```
import os
import pandas as pd
dataset path = "C:/Users/prabh/Desktop/PJ3"
# Initialize empty lists to store data and labels
data = []
labels = []
# Iterate through each folder (Z, O, N, F, S)
for folder_name in ["Z", "0", "N", "F", "S"]:
    folder path = os.path.join(dataset_path, folder_name)
    # Iterate through each file in the folder
    for file name in os.listdir(folder path):
        file path = os.path.join(folder path, file name)
        # Read EEG data from the text file
        with open(file path, 'r') as file:
            eeg data = file.read().splitlines()
        # Append the EEG data to the 'data' list
        data.append(eeg_data)
        # Append the label (folder name) to the 'labels' list
        labels.append(folder name)
# Create a DataFrame from the lists
df = pd.DataFrame({'Data': data, 'Label': labels})
# Display the DataFrame
print(df.head())
                                                Data Label
   [12, 22, 35, 45, 69, 74, 79, 78, 66, 43, 33, 3...
                                                         Z
  [-56, -50, -64, -91, -135, -140, -134, -114, -...
                                                         Z
  [-37, -22, -17, -24, -31, -20, -5, 14, 31, 31,...
                                                         Z
  [-31, -43, -39, -39, -9, -5, 18, 7, -12, -42, ...
                                                         Z
4 [14, 26, 32, 25, 16, 8, 8, 12, 11, 19, 23, 24,...
import os
import pandas as pd
import numpy as np
from sklearn.model selection import train test split
from sklearn.preprocessing import StandardScaler, LabelEncoder
from tensorflow.keras.preprocessing.sequence import pad sequences
# Convert labels to numerical values using LabelEncoder
le = LabelEncoder()
df['Label'] = le.fit transform(df['Label'])
```

```
# Pad sequences to ensure uniform length
max_sequence_length = max(len(seq) for seq in df['Data'])
padded_sequences = pad_sequences(df['Data'],
maxlen=max_sequence_length, padding='post', dtype='float32')
# Standardize the data using StandardScaler
scaler = StandardScaler()
scaled_data =
scaler.fit_transform(np.array(padded_sequences).reshape(-1,
max_sequence_length))
```

Data Splitting

```
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(scaled_data,
df['Label'], test_size=0.2, random_state=42)

# Display the processed data
print("Processed EEG Data:")
print("X_train shape:", X_train.shape)
print("X_test shape:", X_test.shape)
print("y_train shape:", y_train.shape)
print("y_test shape:", y_test.shape)

Processed EEG Data:
X_train shape: (400, 4097)
X_test shape: (100, 4097)
y_train shape: (400,)
y_test shape: (100,)
```

Model Training:

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv1D, MaxPooling1D, Flatten,
Dense
from tensorflow.keras.preprocessing.sequence import pad_sequences

# Build a simple CNN model
model = Sequential()
model.add(Conv1D(filters=32, kernel_size=3, activation='relu',
input_shape=(max_sequence_length, 1)))
model.add(MaxPooling1D(pool_size=2))
model.add(Flatten())
model.add(Dense(64, activation='relu'))
model.add(Dense(5, activation='softmax')) # Adjust the output layer
based on the number of classes
```

