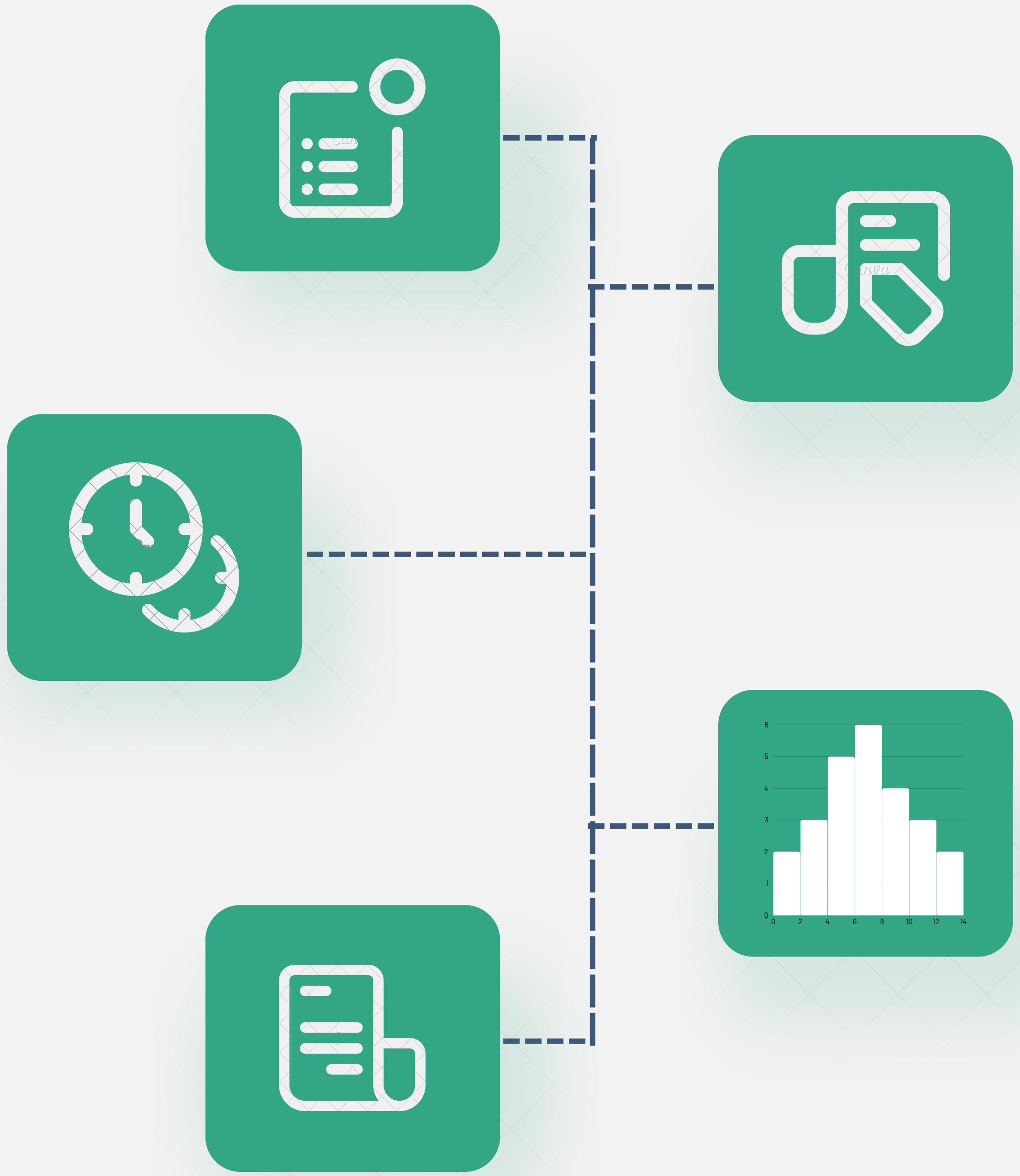
PREDICTION OF HUMAN PERFORMANCE USING EEG DATA TO IMPROVE SAFETY AND PRODUCTIVITY IN THE MINES

OBJECTIVE

The goal of this study is to evaluate and compare raw EEG data gathered from three individuals over a five-hour period. This includes the following critical tasks:

Data Collection:

Collect continuous EEG data from three people for five hours each to ensure a large dataset for analysis



Preprocessing:

Clean and preprocess the raw EEG data to remove artifacts, noise, and other distortions that could impair the analysis' accuracy.

Feature Extraction:

Using advanced signal processing techniques such as Power Spectrum Analysis, extract essential features and frequency components from preprocessed EEG signals and by using Random forest ML model we checked the accuracy of our model

Comparison Analysis:

Use the retrieved features to discover and quantify variations in brainwave patterns and activity between the three subjects.

Interpretation:

Use the variances in EEG data to comprehend potential variations in cognitive states, mental activities, or responses among persons over a given time frame.

