KULLIYYAH OF INFORMATION & COMMUNICATION TECHNOLOGY
DEPARTMENT OF COMPUTER SCIENCE

CSCI 4347 - Brain Computational Analysis

SEMESTER 2 - 2020/2021

SECTION 1

Group 5: Soft-Tach

Analysing student interest in Science subject by using EEG signals

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1.0 INTRODUCTION

The researchers divided interest into two categories: personal interest and situational interest. Situational interest is easily activated and regulated by the situation, whereas both lead to focused attention on the object of interest. As a result, numerous research studies have been conducted in order to explain the science of interest growth and how to apply it to the benefit of students. In a discipline where many students are afraid of and unable to put up the effort, such as science, where "Proficiency in science courses is a huge advantage in industrialised nations" (Maloney, Schaeffer, & Beilock, 2013), situational curiosity has a significant impact.

One way to investigate this interest is to investigate the underlying brain activities. Because of the advanced technology that has made it available at a low cost, the electroencephalogram (EEG) is among the most effective non-invasive equipment in this case. Furthermore, unlike questionnaires, EEG signals cannot be manipulated by participants. As a result, it is widely used in classroom experiments to detect students' attention and engagement.

For our project, we'll analyze the EEG signals data of student's interest in science. We have two datasets to work with: one for eyes close data and one for eyes open data. The datasets have 20 columns, 19 of which contain channel data.

1.1 Problem Statement

Science is one of the most important subjects for students to succeed in school, but many students struggle with it. An emotionally weak student may struggle to understand science, but it is very crucial to identify the demotivating factors affecting the student’s performance in science. It’s very crucial for the improvement of student’s performance in science. We'll analyze the students' EEG data on students' interest in science to determine their emotion while engaging with science assessment in order to improve their performance.

1.2 Project Objective

- ➢ To understand the EEG signals data of students' interest in science.
- ➢ To determine the students emotions using EEG signals.
- ➢ To determine the subjects of emotion while running two datasets of eyes_open and eyes_close.
- ➢ To learn the use of Multi Layer Perceptron(MLP) for EEG data.
- ➢ To determine the accuracy of ANN/ MLP model on selected datasets.

2.0 LITERATURE REVIEW

Norzaliza et al. [1] used EEG to investigate the relationship between a student's precursor emotion and learning interest. They use electroencephalogram (EEG) devices to examine the relationship of precursor emotion to student interest in learning mathematics and science in their paper. The researchers examined the correlation and associated emotion using the 2-D Affective Space Model (ASM) and four basic emotions as reference stimuli: happiness, calmness, fear, and sadness.

While answering the math and science questions, the EEG device was used to extract brain wave signals. The EEG signals were recorded on the student's scalp, and features were extracted using the Mel Frequency Cepstral Coefficient (MPCC). The ASM's valence and arousal axes were classified using a neural network classifier of Multilayer Perceptron (MLP). Their preliminary findings revealed a link between the student's precursor emotions and dynamic emotions while taking the mathematics and science tests. They hope that these findings will help us better understand student behaviour and interest in mathematics and science learning.

M. Alarcão & J. Fonseca [2] presented a survey of neurophysiological research conducted between 2009 and 2016, providing a comprehensive overview of existing works in emotion recognition using EEG signals. They concentrated on analysing and comparing the main aspects involved in the recognition process (e.g., subjects, extracted features, classifiers). Comparisons were made between 63 pieces that fulfil 9 of 14 key criteria according to: subjects, stimuli (and duration of the stimuli), emotions to be retrieved, EEG equipment (with the sample frequency), location of the electrodes, artefact filters, extracted EEG functionality, extraction methods, classification systems used, offline versus online training/test. They proposed a set of good practise recommendations based on this analysis for researchers to follow in order to achieve reproducible, replicable, well-validated, and high-quality results at the end. They intended for the survey to be useful for the research community working on emotion recognition through EEG signals, particularly for those just starting out in this field, because it provides a structured starting point.

Dan et. al. [3] worked on the EEG-Based Attention Analysis in Multimedia m-Learning. The TGAM chip was used to conduct an EEG experiment with a group of iPad-based mobile learners. The researchers investigated the differences in learners' attention across three learning mediums (text, text Plus graphic, and video). To guarantee that the volunteers could engage in the experiment willingly and sign the informed permission form before the experiment, the experimenter explained the scope and method of the experiment to them and assured them that the experiment would not endanger their health. The researcher recruited two specialists with extensive expertise in mobile learning and EEG to confirm that the experimental material was scientific and acceptable. The researchers discovered no significant differences in attention across media, however text media learners had the greatest attention value. After that, the researchers looked at the attention of students with various learning styles and discovered that while utilising video media to learn, active and reflective students' attention differed significantly.

