Inter-subject Attention Recognition from Multi-Channel EEG with Transfer Learning based CNN-LSTM model

Team: Xingqi Pan, Meiyi Yu, Haiqin Zhao**. Project Mentor TA:** Maheshwarran Karthikeyan

1) Abstract

For this project, we tried to detect the human mental states from Electroencephalogram (EEG), a most studied time-sequential signal which has been proven to have the capacity to detect attention, with a Transfer Learning based state-of-the-art deep learning model, to improve study/work efficiency for various people in different scenarios. In this research, we proposed a framework based on the CNN-LSTM model which learns the inter-subject attentive mental state from multi-channel EEG signals. We also delivered an innovative method of EEG signal preprocessing which enhances the correlations among data without adding redundant information. The result shows that the model reaches an average accuracy of 69.36% on 5 participants for leave-one-out inter-subject attention recognition on a public dataset, which is higher than the similar CNN-LSTM model of 65.29% on single-channel EEG signals. It also points out the possibility of applying multiple EEG channels on mental state detection.

2) Introduction

Attention is one of the key parameters of human consciousness which is highly related with study and work efficiency. It is used by people to control details of their awareness and is associated with people's voluntary ability to select among competing items, to correct mistakes and to moderate and adjust their emotions[1]. In the past several years, with scientific and clinical interest increasing, researchers pay attention to appling EEG signal for characterizing and quantifying the neurophysiology of attention-deficit/hyperactivity disorder (ADHD), which shows a possible connection between EEG signal and attention [2]. Electroencephalogram (EEG) is a most studied time-sequential signal of recording brain activity using electrophysiological indicators [3,4]. Recently, researchers introduced Deep Learning algorithms in the domain of EEG signal processing for human mental state recognitions. However, most existing models try to deal only with single channel EEG data, but with the scarcity of dataset, it may not always be possible to find demand signal channels.

In this research, we aim to build a subject-independent learning system, which learns EEG signals from multiple subjects to recognize the attention of the test target, to help people switch their mental states quickly between focus and unfocus. As EEG signals may always be interrupted by other human activities [5], several human activities may affect the accuracy of EEG, hence we introduce a new way of data preprocessing method to deal with the unexpected noises, basically using several filters at first to pick the useful information out and then split into time segments for experiment. To deal with multi-channel signal processing, we designed a transfer learning based attention pattern recognition model from multi-channel EEG based on the current existing CNN-LSTM network using the idea of Transfer learning. In model structure, the Convolutional Neural Network (CNN) layer, as one of the essential machine learning models, is used for feature extraction and a Long Short-Term Memory Layer is implemented for data classification [7,8].

3) Background

EEG with Machine Learning is widely used in brain-computer Interface for medical diagnoses, such as attention deficit hyperactivity disorder(ADHD), epilepsy, sleep disorders, etc. In the previous years, many studies on EEG signals have used traditional machine learning to uncover relevant information for neural classification and neuroimaging. [6] For example, independent component analysis (ICA) for artifact removal, principal component analysis and local Fisher's discriminant analysis (LFDA) for feature dimension reduction [9]; Support Vector Machine and Random Forest for EEG signal Classification.[10] Recently, researchers started to apply machine learning techniques on EEG signal analysis with the advent of deep learning. In [11], the team introduced an MLP neural network as a classifier for the analysis of early diagnosis of ADHD from a single Fp1-A1 EEG signal. This technology is also widely used in the field of mental workload measurement. [12] provides an unsupervised learning model for predicting driver drowsiness from Oz channel. [13] presents an application of DCNN on detecting the attentive mental state from Fp1-Fp2 raw EEG data. [14] delivered a state-of-the-art CNN-LSTM model for detecting subject-independent driver drowsiness, using Oz channel EEG signal collected from 27 subjects performing VR driving tasks. Also, the previous research also shows that the attention level is associated with the signal collected on the posterior cortex in the alpha, beta, theta, and delta band[9].

Our project is built based on [13], and [14]. In our research, different from previous research, we used an EEG signal dataset generated by O1 and O2 electrodes, two electrodes which are located close to Oz and can also provide information about attentive mental states, for multi-channel research. We built models for both single-channel data and multi-channel data for performance comparison.

