19L038 – DEEP LEARNING

MOTOR IMAGERY EEG CLASSIFICATION - IDENTIFYING REST VS. ACTIVE STATES WITH CONVOLUTIONAL NEURAL NETWORKS

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Project report submitted in partial fulfillment of the requirements for the degree of

BACHELOR OF ENGINEERING

Branch: ELECTRONICS AND COMMUNICATION ENGINEERING

of Anna University

OCTOBER 2024

PSG COLLEGE OF TECHNOLOGY

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1. OBJECTIVES

To develop a CNN model to accurately distinguish between active motor imagery states and resting states from EEG data.

To implement effective data preprocessing and segmentation to improve EEG signal clarity and overall classification accuracy of the CNN model.

2. EEG (ELECTRO ENCEPHALO GRAM)

EEG is a non-invasive technique that uses electrodes placed directly on the scalp to measure the electrical fields generated by the joint activity of populations of neurons located in the outer layers of the brain

Brain cells communicate via electrical impulses, and this activity shows up as signals on an EEG recording

As a rule-of-thumb, non-synchronous neural activity gives rise to fast (high frequency), low amplitude waves, while synchronized neural activity yields slow (low frequency), high amplitude waves.

3. DATASET

EEG Motor Movement/Imagery Dataset - A set of 64-channel EEGs from subjects who performed a series of motor/imagery tasks has been contributed to PhysioNet by the developers of the BCI2000 instrumentation system for brain-computer interface research.

The experiments were performed on 109 subjects. Here we consider only 2 subjects.

There are 11 class labels in total, capturing different motor states:

Classes 0-9 represent various active states, including physical and imagined movements of eyes, hands, fists, and feet.

Class 10 represents a resting state with no active or imagined movement.

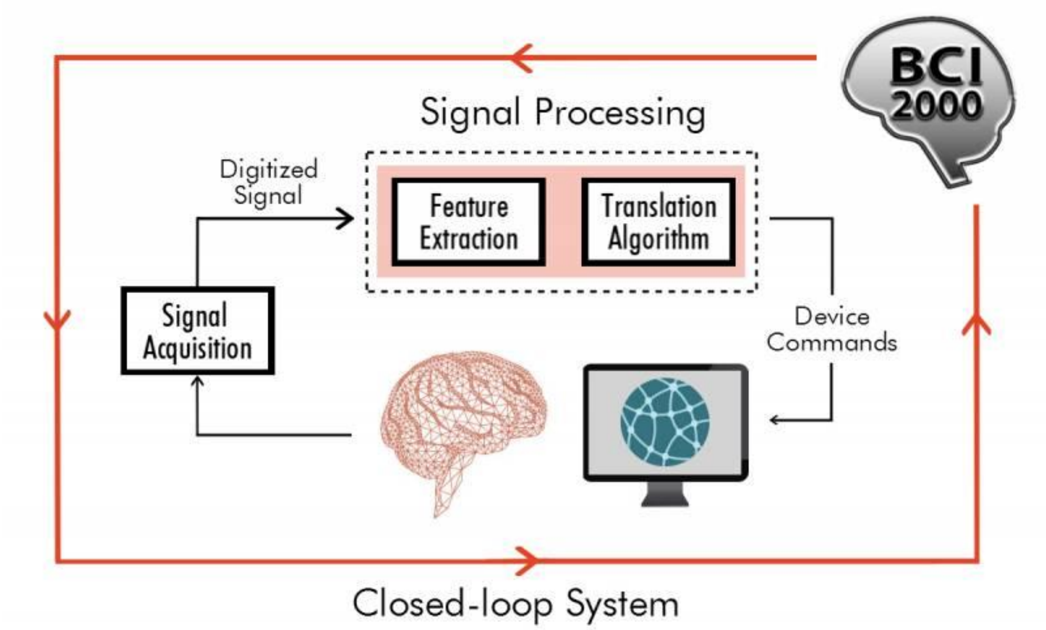

Fig 1 : BCI 2000 System

Shape of the dataset (comprising data of subjects 1,2) [515200, 65]