3.0 PROTOCOL EXPERIMENT

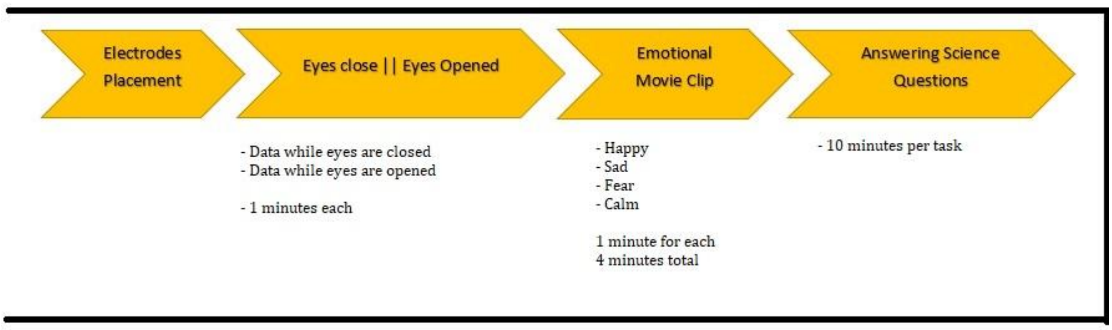

Figure 2.1 Procedures for the experiment

In order to carry out a successful EEG data collection experiment, firstly all the Electrodes are placed properly on various parts of students' scalps. The student's emotional state will be determined based on his or her eyes open and closed. To make sure that the brain activity is properly initialised during open eyes, students look at a white blank screen. Then the four basic emotional movie clips, which represent happiness, fear, calmness and sadness, are shown for a and a half minute by movie clip. The student needs to fill out Manikin's self-assessment following each movie clip. Finally, students are required to complete an exam that includes science questions. There will be ten science questions in this section, with difficulty levels ranging from easy to difficult. For answering the questions, a time limit can be established, such as 15 seconds for simple questions, 30 seconds for medium questions, and 40 seconds for difficult questions. The whole data collection experiment can be done within 15 minutes of the time span.

4.0 METHODOLOGY

4.1 Tools Utilized

We are using MATLAB 2020 as the software to analyze EEG signals of student interests in science subjects. It is appropriate to analyze the data since we have an amount of numeric data in csv files.

4.2 Data Preparation and Preprocessing

1	Time	Fp1-CPz	Fp2-CPz	F3-CPz	F4-CPz	F7-CPz	F8-CPz	C3-CPz	C4-CPz	T7-CPz	T8-CPz	P3-CPz	P4-CPz	P7-CPz	P8-CPz	O1-CPz	O2-CPz	Fz-CPz	Cz-CPz	Pz-CPz
2	2019.07.2	-21.913	-18.078	-19.308	-13.968	-11.385	-15.067	5.364	-3.924	10.02	-8.366	9.104	-25.009	-26.28	-1.935	-34.138	-46.929	-23.227	-19.235	-28.565
3	2019.07.2	-36.499	-14.711	-38.711	-31.769	-21.234	-26.334	14.629	6.049	19.839	-4.535	22.015	-3.035	-19.576	27.285	-29.144	-11.24	-39.352	-29.012	-25.819
4	2019.07.2	-30.989	-1.556	-36.486	-29.104	-17.631	-17.32	14.208	8.257	21.89	4.716	22.328	14.788	-4.945	40.398	-11.939	17.604	-35.856	-23.073	-11.243
5	2019.07.2	-11.57	12.777	-16.643	-10.511	-3.024	5.597	4.809	1.677	17.22	14.584	11.891	19.891	9.804	34.486	8.389	26.038	-17.147	-6.504	6.282
6	2019.07.2	7.344	20.164	5.781	10.164	12.71	27.443	-6.976	-8.184	10.495	19.675	-1.078	12.288	16.584	18.419	20.664	14.719	3.318	9.227	16.314
7	2019.07.2	13.958	18.224	15.897	20.034	19.749	35.493	-13.885	-13.836	6.305	17.404	-8.459	-0.419	12.31	5.372	19.015	-3.937	12.955	14.75	14.083
8	2019.07.2	6.923	10.994	9.221	15.814	15.225	27.764	-13.263	-11.617	6.075	9.499	-7.88	-9.16	0.657	3.165	6.495	-15.873	8.5	9.108	3.315
9	2019.07.2	-5.408	4.958	-6.486	4.594	4.406	13.043	-8.391	-4.18	7.79	0.711	-3.361	-9.777	-10.824	9.685	-7.581	-15.193	-3.11	-0.678	-7.213
10	2019.07.2	-12.868	3.873	-18.478	-3.117	-4.248	3.081	-5.179	2.081	8.337	-4.274	-1	-5.009	-15.961	16.243	-14.362	-6.679	-11.405	-5.904	-10.443
11	2019.07.2	-11.639	6.418	-19.125	-2.018	-5.857	3.523	-7.213	2.313	6.248	-3.585	-3.636	-1.129	-13.712	15.378	-11.185	-0.123	-10.82	-3.013	-5.808
12	2019.07.2	-6.245	8.124	-10.912	4.514	-2.293	10.581	-13.203	-3.174	2.607	1.101	-8.861	-2.414	-7.935	6.615	-2.314	-1.776	-4.269	4.366	1.381
13	2019.07.2	-4.491	5.548	-3.018	8.31	0.343	15.406	-18.621	-9.649	-0.331	6.063	-11.654	-7.985	-3.802	-4.041	5.29	-9.78	0.417	9.305	4.887

