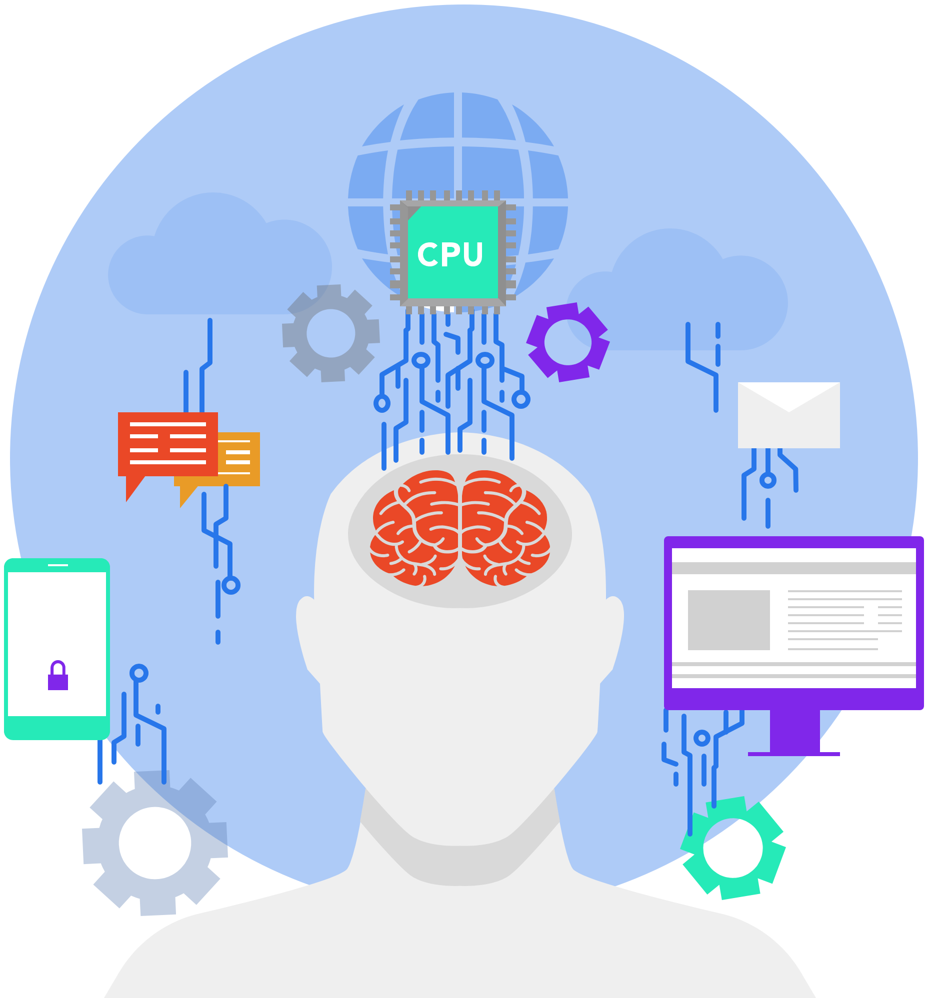

Mini Project Advanced Machine Learning

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Agenda

01 Dataset Overview & Task

02 Data Preprocessing Pipeline

03 Evaluation & Visualizations

04 Comparing Architectures

05 Conclusion

Dataset Overview

EEG Motor Movement/Imagery Dataset (PhysioNet, 2009)

109 subjects

160 Hz sample rate

64 channel EEG

Tasks

- T1 (open and close left or right fist)
- T2 (imagine opening and closing left or right fist)
- T3 (open and close both fists or both feet)
- T4 (imagine opening and closing both fists or both feet)

3 Runs (R04, R08, R12) per Task
90 Trails {T0,T1,T2} per Subject
~ 9810 Trails in DB

Classification Goal

Objective:

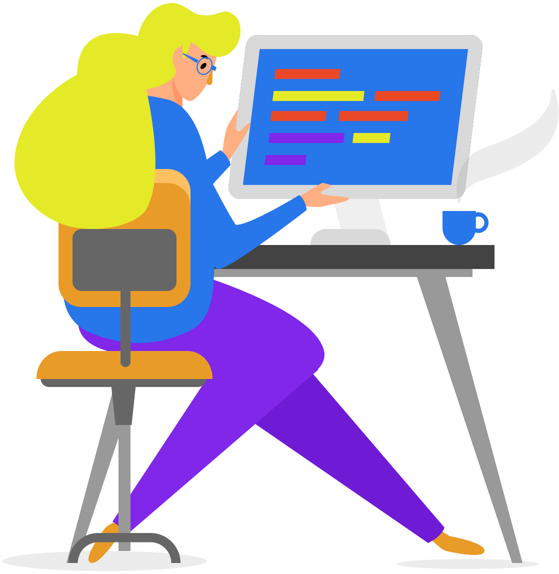
Predict which hand (right/left) the subject imagines moving **based only on EEG signals**