4) Summary of Our Contributions

1. Contribution(s) in Code: N/A
2. Contribution(s) in Application: We modified the existing CNN-LSTM model and applied it in a new field. Previously, the EEG concentration prediction was mostly trained on driver's tasks, but we tailored the CNN network and studied the students' concentration status instead.
3. Contribution(s) in Data: We introduced a new data preprocessing way on EEG signal. The EEG dataset we are dealing with is multichannel signals for length of around 40 minutes. When we cleaned the data, we reserved most of the information by reusing some signal fragments instead of just doing replication padding.
4. Contribution(s) in Algorithm: N/A
5. Contribution(s) in Analysis: N/A

5) Detailed Description of Contributions

5.1 Dataset and Features

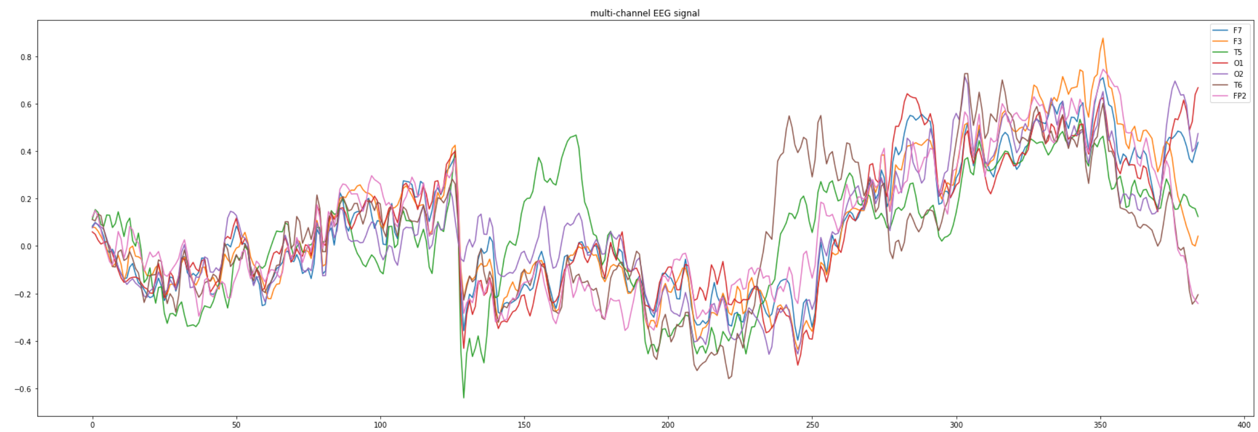

Figure 1 Multi-channel EEG signal

This study used a raw EEG dataset provided by [15] which conducted 34 experiments in 5 subjects for 7 separate days to monitor their mental status as focused, unfocused, drowsy by EMOTIV devices. The signals were collected from 34 experiments for monitoring of attention state in human individuals using passive EEG BCI. There are 14 electrodes AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 corresponding to 14 signal channels. The sampling rate of the signals is 128Hz. Each of the signals record the human attentive mental states over 20 minutes and can be splitted into 3 parts: first 10 minutes are measuring for ‘focus’ state, 10-20 minutes for ‘unfocus’ state, and the left minute as ‘‘sleep”’ state.

5.2 Methods

5.2.1 Data Preprocessing

In our study, our goal is to differentiate people’s concentration levels. To be more specific, we want to tell whether one is focused or unfocused. So we will only utilize the first 20 minutes of the dataset. The size of the data for each experiment after processing is 398*2*447. Based on [13] and [14], Here is our data-preprocessing method:

1. To perform multi-channel analysis, we picked O1, O2 [12] electrodes as our data input, since the occipital (O) region can best represent the concentration level. We stacked these two signals together to inject into the neutral network.
2. Filter the signals to 0.5-40Hz in frequency domain. One reason is that the five classical bands δ (0.5–4 Hz), θ (4–8 Hz), α (8–12 Hz), β(12–30 Hz), and low ϒ(30-40Hz) are most associated with the changes in individuals’ attention state [15]. The other reason is that human brain signals contain many low-frequency artifacts/noise that need to be eliminated.
3. Applied a 3s sliding window on each signal channel, that is, each data has 3s*128Hz = 384 features, which preserve the data information to the greatest extent. To prevent the loss of relations between data after passing through the Convolutional layer, we expanded data to 447 features with some overlapping data sliced from previous and late segments of the continuous EEG time series. Removing the first and the last data in each channel as they are just used for segment expendation.
4. Combining all signal slices from different channels together in time domain as the multi-channel training set. Also, generating labels where focused data labeled with 0 and unfocused data labeled with 1.

