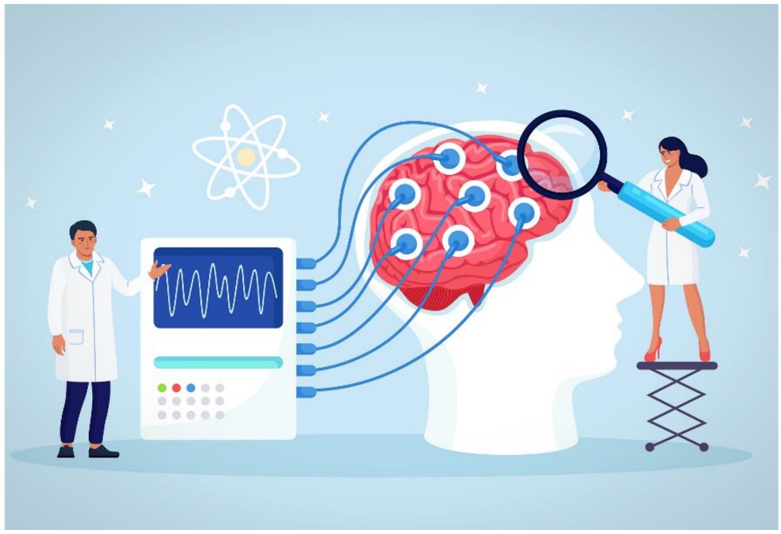


EEG-Mental Fatigue

Dataset description

The dataset captures EEG measurements from the same participant before and after 24 hours of sleep deprivation while performing a working memory task under different conditions. Each trial involves the presentation of pictures, and the participant's task is to recognize and respond correctly. More specifically:

- **Experiment Type:** Working memory paradigm using the n-back test.
- **Task:** Participants are required to recall a picture shown N times before and compare it with the current picture. In this study, N is set to 2, meaning participants need to remember the last two pictures.
- **Experimental Conditions:** There are four conditions, each associated with a specific task or stimulus. Participants indicate their responses by pressing corresponding buttons.
- **Number of Trials:** The experiment consists of 72 trials, with the conditions balanced across these trials.
- **Subjects**: 20 subjects for each session (rested, fatigued)
- **Duration:** The experiment lasts approximately 5 minutes.
- **Inclusion Criteria:** Only correct answers are included in the dataset.
- **Datasets:** There are two datasets corresponding to different states of the participants:
    - **Fatigue State:** After 24 hours of sleep deprivation.
    - **Rested State:** Prior to sleep deprivation.
- **EEG Data Details:**
    - **Sampling Rate:** 256Hz.
    - **Channels:** EEG measurements are recorded from 63 electrode positions (10-20) on the scalp, with each channel providing a time series of data.

Preprocessing

Firstly, the application of a Finite Impulse Response (FIR) filter designed to pass frequencies within the range of 1 to 35 Hz;
secondly, the removal of the baseline through the calculation of its average value, and finally, the detrending of the data to eliminate any remaining trends.

- Loading EEG Data:
    - EEG data is loaded from a CSV file into a Pandas DataFrame.
    - A list of EEG channel names (channels) is specified.

- MNE is used to create an info structure (info) that describes the EEG data (channel names, sampling frequency).

– <u>Creating MNE object:</u>

- MNE's RawArray is used to create a raw EEG data structure (raw) from the Pandas DataFrame.

– <u>Filtering EEG Data:</u>

- The raw EEG data is band-pass filtered between 1 Hz and 35 Hz using a FIR filter (raw.filter(1, 35, fir_design='firwin')).
- EEG signals consist of several frequency bands that are associated with different types of brain activity. These include delta (1–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (12–30 Hz), and gamma (30 Hz and above) waves.
- A bandpass filter allows signals within a specific frequency range to pass through while filtering out signals that fall outside that range.
- By applying a 1-35 Hz bandpass filter, you're preserving the delta, theta, alpha, and beta bands, which are commonly analyzed in EEG studies for various cognitive and neurological insights. This range excludes slower fluctuations that may represent non-neuronal activity (like slow artifact) and higher frequency noise, including muscle artifacts and environmental noise.
- This step is crucial for focusing on the frequencies of interest that are most likely to contain relevant brain activity information.

– <u>Baseline Removal:</u>

- The baseline mean is calculated for each channel, and the baseline is subtracted from the entire EEG data.
- The baseline in EEG data refers to a period where the brain is in a neutral state, and there is no experimental stimulus or task being performed. The average signal in this period is often considered to be a reference or "baseline" level of activity.
- Removing the average baseline involves calculating the mean signal level during this neutral period and then subtracting this value from the entire EEG recording.
- This process is intended to correct for any constant background activity or slow drifts in the EEG signal that are not related to the specific experimental conditions or stimuli.

