can objectively reflect mental states and brain dynamics in humans [3]. Gianluca et al. [7] noted that EEG could be used to quantify and monitor cognitive fatigue; moreover, Saroj and Ashley [14] assert that significant EEG changes occur during mental fatigue, with delta wave and theta wave activities significantly increasing.

*Both authors contributed equally to this research.

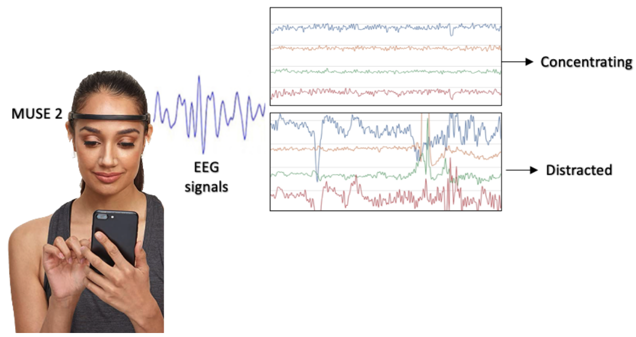

Figure 1. The concept diagram of our system

However, traditional EEG recording methods require research-grade equipment, such as actiCHamp [2] that is neither portable nor affordable for the general public. The emergence of commercial EEG headgear such as MUSE 2 [4] (shown in Figure 2) has resulted in the development of novel approaches to investigate numerous problems that cannot be resolved using conventional methods. Krigolson et al. [13] reports that the ERP data they obtained using the Muse 2 EEG headgear was comparable to the ERPs they obtained using "research grade" equipment. In addition, Aditi et al. [19] successfully recognized human emotions using an LSTM deep learning model based on mEEG, claiming that it is more accurate than the current state-of-the-art approaches.

Therefore, this paper presents a deep learning strategy for concurrently detecting emotions and concentration levels using mEEG signals. Figure 1 depicts an overview diagram of our proposed system. This paper contributes primarily in three ways: portability, joint categorization, and ground truth accuracy. First, the portable EEG headband MUSE 2 makes mental state recognition available to a wider audience. In addition, we present a system for classifying attentiveness and emotions simultaneously. Finally, we employ a number of strategies to improve the accuracy of the ground truth, such as asking individuals to describe and rate the strength of their emotions alongside a questionnaire. Among the various

Figure 2. MUSE 2 product

obstacles we encounter is how to deal with limited and noisy data. For the purpose of training our deep neural network, we require a large amount of EEG data; however, the majority of existing datasets, such as SEED (62-channel) [1], and DEAP (32-channel) [12], were collected using lab-based full-head EEG caps, resulting in data mismatch when compared to the MUSE 2 headband, which has only four channels. We addressed this issue by carefully designing and controlling our experiment and enhancing ground truth accuracy, allowing us to train the model with a manageable amount of data. In addition, compared to "research grade" headphones for EEG signal capture, MUSE 2 tends to be noisier and contain less relevant information. With a controlled environment and sufficient data preprocessing, however, we were able to obtain relevant data.

As for implementation, we used the MUSE 2 headset to acquire EEG signals from eight subjects while they played a video game with and without distraction (concentrating vs. distracted). We used the EEG data as our ground truth accordingly. We developed a CNN model with 75% training and the remainder for testing, achieving an accuracy of over 90%. Consequently, this method will give a more thorough measurement of mental states and will be suitable for the development of a system that proposes effective solutions for inattention.

2 Related Work

Researchers have recently created numerous models for identifying human emotions and mental states from EEG data. Additionally, there are two standard methods for acquiring EEG signals: the classic method uses a research-grade complete headset, while the alternative method uses commodity devices like MUSE. The related work could be divided into three categories as follows:

2.1 Emotion classifications using lab grade EEG

Wang and Nie (2014) [22] introduced an effective feature smoothing technique for eliminating background noise unrelated to the emotion task. They find that the power spectrum feature is superior to the other two types of features, and a linear dynamic system-based feature smoothing method can significantly increase emotion classification accuracy. Besides, Duan et al. (2013) [10] presented differential entropy as a novel practical EEG feature that could convey emotional state features. The average classification accuracies for EEG data gathered in their experiment utilizing the features Differential entropy, Differential asymmetry, Rational asymmetry, and Energy Spectrum are 84.22%, 80.96%, 83.28%, and 76.52%, respectively. This data suggests that DE is superior to ES for emotion recognition.