5.2.2 Design of network

As EEG is a time sequence model, the data on the future stage is dependent on the previous stage. Hence, we used a CNN-LSTM model for measuring drowsiness [14] as the prototype. This model combined both CNN for compress data and LSTM for feature extraction which get an average accuracy of 72.97% on the driver drowsiness set. To promote the model on the set we selected, we change its architecture to fit the multi-channel signal data and try to get better performance on subject-cross classification[16]. The state-of-art data analysis was based on single-channel EEG signals, which only represents activities of specific regions of one's brain. As an improvement, we prepared signals from two different electrodes(O1 and O2) as CNN inputs, and improved the CNN to multi-channel structure, so as to acquire more information and improve the accuracy.

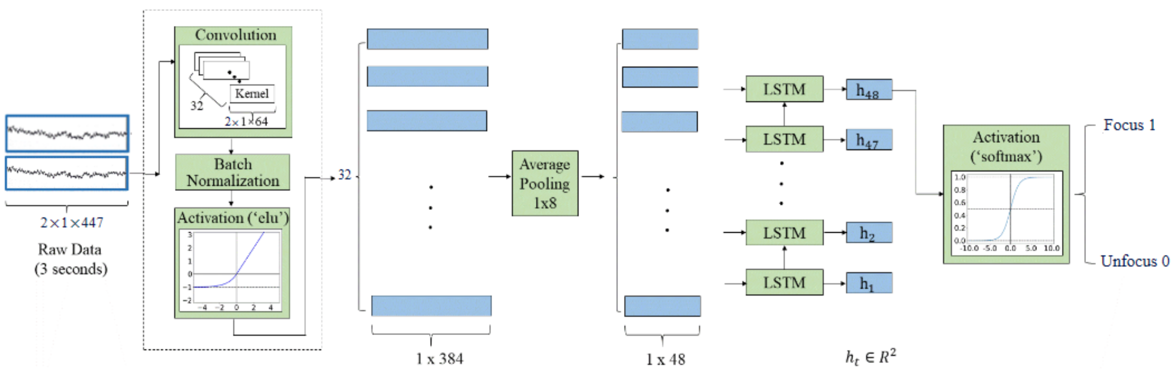

Figure 2 CNN-LSTM Architecture

- The convolutional layer contains 32 kernels with stride 1. Each 2-layer 1-dimensional kernel has the length of 64, as with half of the sampling rate(128Hz), it can capture essential EEG frequencies above 2Hz. The input data has the length of 447 contains the data in 3s period with overlapping signals from the original data to maintain the most information.
- The Batch Normalization layer can remove the internal covariate shift.
- The average pooling layer has the window size of 1 * 8, it can summarize the extracted information and prevent overfitting.
- The LSTM layer maps the feature sequence to hidden states to learn the temporal dependency of the feature sequence.
- The final activation layer performs Softmax function on hidden states to output the classification results.
- The Adam optimizer has been selected for minimizing the loss function properly.

To measure the accuracy on inter-subject level, for each independent experiment, we used a approach call Leave-one-experiment-out cross validation, because in this way we can better showcase the model's capabilities of cross-subject classification. Under this approach, each time the data from one experiment is used for testing, while the data from all the other experiments are used for training. This method encourage the trained model to be able to reveal the concentration status when some new task is performed by some new person.

5.3 Experiments and Results

Different from previous research, we picked a more randomly designed EEG dataset which recorded the change of EEG signals when subjects performed study tasks. Our research goal is to verify whether the current model can also give good prediction results in this new dataset and new application field, and improve the network structure to train better performance. Before the experiment, we made a hypothesis that a multi-channel dataset contains the same or more information, compared with a single channel dataset, hence the multi-channel model has the same performance as the single-channel model. We preprocess and clean the dataset, getting a 398*34 data frames with each column as a trial, and every entry is a 3s signal slice. Two channels(O1, O2) of the original data were being preprocessed and stacked together in the time domain as our training set.