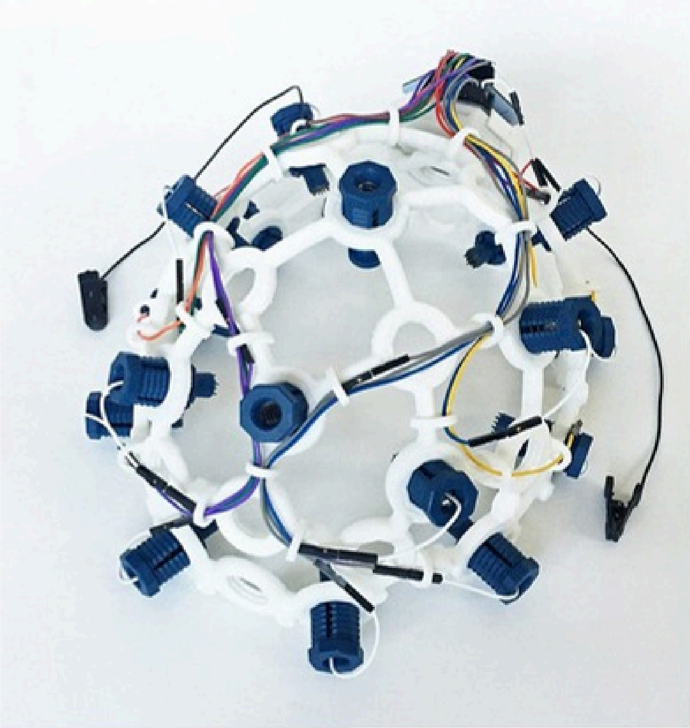
This research seeks to improve understanding of individual changes in brain activity across time and to investigate potential applications in individualized neurofeedback, cognitive status monitoring, and brain-computer interface development

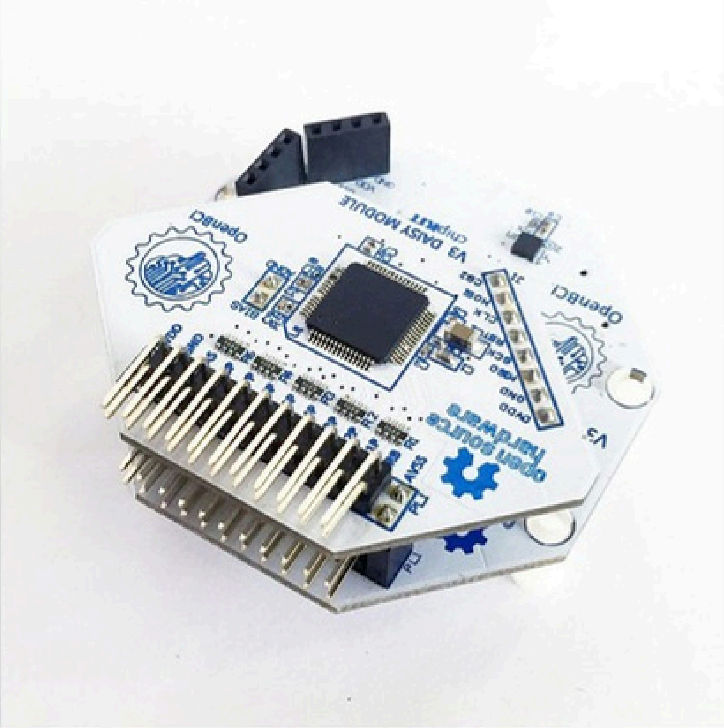
WHAT IS EEG ?

An electroencephalogram (EEG) is a test that measures electrical activity in the brain. This test also is called an EEG.

The test uses small, metal discs called electrodes that attach to the scalp.
Brain cells communicate via electrical impulses, and this activity shows up as wavy lines on an EEG recording.

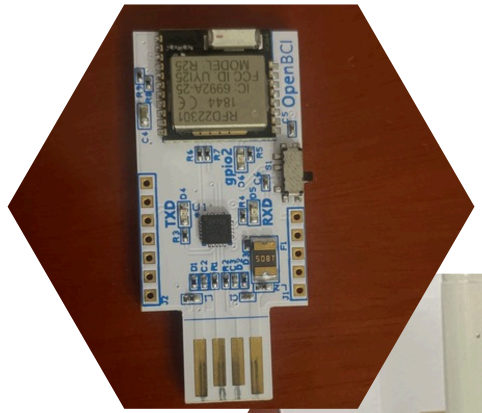
- Used to measure Electrical activity of the brain
- Detects activity of large group of neurons that are active at the same time
- Brain cells are active all the time, even during sleep.





Mechanism Of EEG

- The billions of nerve cells in the brain produce very small electrical signals that form patterns called brain waves.
- During an EEG, small electrodes & wires are attached to the head.
- The OpenBCI board typically supports multiple channels—ranging from 8 to 16 or more—allowing it to capture EEG data from several points on the scalp simultaneously.
- The electrodes detect brain waves
- These signals are typically in the range of microvolts (μV).
- EEG machine amplifies the signals & records them in a wave pattern on graph paper or a computer screen.



EXPERIMENT SETUP

In this experiment, we looked at fluctuations in EEG signals from three students over a five-hour period. The goal was to investigate how brainwave activity varies between individuals over an extended observation period.

