EEG SIGNAL ANALYSIS FOR STROKE PREDICTION

TERM PAPER REPORT

Submitted by

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TABLE OF CONTENTS

INDEX

ABSTRACT

Electroencephalography (EEG) offers a non-invasive method for monitoring brain activity and has shown potential in predicting stroke events through the analysis of neural patterns and anomalies. This study explores the application of EEG analysis in stroke prediction by examining brainwave patterns and connectivity metrics in patients at risk of stroke. We came across few techniques like Time Domain Feature, Frequency Domain Feature (delta, theta, beta, gamma) and Time Frequency Analysis (Short Time Fourier Transform), EEG Spectrograms (For visualizing how frequency content varies over time), EEG Spectrograms (For visualizing how frequency content varies over time), Connectivity Maps (To show connectivity patterns between different brain regions), Short Time Fourier Transformer (Analyze EEG signals as a spectrogram or representation). Here we are planning to proceed with STFT technique, which extracts the time-frequency features from raw EEG data. By implementing the STFT technique, we can segment each EEG data. From the results obtained from the STFT, we can extract features like power spectral density, time – frequency bands. This helps to distinguish between a normal and an abnormal EEG pattern. Depending upon the features, we need to apply dimensionality reduction techniques like principal component analysis (PCA). By choosing a suitable classification algorithms include Support Vector Machines (SVM), random forest or even more complex models. For real time stroke prediction, we need to deploy the model in an environment where it can process incoming EEG data and make predictions. We must continuously monitor the model's performance and update based on new data or changes in the underlying patterns.

CHAPTER – 1
INTRODUCTION

1.1 Introduction to EEG Signal Analysis for Stroke Prediction

Stroke, a significant medical condition leading to neurological impairment, can result from an interruption in the blood supply to the brain, either through a blockage (ischemic stroke) or rupture (hemorrhagic stroke). Early prediction and detection of stroke can greatly improve patient outcomes by enabling timely intervention. While traditional imaging techniques, such as CT scans and MRIs, play a crucial role in diagnosing stroke, Electroencephalography (EEG) signal analysis is emerging as an important tool for predicting and monitoring stroke risk and progression. EEG measures the electrical activity of the brain through electrodes placed on the scalp, offering a non-invasive, cost-effective, and real-time means to assess brain function.

1.2 Importance of EEG in Stroke Prediction

EEG provides valuable insights into brain activity, capturing both normal and abnormal oscillations, which can serve as biomarkers for various neurological conditions, including stroke. Abnormal EEG patterns, such as changes in brain wave frequencies or the presence of specific event-related potentials (ERPs), have been linked to stroke. The ability to detect these changes, sometimes even before clinical symptoms manifest, presents a powerful opportunity for early stroke prediction and diagnosis.

In the context of stroke, EEG analysis offers several advantages:

1. **Non-invasive**: EEG does not require exposure to radiation or the need for contrast agents, making it suitable for repeated monitoring.
2. **Real-time Monitoring**: EEG provides continuous, real-time data about the brain's electrical activity, which is crucial during the acute phase of stroke or during post-stroke recovery.
3. **Cost-Effective**: Compared to other imaging modalities like CT and MRI, EEG is relatively affordable and accessible.
4. **Sensitivity to Brain Function**: EEG can detect subtle changes in brain function, making it useful for identifying early signs of stroke or predicting potential risk factors.

1.3 Mechanisms Behind EEG Changes in Stroke

Stroke leads to a disruption of normal brain activity. Depending on the location, severity, and type of stroke, EEG signals can exhibit various abnormalities:

- **Ischemic Stroke**: In cases of ischemic stroke, a blockage of blood flow can lead to hypoxia and reduced brain activity in the affected region. This is often reflected in EEG as slow-wave activity, loss of alpha and beta rhythms, and the appearance of delta waves (associated with brain injury).
- **Hemorrhagic Stroke**: Bleeding in the brain can cause mechanical damage and alterations in electrical activity. EEG patterns may include widespread cortical disorganization, seizures, or focal abnormalities.

The brain's response to stroke can involve both global and localized changes:

- **Global Changes**: In severe cases, where large regions of the brain are affected, there can be global slowing of the EEG, and even complete suppression of brain waves.
- **Localized Changes**: In milder strokes or when specific brain regions are affected, the EEG may show focal abnormalities, such as increased theta waves or the development of epileptic-like spikes.

1.4 EEG Signal Features in Stroke Prediction

Various features of EEG signals can be extracted and analyzed to detect stroke-related abnormalities. These include:

1. **Frequency Bands**: EEG signals are divided into different frequency bands, each of which is associated with different mental states. Changes in these bands can be indicative of stroke or brain dysfunction.
    - **Delta Waves (1-4 Hz)**: Associated with deep sleep or brain injury. In stroke, delta waves may be seen in regions affected by the ischemic event.
    - **Theta Waves (4-8 Hz)**: Often linked with cognitive impairment. Increased theta activity in certain brain areas can be a sign of dysfunction.
    - **Alpha Waves (8-13 Hz)**: Represent relaxed wakefulness. Suppression or asymmetry of alpha waves can indicate neurological impairment.
    - **Beta Waves (13-30 Hz)**: Associated with active thinking. An increase in beta activity can be a marker for hyperexcitability or epileptic activity post-stroke.
2. **Event-Related Potentials (ERPs)**: These are brain responses to specific stimuli and can help track cortical responses and impairments due to stroke. Alterations in ERPs can indicate difficulties in information processing caused by stroke.
3. **Coherence and Connectivity**: Stroke often disrupts the connectivity between different brain regions. EEG coherence analysis, which measures the synchrony of oscillations between regions, can reveal changes in brain network dynamics due to stroke.

4. **Brain Wave Synchronization**: Abnormal synchronization of brain waves, particularly in the delta and theta bands, can be indicative of stroke-related damage. Loss of synchronization or abnormal synchronization in areas connected to the damaged brain region may be used as an indicator for stroke risk.
5. **Epileptiform Activity**: Post-stroke seizures are common, and EEG can be used to monitor for abnormal spikes or sharp waves, which may indicate epileptiform activity or a predisposition to post-stroke epilepsy.

CHAPTER – 2
LITERATURE SURVEY

[1] Automated stroke prediction using machine learning: An explainable and exploratory study with a web application for early intervention:

The study explores the development and evaluation of a machine learning (ML) model to predict stroke risk, aiming to enable early intervention and improve patient outcomes. Using an unbalanced dataset balanced via SMOTE and multiple classifiers, the researchers determined that the Random Forest and XGB classifiers had the highest accuracy, with a top accuracy of around 90%. To ensure model transparency, they employed explainable AI techniques like SHAPE and LIME, providing insights into how specific factors such as age, glucose levels, and work type influence stroke predictions. They further developed a user-friendly web application based on the model, allowing patients and physicians to input personal health data and receive a stroke risk assessment, enhancing accessibility to preventive care. Future work includes expanding the model to an end-to-end smart healthcare system, potentially on mobile platforms, to offer on-the-go stroke prediction and virtual consultations with healthcare providers.

