EEG Signal Classification for Motor and Imagined Movements Using EEGNet Architecture

Colab

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Abstract

Accurate classification of EEG signals for motor and imagined movements is essential for the development of brain-computer interfaces (BCIs) that benefit impaired individuals and enhance functionalities for healthy users. This study explores various classification methods to improve the accuracy and interpretability of EEG signals. Utilizing a dataset of over 1500 EEG recordings from 109 volunteers, subjects performed a series of motor and imagery tasks while their EEGs were recorded using a 64-channel setup and sampled at 160 Hz[7]. The data underwent preprocessing, including filtering and epoch segmentation, to prepare it for analysis. The core of our model is the EEGNet architecture, designed to capture spatial and temporal features through convolutional layers, depthwise separable convolutions, and robust regularization techniques[8][9]. The model is trained using StratifiedKFold cross-validation, with performance metrics such as accuracy, sensitivity, specificity, PPV, and NPV being evaluated.

Our results indicate a varying performance across different folds, with significant challenges in accurately classifying the "Both fists" and "Rest" classes. The model achieves high overall accuracy but demonstrates a need for further refinement to consistently distinguish between similar classes. This study highlights the potential of the EEGNet architecture in EEG signal classification while also identifying areas for improvement, such as enhancing the model's ability to differentiate between motor and imagined tasks. Future work could involve separating and independently analyzing motor and imagined tasks to provide deeper insights into their classification challenges and comparing the classification performance across motor, imagined, and combined tasks.

INTRODUCTION

The accurate identification of EEG signals, especially for motor and imagined movements, is essential for advancing brain-computer interfaces (BCIs) that can aid impaired individuals and offer new functionalities for healthy users. Several studies have explored different methods to classify EEG signals with a focus on improving accuracy and interpretability.

Velasco et al. (2023) proposed a multivariate time series approach to enhance the classification accuracy of motor imagery EEG signals, achieving high accuracy with reduced variables, which is essential for avoiding overfitting and improving interpretability[1]. Batistic et al. (2023) explored different classifiers for motor imagery, highlighting the superior performance of a ResNet-based CNN, especially with vibrotactile guidance, suggesting improvements in preprocessing and classifier selection for better accuracy[2]. Alizadeh et al. (2023) utilized a deep CNN to classify motor imagery tasks, showing that 2D wavelet-transformed images and CNN architectures like AlexNet and LeNet provide high classification accuracy, emphasizing the potential of image-based EEG classification approaches[3]. Duan (2023) demonstrated that real and imagined knee movements can be classified with high accuracy using a modified LeNet-5 CNN, suggesting that combining motor imagery and movement execution data could enhance BCI applications[4]. Pham et al. (2023) compared tEEG and conventional EEG, finding that tEEG provides better spatial resolution and signal-to-noise ratio, and when used with CNNs, offers high classification accuracy for finger movements[5].

METHOD

Dataset

The dataset used in this project comprises over 1500 EEG recordings from 109 volunteers, collected using the BCI2000 system[7]. The experimental protocol involved subjects performing various motor and imagery tasks while 64-channel EEGs were recorded. Each subject completed 14 runs:

- Two one-minute baseline runs (eyes open and eyes closed).
- Three two-minute runs of four different tasks:
  - **Task 1**: Open and close left or right fist.
  - **Task 2**: Imagine opening and closing left or right fist.
  - **Task 3**: Open and close both fists or both feet.
  - **Task 4**: Imagine opening and closing both fists or both feet.

The EEG signals were sampled at 160 Hz. Annotations indicate **rest (T0)**, cue for motion or imagined motion (**T1 for left fist or both fists**, **T2 for right fist or both feet**)[6].

The data is in EDF+ format, with annotations. The EEGs were recorded from 64 electrodes following the international 10-10 system, excluding specific electrodes.[7]

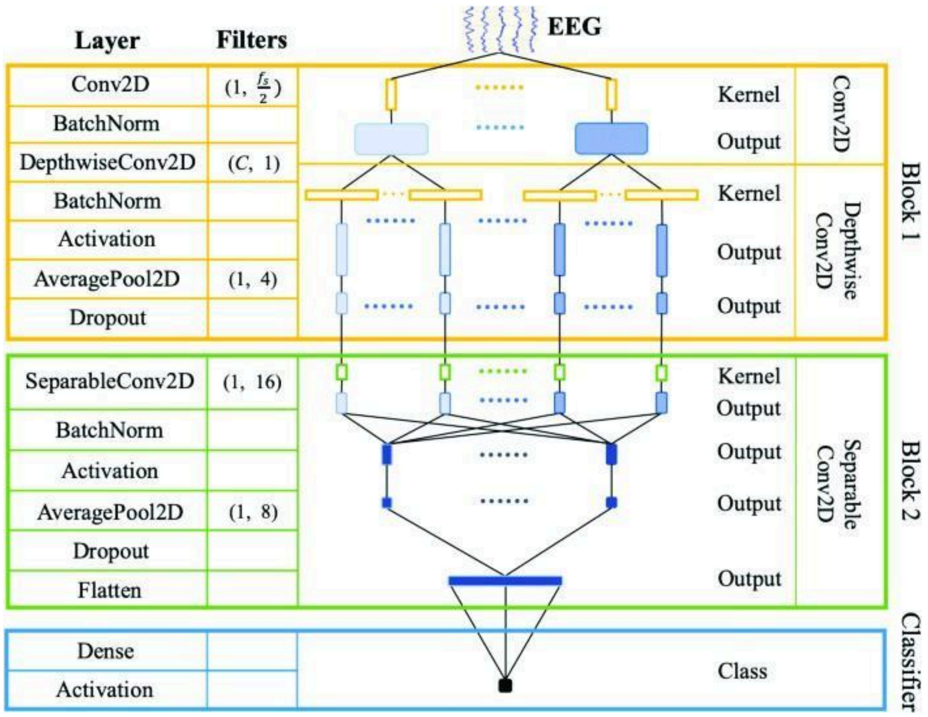
Data Preprocessing

The data processing involves reading EEG data from EDF files, filtering, and segmenting it into epochs. The key steps include:

- **Directory Setup**: The code expects a specific directory structure with EDF files organized by subject and run.
- **Reading and Filtering**: For each EDF file, the mne library is used to read the data, apply a notch filter at 60 Hz to remove powerline noise, and a high-pass filter at 2 Hz.
- **Epoch Creation**:
  - For baseline data (baseline_open, baseline_closed), fixed-length epochs of 60 seconds are created.
  - For task data (task_1 to task_4), epochs are created based on annotations within the EDF file. These epochs are 4.1 seconds long, matching the duration of the tasks.
- **Labeling**: Labels are assigned to each epoch based on the task type and event annotations.
- **Padding/Trimming**: Data is padded or trimmed to ensure all epochs have the same length.
- **Saving Data**: Processed data is saved as .pkl files for later use in model training.