Experiment Setup:

Each student was fitted with an EEG headset, which ensured constant electrode insertion and recording conditions throughout the session. Students were watched in a controlled atmosphere to reduce external effects and artifacts. The EEG data were collected constantly, documenting brainwave activity in real time.

DATA COLLECTION

- The raw EEG data were rigorously recorded over a five-hour period, during which the students engaged in a carefully planned series of exercises. These activities included times of focused labor, in which pupils performed tasks that required concentration and mental effort. This phase intended to record brainwave patterns related to cognitive load and attention.

- Following the intensive work sessions, the students were given time to recuperate, which included less mental activity and more relaxation. During these rest intervals, the EEG data supplied information about baseline brainwave activity and the brain's resting state, in contrast to the more active stages of the experiment.

- In addition, the students engaged in casual contacts and light physical activities such as informal discussions, movement, and other ordinary behaviors.Students also attended classes. These interactions were designed to simulate more natural and diverse cognitive states, capturing the brain's reaction to less planned and spontaneous activities.

- The experiment's goal was to create a complete dataset that covered a wide range of cognitive and mental states by combining these various activities. This method allowed for a more detailed examination of how various types of mental engagement—from severe concentration to relaxation and casual interaction—influence EEG signal characteristics.

DATA CLEANING

- After obtaining the raw EEG data, we began the data processing phase to clean and prepare the signals for further analysis.

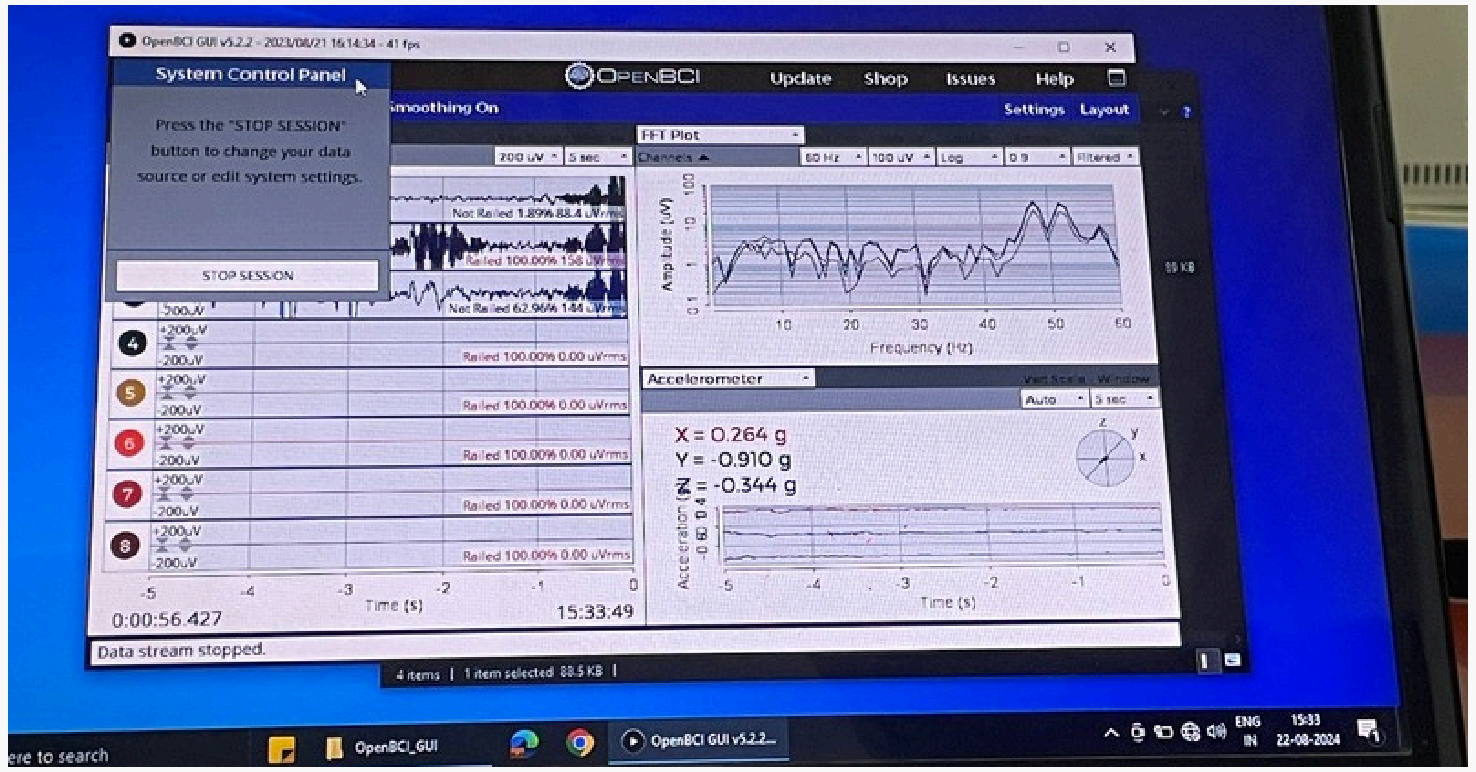
The initial phase was preprocessing, which attempted to remove undesirable noise and artifacts that could affect the accuracy of the results.

