In [1]:
```
!pip install keras-tuner
```

In [2]:
```
!pip install tensorflow
```

In [3]:
```
#importing all the necessary libraries
import os
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
import xgboost as xgb
from scipy.signal import welch
from scipy.stats import entropy
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, confusion_matrix
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from xgboost import XGBClassifier
from sklearn.model_selection import GridSearchCV, train_test_split
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import SimpleRNN, Dense, Dropout
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras import layers
from tensorflow import keras
from tensorflow.keras.optimizers import Adam
from kerastuner.tuners import RandomSearch

warnings.filterwarnings('ignore')
```

```
<ipython-input-3-66d52ae88ba2>:24: DeprecationWarning: `import kerastuner` is deprecated, please use `import keras_tu
ner`.
  from kerastuner.tuners import RandomSearch
```

Data Preprocessing

Download and extract the datasets.

In [4]:
```
# Specify the folder path where your text files are stored
folder_path = 'Project_3'

# Initialize an empty list to store data
data = []

# Loop through each file in the folder
for filename in os.listdir(folder_path):
    if filename.lower().endswith(".txt"):
        # Read the data from the file
        file_path = os.path.join(folder_path, filename)
        with open(file_path, 'r') as file:
            # Read the content of the file and split it into samples
            content = file.read().split()
            # Convert ASCII data to integers (assuming each sample is a single integer)
            samples = [int(value) for value in content]
            # Append the data to the list with the filename as the first element
            data.append([filename] + samples)

# Create a DataFrame from the list of data
column_names = ['Filename'] + [f'Sample_{i}' for i in range(1, 4098)]  # Assuming 4096 samples
df = pd.DataFrame(data, columns=column_names)


# # Create a new column based on the condition
# df['file_code'] = df['Filename'].apply(encode_filename)


# Display the DataFrame
print(df)
```

```
     Filename  Sample_1  Sample_2  Sample_3  Sample_4  Sample_5  Sample_6  \
0    F022.txt        26        29        26        22        18         8   
1    Z099.txt        56        55        38        -5       -47       -72   
2    O093.txt       -83      -120      -123      -119       -93       -45   
3    Z007.txt        -2        20        42        48        27        11   
4    F032.txt        46        41        44        39        42        41   
..        ...       ...       ...       ...       ...       ...       ...   
495  N062.TXT        -1         1        -1         5        -1        -3   
496  O086.txt       -40       -19       -38       -71       -76       -86   
497  Z050.txt        81        68        35         5        -6         6   
498  Z044.txt       -46       -44       -47       -40       -21         4   
499  S047.txt       -10      -658     -1254     -1395      -977      -198   

     Sample_7  Sample_8  Sample_9  ...  Sample_4088  Sample_4089  Sample_4090  \
0          -1       -16       -26  ...           53           55           62   
1         -79       -62       -39  ...          -44           -3           36   
2          17        77       103  ...           72           21          -22   
3           9        48        82  ...           -3            7           -3   
4          41        34        13  ...           50           17          -28   
..        ...       ...       ...  ...          ...          ...          ...   
495        -3         3        12  ...           22           35           40   
496       -79       -60       -89  ...          -52          -51          -64   
497        38        86       107  ...           44           38           33   
498        18        25        -8  ...          -17            1           20   
499       419       785       873  ...         -836         -329          143   

     Sample_4091  Sample_4092  Sample_4093  Sample_4094  Sample_4095  \
0             60           63           69           65           49   
1             41           14          -27          -45          -32   
2            -31          -18           -3           -5          -27   
3            -17          -38          -38          -23          -18   
4            -63          -76          -88          -92          -84   
..           ...          ...          ...          ...          ...   
495           50           49           50           55           53   
496          -72          -68          -60          -59          -46   
497           29           23           20           12           15   
498           32           38           40           48           43   
499          428          639          752          781          678   

     Sample_4096  Sample_4097  
```

```
0              32        -150
1              -4          69
2             -50         -38
3              -6         -37
4             -75        -102
..            ...         ...
495            65          -6
496           -41         -63
497            10          17
498            56          14
499           540       -1852

[500 rows x 4098 columns]
```

The above dataset contains 500 rows and 4100 columns after extracting and encoding.

Explore the data to understand its structure and characteristics.

In [5]:
```
#displaying information about the dataset
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Columns: 4098 entries, Filename to Sample_4097
dtypes: int64(4097), object(1)
memory usage: 15.6+ MB
```

In [6]:
```
#displaying statistics of the dataset
df.describe()
```

Out[6]:

	Sample_1	Sample_2	Sample_3	Sample_4	Sample_5	Sample_6	Sample_7	Sample_8	Sample_9	Sample_10	...
count	500.000000	500.000000	500.000000	500.000000	500.000000	500.000000	500.000000	500.000000	500.000000	500.000000	...
mean	-3.718000	-9.802000	-16.094000	-18.820000	-16.662000	-12.124000	-6.510000	-2.142000	1.882000	4.438000	...
std	145.274622	163.176469	188.246611	201.245888	188.973686	165.080719	153.637922	155.370054	155.850617	155.882831	...
min	-985.000000	-1221.000000	-1406.000000	-1395.000000	-1291.000000	-880.000000	-998.000000	-1156.000000	-1009.000000	-665.000000	...
25%	-48.250000	-54.000000	-52.000000	-52.250000	-53.000000	-57.250000	-55.000000	-56.000000	-58.250000	-57.000000	...
50%	-8.000000	-8.000000	-7.000000	-9.000000	-8.500000	-7.000000	-5.000000	-7.000000	-5.000000	-5.000000	...
75%	36.000000	36.250000	37.250000	38.000000	41.000000	40.000000	38.250000	36.000000	36.000000	32.250000	...
max	800.000000	839.000000	857.000000	876.000000	893.000000	928.000000	973.000000	1045.000000	1381.000000	1502.000000	...

8 rows × 4097 columns

If necessary, preprocess the EEG data, including handling missing values, noise reduction, and data augmentation.

Encoding the labels based on the file names

In [7]:
```
def encode_filename(value):
    if 'F' in value:
        return 1
    elif 'N' in value:
        return 2
    elif 'O' in value:
        return 3
    elif 'S' in value:
        return 4
    elif 'Z' in value:
        return 5

# Create a file_code based on the Filename
df['file_code'] = df['Filename'].apply(encode_filename)
```

Encoding the file set based on the file names

- File set has been taken from the official website

In [8]:
```
def encode_filename_get_set(value):
    if 'F' in value:
        return 'D'
    elif 'N' in value:
        return 'C'
    elif 'O' in value:
        return 'B'
    elif 'S' in value:
        return 'E'
    elif 'Z' in value:
        return 'A'

# Create a file_set based on the Filename
df['file_set'] = df['Filename'].apply(encode_filename_get_set)
```

Encoding the data colletion and recording techniques given in the official paper

In [9]:
```
def encode_filename_get_recording_technique(value):
    if 'F' in value:
        return 'Epileptogenic Zone : Seizure Free'
    elif 'N' in value:
        return 'Hippocampal Formation : Seizure Free'
    elif 'O' in value:
        return 'Eyes Closed : Seizure Free'
    elif 'S' in value:
        return 'Seizure Activity'
    elif 'Z' in value:
        return 'Eyes Open : Seizure Free'

# Create a file_set based on the Filename
df['recording_technique'] = df['Filename'].apply(encode_filename_get_recording_technique)
```

Bringing the categorical values to the begining

In [10]:
```
col = df.columns.tolist()
col = [col[0]] + col [-3:] + col[1:-3]
df = df[col]
df.head()
```

Out[10]:

	Filename	file_code	file_set	recording_technique	Sample_1	Sample_2	Sample_3	Sample_4	Sample_5	Sample_6	...	Sample_4088	Sample_4
0	F022.txt	1	D	Epileptogenic Zone : Seizure Free	26	29	26	22	18	8	...	53	
1	Z099.txt	5	A	Eyes Open : Seizure Free	56	55	38	-5	-47	-72	...	-44	
2	O093.txt	3	B	Eyes Closed : Seizure Free	-83	-120	-123	-119	-93	-45	...	72	
3	Z007.txt	5	A	Eyes Open : Seizure Free	-2	20	42	48	27	11	...	-3	
4	F032.txt	1	D	Epileptogenic Zone : Seizure Free	46	41	44	39	42	41	...	50	

5 rows × 4101 columns

Checking missing values

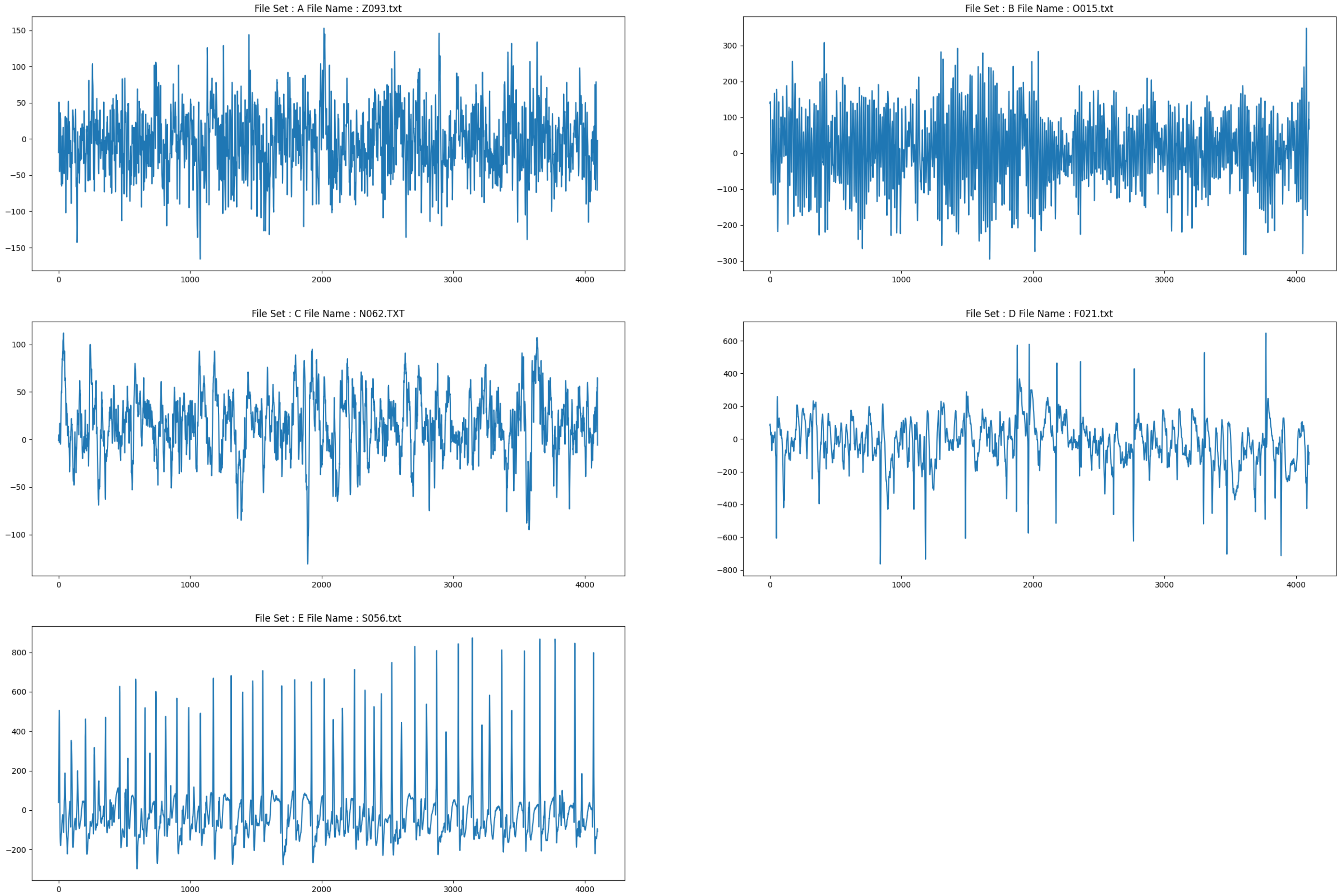
In [11]:
```
df.isnull().sum()
```

Out[11]:
```
Filename             0
file_code            0
file_set             0
recording_technique  0
Sample_1             0
                    ..
Sample_4093          0
Sample_4094          0
Sample_4095          0
Sample_4096          0
Sample_4097          0
Length: 4101, dtype: int64
```