Figure 4.2.1: Data General look

We have two datasets to use which one is for eyes close data while another one is for eyes open data. The datasets have 20 columns and 19 of them are the data of channels. The Data pre-processing part of Eyes close data is shown below as a sample In MATLAB, we are removing the first column which records the time. After that, we assign all columns of channel data into our variables followed by splitting the signals to different bands such as Alpha, Beta, Gamma, Theta, Delta in a dataframe.

```
EFP1 = table2array(EC(:,1));
EFP2 = table2array(EC(:,2));
EF3  = table2array(EC(:,3));
EF4  = table2array(EC(:,4));
EF7  = table2array(EC(:,5));
EF8  = table2array(EC(:,6));
EC3  = table2array(EC(:,7));
EC4  = table2array(EC(:,8));
ET7  = table2array(EC(:,9));
ET8  = table2array(EC(:,10));
EP3  = table2array(EC(:,11));
EP4  = table2array(EC(:,12));
EP7  = table2array(EC(:,13));
EP8  = table2array(EC(:,14));
EO1  = table2array(EC(:,15));
EO2  = table2array(EC(:,16));
EFz  = table2array(EC(:,17));
ECz  = table2array(EC(:,18));
EPz  = table2array(EC(:,19));
```

Figure 4.2.2: Eyes close data

```
[EGamma1,EBeta1,EAlpha1,ETheta1,EDelta1, ESig0601] = splitband(EFP1);
[EGamma2,EBeta2,EAlpha2,ETheta2,EDelta2, ESig0602] = splitband(EFP2);
[EGamma3,EBeta3,EAlpha3,ETheta3,EDelta3, ESig0603] = splitband(EF3);
[EGamma4,EBeta4,EAlpha4,ETheta4,EDelta4, ESig0604] = splitband(EF4);
[EGamma5,EBeta5,EAlpha5,ETheta5,EDelta5, ESig0605] = splitband(EF7);
[EGamma6,EBeta6,EAlpha6,ETheta6,EDelta6, ESig0606] = splitband(EF8);
[EGamma7,EBeta7,EAlpha7,ETheta7,EDelta7, ESig0607] = splitband(EC3);
[EGamma8,EBeta8,EAlpha8,ETheta8,EDelta8, ESig0608] = splitband(EC4);
[EGamma9,EBeta9,EAlpha9,ETheta9,EDelta9, ESig0609] = splitband(ET7);
[EGamma10,EBeta10,EAlpha10,ETheta10,EDelta10, ESig06010] = splitband(ET8);
[EGamma11,EBeta11,EAlpha11,ETheta11,EDelta11, ESig06011] = splitband(EP3);
[EGamma12,EBeta12,EAlpha12,ETheta12,EDelta12, ESig06012] = splitband(EP4);
[EGamma13,EBeta13,EAlpha13,ETheta13,EDelta13, ESig06013] = splitband(EP7);
[EGamma14,EBeta14,EAlpha14,ETheta14,EDelta14, ESig06014] = splitband(EP8);
[EGamma15,EBeta15,EAlpha15,ETheta15,EDelta15, ESig06015] = splitband(EO1);
[EGamma16,EBeta16,EAlpha16,ETheta16,EDelta16, ESig06016] = splitband(EO2);
[EGamma17,EBeta17,EAlpha17,ETheta17,EDelta17, ESig06017] = splitband(EFz);
[EGamma18,EBeta18,EAlpha18,ETheta18,EDelta18, ESig06018] = splitband(ECz);
[EGamma19,EBeta19,EAlpha19,ETheta19,EDelta19, ESig06019] = splitband(EPz);
```

Figure 4.2.3: Eyes close split band

4.3 Feature Extraction

Feature Extraction is a process of dimensionality reduction by which an initial set of raw data is reduced to more manageable groups for processing. More specifically, for our Feature Extraction, we separate all categories of signal to basic elements.

```
Es1ec_bandsG1 = EGamma1;
Es1ec_bandsB1 = EBeta1;
Es1ec_bandsA1 = EAlpha1;
Es1ec_bandsT1 = ETheta1;
Es1ec_bandsD1 = EDelta1;
Es2ec_bandsG2 = EGamma2;
Es2ec_bandsB2 = EBeta2;
Es2ec_bandsA2 = EAlpha2;
Es2ec_bandsT2 = ETheta2;
Es2ec_bandsD2 = EDelta2;
Es3ec_bandsG3 = EGamma3;
Es3ec_bandsB3 = EBeta3;
Es3ec_bandsA3 = EAlpha3;
Es3ec_bandsT3 = ETheta3;
Es3ec_bandsD3 = EDelta3;
Es4ec_bandsG4 = EGamma4;
Es4ec_bandsB4 = EBeta4;
```

