Ministry of Science and Higher Education of the Russian Federation

Federal State Autonomous Educational Institution of Higher Education
«National Research University ITMO»

Faculty of Software Engineering and Computer Engineering

Subject: «Neurotechnologies and Affective Computing»

Project Theme: «Comparison of Effectiveness of Several Classifiers in EEG Emotion Recognition»

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Introduction

As one of the most fundamental human mental processes, emotions play a crucial role in how people interact with the outside world. The emerging field of affective computing is aimed at "calculations that involve, arise from, or intentionally affect emotions". The most commonly used data in affective computing can be divided into human behavior data and physiological data. Because people can subjectively control their behavior, the data loses objectivity and affects the accuracy of experiments. Based on human physiological data, this problem can be well controlled.

The EEG-based approach has a good balance between mechanistic studies and practical applications in the real world. In recent years, electroencephalography (EEG) technology has been used for emotion recognition due to its simplicity, low cost, portability, and ease of use.

Subject: EEG emotion recognition
Purpose: Comparing different types of classifiers for emotion recognition

Main stages of the project:

- Read the paper for an overview of the field of emotion recognition and eeg
- Gain an in-depth look at existing EEG-based emotion recognition technology, understand the specific process, and optional technology
- Select the appropriate experimental paradigm to acquire data
- Choose an appropriate way to preprocess the data and extract appropriate features
- Choose an appropriate classifier, train it and compare the pros and cons of different classifiers from multiple perspectives
- Build applications from optimal models
- Summarize and draw conclusions

Group Division

Each member of the group implements 1-2 classifiers respectively.
One member implements the preprocessing of the data, the other makes the application.
Completing the comparison between classifiers together.

Final Result

The final result of this project is an application using the best classifier model, receiving data through OpenBCI, and outputting the emotions represented by the user data.

Project Repository: [GitHub - DenisAndGzh/EEG-Emotion-Recognition]

Theoretical part

Electroencephalography

The largest part of the human brain is the cortex, which is divided into frontal, temporal, parietal, and occipital lobes (Figure 1). The frontal lobes are responsible for conscious thought. The temporal lobe is responsible for smell and hearing, and processes complex stimuli such as faces and scenes. The parietal lobes are responsible for integrating sensory information from different senses, as well as manipulating objects. Finally, the occipital lobe is responsible for vision.

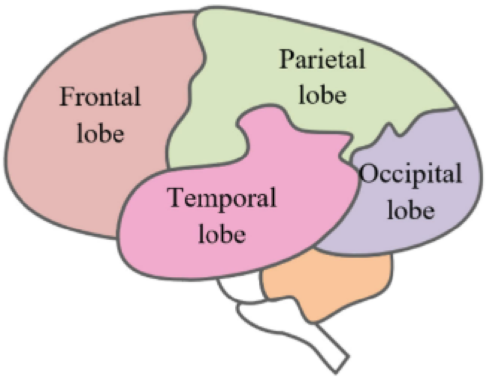


Figure 1. Differential brain map

An EEG is a medical imaging technique that reads the electrical activity of the scalp produced by the structures of the brain, that is, it measures the voltage fluctuations caused by the flow of ionic currents within the neurons of the brain. A typical adult EEG signal, when measured from the scalp, is about 10-100 uV. These signals are divided into specific ranges in the scalp that are more prominent in certain processing states (Figure 2), namely **delta** (1 – 4 Hz), **theta** (4 – 7 Hz), **alpha** (8-13 Hz), **beta** (13-30 Hz) and **gamma** (> 30 Hz).

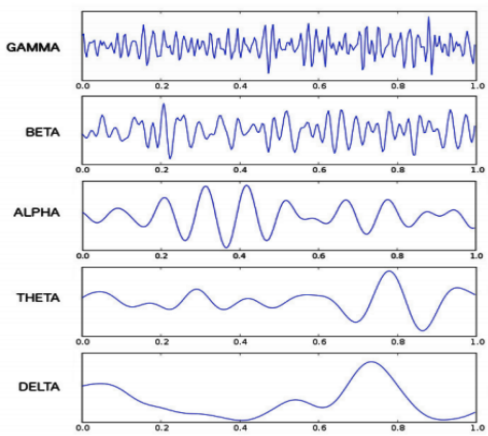


Figure 2. The five brain waves

Delta waves are associated with the unconscious mind and occur during a deep dreamless sleep.
Theta brain waves are associated with the subconscious mind and activities such as dreaming.
Alpha waves are typically associated with a relaxed, yet aware mental state, with high alpha activity being correlated to brain inactivity.
Beta waves are related to an active state of mind during intense, focused mental activity.
Gamma waves are associated with hyper brain activity.