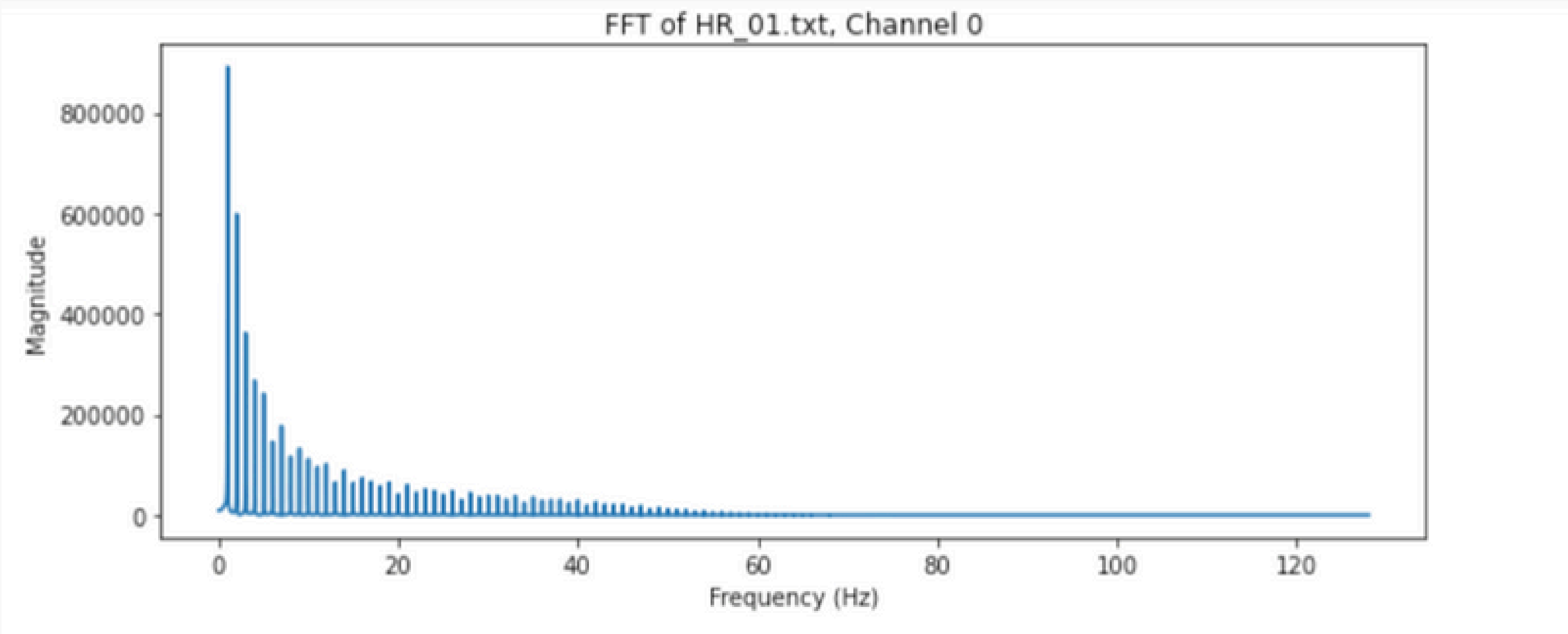
- Common aberrations in EEG readings include eye blinks and muscle movements, which can provide erroneous signals unrelated to brain activity. To overcome this issue, we cleaned the data using digital filters.