In [12]:
```
#displaying sample EEG graph from each set
plt.figure(figsize= (30,20))

plt.subplot(3,2,1)
file_name = 'Z093.txt'
set_code = df[df['Filename'] == file_name].iloc[0,2]

x = [i for i in range(1,4098)]
y = df[df['Filename'] == file_name].iloc[0,4:]

plt.title(f'File Set : {set_code} File Name : {file_name}')
plt.plot(x, y )

plt.subplot(3,2,2)

file_name = 'O015.txt'
set_code = df[df['Filename'] == file_name].iloc[0,2]

x = [i for i in range(1,4098)]
y = df[df['Filename'] == file_name].iloc[0,4:]

plt.title(f'File Set : {set_code} File Name : {file_name}')
plt.plot(x, y )

plt.subplot(3,2,3)
file_name = 'N062.TXT'
set_code = df[df['Filename'] == file_name].iloc[0,2]

x = [i for i in range(1,4098)]
y = df[df['Filename'] == file_name].iloc[0,4:]

plt.title(f'File Set : {set_code} File Name : {file_name}')
plt.plot(x, y )

plt.subplot(3,2,4)
file_name = 'F021.txt'
set_code = df[df['Filename'] == file_name].iloc[0,2]

x = [i for i in range(1,4098)]
y = df[df['Filename'] == file_name].iloc[0,4:]
```

```
plt.title(f'File Set : {set_code} File Name : {file_name}')
plt.plot(x, y )


plt.subplot(3,2,5)
file_name = 'S056.txt'
set_code = df[df['Filename'] == file_name].iloc[0,2]

x = [i for i in range(1,4098)]
y = df[df['Filename'] == file_name].iloc[0,4:]

plt.title(f'File Set : {set_code} File Name : {file_name}')
plt.plot(x, y )
```

Out[12]: [<matplotlib.lines.Line2D at 0x782f47d0f460>]



From the samples timeseries from each set, it can be observed that
A and B looks normal
C has occasional spikes
D has more occasional spikes
where as E has very high number of hikes

There is a chance that Set E contains the values during Seizure

The folders Contains numerous .txt files, each likely representing an individual EEG recording or data file. Each .txt file in these folders probably contains EEG data points. The sample data from each folder ('Z', 'S', 'F', 'N', 'O') appears to be in a similar format. Given this structure, it seems that each file represents a single EEG recording, with each row likely corresponding to a signal measurement at a specific time point. The data is univariate, meaning each file contains measurements from a single EEG channel or a specific feature extracted from the EEG signal.

All the files have the same number of samples (4,097), which indicates a consistency in data collection or recording length. However, the range of values and the mean values vary significantly between files. Such variations are expected in EEG data, as they reflect different brain activities and possibly different conditions (such as epileptic seizures versus normal brain function).

Each .txt file is encoded into 4097 samples and all F.txt files are coded as 1, N as 2, O as 3, S as 4, Z as 5. File set has also be named to F as D, N as C, O as B, S as E, Z as A.

After performing all the steps the totals rows are set to be 500 and columns are 4100.

Feature Extraction

Extract relevant features from the EEG signals. You may consider time-domain and frequency-domain features.

Extracting Time Domain Features

In [13]:
```
def extract_features_time_domain(signal):
    # Time-domain features
    mean_value = np.mean(signal)
    variance = np.var(signal)
    rms_value = np.sqrt(np.mean(signal**2))
    std_dev = np.std(signal)

    return [mean_value, variance, rms_value, std_dev]

# Apply the function to each row in the DataFrame
feature_columns = ['mean', 'variance', 'rms', 'std_dev']

# Create a new DataFrame for features
feature_df = pd.DataFrame(columns=['file_name', 'file_code', 'file_set'] + feature_columns)

# Iterate through rows in the original DataFrame
for index, row in df.iterrows():
    file_name = row['Filename']
    file_code = row['file_code']
    file_set = row['file_set']
    eeg_signal = row.iloc[4:]  # Assuming the EEG signal starts from the second column

    # Extract features from the EEG signal
    features = [file_name]+ [file_code] + [file_set] + extract_features_time_domain(eeg_signal)

    # Append the features to the new DataFrame
    feature_df = feature_df.append(pd.Series(features, index=feature_df.columns), ignore_index=True)

# Display the new DataFrame
feature_df
```

Out[13]:

	file_name	file_code	file_set	mean	variance	rms	std_dev
0	F022.txt	1	D	-16.655846	4874.638209	71.777820	69.818609
1	Z099.txt	5	A	-14.893581	2028.057506	47.432860	45.033959
2	O093.txt	3	B	9.191848	4411.932440	67.055369	66.422379
3	Z007.txt	5	A	-13.334635	2139.935127	48.142991	46.259433
4	F032.txt	1	D	-19.669758	6750.543857	84.483390	82.161693
...	...	...	...	...	...	...	...
495	N062.TXT	2	C	14.933122	1061.053375	35.833664	32.573814
496	O086.txt	3	B	-50.073468	3692.213055	78.737318	60.763583
497	Z050.txt	5	A	3.820356	2488.566703	50.031608	49.885536
498	Z044.txt	5	A	3.562119	1957.717950	44.389263	44.246107
499	S047.txt	4	E	-9.679522	352551.812597	593.839630	593.760737

500 rows × 7 columns

Extracting Frequency Domain Features

In [14]:
```
def calculate_psd(row, fs):
    """ Calculate the Power Spectral Density (PSD) for a row. """
    freqs, psd = welch(row, fs)
    return freqs, psd

def calculate_peak_frequency(row, fs):
    """ Find the peak frequency. """
    freqs, psd = calculate_psd(row, fs)
    peak_freq = freqs[np.argmax(np.abs(psd))]
    return peak_freq

def bandpower(row, fs, band):
    """ Calculate the Band Power within a specific frequency band for a row. """
    freqs, psd = welch(row, fs)
    psd_abs = np.abs(psd)  # Use the absolute value of the PSD
    band_freqs = np.logical_and(freqs >= band[0], freqs <= band[1])
    band_power = np.trapz(psd_abs[band_freqs], freqs[band_freqs])
    return band_power


fs = 173.61  # Sampling rate (in Hz)

# Initialize lists to store the features
peak_frequencies = []
delta_powers = []
theta_powers = []
alpha_powers = []
beta_powers = []
gamma_powers = []

# Iterate over each row in the DataFrame
for index, row in df.iterrows():
    # Calculate each feature
    peak_freq = calculate_peak_frequency(row[4:], fs)
    delta = bandpower(row[4:], fs, [0.5, 4])
    theta = bandpower(row[4:], fs, [4, 8])
```

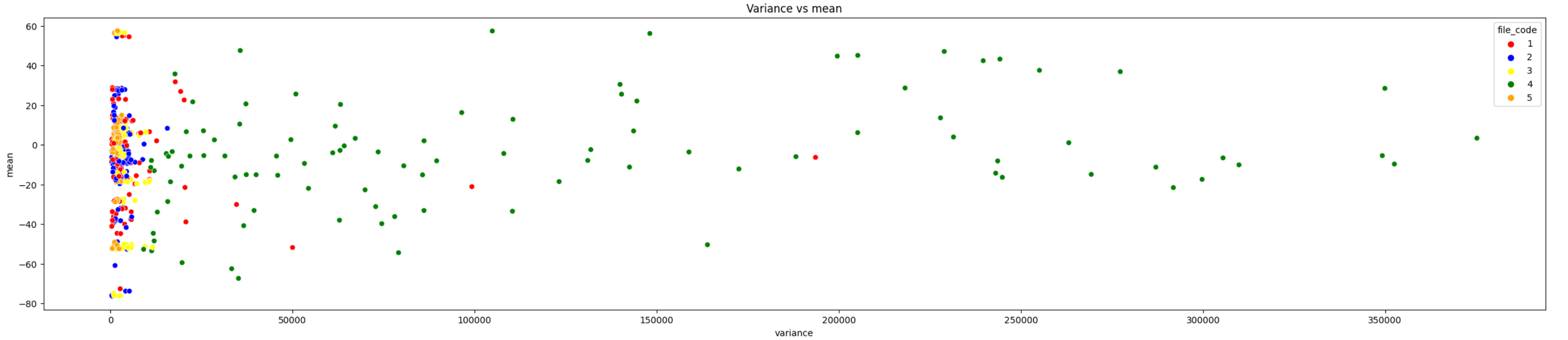
```
    alpha = bandpower(row[4:], fs, [8, 13])
    beta = bandpower(row[4:], fs, [13, 30])
    gamma = bandpower(row[4:], fs, [30, 45])

    # Append the features to the lists
    peak_frequencies.append(peak_freq)
    delta_powers.append(delta)
    theta_powers.append(theta)
    alpha_powers.append(alpha)
    beta_powers.append(beta)
    gamma_powers.append(gamma)

# Add the features as new columns to the DataFrame
feature_df['Peak_Frequency'] = peak_frequencies
feature_df['Delta_Power'] = delta_powers
feature_df['Theta_Power'] = theta_powers
feature_df['Alpha_Power'] = alpha_powers
feature_df['Beta_Power'] = beta_powers
feature_df['Gamma_Power'] = gamma_powers

# Now df has the original data along with the new frequency domain features
feature_df
```

