# A Hybrid Deep Learning Classification Framework for Motor Imagery

## Capstone Project Report

## End-Semester Evaluation


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## Title

A Hybrid Deep Learning Classification Framework for Motor Imagery

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# A Hybrid Deep Learning Classification Framework for Motor Imagery

A dissertation submitted in partial
satisfaction of the requirements for the
degree

B.E. in Computer Engineering

By

Tanya Tomer, Lavish Dhiman, Sehajdeep Singh Multani,

Akshath Kathel, Kashika Purohit

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**ABSTRACT OF THE DISSERTATION**

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This project uses advanced deep learning techniques to classify electroencephalogram (EEG) signals. The main objective is to develop a model that can accurately identify patterns within these signals, which could be beneficial for various biomedical applications.

To achieve this goal, the EEG data was first pre-processed, which included baseline filtering to remove noise and artifacts. The data was then segmented into overlapping windows to capture both spatial and temporal features effectively. We used Multiscale with ResNet a state-of-the-art convolutional neural network, to extract spatial features from the EEG data. Efficient Net's architecture is known for its ability to balance accuracy and efficiency, making it well-suited for capturing detailed spatial patterns in high-dimensional data. For the temporal analysis, we employed 1D CNN, which are capable of learning long-term dependencies in sequential data. This dual approach allows the model to leverage both the spatial information captured by Multi-Scale and the temporal dynamics captured by CNN.

To prevent overfitting, we incorporated dropout regularization, which helps the model generalize better by randomly dropping neurons during training. We also applied L2 regularization to penalize complex models and encourage simpler, more robust ones. Early stopping was used to monitor the validation loss, stopping training when no further improvements were observed, thus avoiding overfitting.

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# CHAPTER 1

## Introduction

Electroencephalography (EEG) is a method to record an electrogram of the spontaneous electrical activity of the brain. It is typically non-invasive, with the EEG electrodes placed along the scalp using the International 10–20 system, or variations of it to record an electrogram. Voltage fluctuations measured by the EEG amplifier and electrodes allow the evaluation of normal brain activity. The observed frequencies are subdivided into various groups: alpha (8–13 Hz), beta (13–30 Hz), delta (0.5–4 Hz), and theta (4–7 Hz). Alpha waves are observed when a person is in a state of relaxed wakefulness and are mostly prominent over the parietal and occipital sites. During intense mental activity, beta waves are more prominent in frontal areas as well as other regions. If a relaxed person is told to open their eyes, one observes alpha activity decreasing and an increase in beta activity. These subdivisions can be used for various applications, including clinical diagnostics, neurorehabilitation, brain-computer interfaces (BCIs), etc. Among its many applications, motor imagery classification is one of the growing areas of research in EEG . Motor imagery refers to the mental simulation of movement without any actual physical movement. It has been shown that imagining a movement activates similar brain regions as actual movement, which can be detected using EEG based on the particular frequency division in the EEG signal. By classifying these motor imagery patterns, researchers can infer the intended movement, which can then be used to control prosthetic limbs or interact with computers. This technique is particularly promising for individuals with motor impairments, offering a non-invasive means of communication and control. However, the inherent complexity of EEG signals and the individual variability in motor imagery patterns to make accurate classification is a challenging task.

There have been approaches to motor imagery classification which have relied on techniques such as Common Spatial Patterns (CSP) and Support Vector Machines (SVMs). While these methods have shown promise, they often struggle with issues such as variability across subjects, low classification accuracy, and limited generalizability to different datasets. Additionally, these methods tend to overlook the intricate spatio-temporal relationships inherent in EEG data, which are crucial for capturing the full spectrum of motor imagery signals.

In this study, we are going to discuss a novelty **Hybrid Multiscaler + ResNet Deep Learning Classification Framework for Motor Imagery tasks**. The study will focus on challenges faced, goals, and organization of the research for achieving the desired results by utilizing EEG signals, and a multi-scalar model integrated with ResNet to classify motor imagery tasks into four distinct classes: right-hand movement, left-hand movement, foot movement, and tongue movement.

## 1.1 Problem Statement

There has been great progress in the area of understanding and classifying motor imagery tasks but there are various problems that persist and are difficult to resolve. These Challenges necessitate the development of a robust and scalable solution. Some of the challenges that will try to overcome with our model are:

1. **Signal Complexity**:

   EEG signals are highly dynamic and non-stationary, with low amplitudes (microvolts) and high susceptibility to noise from muscle movements, eye blinks, and external interference. The Major focus of this project is to capture meaningful neural activity by isolating relevant components from noisy data.

2. **Individual Variability**:

   Different individuals tend to have different brainwaves due to age, physiology, and mental state. These variations affect the activation of neural regions during motor imagery tasks and due to this problem, it becomes challenging to build a generalized classification model.

3. **Limitations of Traditional Methods**:

   Classical techniques like CSP and SVM are inadequate for modeling complex spatial and temporal relationships in EEG data. Their scalability is limited when applied to large, multi-class datasets. With this project, we will try to create a model that is capable of using modern deep learning methods to efficiently classify different motor imagery tasks.

In this research, the primary motivation was to address the above challenges by developing a deep learning model that can overcome the above problems effectively and efficiently.

## 1.2 Objectives

The primary objective of this research is to develop a **Hybrid Deep Learning Framework** for classifying motor imagery tasks using EEG data. However, there are specific objectives that need to be achieved in order to develop an optimized and efficient hybrid model for motor imagery classification.

The major focus of the project will be on Developing a multi-scalar model incorporating **1D CNNs** and **ResNet** architectures to enhance feature extraction and classification accuracy. The specific model is identified after multiple experiments with different models like efficient net, mobile net, etc. producing the required results. Another major objective to achieve is to overcome individual variability because EEG is data that varies with different subjects so the model should be developed such that it can handle invariability in data which can be achieved by building a model that generalizes across subjects and sessions while minimizing the impact of noise and artifacts. Finally, Testing the framework on multiple datasets to ensure robustness, generalizability, and consistency in performance across diverse subjects and experimental setups.

## 1.3 Scope of the Study

The Major scope of this study focuses on addressing key challenges in motor imagery classification using EEG signals. In our research, we cover Dataset Selection which involves using publicly available EEG datasets in GDF format, which focuses on motor imagery tasks involving right-hand, left-hand, feet, and tongue movements. We also try to employ preprocessing techniques, including bandpass filtering (30–80 Hz), Normalization, Segmentation, etc. to remove noise and retain relevant signal components.

For Feature Extraction and Modeling, we Leverage the capability of multi-scalar CNNs and ResNet architectures to capture EEG features. Then we move towards the classification which implies building a model to classify EEG signals into four motor imagery classes with high accuracy and low latency and then Evaluating the model using metrics like accuracy, precision, recall, and F1-score to ensure reliability and robustness. In end, we try to explore the use of framework in real-time BCI systems for assistive technologies, neurorehabilitation, and gaming interfaces

# CHAPTER 2

# Literature Review

## 2.1 Overview

The processing of Motor Imagery (MI) using EEG signals is one of the most active research areas in the field of brain computer interface (BCI). Noninvasive EEG-based BCI systems provide an indirect link between human subjects' brain activity and devices, and, therefore, hold promise for applications in the areas of neurorehabilitation, assistive technologies, and neuroprosthetics. To this end, it is crucial to design efficient and reliable models that can adequately model the MI signals, while addressing issues including subject specific variations, artifacts and the chaotic nature of EEG signals.

The current research has been mainly centered on the use of deep learning approaches which have been shown to provide effective means of identifying patterns in EEG data including spatial, temporal and spectral characteristics. SE blocks, CNNs, LSTM networks, GNNs, and other deep learning models have been used to improve feature extraction and classification results.