- 515200 experimental runs/samples
- 64 features per sample (sampled output signals of the 64 channels) and the last column (65th column) comprises of the labels corresponding to the 64 features

Sample count of each label/class

- y: {0: 19520, 1: 19520, 2: 30992, 3: 28288, 4: 30992, 5: 28288, 6: 30336, 7: 28944, 8: 28864, 9: 30416, 10: 239040}

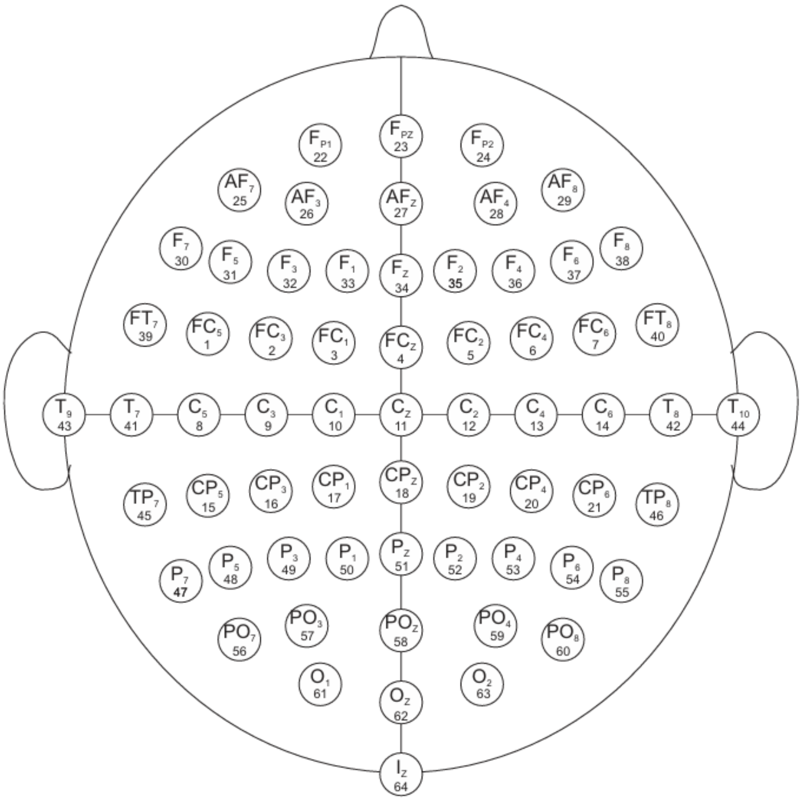

Fig. 2 : Channel Sharbrough

4. DATASET PREPROCESSING

The dataset is structured to train a binary classifier model aimed at predicting whether a person is engaged in physical/imaginary movement (class 0) or is in a state of complete rest (class 1)

Feature_1	Feature_2	Feature_3	Feature_4	Feature_5	Feature_6	Feature_7
24	44	31	46	27	22	32
-5	-46	-40	-14	-63	-42	-32
161	164	275	284	161	226	82
-39	-34	-26	-41	-39	-46	-49
48	48	101	125	68	80	24
2	-44	-74	11	-67	-49	-31
-43	-27	-35	-40	-43	-18	-2
-83	-32	-4	-87	-46	-136	90
-44	-35	-11	1	33	40	35
-73	-91	-93	-92	-75	-63	-46

Feature_64	Label
55	0
-12	0
101	0
105	1
-5	0
-12	1
-194	1
-56	1
-13	1
-28	0

Fig 3 : Restructuring Class Labels

Sample count after grouping labels 0 to 9 into Class 0 and label 10 as Class 1

- y: {276160, 239040}

Feature_1	Feature_2	Feature_3	Feature_4	Feature_5	Feature_6	Feature_7
-2.44344	-1.84066	-1.06494	-2.23324	-1.31837	-2.35414	0.001883
0.208648	-0.45768	0.285336	-0.93564	-1.3694	-0.92865	-0.53208
0.699776	0.662711	0.523619	0.500984	0.814585	0.711524	1.0612
-0.20692	-0.17758	-0.06848	-0.00106	-0.28761	-0.06133	-0.0584
0.185981	0.163787	0.02539	0.076176	-0.14474	0.101826	0.122456
0.752667	0.443885	0.581385	0.555051	0.16143	0.419556	0.837279
-1.9372	-0.91284	-0.46562	-0.95881	-0.88974	-0.70538	-1.54834
-0.25226	-0.26511	-0.51616	-0.43359	-0.78769	-0.02698	-0.74739
0.117978	0.268823	0.53084	-0.09375	0.100197	0.333683	0.621971
-0.01803	0.006232	-0.09014	-0.16326	-0.16515	-0.09568	-0.17898