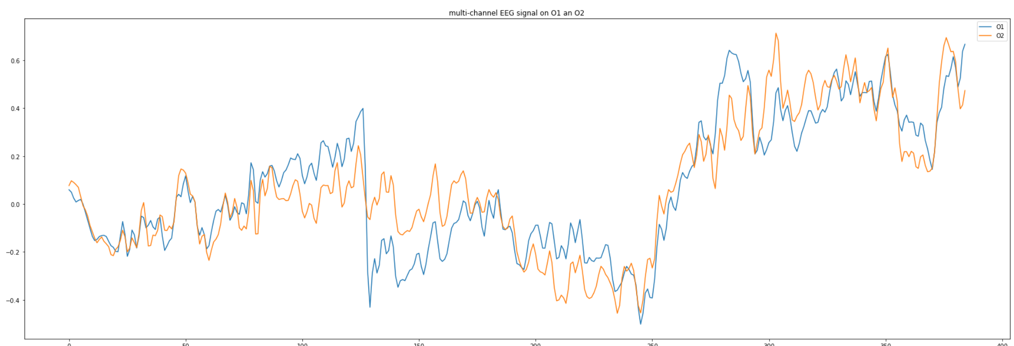

Figure 3 EEG signals in O1 and O2 channel

When we input a single O1 channel EEG signal dataset into the original CNN-LSTM, we got the training accuracy turned out to be 65%, compared to 72% when inputting the driver dataset. The training accuracy for single O2 channel EEG signal dataset is 64.63%. These results show the limitation of the original single channel neural network, and the necessity that we need to re-design the network. With this idea, we combine O1 and O2 electrodes's EEG signals to generate the 2-channel training and testing dataset, and enlarge the CNN to 2 channels. The final accuracy will be the mean of accuracy for each group. The accuracy score can directly reveal the correct rate of our prediction, and it matches the metric used in previous studied baseline model [14]. From figure 4, the final mean accuracy is 69.4%, improved by 4% than the single-channel solution.

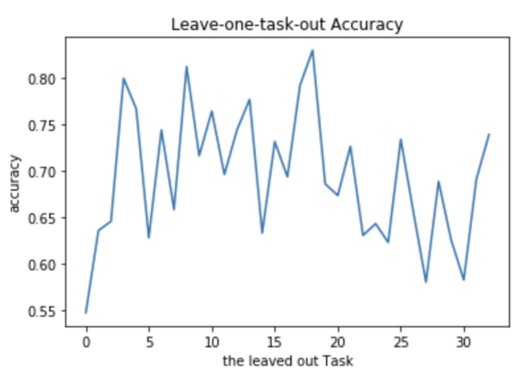

Figure 4 Leave-one-task-out Accuracy for Multi-channel CNN-LSTM

6) Compute/Other Resources Used

In this research project, we used a notebook instance with Amazon SageMaker as our main computing resources which has 10GB EBS volumes, 1 GPUs, 4 vCPUs, 61GiB RAM and high Network Bandwidth. We also use Google Colab for pre-training and program testing.

7) Conclusions

In this research, we applied a state-of-art CNN-LSTM model on EEG signal dataset for measuring the status of student attention. The model prediction accuracy is around 69.36 ± 0.1% on O1 and O2 multi-channels dataset, improved by 4% than the single-channel model, which proves our hypothesis that it is possible to use multi-channel signals for a better performance on classification tasks. We also test different activation functions, like Sigmoid and leakyReLu, and different optimizers like SGD, Softmax as activation function and Adam as optimizer still achieve the highest accuracy. According to recent research [6,17,18], there are more advanced deep learning models that can be used for analyzing and generating time series, like time GANs, N-BEATS, DeepAR and so on. Therefore, we will apply some advanced deep learning models as improvements in the future.

This model is mainly for enhancing study or work efficiency, which would impact education and the medical field. Firstly, educators can better design the homework and workload for students. With simple consumer-grade EEG devices, educators can get the brain signals of a student, send them into our model, and evaluate the concentration state to judge objectively whether the coursework is suitable. Secondly, for early-stage disease diagnoses, such as attention deficit hyperactivity disorder(ADHD)[5], our model can significantly aid the diagnosis process, and generate more valuable data insights for doctors. However, we can not ignore that when this model is widely used in the education and medical fields, a large amount of EEG data will be collected, which may raise a series of data bias and privacy issues. Data and code bias issues, on the one hand, the data we collect, especially the target value, cannot guarantee that there is no bias because whether one is concentrated or not is subjective, and it is difficult for others to judge, which in turn will lead to bias in our training results. Additionally, privacy issues should also be taken into consideration. [19] figured out that a large amount of data can be misused without authorization, and there may be some unreliable data collectors leaking information, which will create a lot of privacy issues.

