# Mental Performance Monitoring App Using EEG and Machine Learning

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***Abstract*—Although a person can be identified physically in a task, it is difficult to determine whether that person is mentally focused on the task and it affects the efficiency of the task. For example, teachers can check whether students are paying attention by observing their expressions, but this is not a very effective method. Also, the accuracy of this method is very low. And it is also difficult to accurately and objectively measure someone's focus and concentration as it is generally known that a person's mental focus or concentration cannot be measured. If there is a way to measure this, it would help with conclusions in the fields of health and neuroscience. Using electroencephalography (EEG) and Machine Learning, we develop an app to monitor the brain's attentional activity and propose a method to accurately and objectively measure one's attention and concentration. As a result, one person can identify how another person is engaged with the tasks they are doing, i.e. their level of attention with that task. Using a dataset created by collecting 25 hours of EEG data from 5 participants with the help of a modified classical EEG headset, various common features are extracted from the raw data. As the first step, we performed the classification using a Support Vector Machine (SVM) classifier and as a next step we hope to use Deep Learning algorithm to compute and analyze the identified features to identify the feature combination that best demonstrates whether someone is paying attention to the task. This proposed method achieved almost 94% accuracy while identifying the attention level of a subject.**

***Keywords—EEG, focus, machine learning, BCI, SVM***

## I. Introduction

Attention is the ability to keep one's cognitive process on a task at a given time, ignoring distracting or irrelevant information. All the time, neurons in the human brain are continuously active, emitting small electromagnetic waves, and these electromagnetic waves are used as electroencephalography (EEG) signals. It is feasible to use EEG signals for this, as without training, people are usually unable to control the fluctuations of their EEG signals.

Based on the frequency range, EEG signals are divided into five wave bands α, β, θ, δ and γ and these are produced as EEG signals from different regions of the brain. Because different areas of the brain produce EEG signals, cerebral electromagnetic activity is traditionally collected using the International 10-20 Electrode Placement System (10-20 System), which involves attaching electrodes to 37 locations on the scalp. This method enables monitoring of all EEG signal changes, but in practice it is extremely difficult and impractical to use this method. Since a person's emotions, mental state, and focus are controlled by different parts of the brain in the frontal region, monitoring EEG signals from this area is a successful way to determine whether someone is paying attention.

There are several wearable technology devices that allow the measurement of important health metrics of a person's body, such as heart activity, blood circulation, etc. Likewise, such a device related to the brain is yet to be invented. This project is being implemented with the aim of finding solutions to this problem by developing an application to measure human attention using EEG and Machine Learning. It will help in monitoring personal mental health and well-being as well as improving users' cognitive performance and productivity.

## II. Scope, Aim and Objectives

### A. Scope

- Measure the user attention under the 3 categories

  In this project, the 3 levels of attention focused, unfocused and drowsiness are identified and given the appropriate output in this system

- Using an EEG band with two channels

  Multiple channels have been used for the research done so far and here we hope to do it using only 2 channels.

- Select the most appropriate ML model

  There are many machine learning models in the world and finding the most suitable model for this is another scope of this project. That is, this model is selected based on accuracy.

- Test models using university students' EEG outputs

  Another scope here is to test the selected model with live data using university students.

### B. Aim

- Measuring a person's attention levels and making the results available through a personal application in such a way that the person can monitor and improve their attention and cognitive function

### C. Objectives

- Preprocessing data

  Understanding the found dataset and cleaning it

- Channel selection (Feature Engineering)

Selecting the necessary features in the identified dataset and deciding the number of EEG channels required to reach the purpose of the project.

- Selecting appropriate machine learning model

  Using the EEG channels and data to test several algorithms for the Machine Learning model and choosing the most suitable algorithm

- Test mode with live data

  Test the model using the user's real-time brain data.

## III. METHODOLOGY

In this project, we are using a dataset which was prepared for a previous research. İt was prepared by Çigdem Inan Acı, Murat Kaya, Yuriy Mishchenko in Turkey, for their research on **Distinguishing mental attention states of humans via an EEG-based passive BCI using machine learning methods**. They used a modified EEG headset which had 14 EEG channels (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4).