The portability and ground truth accuracy of these two research are, however, limited. Both Wang and Nie (2014) [22] and Duan et al. (2013) [10] collected EEG data using laboratory-grade equipment, making it challenging to extend their findings to real-world settings. In addition, the two researchers created a movie induction experiment to assess the effectiveness and collected EEG data from the subjects. However, they all presume that a specific piece will elicit the corresponding emotion, despite the fact that the actual consequence may differ from person to person, hence weakening the accuracy of their ground truth.

2.2 Emotion classifications using mEEG

Sakalle and Tomar developed two systems for classifying emotions based on EEG data from portable EEG devices in their work in 2020 [19] and 2021 [20]. In 2020, they designed an LSTM-based deep learning model that was employed for classification following feature extraction by EMD. It outperformed current state-of-the-art techniques on accuracy [19]. According to the analysis, the classification accuracy of the LSTM-based deep learning model for the four classes of emotions is 83.12%, 86.94%, 91.67%, and 94.12% for cross-validations that are 50-50, 60-40, 70-30, and 10-fold.

For the research in 2021, Sakalle and Tomar [20] evaluate and compare the efficacy of Multilayer Perceptron (MLP), Support Vector Machine (SVM), Genetic Programming (GP), and Hybrid Mutation-based Genetic Programming (HMGP) in detecting emotions based on brainwaves. Their experimental results show that the proposed portable brainwave-based emotion detection model provides 84.44% classification accuracy for two classes using the HMGP classifier.

Utilizing commercial EEG headsets has increased the portability of these two studies compared to the previous subsection; however, the accuracy of ground truth remains to be enhanced for the same reason stated previously. This provides an opportunity to improve the accuracy of the ground truth data used in their research.

2.3 Concentration levels using mEEG

The mEEG signal has likewise been applied in studies to detect attention levels. In order to assess the subjects' EEG signals when attentive and inattentive, Liu and Chiang (2013) [15] designed two scenarios involving an English exam were

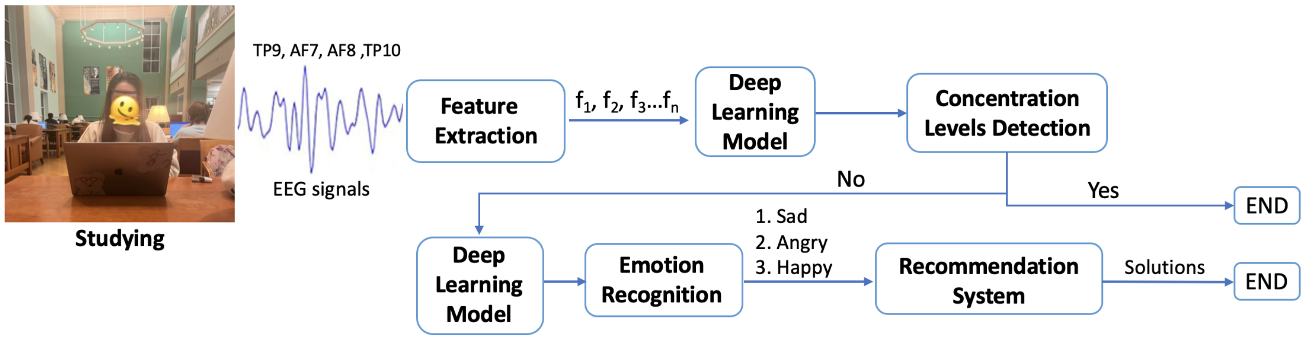

Figure 3. Overall flow chart of the application.

created, with the latter containing distraction to cause distracted behavior. An SVM classifier was utilized to determine if students were paying attention based on EEG data from portable sensors. The method suggested in this paper has a classification accuracy of up to 76.82%, according to the evaluation results.

Purnamasari and Junika (2019) [18] use a non-invasive brain-computer interface (BCI) device is used to collect the EEG signals, which are then analyzed using frequency-based feature extraction and an RBF kernel SVM classifier. The power spectral density (PSD) from the Fast Fourier Transform (FFT) and the energy from the Discrete Wavelet Transform (DWT) were two feature extraction methods that were compared in the paper. The accuracy of the system using DWT is higher by 18% compared to the system using FFT, making it a superior option for feature extraction than FFT. In identifying human concentration, SVM with RBF kernel as the classifier showed strong performance with 91% accuracy.