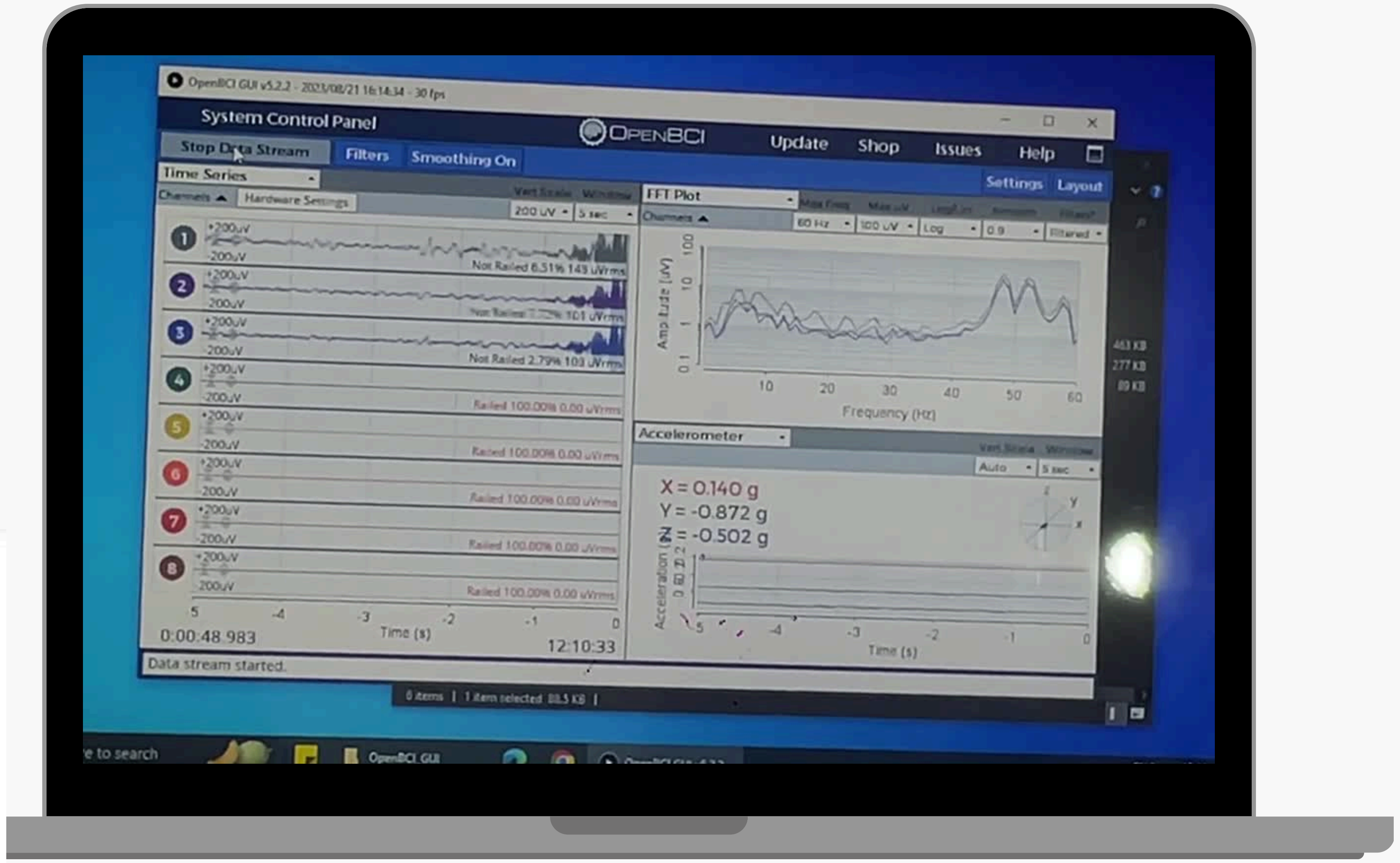
These filters helped to reduce both high-frequency noise and gradual drifts, resulting in cleaner and more trustworthy EEG readings.

- We apply a bandpass filter to the EEG data. This filter keeps only the frequency components of interest (between 0.5 and 50 Hz), which are relevant for brainwave analysis. The filter removes noise and irrelevant frequency data.