Model

The neural network architecture illustrated in Figure 1 is EEGNet, designed specifically for processing EEG (Electroencephalography) signals. EEGNet is widely used in brain-computer interface applications due to its efficiency and effectiveness in handling EEG data.[9] The architecture comprises three main blocks: initial convolutional layers, depthwise separable convolutional layers, and a final classification layer. [8]



Layer	Filters
Conv2D	$(1, \frac{f_s}{2})$
BatchNorm	
DepthwiseConv2D	$(C, 1)$
BatchNorm	
Activation	
AveragePool2D	(1, 4)
Dropout	
SeparableConv2D	(1, 16)
BatchNorm	
Activation	
AveragePool2D	(1, 8)
Dropout	
Flatten	
Dense	
Activation	

Figure 1 – EEGNet

Block 1: Initial Convolutional and Depthwise Convolutional Layers

The first block aims to capture essential spatial and temporal features from the EEG data.

1. **Conv2D Layer**:
   - The initial layer applies a two-dimensional convolution to the input EEG data, utilizing 1 output channels, 2 input channel and f_s

     where f_s denotes the sampling frequency of the EEG signals.
2. **Batch Normalization**:
   - Following the Conv2D layer, batch normalization is applied to stabilize and accelerate the training process by normalizing the activations.
3. **DepthwiseConv2D Layer**:
   - This layer performs depthwise convolution with C filters, where C corresponds to the number of EEG channels. This operation processes each channel independently, preserving spatial information.
4. **Batch Normalization**:

- Another batch normalization layer is used to normalize the activations post-depthwise convolution.

5. **Activation Function**:
   - An activation function, such as ReLU, is applied to introduce non- linearity, enabling the network to learn more complex patterns.
6. **Average Pooling (AveragePool2D)**:
   - Average pooling with a filter size of 1×4 reduces the spatial dimensions by averaging over non-overlapping 4x4 blocks.
7. **Dropout**:
   - Dropout regularization is implemented to prevent overfitting by randomly setting a fraction of the input units to zero during training.

Block 2: Depthwise Separable Convolutional Layers

The second block is designed to further process the features extracted by the initial block in a parameter-efficient manner.

1. **SeparableConv2D Layer**:
   - This layer employs depthwise separable convolutions with 16 filters, decomposing the convolution operation into a depthwise spatial convolution followed by a pointwise convolution, significantly reducing the computational complexity.
2. **Batch Normalization**:
   - Batch normalization is again utilized to normalize the activations from the SeparableConv2D layer.
3. **Activation Function**:
   - An activation function is applied to introduce additional non-linearity.
4. **Average Pooling (AveragePool2D)**:
   - Average pooling with a filter size of 1×8 is used to further downsample the spatial dimensions.
5. **Dropout**:
   - Dropout regularization is included to mitigate overfitting.
6. **Flatten Layer**:

    - This layer flattens the multi-dimensional feature maps into a one-dimensional vector, making it suitable for subsequent fully connected layers.

Classifier

The final component of the architecture is the classifier, which consists of:

1. **Dense Layer**:
    - A fully connected dense layer that consolidates the features from the previous layers to make a prediction.
2. **Activation Function**:
    - The final activation function, typically softmax, is applied to convert the network outputs into class probabilities.

This architecture effectively balances complexity and computational efficiency, making it well-suited for processing and analyzing EEG data. By leveraging initial convolutional layers to capture spatial-temporal features, depthwise separable convolutions for efficient feature extraction, and robust regularization techniques, it achieves a high degree of performance in EEG signal classification tasks.

Model Training

Cross-Validation Approach

The model is trained using **StratifiedKFold cross-validation** to ensure each fold has a similar class distribution, reducing the risk of overfitting and providing a robust assessment of the model's performance. Specifically, the dataset is split into **5 folds**:

Model Implementation

The implementation of **EEGNet v4** model is from braindecode.

Training Process

The training process involves initializing the model weights using **Glorot uniform initialization** and biases set to zero. For each fold in the cross-validation, the model is trained for **400 epochs** using the **Adam optimizer** and **cross-entropy loss** with a **learning rate of 0.005** and **batch size of 2048**. After training each fold, the model's performance is evaluated on the validation set, and metrics such as **accuracy**, **sensitivity**, **specificity**, **PPV**, and **NPV** are calculated using **confusion matrices**. The trained models for each fold are saved to disk for later use and comparison. Finally, the models are evaluated on a separate test set to assess their generalization performance.

1. **Initialize Model**:
    - Use **Glorot uniform initialization** for weights.
    - Set biases to zero.
    - EEGNet v4
        - Number of channels: **64**
        - Number of output classes: **5**
        - Kernel length: **32**
2. **Training Configuration**:
    - Optimizer: **Adam**
    - Loss Function: **Cross-entropy loss**
    - Learning Rate: **0.005**
    - Batch Size: **2048**
    - Epochs: **400**
3. **Cross-Validation**:
    - **Stratified K-Fold Cross-Validation** to ensure each fold has the same proportion of each class.
    - Number of Folds: **5**
4. **Performance Metrics**:
    - **Accuracy**
    - **Sensitivity**
    - **Specificity**
    - **PPV** (Positive Predictive Value)
    - **NPV** (Negative Predictive Value)
    - **Confusion Matrices**
5. **Save Models**:
    - Save the trained models for each fold to disk
6. **Evaluate on Test Set**:
    - Assess the generalization performance of the models on a separate test set.

Testing

After training with cross-validation, the models are evaluated on a separate test set comprising subjects after S095. The same metrics (accuracy, confusion matrix, sensitivity, specificity, PPV, and NPV) are calculated to assess the model's generalization performance.

This approach ensures a comprehensive evaluation of the EEGNet v4 model across different data splits, highlighting areas for improvement and providing a reliable measure of its classification capabilities.

