Harmful Brain Activity Classification (HMS)

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Background

Purpose:

- Develop a model to accurately detect neurological disorders using EEG and spectrogram patterns.

Vision:

- Early prediction and better treatment of neurological disorders.
- Enhanced accuracy in interpreting EEG imaging.

Problems

Significant Discrepancy:

-> Average seizure prediction by 119 annotators: 18.8%

Collected data visualization

Need for Expert Training!

Motivations

Expertise is Crucial:

- Experts provide more accurate annotations.
- Reducing misclassifications by focusing on expert data.

Current Challenges:

- Manual EEG analysis is labor-intensive and prone to errors.
- Automation can enhance speed and reliability.

Review of Related Works

Hasan et al. (2020): (Deep Learning Techniques for Electroencephalogram (EEG) Signal Analysis: A Review)

- Relevance of CNNs for tasks involving image data.

Tabar and Halici (2017): (Deep Learning Approaches for EEG Signal Classification: A Review)

- Emphasis on CNNs for capturing spatial dependencies.

Fatourechi et al. (2007): ("EEG-Based Brain-Computer Interface: Active Mental Tasks Classification Using Wavelet Features and Bayesian Approach")

- Classification using wavelet features and Bayesian methods.
- Insights into evaluation metrics and experimental design.

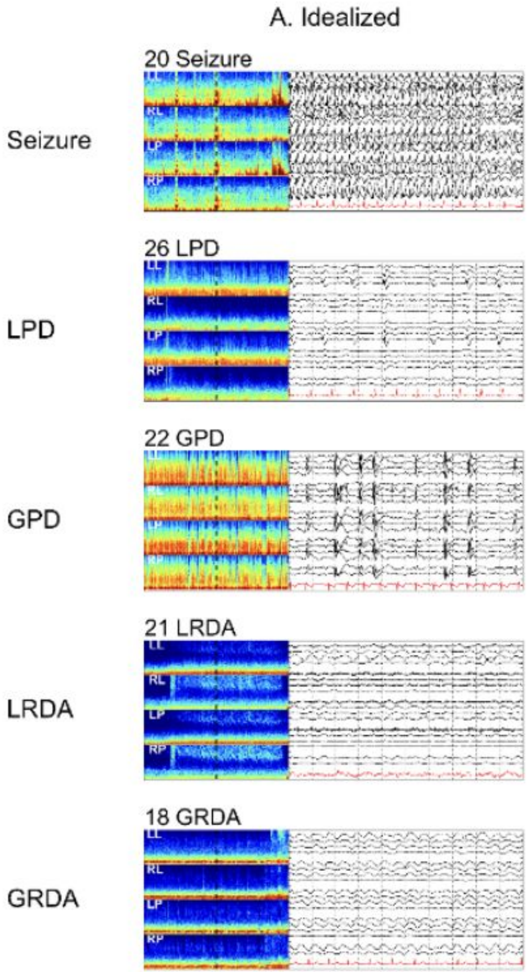
Study	Feature extraction	Decoding problem	Architecture	Accuracy
[35]	EEG motor imagery signals	BCI	CNN+SAE	90.0%
[54]	EEG data	BCI	CDBN	88%
[55]	EEG data	Epileptic Seizure Detection	CNN	90.5

Figure: Taken from Paper 1 specifying the use of CNN models for higher accuracy rate in decoding EEG data for epileptic seizure detection

Dataset Overview and Processing

Dataset - Classifications

- 6 classifications:
  - SZ - seizure (sudden, uncontrolled)
  - LPD - lateralized periodic discharges.
  - GPD - generalized periodic discharges
  - LRDA - lateralized rhythmic delta activity
  - GRDA - generalized rhythmic delta activity
  - Other

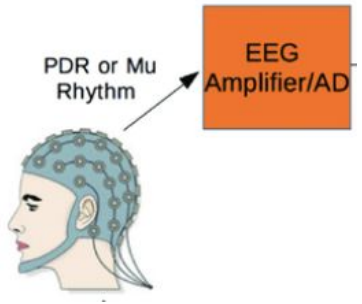


Dataset - Expert Consensus

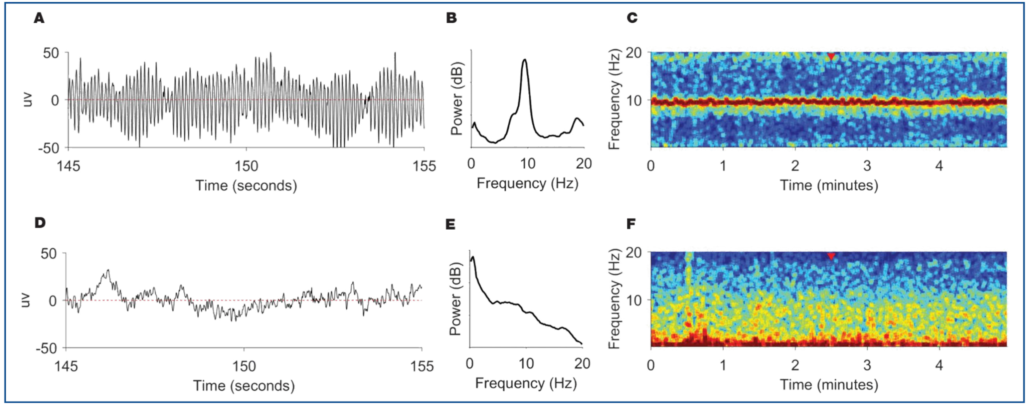
- A portion of dataset has uncertain classifications, rated by experts
- Includes each expert’s vote on which disease it is
- Dataset includes the majority vote of expert’s opinion on classification
- For greater consideration, should factor in the uncertainty of votes
- For our purposes, we use the majority experts’ consensus