The dataset consists of the results of experiments for monitoring human individuals' attention state using passive EEG BCI (Brain Computer Interface). The dataset contains the data of 34 experiments which happened during 35 - 55 mins each. In the first 10 mins, the participants have engaged in a focused task and paid special attention to the task. They have dropped their focus for the next 10 mins and then they have remained drowsy till the end of the experiment. Since the sample frequency of the used headset is 128Hz, we can divide each Matlab file as follows and label the data records,

- 'Focused': row=0 to row=128x10x60
- 'Unfocused': row=128x10x60 to row=128x20x60
- 'Drowsy': row=128x20x60 to last row

### A. Data Preprocessing

*(i) Initial Channels Selection*

Since there were 14 EEG channels, first, we have to identify whether all the channels are useful or not. If not, we should identify which channels we should use for data preprocessing and further analysis. We plotted graphs for each channel (to represent how the amplitude has changed against time). According to the plots, we selected (F7, F3, P7, O1, O2, P8, AF4) channels as the useful channels, as we could see big amplitude changes in these plots.

*(ii) Separating data of each file based on attention state*

After selecting the channels, we separated each data file into 3 dictionaries based on the 3 attention states considering the row numbers. Then we could use these data dictionaries for further preprocessing and feature extraction.

*(iii) High-pass filtering*

For each channel and each trial, we passed the EEG data through a high-pass filter with a cutoff frequency of 0.16 Hz. In order to focus on higher-frequency activity in the EEG signals, the filtering procedure helps remove low-frequency components from the data. The filtered data is then kept in the relevant dictionaries for later analysis.

### B. Feature Extraction

*(i) Short-Time Fourier Transform (STFT)*

We calculated the STFT on the EEG data for each channel and state (focused, unfocused, drowsy). The STFT represents the frequency content of the EEG signals in a time-varying manner. The STFT calculation is used in the next steps in order to calculate the Power Spectral Densities signals. STFT equation can be defined as follows,

$$X_{STFT}(t,\omega) = \sum_{t'=-\infty}^{\infty} x(t')w(t'-t)e^{-j\omega t'}$$

*(ii) Windowing the signal*

To reduce spectral leakage and increase frequency resolution, we used the 'Blackman window' function. Its smooth tapering

reduces distortions at signal segment boundaries, allowing for more precise frequency analysis and better identification of frequency components in the signal.

The Blackman window function can be defined as follows,

$$w(\hat{t}) = \left\{ \begin{array}{l} 0.42-0.5cos\frac{2\pi\hat{t}}{M-1}+0.08cos\frac{4\pi\hat{t}}{M-1}, 0\leq\hat{t}\leq M \\ 0, otherwise \end{array} \right\}$$

$M$ = total amount of time points within the window

$\hat{t}$ = 0, 1, …, M−1, a discrete time-index in the window.

*(iii) Calculating the Power Spectral Densities (PSD)*

After calculating STFT and Windowing, we calculated the Power Spectral Densities and saved them in different dictionaries for each channel and trial. The power of a particular frequency component at a given time-frequency point is represented by each PSD value. The PSD values provide information about the relative contribution or strength of various frequency components in the signal. This information can be applied to study the dominant frequency components in each state (focused, unfocused, and drowsy) and acquire a better understanding of the signal's frequency properties. We selected PSD as the feature in the first set of experiments.

### C. Training Machine Learning Models for Each Participant's Data

For our first set of experiments, we selected SVM as our ML algorithm because most of the related researches have used it as their most accurate algorithm. First, we calculated average power values and stored them in 3 separate dictionaries based on the attention states. After that, we converted the average power values into vectors for an SVM model's training. These vectors were saved in dictionaries by state (focused, unfocused, drowsy), trail name, and time-frequency bin. The vectors are then subjected to the logarithmic transformation.

Then we concatenated the data of each state of the Participant 1 and trained the SVM model. We used an RBF kernel to train the SVM model and tested its accuracy on both training and testing data.