Figure 4.2.4: Feature Extraction for Eyes Close

4.4 Modeling

In our case, we are applying Multi Layer Perceptron as the classification technique. Before we implement this classification, the Eyes closed data and Eyes open data are supposed to be combined and randomized. A Neural Network is trained which contains 1 input layer, 1 output layer and 3 hidden layers. The algorithms that are used are as follows for error checking,

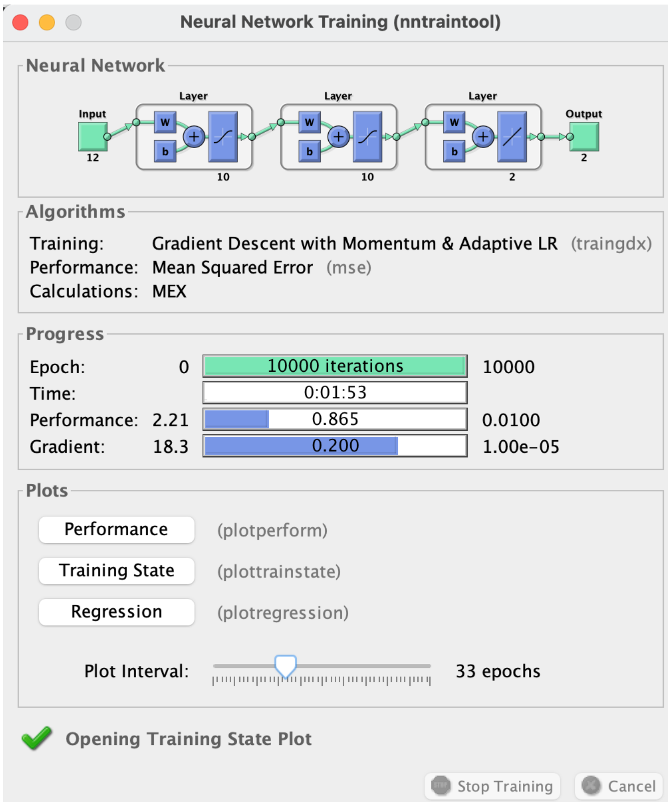

Figure 4.3: Neural Network Training

The model for eyes open has gone through 10,000 Epoch as seen on figure 4.3. The time taken for this model to train was around 1 minute and 53 seconds. There are 3 hidden layers, 1 input and 1 output layer as seen on the figure above. For training the model, Gradient Descent with Momentum & Adaptive LP Algorithm is used and for measuring the performance Mean Squared Error(MSE) is used.

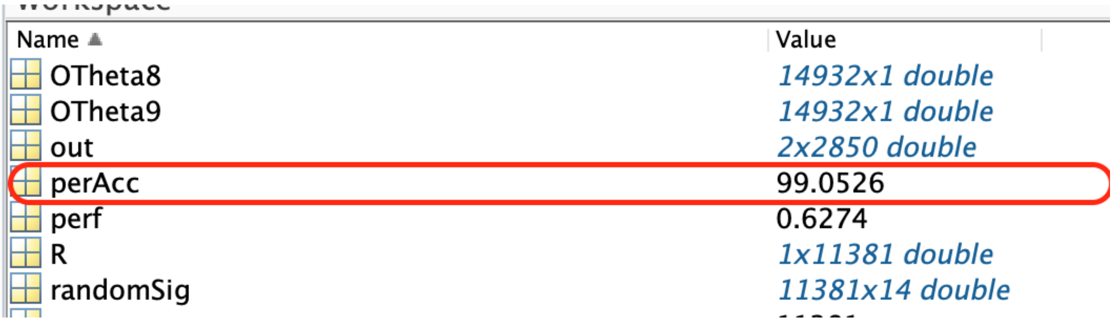

Figure 4.4: Model Performance EC

As seen on figure 4.4 the performance for eyes closed model has an accuracy of 99.05% which is an excellent result to deploy the model.

Figure 4.5: Model Performance EO

For eyes opened the performance accuracy is slightly better as seen on figure 4.5 than eyes closed (figure 4.4). The results are more than good enough to evaluate the emotion and identify the mood of the patient.