These two papers have enhanced the accuracy of the ground truth and achieved portability, but there is currently no mechanism for identifying emotions and attentiveness simultaneously. As a result, in this study, we introduce the joint classification of emotions and degrees of concentration utilizing a deep learning model with a portable, quick, and lightweight 4-channel EEG device. Table 1 shows the comparison of multiple different approaches for emotion and concentration recognition. Our system outperforms competing methods in terms of portability, joint classification, and ground truth precision. Additionally, by suggesting an EEG-based framework, manipulating subjective measurements acquired to study emotions as well as direct physical responses can be avoided.

3 System Overview

Three primary components comprise the working system: input EEG signals, feature extraction, and a deep learning model. Figure 3 demonstrates the ideal flowchart. The input EEG data are collected using the portable EEG headband

Table 1. Table of comparison of related works with the metric of our proposal.

Approach	Portability	Joint Classification	Ground Truth Accuracy
Emotion Classification using Lab grade EEG	N [22] N [10]	N [22] N [10]	N [22] N [10]
Emotion Classification using mEEG	Y [19] Y[20]	N [19] N [20]	N [19] N [20]
Concentrate level detection using mEEG	Y[15] Y [18]	N [15] N [18]	N [15] N [18]
Our approach	Y	Y	Y

MUSE 2. As depicted in Figure 4, it has four dry electrodes positioned at AF7, AF8, TP9, and TP10 according to the 10–20 international electrode placement standard. Then, using a sliding window technique, we extract statistical features such as Max, Min, and Derivatives, Log-covariance features, Shannon entropy, and Log-energy entropy. Based on extracted features, the deep learning model employs a Convolutional Neural Network (CNN) model-based network to classify emotions and concentration levels.

4 Proposed Approach

This section describes the core modules for deep learning network-based concentration and emotion recognition. It begins with a discussion of the dataset acquisition, including subjects and experimental procedures, followed by a detailed description of feature extraction and classification model training. The first phase is collecting EEG data for identifying concentration levels, and the second for emotion classifications.

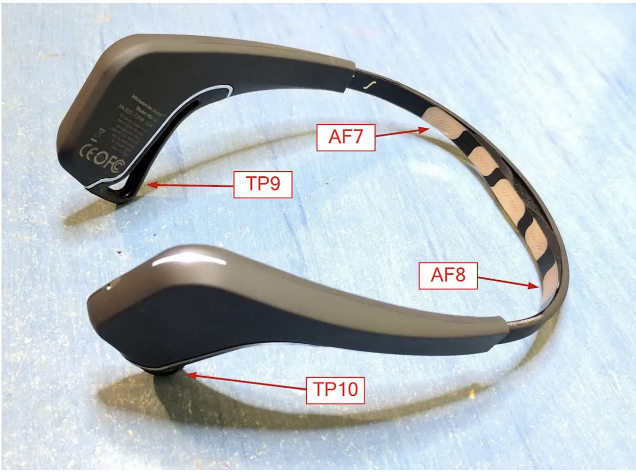

Figure 4. Electrodes on MUSE 2

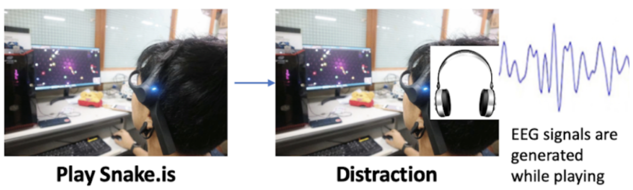

Figure 5. EEG data acquisition for different concentration levels

4.1 Subjects

Eight healthy subjects (4 males and 4 females) pool was considered for this research work. Participants have participated voluntarily in this research study. All participants are college students aged 20-30 years.

4.2 Concentration Dataset

Participants wore the MUSE 2 and faced the laptop screen at the optimal distance during data collection (50–70 cm). The device is depicted in Figure 2, and the experiment is shown in Figure 5. The computer screen would display a game called "Snake.is." The participants were then given six minutes to play the game. The signal will be recorded between the third and fourth minutes. The initial minutes will not be recorded because they are considered activation time. After completing the first experiment, participants rested for five minutes in a comfortable position and drank a glass of water before proceeding to the next phase.

In the second experiment, individuals play the same game under identical conditions but with a distraction. The distraction is provided by exposing participants to some low-tempo. The earphones were used to hear this music. The experiment was done and recorded in the same manner as prior studies.