Binary classification

- Class 0 → Imagined Left Fist (T1)
- **Class 1 → Imagined Right Fist (T2)**

❗ **Idle (T0) removed** → model learns only motor imagery

Data Processing Pipeline



01 Load EDF

Runs: R4, R8, R12

02 Bandpass Filter (4–40 Hz)

μ (8-13Hz) and β (13-30Hz) rhythms - Motor

03 CAR (Reference)

subtracts the mean activity across all channels

04 Epoching (4s)

extracting 4-second windows (T0, T1, T2)

05 Normalize

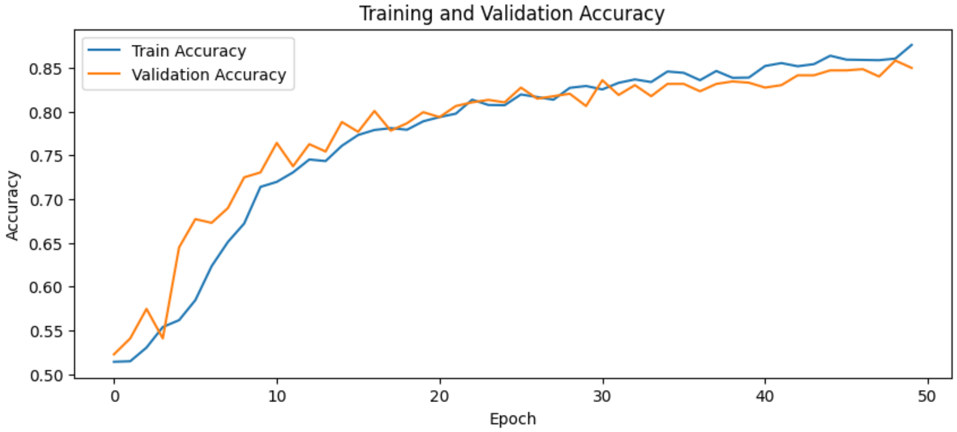
per channel within each trial
Prevents learning subject specific patters

06 Split by Subjects

80% train, 10% validation, and 10% test

Evaluation and Visualisations

Evaluation - EEG

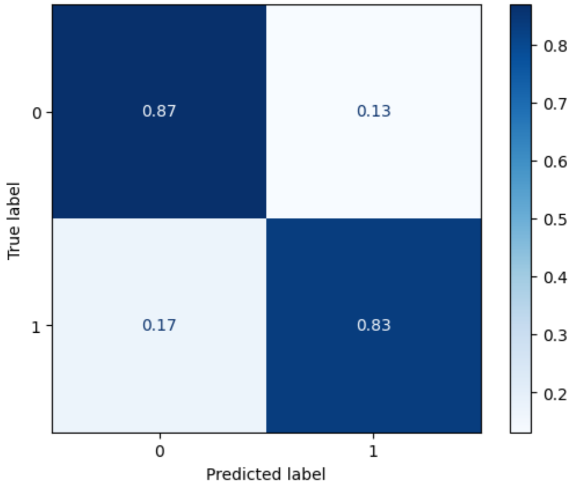


Hyperparameters:

Dropout rate: 0.5
Learning rate: 0.001
Batch size: 64

Evaluation - EEG

EEGNet Confusionmatrix

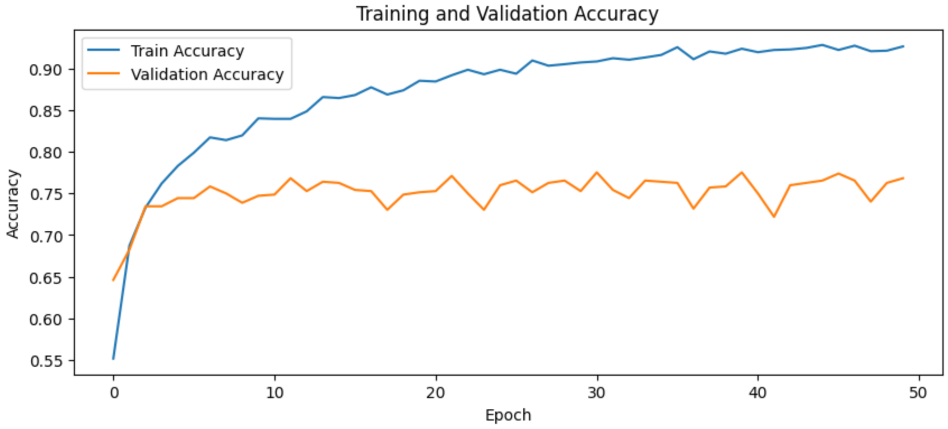


Accuracy: 0.85

Recall: 0.83

Precision: 0.86

Evaluation - ShallowNet

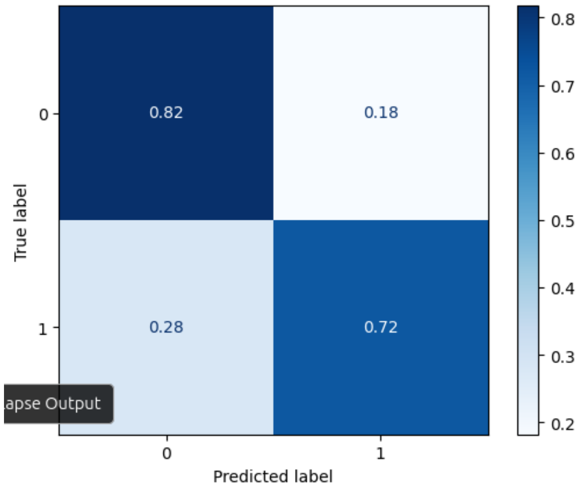


Hyperparameters:

Dropout rate: 0.5
Learning rate: 0.001
Batch size: 64

Evaluation - ShallowNet

ShallowNet Confusionmatrix

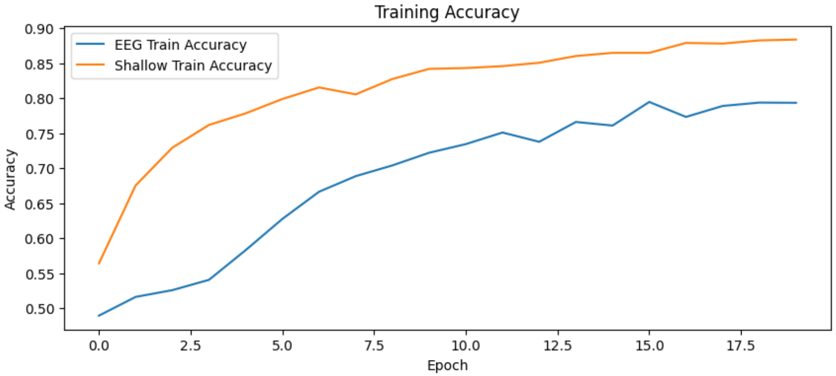


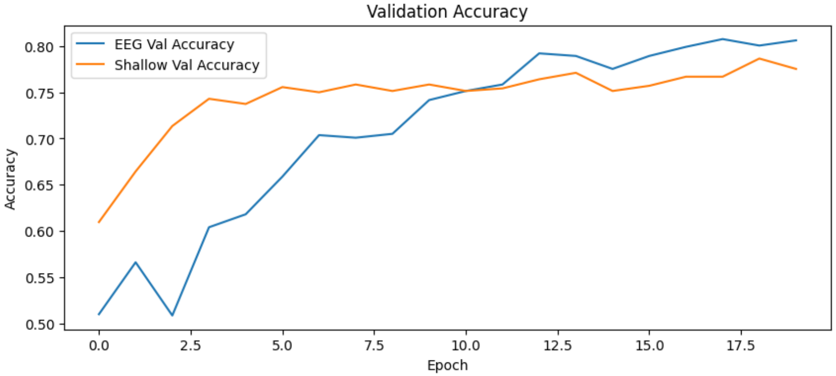
Accuracy: 0.77

Recall: 0.7

Precision: 0.8

Comparison EEG - Shallow





	EEG	Shallow
Accuracy	0.85	0.77
Recall	0.83	0.7
Precision	0.86	0.8

Architecture Comparison

Architecture Comparison - Similarities

- EEG classification task
  - Small datasets
  - Time-series as input
- First block follows FBCSP pipeline
  - Temporal Convolution
  - Spatial (Depthwise) Convolution

Figure 1

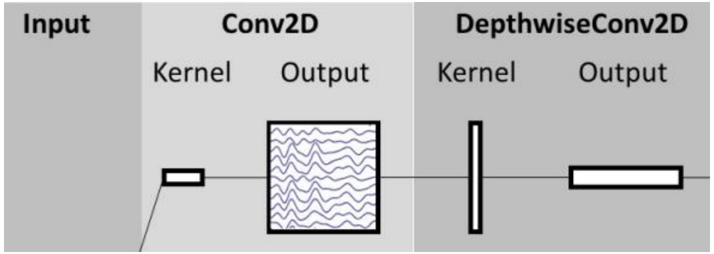


Figure 2

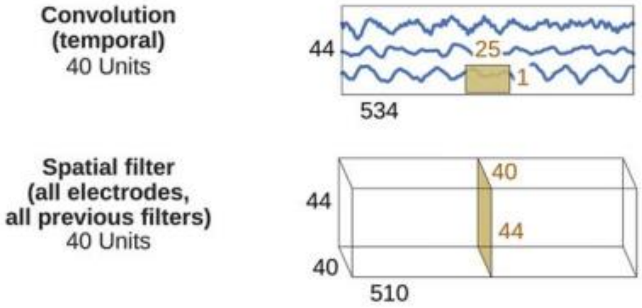


Figure 1. Overall visualization of the EEGNet architecture. EEGNet: A Compact Convolutional Neural Network for EEG-based Brain-Computer Interfaces, Lawhern et. Al (2018)