RESULTS

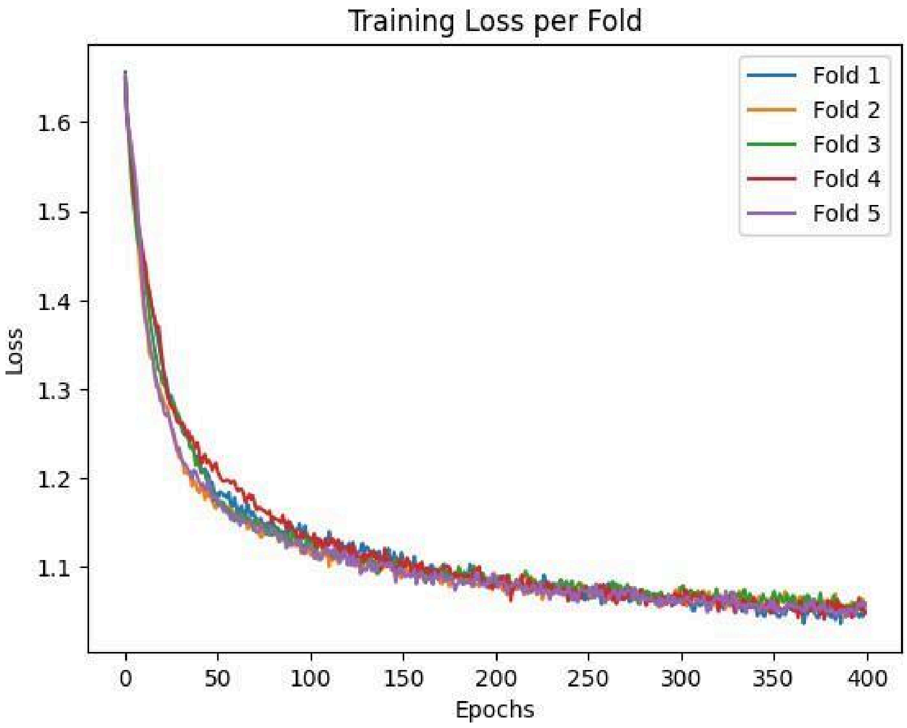


Figure 2 – Loss per Fold

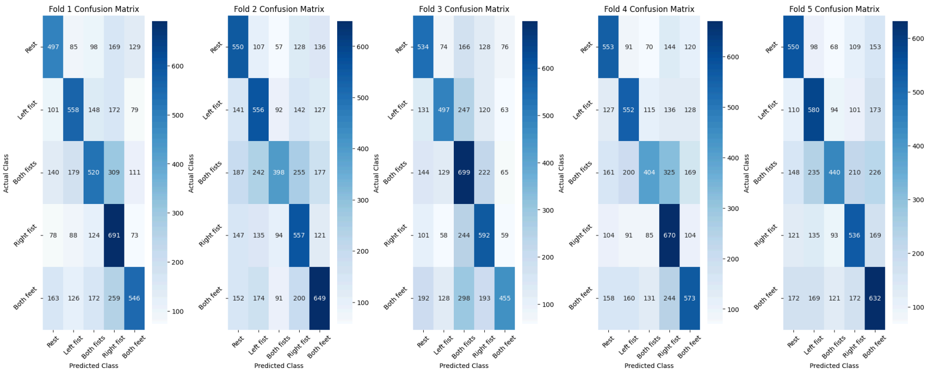


Figure 3 – Confusion Matrix for each fold

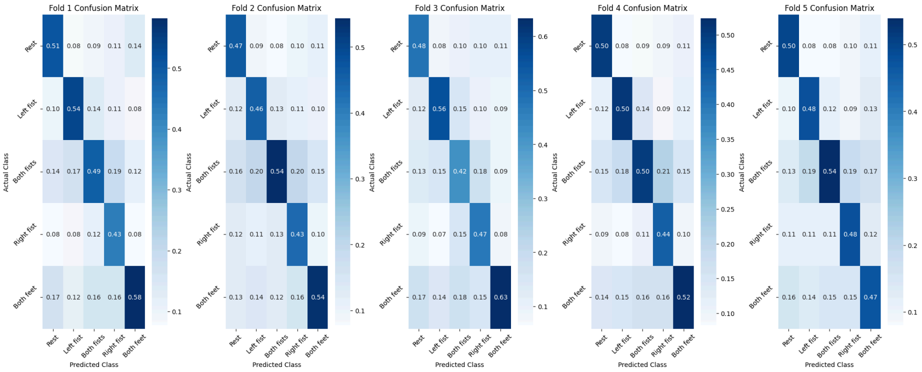


Figure 4 – Predicted(Column) Normalized Confusion Matrix for each fold

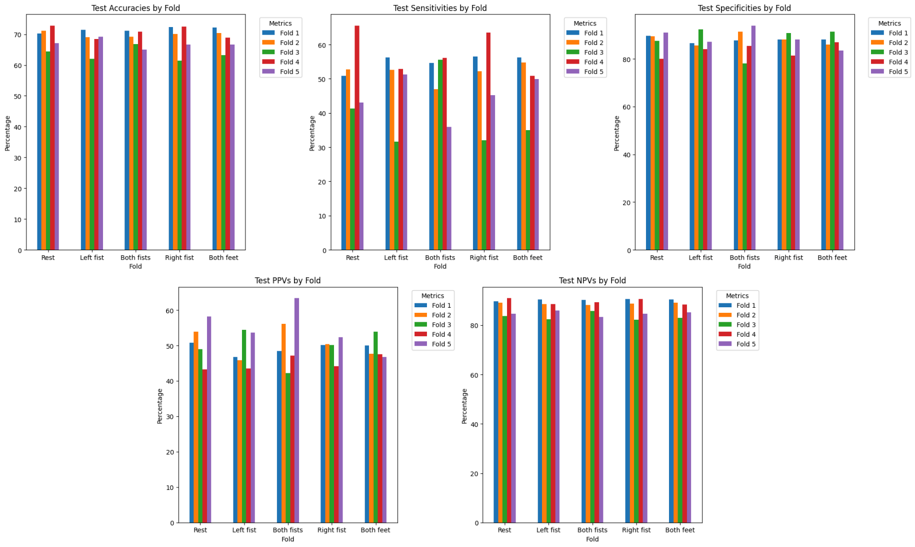


Figure 5 – Bar Charts for various metrics

DISCUSSION

Fold 1

- A significant number of "Rest" instances are misclassified as "Right fist," indicating a challenge in distinguishing these two classes.
- Many instances of "Both fists" are misclassified into other categories, suggesting difficulty in accurately identifying this class.
- The model struggles particularly with distinguishing "Both fists" from other classes.

Fold 2

- The "Rest" class has a notable number of misclassifications into other classes, indicating less clarity in identifying resting state signals.
- The "Both fists" and "Both feet" classes show significant misclassifications, which affects the model's overall accuracy and precision for these classes.
- There is a need for improvement in accurately classifying the "Both fists" and "Both feet" classes.

Fold 3

- The model shows a high rate of misclassification for the "Both fists" class, significantly affecting performance.
- The "Rest" class is frequently misclassified as other classes, showing the model's difficulty in identifying resting state signals.
- This fold demonstrates significant challenges in distinguishing between "Rest" and other movements, with "Both fists" being particularly problematic.

Fold 4

- There is a notable confusion between the "Rest" and "Left fist" classes, which affects accuracy.
- The "Both fists" class continues to be problematic with many misclassifications.
- Similar issues as other folds with additional confusion between "Rest" and "Left fist" classes.

Fold 5

- Compared to other folds, fold 5 shows lower misclassification rates, indicating better performance.

- Despite better overall performance, there is still some confusion between the "Rest" and "Both feet" classes.

- Fold 5 performs comparatively better but still faces challenges in distinguishing certain classes.

Common challenges observed:

- Frequent misclassifications suggest that the model struggles to identify the resting state accurately.

- High misclassification rates for the "Both fists" class are observed across most folds.

- The model shows variability in performance across folds, indicating a need for more robust training and validation processes.

One potential avenue for future work is to separate the motor and imagined tasks and analyze their performance independently. This can provide insights into the specific challenges and differences in classifying motor and imagined movements. Another interesting direction for future work is to compare the results of classifying motor, imagined, and combined motor and imagined tasks. This can help identify any differences in performance and provide a better understanding of the capabilities and limitations of the model in different scenarios.