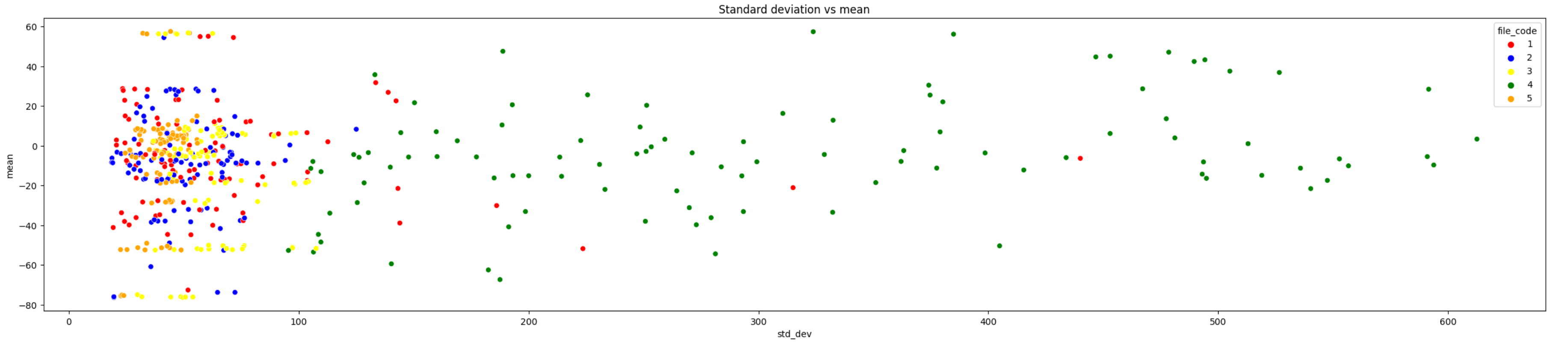
Out[14]:

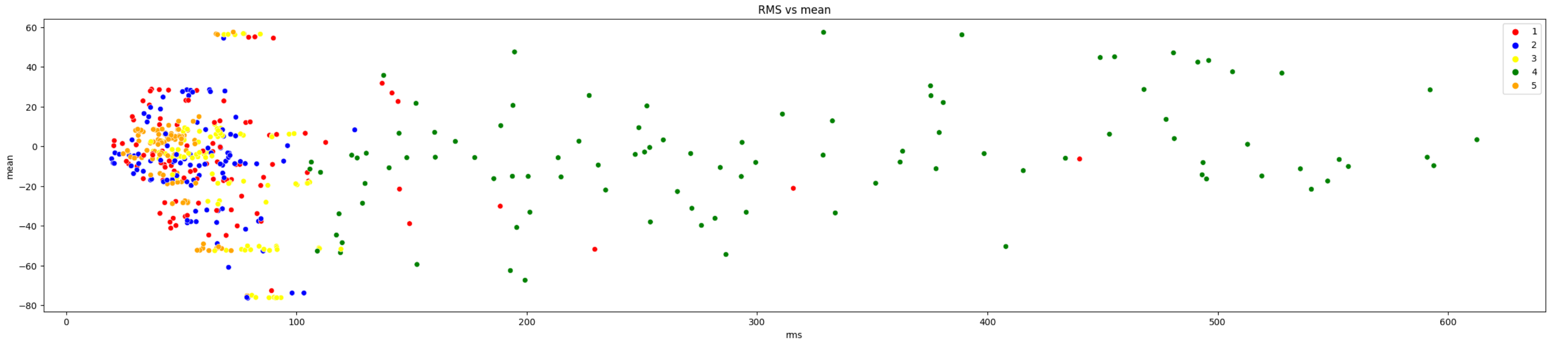
	file_name	file_code	file_set	mean	variance	rms	std_dev	Peak_Frequency	Delta_Power	Theta_Power	Alpha_Power
0	F022.txt	1	D	-16.655846	4874.638209	71.777820	69.818609	1.356328	3320.813346	449.318424	393.029683
1	Z099.txt	5	A	-14.893581	2028.057506	47.432860	45.033959	0.678164	396.343234	312.443404	485.336957
2	O093.txt	3	B	9.191848	4411.932440	67.055369	66.422379	11.528789	474.041195	446.161776	2208.933118
3	Z007.txt	5	A	-13.334635	2139.935127	48.142991	46.259433	0.678164	493.876892	286.862642	550.402647
4	F032.txt	1	D	-19.669758	6750.543857	84.483390	82.161693	0.678164	2205.736373	729.659136	531.871816
...	...	...	...	...	...	...	...	...	...	...	...
495	N062.TXT	2	C	14.933122	1061.053375	35.833664	32.573814	1.356328	571.895175	141.127870	87.234560
496	O086.txt	3	B	-50.073468	3692.213055	78.737318	60.763583	13.563281	438.644054	557.372320	923.177402
497	Z050.txt	5	A	3.820356	2488.566703	50.031608	49.885536	0.678164	700.090973	283.666064	455.052457
498	Z044.txt	5	A	3.562119	1957.717950	44.389263	44.246107	0.678164	509.261613	315.749318	338.584501
499	S047.txt	4	E	-9.679522	352551.812597	593.839630	593.760737	14.919609	26909.899427	38627.176733	46978.789521

500 rows × 13 columns

In [15]:
```
plt.figure(figsize=(30,20))
plt.subplot(3,1,1)
sns.scatterplot(x='variance', y = 'mean', data = feature_df, hue = 'file_code', palette=['red', 'blue', 'yellow', 'gre
en',  'orange'])
plt.title("Variance vs mean")

plt.subplot(3,1,2)
sns.scatterplot(x='std_dev', y = 'mean', data = feature_df, hue = 'file_code', palette=['red', 'blue','yellow', 'gree
n', 'orange'])
plt.title("Standard deviation vs mean")

plt.subplot(3,1,3)
sns.scatterplot(x='rms', y = 'mean', data = feature_df, hue = 'file_code', palette=['red', 'blue', 'yellow', 'green',
'orange'])
plt.title("RMS vs mean")

plt.legend()
plt.show()
```







From the Above graphs based on time based features it can be observed that values of Set S differ from all others significantly, Set D values has occasionally differ from other.

From the given paper:
Volunteers were relaxed in an awake state with eyes open ~A! and eyes closed ~B!, respectively. Sets C, D, and E originated from our EEG archive of presurgical diagnosis. For the present study EEGs from five patients were selected, all of whom had achieved complete seizure control after resection of one of the hippocampal formations, which was therefore correctly diagnosed to be the epileptogenic zone ~cf. Segments in set D were recorded from within the epileptogenic zone, and those in set C from the hippocampal formation of the opposite hemisphere of the brain. While sets C and D contained only activity measured during seizure free intervals, set E only contained seizure activity. Here segments were selected from all recording sites exhibiting ictal activity.

Hence it is given that Set E has been collected during activity and it can also be observed in the above charts. Labelling the rows from Set E as 1 indicating it is a seizure.

In [16]:
```
# Function to check if 'S' is present in the value
def labelling(value):
    if 'E' in value:
        return 1
    else:
        return 0


# Create a new column based on the condition
df['label'] = df['file_set'].apply(labelling)
feature_df['label'] = feature_df['file_set'].apply(labelling)
df
```

Out[16]:

	Filename	file_code	file_set	recording_technique	Sample_1	Sample_2	Sample_3	Sample_4	Sample_5	Sample_6	...	Sample_4089	Sample
0	F022.txt	1	D	Epileptogenic Zone : Seizure Free	26	29	26	22	18	8	...	55	
1	Z099.txt	5	A	Eyes Open : Seizure Free	56	55	38	-5	-47	-72	...	-3	
2	O093.txt	3	B	Eyes Closed : Seizure Free	-83	-120	-123	-119	-93	-45	...	21	
3	Z007.txt	5	A	Eyes Open : Seizure Free	-2	20	42	48	27	11	...	7	
4	F032.txt	1	D	Epileptogenic Zone : Seizure Free	46	41	44	39	42	41	...	17	
...	...	...	...	...	...	...	...	...	...	...	...	...	
495	N062.TXT	2	C	Hippocampal Formation : Seizure Free	-1	1	-1	5	-1	-3	...	35	
496	O086.txt	3	B	Eyes Closed : Seizure Free	-40	-19	-38	-71	-76	-86	...	-51	
497	Z050.txt	5	A	Eyes Open : Seizure Free	81	68	35	5	-6	6	...	38	
498	Z044.txt	5	A	Eyes Open : Seizure Free	-46	-44	-47	-40	-21	4	...	1	
499	S047.txt	4	E	Seizure Activity	-10	-658	-1254	-1395	-977	-198	...	-329	

500 rows × 4102 columns

Data Splitting

Split the data into training, validation, and test sets.

In [17]:
```python
# Assuming feature_df is your DataFrame with features
# 'file_name' column is dropped as it's not used for training
X = feature_df[['mean', 'variance', 'rms', 'std_dev','Peak_Frequency', 'Delta_Power','Theta_Power','Alpha_Power', 'Beta_Power', 'Gamma_Power']].values
y = feature_df['label'].values

# Standardize the data
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=40, stratify=y)
```

Model Selection and Model Training and Model Evaluation with Hyper Parameter Tuning.

Training the Random Forest Model

- Hyper parameter tuning is being performed using Grid Search CV
- Class weights has been calculated to balance the imbalance in the data

Calculate the weights as follows:

- Weight for class 0 = Total Instances / (Number of Classes *Instances in Class 0) = 500 / (2* 400) = 0.625
- Weight for class 1 = Total Instances / (Number of Classes *Instances in Class 1) = 500 / (2* 100) = 2.5

In [18]:
```
#Random Forest
# Define the parameter grid
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [3, 5, 7],
    'min_samples_split': [2, 4, 6],
    'min_samples_leaf': [1, 2, 3]
}

# Create a RandomForest model
rf = RandomForestClassifier(random_state=42, class_weight={0: 0.625, 1: 2.5})

# Set up GridSearchCV
grid_search = GridSearchCV(estimator=rf, param_grid=param_grid, cv=5, n_jobs=-1, scoring='accuracy')

# Perform grid search
grid_search.fit(X_train, y_train)

# Best parameters and best score
print(f"Best parameters: {grid_search.best_params_}")
print(f"Best score: {grid_search.best_score_}")

# Use the best estimator for making predictions
best_rf = grid_search.best_estimator_
```

```
Best parameters: {'max_depth': 3, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 100}
Best score: 0.9800000000000001
```

Training the XgBoost Model

- Hyper parameter tuning is being performed using Grid Search CV
- Imbalance in the data has been dealt using scale_pos_weight

In [19]:
```
#XGBoost

# Define the parameter grid
param_grid = {
    'max_depth': [3, 4, 5],
    'learning_rate': [0.01, 0.1, 0.2],
    'n_estimators': [100, 200, 300],
    'subsample': [0.8, 0.9, 1.0],
    'colsample_bytree': [0.8, 0.9, 1.0]
}

# Create a XGBClassifier model
xgb_model = XGBClassifier(
    objective='binary:logistic',
    eval_metric='logloss',
    random_state=42,
    scale_pos_weight=4  # Set the scale_pos_weight parameter as in your original model
)

# Set up GridSearchCV
grid_search = GridSearchCV(
    estimator=xgb_model,
    param_grid=param_grid,
    cv=5,
    n_jobs=-1,
    scoring='accuracy'
)

# Perform grid search
grid_search.fit(X_train, y_train)

# Best parameters and best score
print(f"Best parameters: {grid_search.best_params_}")
print(f"Best score: {grid_search.best_score_}")

# Use the best estimator for making predictions
best_xgb = grid_search.best_estimator_
```

```
Best parameters: {'colsample_bytree': 0.8, 'learning_rate': 0.1, 'max_depth': 4, 'n_estimators': 200, 'subsample': 0.
9}
Best score: 0.9825000000000002
```