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Feature_64	Label
-3.29212007	0
0.31613271	1
0.33517362	1
0.04955994	1
1.15393282	1
0.10668268	0
-1.53083573	0
0.85879869	1
-0.51214695	0
-0.11228781	0

Fig 4: Normalisation of the Dataset

StandardScaler (Scikit-Learn) normalizer is applied on the dataset to standardize the features

Scales each feature to have a mean of 0 and standard deviation of 1

Test Set Size = 10% of Training Set

5. 2D CNN ON MULTIVARIATE TIME SERIES DATA

CNNs are ideal for learning spatial and temporal patterns in multivariate EEG data, allowing the model to capture intricate relationships between channels and across time.

The 2D convolutional layers effectively handle the high-dimensional structure of EEG signals.

By using CNNs, we leverage a powerful architecture capable of extracting robust features from noisy EEG data.

6. TEMPORAL WINDOWING EXAMPLE ILLUSTRATION

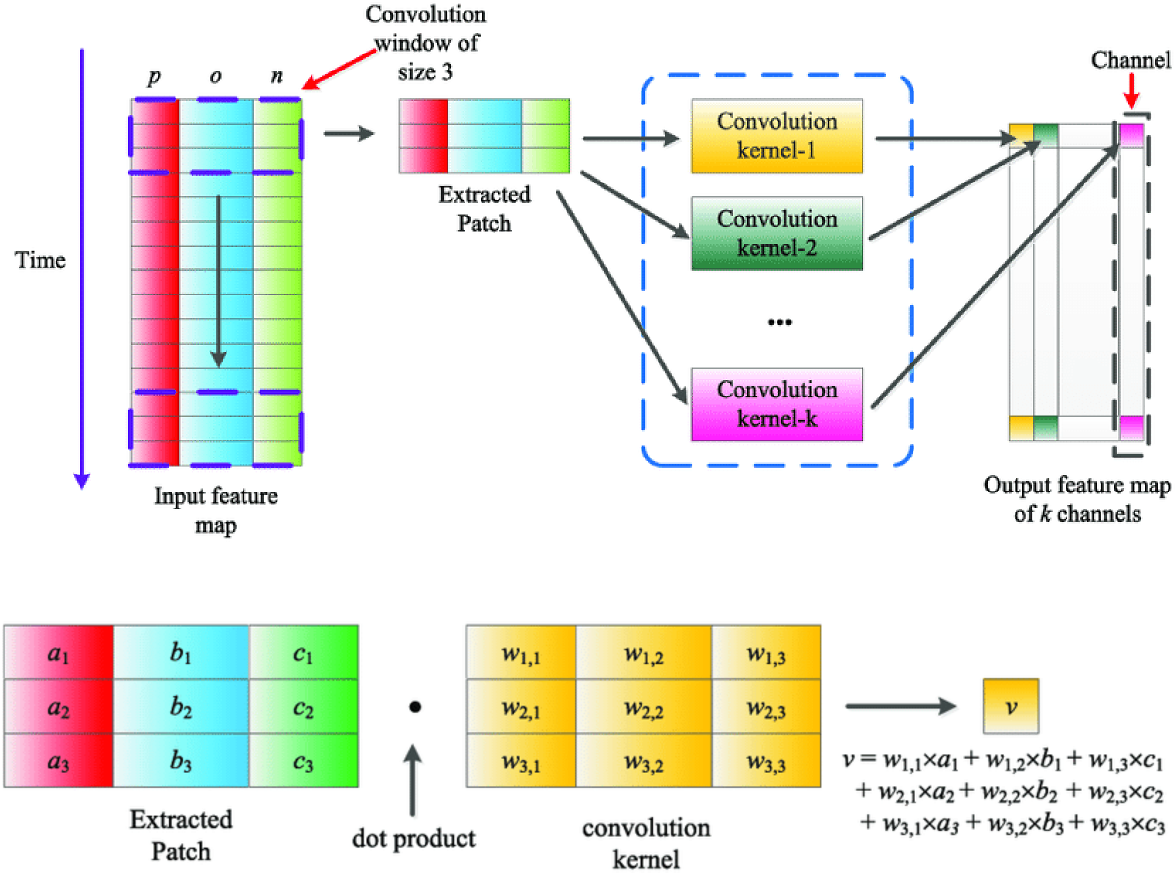


Fig 5: 2D convolution operation on a multivariate time-series dataset

7. TEMPORAL WINDOWING AND LABEL AGGREGATION

Applying the sliding window technique to segment the EEG data into overlapping time windows, capturing temporal dynamics in the data.

- Window size = 24
- 50% Overlapping (Step size = 24/2 = 12)