PRESENTATION OF GRAPHICS

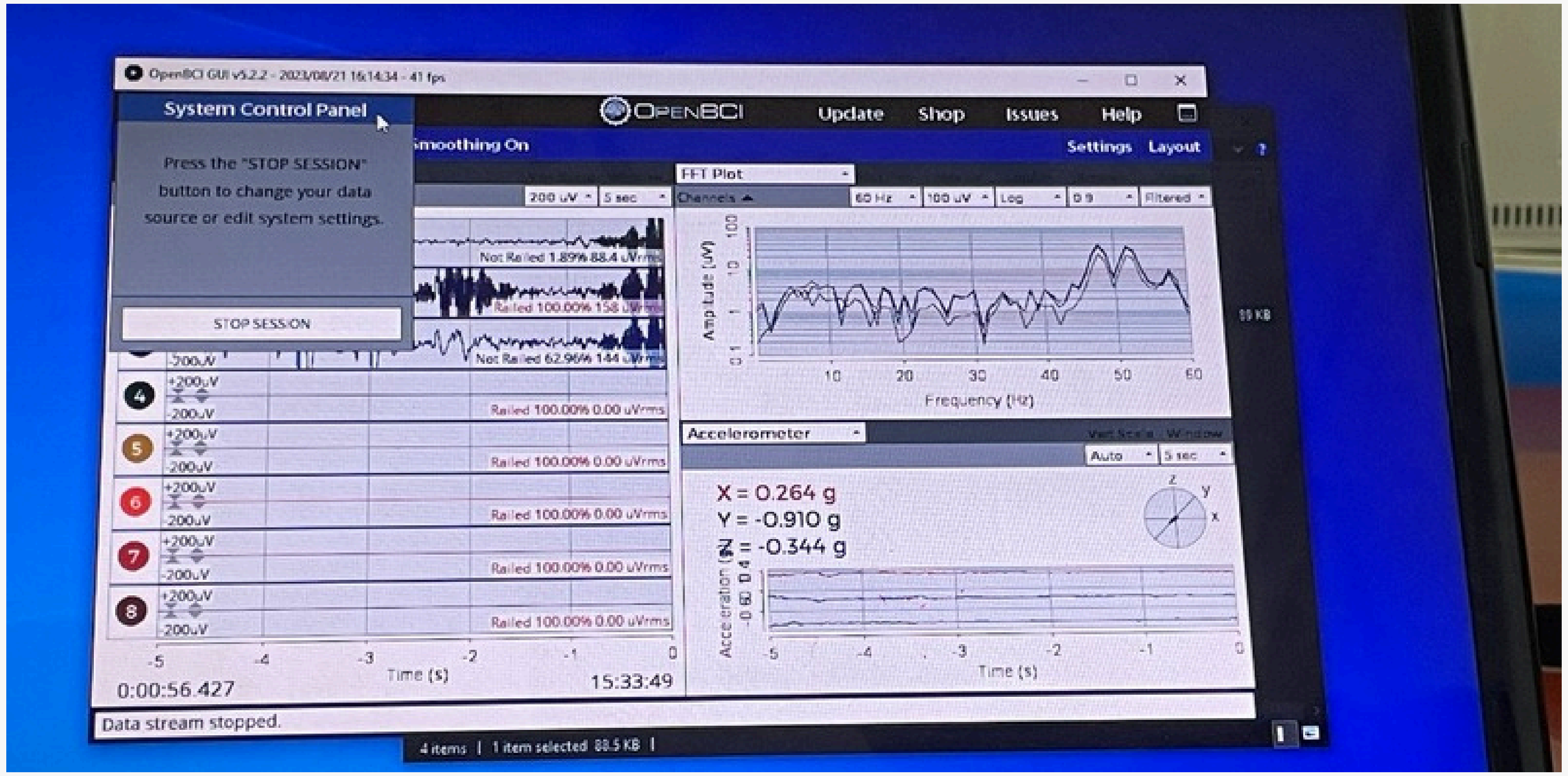


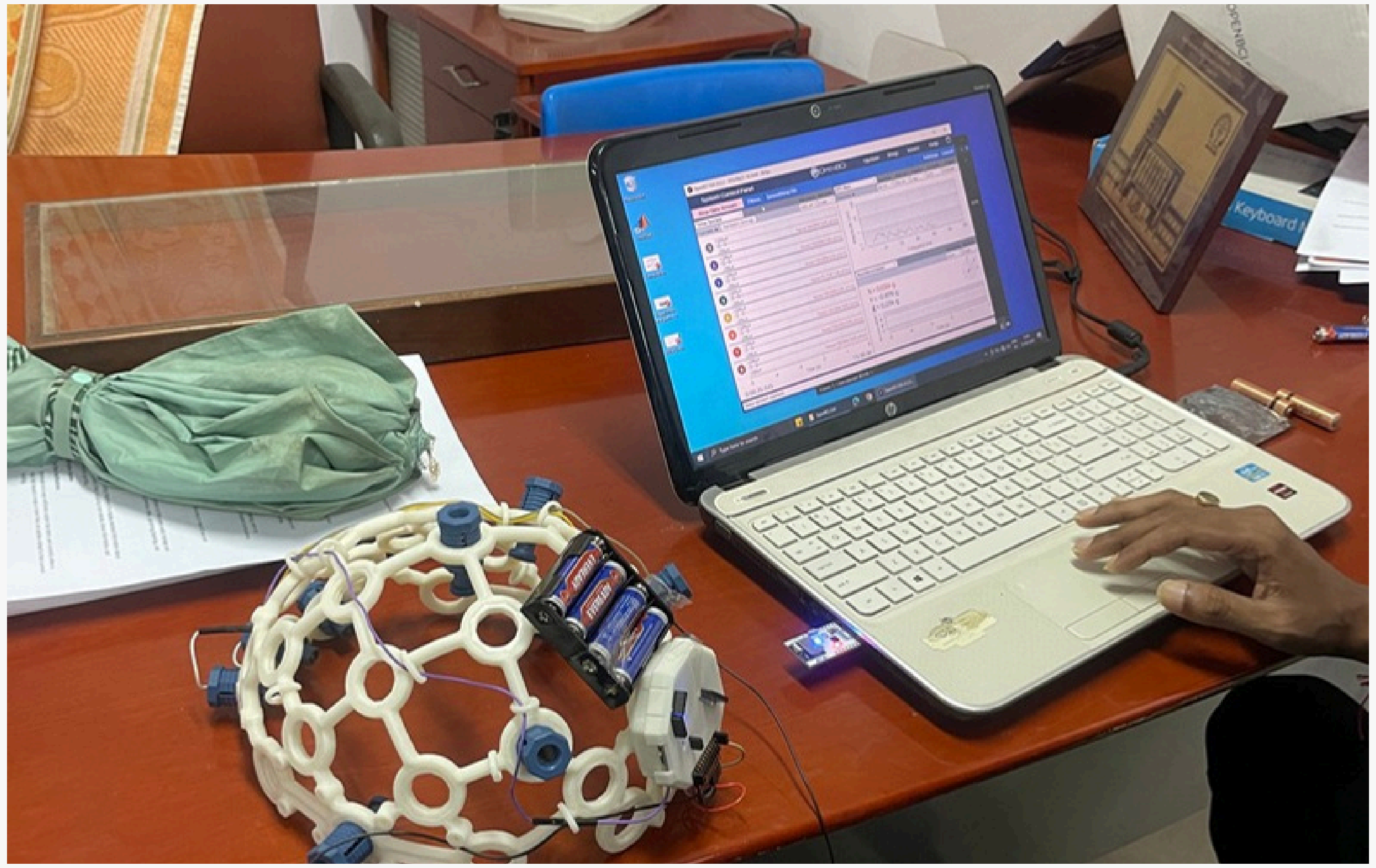




DATA PRE PROCESSING

- A bandpass filter is used to focus on specific frequency components of interest. The primary goal of applying this filter is to enhance the quality of the data by isolating the frequencies that are most relevant for brainwave analysis, which typically range between 0.5 and 50 Hz. This frequency range encompasses the various brainwave bands, such as delta, theta, alpha, beta, and gamma waves, which are critical for understanding different states of brain activity.
- The bandpass filter works by allowing only the frequencies within this designated range to pass through this range. Low-frequency noise, such as those like eye blinks, is often present in EEG signals. These unwanted components can obscure the true brainwave patterns and make it difficult to accurately interpret the data. By filtering out these extraneous frequencies, the bandpass filter helps to reduce noise and enhance the signal-to-noise ratio.