Training the RNN Model

- Hyper parameter tuning is being performed using Kears Tuner
- Class weights has been calculated to balance the imbalance in the data
- RNN creates a set of Validation set from training set and calculates the validation loss and validation accuracy

In [20]:
```
#RNN with keras tuner

def build_model(hp):
    model = Sequential()
    model.add(SimpleRNN(units=hp.Int('units', min_value=32, max_value=128, step=32),
                        input_shape=(X_train.shape[1], 1),
                        activation='relu',
                        return_sequences=True))
    model.add(Dropout(rate=hp.Float('dropout', min_value=0.2, max_value=0.5, step=0.1)))
    model.add(SimpleRNN(units=hp.Int('units', min_value=32, max_value=128, step=32),
                        activation='relu'))
    model.add(Dropout(rate=hp.Float('dropout', min_value=0.2, max_value=0.5, step=0.1)))
    model.add(Dense(1, activation='sigmoid'))

    model.compile(optimizer=Adam(hp.Choice('learning_rate', values=[1e-2, 1e-3, 1e-4])),
                  loss='binary_crossentropy',
                  metrics=['accuracy'])
    return model
class_weight = {0 : 0.625, 1: 2.5}
# Define early stopping callback
early_stopping = EarlyStopping(monitor='val_loss', patience=10, restore_best_weights=True)

# Define the Keras Tuner RandomSearch
tuner = RandomSearch(
    build_model,
    objective='val_loss',
    max_trials=5,  # You can increase this based on your computational resources
    directory='keras_tuner_dir',
    project_name='rnn_hyperparameter_tuning'
)

# Search for the best hyperparameters
tuner.search(X_train, y_train, epochs=200, batch_size=32, validation_split=0.2, callbacks=[early_stopping], class_weig
ht = class_weight)

# Get the best hyperparameters
rnn_best_hps = tuner.get_best_hyperparameters(num_trials=1)[0]
print("Best Hyperparameters:", rnn_best_hps)

# Build the final model with the best hyperparameters
```

```
rnn_final_model = tuner.hypermodel.build(rnn_best_hps)
rnn_final_model.summary()

# Train the final model
rnn_final_model.fit(X_train, y_train, epochs=100, batch_size=32, validation_split=0.2)
```

```
Reloading Tuner from keras_tuner_dir/rnn_hyperparameter_tuning/tuner0.json
Best Hyperparameters: <keras_tuner.src.engine.hyperparameters.hyperparameters.HyperParameters object at 0x782f3ff3494
0>
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 simple_rnn (SimpleRNN)      (None, 10, 32)            1088      
                                                                 
 dropout (Dropout)           (None, 10, 32)            0         
                                                                 
 simple_rnn_1 (SimpleRNN)    (None, 32)                2080      
                                                                 
 dropout_1 (Dropout)         (None, 32)                0         
                                                                 
 dense (Dense)               (None, 1)                 33        
                                                                 
=================================================================
Total params: 3,201
Trainable params: 3,201
Non-trainable params: 0
_________________________________________________________________
Epoch 1/100
10/10 [==============================] - 4s 92ms/step - loss: 0.3744 - accuracy: 0.8625 - val_loss: 0.1667 - val_accu
racy: 0.9875
Epoch 2/100
10/10 [==============================] - 0s 17ms/step - loss: 0.1773 - accuracy: 0.9312 - val_loss: 0.1365 - val_accu
racy: 0.9625
Epoch 3/100
10/10 [==============================] - 0s 18ms/step - loss: 0.1373 - accuracy: 0.9500 - val_loss: 0.0892 - val_accu
racy: 0.9875
Epoch 4/100
10/10 [==============================] - 0s 16ms/step - loss: 0.0953 - accuracy: 0.9594 - val_loss: 0.0792 - val_accu
racy: 0.9625
Epoch 5/100
10/10 [==============================] - 0s 12ms/step - loss: 0.0821 - accuracy: 0.9781 - val_loss: 0.0610 - val_accu
racy: 0.9750
Epoch 6/100
10/10 [==============================] - 0s 12ms/step - loss: 0.0446 - accuracy: 0.9812 - val_loss: 0.0625 - val_accu
racy: 0.9750
```

```
Epoch 7/100
10/10 [==============================] - 0s 11ms/step - loss: 0.0398 - accuracy: 0.9812 - val_loss: 0.1461 - val_accu
racy: 0.9500
Epoch 8/100
10/10 [==============================] - 0s 14ms/step - loss: 0.2345 - accuracy: 0.9469 - val_loss: 0.1475 - val_accu
racy: 0.9625
Epoch 9/100
10/10 [==============================] - 0s 12ms/step - loss: 0.1553 - accuracy: 0.9750 - val_loss: 0.0552 - val_accu
racy: 0.9875
Epoch 10/100
10/10 [==============================] - 0s 13ms/step - loss: 0.0987 - accuracy: 0.9531 - val_loss: 0.0749 - val_accu
racy: 0.9625
Epoch 11/100
10/10 [==============================] - 0s 13ms/step - loss: 0.0495 - accuracy: 0.9969 - val_loss: 0.0403 - val_accu
racy: 0.9875
Epoch 12/100
10/10 [==============================] - 0s 12ms/step - loss: 0.0376 - accuracy: 0.9906 - val_loss: 0.0731 - val_accu
racy: 0.9625
Epoch 13/100
10/10 [==============================] - 0s 12ms/step - loss: 0.0437 - accuracy: 0.9719 - val_loss: 0.0725 - val_accu
racy: 0.9625
Epoch 14/100
10/10 [==============================] - 0s 12ms/step - loss: 0.0522 - accuracy: 0.9844 - val_loss: 0.0382 - val_accu
racy: 0.9875
Epoch 15/100
10/10 [==============================] - 0s 11ms/step - loss: 0.0240 - accuracy: 0.9906 - val_loss: 0.0492 - val_accu
racy: 0.9875
Epoch 16/100
10/10 [==============================] - 0s 14ms/step - loss: 0.0380 - accuracy: 0.9844 - val_loss: 0.1378 - val_accu
racy: 0.9500
Epoch 17/100
10/10 [==============================] - 0s 11ms/step - loss: 0.1001 - accuracy: 0.9719 - val_loss: 0.0669 - val_accu
racy: 0.9750
Epoch 18/100
10/10 [==============================] - 0s 11ms/step - loss: 0.0493 - accuracy: 0.9906 - val_loss: 0.0544 - val_accu
racy: 0.9750
Epoch 19/100
10/10 [==============================] - 0s 12ms/step - loss: 0.0482 - accuracy: 0.9750 - val_loss: 0.0480 - val_accu
racy: 0.9750
Epoch 20/100
10/10 [==============================] - 0s 11ms/step - loss: 0.0283 - accuracy: 0.9875 - val_loss: 0.0651 - val_accu
```

```
racy: 0.9625
Epoch 21/100
10/10 [==============================] - 0s 12ms/step - loss: 0.0207 - accuracy: 0.9969 - val_loss: 0.0730 - val_accu
racy: 0.9625
Epoch 22/100
10/10 [==============================] - 0s 13ms/step - loss: 0.0174 - accuracy: 0.9937 - val_loss: 0.0636 - val_accu
racy: 0.9750
Epoch 23/100
10/10 [==============================] - 0s 12ms/step - loss: 0.0103 - accuracy: 0.9969 - val_loss: 0.0559 - val_accu
racy: 0.9875
Epoch 24/100
10/10 [==============================] - 0s 12ms/step - loss: 0.0094 - accuracy: 0.9969 - val_loss: 0.0843 - val_accu
racy: 0.9750
Epoch 25/100
10/10 [==============================] - 0s 13ms/step - loss: 0.0047 - accuracy: 1.0000 - val_loss: 0.0813 - val_accu
racy: 0.9875
Epoch 26/100
10/10 [==============================] - 0s 12ms/step - loss: 0.0021 - accuracy: 1.0000 - val_loss: 0.0927 - val_accu
racy: 0.9875
Epoch 27/100
10/10 [==============================] - 0s 12ms/step - loss: 0.0014 - accuracy: 1.0000 - val_loss: 0.1040 - val_accu
racy: 0.9875
Epoch 28/100
10/10 [==============================] - 0s 11ms/step - loss: 0.0024 - accuracy: 1.0000 - val_loss: 0.1253 - val_accu
racy: 0.9750
Epoch 29/100
10/10 [==============================] - 0s 13ms/step - loss: 0.0025 - accuracy: 1.0000 - val_loss: 0.1270 - val_accu
racy: 0.9750
Epoch 30/100
10/10 [==============================] - 0s 12ms/step - loss: 2.9143e-04 - accuracy: 1.0000 - val_loss: 0.1343 - val_
accuracy: 0.9750
Epoch 31/100
10/10 [==============================] - 0s 13ms/step - loss: 6.9284e-04 - accuracy: 1.0000 - val_loss: 0.1586 - val_
accuracy: 0.9750
Epoch 32/100
10/10 [==============================] - 0s 12ms/step - loss: 9.2498e-04 - accuracy: 1.0000 - val_loss: 0.1684 - val_
accuracy: 0.9750
Epoch 33/100
10/10 [==============================] - 0s 13ms/step - loss: 0.0014 - accuracy: 1.0000 - val_loss: 0.1326 - val_accu
racy: 0.9750
Epoch 34/100
```

```
10/10 [==============================] - 0s 12ms/step - loss: 0.0565 - accuracy: 0.9844 - val_loss: 0.1765 - val_accu
racy: 0.9750
Epoch 35/100
10/10 [==============================] - 0s 12ms/step - loss: 0.1283 - accuracy: 0.9656 - val_loss: 0.0585 - val_accu
racy: 0.9875
Epoch 36/100
10/10 [==============================] - 0s 13ms/step - loss: 0.0759 - accuracy: 0.9937 - val_loss: 0.0458 - val_accu
racy: 0.9875
Epoch 37/100
10/10 [==============================] - 0s 11ms/step - loss: 0.0773 - accuracy: 0.9750 - val_loss: 0.0415 - val_accu
racy: 0.9875
Epoch 38/100
10/10 [==============================] - 0s 12ms/step - loss: 0.0669 - accuracy: 0.9812 - val_loss: 0.0746 - val_accu
racy: 0.9750
Epoch 39/100
10/10 [==============================] - 0s 11ms/step - loss: 0.0502 - accuracy: 0.9906 - val_loss: 0.0703 - val_accu
racy: 0.9875
Epoch 40/100
10/10 [==============================] - 0s 10ms/step - loss: 0.0259 - accuracy: 0.9906 - val_loss: 0.0841 - val_accu
racy: 0.9750
Epoch 41/100
10/10 [==============================] - 0s 11ms/step - loss: 0.0191 - accuracy: 0.9906 - val_loss: 0.0694 - val_accu
racy: 0.9750
Epoch 42/100
10/10 [==============================] - 0s 11ms/step - loss: 0.0110 - accuracy: 0.9969 - val_loss: 0.0672 - val_accu