Common EEG paradigms

To understand how to assess changes in EEG activity, researchers have proposed the most commonly used paradigms: sensory evoked potentials (SEPs), event-related potentials (ERPs), and event-related desynchronization/synchronization (ERD/ERS).
Evoked potentials correspond to potential signals recorded after the stimulus is presented. Based on different evoked methods, there are three types: auditory evoked potential (AEP), visual evoked potential (VEP), and somatosensory evoked potential (SsEP).
ERP has high temporal resolution and can measure immediate responses to short stimuli. They are usually measured as the latencies and amplitudes of positive and negative potentials at specific millisecond intervals after stimulation.
ERD/ERS analysis evaluates power changes within a specified frequency band with high temporal resolution. Responses that occur within milliseconds of stimulus presentation were assessed by measuring rapid changes in power over a defined frequency band.

Emotion Recognition in EEG

In order to use EEG signals to identify emotions, the following steps need to be performed (Figure 3):
1) stimulate emotions through experiments;
2) record changes in the brain through eeg;
3) remove noise and artifacts from the signals;
4) Extract features from the signal;
5) based on training Sets, using the computed features, trains a classifier, and interprets the raw brain signals.

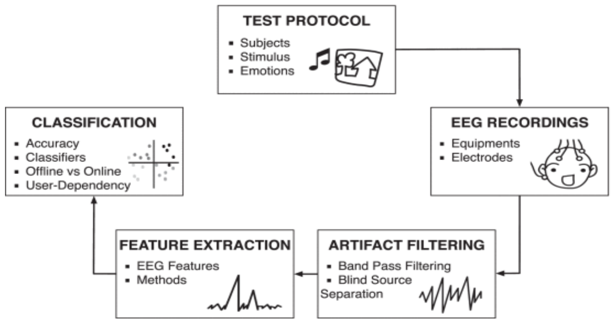


Figure 3. Process of emotions recognition

Electrode location of EEG

To generate reproducible setups, there are standardized sets of electrode positions on the skull, such as the International 10/20 System (IS) (Figure 4).

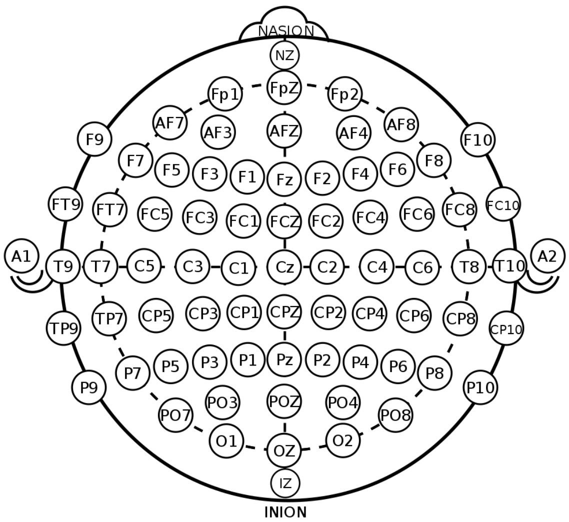


Figure 4. International 10-20 system

Emotion Model

Emotion is a complex mental state. There are two different perspectives on emotion representation.

The first view holds that basic emotions evolved through natural selection. Plutchik proposes eight basic emotions: anger, fear, sadness, disgust, surprise, curiosity, acceptance, and joy. All other emotions can be composed of these basic emotions (for example, disappointment is composed of surprise and sadness).

The second view is based on cognition and believes that emotion can be mapped to three dimensions: valence, arousal, and dominance (VAD). Valence ranges from very positive to very negative feelings (or from unhappy to happy); arousal ranges from sleepy to excited states; and finally, dominance corresponds to emotional intensity. The most commonly used model is the Circumplex Model (Figure 5) of emotion, which only considers valence and arousal.