REFERENCES

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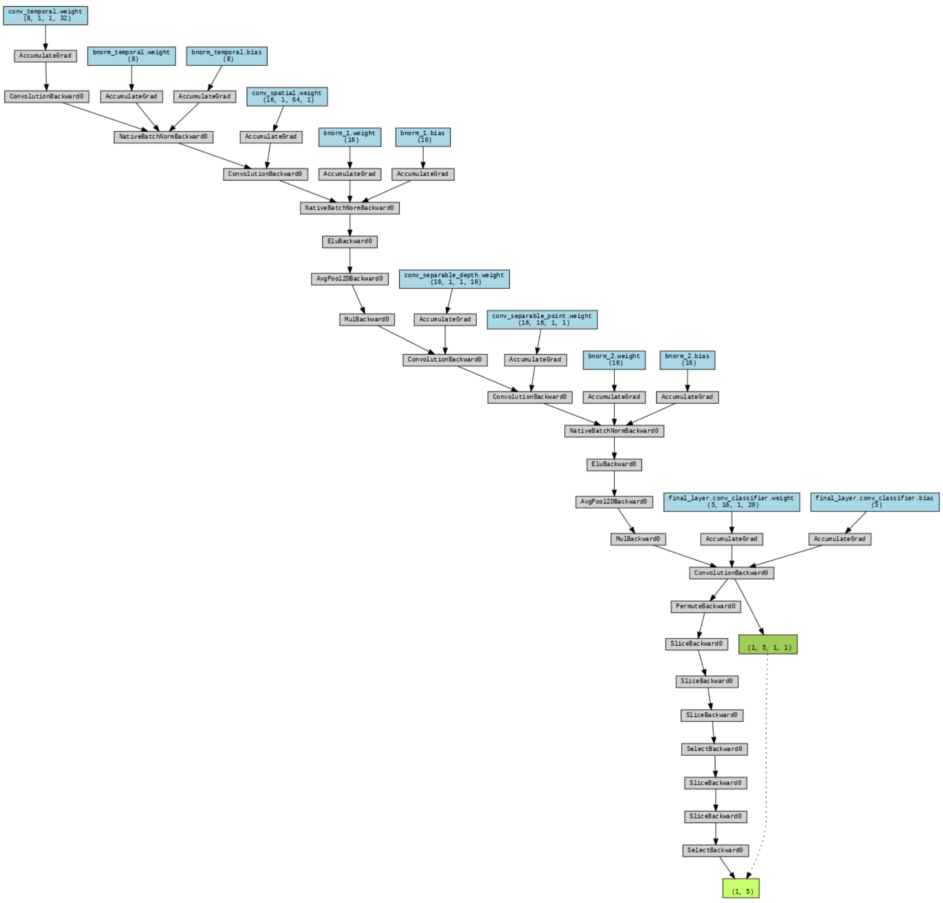
APPENDIX



```
# preprocess.py

import os
import numpy as np
import mne
import pickle

# Directory where the data is stored
data_dir = 'data' # Change this to your actual data director

# Mapping of run indices to tasks/baselines
run_mapping = {
    1: 'baseline_open',
    2: 'baseline_closed',
    3: 'task_1',
    4: 'task_2',
    5: 'task_3',
    6: 'task_4',
    7: 'task_1',
    8: 'task_2',
    9: 'task_3',
    10: 'task_4',
    11: 'task_1',
    12: 'task_2',
    13: 'task_3',
    14: 'task_4'
}

# Mapping of event IDs to labels
event_id_mapping = {
    'T0': 1, # Rest
    'T1_left': 2, # Left fist
    'T1_both': 3, # Both fists
    'T2_right': 4, # Right fist
    'T2_both': 5 # Both feet
}

def process_run(edf_path, run_index, tmin=0, tmax=4.1):
    task_label = run_mapping.get(run_index, 'unknown')
    raw = mne.io.read_raw_edf(edf_path, preload=True)
    raw.notch_filter(freqs=60.0) # powerline notch filter
    raw.filter(2, None, method='iir') # High-pass filter at

    # Define event annotations
    events, event_id = mne.events_from_annotations(raw)
    labels = []
    epochs_data_list = []

    # Handle baselines differently since they are long T0 per

    if task_label in ['baseline_open', 'baseline_closed']:
    tmin_baseline = 0 # start from the beginning
        tmax_baseline = 60 # 60 seconds for baseline
        epochs = mne.make_fixed_length_epochs(raw, duration=t
        epochs_data = epochs.get_data() * 1000 # Convert to

        labels = [event_id_mapping['T0']] *
        epochs_data.shape if epochs_data.shape[0] > 0: #
        Only append if there
            epochs_data_list.append(epochs_data)
    else:
        # Create epochs based on static tmin and tmax values
        epochs = mne.Epochs(raw, events, event_id,
        tmin=tmin, epochs_data = epochs.get_data() * 1000 #
        Convert to

        for i, event in enumerate(epochs.events):
            if task_label in ['task_1', 'task_2']:
                if event[2] == event_id.get('T0'):
                    labels.append(event_id_mapping['T0'])
                elif event[2] == event_id.get('T1'):
                    labels.append(event_id_mapping['T1_left'
                ] elif event[2] == event_id.get('T2'):
                    labels.append(event_id_mapping['T2_right
            ' elif task_label in ['task_3', 'task_4']:
                if event[2] == event_id.get('T0'):
                    labels.append(event_id_mapping['T0'])
                elif event[2] == event_id.get('T1'):
                    labels.append(event_id_mapping['T1_both'
                ] elif event[2] == event_id.get('T2'):
                    labels.append(event_id_mapping['T2_both']
            else:
                labels.append(event_id_mapping['T0'])
            print(labels)

        if epochs_data.shape[0] > 0: # Only append if there
            epochs_data_list.append(epochs_data)
    return epochs_data_list, labels, task_label

def pad_or_trim(data, target_length):
    def pad(array):
        if array.shape[2] < target_length:
            pad_width = target_length - array.shape[2]
            return np.pad(array, ((0, 0), (0, 0), (0, pad_wid
        return array[:, :, :target_length]
    return np.concatenate([pad(d) for d in data], axis=0)

def save_data(data_dir, tmin=0, tmax=4.1):

    subjects = [d for d in os.listdir(data_dir) if os.path.is

    max_samples = int((tmax - tmin) * 160) # Assuming a samp
    baseline_samples = 60 * 160 # Assuming 60 seconds for ba

    for subject in subjects:
        subject_dir = os.path.join(data_dir, subject)
        edf_files = [f for f in os.listdir(subject_dir) if f.

        for edf_file in edf_files:
            edf_path = os.path.join(subject_dir, edf_file)
            run_index = int(edf_file.split('R')[1].split('.')
            epochs_data_list, labels, task_label = process_ru

            if len(labels) > 0 and epochs_data_list: # Only
                if task_label in ['baseline_open', 'baseline_
                    padded_data = pad_or_trim(epochs_data_lis
                else:
                    padded_data = pad_or_trim(epochs_data_lis

                labels = np.array(labels)

                # Create the save directory
                save_dir = os.path.join('preprocessed_data',
                os.makedirs(save_dir, exist_ok=True)

                # Save the data for each run
                save_path = os.path.join(save_dir,
                f"run_{run with open(save_path, 'wb') as f:
                    pickle.dump({'X': padded_data, 'y': label
                print(f"Saved {subject} - {task_label} - run

# Save preprocessed data for all subjects
save_data(data_dir)

print("All preprocessed data saved.")
```

```
# -*- coding: utf-8 -*-
"""iter_3.ipynb

Automatically generated by Colab.

Original file is located at
    https://colab.research.google.com/drive/1AGGrjq0ox8C4qWjQ
"""

from google.colab import drive
drive.mount('/content/drive')

!nvidia-smi

import multiprocessing
num_cores = multiprocessing.cpu_count()
print(f"Number of CPU cores: {num_cores}")

!pip3 install torch --upgrade -q
!pip install numpy scikit-learn matplotlib visualkeras
braind # !python
/content/drive/MyDrive/bme442/bme442project/preproc import
numpy as np
import pickle
import mne
import pandas as pd

import torch
import torch.optim as optim
from torch import nn
from torch.nn.functional import elu
from torch.utils.data import DataLoader, Dataset
from torchsummary import summary
from torchviz import make_dot

from braindecode.models.base import EEGModuleMixin,
deprecate from braindecode.models.functions import
squeeze_final_output from braindecode.models.modules import
Ensure4d, Expression

from skorch import NeuralNetClassifier
from skorch.callbacks import LRScheduler, TrainEndCheckpoint

from sklearn.model_selection import StratifiedKFold
from sklearn.metrics import confusion_matrix,

ConfusionMatrix from einops.layers.torch import Rearrange
```

```
import matplotlib.pyplot as plt
import matplotlib.gridspec as gridspec
import matplotlib as mpl
import os
import concurrent.futures
import logging
import time
from tqdm import tqdm
import seaborn as sns

cuda = torch.cuda.is_available()

logging.basicConfig(level=logging.INFO, format='%(asctime)s -
base_dir = '/content/drive/MyDrive/bme442/bme442project'