racy: 0.9750
Epoch 43/100
10/10 [==============================] - 0s 12ms/step - loss: 0.0132 - accuracy: 0.9969 - val_loss: 0.0714 - val_accu
racy: 0.9875
Epoch 44/100
10/10 [==============================] - 0s 12ms/step - loss: 0.0391 - accuracy: 0.9937 - val_loss: 0.0656 - val_accu
racy: 0.9750
Epoch 45/100
10/10 [==============================] - 0s 14ms/step - loss: 0.0191 - accuracy: 0.9906 - val_loss: 0.0779 - val_accu
racy: 0.9875
Epoch 46/100
10/10 [==============================] - 0s 13ms/step - loss: 0.0234 - accuracy: 0.9906 - val_loss: 0.0381 - val_accu
racy: 0.9750
Epoch 47/100
10/10 [==============================] - 0s 12ms/step - loss: 0.0179 - accuracy: 0.9969 - val_loss: 0.0492 - val_accu
racy: 0.9750
```

```
Epoch 48/100
10/10 [==============================] - 0s 12ms/step - loss: 0.0063 - accuracy: 0.9969 - val_loss: 0.0807 - val_accu
racy: 0.9750
Epoch 49/100
10/10 [==============================] - 0s 14ms/step - loss: 0.0043 - accuracy: 1.0000 - val_loss: 0.1019 - val_accu
racy: 0.9750
Epoch 50/100
10/10 [==============================] - 0s 12ms/step - loss: 0.0107 - accuracy: 0.9969 - val_loss: 0.0795 - val_accu
racy: 0.9750
Epoch 51/100
10/10 [==============================] - 0s 11ms/step - loss: 0.0143 - accuracy: 0.9969 - val_loss: 0.0638 - val_accu
racy: 0.9750
Epoch 52/100
10/10 [==============================] - 0s 14ms/step - loss: 0.0153 - accuracy: 0.9969 - val_loss: 0.1169 - val_accu
racy: 0.9750
Epoch 53/100
10/10 [==============================] - 0s 14ms/step - loss: 0.0104 - accuracy: 0.9969 - val_loss: 0.1129 - val_accu
racy: 0.9875
Epoch 54/100
10/10 [==============================] - 0s 12ms/step - loss: 0.0352 - accuracy: 0.9844 - val_loss: 0.0885 - val_accu
racy: 0.9625
Epoch 55/100
10/10 [==============================] - 0s 13ms/step - loss: 0.0179 - accuracy: 0.9937 - val_loss: 0.0608 - val_accu
racy: 0.9875
Epoch 56/100
10/10 [==============================] - 0s 12ms/step - loss: 0.0064 - accuracy: 1.0000 - val_loss: 0.0506 - val_accu
racy: 0.9875
Epoch 57/100
10/10 [==============================] - 0s 13ms/step - loss: 0.0068 - accuracy: 1.0000 - val_loss: 0.0717 - val_accu
racy: 0.9875
Epoch 58/100
10/10 [==============================] - 0s 12ms/step - loss: 0.0040 - accuracy: 1.0000 - val_loss: 0.0978 - val_accu
racy: 0.9875
Epoch 59/100
10/10 [==============================] - 0s 11ms/step - loss: 0.0010 - accuracy: 1.0000 - val_loss: 0.0990 - val_accu
racy: 0.9875
Epoch 60/100
10/10 [==============================] - 0s 12ms/step - loss: 0.0019 - accuracy: 1.0000 - val_loss: 0.0960 - val_accu
racy: 0.9875
Epoch 61/100
10/10 [==============================] - 0s 10ms/step - loss: 3.2645e-04 - accuracy: 1.0000 - val_loss: 0.0940 - val_
```

```
accuracy: 0.9875
Epoch 62/100
10/10 [==============================] - 0s 12ms/step - loss: 6.2329e-04 - accuracy: 1.0000 - val_loss: 0.0954 - val_
accuracy: 0.9875
Epoch 63/100
10/10 [==============================] - 0s 12ms/step - loss: 1.7098e-04 - accuracy: 1.0000 - val_loss: 0.0952 - val_
accuracy: 0.9875
Epoch 64/100
10/10 [==============================] - 0s 12ms/step - loss: 6.1069e-04 - accuracy: 1.0000 - val_loss: 0.0903 - val_
accuracy: 0.9875
Epoch 65/100
10/10 [==============================] - 0s 14ms/step - loss: 0.0014 - accuracy: 1.0000 - val_loss: 0.0981 - val_accu
racy: 0.9875
Epoch 66/100
10/10 [==============================] - 0s 12ms/step - loss: 4.4574e-04 - accuracy: 1.0000 - val_loss: 0.0969 - val_
accuracy: 0.9875
Epoch 67/100
10/10 [==============================] - 0s 13ms/step - loss: 4.7941e-04 - accuracy: 1.0000 - val_loss: 0.0946 - val_
accuracy: 0.9875
Epoch 68/100
10/10 [==============================] - 0s 13ms/step - loss: 3.8316e-04 - accuracy: 1.0000 - val_loss: 0.0947 - val_
accuracy: 0.9875
Epoch 69/100
10/10 [==============================] - 0s 13ms/step - loss: 5.2160e-04 - accuracy: 1.0000 - val_loss: 0.1207 - val_
accuracy: 0.9875
Epoch 70/100
10/10 [==============================] - 0s 12ms/step - loss: 6.4375e-04 - accuracy: 1.0000 - val_loss: 0.1245 - val_
accuracy: 0.9875
Epoch 71/100
10/10 [==============================] - 0s 11ms/step - loss: 3.8674e-04 - accuracy: 1.0000 - val_loss: 0.1169 - val_
accuracy: 0.9875
Epoch 72/100
10/10 [==============================] - 0s 11ms/step - loss: 2.3447e-04 - accuracy: 1.0000 - val_loss: 0.1154 - val_
accuracy: 0.9875
Epoch 73/100
10/10 [==============================] - 0s 14ms/step - loss: 1.5527e-04 - accuracy: 1.0000 - val_loss: 0.1176 - val_
accuracy: 0.9875
Epoch 74/100
10/10 [==============================] - 0s 13ms/step - loss: 5.3016e-04 - accuracy: 1.0000 - val_loss: 0.0799 - val_
accuracy: 0.9875
Epoch 75/100
```

```
10/10 [==============================] - 0s 12ms/step - loss: 6.2051e-04 - accuracy: 1.0000 - val_loss: 0.1326 - val_
accuracy: 0.9750
Epoch 76/100
10/10 [==============================] - 0s 13ms/step - loss: 2.1779e-04 - accuracy: 1.0000 - val_loss: 0.1534 - val_
accuracy: 0.9750
Epoch 77/100
10/10 [==============================] - 0s 12ms/step - loss: 0.0017 - accuracy: 1.0000 - val_loss: 0.1483 - val_accu
racy: 0.9750
Epoch 78/100
10/10 [==============================] - 0s 11ms/step - loss: 7.4217e-05 - accuracy: 1.0000 - val_loss: 0.1536 - val_
accuracy: 0.9750
Epoch 79/100
10/10 [==============================] - 0s 11ms/step - loss: 1.2098e-04 - accuracy: 1.0000 - val_loss: 0.1499 - val_
accuracy: 0.9750
Epoch 80/100
10/10 [==============================] - 0s 11ms/step - loss: 1.9948e-04 - accuracy: 1.0000 - val_loss: 0.1482 - val_
accuracy: 0.9750
Epoch 81/100
10/10 [==============================] - 0s 13ms/step - loss: 0.0020 - accuracy: 1.0000 - val_loss: 0.3190 - val_accu
racy: 0.9625
Epoch 82/100
10/10 [==============================] - 0s 11ms/step - loss: 0.0553 - accuracy: 0.9844 - val_loss: 0.2425 - val_accu
racy: 0.9625
Epoch 83/100
10/10 [==============================] - 0s 16ms/step - loss: 0.0380 - accuracy: 0.9812 - val_loss: 0.0528 - val_accu
racy: 0.9875
Epoch 84/100
10/10 [==============================] - 0s 19ms/step - loss: 0.0459 - accuracy: 0.9906 - val_loss: 0.0349 - val_accu
racy: 0.9875
Epoch 85/100
10/10 [==============================] - 0s 20ms/step - loss: 0.0449 - accuracy: 0.9844 - val_loss: 0.2321 - val_accu
racy: 0.9375
Epoch 86/100
10/10 [==============================] - 0s 16ms/step - loss: 0.0638 - accuracy: 0.9656 - val_loss: 0.0881 - val_accu
racy: 0.9875
Epoch 87/100
10/10 [==============================] - 0s 20ms/step - loss: 0.0228 - accuracy: 0.9906 - val_loss: 0.0968 - val_accu
racy: 0.9750
Epoch 88/100
10/10 [==============================] - 0s 16ms/step - loss: 0.0327 - accuracy: 0.9875 - val_loss: 0.0320 - val_accu
racy: 0.9875
```

```
Epoch 89/100
10/10 [==============================] - 0s 16ms/step - loss: 0.0203 - accuracy: 0.9937 - val_loss: 0.0877 - val_accu
racy: 0.9750
Epoch 90/100
10/10 [==============================] - 0s 18ms/step - loss: 0.0130 - accuracy: 0.9969 - val_loss: 0.0553 - val_accu
racy: 0.9875
Epoch 91/100
10/10 [==============================] - 0s 16ms/step - loss: 0.0056 - accuracy: 1.0000 - val_loss: 0.0832 - val_accu
racy: 0.9875
Epoch 92/100
10/10 [==============================] - 0s 16ms/step - loss: 0.0052 - accuracy: 1.0000 - val_loss: 0.0872 - val_accu
racy: 0.9750
Epoch 93/100
10/10 [==============================] - 0s 22ms/step - loss: 0.0113 - accuracy: 0.9937 - val_loss: 0.0980 - val_accu
racy: 0.9750
Epoch 94/100
10/10 [==============================] - 0s 18ms/step - loss: 0.0422 - accuracy: 0.9937 - val_loss: 0.1404 - val_accu
racy: 0.9750
Epoch 95/100
10/10 [==============================] - 0s 19ms/step - loss: 0.0125 - accuracy: 0.9969 - val_loss: 0.1112 - val_accu
racy: 0.9875
Epoch 96/100
10/10 [==============================] - 0s 19ms/step - loss: 0.0301 - accuracy: 0.9969 - val_loss: 0.1181 - val_accu
racy: 0.9625
Epoch 97/100
10/10 [==============================] - 0s 20ms/step - loss: 0.0324 - accuracy: 0.9906 - val_loss: 0.0775 - val_accu
racy: 0.9875
Epoch 98/100
10/10 [==============================] - 0s 16ms/step - loss: 0.0126 - accuracy: 1.0000 - val_loss: 0.1047 - val_accu
racy: 0.9750
Epoch 99/100
10/10 [==============================] - 0s 18ms/step - loss: 0.0010 - accuracy: 1.0000 - val_loss: 0.1443 - val_accu
racy: 0.9625
Epoch 100/100
10/10 [==============================] - 0s 18ms/step - loss: 0.0056 - accuracy: 0.9969 - val_loss: 0.0997 - val_accu
racy: 0.9750
```

Out[20]:

```
<keras.callbacks.History at 0x782f3d4e5e10>
```

In the process of selecting an appropriate model for our project, careful consideration was given to the size and nature of our dataset. With an initial dataset consisting of 500 samples, each with 4097 features, preprocessing efforts have resulted in a more streamlined dataset of 500 samples with only 4 features. This reduction in dimensionality raises concerns about the suitability of certain models, particularly Convolutional Neural Networks (CNNs). CNNs are renowned for their efficacy in handling image data with inherent spatial relationships, often represented as 2D grids. Given the transformed nature of our dataset, which lacks the grid-like structure associated with images, opting for a model tailored to tabular data or simpler structures appears more prudent.