[2] Detection of stroke-induced visual neglect and target response prediction using augmented reality and Electroencephalography

This paper demonstrates the development of the AREEN system, an innovative integration of augmented reality (AR) and EEG technologies designed to detect and assess spatial neglect (SN) in stroke patients. The system uses a brain-computer interface (BCI) that presents visual targets within an AR environment via a headset while recording EEG data to evaluate brain responses to visual stimuli. By identifying EEG patterns specific to neglected versus observed visual fields, the system accurately detects SN through key spatial spectral features, especially within delta, theta, and beta frequency bands in certain brain areas. Machine learning, particularly using RDA+KDE classification, helps differentiate between fast and slow responses, mapping neglected visual areas. Preliminary findings support the system's accuracy, suggesting potential for real-time neurofeedback to aid rehabilitation by prompting patients to attend to neglected areas, enhancing recovery in a practical, dynamic environment. The study highlights the potential of EEG-AR integration for improving stroke rehabilitation with a system that tracks real-world responses to stimuli.

[3] Explainable artificial intelligence model for stroke prediction using EEG signal:

The paper presents an explainable AI model that uses EEG data to predict ischemic stroke, employing machine learning (ML) classifiers such as Adaptive Gradient Boosting, XGBoost, and LightGBM. These models classify patients by analyzing neural patterns in active states (e.g., walking, reading), achieving high accuracy, especially with Adaptive Gradient Boosting. Explainability tools, Eli5 and LIME, are used to identify EEG features—primarily delta and theta waves in the frontal and central brain regions—that are critical for prediction, thus enhancing transparency in model decision-making. This explainable approach provides valuable insights for clinicians and contributes to potential improvements in stroke diagnosis, treatment, and post-stroke recovery planning.

[4] Encoding rich frequencies for classification of stroke patients:

The stroke, which is a sudden cut in the blood supply in the brain, has become a severe phenomenon. It has affected around 15 million people annually worldwide. Methods of stroke discovery and monitoring the patient's recovery are a long process, ranging from the analysis of medical images to frequent reporting of the patients for progress assessment. In this paper, we aim to process stroke patient EEG signals by a deep learning approach, and classify a given EEG signal into stroke/non-stroke. In particular, our model consists of several sub-modules which convert and re-model widely used signal processing techniques such as the Fast Fourier Transform (FFT).

[5] EEG signal processing for medical diagnosis, healthcare, and monitoring: A comprehensive study:

This paper provides an extensive overview of the most popular datasets, feature domains, artifacts, and preprocessing methods used to perform more accurate analyses of EEG for the automatic detection of brain disorders, especially epilepsy. An examination of EEG characteristics and the procedures utilized to extract those characteristics, along with a discussion of the benefits and drawbacks of each method, are presented in this article. In addition, this study examines the current trends regarding feature engineering and classification techniques. Several academic papers have provided the source material for these methodologies and the findings associated with them.

[6] EEG Signal Analysis for Stroke Prediction

The paper titled "EEG Signal Analysis for Stroke Prediction: A Comprehensive Review" provides a foundational understanding of the methodologies employed in EEG analysis, including time-frequency analysis and machine learning techniques. It highlights the importance of feature extraction methods, such as wavelet transform and power spectral density, in identifying patterns associated with stroke risk. The review underscores the variability in results across studies, which is often attributed to differences in sample sizes, EEG setups, and analytical approaches.

[7] Applications of EEG in Stroke Rehabilitation

In the review "Applications of EEG in Stroke Rehabilitation: A Review," the authors discuss the dual role of EEG in both predicting stroke and aiding rehabilitation post-stroke. They note that EEG can be used to monitor recovery progress and evaluate the effectiveness of therapeutic interventions. The integration of EEG with brain-computer interfaces (BCIs) is particularly promising, as it enables real-time feedback and adaptive training for stroke survivors.

[8] Neurophysiological Markers of Stroke

The article “Neurophysiological Markers of Stroke: A Review of EEG Studies” explores specific EEG patterns that serve as neurophysiological markers for stroke risk. The review identifies several key markers, including changes in alpha and beta wave activity, that have been linked to stroke events. The authors emphasize the need for standardized protocols to enhance the reproducibility of findings and improve the clinical utility of EEG in stroke prediction.

[9] Machine Learning Techniques for EEG Signal Analysis

The review “Machine Learning Techniques for EEG Signal Analysis in Stroke Patients: A Review” examines the application of machine learning algorithms to EEG data for stroke prediction. The authors highlight various techniques, such as support vector machines and convolutional neural networks, that have shown promise in classifying EEG signals associated with stroke. The paper discusses the challenges in feature selection and model training, advocating for larger datasets to improve the accuracy and generalizability of machine learning models.

[10] Towards Real-Time EEG-Based Stroke Prediction Systems

Finally, the paper “Towards Real-Time EEG-Based Stroke Prediction Systems: A Review” focuses on the development of real-time systems that can analyze EEG data and predict stroke risk dynamically. The review discusses the integration of advanced signal processing techniques and real-time monitoring technologies, highlighting the potential for these systems to provide timely alerts for at-risk patients. It calls for further research to address technical challenges and validate these systems in clinical settings.

CHAPTER - 3
METHODOLOGY

The first step in predicting stroke using EEG signals is to extract meaningful features from the raw data. These features might include the power spectrum of different frequency bands (delta, theta, alpha, beta), coherence between brain regions, and the detection of abnormal oscillatory patterns. The process of extracting the power spectrum of different EEG frequency bands (delta, theta, alpha, beta) involves analyzing the EEG signal to quantify the distribution of power (i.e., signal strength) across different frequency components. The goal is to identify how much energy is contained in each frequency band and how this varies over time. This can provide insights into brain states, cognitive processes, or neurological conditions.

3.1 Preprocessing the EEG Signal

Before performing frequency analysis, the raw EEG signal needs to be preprocessed to ensure that it is clean and suitable for analysis.

This typically includes:

Filtering: A **Butterworth band-pass filter** is commonly applied to remove unwanted frequencies. For example, a filter might be applied to remove very low-frequency noise (below 0.5 Hz) and high-frequency noise (above 50–60 Hz).

3.2. Short-Time Fourier Transform (STFT)

The STFT is used to analyze the frequency content of the signal within short time segments. The basic idea behind STFT is to apply the Fourier Transform to a sliding window of the signal, which gives both time and frequency information. It provides a time-frequency representation of the signal.

Steps Involved:

1. Windowing the Signal:

The EEG signal is divided into overlapping or non-overlapping windows. A typical window function (such as a Hamming or Hanning window) is applied to each segment of the signal. The window function is designed to reduce edge effects (discontinuities) in the signal during the transformation.