## 2.2 Research Findings

| S. No. | Paper Title | Technology | Findings | Citations |
|---|---|---|---|---|
| 1 | A Temporal - Spectral-Based Squeeze-and Excitation Feature Fusion Network for Motor Imagery EEG Decoding | SE Blocks For Feature extraction | This study proposes a novel MI-EEG decoding framework using a temporal-spectral-based squeeze-and-excitation feature fusion network, achieving improved performance by effectively integrating temporal and spectral features. | Li, Y., Guo, L., Liu, Y., Liu, J., & Meng, F. (2021). A Temporal- Spectral-Based squeeze-and-excitation feature fusion network for motor imagery EEG decoding. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 29, 1534–1545. https://doi.org/10.1109/tnsre.2021.3099908 |
| 2. | Physics-Informed Attention Temporal Convolutional Network for EEG-Based Motor | MobileNet-with Squeeze-Excitation Blocks | CNN classifier for improving Brain-Computer Interface (BCI) systems. Temporal-Spatial Processing Layers for | Altaheri, H., Muhammad, G., & Alsulaiman, M. (2023). Physics- Informed Attention Temporal Convolutional Network f |

| | | | | |
|---|---|---|---|---|
| | Imagery Classification | | enhancing feature extraction. | EEG- Based motor imagery classification. IE Transactions on Industrial Informatics, 19(2) 2249–2258. https://doi.org/10.1109/tii.2022.3 197419 |
| 3. | EEG Motor Imagery Classification With Sparse Decomposition and Deep Learning | SSD - SE - CNN | Squeeze-and-Excitation (SE) blocks to adaptively recalibrate channel-wise feature responses, further improving performance. | Sun, B., Zhao, X., Zhang, H., Bai, R Li, T. (2021). EEG Motor imagery classification with sparse spectro-temporal decomposition a deep learning. IEEE Transactions on Automa Science and Engineering, 18(2), 541–551. https://doi.org/10.1109/tase.2020. 3021456 |
| 4 | Attention-Inception and Long-Short-Term Memory-Based EEG Classification for Motor Imagery Tasks in Rehabilitation | Attention-Inception convolutional neural network with long short- term | The proposed model is a lightweight deep learning model that integrates an attention-inception convolutional neural network with long short-term memory (LSTM), designed to be efficient in terms of parameters and computational | Amin, S. U., Altaheri, H., Muhamm G., Abdul, W., & Alsulaiman, M. (2022). Attention-Inception and Long- Short-Term Memory-Based EEG classification for motor imagery tasks in rehabilitation. IEEE |

| | | | | |
|---|---|---|---|---|
| | | memory (LSTM) | time while delivering high accuracy. | Transactions on Industrial Informatics, 18(8), 5412–5421. https://doi.org/10.1109/tii.2021.3 132340 |
| 5 | A Lightweight End-to- End- Neural Networks for Decoding of Motor Imagery Brain Signal | Depthwise convolution with Squeeze and Excitation Blocks | Depthwise Convolution technique reduces computational complexity by focusing on the intrinsic features of each EEG channel, thereby making the network more efficient Squeeze-and-Excitation (SE) Blocks adaptively recalibrate the channel- wise feature responses, enhancing the model's ability to capture important features from the data. | Lee, H. K., Myoung, J., & Choi, Y. (2022). A lightweight End-to- End neural networks for decoding of motor imagery brai signal. 2022 Thirteenth International Confere on Ubiquitous and Future Networks (ICUFN) https://doi.org/10.1109/icufn5511 9.2022.982 |
| 6 | Classification Motor of Imagery EEG Signals Based on Deep Autoencoder and Convolutional Neural Network Approach | autoencoder | Deep Autoencoders (DAE) are used for dimensionality reduction. DAE is used because it effectively extracts event-related potential (ERP) and morphological features from EEG signals.<br><br>EEG data often exhibit non-linear and dynamic patterns that | Hwaidi, Jamal F., and Thomas M. Chen. "Classification of motor imagery EEG signals based on deep autoencoder and convolutional neural network approach." IEE access 10 (2022): |

| | | | | |
|---|---|---|---|---|
| | | | may not be adequately captured by fixed hierarchical representations used by the DAE and CNN model. | 48071-48081. |
| 7 | Graph Neural Networks on SPD Manifolds for Motor Imagery Classification:A Perspective From the Time–Frequency Analysis | Graph-CSP Net | This paper introduces Graph-CSPNet. It leverages graph topology to capture discriminative patterns from EEG spatial covariance matrices in the context of motor imagery classification. | Ju, Ce, and Cuntai Guan. "Graph Ne Networks on SPD Manifolds for Motor Imag Classification: A Perspective From the Time Frequency Analysis." IEEE Transactions on Neural Networks and Learning Systems (2022) |
| 8 | Improving Generalization of CNN- Based Motor- Imager EEG Decoders via Dynamic Convolutions | CNN | This paper uses dynamic convolutions to tackle the challenges associated with inter-subject variability.<br><br>One limitation is the inevitable increase in trainable parameters, which increases with the number of available subjects in the dataset. | Barmpas, Konstantinos, et al. "Improving Generalization of CNN-based M Imagery EEG Decoders via Dynamic Convolutions." IEEE Transactions on Neural Systems and Rehabilitation Engineering (2023) |
| 9 | On the Deep Learning Models for EEG- Based Brain-Computer Interface | Comparison of various models | Compares five deep learning models on two datasets. The five deep learning models: EEGNet, ShallowNet, DeepConvNet, Para Att, MB3D | Zhu, Hao, Dylan Forenzo, and Bin "On the deep learning models for EEG-based brain-computer interface using motor |

| | | | | |
|---|---|---|---|---|
| | Using Motor Imagery | | | imager IEEE Transactions on Neural Systems and Rehabilitation Engineering 30 (2022): 2283-<br>2291. |

Table 2.1: Literature reviews

These papers in the field of EEG motor imagery classification have suggested innovative methodologies and promising results. Li et al. (2021) introduced a temporal-spectral-based SE feature fusion framework, which significantly improves decoding performance by integrating both temporal and spectral features. Similarly, Altaheri et al. (2023) enhanced BCI systems using a physics-informed temporal CNN that incorporates attention mechanisms to focus on spatial-temporal EEG processing, ensuring robust classification. Sun et al. (2021) combined sparse spectro-temporal decomposition with SE blocks to adaptively recalibrate channel-wise features, achieving high precision.

Amin et al. (2022) proposed a lightweight model using attention mechanisms, inception layers, and LSTM networks for efficient and accurate MI classification. In a different vein, Ju and Guan (2022) explored the use of graph neural networks (Graph-CSPNet), leveraging graph topology to capture spatial covariance patterns and offering a novel representation of EEG data. Addressing inter-subject variability, Barmpas et al. (2023) implemented dynamic convolutional layers in CNNs, which enhanced generalization while slightly increasing trainable parameters.

These studies highlight several trends in EEG motor imagery research. The integration of SE blocks has proven effective for adaptive feature recalibration. Lightweight architectures are increasingly adopted to reduce computational complexity. Graph-based and manifold learning techniques offer advanced methods for capturing EEG spatial structures. Additionally, the combination of spatial, temporal, and spectral features is emphasized for comprehensive EEG analysis.

There are still certain challenges and research gaps that need to be taken into consideration:

1. **Inter-Subject Variability**: Models often struggle with generalization across subjects due to physiological differences.
2. **Computational Complexity**: High-performance models frequently require significant computational resources, limiting real-time application potential.
3. **Limited Dataset Sizes**: Small datasets hinder the training of complex deep learning architectures, leading to overfitting.
4. **Lack of Multiscale Integration**: Many models fail to fully exploit multiscale features that encapsulate intricate spatial and temporal dynamics.

Our proposed model incorporates **Multiscale CNNs, ResNet, and DenseNet** architectures to address the identified research gaps and challenges:

- **Multiscale Feature Extraction**: By integrating multiscale techniques, our model captures spatial-temporal variations at varying resolutions, ensuring a comprehensive feature set.
- **ResNet for Residual Learning**: ResNet's skip connections alleviate the vanishing gradient problem, facilitating the training of deeper networks.
- **DenseNet for Efficient Connectivity**: DenseNet leverages feature reuse, reducing the number of parameters and improving model efficiency without compromising performance.

This combination is particularly suited for classifying four classes of MI-EEG signals, addressing inter-subject variability and enhancing generalization capabilities.

# CHAPTER 3

# Proposed Methodology

In this chapter, we will discuss the systematic approach employed to achieve the goals of our project, which majorly focuses on the accurate identification of motor imagery tasks. Various experimental approaches were performed before finalizing our path to optimized results. This chapter will focus on the finalized approach, which has four key parts: data acquisition, preprocessing, Feature Extraction, training, and evaluation.

The Data Acquisition ensures the CSV file extraction and labeling, and the Pre-processing module ensures clean and standardized input data, removing extra channels and applying normalization. The Feature Extraction module leverages the Multiscalar-resnet capability for extraction of good and dense features. Finally, the Training and Evaluation module integrates these features into a hybrid model for classification and assesses its performance using robust validation techniques.