Model Evaluation and Testing

In [21]:
```
# Evaluation Metric

evaluation_df = pd.DataFrame(columns=['Model', 'Accuray', "Precision", 'Recall', 'F1 Score'])

# Predictions on test data
rf_y_pred = best_rf.predict(X_test)

# Efficiency metrics
rf_accuracy = accuracy_score(y_test, rf_y_pred)
rf_precision = precision_score(y_test, rf_y_pred)
rf_recall = recall_score(y_test, rf_y_pred)
rf_f1 = f1_score(y_test, rf_y_pred)
rf_conf_matrix = confusion_matrix(y_test, rf_y_pred)

new_row = {'Model': 'Random Forest', 'Accuray': rf_accuracy, 'Precision' : rf_precision, 'Recall' : rf_recall, 'F1 Sco
re' : rf_f1}
evaluation_df = evaluation_df.append(new_row, ignore_index= True)


# Predictions on test data
xgb_y_pred = best_xgb.predict(X_test)

# Efficiency metrics
xgb_accuracy = accuracy_score(y_test, xgb_y_pred)
xgb_precision = precision_score(y_test, xgb_y_pred)
xgb_recall = recall_score(y_test, xgb_y_pred)
xgb_f1 = f1_score(y_test, xgb_y_pred)
xgb_conf_matrix = confusion_matrix(y_test, xgb_y_pred)

new_row = {'Model': 'XgBoost', 'Accuray': xgb_accuracy, 'Precision' : xgb_precision, 'Recall' : xgb_recall, 'F1 Score'
: xgb_f1}
evaluation_df = evaluation_df.append(new_row, ignore_index= True)


 # Evaluate the final model on test data
rnn_y_pred_probs = rnn_final_model.predict(X_test)
rnn_y_pred = (rnn_y_pred_probs > 0.5).astype(int)

# Efficiency metrics
rnn_accuracy = accuracy_score(y_test, rnn_y_pred)
```

```
rnn_precision = precision_score(y_test, rnn_y_pred)
rnn_recall = recall_score(y_test, rnn_y_pred)
rnn_f1 = f1_score(y_test, rnn_y_pred)
rnn_conf_matrix = confusion_matrix(y_test, rnn_y_pred)

new_row = {'Model': 'RNN', 'Accuray': rnn_accuracy, 'Precision' : rnn_precision, 'Recall' : rnn_recall, 'F1 Score' : r
nn_f1}
evaluation_df = evaluation_df.append(new_row, ignore_index= True)



print("\nEvaluaion Metrics on Test Data \n")
display(evaluation_df)
```

```
4/4 [==============================] - 0s 4ms/step

Evaluaion Metrics on Test Data
```

	Model	Accuray	Precision	Recall	F1 Score
0	Random Forest	0.99	0.952381	1.0	0.975610
1	XgBoost	0.97	0.947368	0.9	0.923077
2	RNN	0.99	0.952381	1.0	0.975610

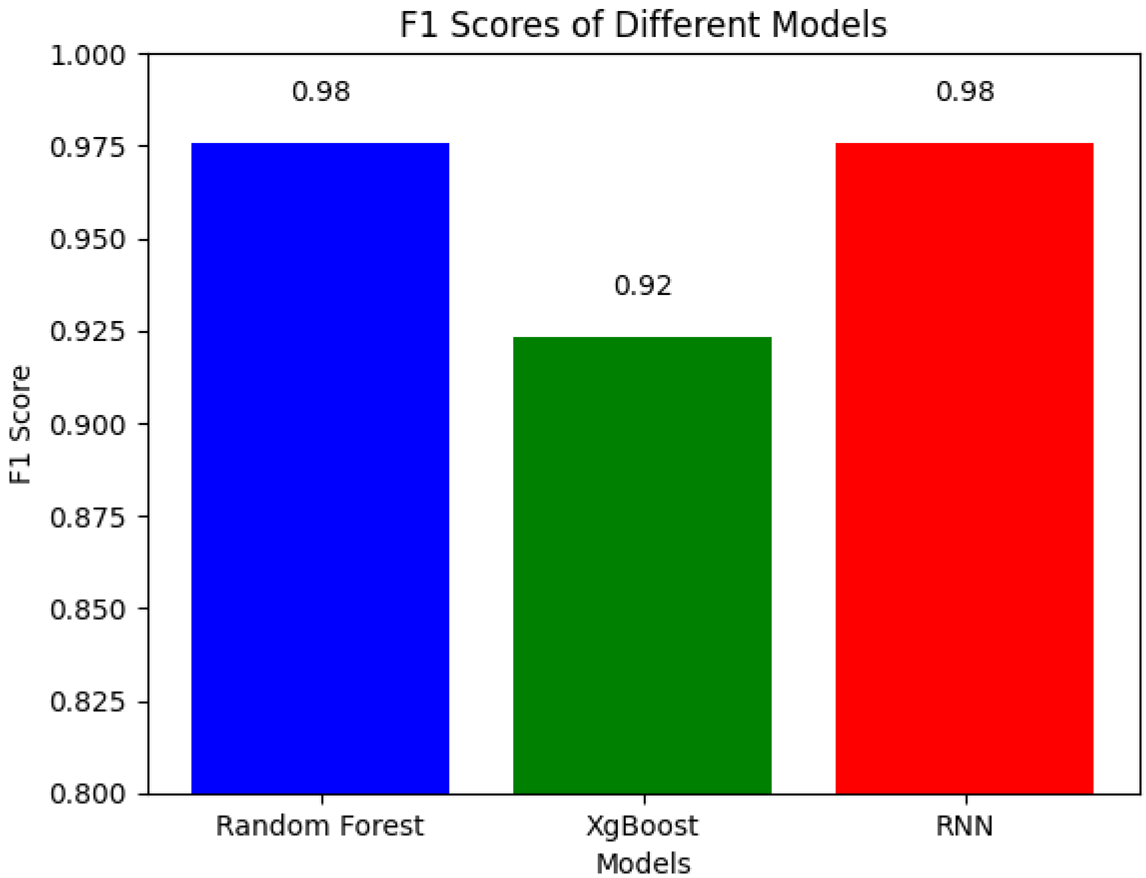
The Random Forest model shows exceptional performance with an accuracy of 99% and a perfect recall of 1.00, indicating its proficiency in identifying all relevant cases. Its F1 score of approximately 0.976 suggests a strong balance between precision and recall. The XgBoost model, with an accuracy of 97% and an F1 score of around 0.923, also performs admirably, balancing precision and recall effectively. Lastly, the RNN model, while matching the 97% accuracy of XgBoost, stands out with a perfect precision of 1.00, though its recall is slightly lower at 0.85, as reflected in its F1 score of approximately 0.919.

Results and Visualization

Visualize the EEG data and model predictions. Create plots and graphs to illustrate your findings.

Visualizing the F1 Score

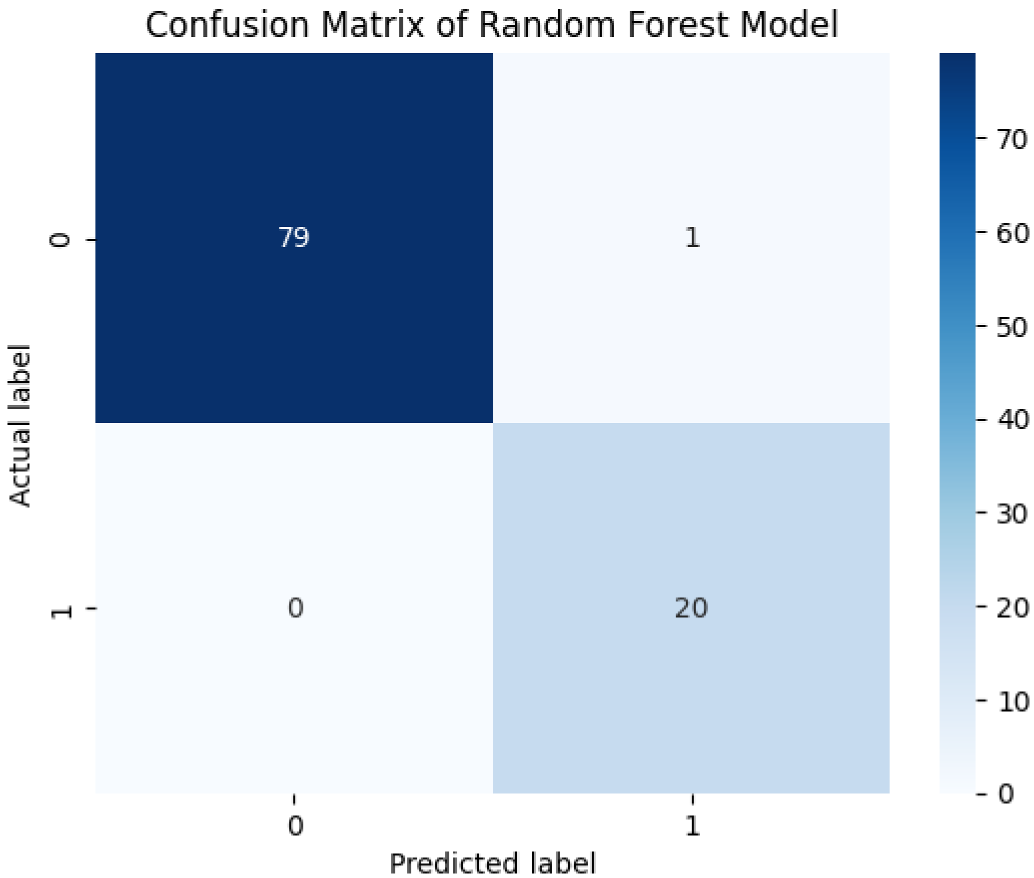
In [22]:
```
# F1 scores for each model
models = ['Random Forest', 'XgBoost', 'RNN']
scores = [rf_f1, xgb_f1, rnn_f1]

# Creating the bar chart
plt.bar(models, scores, color=['blue', 'green', 'red'])

# Annotating the F2 scores on the bars
for i, score in enumerate(scores):
    plt.text(i, score + 0.01, f'{score:.2f}', ha='center', va='bottom')

# Adjusting the y-axis limits
plt.ylim(0.8, 1)

# Adding title and labels
plt.title('F1 Scores of Different Models')
plt.xlabel('Models')
plt.ylabel('F1 Score')

# Display the chart
plt.show()
```