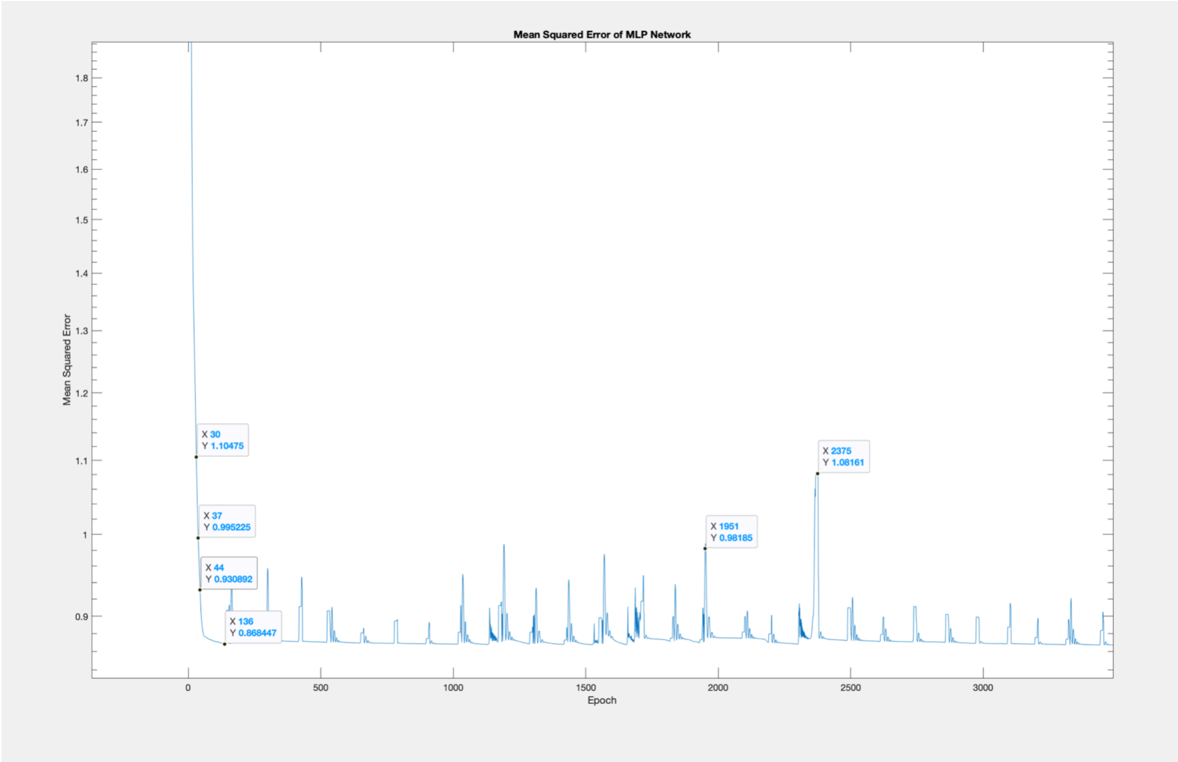

Figure 4.6 Mean Squared Error EO

The Mean Square Error as seen above on figure 4.6 has drastically reduced right around 37 to 44 Epoch and continued to reduce and it is understandable as it is the beginning of the training. There was a sudden spike at Epoch 2375 but after that the rest of the MSE were consistent and evenly distributed.