preprocessed_data_dir = os.path.join(base_dir, 'preprocessed_

# someList = []
# with
open('/content/drive/MyDrive/bme442/bme442project/prep #
data = pickle.load(f)
#     print('X: ', data['X'])
#     #
someList.append(data['X'][28]) #
print('y: ', data['y'])

# # print(someList)

def process_run(run_path, test_flag):
    logging.info(f"Processing file: {run_path}")
    with open(run_path, 'rb') as f:
        data = pickle.load(f)

        # Get indices of all `1`s in `data['y']`
        one_indices = [i for i, y in enumerate(data['y']) if

        # Create a set of indices to filter out: 4 out of eve
        filter_indices = set(one_indices[1::5] + one_indices[

        # Filter data
        filtered_X = [x for i, x in enumerate(data['X']) if
        i filtered_y = [y for i, y in enumerate(data['y'])
        if i

        if test_flag:
            return filtered_X, filtered_y, 'test'
        else:
            return filtered_X, filtered_y, 'train'

def process_subject(subject):
    global test_flag
    subject_dir = os.path.join(preprocessed_data_dir,
    subject tasks = ['task_1', 'task_2', 'task_3', 'task_4']
    results = []

    if subject == 'S095':
        test_flag = True

    if os.path.isdir(subject_dir):
        for task in tasks:
            task_dir = os.path.join(subject_dir, task)
            if os.path.isdir(task_dir):
                for run_file in os.listdir(task_dir):
                    if run_file.endswith('.pkl'):
                        run_path = os.path.join(task_dir, run
                        results.append((run_path, test_flag))

    return results

test_flag       =
False  X_combined
= []
y_combined = []
X_combined_test    =
[]   y_combined_test
= [] all_runs = []
counter = 0

# Process all subjects concurrently
with concurrent.futures.ThreadPoolExecutor() as subject_execu
    subject_futures = {subject_executor.submit(process_subjec

    for future in
        tqdm(concurrent.futures.as_completed(subjec try:
            subject_runs = future.result()
            all_runs.extend(subject_runs)
        except Exception as e:
            subject = subject_futures[future]
            print(f"Error processing subject {subject}: {e}")

# Process all runs concurrently
with concurrent.futures.ThreadPoolExecutor() as executor:
    futures = []
    for run_path, flag in all_runs:
        futures.append(executor.submit(process_run, run_path,

    for                       future                          in
        tqdm(concurrent.futures.as_completed(future
        filtered_X,      filtered_y,      dataset_type      =
        future.result( if dataset_type == 'test':
            X_combined_test.extend(filtered_X)
            y_combined_test.extend(filtered_y)
        else:
            X_combined.extend(filtered_X)
            y_combined.extend(filtered_y)

# Subtract one from every y value
y_combined = [y - 1 for y in y_combined]
y_combined_test = [y - 1 for y in y_combined_test]

y_combined = np.array(y_combined)
X_combined = np.array(X_combined)
y_combined_test = np.array(y_combined_test)
X_combined_test = np.array(X_combined_test)
y_combined.shape, X_combined.shape, y_combined_test.shape, X_

print("X_combined shape:", X_combined.shape)

print("y_combined shape:", y_combined.shape)

unique, counts = np.unique(y_combined, return_counts=True)
print(dict(zip(unique, counts)))

if X_combined.shape[0] != y_combined.shape[0]:
    raise ValueError("Mismatch between number of samples in X

if X_combined_test.shape[0] != y_combined_test.shape[0]:
    raise ValueError("Mismatch between number of samples in X

class Conv2dWithConstraint(nn.Conv2d):
    def _init_(self, *args, max_norm=1, **kwargs):
        self.max_norm = max_norm
        super(Conv2dWithConstraint, self)._init_(*args, **k

    def forward(self, x):
        self.weight.data = torch.renorm(
            self.weight.data, p=2, dim=0, maxnorm=self.max_no
        )
        return super(Conv2dWithConstraint, self).forward(x)

def _glorot_weight_zero_bias(model):
    """Initialize parameters of all modules by initializing w
    glorot
     uniform/xavier initialization, and setting biases to
     zer batch norm layers are set to 1.

    Parameters
    ----------
    model: Module
    """
    for module in model.modules():
        if hasattr(module, "weight"):
            if "BatchNorm" not in module._class_._name_:
                nn.init.xavier_uniform_(module.weight, gain=
            else:
                nn.init.constant_(module.weight, 1)
        if hasattr(module, "bias"):
            if module.bias is not None:
                nn.init.constant_(module.bias, 0)

# Set up logging configuration
logging.basicConfig(level=logging.INFO, format='%(asctime)s -
logger = logging.getLogger(_name_)

class EEGNetv4(EEGModuleMixin, nn.Sequential):
    """EEGNet v4 model from Lawhern et al
    2018.
    See details in [EEGNet4]_.

    Parameters

    ----------
    final_conv_length : int | "auto"
        If int, final length of convolutional filters.
    in_chans :
        Alias for n_chans.
    n_classes:
        Alias for n_outputs.
    input_window_samples :
        Alias for n_times.

    Notes
    -----
    This implementation is not guaranteed to be correct, has
    by original authors, only reimplemented from the paper
    de

    References
    ----------
    .. [EEGNet4] Lawhern, V. J., Solon, A. J., Waytowich, N.
       S. M., Hung, C. P., & Lance, B. J. (2018).
       EEGNet: A Compact Convolutional Network for
       EEG-based Brain-Computer Interfaces.
       arXiv preprint arXiv:1611.08024.
    """

    def _init_(
        self,
        n_chans=None,
        n_outputs=None,
        n_times=None,
        final_conv_length="auto",
        pool_mode="mean",
        F1=8,
```

```python
        D=2,
        F2=16, # usually set to F1*D (?)
        kernel_length=64,
        third_kernel_size=(8, 4),
        drop_prob=0.25,
        chs_info=None,
        input_window_seconds=None,
        sfreq=None,
        in_chans=None,
        n_classes=None,
        input_window_samples=None,
    ):
        n_chans, n_outputs, n_times = deprecated_args(
            self,
            ("in_chans", "n_chans", in_chans, n_chans),
            ("n_classes", "n_outputs", n_classes, n_outputs),
            ("input_window_samples", "n_times", input_window_
        )
        super()._init_(