4.3 Emotion Dataset

Participants' brainwaves are recorded using the MUSE 2 EEG device to generate a data set. The experiment is shown in Figure 6. First, each participant wore headphones and Muse 2 while remaining relaxed. Then, stimulus clips were viewed from the identified stimulus dataset, which contains clips of popular films depicting positive and negative emotions. The clips are arbitrarily combined, and each clip is given two minutes to neutralize its emotions.

All the video clips have been edited to the exact resolution, and the volume has been adjusted so that the audience can enjoy a speech in peace. Participants were instructed to sit in a closed room with Bluetooth, and wireless turned off to prevent potential intrusion. Participants were seated approximately 0.5 meters from the screen's center. Brain waves are recorded while the subject watches stimulation clips. Consequently, an EEG emotion dataset is created.

Regarding the correct labels for emotions, participants are asked to respond to specific questions about their current emotions. The ground truth values take into account both the anticipated emotions and the self-reported outcomes. Except for the neutral videos, every selected clip evokes extremely intense emotions. To ensure performance, the order of the clips was shuffled.

Figure 6. EEG data acquisition for different emotions

4.4 Feature Engineering

In brain-computer interface (BCI) applications, feature extraction of EEG signals is a central issue. The complexity of the signal, which is non-linear, non-stationary, and random by nature, presents a challenge for EEG feature extraction. In light of the fact that signals are considered stationary only during brief intervals, the best method for satisfying this requirement is to employ the sliding windowing technique, as shown in Figure 7. The specific method was contributed to Bird [5]. All proposed features for classifying mental states are computed based on the temporal distribution of the signal within a given time window. This sliding window is defined as a period of one second at a frequency of 250 Hz, and a 0.5-second overlap is used. Thus, temporal window 1 (w1) begins at 0 seconds and ends at 1 second; w2 begins at 1.5 seconds and ends at 2.5 seconds; w3 begins at 2 seconds and ends at 3 seconds, and so on.

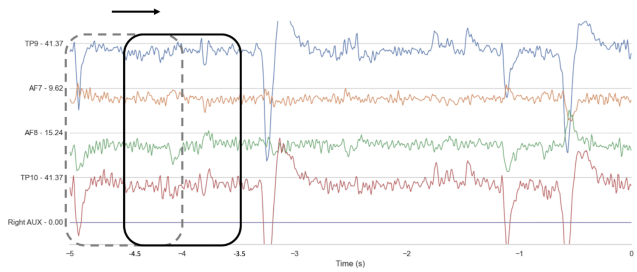

Figure 7. Sliding window technique for EEG data

Consequently, this subsection describes the set of characteristics considered in this study in order to distinguish between distinct classes.

4.4.1 Statistical Features. There are three main statistical characteristics: (a) Given a sequence of obtained data values $\{x_1, x_2, ...x_N\}$ in each temporal window, the sequence's mean value $\mu = \frac{1}{N}\sum_i^N x_i$ is determined; (b) the standard deviation $\sqrt{\frac{1}{N}\sum_i^N (x_i - \mu)^2}$; (c) the statistical moments of the third and fourth order, skewness and kurtosis, measure the asymmetry of the data and the peakedness of the probability distribution of the data, correspondingly [5]. Following is how the statistical features are calculated:

$$y = \frac{\mu^k}{\sigma^k} \tag{1}$$

$$\mu^k = \frac{1}{N}\sum_i^N (x_i - \mu)^k \tag{2}$$

where and y = {skewness, k= 3; kurtosis, k = 4} and $\mu^k = \{3^r d, 4^t h\}$ moment regarding the mean.

4.4.2 Max, Min, and Derivatives. To improve the variety of feature types, the maximum and minimum values are computed within a 1-second time window. Additionally, derivatives are computed as temporal characteristics. For each time window, we divide the time window by 2, such that $\frac{w}{2} = 0.5sec$ and $w = 1sec$, resulting in two data sequences at around 125 Hz [5]. We then compute:

$$uv = \frac{\mu^w - \mu^{w/2}}{2} \tag{3}$$

where w and w/2 represent the first and second halves of the data sequence in a 1-second time window. The same method is used to obtain the derivative given the maximum and minimum features in sub-time windows:

$$max_t = \frac{max^w - max^{w/2}}{2} \tag{4}$$

$$min_t = \frac{min^w - min^{w/2}}{2} \tag{5}$$

4.4.3 Log-covariance features. Considering the preceding 150 temporal features, we eliminate the last six features to arrive at 144 features in order to construct a 12 × 12 square matrix for computing the log-covariance using the following equation:

$$lcM = U(\log_m(cov(M))) \tag{6}$$

in this situation, lcM is a vector carrying the upper triangular components of the matrix following computing the matrix logarithm over through the covariance matrix M; U(...) is a function that returns the upper triangular components; $\log_m(...)$ is the matrix logarithm function; and $cov(M) = cov_{ij} = 1/N\sum_k^N (x_{ik} - \mu_i)(x_{kj} - \mu_i)$ represents the covariance matrix [5]. Log-covariance is based on the mapping of the convex conical of a covariance matrix to such vector space by means of the matrix logarithm so that it does not belong in Euclidean space.

4.4.4 Shannon entropy and Log-energy entropy. Nonlinear analysis, such as Shannon entropy, has demonstrated its effectiveness in filtering and time series, as the unpredictability of non-linear data is well represented by computing entropies over the time series. Entropy is a measure of uncertainty and in brain-machine operated, it is used to estimate the extent of system chaos because it is a non-linear estimate of the data's complexity. Shannon entropy in information theory is provided by:

$$h = -\sum_j S_j \times \log(S_i) \tag{7}$$

h is a feature generated in each 1-second time window, and S_j is each element of the temporal window. Then, given the same time window, we split into two to compute the log-energy entropy as follows:

$$\log e = \sum_i \log(S_i^2) + \sum_j \log(S_j^2) \tag{8}$$

where i is an index for the items of the first sub-window and j is an index for the elements of the second sub-window.

4.5 Classification Algorithm

Various machine learning algorithms are used to recognize and categorize emotions in the literature. In this study, a Convolutional Neural Network (CNN) model-based deep learning network is employed to classify emotions and levels of concentration based on EEG signals. The CNN model architecture is illustrated in Figure 8.

Initialization of the proposed CNN network is performed using the parameters specified in Table 2. The extracted features are fed to the proposed CNN network, and the performance of our model is analyzed across 30 epochs. As for output, the CNN-based deep learning model categorizes the EEG data into three concentration-level classes.

In the discipline of machine learning, the dataset is typically divided into two distinct sets, namely the training set

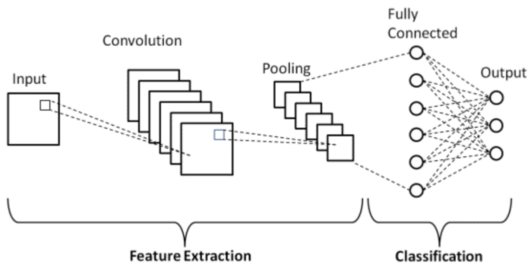

Figure 8. CNN architecture diagram

Table 2. Parameter values used to create the CNN model.

Parameter	Value
Optimizer	Adam
Loss Function	Categorical Crossentropy
Validation Split	0.2

Table 3. Training Records for three classes of concentration levels.

Class	No. of Training Records
Total	1809 (out of 2479)
Relaxed	605
Neutral	595
Concentrating	609

and the testing set. In this study, 75% (6 subjects) of the training data and 25% (2 subjects) of the testing data were split. The details of the dataset, the total number of samples, and the training–testing partition are presented in Table 3.

The Keras library in Python is utilized to construct a convolutional neural network (CNN).

5 Implementation

5.1 Device Description

The Muse 2 brainwave Headband was utilized to collect mEEG data. It is a portable, lightweight, commercial, and inexpensive EEG sensing device with five dry application sensors, one of which is used as a reference point (NZ) and four of which capture EEG data at a sampling rate of 256 Hz. Two sensors are located on the forehead (AF7, AF8), and two are located behind the ears (TP9, TP10). The headband also includes a single accelerometer module capable of recording three-axis head movement, which is used to filter out noisy data acquired owing to head movement. This is a wireless EEG headband with Bluetooth pairing capability that can connect to any smartphone in order to record EEG data that can be transferred offline for additional processing. The output data consists of five EEG bands (1–100 Hz): delta (1–4 Hz), theta (4–7 Hz), alpha (8–12 Hz), beta (12–25 Hz), and gamma (25–55 Hz), which are fed to a deep learning network for classification of focus and emotion based on EEG signals.