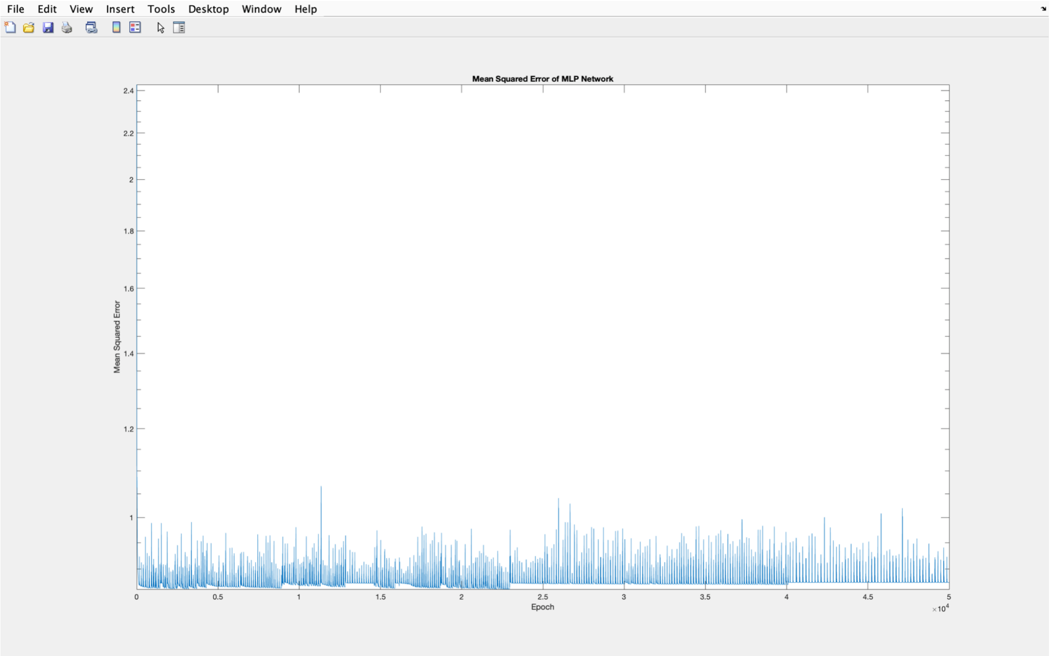

Figure 4.6.1 Mean Squared Error EC

The Mean Square Error as seen above on figure 4.6.1 has drastically reduced at the early stage as expected, just like the one on eyes opened model and continued to reduce. For eyes closed the model was trained for 50,000 Epoch instead of the default 10,000 Epoch. For eyes closed this time the mode has gone through 5 times more Epoch because we wanted to check if there are other patterns in the MSE and there are surprising results as seen on figure above. The spike has spread out slightly after 20,000 to 25,000 Epoch which shows that increasing the Epoch does make a difference in the MSE.

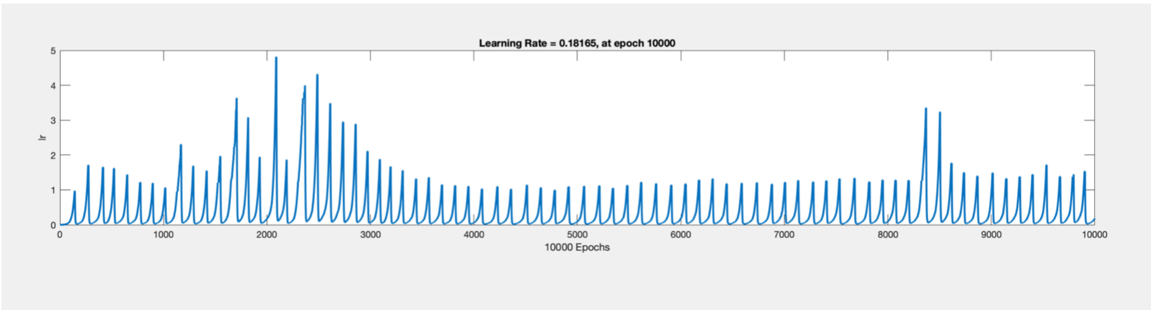

Figure 4.7 Learning rate EO

The learning rate for eyes opened after 10,000 Epoch is at 0.18165.

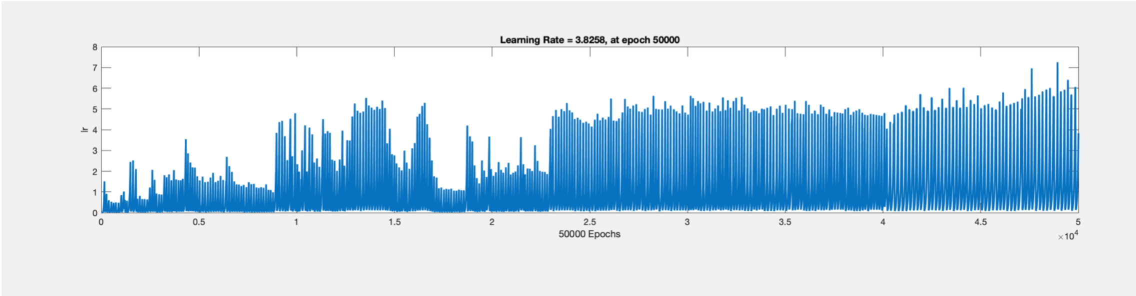

Figure 4.8 Learning rate EC

The learning rate for eyes closed after 50,000 Epoch is at 3.8258. Seems like a big jump due to the higher number of Epochs.