(Exempted from page limit) Other Prior Work / References (apart from Sec 3) that are cited in the text:

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A compact and interpretable convolutional neural network for cross-subject driver drowsiness detection from single-channel EEG.
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[19]. K.D. Martin, A. Borah and R.W. Palmatier Marketing Science Institute Working Paper Series (2016) (Report No. 16-104)

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If your answer to the above question is yes, are there any other links to github / youtube / blog post / project website that you would like to publish alongside the report? If so, list them here.

(Exempted from page limit) **Work Report: This may look like your GANTT chart from the midway report, with more completed steps now. Okay to modify.** (Mark completed steps in green, as shown here. For convenience, you may split into two charts, one till Nov 8, and another for after Nov 8, placed one below the other.)

PERSON (S)	TASK (S)	Wk11-12				Wk13				Wk14				Wk15				Wk16			
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		W 23	S 27	S 3	Th 7	S 10	M 11	W 13	Th 14	S 17	M 18	W 20	Th 21	S 24	M 25	W 27	Th 27	S 30	S 1	W 4	Th 5
Xingqi Pan, Meiyi Yu, Haiqin Zhao	Data preprocessing																				
Xingqi Pan, Meiyi Yu, Haiqin Zhao	Model Construction																				
Xingqi Pan, Meiyi Yu, Haiqin Zhao	Train and test model																				
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Xingqi Pan, Meiyi Yu, Haiqin Zhao	Performance evaluatiom																				
Xingqi Pan, Meiyi Yu, Haiqin Zhao	Final report writing																				
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(Exempted from page limit) Attach your midway report here, as a series of screenshots from Gradescope, starting with a screenshot of your main evaluation tab, and then screenshots of each page, including pdf comments. This is similar to how you were required to attach screenshots of the proposal in your midway report.

Project Mid-way Report

GRADED

GROUP

Xingqi Pan

Haiqin Zhao

Meiyi YU

View or edit group

TOTAL POINTS

7 / 7 pts

QUESTION 1

Evaluation Question [Select all pages] 7 / 7 pts

✔	+ 1 pt	Does the report follow the provided template including the 4-page limit (excluding exempted portions), with reasonable responses to all questions?
✔	+ 2 pts	Has feedback from the last round been effectively addressed?
✔	+ 1 pt	Has the team identified a clear topic and viable new target contribution, as per the project specifications provided in class?
✔	+ 1 pt	Has the team moved in a non-trivial way towards their target contribution?
✔	+ 2 pts	Has a clear and systematic work plan been formulated for the remaining weeks?

Inter-subject Attention Recognition from multi-channel EEG with Transfer Learning based CNN-LSTM model

Team: Xingqi Pan, Meiyi Yu, Haiqin Zhao. **Project Mentor TA:** Maheshwarran Karthikeyan

1) Introduction

Set up the problem:

In this research, we aim to build a subject-independent learning system, which learns EEG signals from multiple subjects to recognize the attention of the test target.

Among different features for recognizing a human's mental state, electroencephalography(EEG) is the most studied time-sequential signal to detect attention. As EEG signals may always be interrupted by other human activities, several human activities may affect the accuracy of EEG, hence we also introduce a new way of data preprocessing method to deal with the unexpected noises, basically using several filters at first to pick the useful information out and then split into time segments for experiment.

For the training model, we use the idea of Transfer learning, based on the current existing CNN-LSTM network, we designed a transfer learning based attention pattern recognition model from multi-channel EEG.

For model evaluation, we will use both quantitative and visualization ways. For quantitative methods, we will show the classification average accuracy on training and test set, and our target of model accuracy is beyond 72.97%.[J. Cui et al., 2021] We also provide a visualization method which can reveal which part of waves contains the necessary information of human mental states in the view of waves[J. Cui et al., 2021].

Motivation:

Our main target for this research is to improve study/work efficiency: the detection and prediction of students' attention can be applied to many different research scenarios. For example, we can detect the brain signals of students corresponding to different school hours, courses, and teaching methods and obtain the time and area when students' brain signals are most active to help students improve their concentration and learning efficiency.