Figure 2. Shallow ConvNet architecture. Deep Learning with Convolutional Neural Networks for EEG Decoding and Visualization, Schirrmeister et. Al (2017)

Shallow ConvNet Architecture

- Sticks to FBCSP workflow
  - Square + pooling + log
- Temporal kernel considers ~100 ms worth of input
- 40 Filters each for temporal and spatial
  - Results in many parameters
  - 103040 weights in our case

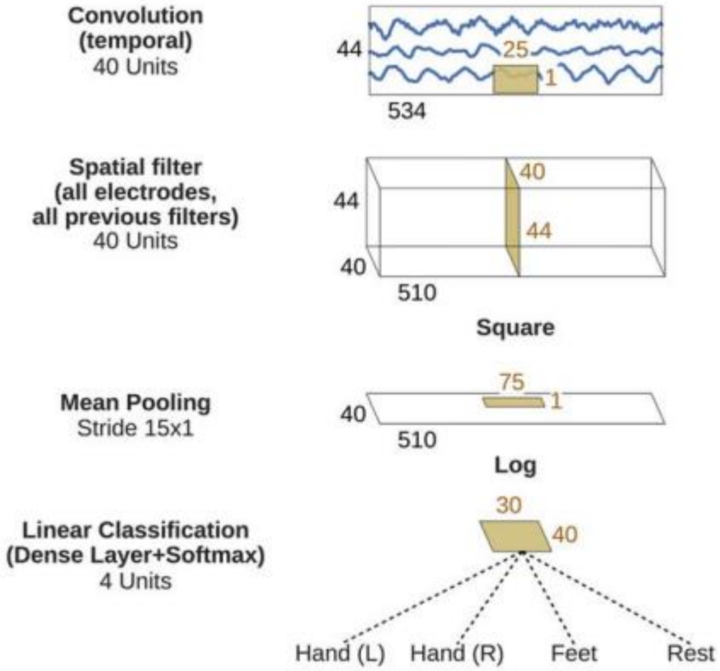


Figure 2. Shallow ConvNet architecture. Deep Learning with Convolutional Neural Networks for EEG Decoding and Visualization, Schirrmeister et. Al (2017)

EEGNet Architecture

- ELU + pooling
  - Generalizable
- Temporal Kernel considers ~500ms worth of input
- Only 4 (or 8) temporal filters with 8 (or 16) spatial filters
  - 768 (or 1536) parameters
- Adds Separable Convolution
  - Depthwise + Pointwise
  - 192 (or 512)
  - Allows deeper nets with few weights

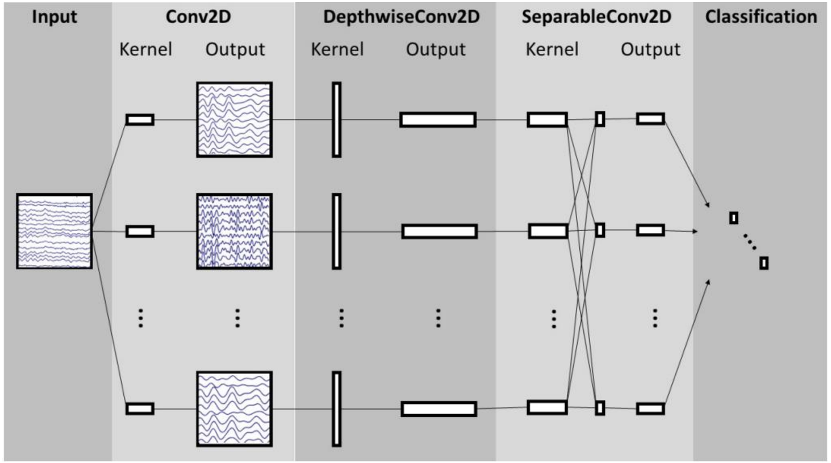


Figure 1. Overall visualization of the EEGNet architecture. EEGNet: A Compact Convolutional Neural Network for EEG-based Brain-Computer Interfaces, Lawhern et. Al (2018)

CONCLUSION / OUTLOOK

- K-Fold data splitting
  - Improve robustness of model
- Hyperparameter optimization
  - Grid search
- Compare different tasks
  - Imaginary vs real individually trained
  - Trained on combined tasks

Q & A

THANK

YOU