Calculating the average of labels within each window to create a representative label for the window, especially useful in tasks where activities are continuous.

Dataset Shape Transformation: (515200, 65) ⟶ (42932, 24, 64, 1)

[42932 windows, 24 samples per window, 64 features per sample and 1 class label per window]

8. TRAINING THE CNN MODEL

The architecture is as follows:

Table 1: CNN Architecture

Layer Type	**Output Shape**	**Parameters**
Conv2D	(None, 24, 64, 16)	144
ReLU	(None, 24, 64, 16)	0
MaxPooling2D	(None, 12, 16, 16)	0
Conv2D	(None, 12, 16, 32)	2,080
ReLU	(None, 12, 16, 32)	0

MaxPooling2D	(None, 6, 8, 32)	0
Flatten	(None, 1536)	0
Dense	(None, 128)	196,736
Dropout	(None, 128)	0
Dense	(None, 2)	258

9. HYPER PARAMETERS

The following are the hyperparameters used:

- Convolution Filter (Kernel) Size = (2,4) and Stride = 1
- Max Pooling Filter (Kernel) Size = (2,2)
- Binary Softmax Output – 2 neurons in the Final Dense layer
- Loss Function – Sparse Categorical Cross Entropy Loss
- Adam Optimizer
- Learning Rate = 0.001
- Batch Size = 128 and Total no. of Epochs = 40

10. RESULTS AND ANALYSIS

Table 2: Training Set Classification Report

Class	Precision	Recall	F1-Score	Support
Class 0-9	0.98	0.99	0.99	20818
Class 10	0.99	0.98	0.98	17820
Accuracy			**0.98**	38638
Macro Avg	0.98	0.98	0.98	38638
Weighted Avg	0.98	0.98	0.98	38638