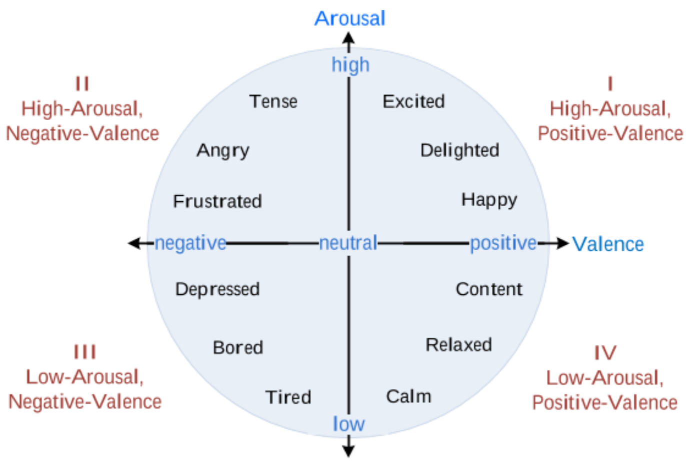


Figure 5. Circumplex Model

Emotions Induced

Before EEG signal acquisition, subjects must be in the mood required for emotion recognition. Commonly used emotion induction methods include imagination induction method and event induction method.

Imagination Induction Method, by prompting the subjects to recall the corresponding events and induce emotions.

Event Induction Method, By playing music, showing pictures and videos to the subjects, make them emotional.

EEG Emotion Recognition Dataset

[DEAP Dataset](): A multimodal dataset for the analysis of human affective states.

[SEED Dataset](): The SJTU Emotion EEG Dataset (SEED), is a collection of EEG datasets provided by the BCMI laboratory, which is led by Prof.

[DREAMER Dataset](): A multi-modal database consisting of electroencephalogram and electrocardiogram signals recorded during effect elicitation by means of audio-visual stimuli.

Practical Part

Project Information

Project Dataset: SEED
Emotion Model: Positive Activation – Negative Activation (PANA) model
Categories of Emotions: negative, neutral, positive
EEG Equipment: OpenBCI (Cyton Daisy 6 channels)
Electrode location: F7, F8, T7, T8 (According to research, the data obtained from this 4 EEG electrodes are most closely related to emotions)
Experimental setup: Using the event induction method, evoked the emotions of the subjects through movie clips with a tendency to be negative, neutral, positive

Experiment Setup

In the SEED dataset experiment, movie clips were chosen to elicit emotional states.
A 62-channel electrode cap was used to collect the EEG signals of the subject during the experiment, and ESI NeuroScan System was applied to record the data with the sample rate 1000Hz synchronously.
We will use the SEED dataset as the training dataset for the model, and through similar experiments, use the OpenBCI EEG cap to obtain test data.
In our experiment, the subject's EEG signals will be continuously collected during the movie clip playing, and the subject will self-assess their emotional state after the movie clip is played. We will crop the data and keep the last 100 seconds of data as the actual test data for emotion recognition.

Emotion Classification Model Build

Data Preprocessing

In the SEED dataset, the raw data has been downsampled to 200 Hz and filtered with a 0-75 Hz bandpass filter, So we don't need to do data preprocessing.

Data Artifact Filtering

Filter the data with a bandpass filter to obtain the data of five frequency bands (delta: 1–3 Hz theta: 4–7 Hz, alpha: 8–13 Hz, beta: 14–30 Hz, gamma: 31–50 Hz).

Data Feature Extraction

The differential entropy of each frequency band is calculated separately, DE(differential entropy) is defined as:

$$\textbf{DE} = -\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma}} \exp \frac{(x-\mu)^2}{2\sigma^2} \ln\left(\frac{1}{\sqrt{2\pi\sigma}} \exp \frac{(x-\mu)^2}{2\sigma^2}\right) dx = \frac{1}{2} \ln 2\pi e \sigma^2$$

According to research the DE feature is more suited for emotion recognition than traditional feature ES(energy spectrum).

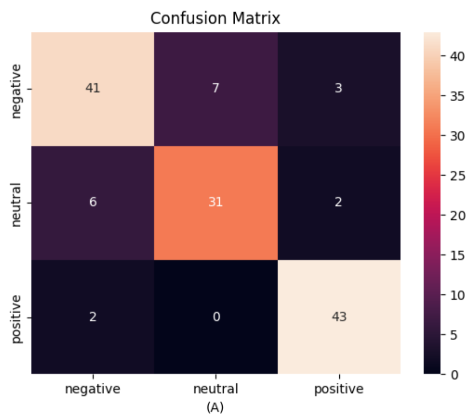
Emotion Data Classifier

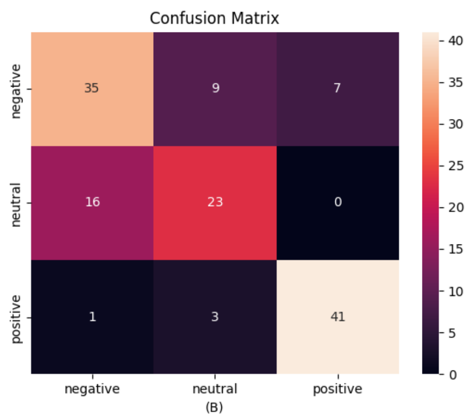
We train and test different classifiers and get the following accuracy table of each classifier:

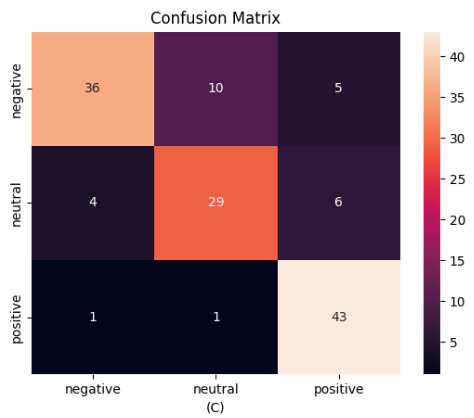
	precision	recall	f1-score
SVM	**0.73**	**0.74**	**0.73**
KNN	0.59	0.60	0.58
Random Forest	0.62	0.63	0.62
GaussianNB	0.58	0.60	0.59
Decision Tree	0.52	0.51	0.51
Ada Boost	**0.71**	**0.70**	**0.70**
Neural Network	**0.70**	**0.70**	0.69

It is known from the table that for a given dataset, the accuracy of SVM, Ada Boost, Neural Network is greater than 0.70.
We will calculate the parameters for which the three classifiers are most accurate.
Finally, for the same training and testing datasets, we get the following accuracy:

	precision	recall	f1-score
SVM	0.85	0.85	0.85
Ada Boost	0.73	0.73	0.73
Neural Network	0.81	0.80	0.80







The confusion matrix of different classifiers.
Here the number inside the figures denotes the recognition accuracy in percentage.
(A) SVM. (B) AdaBoost. (C) MLP.

Compare and Analyze

SVM is very easy to understand, it separates the points on the hyperplane by a few lines, and divides these points into different classes.However, when the parameters are incorrect, it is easy to cause the problem of overfitting.
SVM is a convex optimization problem, so the solution obtained must be a global optimum rather than a local optimum and data with a high-dimensional sample space can also use SVM, because the complexity of the dataset only depends on the support vector rather than the dimension of the dataset. And it takes the shortest time to train compared to other classifiers and it can solve machine learning problems with small samples.
Therefore, the SVM algorithm is a classifier that is very suitable for EEG emotion recognition.

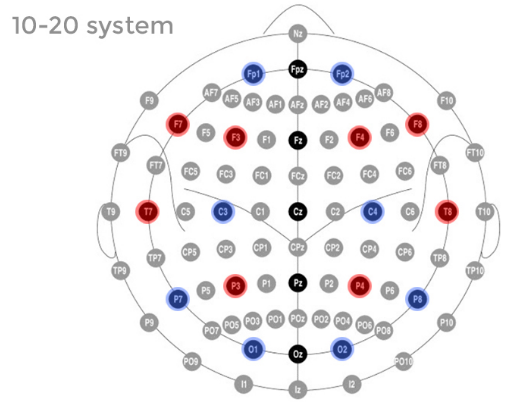
The principle for AdaBoost is that the weights of samples that were misclassified by the previous base classifier will increase, while the weights of correctly classified samples will decrease, and are used again to train the next base classifier. At the same time, in each round of iteration, a new weak classifier is added, and the final strong classifier is not determined until a predetermined small enough error rate or a pre-specified maximum number of iterations is reached. EEG data contains a lot of noise compared to other types of data.
Therefore, since the AdaBoost algorithm is sensitive to abnormal samples, abnormal samples may get higher weights in iterations, which will eventually affect the prediction accuracy of the strong learner. Meanwhile, compared to SVM, it takes a lot more time to train the model.
However, compared with the other two classifiers, AdaBoost can use a simple weak classifier without filtering features, and there is no overfitting phenomenon.