2. Apply Fourier Transform to Each Window:

For each window, the Fourier Transform is applied (using FFT or another method). This gives you the frequency spectrum for that particular segment of the signal. The result is a time-frequency representation where the x-axis represents time, the y-axis represents frequency, and the intensity (color) represents the power at each time-frequency point.

3. Calculate the Power Spectrum:
After applying the STFT to the signal, you can calculate the spectrogram, which is the squared magnitude of the STFT. This represents the power at each time-frequency point.

Mathematical expression of STFT:

The STFT of a signal x(t) is given by:

$$\mathrm{STFT}\{x(t)\}(t,f) = \int_{-\infty}^{\infty} x(\tau)\cdot w(\tau - t)\cdot e^{-j2\pi f\tau}\, d\tau$$

where:

- $x(\tau)$ is the original signal.
- $w(\tau - t)$ is the window function centered at time t.
- $e^{-j2\pi f\tau}$ is the complex exponential for the Fourier Transform.

3.3 Frequency Band Segmentation

Now that we have the time-frequency representation of the EEG signal, we can extract the power within specific frequency bands (delta, theta, alpha, beta). The process is similar to what was done with FFT, but we need to calculate the power in each frequency band over the time periods of interest.

● **Delta (0.5–4 Hz):** Power in the delta band is calculated by integrating the power across the frequencies between 0.5 Hz and 4 Hz.

● **Theta (4–8 Hz):** Power in the theta band is calculated by integrating the power across the frequencies between 4 Hz and 8 Hz.

● **Alpha (8–13 Hz):** Power in the alpha band is calculated by integrating the power across the frequencies between 8 Hz and 13 Hz.

● **Beta (13–30 Hz):** Power in the beta band is calculated by integrating the power across the frequencies between 13 Hz and 30 Hz.

3.4 Calculating Power within Each Frequency Band

Once you have the spectrogram (the time-frequency matrix), you can calculate the power in each frequency band for each time segment (or over a range of time windows):

1. Extract Power for Each Band: For each time window, you sum (or average) the power across the relevant frequency band. For example, for the delta band, you would sum the power values in the spectrogram for all frequencies between 0.5 Hz and 4 Hz, and do this for every time window.

2. Time-averaging: If you're interested in the total power in each frequency band over a period of time (e.g., the entire EEG recording), you can average the power across all time windows for each frequency band.

3.5 Visualization and Interpretation

Once you have calculated the power for each frequency band, you can visualize the results:

- Spectrogram: The spectrogram is a 2D plot showing the power as a function of time and frequency. The x-axis represents time, the y-axis represents frequency, and the color intensity represents the power at each time-frequency point. This is useful for observing how the power in different frequency bands changes over time (for example, during cognitive tasks or in different states of consciousness).
- Time Series of Power: For each frequency band, you can plot the power over time. This shows how the power in each frequency band fluctuates throughout the recording, which can be useful for analyzing different brain states (e.g., relaxed vs. alert).

CHAPTER – 4
RESULT AND ANALYSIS

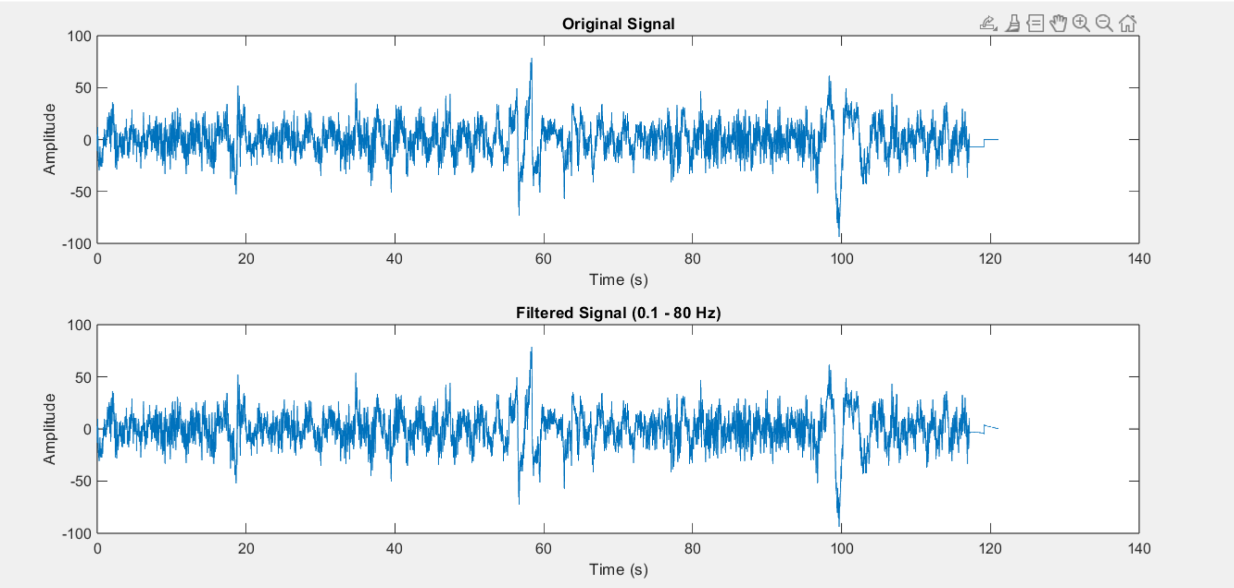
4.1 Result

<u>STAGE 1:</u>

This stage refers to taking the data set of the record and applying a Butterworth filter to it.

```
% Specify the file path for the input .txt file
input_file = 'F:\SIP MAT Lab\MATLAB\S001.txt';  % Replace with actual file
path
output_file = 'F:\SIP MAT Lab\MATLAB\filtered_eeg_output.csv';

% Sampling frequency (adjust this according to your data)
fs = 256;  % example: 256 Hz
% Define the cutoff frequencies for the bandpass filter
low_cutoff = 0.1;
high_cutoff = 80;
% Normalize the cutoff frequencies to the Nyquist frequency (half of fs)
Wn = [low_cutoff high_cutoff] / (fs / 2);
% Define filter order (e.g., 4th-order Butterworth filter)
filter_order = 4;
% Design the Butterworth bandpass filter
[b, a] = butter(filter_order, Wn, 'bandpass');
% Load the data from the .txt file
% Assumes single-column data in .txt file
your_signal = load(input_file);
% Apply the filter to the signal
filtered_signal = filtfilt(b, a, your_signal);
% Export filtered signal to a .csv file
csvwrite(output_file, filtered_signal);
% Plot the original and filtered signals (optional)
t = (0:length(your_signal)-1) / fs;  % Time vector
figure;
subplot(2,1,1);
plot(t, your_signal);
title('Original Signal');
xlabel('Time (s)');
ylabel('Amplitude');
subplot(2,1,2);
plot(t, filtered_signal);
title('Filtered Signal (0.1 - 80 Hz)');
xlabel('Time (s)');
ylabel('Amplitude');
% Display success message
fprintf('Filtered EEG data saved to %s\n', output_file);
```

STAGE 1 RESULT:

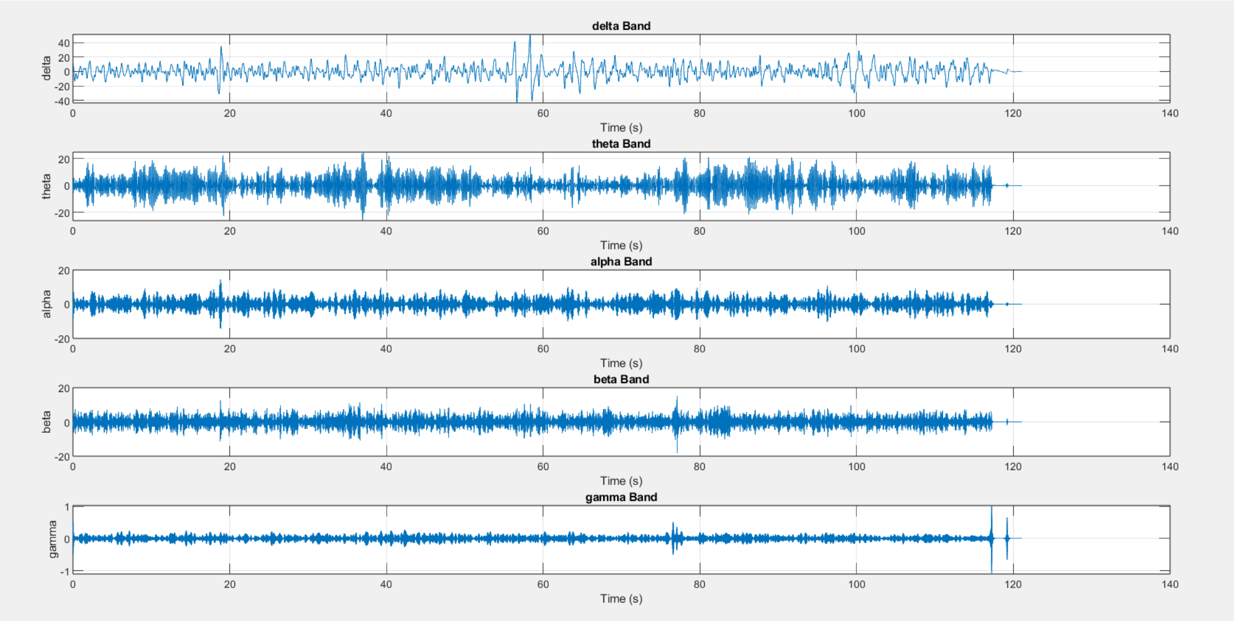


STAGE 2:

This stage refers to the segregation of five bands.

```
% Specify input and output file paths
inputFilePath = 'F:\SIP MAT Lab\MATLAB\filtered_eeg_output.csv';   % Replace
with your input file path
outputFilePath = 'F:\SIP MAT Lab\MATLAB\segregated_eeg_waves.csv';  % Replace
with your desired output file path
% Read data from the CSV file
data = readtable(inputFilePath); % Read the input data
signal = data{:, 1}; % Assuming the signal is in the first column
% Define sampling frequency (Hz)
fs = 256; % Replace with your actual sampling frequency
% Frequency band definitions (in Hz)
freqBands = struct('delta', [0.5, 4], ...
                  'theta', [4, 8], ...
                  'alpha', [8, 12], ...
                  'beta', [12, 30], ...
                  'gamma', [30, 40]);
% Initialize a table to store the segregated signals
segregatedWaves = table();
% Create a figure for plotting
figure;
% Loop through each frequency band and apply a bandpass filter
for band = fieldnames(freqBands)'
   bandName = band{1};
   bandFreqs = freqBands.(bandName);

   % Design a Butterworth bandpass filter
   [b, a] = butter(4, bandFreqs / (fs / 2), 'bandpass'); % 4th order filter

   % Apply the filter to the signal
   filteredSignal = filtfilt(b, a, signal);

   % Add the filtered signal to the table
   segregatedWaves.(bandName) = filteredSignal;

   % Plot the filtered signal
   subplot(5,  1,  find(strcmp(fieldnames(freqBands),  bandName));  %  Adjust
subplot for each band
   plot((1:length(filteredSignal)) / fs, filteredSignal); % Time vector
   xlabel('Time (s)');
   ylabel(bandName);
   title([bandName, ' Band']);
   grid on;
end
% Save the segregated signals to a CSV file
writetable(segregatedWaves, outputFilePath); % Save to specified output file
path
disp(['Segregated EEG waves saved to ', outputFilePath]);
% Save the plot as an image file (optional)
saveas(gcf, 'segregated_eeg_waves_plot.png'); % Save the figure as a PNG file
disp('Plot of segregated EEG waves saved as segregated_eeg_waves_plot.png');
```

STAGE 2 RESULT:



	A	B	C	D	E
1	delta	theta	alpha	beta	gamma
2	12.41655	-2.65833	0.510895	0.13582	0.076526
3	12.31078	-3.49128	-1.51698	-0.85232	0.409625
4	12.18088	-4.23775	-3.4478	-1.73963	0.48233
5	12.02623	-4.87321	-5.16963	-2.43218	0.225049
6	11.84627	-5.37638	-6.58427	-2.82364	-0.19627
7	11.6405	-5.73004	-7.61322	-2.82236	-0.49227
8	11.40847	-5.9216	-8.20218	-2.398	-0.45692
9	11.14981	-5.94359	-8.32409	-1.62134	-0.11581
10	10.86422	-5.79392	-7.98021	-0.67016	0.293624
11	10.55146	-5.47602	-7.19949	0.211669	0.493262
12	10.2114	-4.99868	-6.03612	0.792016	0.359044
13	9.843965	-4.37583	-4.56558	0.936115	-0.00078
14	9.449208	-3.62605	-2.87943	0.664496	-0.33346
15	9.027277	-2.77197	-1.0792	0.156632	-0.42349