FEATURE EXTRACTION WITH FFT & POWER SPECTRUM

After the data was cleaned, we used the Fast Fourier Transform (FFT). FFT is a mathematical technique for converting EEG signals from the time domain to the frequency domain. In layman's words, it breaks down complex brainwave signals into their component frequencies, revealing how much of each frequency is present in the data. This change enables us to recognize and evaluate numerous brainwave patterns, including alpha, beta, delta, and theta waves, which are linked to different mental states.

Fast Fourier Transform (FFT):

- Converts EEG signals from the time domain to the frequency domain.
- Breaks complex brainwave signals into their component frequencies.
- Allows identification and analysis of brainwave patterns like alpha, beta, delta, theta, and gamma waves.

Frequency Domain Analysis:

- Enables the study of how much of each frequency is present in the EEG data.
- Reveals specific brainwave activities that correspond to different cognitive or mental states.

Power Spectrum Analysis:

- Measures the power (strength) of different frequency components.
- Identifies the most prominent brainwave activities by calculating the power in specific frequency bands.

Overall, the data processing entailed cleaning the raw signals, converting them to the frequency domain using FFT, and assessing the power of different frequencies to acquire a better understanding of the brainwave patterns

EEG Frequency Bands:

- Delta (0.5 – 4 Hz): Deep sleep, unconsciousness.
- Theta (4 – 8 Hz): Light sleep, meditation.
- Alpha (8 – 12 Hz): Relaxation, calm focus.
- Beta (12 – 30 Hz): Active thinking, concentration.
- Gamma (30 – 50 Hz): High-level cognitive processing.

Bandpower Calculation:

- Computes the average power in specific frequency bands (delta, theta, alpha, beta, gamma).
- Helps quantify brainwave activities and allows comparison between cognitive states.

Extracted Features:

- Feature matrix includes bandpower values for each EEG channel.
- Useful for machine learning models to classify different mental states.

APPLYING MACHINE LEARNING:

RANDOM FOREST CLASSIFIER TO PREDICT STRESS LEVELS

Random Forest Classifier:

- A robust ensemble learning method used for classification tasks.
- Consists of multiple decision trees that operate as an ensemble to improve accuracy and prevent overfitting.
- Each tree gives a classification output, and the final prediction is based on majority voting.

Objective:

- Train the model to predict stress levels based on extracted EEG features (such as bandpower values for different frequency bands).
- Classify the data into different cognitive or stress levels based on brainwave patterns.

Training Data

- Features: Power spectrum values from different frequency bands (delta, theta, alpha, beta, gamma).
- Labels: Stress level classifications, derived from predefined thresholds in EEG signals or provided annotations.

Model Training:

- Split the dataset into training and test sets.
- Train the Random Forest classifier using the training data.
- Adjust hyperparameters (e.g., number of trees, depth) to optimize performance.

Prediction of Stress Levels:

- Input new EEG data (feature matrix) into the trained Random Forest model.
- The model outputs predicted stress levels for each data sample.

Performance Evaluation:

- Use metrics like accuracy, precision, recall, and F1-score to evaluate the model's performance.
- Analyze confusion matrix to understand classification errors.

Benefits of Using Random Forest:

- Handles high-dimensional EEG data effectively.
- Provides feature importance, helping to identify the most critical EEG features influencing stress prediction.
- Resistant to overfitting due to ensemble nature.