For further concern, we hope to discover the underlying relationship between brain waves and human mental diseases to provide humans, especially doctors, for early stage disease diagnosis, such as attention deficit hyperactivity disorder(ADHD)[A. Allahverdy, 2017], analyzing EEG of ADHD patients can carry out targeted therapy for the lesion location.

2) How We Have Addressed Feedback From the Proposal Evaluations

The issues from the Feedback can be split into 3 parts followed with possible solution:

- **Suspect contribution**: we will build up a deep convolutional neural network for attentional pattern recognition for EEG. To be more specific, we will train a model combined CNN and LSTM on the unseen dataset and try to enhance the accuracy of it by changing its architecture, provide innovative signal processing ideas for data preparation, and modify model structure to get better performance.

- **Dataset**: Among eyeblink, EEG, noise, we researched and found EEG as most presentative feature, so the dataset will be a 14-channel time sequential EEG recorded with 128 Hz sampling frequency.
- **Self-collect Dataset**: Because there exist difficulties in collecting EEG data by ourselves, we decided to use the dataset online to train our model with some innovative data augmentation techniques.

3) Prior Work We are Closely Building From

A. JianCui, Zirui Lan, YisiLiu, A compact and interpretable convolutional neural network for cross-subject driver drowsiness detection from single-channel EEG
   a. Paper URL: https://www.sciencedirect.com/science/article/pii/S1046202321001092?via%3Dihub
   b. Code URL: https://github.com/cuijiancorbin/A-Compact-and-Interpretable-Convolutional-Neural-Network-for-Single-Channel-EEG
   c. This paper uses Oz channel EEG signal collected from 27 subjects perform VR driving tasks, after preprocessing the data become 1*384, and then send these data series into a cross-subject CNN network. Finally it visualizes the features to better understand the result.

B. Fatemeh Fahimi, Inter-subject transfer learning with an end-to-end deep convolutional neural network for EEG-based BCI
   a. Paper URL: https://iopscience.iop.org/article/10.1088/1741-2552/aaf3f6
   b. This paper uses Fp1-Fp2 bi-polar single channel EEG signals collected from 120 healthy subjects performed the Stroop color attention test, avoided most pre-feature extraction and sent these almost raw EEG data into the end-to-end CNN classification network for inter-subject transfer learning.

4) What We are Contributing

1. **Contribution(s) in Code: N/A**
2. **Contribution(s) in Application: Apply the existing CNN-LSTM model on previous unseen multi channel EEG dataset.**
3. **Contribution(s) in Data: Introducing a new data preprocessing way on EEG signal.**
4. **Contribution(s) in Algorithm: N/A**
5. **Contribution(s) in Analysis: N/A**

5) Detailed Description of Each Proposed Contribution, Progress Towards It, and Any Difficulties Encountered So Far

5.1 Methods

- Data Preprocessing::
  EEG data usually contained multiple channels and stored as signals with some sample frequency. Here we used a raw EEG dataset provided by [C.I. Acı, 2019] which

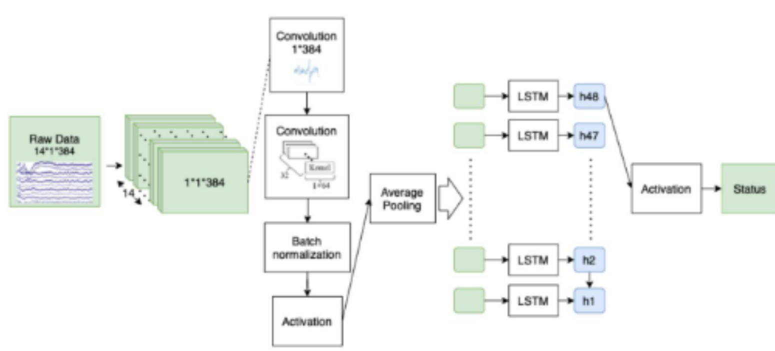
conducted 34 experiments in 5 subjects for 7 separate days to monitor their mental status as focused, unfocused, drowsy by EMOTIV devices. The EEG signal in this dataset is a time sequence data which is more than 30 mins long with 14 channels and a sample frequency of 128 Hz . Each of them can be splitted into 3 parts: first 10 minutes are measuring for 'focus' state, 10-20 minutes for 'unfocus' state, and the left minute as "drowsy' state.