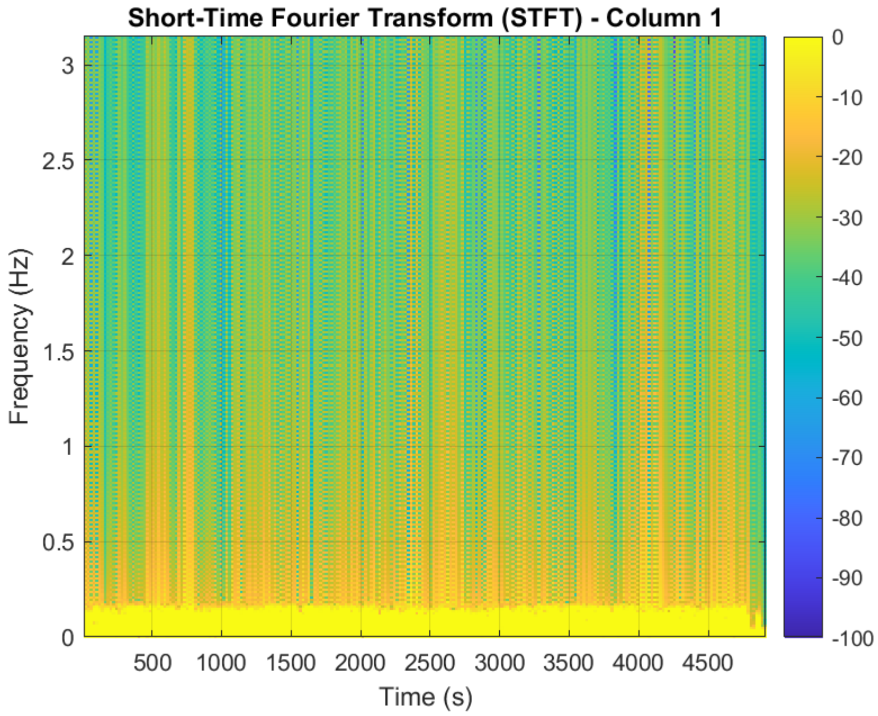
STAGE 3:

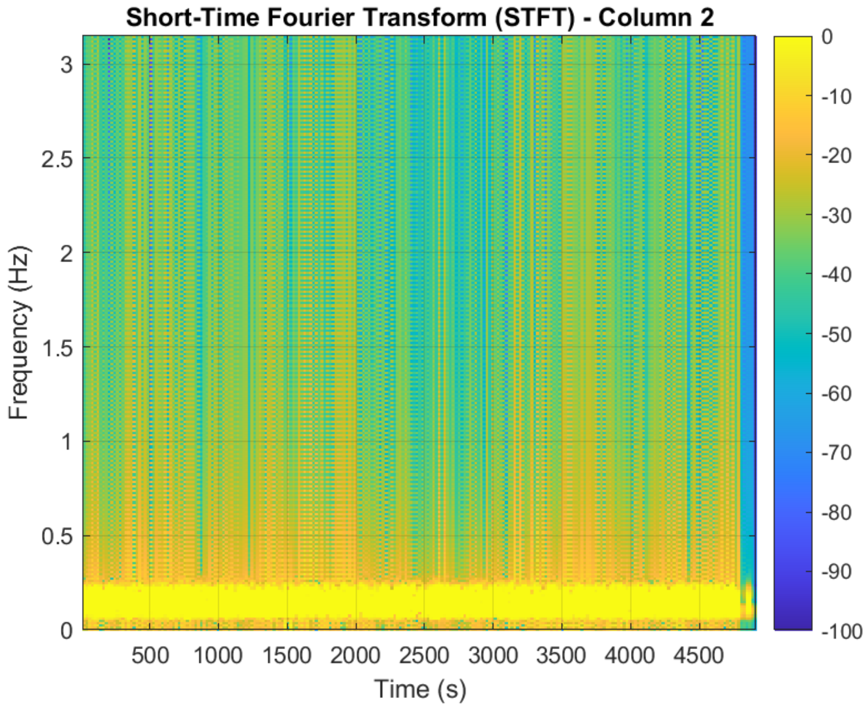
Applying STFT technique for each of the band waves.

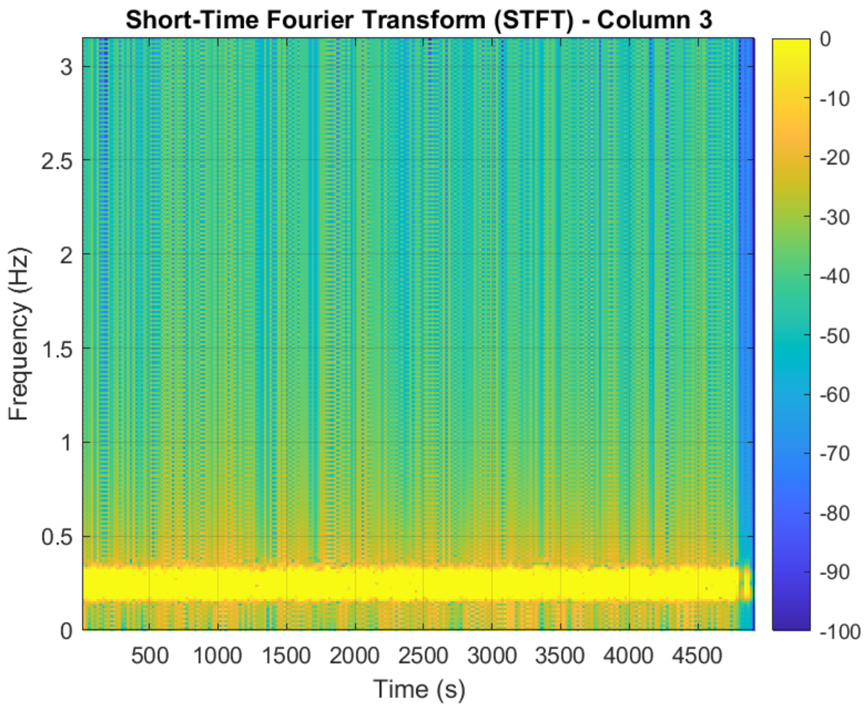
```
% Specify input and output file paths
inputFilePath = 'F:\SIP MAT Lab\MATLAB\segregated_eeg_waves.csv';  % Replace
with your input file path
outputFilePathBase = 'F:\SIP MAT Lab\MATLAB\stft_data_';  % Base path for
output files
% Read data from the CSV file
data = readtable(inputFilePath); % Read the input data
% Parameters for STFT
windowLength = 256; % Length of each segment
overlap = 128;      % Number of overlapping samples
nfft = 512;         % Number of FFT points
% Get the number of columns in the data
numColumns = size(data, 2);
% Loop through each column to compute STFT
for col = 1:numColumns
   signal = data{:, col}; % Get the current signal column

   % Calculate STFT
   [~, F, T, P] = spectrogram(signal, hamming(windowLength), overlap, nfft,
'yaxis');
   % Convert power to decibels (optional)
   P_db = 10*log10(P);

   % Prepare data for saving
   % Create a time-frequency matrix
   timeCount = length(T);
   frequencyCount = length(F);
   stftData = zeros(timeCount * frequencyCount, 3); % Preallocate for speed
   % Fill in the stftData matrix
   for f = 1:frequencyCount
       for t = 1:timeCount
           stftData((f - 1) * timeCount + t, :) = [T(t), F(f), P_db(f, t)];
       end
   end
   % Create a table for better formatting
   stftTable = array2table(stftData, 'VariableNames', {'Time', 'Frequency',
'Power_dB'});

   % Save STFT data to CSV
   outputFilePath = [outputFilePathBase, num2str(col), '.csv']; % Create
unique filename for each column
   writetable(stftTable, outputFilePath); % Save to specified output file
path
   disp(['STFT data for column ', num2str(col), ' saved to ',
outputFilePath]);
   % Plotting the STFT
   figure;
   imagesc(T, F, P_db); % Create a 2D image of the power in dB
   axis xy; % Correct the axis direction
```