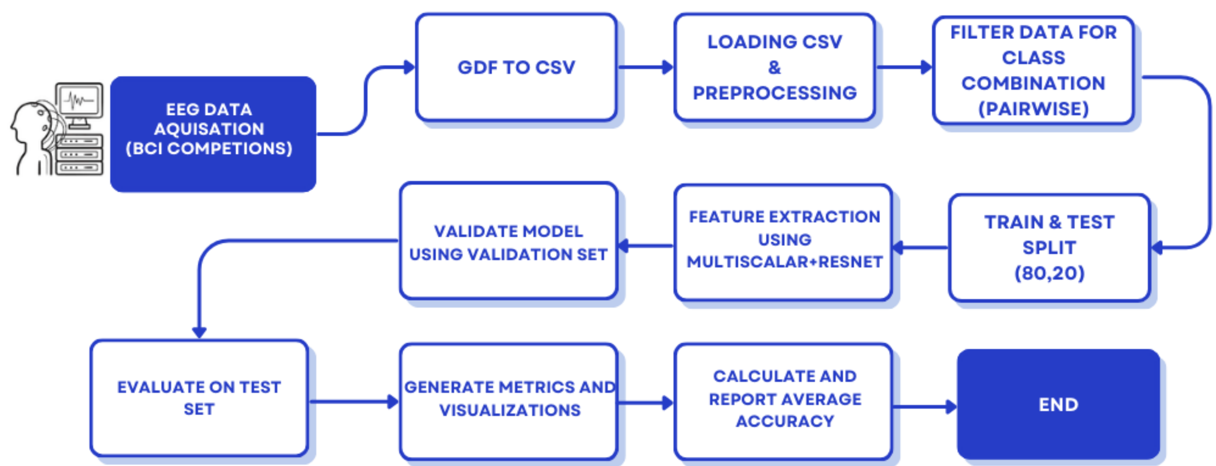


Figure 3.1: Block Diagram Representing the Methodology Followed.

## 3.1 Data Preprocessing

The preprocessing of EEG data plays a critical role in ensuring the quality and reliability of subsequent analyses and classification tasks. In this study, EEG signals were obtained from the publicly available BCI Competition IV dataset 2a, which contains data recorded from nine subjects performing four motor imagery (MI) tasks: left limb, right limb, tongue, and both feet. Below, we detail the preprocessing steps applied to the dataset to prepare it for analysis:

1. **Data Acquisition and Initial Processing**

The dataset, provided in GDF format, was first acquired from the BCI Competition IV repository. The GDF files contain EEG recordings collected using 22 EEG channels and three EOG channels. These recordings include the four Motor Imagery tasks performed by each subject. The raw data was imported into the processing environment for further processing.

**2. Bandpass Filtering**

To extract the frequency components most relevant to motor imagery tasks, a bandpass filter was applied to the EEG signals. The filter was designed to retain frequencies in the range of 10 to 30 Hz, corresponding to the mu (8-13 Hz) and beta (13-30 Hz) bands. These frequency bands are known to carry significant information related to MI activity. Filtering was performed using a finite impulse response (FIR) filter to minimize phase distortion.

3**. Conversion to CSV Format**

The filtered EEG data was then converted from GDF to CSV format for ease of manipulation and further analysis. This conversion facilitated compatibility with various data processing tools and machine learning frameworks.

4. **Removal of EOG Channels**

The three EOG channels, which primarily capture eye movement artifacts, were removed from the dataset. The exclusion of these channels reduced the dimensionality of the data and ensured that only EEG signals were used for classification.

5. **Normalization**

To ensure consistency across subjects and channels, the EEG signals were normalized. Normalization was performed by scaling each channel's data to a standard range (e.g., zero mean and unit variance). This step helped address inter-subject and inter-channel variability, improving the robustness of subsequent analyses.

6. **Labeling**

The EEG signals were labeled into four distinct classes, corresponding to the four motor imagery tasks: left limb, right limb, tongue, and both feet. This labeling was essential for supervised learning approaches used in subsequent stages of the study.

7. **Class-Specific CSV Files**

The normalized and labeled data was divided into four separate CSV files, each containing the EEG data corresponding to a specific motor imagery class. This segregation facilitated the organization and analysis of class-specific patterns in the EEG signals.

8. **Segmentation**

To prepare the data for input into machine learning models, the EEG signals were segmented into non-overlapping windows of 500 samples each. This window size was chosen to balance temporal resolution and computational efficiency. Each segment was treated as an independent sample, preserving temporal dynamics within each window while allowing the dataset to be used effectively in training and testing pipelines.

## 3.2 Feature Extraction

In this study, a Multi-Scalar Residual Neural Network (ResNet) was employed to extract features from segmented EEG data which is capable of capturing features across multiple receptive fields. Our feature extraction block comes after the preprocessing and segmentation of data. The process of extraction begins at input layer, this layer accepts segmented EEG data with a shape of (500, 22), where 500 is the window size and 22 represents the number of EEG channels. This input data is passed to **Multi-Scalar ResNet Block** where main extraction work takes place. At the core of the model is a ResNet block with three branches, each using different kernel sizes (3, 5, and 7).

These branches extract features at varying scales. Each branch includes two 1D convolutional layers with ReLU activation and batch normalization and a global average pooling layer to reduce the dimensionality of features while preserving spatial information. Once each kernel is processed and information is stored, outputs from all branches are concatenated to form a comprehensive feature representation that incorporates multi-scale information. The concatenated features are passed through a dense layer with 512 units and ReLU activation for further feature refinement. A dropout layer with a rate of 0.6 is applied to prevent overfitting. The final output layer provides a high-dimensional feature vector for each EEG segment, which serves as input to subsequent training and evaluation tasks. In this study the **pairwise** approach is used for feature extraction, training and evaluation purposes where the results of pairwise features are combined. The study is based on a **1D Multiscale + Resnet** model so using pairwise approach with such model enhances the overall performance of the model.

## 3.3 Model Architecture

In this study the model specifically used for feature extraction is the novelty model which is a hybrid of Multiscale and residual networks. This architecture leverages multi-scale feature extraction using parallel convolutional pathways to process information at varying resolution and use of Resnet blocks to avoid vanishing gradient problems, ensuring robust representation of EEG signals. The detailed architecture of the model is depicted in figure-a .

Initially, the model takes in input through the input layer having the shape of (none,500,22) where 500 represents the normal size, and 22 represents the 22 EEG channels. Then the input is passed into 3 different branches of the multiscale model each designed with varying kernel sizes (3,5,7) for convolutional operations. Each branch has 2 consecutive sequential convolution layers, each with Resnet built into them so each convolution block also applies the resnet features to avoid vanishing gradients. The branch one uses a kernel of size 3 which helps apply a convolution to detect short-term patterns in the data. Brach 2 uses a kernel of size 5 which helps detect medium-term patterns in the data and branch 3 uses the kernel of size 7 which captures long-term dependencies and trends in the data. The purpose of the second layer of convolution is to further refine the features by extracting more complex patterns and also by stacking different convolutions, it deepens the model to learn higher-level abstractions. Each branch also uses batch normalization after each convolution which normalizes the activations across a batch to stabilize training and also helps in speeding the convergence process. At the end of all the branches, a global average pooling layer is applied which reduces the spatial dimensions of the feature maps down to a single value per feature map. This helps to reduce overfitting and prevents information loss as it preserves more information by averaging the values in the feature map.