            n_outputs=n_outputs,
            n_chans=n_chans,
            chs_info=chs_info,
            n_times=n_times,
            input_window_seconds=input_window_seconds,
            sfreq=sfreq,
        )
        del n_outputs, n_chans, chs_info, n_times,
        input_wind del in_chans, n_classes,
        input_window_samples
        if final_conv_length == "auto":
            assert self.n_times is not None
        self.final_conv_length = final_conv_length
        self.pool_mode = pool_mode
        self.F1 = F1
        self.D = D
        self.F2 = F2
        self.kernel_length = kernel_length
        self.third_kernel_size = third_kernel_size
        self.drop_prob = drop_prob
        # For the load_state_dict
        # When padronize all layers,
        # add the old's parameters here
        self.mapping = {
            "conv_classifier.weight": "final_layer.conv_class
            "conv_classifier.bias": "final_layer.conv_classif
        }

        pool_class = dict(max=nn.MaxPool2d, mean=nn.AvgPool2d
        self.add_module("ensuredims", Ensure4d())

        self.add module("dimshuffle", Rearrange("batch ch t
        self.add_module(
            "conv_temporal",
            nn.Conv2d(
                1,
                self.F1,
                (1, self.kernel_length),
                stride=1,
                bias=False,
                padding=(0, self.kernel_length // 2),
            ),
        )
        self.add_module(
            "bnorm_temporal",
            nn.BatchNorm2d(self.F1, momentum=0.01, affine=Tru
        )
        self.add_module(
            "conv_spatial",
            Conv2dWithConstraint(
                self.F1,
                self.F1 * self.D,
                (self.n_chans, 1),
                max_norm=1,
                stride=1,
                bias=False,
                groups=self.F1,
                padding=(0, 0),
            ),
        )

        self.add_module(
            "bnorm_1",
            nn.BatchNorm2d(self.F1 * self.D, momentum=0.01, a
        )
        self.add_module("elu_1", Expression(elu))

        self.add_module("pool_1", pool_class(kernel_size=(1,
        self.add_module("drop_1", nn.Dropout(p=self.drop_prob

        # https://discuss.pytorch.org/t/how-to-modify-a-conv2
        self.add_module(
            "conv_separable_depth",
            nn.Conv2d(
                self.F1         *
                self.D,   self.F1
                *   self.D,   (1,
                16),
                stride=1,
                bias=False,
                groups=self.F1 * self.D,
                padding=(0, 16 // 2),
            ),
        )
        self.add_module(
            "conv_separable_point",
            nn.Conv2d(
                self.F1 * self.D,
                self.F2,
                (1, 1),
                stride=1,
                bias=False,
                padding=(0, 0),
            ),
        )

        self.add_module(
            "bnorm_2",
            nn.BatchNorm2d(self.F2, momentum=0.01, affine=Tru
        )
        self.add_module("elu_2", Expression(elu))
        self.add_module("pool_2", pool_class(kernel_size=(1,
        self.add_module("drop_2", nn.Dropout(p=self.drop_prob

        output_shape = self.get_output_shape()
        n_out_virtual_chans = output_shape[2]

        if self.final_conv_length == "auto":
            n_out_time = output_shape[3]
            self.final_conv_length = n_out_time

        # Incorporating classification module and subsequent
        module = nn.Sequential()

        module.add_module(
            "conv_classifier",
            nn.Conv2d(
                self.F2,
                self.n_outputs,
                (n_out_virtual_chans, self.final_conv_length)
                bias=True,
            ),
        )

        if self.add_log_softmax:
            module.add_module("logsoftmax", nn.LogSoftmax(dim

        # Transpose back to the logic of
        braindecode, # so time in third dimension
        (axis=2)
        module.add_module(
            "permute_back",
            Rearrange("batch x y z -> batch x z y"),
        )

        module.add_module("squeeze", Expression(squeeze_final

        self.add_module("final_layer", module)

        _glorot_weight_zero_bias(self)

    def forward(self, x):
        logger.info(f'Input shape: {x.shape}')
        x = super().forward(x)
        logger.info(f'Output shape: {x.shape}')
        return x

# Ensure device is correctly set
device = torch.device("cuda" if torch.cuda.is_available() els

# Step 1: Check for NaN or infinite values in the data
assert  not  np.isnan(X_combined).any(),  "X_combined  contains
N    assert    not    np.isinf(X_combined).any(),    "X_combined
contains     i    assert    not    np.isnan(y_combined).any(),
"y_combined         contains         N         assert         not
np.isinf(y_combined).any(), "y_combined contains i

# Step 2: Convert to PyTorch tensors on CPU first
X_combined_tensor_cpu =
torch.from_numpy(X_combined).float() y_combined_tensor_cpu
= torch.from_numpy(y_combined).long()

# Check the tensors on CPU
print(f"Shape of X_combined_tensor_cpu: {X_combined_tensor_cp
print(f"Shape of y_combined_tensor_cpu: {y_combined_tensor_cp

# Test with a small batch
small_batch_X = X_combined_tensor_cpu[:10]
small_batch_y = y_combined_tensor_cpu[:10]

try:
    small_batch_X_cuda                         =
    small_batch_X.to(device)   small_batch_y_cuda
    =    small_batch_y.to(device)    print("Small
    batch transfer successful")
except RuntimeError as e:
    print(f"Error during small batch transfer: {e}")

# Inspect the data for unusual values
print("X_combined max:", X_combined.max())
print("X_combined min:", X_combined.min())
print("X_combined mean:", X_combined.mean())

print("y_combined unique values:", np.unique(y_combined))
```

```
# Enable CUDA debugging mode
os.environ['CUDA_LAUNCH_BLOCKING'] = "1"

# Move the tensors to the CUDA device again
try:
    X_combined_tensor =
    X_combined_tensor_cpu.to(device) y_combined_tensor
    = y_combined_tensor_cpu.to(device) print("Data
    transfer to CUDA successful")
except RuntimeError as e:
    print(f"Error during data transfer to CUDA: {e}")

def process_fold(train_index, test_index, X_combined, y_combi
    print("process_fold called")
    assert torch.cuda.is_available(), "CUDA is not
    available. torch.backends.cudnn.enabled = False #