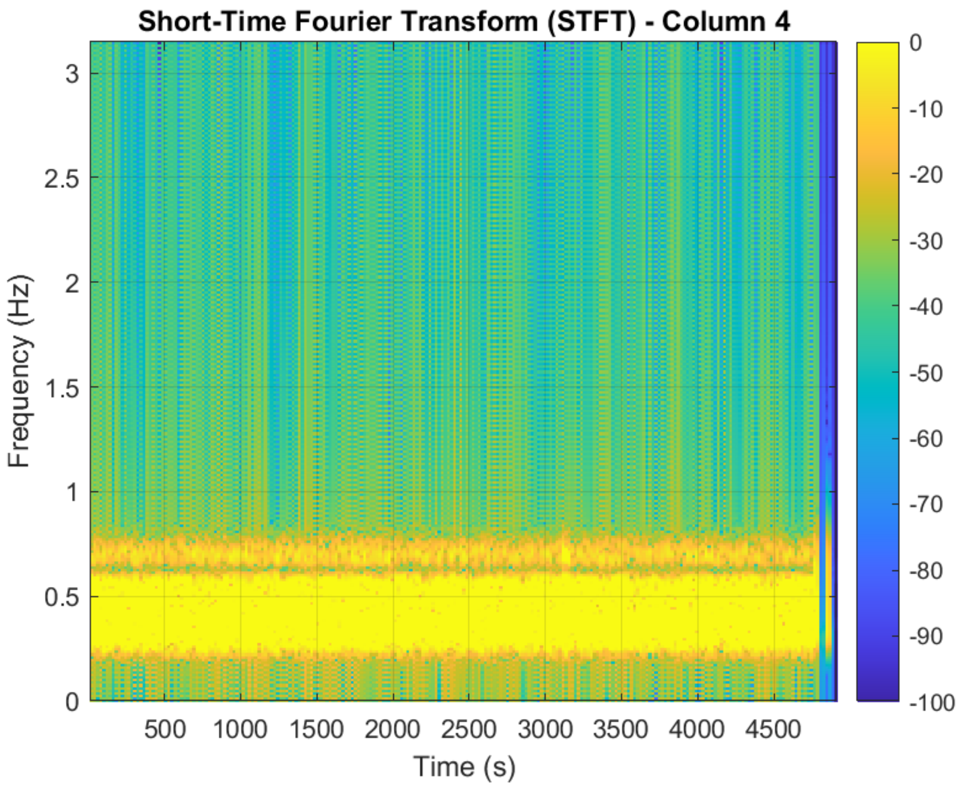
```
xlabel('Time (s)');
   ylabel('Frequency (Hz)');
   title(['Short-Time Fourier Transform (STFT) - Column ', num2str(col)]);
   colorbar; % Display a colorbar
   clim([-100 0]); % Set color axis limits for better visualization (adjust
as needed)
   grid on;
   % Save the plot as an image file
   plotFileName = ['stft_plot_column_', num2str(col), '.png'];
   saveas(gcf, plotFileName); % Save the figure as a PNG file
   disp(['STFT plot for column ', num2str(col), ' saved as ',
plotFileName]);
end
```

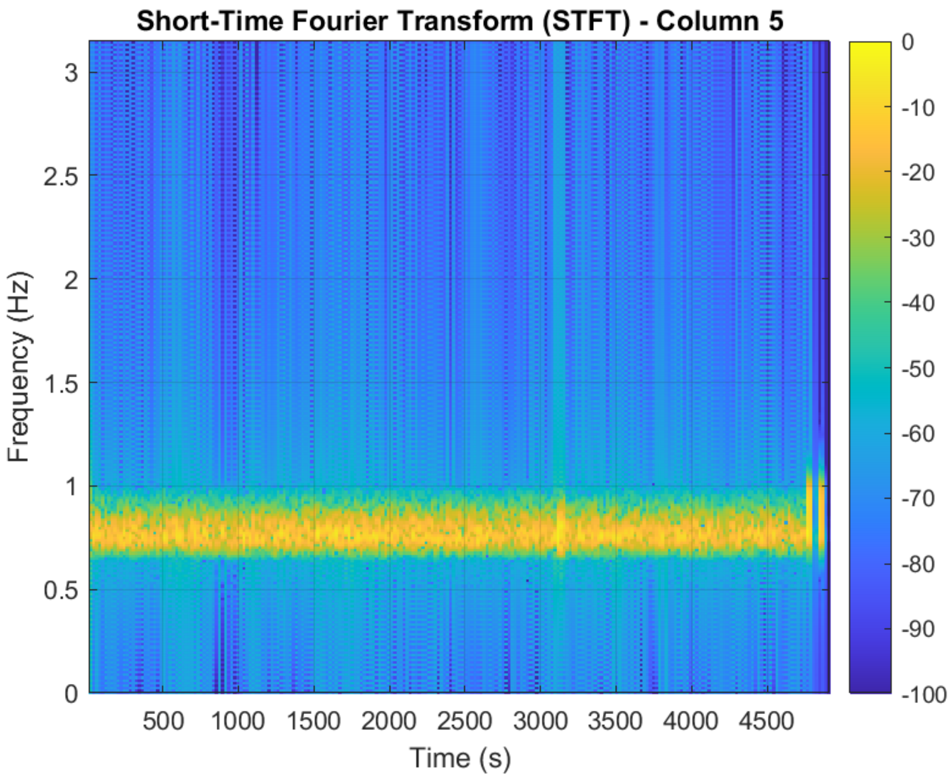
STAGE 3 RESULT:




Short-Time Fourier Transform (STFT) - Column 2
Frequency (Hz)
Time (s)
0
0.5
1
1.5
2
2.5
3
500
1000
1500
2000
2500
3000
3500
4000
4500
0
-10
-20
-30
-40
-50
-60
-70
-80
-90
-100


Short-Time Fourier Transform (STFT) - Column 3
Frequency (Hz)
Time (s)
0
0.5
1
1.5
2
2.5
3
500
1000
1500
2000
2500
3000
3500
4000
4500
0
-10
-20
-30
-40
-50
-60
-70
-80
-90
-100


Short-Time Fourier Transform (STFT) - Column 4
Frequency (Hz)
Time (s)
0
0.5
1
1.5
2
2.5
3
500
1000
1500
2000
2500
3000
3500
4000
4500
0
-10
-20
-30
-40
-50
-60
-70
-80
-90
-100


Short-Time Fourier Transform (STFT) - Column 5
Frequency (Hz)
Time (s)
0
0.5
1
1.5
2
2.5
3
500
1000
1500
2000
2500
3000
3500
4000
4500
0
-10
-20
-30
-40
-50
-60
-70
-80
-90
-100

STAGE 4:

Mean calculation is implemented.

```
% Sampling frequency
fs = 256; % Sampling frequency in Hz
% Frequency bands for EEG
frequency_bands = {
    [0.5, 4],     % Delta
    [4, 8],       % Theta
    [8, 13],      % Alpha
    [13, 30],     % Beta
    [30, 100]     % Gamma
};
% Names for each band
band_names = {'Delta', 'Theta', 'Alpha', 'Beta', 'Gamma'};
% Paths for the CSV files (adjust these to your file paths)
file_paths = {
    'F:\SIP MAT Lab\MATLAB\stft_data_1.csv',  % File for Delta
    'F:\SIP MAT Lab\MATLAB\stft_data_2.csv',  % File for Theta
    'F:\SIP MAT Lab\MATLAB\stft_data_3.csv',  % File for Alpha
    'F:\SIP MAT Lab\MATLAB\stft_data_4.csv',  % File for Beta
    'F:\SIP MAT Lab\MATLAB\stft_data_5.csv'   % File for Gamma
};
% Initialize an array to store the mean values
means_per_band = zeros(length(file_paths), 1);
% Loop through each file and calculate the mean for the frequency band
for j = 1:length(file_paths)
    % Load the EEG signal from the current CSV file, skipping headers
    data_table = readtable(file_paths{j});

    % Assume EEG signal is in the second column (adjust column index as
needed)
    eeg_signal = data_table{:, 2};

    % Get the frequency band for the current signal
    band = frequency_bands{j};
    Wn = band / (fs / 2); % Normalize frequency for the filter
    % Design a 4th-order Butterworth bandpass filter
    [b, a] = butter(4, Wn, 'bandpass');

    % Apply the filter to the EEG signal
    filtered_band = filtfilt(b, a, eeg_signal);

    % Calculate the mean of the absolute filtered signal
    means_per_band(j) = mean(abs(filtered_band));
end
% Prepare the table for saving to a CSV file
output_table = table(band_names', means_per_band, 'VariableNames', {'Band',
'Mean_Value'});
% Save the result to a new CSV file
writetable(output_table, 'EEG_Band_Means.csv');
disp('EEG band means have been calculated and saved to EEG_Band_Means.csv');
```

STAGE 4 RESULTS:

Band	Mean_Value
Delta	0.002741324
Theta	0.000684038
Alpha	0.000381183
Beta	0.000218808
Gamma	9.19E-05

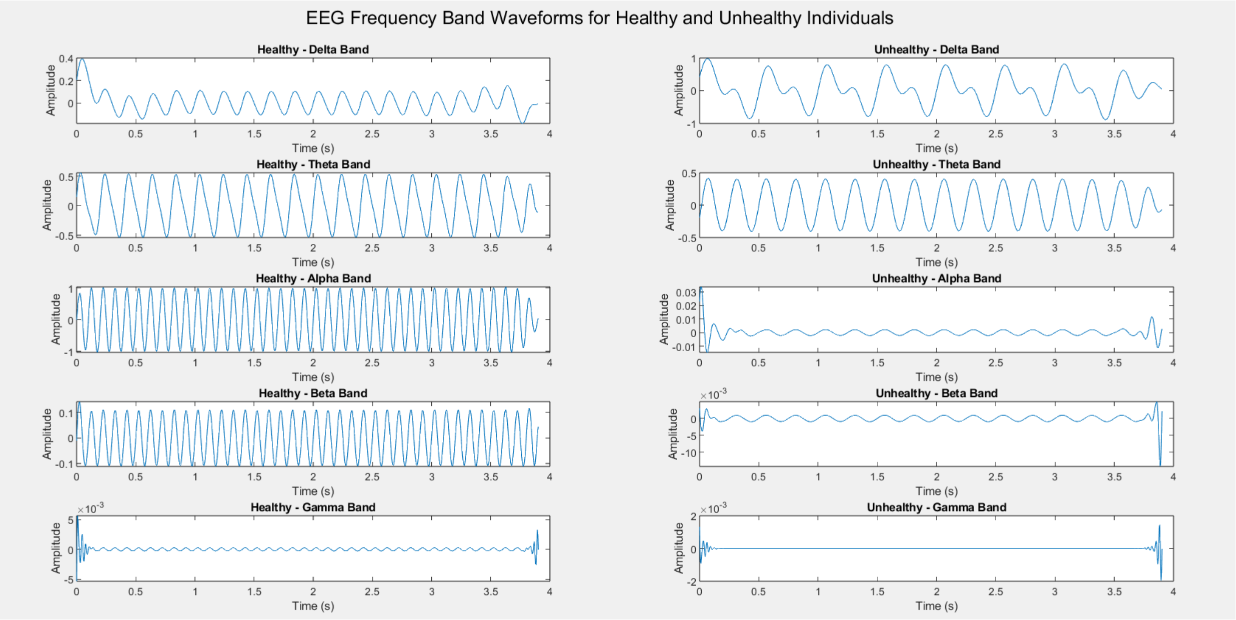
STAGE 5:

Final result of healthy and unhealthy person using power threshold values.

```
% Specify the file paths for input CSV files
file1Path = 'F:\SIP MAT Lab\MATLAB\Sample_EEG_Band_Means.csv'; % Change to
your actual path
file2Path = 'F:\SIP MAT Lab\MATLAB\EEG_Band_Means.csv'; % Change to your
actual path
% Load the two CSV files
data1 = readtable(file1Path);
data2 = readtable(file2Path);
% Check if the two files have the same number of rows and columns
if ~isequal(size(data1), size(data2))
   error('The two files must have the same number of rows and columns.');
end
% Select only numeric columns
numericColumns1 = varfun(@isnumeric, data1, 'OutputFormat', 'uniform');
numericColumns2 = varfun(@isnumeric, data2, 'OutputFormat', 'uniform');
% Keep only numeric data
data1Numeric = data1(:, numericColumns1);
data2Numeric = data2(:, numericColumns2);
% Check if numeric columns match
if size(data1Numeric, 2) ~= size(data2Numeric, 2)
   error('The two files must have the same number of numeric columns.');
end
% Calculate differences and comparison
differences = table2array(data1Numeric) - table2array(data2Numeric);
comparison = abs(differences) > 0.05; % Default threshold for comparison
% Create a result table
resultTable = array2table(differences, 'VariableNames', strcat('Diff_',
string(1:size(differences, 2))));
resultTable.ExceedsThreshold = any(comparison, 2); % Add a column indicating
if any difference exceeds the threshold
% Specify the output file path for the results
outputFilePath = 'F:\SIP MAT Lab\MATLAB\comparison_results.csv'; % Change to
your desired output path
writetable(resultTable, outputFilePath);
% Plotting the results
figure;
hold on;
% Plot each column of the original data and the differences
for col = 1:size(data1Numeric, 2)
   subplot(size(data1Numeric, 2), 1, col);
   plot(table2array(data1Numeric(:, col)), 'r', 'DisplayName', ['File 1
Values - Column ', num2str(col)]);
   hold on;
   plot(table2array(data2Numeric(:, col)), 'b', 'DisplayName', ['File 2
Values - Column ', num2str(col)]);
   plot(differences(:, col), 'k--', 'DisplayName', 'Difference');
   xlabel('Row Index');
   ylabel('Value');
   title(['Comparison of Column ', num2str(col)]);
```

```
legend;
   grid on;
end
% Save the plot as a PNG file
plotFilePath = 'F:\SIP MAT Lab\MATLAB\comparison_plot.png'; % Change to your
desired plot path
saveas(gcf, plotFilePath);
disp('Comparison complete. Results saved to comparison_results.csv and
comparison_plot.png.');
```