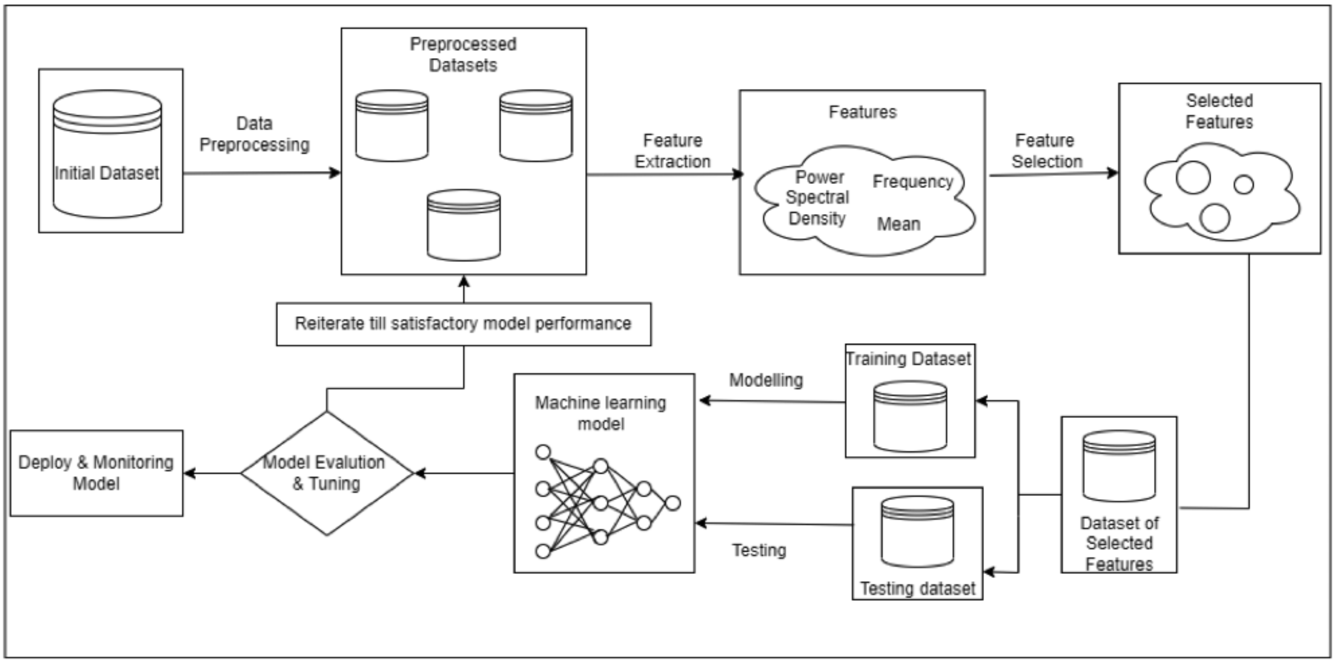


Fig. 1. Development process diagram

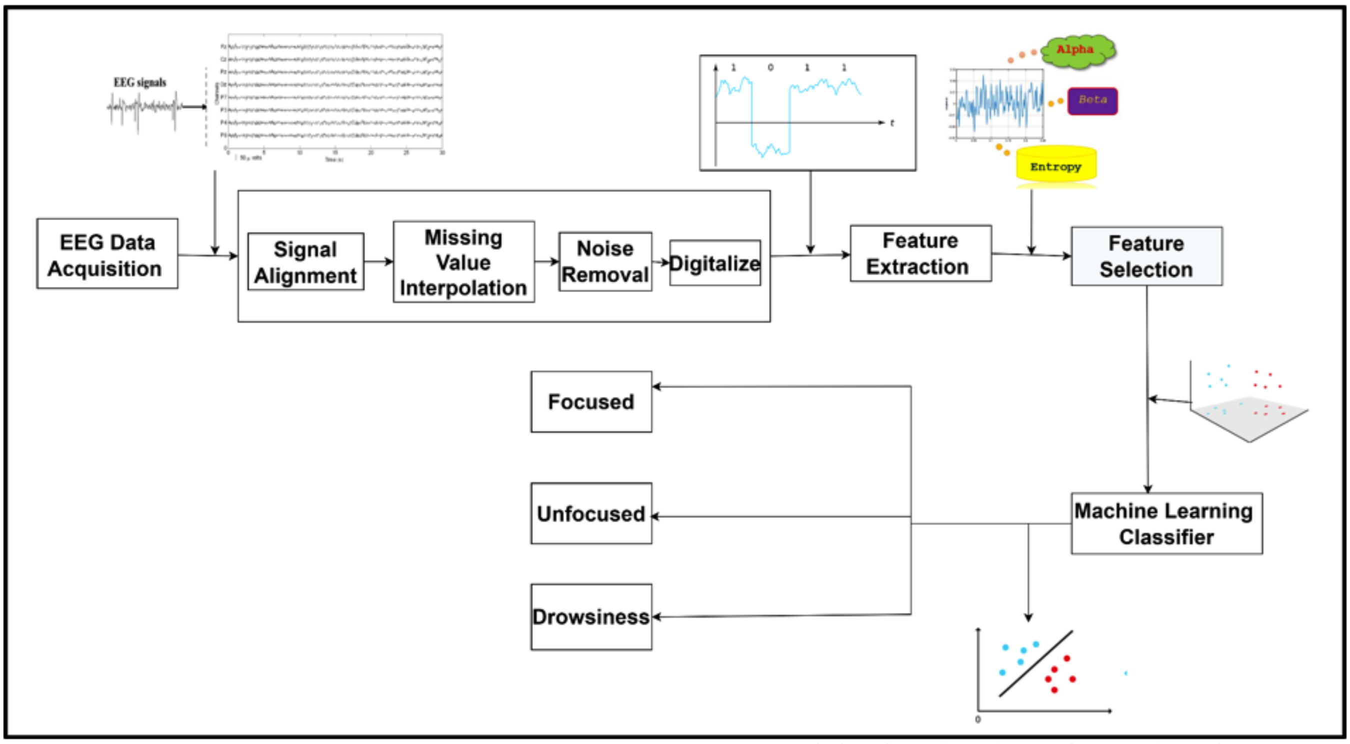


Fig. 2. Live data testing diagram

In our second major experiment, we wanted to bring a Deep Learning model as it is relatively modern when compared with SVM, and we expected we can achieve more accuracy using a Deep Learning model. After some research, we decided to develop a Recurrent Neural Network model with Long-Short Term Memory (LSTM). Using an RNN, we can effectively model EEG data which contains sequential information. LSTM has the ability of capturing temporal relationships in sequential data. Multiple LSTM layers will be used in the model, enabling it to recognize and understand complex patterns in EEG data. Moreover, end-to-end learning is made possible by LSTMs, which means that they may use raw EEG data as input and simultaneously learn feature extraction and classification. This makes the modeling process easier and frequently produces models that are more accurate and effective.

### D. *Testing the Trained Model Using Live Data*

Here is how to test the model created in the Development Process described above using live data. Accordingly, university students are used to extract their EEG data under suitable environmental conditions, preprocess the data and send it through the model created in the development process, and at that time, the student's state of focused, unfocused, and drowsiness will be identified and outputted.

## IV. RESULTS

In the first set of experiments, we used the SVM algorithm and developed 5 distinct models using the calculated power spectral densities of each participant's data. We used 80% from each dataset for training each model and tested with the rest of the data (20%). In that testing phase, we achieved accuracies in the range of 90.4 - 96%. In the second testing phase, we tested each model using other datasets and the accuracies vary between 36.1 - 67.5