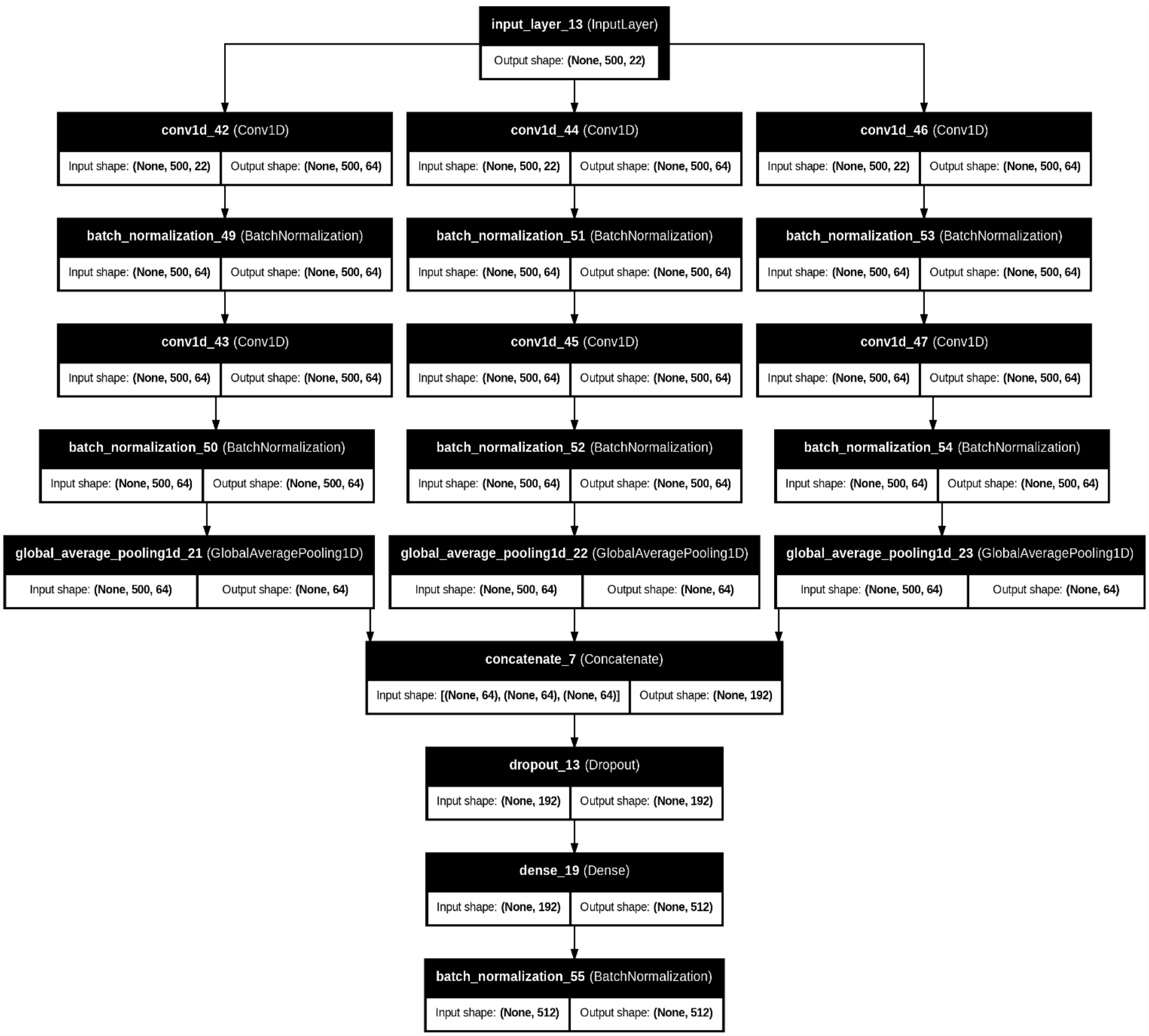


Figure-3.2: Architecture of the Multiscaler + Resnet Model

After all the processing at different branches, the output is concatenated at the concatenation layer to preserve all the relevant information and features extracted by the multiscalar model. The concatenation serves as an implicit multi-path aggregation of features, which embodies the ResNet idea of combining shallow and deep features. The skipping connection part of the Resnet Block is part of the concatenation operation in this model. The concatenated features are passed through a fully connected dense layer which learns high-level features based on the concatenated multiscale features. After this, the feature passes through one more layer of batch normalization to stabilize and generalize the data before transferring it for training and evaluation purposes.

## 3.4 Training and Evaluation

Training and evaluation of models is an important step towards analyzing the model's performance and to verify training of the model to make modifications to achieve optimized results. It helps to decide the scope of different classification models about how much further they can be stretched or modified for good results.

In this model the training and evaluation part starts before the feature extraction part where the train and test split were performed. At this point the segmented EEG data was divided into training and testing sets using an 80:20 split. To ensure balanced representation of all motor imagery classes in both sets, Stratified sampling was used. After the split the feature extraction model extracts features for both training and test sets and only training set features are used for training the binary classifier and test set will be used for evaluation purposes, the earlier division helps to properly evaluate the model for best results. The features extracted using the Multi-Scalar ResNet model generates High-dimensional feature vectors for each segment (500 sized window) and served as inputs to the classifier. These feature vectors were standardized to ensure uniformity across samples.

After these steps the Binary classifier is used which accepts these High dimensional features as input to train the model. The classifier has some hidden layers such as a dense layer with 64 units and ReLU activation followed by a dropout layer (rate: 0.6) to prevent overfitting. After these layers the data is passed to output layer which is a single unit with sigmoid activation for binary classification. The output layer consists of a single neuron (unit). This is because binary classification only requires one output value, representing the probability of the input belonging to one of the two classes. The single unit applies the sigmoid activation function, which maps its input to a value between 0 and 1. This value can be interpreted as probability. If the output probability is greater than a threshold (usually 0.5), the input is classified as belonging to the positive class. Otherwise, it is classified as the negative class (class 0). The binary classifier is specifically used because of the pairwise evaluation process where the 6 different pairs of 4 different classes in constructed using permutation and then training and evaluation of all the 6 pairs is performed. The binary classifier was optimized using the Adam optimizer with a learning rate schedule and early stopping with a patience of 10 epochs to prevent overfitting. This is how the overall training and evaluation is being performed in this model.

### 3.4.1 Inputs to Output Layer of Binary Classifier:

1. **Predictions (*y*^ )**: The output of the sigmoid activation in the range [0,1][0, 1][0,1]. These are probabilities, and a threshold (usually 0.5) is applied to convert them into binary class labels (*y*^binary∈ {0,1}).

2. **Ground Truth (*y*)**: The actual binary labels (y∈{0,1}) for the samples in the dataset.

### 3.4.2 Evaluation Metrics:

In our study the performance of the classifiers was evaluated using the following metrics:

1. **Accuracy:** The proportion of correctly classified samples out of the total number of samples. Accuracy was computed for each binary classification task and averaged across all class combinations.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

2. **Confusion Matrix:** A confusion matrix was generated for each binary classification task to analyze the distribution of true positives, true negatives, false positives, and false negatives.

| | Predicted (y^binary=0) | Predicted (y^binary=0) |
|---|---|---|
| Actual 0 (y=0) | True Negative (TN) | False Positive (FP) |
| Actual 1 (*y=1*) | False Negative (FN) | True Positive (TP) |

Table 3.1: Calculations for Confusion Matrix

Each value (TP, TN, FP, FN) is calculated as:

- TP=Count of (y^binary = 1 and y=1)
- TN=Count of (y^binary = 0 and y=0)
- FP=Count of (y^binary =1 and y=0)
- FN=Count of (y^binary = 0 and y=1)

3. **Precision**: Measures the proportion of true positives among the samples predicted as positive. It is important when false positives are costly.
   Precision = TP / (TP + FP)

4. **Recall**: Measures the proportion of true positives among the actual positive samples. It is useful when false negatives are critical .
   Recall = TP / (TP + FN)

5. **F1-Score**: Harmonic mean of precision and recall, providing a single score that balances both metrics.
   F1 = 2 * (Precision * Recall) / (Precision + Recall)

6. **Learning Curves:** Training and validation loss and accuracy were plotted over epochs to visualize the model's convergence and detect potential overfitting or underfitting.

# CHAPTER 4

## Results and Discussions

In this section, a detailed presentation of findings from the experiments conducted to evaluate the performance of the developed model will be given. The experiment was conducted on 9 different datasets corresponding to the EEG signal of 9 different individuals which was pre-recorded. The results generated were carefully studied for further optimizations and final results will be presented, showing the capability of our novelty model. The subsequent subsections will detail the outcomes of different stages of the model's evaluation, including the performance of individual modules, overall classification results, and analysis of the model's strengths and limitations.

### 4.1 Dataset Description

The Dataset used for evaluations was occupied from the BCI competition website, The specific dataset used is the BCI Competition 4 dataset 2a. This data set consists of EEG data from 9 subjects. The cue-based BCI paradigm consisted of four different motor imagery tasks, namely the imagination of movement of the

- Left Hand (class 1)
- Right Hand (class 2)
- Both Feet (class 3)
- Tongue (class 4)

Two sessions on different days were recorded for each subject. Each session is comprised of 6 runs separated by short breaks. One run consists of 48 trials (12 for each of the four possible classes), yielding a total of 288 trials per session. The dataset is prerecorded for evaluation and training purposes at a sampling rate of 250Hz. It also consists of 3 EOG channels for reference of artifact removal and is not to be used for evaluation purposes.

## 4.2 Performance Metrics

The performance of the proposed Multi-scaler ResNet-CNN model was evaluated for pairwise classification tasks using the BCI Competition 2a dataset. The performance metrics used for the evaluation are the average Accuracy of all the pairs, Precision, Recall, and F1-score. The individual accuracy of each pairwise combination is shown in figure 4.0 for 9 different subjects. The best accuracy achieved by the model is 89.7% for the subject 5. From figure 4.0 we can infer that subject 5 has shown a quite good result with almost all classifications above 90 % accuracy.

| | 1v2 | 1v3 | 1v4 | 2v3 | 2v4 | 3v4 | avg |
|---|---|---|---|---|---|---|---|
| 1 | 100 | 72.6 | 100 | 99.1 | 51.7 | 99.1 | 87.08333 |
| 2 | 100 | 84.4 | 87.1 | 88.7 | 88.7 | 50 | 83.15 |
| 3 | 94.8 | 76.7 | 82.9 | 77.5 | 77.5 | 50 | 76.56667 |
| 4 | 54.7 | 86.4 | 76.7 | 93.8 | 64.4 | 92.2 | 78.03333 |
| 5 | 100 | 97.4 | 94.8 | 97.4 | 99.1 | 50 | 89.78333 |
| 6 | 50 | 54.3 | 65.5 | 50 | 56 | 68.1 | 57.31667 |
| 7 | 100 | 87 | 93.1 | 90.5 | 95.6 | 50 | 86.03333 |
| 8 | 93.1 | 69.8 | 75.2 | 72.4 | 67.2 | 50 | 71.28333 |
| 9 | 50 | 50 | 60.3 | 50 | 61.2 | 51.7 | 53.86667 |

Figure 4.0 : Pairwise accuracy of different classes for 9 subjects

The F1 score calculation comes out to be 0.77% with Precision at 0.80%, having Recall to be around 76% and ROC around 89%. From the above figure, we can infer that the model is highly generalized for different individuals as the average accuracy lies between 70% to 90%, thus at the initial stages the model is performing really well for the motor imager classifications.