– <u>Detrending EEG Data:</u>

- Over time, EEG signals can exhibit trends that are not related to the brain's electrical activity. These trends can be due to a variety of factors like slow shifts in electrode potentials or physiological artifacts (e.g., changes in impedance).
- Detrending refers to the removal of these linear or non-linear trends from the data.
- The process typically involves fitting a trend line to the time series data and then subtracting this trend from the original signal.
- This is important for both visual interpretation of the EEG waveforms and for computational analyses, as it can reduce the risk of spurious results that are due to these unrelated trends rather than true brain activity.
- The detrending operation is applied to the baseline-corrected EEG data using scipy.signal.detrend().

Feature extraction

We use <u>two</u> types of <u>features</u> for two different analysis methods (<u>statistical tests</u>, <u>classification</u>). For the first we extract mean spectral features with 1s sliding window we extract differential entropy on five frequency 5 bands and for the second temporal features with a 3 second segmentation.

Spectral features

The code **mean_preprocess.py** after cleaning the EEG data with the previous methods, extracts features (differential entropy) on 5 frequency bands, and we extract the mean values for every subject. The resulting features and labels are then saved on the file named **subj_mean_mental.npz** for further analysis.

The differential entropy is extracted on these 5 bands:

Delta Band (1-4 Hz):

- Delta waves are the slowest EEG waves and are typically associated with the deepest levels of relaxation and restorative, dreamless sleep.

Theta Band (4-8 Hz):

- Theta waves are associated with light sleep, drowsiness, or arousal in older children and adults. In the context of waking states, they are thought to reflect cognitive processes related to memory and spatial navigation.
- Extracting features from the Theta band can provide insights into a person's level of drowsiness, or, in cognitive tasks, how engaged they are with memory processing and navigation.

Alpha Band (8-13 Hz):

- Alpha waves are associated with relaxed, calm, and resting states. They are often present when the eyes are closed and disappear with eye opening or mental exertion.
- Alpha activity is also considered when assessing a person's relaxation level or readiness for a cognitive task.

Beta Band (13-30 Hz):

- Feature extraction from this band can be used to analyze levels of alertness, agitation, or engagement in problem-solving activities.

Gamma Band (30-35 Hz):

- Gamma waves are involved in higher mental activity, including perception, problem-solving, fear, and consciousness. They are the fastest of the EEG waveforms.
- Features from the Gamma band can be quite informative for cognitive tasks that require high levels of processing, or they may indicate certain types of brain pathologies when observed in resting states.

The entropy is extracted with these methods:

- Five frequency bands (bands) associated with different EEG rhythms (Delta, Theta, Alpha, Beta, Gamma) are defined
- For each channel and frequency band, we use an fir filter for calculating the frequencies of each EEG signal and then we calculate differential entropy using a 1s sliding window approach.
- The calculated differential entropy values are stored in a 3D NumPy array (differential_entropy)

We preprocess EEG data recorded during fatigued and rested states, extracting features based on entropy values in different frequency bands and time windows. It utilizes MNE-Python for EEG data handling and implements bandpass filtering, baseline correction, and detrending. The processed data is categorized by subject and state (fatigued, rested), and mean entropy features are computed. The resulting feature set and corresponding labels, indicating the mental state (fatigued or rested), are saved in a compressed NumPy file for subsequent analysis. The code effectively transforms raw EEG data into a feature representation suitable for statistical tests and the resulting data have the dimensions (40 subjects x 63 channels x 5 bands) which represents the mean differential entropy values for each subject each band and each channel.

Temporal features

The python script **raw_preprocess.py** processes EEG data related to "fatigued" and "rested" conditions. It employs MNE-Python and SciPy for preprocessing, including bandpass filtering, and detrending. Then it extracts the raw preprocessed EEG data as temporal features with a 3s time segmentation. The resulting EEG raw data have the dimensions (2401 samples x 63 channels x769 time points). Processed EEG data and labels are stored as NumPy arrays in the file **raw_mental.npz** that will be used in a classification model.