In our study, we separate the data preprocessing into two parts: single channel separation and multi-channel data separation. There are 14 electrodes AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 for 14 signal channels. For a multi-channel dataset, we selected all channels together for processing. To get a single channel EEG signal, we selected O1 and O2 channels and differentiate them as our single bi-polar channel input.[N.R. Pal, 2008] Based on [Fahimi, 2019] and [Jian Cui, 2021], our preprocessing plan is:

1. For each subject's experiments, we only choose the last five, as out of these 7 trials, the first 2 were for getting habitual with the process.
2. Filter the signals at 4 classical bands: δ (0.5–4 Hz), θ (4–8 Hz), α (8–12 Hz), β (12–30 Hz), which are most associated with the changes in individuals' attention state [C.I. Acı, 2019] and can eliminate the low-frequency artifacts. Applied a 3s sliding window with 50% overlapping to segment the continuous EEG time series.
3. We may also consider minimizing eye movement influence by Independent component analysis (ICA) [M. Samavati, 2021] in the further research, depending on the remaining time.

- Design of network

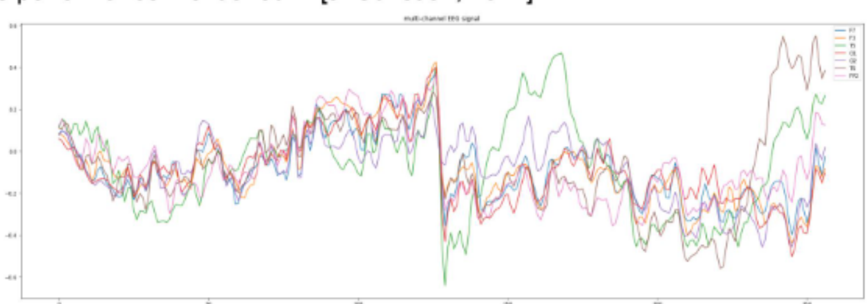
As EEG is a time sequence model, the data on the future stage is dependent on the previous stage. Hence, we used a CNN-LSTM model for measuring driver drowsiness [J. Cui et al., 2021] as our main research model. This model combined both CNN for compress data and LSTM for feature extraction which get an average accuracy of 72.97% on the driver drowsiness set. To promote the model on the set we selected, we change its architecture to fit the multi-channel signal data and try to get better performance on subject-cross classification[Schirrmeister RT, 2017]. We will also try to enhance the model performance by changing the loss function and activation function.



- Difficulties Encountered
  The current dataset needs further cleaning and clipping to better reveal the features, which depends on details of EEG waves and we are still researching it. We tried to minimize the effect of eye movement on brain signals by using Independent component analysis (ICA) [M. Samavati, 2021], but the noises still exist. So for now we are using the dataset under most "basic" preprocessing just to test the feasibility of the model.

5.2 Experiments and Results

- Key questions: we supposed that there were some patterns of brain waves which are associated with human mental status, like attention or drowsiness, so we aim to use machine learning techniques in order to understand how the brain waves correlate with attention or drowsiness.
- Baselines: Our baseline for machine learning model is LSTM and CNN, and for data preprocessing, we highly depend on signal processing methods.
- Metrics: we will use both quantitative and visualization ways. As a common way to determine the performance of a machine learning model, we will calculate the average accuracy of the training and testing and compare it to the current existing models. Our target of model accuracy is beyond 72.97%.[J. Cui et al., 2021] We also provide a visualization method which can reveal which part of waves contains the necessary information of human mental states to help us better understand the result and easier compare it with current related research for verification[J. Cui et al., 2021].
- Progress: Currently, we preprocessed the signals by filters and recreate machine learning models. The result of EEG after passing through a 2-40 Hz band pass filter is shown below, which removes the influence of noise and is ready for training. The regenerated CNN-LSTM model has an average accuracy of 72.36% which is closed to the performance mentioned in [J. Cui et al., 2021].