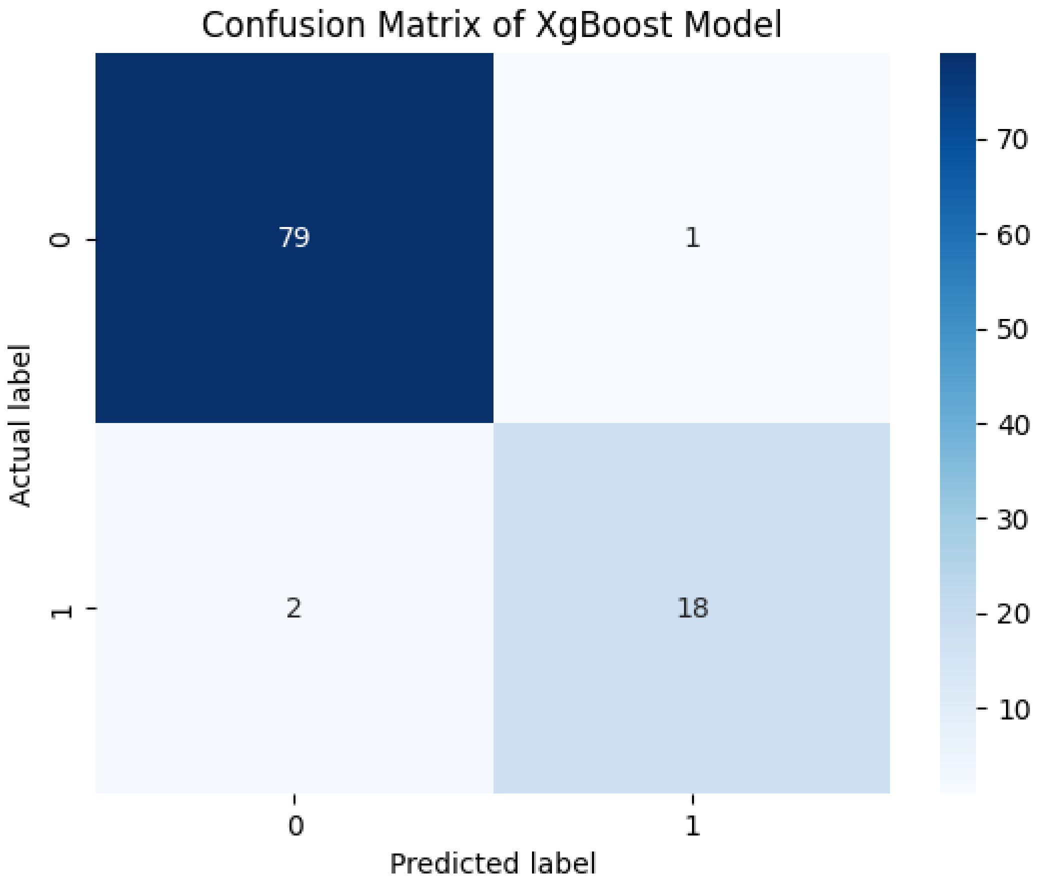


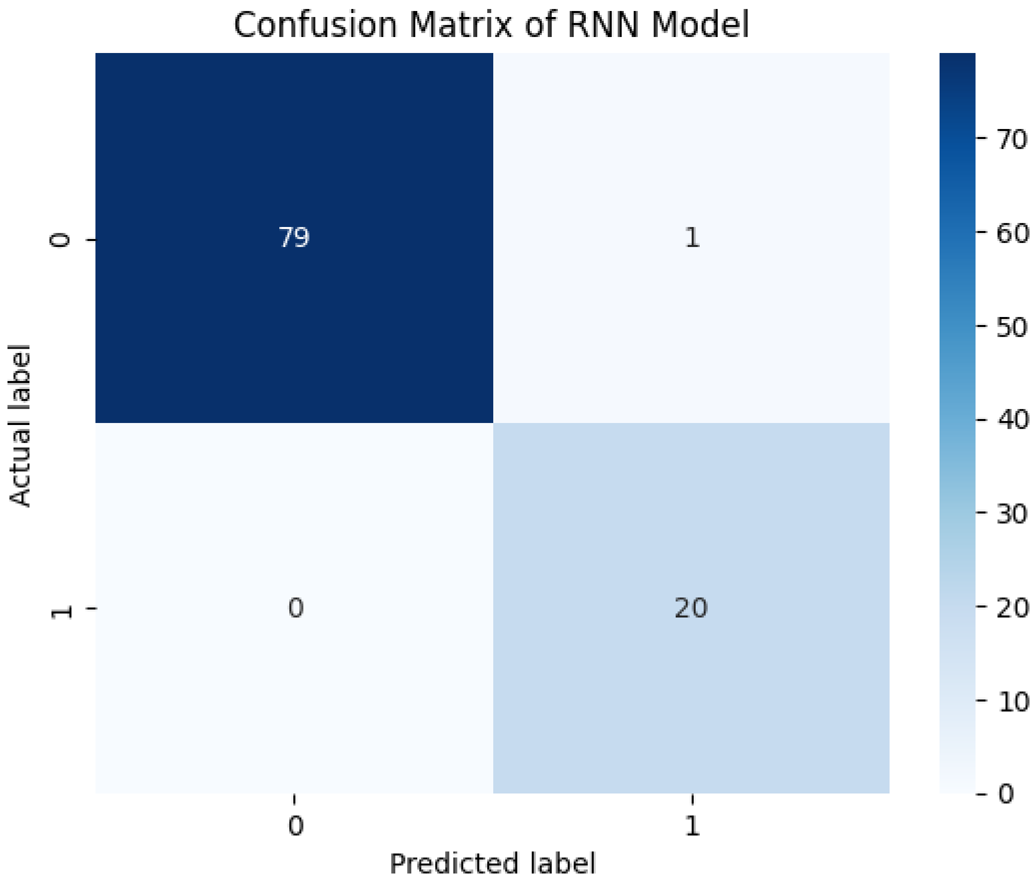
Random Forest and RNN have high scores around 0.98, while XgBoost has a slightly lower score of 0.92. The accompanying text indicates strong performance in precision-recall trade-off for the Random Forest and XgBoost models, with RNN slightly behind. With Random Forest and RNN outperforming XgBoost, all scoring above 0.90, indicating a high level of precision and recall in their performance.

Visualizing the confusion matrix of different models

In [23]:
```
# Creating the heatmap
sns.heatmap(rf_conf_matrix, annot=True, fmt='d', cmap='Blues',
            xticklabels=['0', '1'],
            yticklabels=['0', '1'])

# Adding title and labels
plt.title('Confusion Matrix of Random Forest Model')
plt.ylabel('Actual label')
plt.xlabel('Predicted label')

# Display the heatmap
plt.show()

# Creating the heatmap
sns.heatmap(xgb_conf_matrix, annot=True, fmt='d', cmap='Blues',
            xticklabels=['0', '1'],
            yticklabels=['0', '1'])

# Adding title and labels
plt.title('Confusion Matrix of XgBoost Model')
plt.ylabel('Actual label')
plt.xlabel('Predicted label')

# Display the heatmap
plt.show()

# Creating the heatmap
sns.heatmap(rnn_conf_matrix, annot=True, fmt='d', cmap='Blues',
            xticklabels=['0', '1'],
            yticklabels=['0', '1'])

# Adding title and labels
plt.title('Confusion Matrix of RNN Model')
plt.ylabel('Actual label')
plt.xlabel('Predicted label')

# Display the heatmap
plt.show()
```

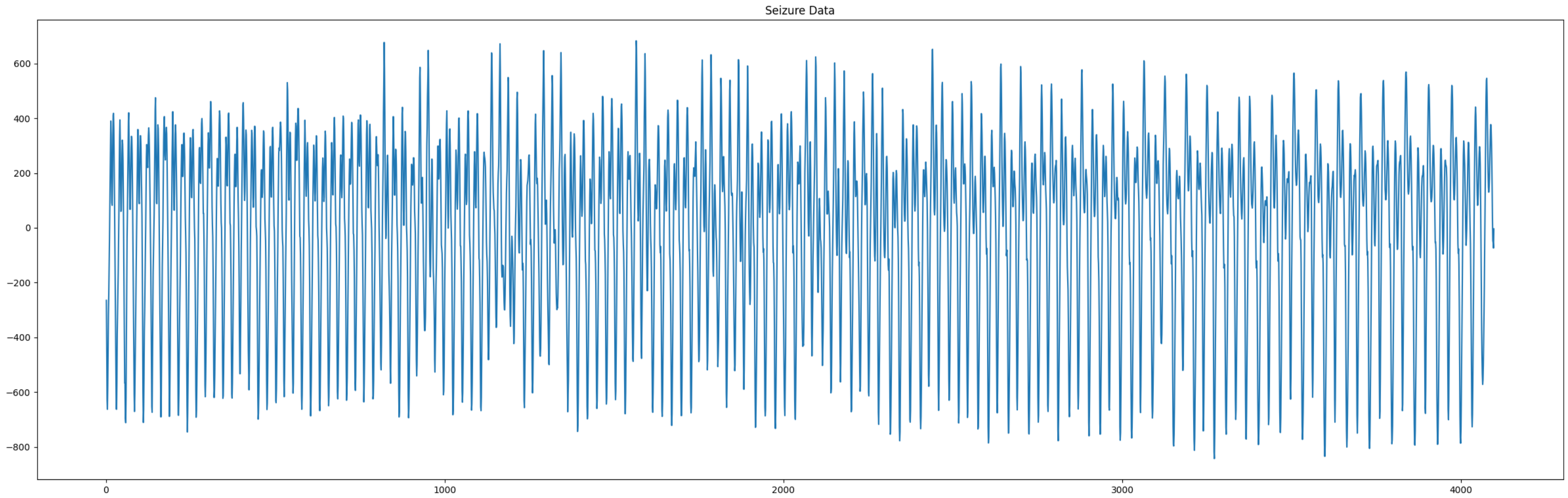

Confusion Matrix of Random Forest Model
Actual label
Predicted label
0
1
0
1
79
1
0
20
70
60
50
40
30
20
10
0