Statistical Analysis:

The EEG features are seperated into the 2 groups,fatigued,labelled as 0 and rested labelled as 1.The mean entropy is calculated for every subject across all 63 channels and all events in each group and for the 5 frequency bands.Entropy shows how complex the EEG signal is and therefore it provides information about the different state of the brain and its pathological conditions.In addition,the mean entropy is calculated across all subjects of each group again in all bands,in order to do a t-statistic test. For the statistical tests the file **subj_mean_mental.npz** is loaded and used on the notebook **statistical_tests.ipynb**

Mean of 20 fatigued subjects across all events and channels:

Delta Band	Theta Band	Alpha band	Beta band	Gamma band
3.08449923	3.19330675	3.24860949	3.29406844	3.27953932

Mean of 20 rested subjects across all events and channels:

Delta Band	Theta Band	Alpha band	Beta band	Gamma band
3.0868449	3.19324698	3.24531775	3.29224769	3.27853103

T-Statistic test is used in order to compare the mean entropy of each band from the fatigued group to the rested group,relative to the variability within the groups.

Null Hypothesis :There is no significant difference in the mean entropy values between the 2 groups in each of the 5 frequency bands.

Alternative Hypothesis :There is significant difference in the mean entropy values between the 2 groups in each of the 5 frequency bands.

The basic mathematical expressions of t-statistic test are the below:

$$t = \frac{\bar{X}_1 - \bar{X}_2}{s_p \cdot \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}},$$

, where

$$s_p = \sqrt{\frac{(n_1 - 1)s_{X_1}^2 + (n_2 - 1)s_{X_2}^2}{n_1 + n_2 - 2}}$$

- X1 and X2 are the mean values of entropy of the 2 groups.
- Sp is the pooled variance of the bands of the 2 groups,which is calculated through the variances s1 and s2 from the 2 groups respectively.
- N1 and n2 are the number of subjects in each group.

This procedure is done for each band and the p-values are then calculated.P-value shows whether the difference in the mean entropy of each group and for the 5 bands is statistically significant.The larger the t ,the larger the difference in the mean entropy values of the 2 groups is.Values of t near 0 indicate that the 2 means are approximately the same.A widely accepted significance level threshold is a=0.05,so if p-value is lower than a,the null hypothesis is rejected and if it is higher than a, null hypothesis is not rejected.In general p value is determined through t and through the degrees of freedom,which in this case are 38.

Results: The following table shows the t-statistic and p-values for the 5 bands:

Bands	Delta	Theta	Alpha	Beta	Gamma
T-statistic	-0.8634906432707189	0.026798838308703613	0.8166411393371195	0.7015748060538034	0.4057636461224721
P-value	0.39328538606656693	0.9787604255868243	0.4192238835141586	0.48721914782158204	0.6871920588784122

Conclusions:

In overall,there are differences in the mean entropy values of bands between the 2 groups,but since all p-values are much higher than the threshold 0.05,there is not sufficient evidence to reject the null hypothesis.So, all 5 frequency bands do not show statistically significant changes in the mean entropy values between the fatigued and the rested groups.

Classification

Our model presented in the file **2d_classify.py** is a classification approach for time series data with multiple channels, focusing on distinguishing between fatigued and rested states from the preprocessed dataset. Traditional convolutional neural networks (CNNs) may not capture the varying importance of different channels, so our attention-enhanced CNN addresses this by using both temporal and spatial information of the EEG dataset.

Model Architecture:

The model is fed with EEG inputs of shape (63 channels x 769 time points) for each of the 2401 samples from the loaded file **raw_mental.npz** δεν συμπεριλήφθηκε στο συμπιεσμένο αρχείο λόγω μεγέθους μπορείτε να το εξάγεται με το **raw_preprocess.py**.

The architecture is the following:

Convolution and MaxPooling layers: Two 2D Convolution layers with relu activation functions to extract temporal and spatial features from the raw EEG signals. 2D convolutions apply a 2-dimensional filter to the dataset and the filter moves in 2-direction (x, y) to calculate the low level feature representations The feature maps connected to multiple adjacent time points of the previous layer which can obtain deeper time information. Each convolution layer is followed by MaxPooling layers to reduce temporal features and overfitting.

The kernel sizes are (3x3) for convolution and (1x2) for max pooling, for an aggressive filtering for the temporal dimension.

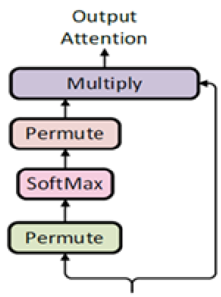
Attention Modules: Two attention modules follow the convolution layers for spatial feature extraction. Various regions of the brain, for example, the prefrontal and temporal brain regions, occupy different weights in the process of working memory, so the enhancement or suppression of a certain brain region will affect the classification. Attention mechanism can learn the weight map of different EEG channels to enhance the EEG channels with high correlation and suppress the EEG channels with low correlation. Each attention module is consisted of 4 layers:

Permute: Changes the order of the weight matrixes for each channel.

Dense: Uses softmax to learn the attention weight matrix of the channel.

Permute: Reverts the dimension order.

Multiply: Fuses the AM block input and weight matrix.