6) Risk Mitigation Plan

The major risk is that the dataset cannot be cleaned appropriately as we lack deep understanding of EEG signals, leading to low accuracy. So we would use the dataset with fewer complexity to implement our algorithm and complete this step as early as possible. When the project succeeds, we optimize it and use our pre-prepared full dataset to train; when it fails, we will try to adjust the model by changing structure or parameters. Finally, if all approaches do not work, we will compare against successful models to find gaps, submit failed problems and unsuccessful solutions in our project report, and develop potential solutions.

(Exempted from page limit) Other Prior Work / References (apart from Sec 3) that are cited in the text:

1. Schirrmeister RT, Springenberg JT, Fiederer LDJ, Glasstetter M, Eggensperger K, Tangermann M, Hutter F, Burgard W, Ball T. Deep learning with convolutional neural networks for EEG decoding and visualization. Hum Brain Mapp. 2017 Nov;38(11):5391-5420. doi: 10.1002/hbm.23730. Epub 2017 Aug 7. PMID: 28782865; PMCID: PMC5655781.
2. C.I. Acı, M. Kaya, Y. Mishchenko, "Distinguishing mental attention states of humans via an EEG-based passive BCI using Machine Learning Methods", Expert Systems with Applications, vol. 134, pp. 153-166, 2019.
3. M. Samavati, A. Motie Nasrabadi and M. R. Mohammadi, "Automatic minimization of eye blink artifacts using fractal dimension of independent components of multichannel EEG," 20th Iranian Conference on Electrical Engineering (ICEE2012), 2012, pp. 1576-1578, doi: 10.1109/IranianCEE.2012.6292611.
4. N.R. Pal, et al., EEG-based subject-and session-independent drowsiness detection: an unsupervised approach, EURASIP J. Adv. Signal Process. 2008 (1) (2008), 519480.
5. Jian Cui, Zirui Lan, Yisi Liu, Ruilin Li, Fan Li, Olga Sourina, & Wolfgang Müller-Wittig (2021). A compact and interpretable convolutional neural network for cross-subject driver drowsiness detection from single-channel EEG.
6. Vernon J Lawhern, Amelia J Solon, Nicholas R Waytowich, Stephen M Gordon, Chou P Hung, & Brent J Lance (2018). EEGNet: a compact convolutional neural network for EEG-based brain computer interfaces. Journal of Neural Engineering, 15(5), 056013.
7. C. -S. Wei, Y. -T. Wang, C. -T. Lin and T. -P. Jung, "Toward Drowsiness Detection Using Non-hair-Bearing EEG-Based Brain-Computer Interfaces," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 26, no. 2, pp. 400-406, Feb. 2018, doi: 10.1109/TNSRE.2018.2790359.
8. A. Allahverdy, A. K. Moghadam, M. R. Mohammadi, and A. M. Nasrabadi, "Detecting ADHD children using the attention continuity as nonlinear features of EEG," Frontiers Biomed. Technol., vol. 3, nos. 1–2, pp. 28–33, 2017.

(Exempted from page limit) **Full Work Plan, including the previous work plan with completed/incomplete steps (okay to modify from the proposal), and the remaining steps:** (create additional columns with deadlines for steps towards the final report, assigning responsibilities to individual team members to the extent possible. The GANTT chart you used in the proposal will be a good starting point. Mark completed steps in green, as shown here. For convenience, you can split into two charts, one till Nov 8, and another for after Nov 8, placed one below the other.)

		Wk11-12				Wk13				Wk14				Wk15				Wk16			
		Mar/Apr																	May		
PERSON (S)	**TASK (S)**	W 23	S 27	S 3	Th 7	S 10	M 11	W 13	Th 14	S 17	M 18	W 20	Th 21	S 24	M 25	W 27	Th 27	S 30	S 1	W 4	Th 5
Xingqi Pan, Meiyi Yu, Haiqin Zhao	Data preprocessing																				
Xingqi Pan, Meiyi Yu, Haiqin Zhao	Model Construction																				
Xingqi Pan, Meiyi Yu, Haiqin Zhao	Train and test model																				
Xingqi Pan, Meiyi Yu, Haiqin Zhao	Running and processing																				
Xingqi Pan, Meiyi Yu, Haiqin Zhao	Performance evaluatiom																				
Xingqi Pan, Meiyi Yu, Haiqin Zhao	Final report writing																				
...	Task 7																				
...	Task 8																				
...	Task 9																				
...	Task 10																				

(Exempted from page limit) Supplementary Materials if any (but not guaranteed to be considered during evaluation):