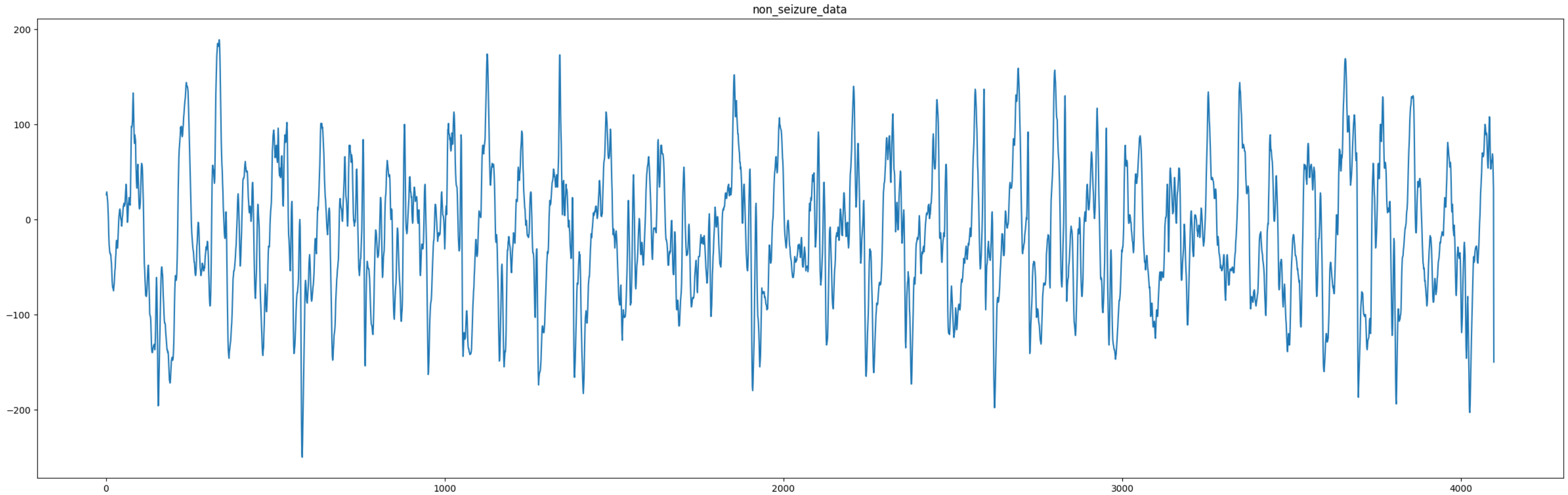

Confusion Matrix of XgBoost Model
79
1
2
18
Actual label
Predicted label
0
1
0
1
70
60
50
40
30
20
10



Random Forest, XgBoost, and RNN, as part of a binary classification task. All three models show a significant number of true positives (79) and true negatives (20 for Random Forest and RNN, 18 for XgBoost), with very few false negatives and false positives, indicating high performance. The Random Forest and RNN models have no false negatives, while the XgBoost model has two. These results suggest that the Random Forest and RNN models are slightly better at correctly classifying both positive and negative classes than XgBoost in this particular task. These matrices underscore the models' robustness in correctly classifying the majority of the test data.

In [24]:
```
#visualising EEG data
seizure_data = df[df['label'] == 1].iloc[0,4:-1].tolist()
non_seizure_data = df[df['label'] == 0].iloc[0,4:-1].tolist()

plt.figure(figsize= (30,20))

plt.subplot(2,1,1)

x = [i for i in range(1,4098)]
y = seizure_data

plt.title(f'Seizure Data')
plt.plot(x, y )

plt.subplot(2,1,2)

x = [i for i in range(1,4098)]
y = non_seizure_data

plt.title(f'non_seizure_data')
plt.plot(x, y )

plt.show()
```


Seizure Data
600
400
200
0
−200
−400
−600
−800
0
1000
2000
3000
4000


non_seizure_data
200
100
0
−100
−200
0
1000
2000
3000
4000

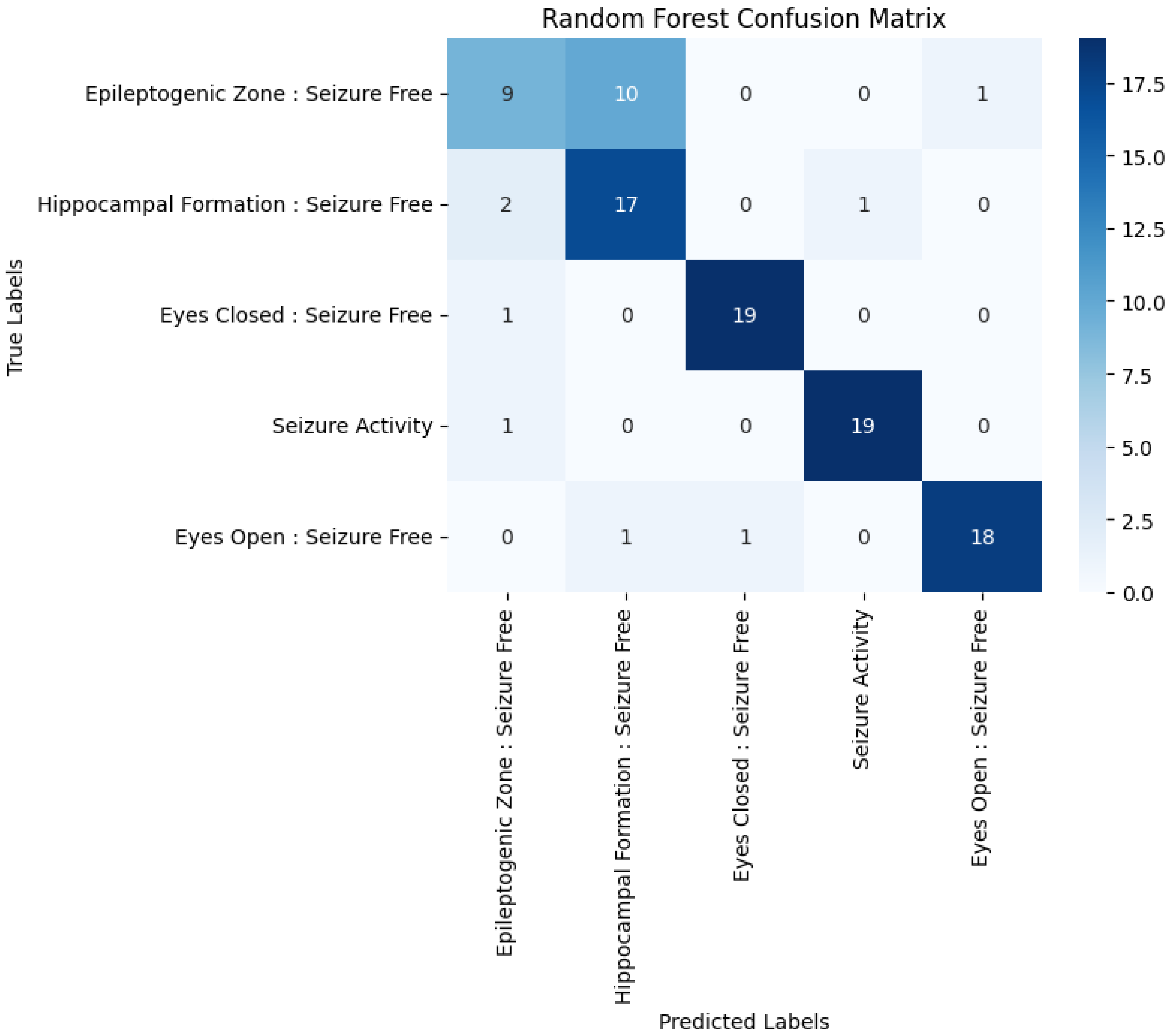
Multi Class Classification

- As random forest has performed best in the binary classification of Seizure or non seizure data.
- Random forest has been used for multi class clasification to classify data to multi classes bases on the EEG data

In [26]:
```
# Assuming feature_df is your DataFrame with features
# 'file_name' column is dropped as it's not used for training
X = feature_df[['mean', 'variance', 'rms', 'std_dev','Peak_Frequency', 'Delta_Power','Theta_Power','Alpha_Power', 'Bet
a_Power', 'Gamma_Power']].values
y = df['file_code'].values

# Standardize the data
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=40, stratify=y)

#Random Forest
# Define the parameter grid
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [3, 5, 7],
    'min_samples_split': [2, 4, 6],
    'min_samples_leaf': [1, 2, 3]
}

# Create a RandomForest model
rf = RandomForestClassifier(random_state=42)

# Set up GridSearchCV
grid_search = GridSearchCV(estimator=rf, param_grid=param_grid, cv=5, n_jobs=-1, scoring='accuracy')

# Perform grid search
grid_search.fit(X_train, y_train)

# Best parameters and best score
print(f"Best parameters: {grid_search.best_params_}")
print(f"Best score: {grid_search.best_score_}")

# Use the best estimator for making predictions
best_rf = grid_search.best_estimator_

# Predictions on test data
rf_y_pred = best_rf.predict(X_test)
```

```python
# Efficiency metrics
rf_accuracy = accuracy_score(y_test, rf_y_pred)
rf_precision = precision_score(y_test, rf_y_pred, average='weighted')
rf_recall = recall_score(y_test, rf_y_pred, average='weighted')
rf_f1 = f1_score(y_test, rf_y_pred, average='weighted')
rf_conf_matrix = confusion_matrix(y_test, rf_y_pred)

print(f'Accuracy: {rf_accuracy:.4f}')
print(f'Precision: {rf_precision:.4f}')
print(f'Recall: {rf_recall:.4f}')
print(f'F1 Score: {rf_f1:.4f}')

# Define class labels
class_labels = ['Epileptogenic Zone : Seizure Free', 'Hippocampal Formation : Seizure Free', 'Eyes Closed : Seizure Fr
ee', 'Seizure Activity', 'Eyes Open : Seizure Free']

# Plot the confusion matrix using Seaborn heatmap
sns.heatmap(rf_conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=class_labels, yticklabels=class_labels)
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.title('Random Forest Confusion Matrix')
plt.show()
```

```
Best parameters: {'max_depth': 7, 'min_samples_leaf': 1, 'min_samples_split': 4, 'n_estimators': 100}
Best score: 0.8275
Accuracy: 0.8200
Precision: 0.8294
Recall: 0.8200
F1 Score: 0.8154
```


Random Forest Confusion Matrix
True Labels
Epileptogenic Zone : Seizure Free
Hippocampal Formation : Seizure Free
Eyes Closed : Seizure Free
Seizure Activity
Eyes Open : Seizure Free
9 10 0 0 1
2 17 0 1 0
1 0 19 0 0
1 0 0 19 0
0 1 1 0 18
Predicted Labels
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0

The Random Forest model, used for multi-class classification of EEG data, leveraged features like mean and power bands. After standardizing the data, the model was fine-tuned using GridSearchCV. This resulted in an accurate classifier capable of differentiating between various brain activity states. The effectiveness of the model was demonstrated through a confusion matrix.

In [ ]:

```

```