5.2 API

BlueMuse and MuseLSL were utilized in this experiment to collect EEG data from MUSE 2. BlueMuse is software that connects to Muse headsets and streams data using the UCSD-developed Lab-Streaming Layer (LSL) software package and protocol. BlueMuse permits users to connect to a Muse device, and stream data in LSL format [9]. MuseLSL is a system for the uniform collection of measuring time series in research trials that manages networking, time-synchronization, near-real-time access, and, if desired, the centralized collecting, display, and disk recording of the data [11]. The EEG signals obtained are shown in Figure 9.

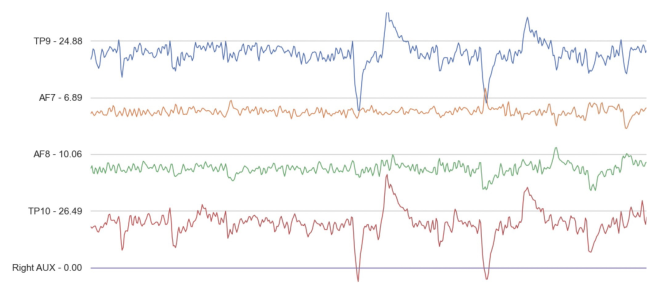

Figure 9. EEG data obtained using BlueMuse and MuseLSL

6 Evaluation

6.1 Metrics

Analytical evaluations, including confusion matrix, accuracy, F1-score, precision, and recall, are used to measure the performance of the CNN-based deep learning network classifier. These performance metrics are described as follows:

6.1.1 Confusion Matrix.

A confusion matrix measures the performance of a classification algorithm on a batch of samples for which the true values are recognized. The multi-class confusion matrix is provided in this study for our three-class scenario.

6.1.2 Accuracy.

Accuracy is the measure of a classifier's ability to correctly assign inputs to the appropriate category.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{9}$$

6.1.3 F1-score.

The F1 score is an important metric for evaluating classifiers based on unbalanced datasets, and it is typically more useful than accuracy. It can be calculated using the following formula:

$$F1 = \frac{2 \times precision \times recall}{precision + recall} \tag{10}$$

Accuracy works best when the cost of false positives and false negatives is equivalent. If the cost of false positives and false negatives varies substantially, it is preferable to consider both Precision and Recall. In our situation, false negatives are more expensive as it fails to detect mental weariness. Recall and Precision can be calculated using the following formula:

$$Recall = \frac{TP}{TP + FN} \tag{11}$$

$$Precision = \frac{TP}{TP + FP} \tag{12}$$

6.2 Baseline

This paper chose two separate studies as baseline comparisons for our joint system. For the concentration levels detection, we chose Liu and Chiang's (2013) [15] work, which conducted a study using EEG signals to detect whether students are attentive or unattentive during instruction by a support vector machine (SVM) classifier. In the experiment with 24 test subjects, 12 men and 12 women, they achieve a classification accuracy of up to 76.82%. For emotion recognition, LSTM is often utilized to deal with high-level EEG signal patterns [17]. In the research of Sakalle et al. [19], they develop an LSTM-based model. By testing it with fifty healthy participants, 25 males, and 25 females, using forty film clips for elicitation; they determined that the classification performance of their work could reach 95%.

6.3 Performance Measurement

6.3.1 Ground Truth. The data was collected from eight people (4 males, and 4 females) for 60 seconds per state - neutral, concentrating, and relaxed, using a Muse 2 EEG headband with four dry electrodes (TP9, AF7, AF8, and TP10). The experimental procedures for obtaining ground truth are described below:

- Neutral: No stimulus. Participants were asked to sit for 60 seconds. This test was carried out first in order to prevent the lingering effects of a relaxed or focused mental state.
- Concentrating: The individuals were advised to follow "snake.io" with undivided attention in an effort to score enough points.
- Relaxed: Subjects were instructed to play the game while listening to low-tempo music in an attempt to relax. The headphones were worn to listen to the music.

6.3.2 Results. Using the feature extraction technique and deep learning model described in the preceding section, our system is able to accomplish the outcomes listed below. Figure 10 depicts the confusion matrix of our classification method, whereas Figure 11 depicts the precision, recall, F1 score, and accuracy.