Dropout Layer: Included to reduce overfitting by randomly omitting a subset of features during training.

Flattening and Fully Connected Layers:

Flatten: Converts the multi-dimensional tensor into a 1D array.

FC1: A dense layer with relu activation processes the flattened data.

FC2: The final output layer with softmax activation yields the classification probabilities for the two states.

CNN attention model

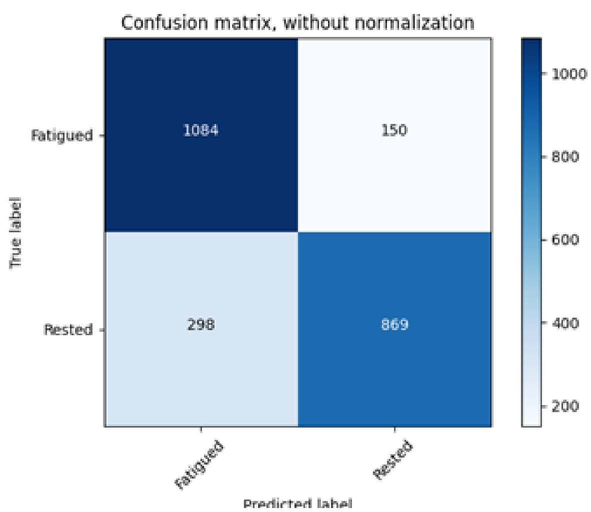
Layer	Output shape	Kernel size	Activation function
Input	-	-	-
Conv2D	63 × 769 × 32	3 × 3	relu
MaxPoolin2D	63 × 384 × 32	1 × 2	-
Conv2D	63 × 384 × 64	3 × 3	relu
MaxPoolin2D	63 × 192 × 64	1 × 2	-
Permute	64 × 192 × 63	-	-
Dense	64 × 192 × 63	-	softmax
Permute	63 × 192 × 64	-	-
Multiply	63 × 192 × 64	-	-
Permute	64 × 192 × 63	-	-
Dense	64 × 192 × 63	-	softmax
Permute	63 × 192 × 64	-	-
Multiply	63 × 192 × 64	-	-
Dropout	63 × 192 × 64	-	-
Flatten	774144	-	-
FC1	512	-	relu
FC2	2	-	softmax

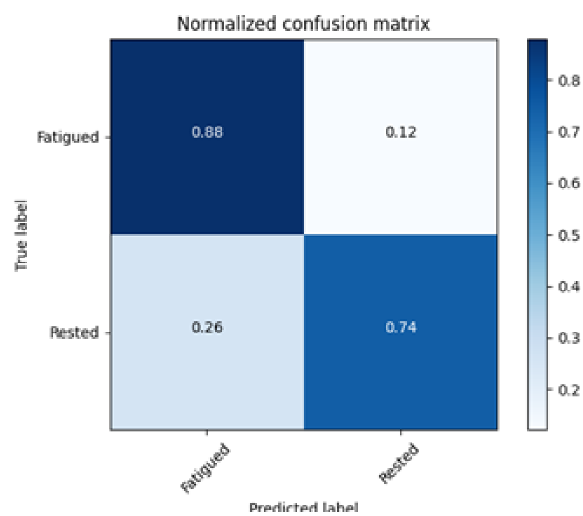
Validation

For the validation of the performance of the model a 5-fold cross validation is employed, and we use the metrics of average accuracy from the validation accuracies of all the folds and the confusion matrices are plotted for more details on sensitivity and specificity.

The **average accuracy** of this model is 81.34% with a varying performance of **std** = 2.95% across different validation sets.

Confusion matrices





From the first confusion matrix we have the following results:

True Positives (TP) for 'Fatigued': 1084 (correctly predicted as Fatigued)

False Negatives (FN) for 'Fatigued': 150 (incorrectly predicted as Rested)

False Positives (FP) for 'Rested': 298 (incorrectly predicted as Fatigued)

True Negatives (TN) for 'Rested': 869 (correctly predicted as Rested)

From the normalized confusion matrix, we have the following results:

Sensitivity/Recall for Fatigued: 0.88 (88% of the actual Fatigued instances were correctly predicted)

Specificity for Rested: 0.74 (74% of the actual Rested instances were correctly predicted)

After these results we conclude that the CNN model with attention shows a strong ability to classify the Fatigued state, with higher sensitivity and there is room for improvement on recognizing the Rested state. Overall, the model shows a strong ability to distinguish between the two states of Fatigued and Rested with an 81.34% average accuracy utilizing well the raw EEG data from 40 subjects. That is mainly because of the temporal and spatial feature extraction with the use of CNN layers and attention modules.