## 4.3 Comparison with Baseline Models

| Model | Reported Accuracy | Key Features |
|---|---|---|
| CSP + SVM | 73% | Traditional feature extraction method |
| Shallow Convolutional Neural Network (Schirrmeister et al., 2017) | 76% | A lightweight deep-learning approach |
| Deep ConvNet (Lawhern et al., 2018) | 80% | End-to-end deep learning |
| EEGNet (Lawhern et al., 2018) | 84% | Compact architecture for EEG analysis |
| Proposed 1D Multi-scaler ResNet- CNN | 89% | Advanced spatiotemporal feature extraction |

Table 4.1: Comparison with different baseline models

Based on the comparisons with other models performing motor imagery classifications the results and outcomes of the model are promising and achieve the objective of high accuracy as currently the highest achieved by the model is 89 % which is higher in comparison to some of the other baseline models.

## 4.4 Training and Validation Curves

The Training and validation curves are represented here that are curated in this study based on the performance of the 1D Mutiscalar + Resnet Model.

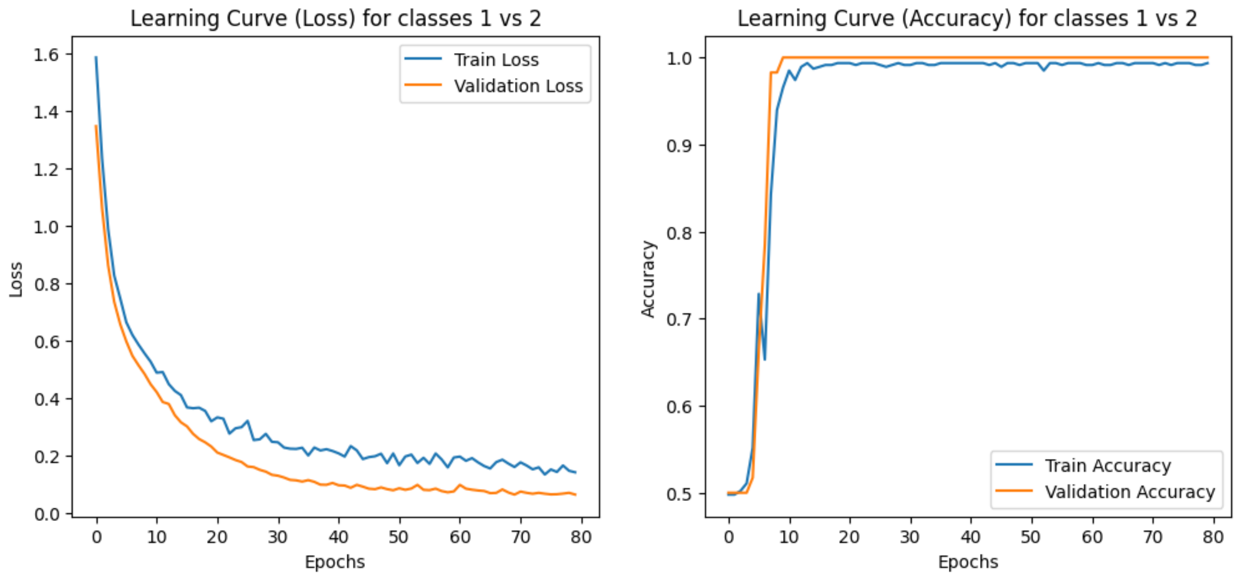


Figure 4.1: Learning Curve for Loss and Accuracy for class pair 1 vs 2.

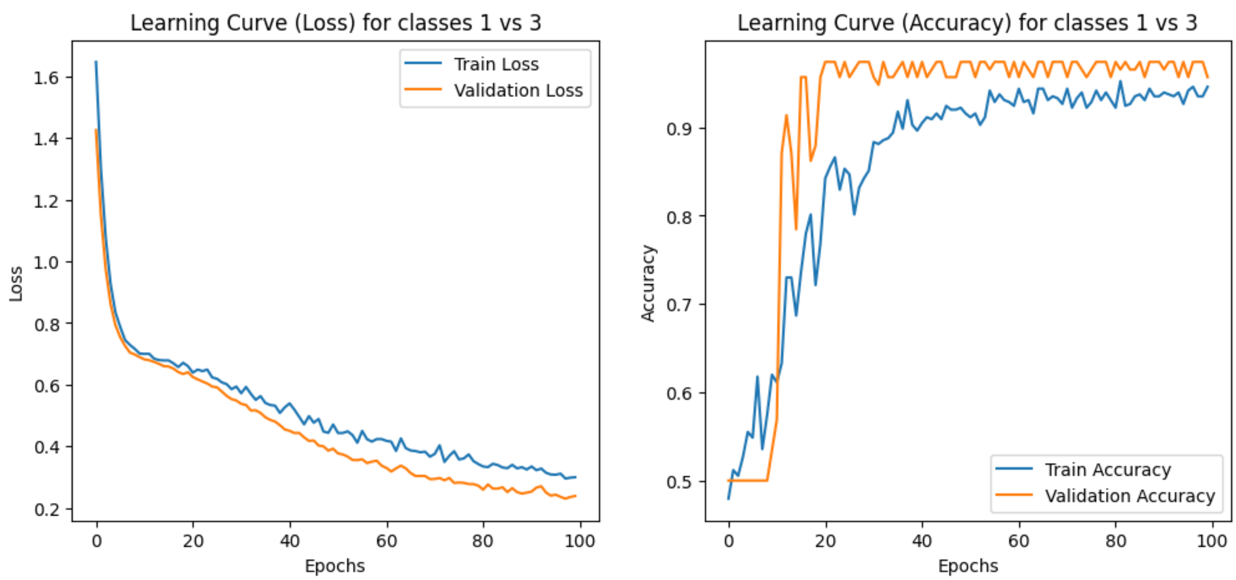

Figure 4.2: Learning Cureve for Loss and Accuracy for class pair 1 vs 3.

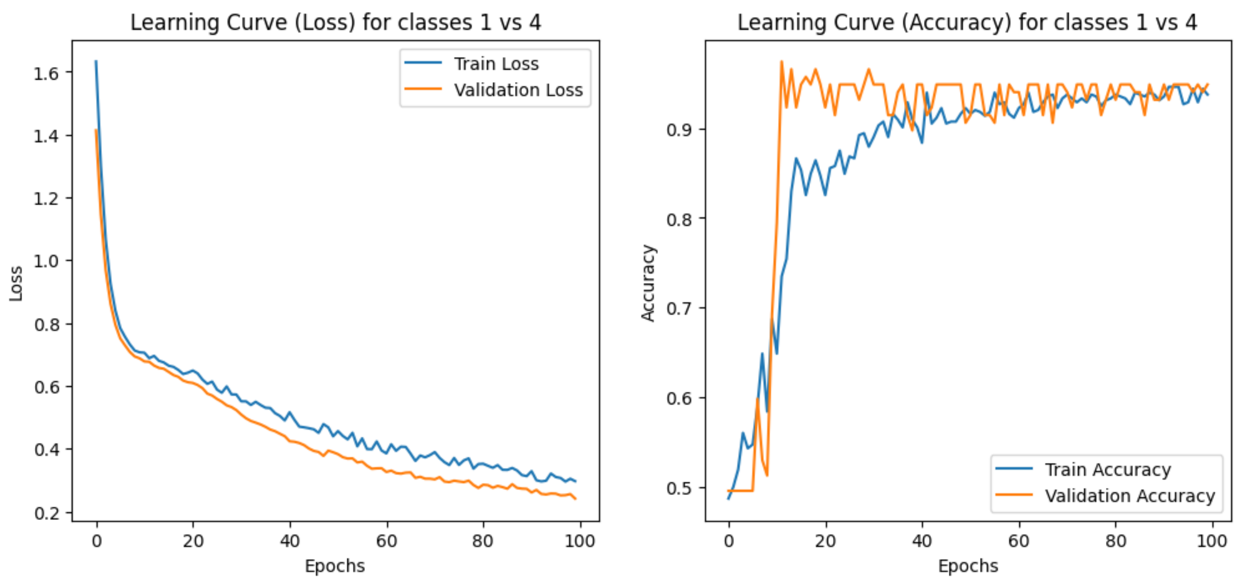


Figure 4.3: Learning Cureve for Loss and Accuracy for class pair 1 vs 4.