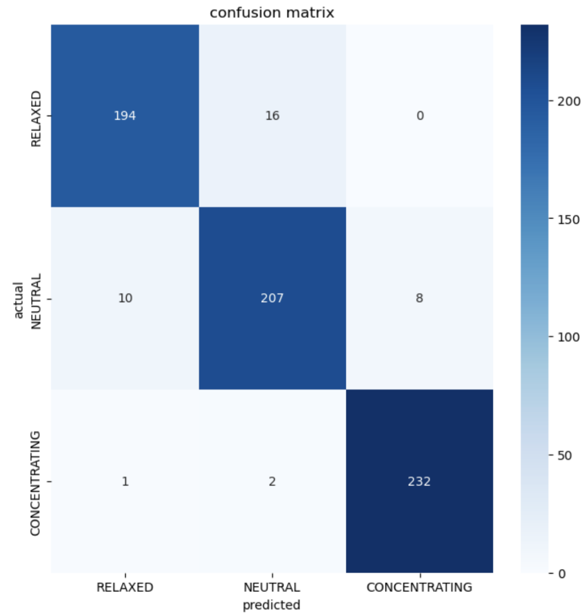

Figure 10. Confusion Matrix

Classification Report:

	precision	recall	f1-score	support
RELAXED	0.95	0.92	0.93	210
NEUTRAL	0.92	0.92	0.92	225
CONCENTRATING	0.97	0.99	0.98	235
accuracy			0.94	670
macro avg	0.94	0.94	0.94	670
weighted avg	0.94	0.94	0.94	670

Figure 11. Classification Report

We can observe that when classifying the EEG signals into three classes of concentration levels, our deep learning model achieved above 90% accuracy and F1-score.

7 Conclusion and Future Work

This paper presented a study on jointly identifying concentration levels and emotions based on EEG signals. We were able to obtain good accuracy with a simplified deep-learning model and limited dataset. For concentration level detection, it utilized a short-term windowing technique to extract features from EEG signals acquired from MUSE 2 and classified them into three states: neutral, relaxed, and concentrating. The dataset was collected from eight individuals during 60-second sessions for each state. Due to a lack of time, this paper was unable to implement emotion recognition. Nevertheless, based on the outcomes of the preceding stage, we believe it is also doable.

Regarding future work, there are three elements to consider. The first step is to implement the joint system discussed previously thoroughly. Second, we defer a comprehensive comparison between our system and the baseline research to future work. Finally, as our method provides a thorough measurement of mental states, it is suitable for the development of a recommendation system on mobile devices that suggests viable solutions for inattention.

References

[1] 2022. https://bcmi.sjtu.edu.cn/home/seed/

[2] 2022. ACTICHAMP series: Brain Products GmbH gt; Solutions. https://www.brainproducts.com/solutions/actichamp/

[3] 2022. Electroencephalography. https://en.wikipedia.org/wiki/Electroencephalography

[4] 2022. muse 2: brain sensing headband - technology enhanced meditation. https://choosemuse.com/muse-2/

[5] Jordan J. Bird, Luis J. Manso, Eduardo P. Ribeiro, Anikó Ekárt, and Diego R. Faria. 2018. A Study on Mental State Classification using EEG-based Brain-Machine Interface. In *2018 International Conference on Intelligent Systems (IS)*. 795–800. https://doi.org/10.1109/IS.2018.8710576

[6] Maarten A.S. Boksem, Theo F. Meijman, and Monicque M. Lorist. 2005. Effects of mental fatigue on attention: An ERP study. *Cognitive Brain Research* 25, 1 (2005), 107–116. https://doi.org/10.1016/j.cogbrainres.2005.04.011

[7] Gianluca Borghini, Laura Astolfi, Giovanni Vecchiato, Donatella Mattia, and Fabio Babiloni. 2014. Measuring neurophysiological signals in aircraft pilots and car drivers for the assessment of mental workload, fatigue and drowsiness. *Neuroscience Biobehavioral Reviews* 44 (2014), 58–75. https://doi.org/10.1016/j.neubiorev.2012.10.003 Applied Neuroscience: Models, methods, theories, reviews. A Society of Applied Neuroscience (SAN) special issue..