Apply a machine learning classifier (Random Fores

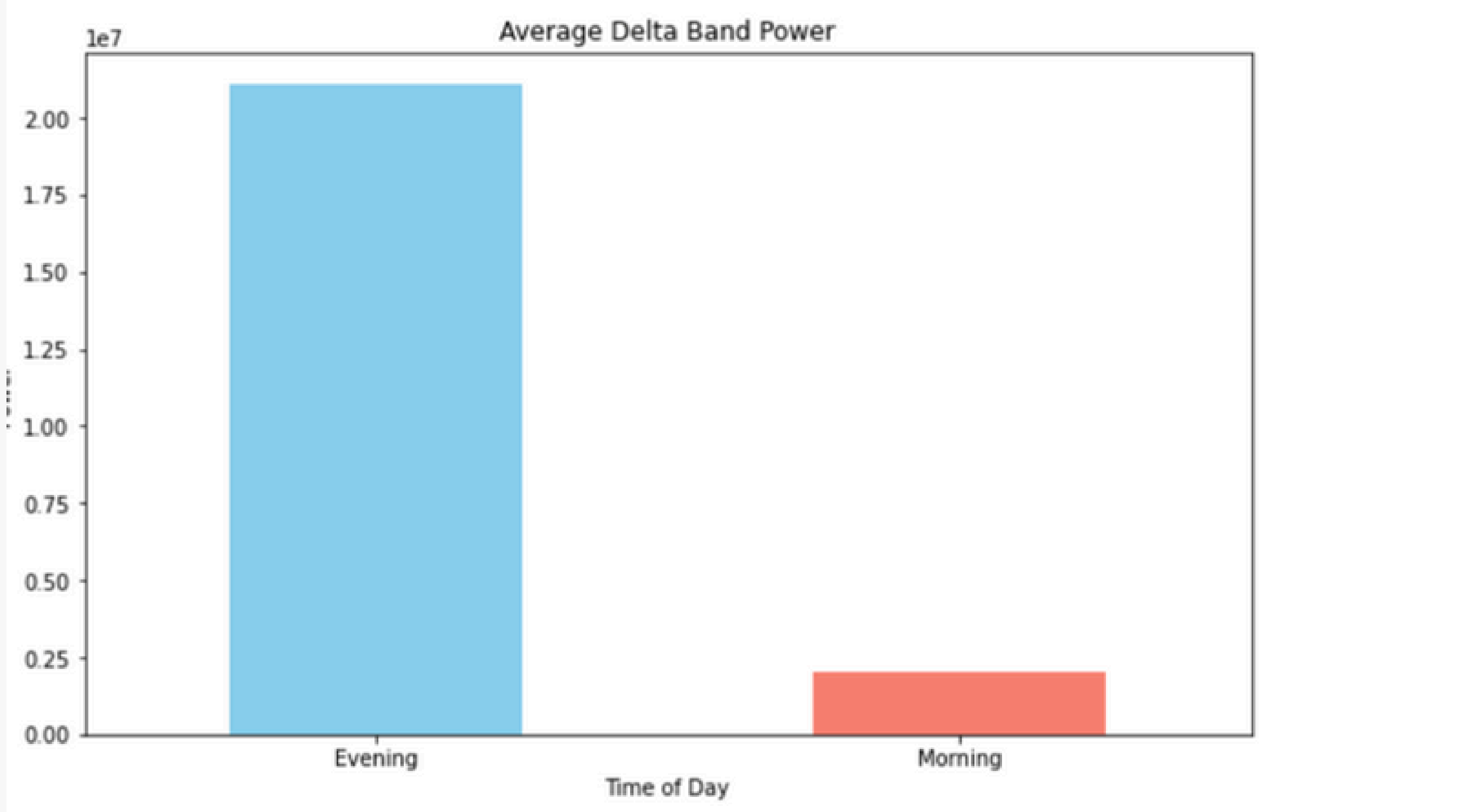
```
from sklearn.model_selection import tr
from sklearn.ensemble import RandomFor
from sklearn.metrics import accuracy_s

# Prepare features and labels for ML
X = np.concatenate([features[name] for
y = np.array([labels[name] for name in

# Split into training and test sets
X_train, X_test, y_train, y_test = tra

# Train Random Forest classifier
model = RandomForestClassifier(n_estim
model.fit(X_train, y_train)

# Make predictions and evaluate
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pr
print(f'Model accuracy: {accuracy * 10
```

```
Model accuracy: 70.45%
```

EVALUATE AND COMPARE

COMPARE THE MORNING AND EVENING DATA BASED ON THE EXTRACTED FEATURES AND MODEL PREDICTIONS

After the data was cleaned, we used the Fast Fourier Transform (FFT). FFT is a mathematical technique for converting EEG signals from the time domain to the frequency domain. In layman's words, it breaks down complex brainwave signals into their component frequencies, revealing how much of each frequency is present in the data. This change enables us to recognize and evaluate numerous brainwave patterns, including alpha, beta, delta, and theta waves, which are linked to different mental states.
Overall, the data processing entailed cleaning the raw signals, converting them to the frequency domain using FFT, and assessing the power of different frequencies to acquire a better understanding of the brainwave patterns



Compare Morning and Evening Data

Calculate the average power in each band for morning and evening sessions and perform a comparison.

```python
# Calculate average power in each band for morning and evening
average_powers = features_df.groupby(['Time']).mean()

# Print average powers
print("Average Power in Different Bands:")
print(average_powers)
```

```
Average Power in Different Bands:
                delta         theta          alpha           beta  \
Time
Evening  2.107691e+07  1.159498e+06  290641.329291  279661.586106
Morning  2.012716e+06  4.321647e+03     538.038676     905.139675

                gamma
Time
Evening  21198.874496
Morning    100.832411
```

Conclusion

This complete process covers:

- Data loading and cleaning from multiple .txt files.
- Bandpass filtering to remove noise.
- FFT analysis to convert EEG signals into the frequency domain.
- Feature extraction from different EEG bands.
- Machine learning to classify mental states.
- Comparison of morning vs. evening EEG data to assess stress.
- This approach allows you to measure mental fatigue or stress using EEG data and machine learning.

THANK YOU