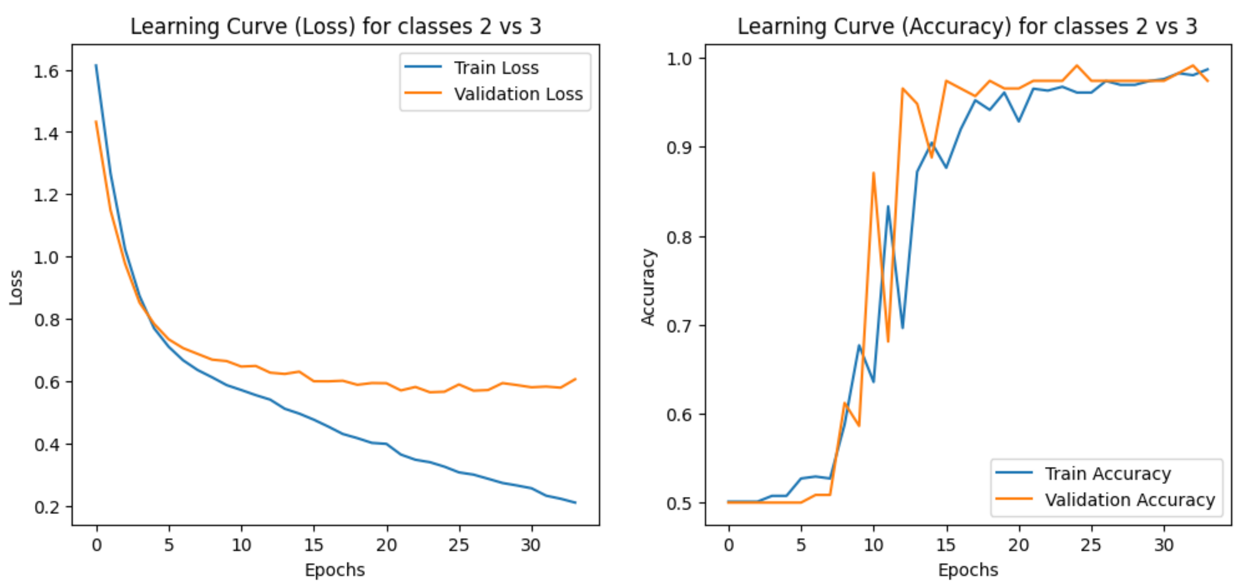


Figure 4.4: Learning Cureve for Loss and Accuracy for class pair 2 vs 3.

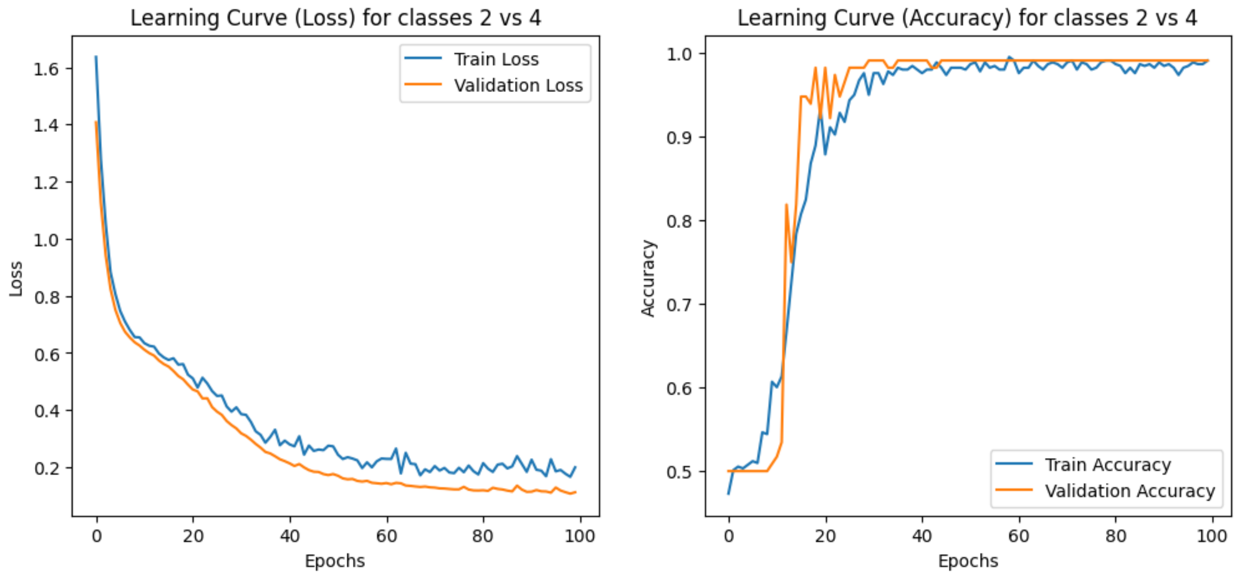


Figure 4.5: Learning Cureve for Loss and Accuracy for class pair 2 vs 4.

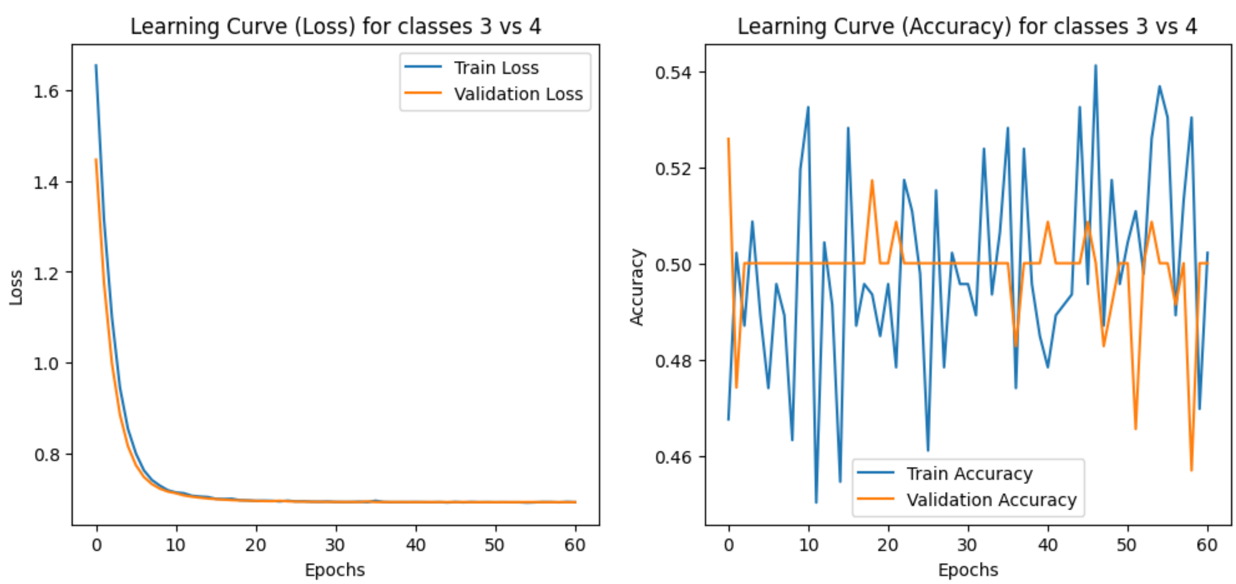


Figure 4.6: Learning Cureve for Loss and Accuracy for class pair 3 vs 4.

## 4.5 Confusion Matrix

This section will include the pairwise confusion matrix for all different pairs of the classes in the dataset.