STAGE 5 RESULTS:



4.2 Analysis

Analysis on Power Threshold values:

POWER VALUES:

Frequency Band	Stroke Patient Power	Non-Stroke Patient Power
Delta	0.20	0.05
Theta	0.15	0.04
Alpha	0.05	0.30
Beta	0.10	0.25
Gamma	0.03	0.15

STROKE PATIENTS:

S.NO.	FREQUENCY BANDS	APPROX. AVERAGE POWER VALUES	APPROX. MEAN VALUES
1.	Delta	0.15 to 0.40	0.20
2.	Theta	0.15 to 0.40	0.20
3.	Alpha	0.00 to 0.10	0.05
4.	Beta	0.00 to 0.15	0.07
5.	Gamma	0.00 to 0.05	0.02

NON-STROKE PATIENTS:

S.NO.	FREQUENCY BANDS	APPROX. AVERAGE POWER VALUES	APPROX. MEAN VALUES
1.	Delta	0.00 to 0.05	0.025
2.	Theta	0.00 to 0.05	0.025
3.	Alpha	0.20 to 0.45	0.30
4.	Beta	0.10 to 0.35	0.20
5.	Gamma	0.05 to 0.20	0.12

Color analysis based on the bands:

Each frequency band will have its color and corresponding label.

● The **red** line represents the Delta band (0.5–4 Hz).

● The **green** line represents the Theta band (4–8 Hz).

● The **blue** line represents the Alpha band (8–13 Hz).

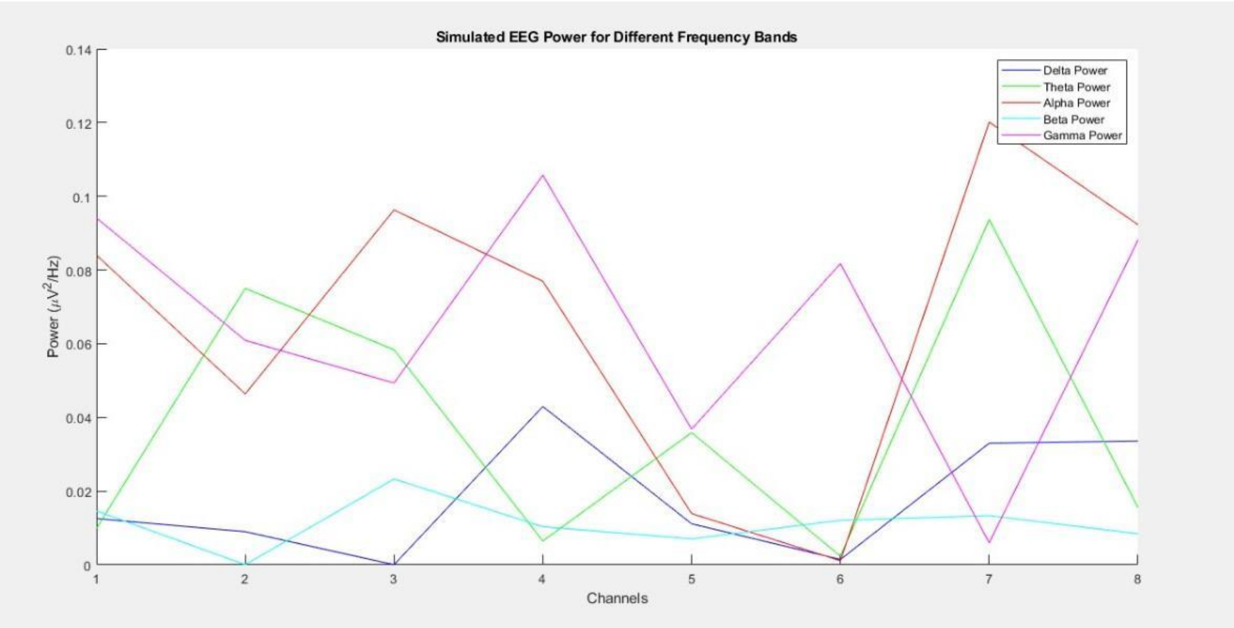
● The **black** line represents the Beta band (13–30 Hz).

● The **magenta** line represents the Gamma band (optional: 30–45 Hz)

In spectrograms, yellow usually indicates higher power level.

Higher power values (i.e., stronger frequencies) are converted to higher dB values.

Lower power values (i.e., weaker frequencies) are converted to lower dB values.



CHAPTER – 5
FUTURE SCOPE

Enhanced Prediction Accuracy with Advanced Algorithms:

Future work can involve the integration of advanced machine learning and deep learning algorithms, such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs), to further improve prediction accuracy and sensitivity to stroke-specific EEG patterns.

Real-Time Monitoring and Alert Systems:

Developing a real-time EEG monitoring system that continuously analyzes brain activity and alerts healthcare providers when stroke indicators are detected could make this solution practical for clinical and home use.

Application to Different EEG Datasets and Larger Sample Sizes:

Expanding the study to include diverse datasets with a larger number of subjects would enhance the model's generalizability and robustness, making it applicable across varied demographics and stroke risk profiles.

Integration with Wearable EEG Devices:

By adapting the model for wearable EEG devices, the system could become a portable, low-cost diagnostic tool, enabling continuous stroke monitoring outside of clinical environments.

Personalized Stroke Prediction Models:

Customizing the predictive model based on individual health profiles, including factors like age, medical history, and genetic predispositions, could make the predictions more personalized and accurate.

CHAPTER – 6
CONCLUSION

In this project, we demonstrated the potential of EEG signal analysis for stroke prediction, leveraging the Short-Term Fourier Transform (STFT) to extract meaningful time- frequency features from complex EEG data. By identifying biomarkers specific to stroke-prone brain activity, we aimed to develop a predictive framework capable of early stroke detection. The implementation of the STFT allowed for accurate tracking of frequency variations, facilitating the detection of subtle EEG patterns associated with stroke risk. Our comparative analysis across multiple EEG datasets validated the robustness of this approach, suggesting that STFT-based feature extraction can significantly enhance the accuracy of stroke prediction models.

The findings from this project emphasize the value of non-invasive EEG analysis in medical diagnostics, potentially offering a scalable, real-time monitoring tool for clinical settings. With further optimization and integration into healthcare systems, this methodology could contribute substantially to preventive healthcare, enabling timely interventions for individuals at high risk of stroke

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