[8] Guillermo Borragán, Hichem Slama, Arnaud Destrebecqz, and Philippe Peigneux. 2016. Cognitive Fatigue Facilitates Procedural Sequence Learning. *Frontiers in Human Neuroscience* 10 (2016). https://doi.org/10.3389/fnhum.2016.00086

[9] David Medine Arnaud Delorme Christian Kothe Chadwick Boulay, Tristan Stenner. 2022. SCCN/labstreaminglayer: Labstreaminglayer super repository comprising submodules for LSL and associated apps. https://github.com/sccn/labstreaminglayer

[10] Ruo-Nan Duan, Jia-Yi Zhu, and Bao-Liang Lu. 2013. Differential entropy feature for EEG-based emotion classification. In *2013 6th International IEEE/EMBS Conference on Neural Engineering (NER)*. 81–84. https://doi.org/10.1109/NER.2013.6695876

[11] Stephen Wicklund Jason Kowaleski. 2022. Kowalej/BlueMuse: Windows 10 app to stream data from Muse EEG headsets via LSL (lab streaming layer). https://github.com/kowalej/BlueMuse

[12] Sander Koelstra. 2022. DEAP: A dataset for emotion analysis using physiological and audiovisual signals. https://www.eecs.qmul.ac.uk/mmv/datasets/deap/

[13] Olave E. Krigolson, Mathew R. Hammerstrom, Wande Abimbola, Robert Trska, Bruce W. Wright, Kent G. Hecker, and Gordon Binsted. 2021. Using Muse: Rapid Mobile Assessment of Brain Performance. *Frontiers in Neuroscience* 15 (2021). https://doi.org/10.3389/fnins.2021.634147

[14] SAROJ K.L. LAL and ASHLEY CRAIG. 2002. Driver fatigue: Electroencephalography and psychological assessment. *Psychophysiology* 39, 3 (2002), 313–321. https://doi.org/10.1017/S0048577201393095

[15] Ning-Han Liu, Cheng-Yu Chiang, and Hsuan-Chin Chu. 2013. Recognizing the Degree of Human Attention Using EEG Signals from Mobile Sensors. *Sensors* 13, 8 (2013), 10273–10286. https://www.mdpi.com/1424-8220/13/8/10273

[16] Monicque M. Lorist, Maarten A.S. Boksem, and K. Richard Ridderinkhof. 2005. Impaired cognitive control and reduced cingulate activity during mental fatigue. *Cognitive Brain Research* 24, 2 (2005), 199–205. https://doi.org/10.1016/j.cogbrainres.2005.01.018

[17] P. Nagabushanam, S. George, and S. Radha. 1970. EEG Signal Classification using LSTM and improved neural network algorithms: Semantic scholar. https://www.semanticscholar.org/paper/EEG-signal-classification-using-LSTM-and-improved-Nagabushanam-George/a8296c6cf8a5121b5e3c97910e0cc443e706666f

[18] Prima Dewi Purnamasari and Tsalsabilla Winny Junika. 2019. Frequency-based EEG Human Concentration Detection System Methods with SVM Classification. In *2019 IEEE International Conference on Cybernetics and Computational Intelligence (CyberneticsCom)*. 29–34. https://doi.org/10.1109/CYBERNETICSCOM.2019.8875677

[19] Aditi Sakalle, Pradeep Tomar, Harshit Bhardwaj, Divya Acharya, and Arpit Bhardwaj. 2021. A LSTM based deep learning network for recognizing emotions using wireless brainwave driven system. *Expert Systems with Applications* 173 (2021), 114516. https://doi.org/10.1016/j.eswa.2020.114516

[20] Aditi Sakalle, Pradeep Tomar, Harshit Bhardwaj, and Arpit Bhardwaj. 2021. Emotion Recognition Using Portable EEG Device. In *Artificial Intelligence and Sustainable Computing for Smart City*, Arun Solanki, Sanjay Kumar Sharma, Sandhya Tarar, Pradeep Tomar, Sandeep Sharma, and Anand Nayyar (Eds.). Springer International Publishing, Cham, 17–30.

[21] Eike A. Schmidt, Michael Schrauf, Michael Simon, Martin Fritzsche, Axel Buchner, and Wilhelm E. Kincses. 2009. Drivers‚Äô misjudgement of vigilance state during prolonged monotonous daytime driving. *Accident Analysis Prevention* 41, 5 (2009), 1087–1093. https://doi.org/10.1016/j.aap.2009.06.007

[22] Xiao-Wei Wang, Dan Nie, and Bao-Liang Lu. 2014. Emotional state classification from EEG data using machine learning approach. *Neurocomputing* 129 (2014), 94–106. https://doi.org/10.1016/j.neucom.2013.06.046