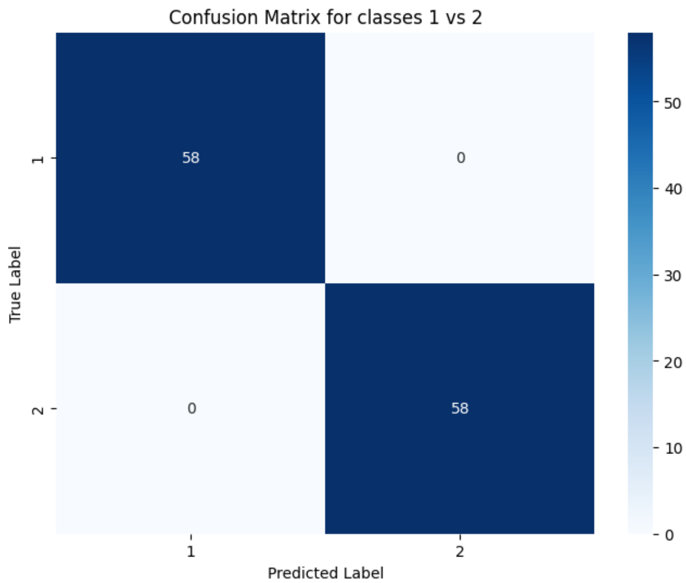


Figure 4.7: Confusion Matrix for class pair 1 vs 2.

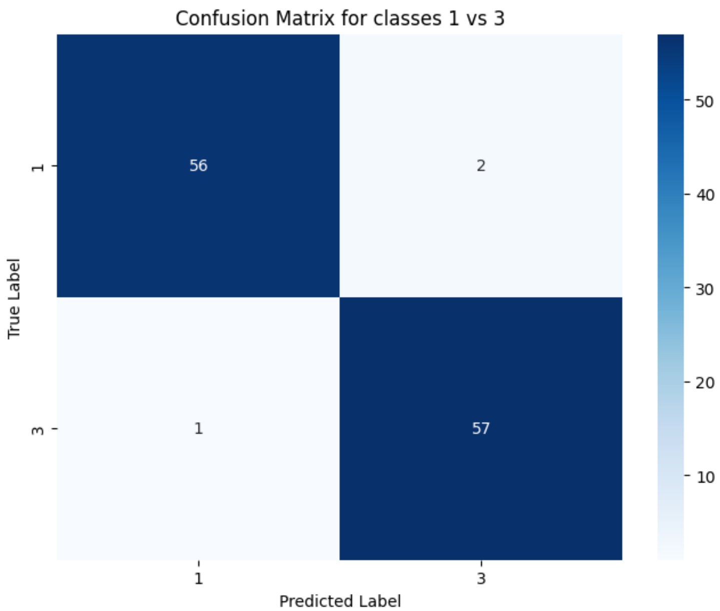


Figure 4.8: Confusion Matrix for class pair 1 vs 3.

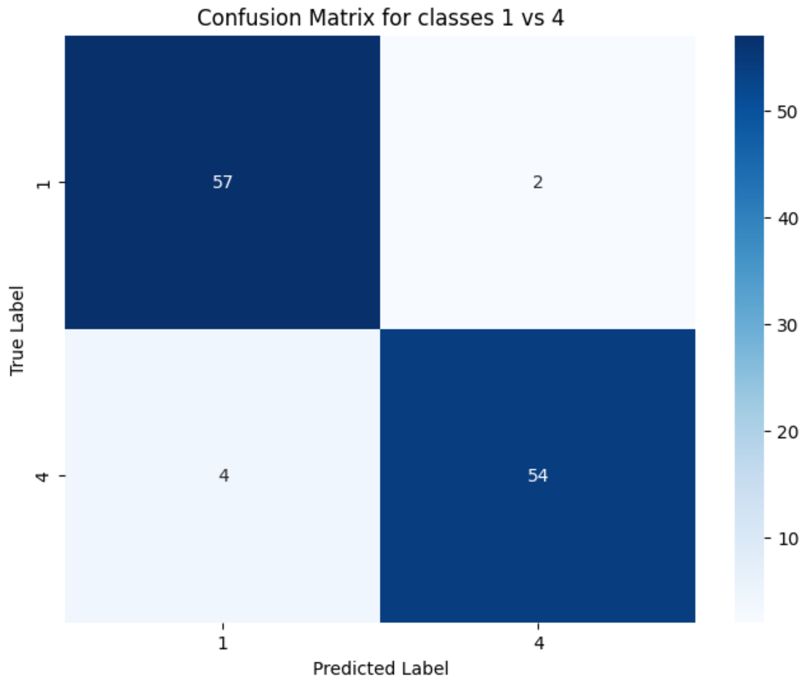


Figure 4.9: Confusion Matrix for class pair 1 vs 4.

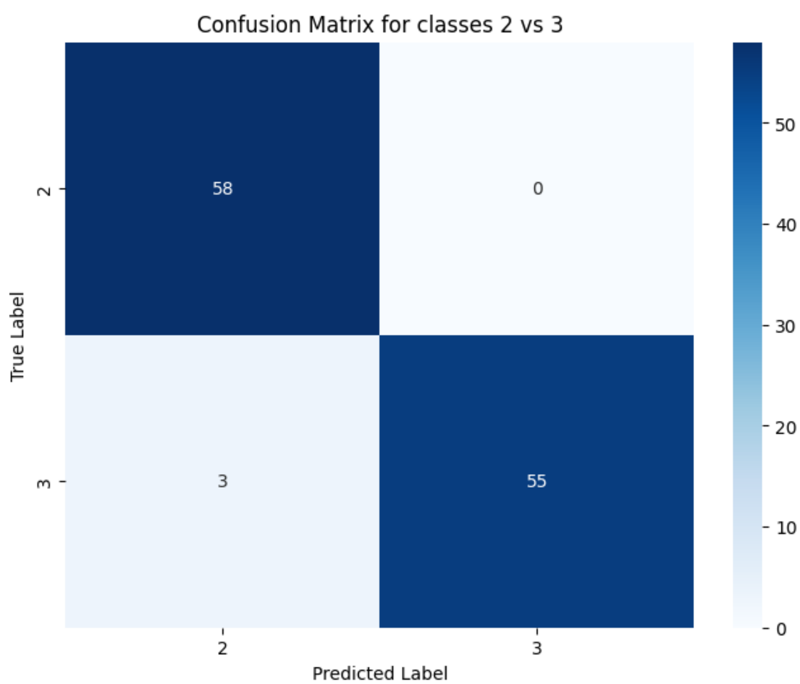


Figure 4.10: Confusion Matrix for class pair 2 vs 3.

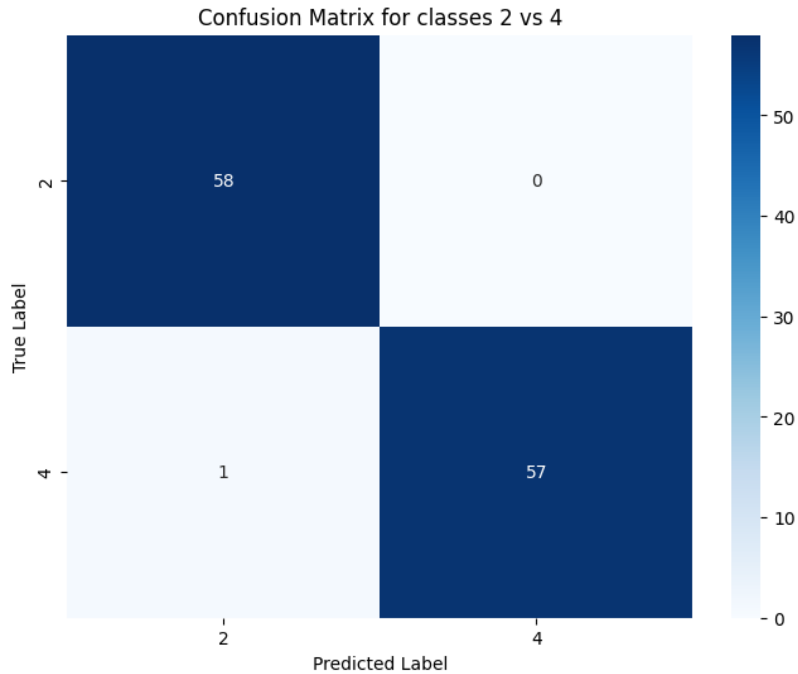


Figure 4.11: Confusion Matrix for class pair 2 vs 4.