    Disable cuDNN for

    device = torch.device('cuda' if
    torch.cuda.is_available() logger.info(f"Using device:
    {device}")

    X_train, X_test = X_combined[train_index],
    X_combined[tes y_train, y_test =
    y_combined[train_index], y_combined[tes

    # Check for NaN or infinite values in the data
    assert not np.isnan(X_train).any(), "X_train contains
    NaN assert not np.isinf(X_train).any(), "X_train
    contains inf assert not np.isnan(X_test).any(), "X_test
    contains NaN v assert not np.isinf(X_test).any(),
    "X_test contains infin assert not
    np.isnan(y_train).any(), "y_train contains NaN assert
    not np.isinf(y_train).any(), "y_train contains inf
    assert not np.isnan(y_test).any(), "y_test contains NaN
    v assert not np.isinf(y_test).any(), "y_test contains
    infin

    # Convert data to PyTorch tensors
    X_train_tensor_cpu = torch.from_numpy(X_train).float()
    X_test_tensor_cpu = torch.from_numpy(X_test).float()
    y_train_tensor_cpu = torch.from_numpy(y_train).long()
    y_test_tensor_cpu = torch.from_numpy(y_test).long()

    # Transfer full tensors to the CUDA device
    X_train = X_train_tensor_cpu.to(device)
    X_test = X_test_tensor_cpu.to(device)
    y_train = y_train_tensor_cpu.to(device)
    y_test = y_test_tensor_cpu.to(device)

    # Define the model
    model = EEGNetv4(n_chans=64, n_outputs=5, n_times=656,
ke model = model.to(device)
```

```
# Define the loss function and optimizer
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.005, capt

# Training loop
def train_model(model, criterion, optimizer, X_train, y_t
    model.train()
    dataset = torch.utils.data.TensorDataset(X_train,
    y_t dataloader =
    torch.utils.data.DataLoader(dataset, bat

    loss_history = []

    for epoch in range(n_epochs):
        epoch_start_time = time.time()
        running_loss = 0.0
        for batch_idx, (inputs, labels) in enumerate(data
            batch_start_time = time.time()
            inputs, labels = inputs.to(device), labels.to

            optimizer.zero_grad()
            outputs = model(inputs)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()
            running_loss += loss.item()
            batch_end_time = time.time()
            print(f'Batch {batch_idx + 1}/{len(dataloader

        avg_loss = running_loss / len(dataloader)
        loss_history.append(avg_loss)
        epoch_end_time = time.time()
        logger.info(f'Epoch [{epoch + 1}/{n_epochs}] comp

    return model, loss_history

logger.info('Starting model training...')
print('Starting model training...')
model, loss_history = train_model(model, criterion, optim
logger.info('Model training completed.')
print('Model training completed.')

# Predict and evaluate
logger.info('Starting prediction...')
print('Starting prediction...')
model.eval()
with torch.no_grad():
    outputs = model(X_test)
```

```
        _, y_pred = torch.max(outputs, 1)

    y_pred = y_pred.cpu().numpy()
    accuracy = accuracy_score(y_test.cpu().numpy(), y_pred)
    logger.info(f'Fold accuracy: {accuracy:.4f}')
    print(f'Fold accuracy: {accuracy:.4f}')

    # Generate confusion matrix
    cm = confusion_matrix(y_test.cpu().numpy(), y_pred)
    logger.info(f'Confusion Matrix:\n{cm}')
    print(f'Confusion Matrix:\n{cm}')

    # Calculate sensitivities, specificities, PPVs, and NPVs
    fold_sensitivities    =
    []   fold_specificities
    = [] fold_ppvs = []
    fold_npvs = []

    for i in range(5):
        tp = cm[i, i]
        fn = cm[i, :].sum() - tp
        fp = cm[:, i].sum() - tp
        tn = cm.sum() - (tp + fn + fp)

        sensitivity = tp / (tp + fn) if (tp + fn) > 0 else
        0 specificity = tn / (tn + fp) if (tn + fp) > 0
        else 0 ppv = tp / (tp + fp) if (tp + fp) > 0 else 0
        npv = tn / (tn + fn) if (tn + fn) > 0 else 0

        fold_sensitivities.append(sensitivity
        )
        fold_specificities.append(specificity
        ) fold_ppvs.append(ppv)
        fold_npvs.append(npv)

    logger.info(f'Fold sensitivities:
    {fold_sensitivities}') print(f'Fold sensitivities:
    {fold_sensitivities}')
    logger.info(f'Fold specificities:
    {fold_specificities}') print(f'Fold specificities:
    {fold_specificities}')
    logger.info(f'Fold PPVs: {fold_ppvs}')
    print(f'Fold PPVs: {fold_ppvs}')
    logger.info(f'Fold NPVs: {fold_npvs}')
    print(f'Fold NPVs: {fold_npvs}')

    return model, fold_sensitivities, fold_specificities, fol

skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=
all_sensitivities = []
all_specificities = []
all_ppvs = []
```

```
all_npvs = []
models = []
cms = []
loss_histories = []

# Check if the trained_models directory exists and create if
os.makedirs(os.path.join(base_dir, 'trained_models'), exist_o

# Check for existing models
existing_models = os.listdir(os.path.join(base_dir, "trained_

if existing_models:
    print("Loading existing models...")
    for fold_index, model_file in enumerate(existing_models,
        model_path = os.path.join(base_dir,
        'trained_models', model = EEGNetv4(n_chans=64,
        n_outputs=5, n_times=656
        model.load_state_dict(torch.load(model_path))
        models.append(model)
        print(f"Loaded model for fold {fold_index}")
else:
    print("Starting                   StratifiedKFold

    cross-validation") fold_index = 1

    for  train_index,  test_index  in  skf.split(X_combined,
        y_co print(f"Processing fold {fold_index}")
        model, sensitivities, specificities, ppvs, npvs, cm,
        if  sensitivities  and  specificities  and  ppvs  and
        npvs:
            all_sensitivities.append(sensitivities
            )
            all_specificities.append(specificities
            ) all_ppvs.append(ppvs)
            all_npvs.append(npvs)
        models.append(model)
        cms.append(cm)
        loss_histories.append(loss_history)
        model_save_path = os.path.join(base_dir, 'trained_mod
        torch.save(model.state_dict(), model_save_path)
        print(f"Completed fold {fold_index}")
        fold_index += 1

    print("Completed StratifiedKFold cross-validation")

# Convert lists to numpy arrays for further analysis
all_sensitivities                                =
np.array(all_sensitivities)   all_specificities
=    np.array(all_specificities)    all_ppvs    =
np.array(all_ppvs)
all_npvs = np.array(all_npvs)