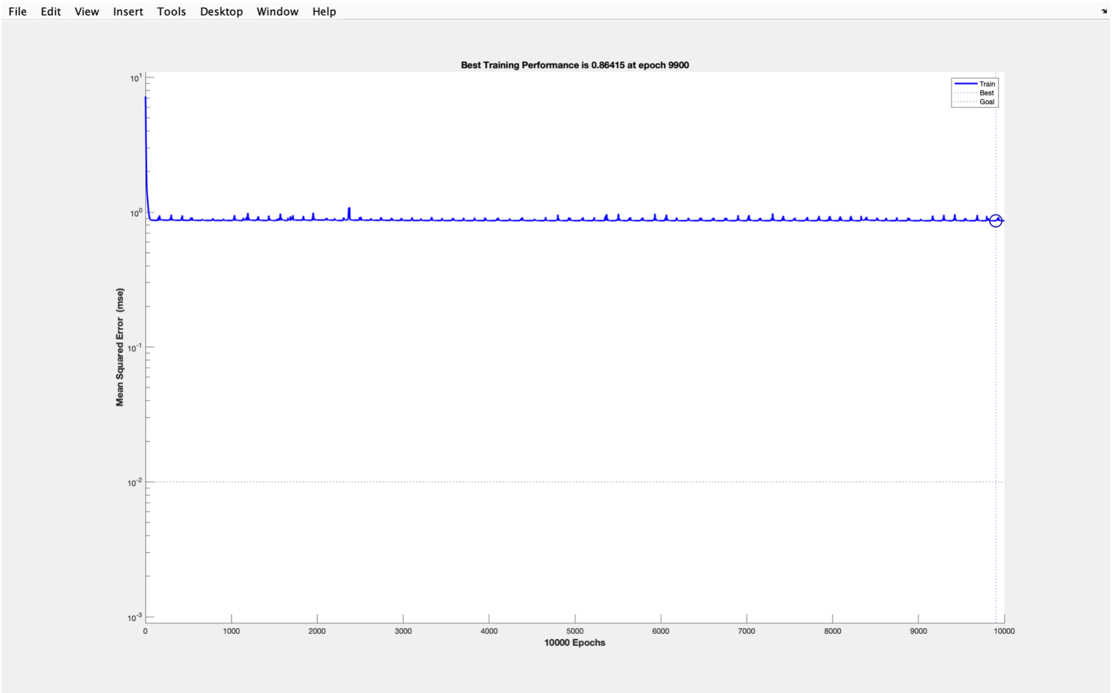

Figure 4.9 Best training performance EO

The best performance for eyes opened is at 9,900 Epochs. Better performance could be acviehd if the epoch size were increased just like Eye closed where the Epoch was 50,000.

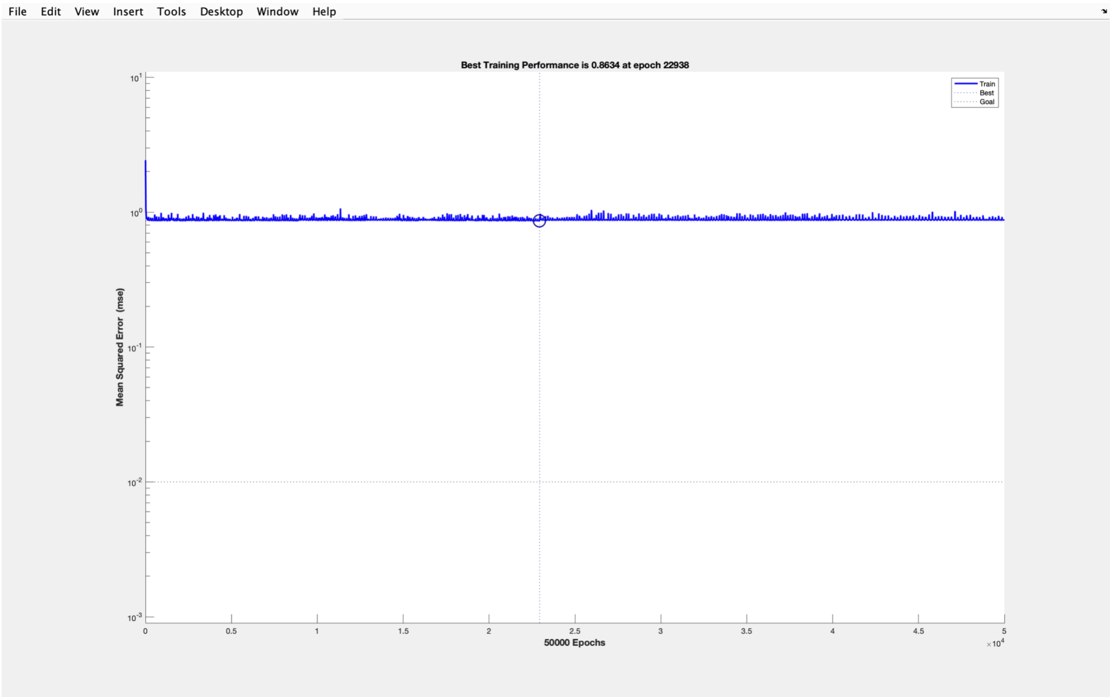

Figure 5.0 Best training performance EC

The best performance for an eyes closed model is at Epoch number 22,938 which is much better than the performance for eyes opened.