TABLE 1: ACCURACIES OF SVM MODELS

| Model | Accuracy with | | | | | | |
|---|---|---|---|---|---|---|---|
| | Same Dataset (0.2 split) | Subject 1 Dataset | Subject 2 Dataset | Subject 3 Dataset | Subject 4 Dataset | Subject 5 Dataset | Average |
| 1 | 90.44% | | 67.52% | 61.49% | 39.06% | 54.27% | 55.58% |
| 2 | 95.37% | 62.31% | | 65.16% | 36.32% | 48.58% | 53.09% |
| 3 | 93.12% | 54.93% | 65.63% | | 39.20% | 58.74% | 54.62% |
| 4 | 96.02% | 37.89% | 34.46% | 33.45% | | 54.43% | 40.05% |
| 5 | 92.68% | 37.86% | 36.10% | 36.72% | 46.52% | | 39.30% |

In Tab. 1, we have summarized the testing results of each SVM model and the cross-validation results with each other's data sets. In the first column, there are references to the relevant SVM models and the second column represents their testing accuracies using 20% of the relevant dataset. Cross validation test results with other participants' data are included in the next 5 columns and the last column represents the average accuracy of the relevant SVM model.

TABLE 2: MAIN SVM MODELS EVALUATION

| | Recall | Precision | F1-Score |
|---|---|---|---|
| Focused | 0.965 | 0.960 | 0.962 |
| Unfocused | 0.949 | 0.940 | 0.945 |
| Drowsy | 0.974 | 0.988 | 0.981 |

In Tab. 2, we have shown the Recall, Precision and F1-Score values of each status of the SVM models. These metrics are used to evaluate the performance of these models. The 1st column represents the status, which we are considering in this project. In the second column, there are recall values which is the true positive rate of the models. we called them sensitivity of the model. This represents the ability of the model to correctly identify instances of each state among all actual instances of the states. In the third column, there are precision values which are the accuracy of the model when it predicts a positive class. The last column represents the F1-Score, which is the harmonic mean of precision and recall. It provides a balanced measure that considers both false positives and false negatives. In the first row, there are the performance metrics for the model specially for the “Focused” state. In this status, A recall of 0.965 indicates that the model correctly identified 96.5% of the actual instances of "Focused" states. Also, A precision of 0.960 means that out of all instances predicted as "Focused," 96% were correct. And the F1-Score of 0.962 indicates a good balance between precision and recall. Accordingly, the high values for recall, precision, and F1-Score of 1st row suggest that the model is effective in correctly identifying instances of "Focused" states while minimizing false positives and false negatives. Therefore, the model appears to be reliable in detecting the targeted mental state. Considering the other rows, we can get the same conclusion for the other two states.

## V. CONCLUSION

It is difficult to accurately and objectively measure someone's focus and concentration because we cannot measure a person's mental focus or concentration as we generally know. As a solution to this, suitable models are created to determine attention levels from patterns extracted from brain EEG data. It is also expected to use a two-channel EEG tape to measure user attention under 3 categories and to create models using university students. Also, one of the objectives of this machine learning model is to obtain the highest accuracy and as a result of this design, it is possible to identify how much correlation a person has with the tasks they are doing, i.e. the level of attention with that task.

The results thus obtained can be used to help the conclusions in the fields of healthcare and neuroscience. The app helps to increase and increase the role that lifestyle factors such as sleep, exercise and diet can play in maintaining optimal brain health. It can also be used by athletes looking to improve mental focus and performance, or even healthcare professionals looking to monitor and treat neurological disorders. With the potential to be used in education to monitor student attention and engagement, to optimize productivity in the workplace, and in research to study the complex functions of the brain, it is hoped that this application will lead to greater attention to brain health in society.

This project has been done by using a data set created in a previous research. Since most of the research has been done with SVM, our model was created using the SVM algorithm and the training was done using the individualized modeling method.

In this project, we hope to use more types of algorithms to check the accuracy and select the most appropriate algorithm model, and we hope to use university students to collect data under suitable environmental conditions and use that data to test the selected model. Also, we hope to bring a Deep Learning model as it is relatively modern when compared with SVM, and we expect to achieve more accuracy using a Deep Learning model.

By improving the understanding of the brain and its functions, this application that can open up new levels of performance and potential in all areas of life is a brand-new idea that has never been born in the world and the proposed plan of action is created on a logical basis.

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