```
# Compile the model
model.compile(optimizer='adam',
loss='sparse categorical crossentropy', metrics=['accuracy'])
# Train the model
model.fit(X_train, y_train, epochs=10, batch_size=32,
validation data=(X test, y test))
Epoch 1/10
- accuracy: 0.2725 - val_loss: 1.3086 - val_accuracy: 0.4500
Epoch 2/10
accuracy: 0.5000 - val loss: 1.2580 - val accuracy: 0.3700
Epoch 3/10
accuracy: 0.6800 - val loss: 1.1875 - val accuracy: 0.5600
Epoch 4/10
accuracy: 0.7500 - val loss: 1.0161 - val accuracy: 0.5800
Epoch 5/10
accuracy: 0.8325 - val loss: 0.9398 - val accuracy: 0.6000
Epoch 6/10
accuracy: 0.9200 - val_loss: 0.8382 - val_accuracy: 0.7000
Epoch 7/10
accuracy: 0.9700 - val_loss: 0.7908 - val_accuracy: 0.6600
Epoch 8/10
accuracy: 0.9750 - val loss: 0.7690 - val_accuracy: 0.7000
Epoch 9/10
accuracy: 0.9875 - val loss: 0.6732 - val accuracy: 0.7200
Epoch 10/10
accuracy: 1.0000 - val_loss: 0.8008 - val_accuracy: 0.7100
<keras.src.callbacks.History at 0x1ff4b5d20d0>
```

Model Evaluation:

Testing:

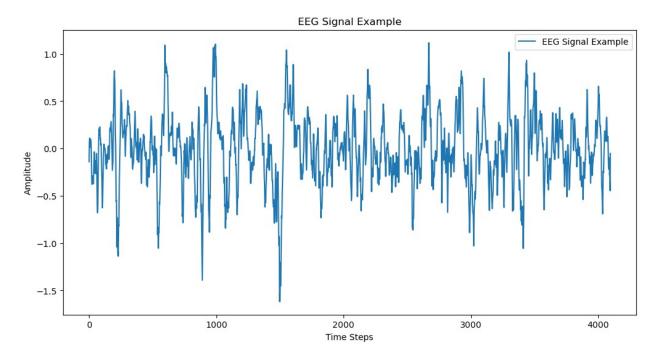
```
# Assuming the model is already trained
# Make predictions on the test set
predictions = model.predict(X test)
# Convert predictions to class labels
predicted labels = np.argmax(predictions, axis=1)
# Display the predicted labels and true labels
df results = pd.DataFrame({'True Labels': y test, 'Predicted Labels':
predicted labels})
print(df results.head())
4/4 [=======] - 0s 15ms/step
    True Labels Predicted Labels
361
              0
                                0
73
              4
                                4
374
              0
                                0
              2
                                2
155
              2
                                2
104
```

Results and Visualization:

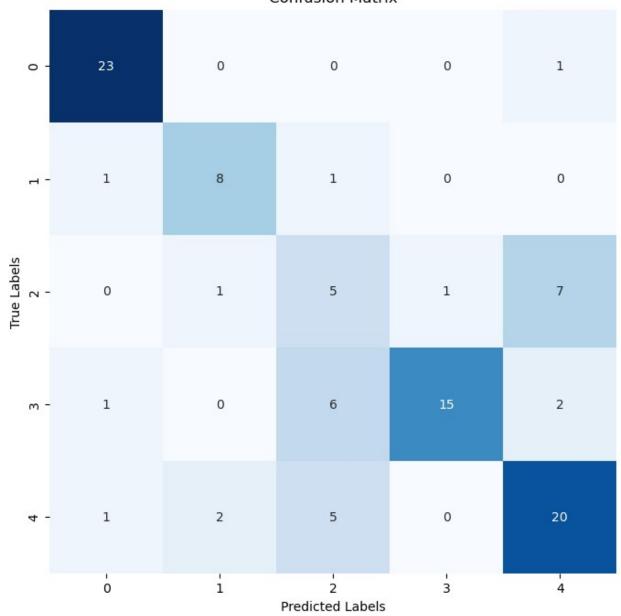
```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion matrix
from sklearn.metrics import classification report
# Visualize EEG data
plt.figure(figsize=(12, 6))
plt.plot(X test[0].flatten(), label='EEG Signal Example')
plt.title('EEG Signal Example')
plt.xlabel('Time Steps')
plt.ylabel('Amplitude')
plt.legend()
plt.show()
# Visualize confusion matrix
cm = confusion matrix(y test, predicted labels)
plt.figure(figsize=(8, 8))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", cbar=False)
plt.title('Confusion Matrix')
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.show()
# Visualize classification report
print("Classification Report:")
```

```
print(classification_report(y_test, predicted_labels))

# Visualize model predictions vs. true labels
plt.figure(figsize=(12, 6))
plt.scatter(range(len(y_test)), y_test, label='True Labels',
alpha=0.5)
plt.scatter(range(len(predicted_labels)), predicted_labels,
label='Predicted Labels', alpha=0.5)
plt.title('True vs. Predicted Labels')
plt.xlabel('Sample Index')
plt.ylabel('Class Labels')
plt.legend()
plt.show()
```



Confusion Matrix



Classificatio	n Report:				
	precision	recall	f1-score	support	
0	0.00	0.06	0 02	2.4	
0 1	0.88 0.73	0.96 0.80	0.92 0.76	24 10	
2	0.73	0.36	0.70	14	
3	0.94	0.62	0.75	24	
4	0.67	0.71	0.69	28	
accuracy	0.70	0.60	0.71	100	
macro avg	0.70	0.69	0.69	100	

weighted avg 0.74 0.71 0.72 100