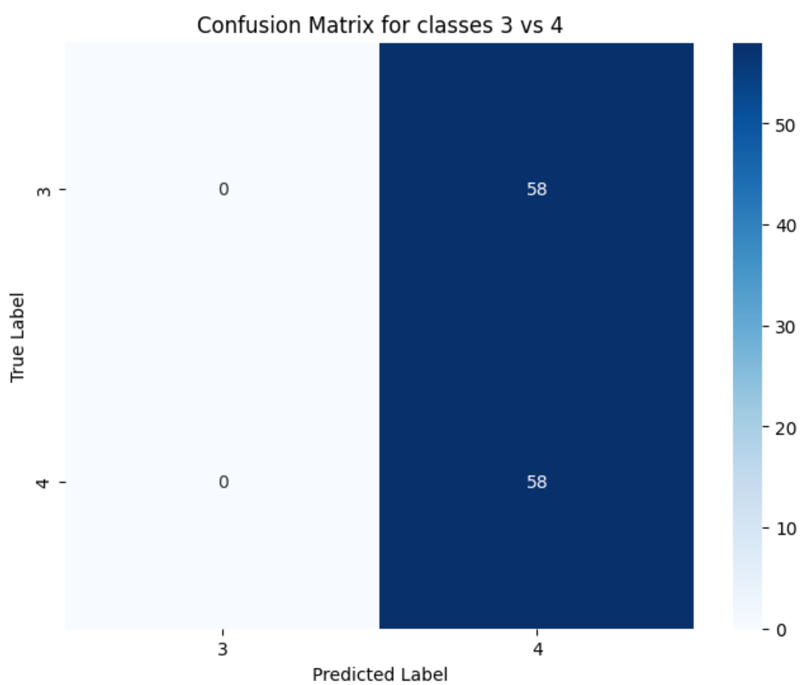


Figure 4.12: Confusion Matrix for class pair 3 vs 4.

## 4.6 Discussion

The model achieved an overall accuracy of 89%, which is a promising result, indicating that the proposed approach is effective in distinguishing between most class combinations. However, a deeper analysis of the results reveals some critical areas for improvement that need to be addressed to further enhance the performance and reliability of the model.

While the overall accuracy is high, the performance of **subject 9** is notably poor. The classification accuracy for subject 9 is significantly lower than other subjects, which suggests that the model struggles to generalize well for this specific subject. This could be due to unique characteristics in the EEG data for subject 9 that the model fails to capture or insufficient representation of subject 9's data in the training process, leading to biased learning.

Also, the models that are performing well have some pairs that are performing poorly example subject 5 has a very poor confusion matrix and learning curve suggesting the model is struggling with that pair for subject 5 and similarly various other subjects face the same problem which can be resolved by further optimizing the model.

While the training accuracy is consistently high, the discrepancy in performance across different class pairs and subjects suggests that the model may be overfitting to certain patterns in the training data. Overfitting reduces the ability of the model to generalize well to unseen data and leads to inconsistent results.

The model demonstrates strong overall performance, but the challenges observed, particularly for subject 9 and certain class pairs—highlight areas where further work is necessary. By addressing issues such as overfitting, class imbalance, and subject-specific variability, the model's robustness and generalization can be significantly improved. Future work will focus on implementing these improvements to achieve more consistent and reliable classification outcomes across all subjects and class combinations.

# CHAPTER 5

# Future Scope and Conclusion

## 5.1 Summary of Contributions

In this research we have made a framework for a motor imaginary Classification using EEG Signals. This Framework uses advanced deep learning Techniques especially a **1D CNN Multi Scale with ResNet** architecture that is using Resnet to improve its performance to extract spatiotemporal features from the EEG data that informs us about the motion of our body. Now this approach that we used has demonstrated some robust classification performance across divorce data sets and we are achieving significant improvements in accuracy compared to the traditional methods that were used. This framework tries to capture the spatial patterns across the EEG channels over time providing a comprehensive representation of the motor imagery tasks.

Now in this we have applied preprocessing of data which includes bandpass filter, normalization and we are also segmenting it into smaller windows all this ensures the quality of the input data. By doing all this we are enhancing the model's ability to generalize across diverse datasets which is mitigating the variability inherent by the EEG signals. The performance of multi scale was good but the integration of ResNet's skip connections had further optimize the model by addressing the vanishing gradient issue due to this the model had improved the feature extraction and classification accuracy

Our experimental results are demonstrating that the proposed framework significantly outperforms some of the traditional methods such as Common Spatial Pattern (CSP) and support vector machines (SVMs) through which the features were extracted and classified with a low accuracy and robustness. And therefore, it makes it very suitable for practical implementation in neuro prosthetics and brain computer interface (BCIs), where timely and accurate motor imagery classification is critical.

Now this model not only advances the state of art motor music classification but also Set the stage for future elephants to improving remotely in assistive technologies. Now by addressing the limitations of existing approach and demonstrating the potential for real world integration this research paves the way of enhanced systems of neuro prosthetic and more accessible BCI solutions

## 5.2 Limitations

Now while our framework demonstrates promising results there are certain limitations that are stopping it from performing on the best level of robustness and applicability. One key challenge lies with the variability across different EEG datasets that is every data set of a different person can vary very much due to which our models performance is significantly influenced EEG signals are inherently non stationary making it difficult to achieve some consistent results This underscores the importance of developing more robust data preprocessing techniques to ensure some reliability or uniformity across these diverse data sets

Another critical issue can be the sensitivity of framework to noise and artefacts that are usually present in raw EEG signals the Artifacts can be such as muscle activity, eye blinks or some external interference that can hide or obscure the meaningful patterns that we are looking for, Due to this the classification accuracy can be decreased a lot. Now while bandpass filtering and artifact rejection was employed in this model to help in improving this, we need to research further into using more sophisticated noise reduction techniques which could mitigate the effects of these noise more and improve the model's resilience to noise inputs

Now as we are using a very big data set that uses time-based inputs, the computational complexity is very high for this framework, which is another limitation especially when we are scaling for real time applications. While the Multi Scale ResNet architecture is effective in capturing these Spatio-temporal features it still requires some substantial Processing power and memory which is a very big constraint in a resource limited environment. We can try to add some of the optimization strategies such as model pruning quantization or some lightweight architecture which can be explored to reduce the computational burden but without compromising the performance

Finally, We feel that the reliance on specific hardware configurations like we need high performing GPUs and CPUs which hinders the adoption of this framework on a much larger scale. Because many of the potential users, especially the in clinical fields or using an assistive setting may not have these resources that are required to work with this framework. Addressing these limitations will require designing models that are compatible with more general-purpose hardware, or we can also try leveraging cloud-based processing to ensure broader accessibility.

These Limitations that we listed highlight the need to continue the research and development of this framework to refine and address the current constraints. Overcoming these challenges would be very crucial for translating the result of the model into real-life applications such as the neuro prosthetics and brain computer interfaces

## 5.3 Future Scope

We have created a base for any future research and development as our model has some limitations as discussed before. Addressing these limitations can help to enhance the framework's practical applicability and extend its utility in real world scenarios. The main field we are focusing on developing is to make the model better for dynamic environments such as neuro prosthetics control or brain computer interface applications. This development should involve optimizing the computational efficiency of the model through techniques like model pruning, Quantization and hardware acceleration to ensure compatibility to cope up with the less performing hardware

Exploring the techniques of advanced neural network architecture can help making the model perform better and faster can be a part of future work. By adding architectures such as lightweight convolutional networks, transformer-based models, or graph neural networks (GNNs) could give improved feature extraction and classification results by maintaining the computation efficiency. These models can also enhance the current model to better capture and the complex Spatio-Temporal data of EEG.

We also need to develop a noise-resilient model to enhance the robustness of the framework. This can include employing some advanced noise-reduction techniques like adaptive filtering, generative adversarial networks (GANs) for artifact removal, or self-supervised learning to handle the noisy datasets. This can help our model to operate efficiently in less controlled environments where EEG Signal are more subject to significant noise and interference.

To make our model work on more General and robust features, we can incorporate a broader range of dataset representing diverse population, tasks performed, and the recording conditions. By expanding the diversity of the dataset, we can mitigate the effects of inter-subject and inter-variability ensuring that the model performs reliability across a wide set of test cases.

By addressing these areas mentioned above, future research can build on the current framework's foundation, advancing its capabilities and impact in the field of neuroscience, Assistive Technology, and BCI.

## 5.4 Conclusion

This research makes significant contribution to analyze the EEG signal, by introducing and the innovative methodologies that address critical challenges in motor imagery classification. This is done by implementing advanced deep learning techniques like 1D CNN Multi Scale with ResNet architecture, our study has successfully demonstrated robust spatio-temporal feature extraction and classification, making a new benchmark for accuracy and efficiency in EEG based system. Our model lays the groundwork for practical applications in BCI and Neuro prosthetics, this enables the development of systems that are not only accurate but also more adaptable to real world scenarios.

The methods that are employed in this research provide a strong foundation for future explorations in spatio-temporal EEG signal analysis. By adding advanced preprocessing techniques and neural architecture we reduced the variability of data and the noise present in it for better results. This work shows the importance of scalability and generalization for broader adaptation of EEG based technologies and assistive applications.

Despite its giving limitations, such as sensitivity to noise and computational complexity, the research advances the practical use of EEG in assistive technologies. By addressing these challenges, we are paving the way for more accessible, and real time neuro-controlled devices. This works not only contributes to the academic understanding of EEG signal processing but also serves as a steppingstone towards creating an impactful solution for individual with motor impairments, enhancing their quality of life

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