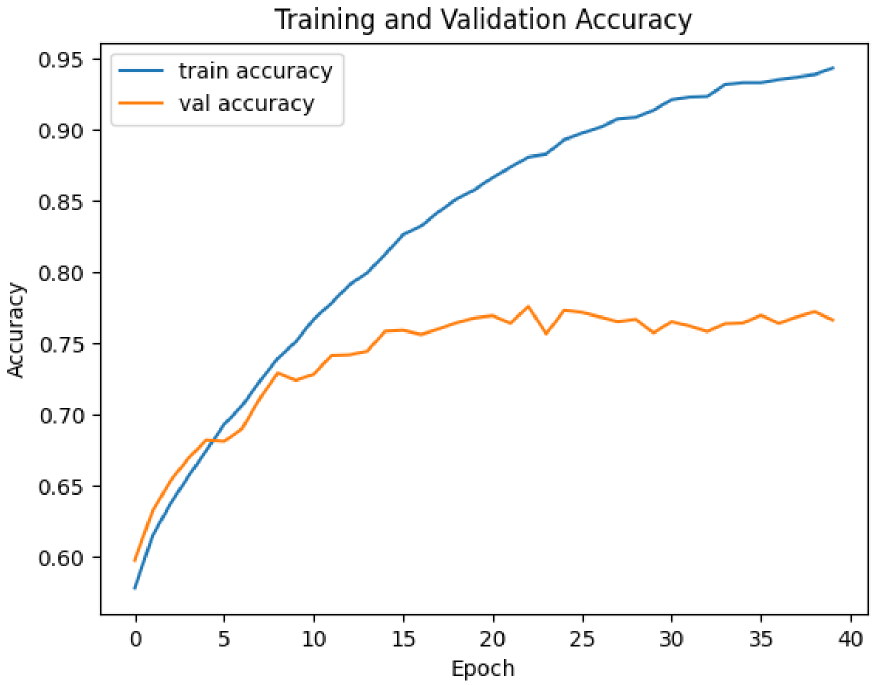
The f*inal Training Set accuracy – 98%*

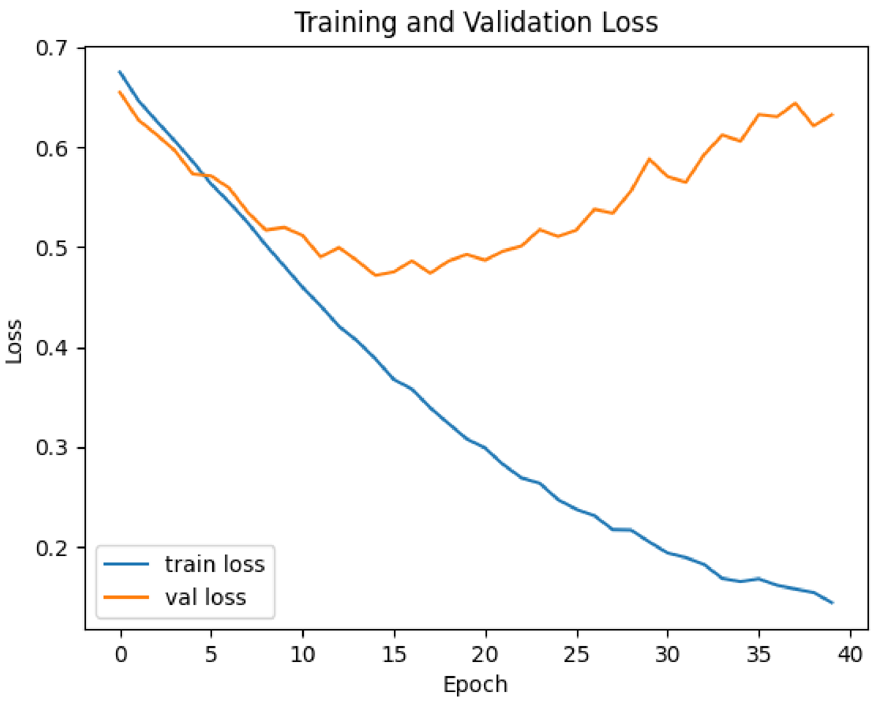
Table 3 : Validation Set Classification Report

Class	Precision	Recall	F1-Score	Support
Class 0-9	0.77	0.8	0.79	2314
Class 10	0.76	0.73	0.74	1980
Accuracy			**0.77**	4294
Macro Avg	0.77	0.76	0.76	4294
Weighted Avg	0.77	0.77	0.77	4294

The final Validation Set accuracy – 77%

The validation set comprises 10% of the original dataset. The samples were selected randomly and model gives 77% accuracy on this unseen dataset.


Training and Validation Accuracy
train accuracy
val accuracy
Accuracy
0.95
0.90
0.85
0.80
0.75
0.70
0.65
0.60
0
5
10
15
20
25
30
35
40
Epoch


Training and Validation Loss
train loss
val loss
Loss
0.7
0.6
0.5
0.4
0.3
0.2
0
5
10
15
20
25
30
35
40
Epoch

12. CONCLUSION

This project developed a CNN model to classify EEG data, effectively distinguishing between motor imagery/physical movement and resting states.

The approach utilized windowing techniques and data preprocessing to enhance model performance, achieving high classification accuracy on the training and test set.