print(f'Mean Sensitivities per fold: {all_sensitivities.mean(
print(f'Mean         Specificities         per         fold:
{all_specificities.mean(   print(f'Mean   PPVs   per   fold:
{all_ppvs.mean(axis=0)}')
print(f'Mean NPVs per fold: {all_npvs.mean(axis=0)}')

# Plot loss graphs fold by fold
def plot_loss_graphs(loss_histories):
    fig, ax = plt.subplots()
    for fold, loss_history in enumerate(loss_histories, start
        ax.plot(loss_history, label=f'Fold {fold}')
    ax.set_xlabel('Epochs')
    ax.set_ylabel('Loss')
    ax.set_title('Training Loss per Fold')
    ax.legend()
    plt.show()

plot_loss_graphs(loss_histories)

#  Test  the  resulting  models  with  y_combined_test  and
X_combin              X_combined_test_tensor              =
torch.from_numpy(X_combined_test).fl   y_combined_test_tensor
= torch.from_numpy(y_combined_test).lo

all_test_sensitivities    =
[]   all_test_specificities
= [] all_test_ppvs = []
all_test_npvs    =
[] test_cms = []

cms = []

for i, model in enumerate(models, 1):
    model.to(device) # Ensure the model is on the same devic
    model.eval()
    with torch.no_grad():
        outputs = model(X_combined_test_tensor)
        _, y_pred = torch.max(outputs, 1)

    y_pred = y_pred.cpu().numpy()
    cm = confusion_matrix(y_combined_test, y_pred)
    cms.append(cm)
    test_cms.append(cm)
    print(f'Confusion Matrix for model {i}:\n{cm}')
    # torch.save(model.state_dict(), os.path.join(base_dir, '

    # Calculate sensitivities, specificities, PPVs, and NPVs
    test_sensitivities    =
    []   test_specificities
    = [] test_ppvs = []
    test_npvs = []
    for j in range(len(cm)):  # Adjusted to use len(cm) for t
        tp = cm[j, j]
        fn = cm[j, :].sum() - tp
        fp = cm[:, j].sum() - tp
        tn = cm.sum() - (tp + fn + fp)

        sensitivity = tp / (tp + fn) if (tp + fn) > 0 else
        0 specificity = tn / (tn + fp) if (tn + fp) > 0
        else 0 ppv = tp / (tp + fp) if (tp + fp) > 0 else 0
        npv = tn / (tn + fn) if (tn + fn) > 0 else 0

        test_sensitivities.append(sensitivity
        )
        test_specificities.append(specificity
        ) test_ppvs.append(ppv)
        test_npvs.append(npv)

    all_test_sensitivities.append(test_sensitivities
    )
    all_test_specificities.append(test_specificities
    ) all_test_ppvs.append(test_ppvs)
    all_test_npvs.append(test_npvs)

print("Completed testing models on the test set")

# Convert the confusion matrices to pandas DataFrames
df_cms = []
for i, cm in enumerate(cms, 1):
    df_cm = pd.DataFrame(cm, columns=[f'Predicted Class
    {i}' df_cms.append(df_cm)

# Define the class names
class_names = ['Rest', 'Left fist', 'Both fists', 'Right fist

# Create a figure with subplots for each fold, adjusting layo
fig, axes = plt.subplots(1, len(df_cms), figsize=(20, 8), con

# Plot each confusion matrix
for i, df_cm in enumerate(df_cms, 1):
    sns.heatmap(df_cm, annot=True, fmt='g', cmap='Blues',
    ax= axes[i-1].set_xlabel('Predicted Class')
    axes[i-1].set_ylabel('Actual Class')
    axes[i-1].set_title(f'Fold {i} Confusion
    Matrix') axes[i-1].tick_params(axis='x',
    rotation=45)
    axes[i-1].tick_params(axis='y', rotation=45)

plt.show()

all_test_sensitivities                                  =
np.array(all_test_sensitivities)   all_test_specificities
=    np.array(all_test_specificities)    all_test_ppvs    =
np.array(all_test_ppvs)
```

```
all_test_npvs = np.array(all_test_npvs)

all_test_accuracies = (all_test_sensitivities + all_test_spec

print(f'Mean Test Sensitivities:
{all_test_sensitivities.mean print(f'Mean Test
Specificities: {all_test_specificities.mean print(f'Mean
Test PPVs: {all_test_ppvs.mean(axis=0)}')
print(f'Mean Test NPVs: {all_test_npvs.mean(axis=0)}')

# Convert to DataFrames with class names as indices
df_sensitivities = pd.DataFrame(all_test_sensitivities *
100, df_specificities = pd.DataFrame(all_test_specificities
* 100, df_ppvs = pd.DataFrame(all_test_ppvs * 100,
index=class_names df_npvs = pd.DataFrame(all_test_npvs *
100, index=class_names df_accuracies =
pd.DataFrame(all_test_accuracies * 100, index


# Print the tables
print("Test Sensitivities by Fold")
print(df_sensitivities)
print("\nTest Specificities by Fold")
print(df_specificities)
print("\nTest PPVs by Fold")
print(df_ppvs)
print("\nTest NPVs by Fold")
print(df_npvs)
print("\nTest Accuracies by Fold")
print(df_accuracies)

# List of DataFrames and their corresponding titles
dataframes = [
    (df_accuracies, 'Test Accuracies by Fold'),
    (df_sensitivities, 'Test Sensitivities by
    Fold'), (df_specificities, 'Test Specificities
    by Fold'), (df_ppvs, 'Test PPVs by Fold'),
    (df_npvs, 'Test NPVs by Fold')
]

# Define the function to display bar charts in a custom grid
def display_combined_bar_charts(dataframes):
    fig = plt.figure(figsize=(20, 12))
    spec = gridspec.GridSpec(ncols=6, nrows=2, figure=fig)

    axes = []
    axes.append(fig.add_subplot(spec[0, 0:2])) # row 0, span
    axes.append(fig.add_subplot(spec[0, 2:4])) # row 0, span
    axes.append(fig.add_subplot(spec[0, 4:]))  # row 0, span
    axes.append(fig.add_subplot(spec[1, 1:3])) # row 1, span
    axes.append(fig.add_subplot(spec[1, 3:5])) # row 1, span
    for ax, (df, title) in zip(axes, dataframes):
        df.plot(kind='bar', ax=ax)
        ax.set_title(title)
        ax.set_xlabel('Fold')
        ax.set_ylabel('Percentage')
        ax.legend(title='Metrics', bbox_to_anchor=(1.05,
        1), ax.set_xticklabels(df.index, rotation=0)

    plt.tight_layout()
    plt.show()

display_combined_bar_charts(dataframes)

df_cms = [np.array(cm) for cm in

df_cms]

# Normalize the confusion matrices along the columns
df_cms_normalized = [cm.astype('float') / cm.sum(axis=0)[np.n

# Define the class names
class_names = ['Rest', 'Left fist', 'Both fists', 'Right fist

# Create a figure with subplots for each fold, adjusting
layo fig, axes = plt.subplots(1, len(df_cms_normalized),
figsize=( # Plot each normalized confusion matrix
for i, df_cm in enumerate(df_cms_normalized, 1):
    sns.heatmap(df_cm, annot=True, fmt='.2f', cmap='Blues',
    a axes[i-1].set_xlabel('Predicted Class')
    axes[i-1].set_ylabel('Actual Class')
    axes[i-1].set_title(f'Fold {i} Confusion
    Matrix') axes[i-1].tick_params(axis='x',
    rotation=45)
    axes[i-1].tick_params(axis='y', rotation=45)

plt.show()
```