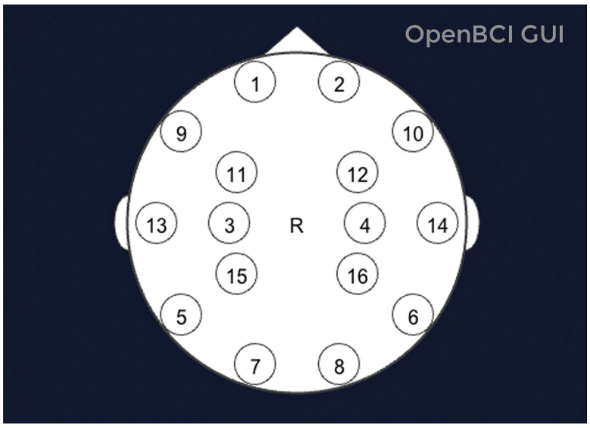
MLP is a forward-structured ANN artificial neural network, which can deal with non-linear separable problems. Its accuracy largely depends on the design of the number of neurons in different layers and choice of activation function and loss function. MLP is easy to overfit in the training process, and the training time is long because the computational complexity is proportional to the network complexity, sometimes trapped in local extrema.It is very difficult to select the number of hidden nodes in the network.
However, as an artificial neural network, MLP has very strong self-adaptive, self-learning, associative memory functions, and has good fault tolerance. If the parameters are selected correctly, it is still a very suitable algorithm for EEG emotion recognition.

Emotion Recognition Application

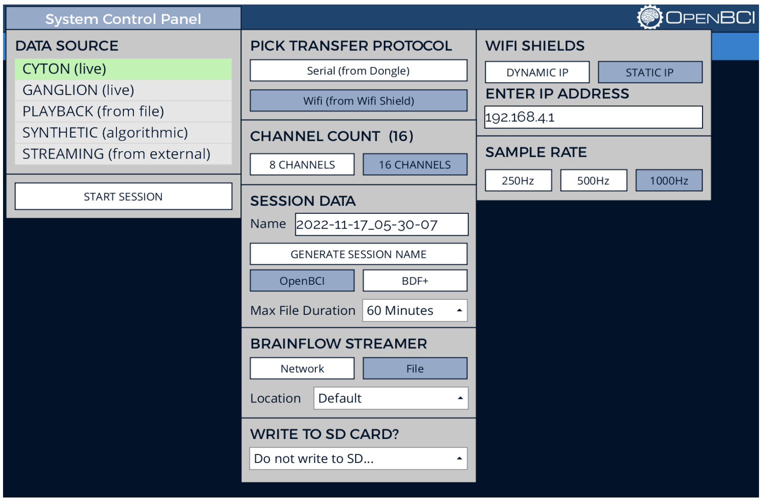
EEG data recording

1.First set the EEG cap electrodes, we only use four electrodes (F7, F8, T7, T8). Respectively, corresponding to the positions of 9, 10, 13, 14 in the figure below:

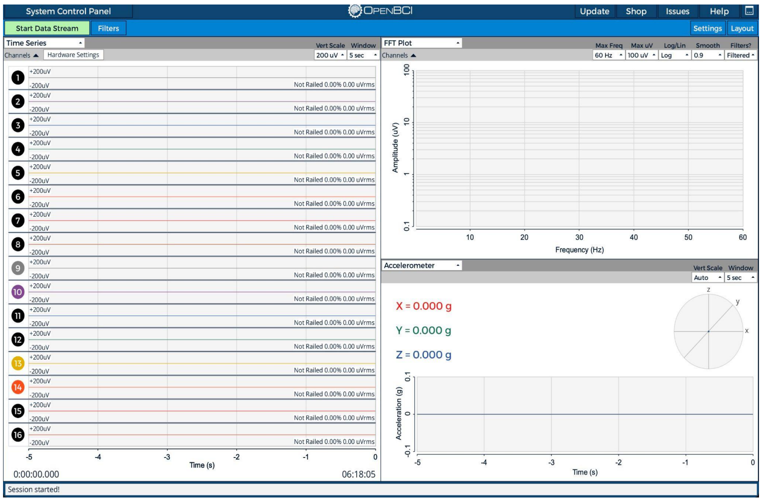




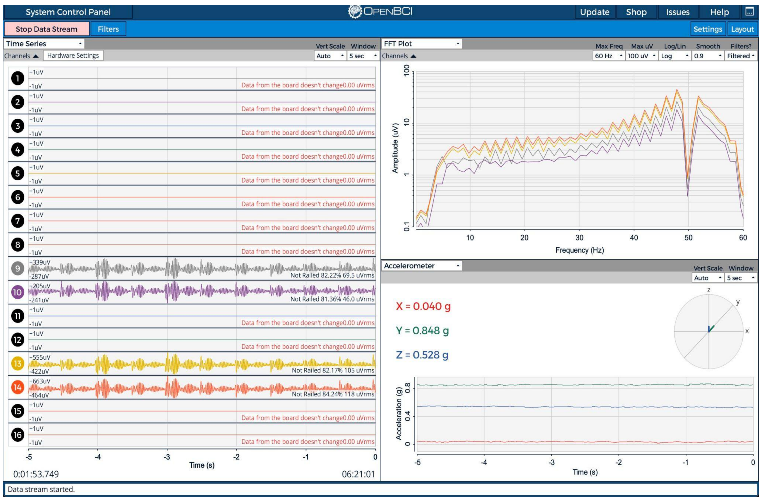
2.Turn on the EEG cap and connect it's WIFI, and use the following parameters to connect the EEG hat:



3.Click START SESSION to connect the EEG cap, and close the unnecessary channels, only keep 9, 10, 13, 14:

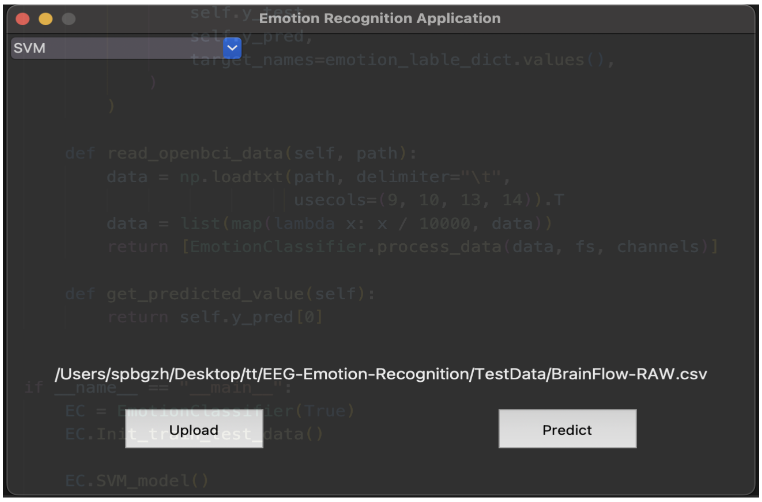


4.Watch movie clips and start recording data, and after the movie segment ends, end the recording data:

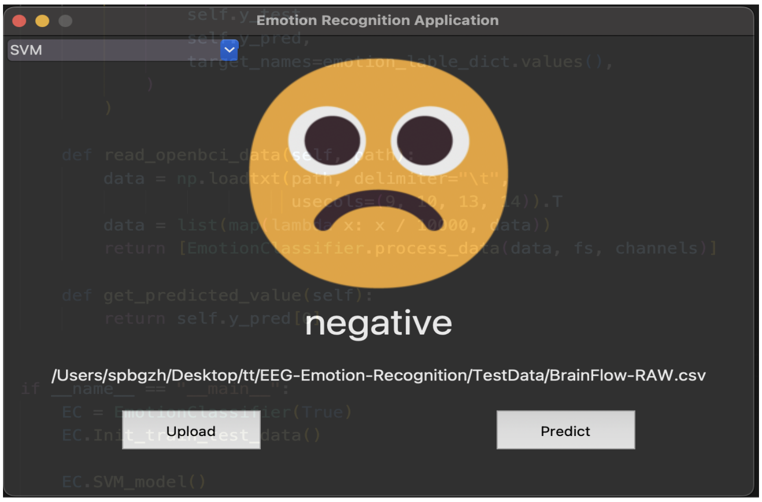


Use Application to predict emotion

1.Run the app, click upload, find the EEG data just recorded and upload it:



2.Select the classification model, click Predict, and wait for the running result:



Summarize

In this project, we implement three emotion recognition models through EEG, and implement an emotion recognition application through these three models.
By reading the papers and practice, we have a preliminary understanding of the entire EEG signal analysis process. At the same time, through this course, we learned emotion theory, emotion model, and the process of emotion recognition in different media such as audio and pictures.
Through this project, we have mastered the use of multiple python libraries, and learned a variety of sklearn machine learning classifiers, as well as methods to find the best parameters of the model, and how to evaluate the model.
Also, we learned how to build an application via python and combine it with the model we trained.
From this project we gained valuable experience in finding and reading papers and literature, and distilling the valuable information into our own projects.
Thank the professor for signing the SEED dataset for us, and giving us valuable advice.

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