4.5 Result Analysis

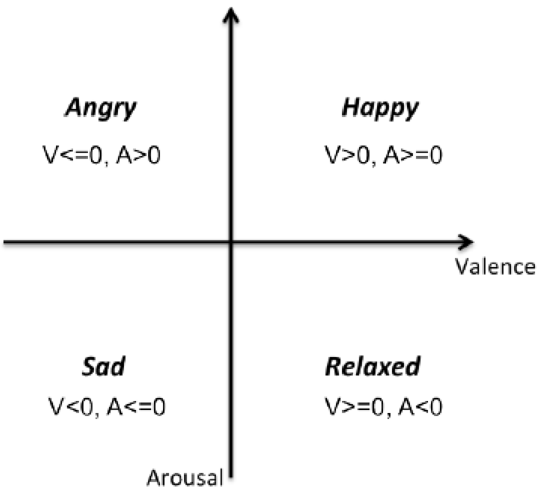

Figure 5.1 Russell's model for reference

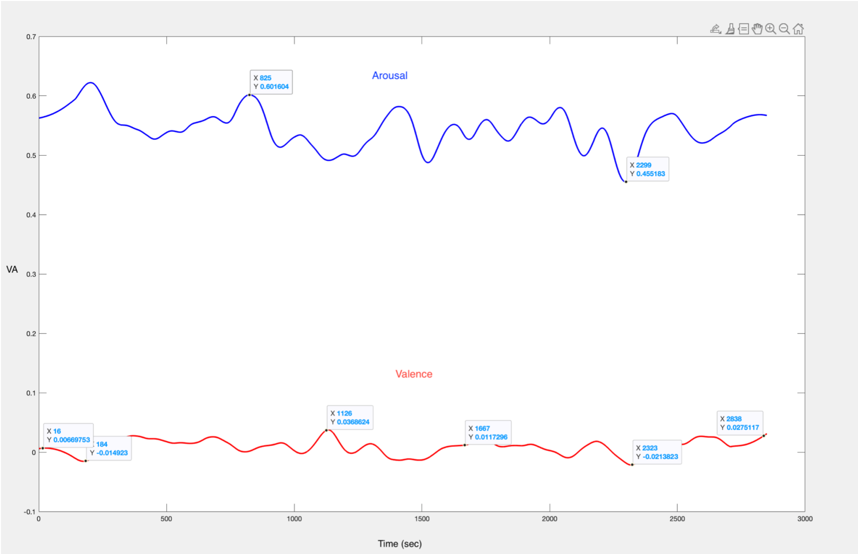

Figure 4.4.1: Result Eyes open

In the case of eyes open data as seen above on figure 4.4.1, the brain signal for Valence starts out positive (+ve), but after some time, it becomes negative (-ve) and back to (+ve). From our in depth analysis we can say that the emotion of this patient is happy and slightly agitated.

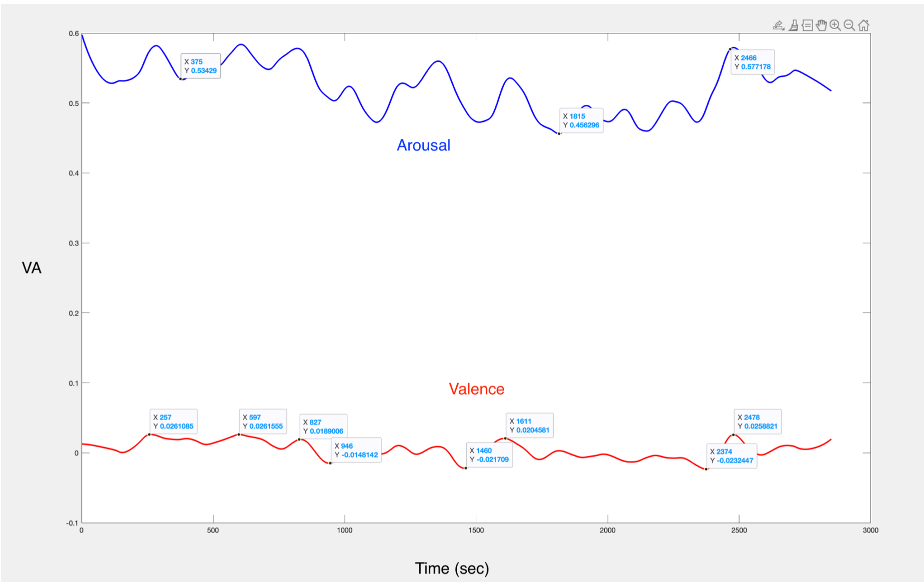

Figure 4.4.2: Result Eyes closed

This graph is for the Eyes closed dataset as shown above on figure 4.4.2. The red line denotes valence, whereas the blue line denotes arousal. We discovered that the Valence is also fluctuating between (-ve) and (+ve). Therefore we had to do a bit more analysis and drew a line to evaluate the valence which side does it fall most of the time. After the analysis we come to the conclusion that the patient is happy with a bit of fear.

5.0 CONCLUSION

In conclusion, our model is performanced well as it is supposed to and we were able to identify the patient's emotion based on the data we have collected. Our models accuracy for both eyes closed and eyes open is well over 99% and we are satisfied with the results.

References

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