Dataset - EEGs vs. Spectrograms

- EEGs:
  - Measures electrical activity in brain using electrodes attached to scalp
  - Electrical impulse from brain activity show up as wavy lines in the EEG recording

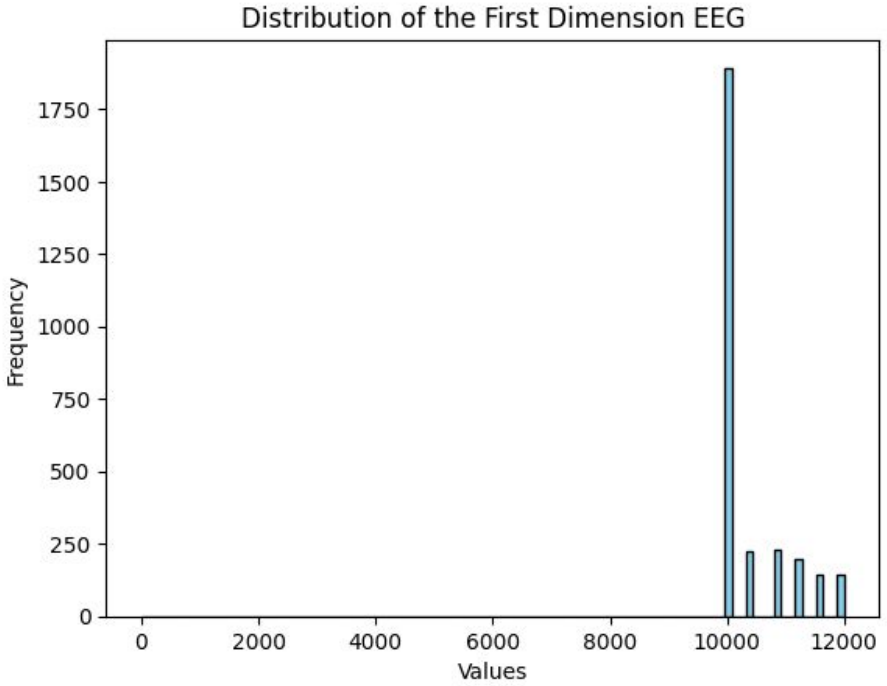


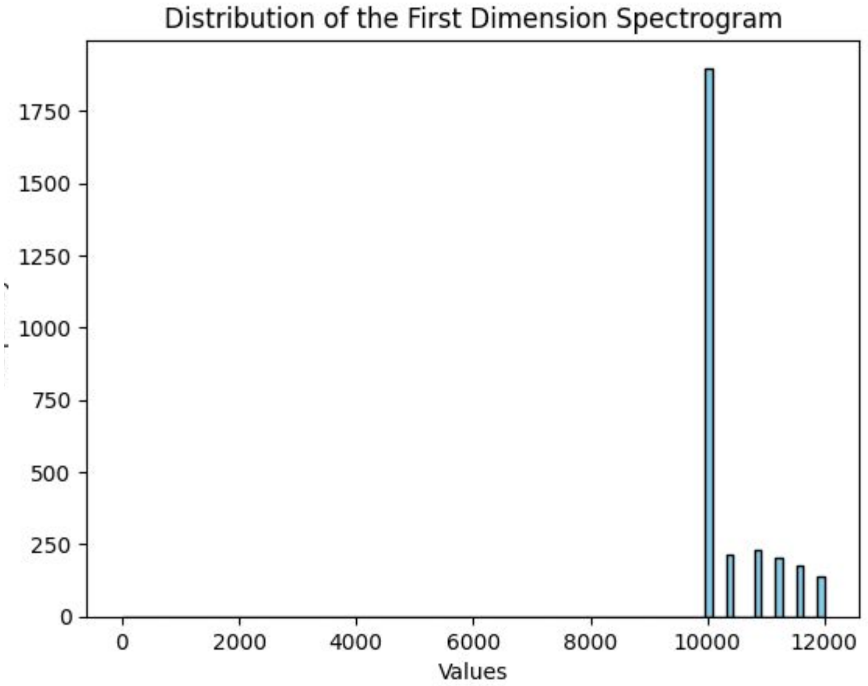
- Spectrograms:
  - A frequency-dependent representation of the EEG
  - Same data as EEG, represents data in a different output



Trimming

Data shape: (timestep, features)





Data Preparation

- Issues loading the entire dataset due to Colab RAM and GPU limits
  - We loaded 30% of the dataset to train on with random sampling
- Unevenly distributed data points in classes:

Seizure	LPD	GPD	LRDA	GRDA	Other
94	158	123	25	76	735
0.078	0.130	0.102	0.021	0.064	0.607

- Simple majority classifier accuracy: 0.607

Data Splitting and Standardization

- Divide dataset into training, validation, and test dataset
- Perform a 20-80 split for testing & training set
- Perform a 20-80 split on the training set again for training & validation set
- Standardize data by subtracting by mean and dividing by standard dev.
- Eliminate NaNs data points by changing values to 0’s
- One-hot encoding for the Y-label set

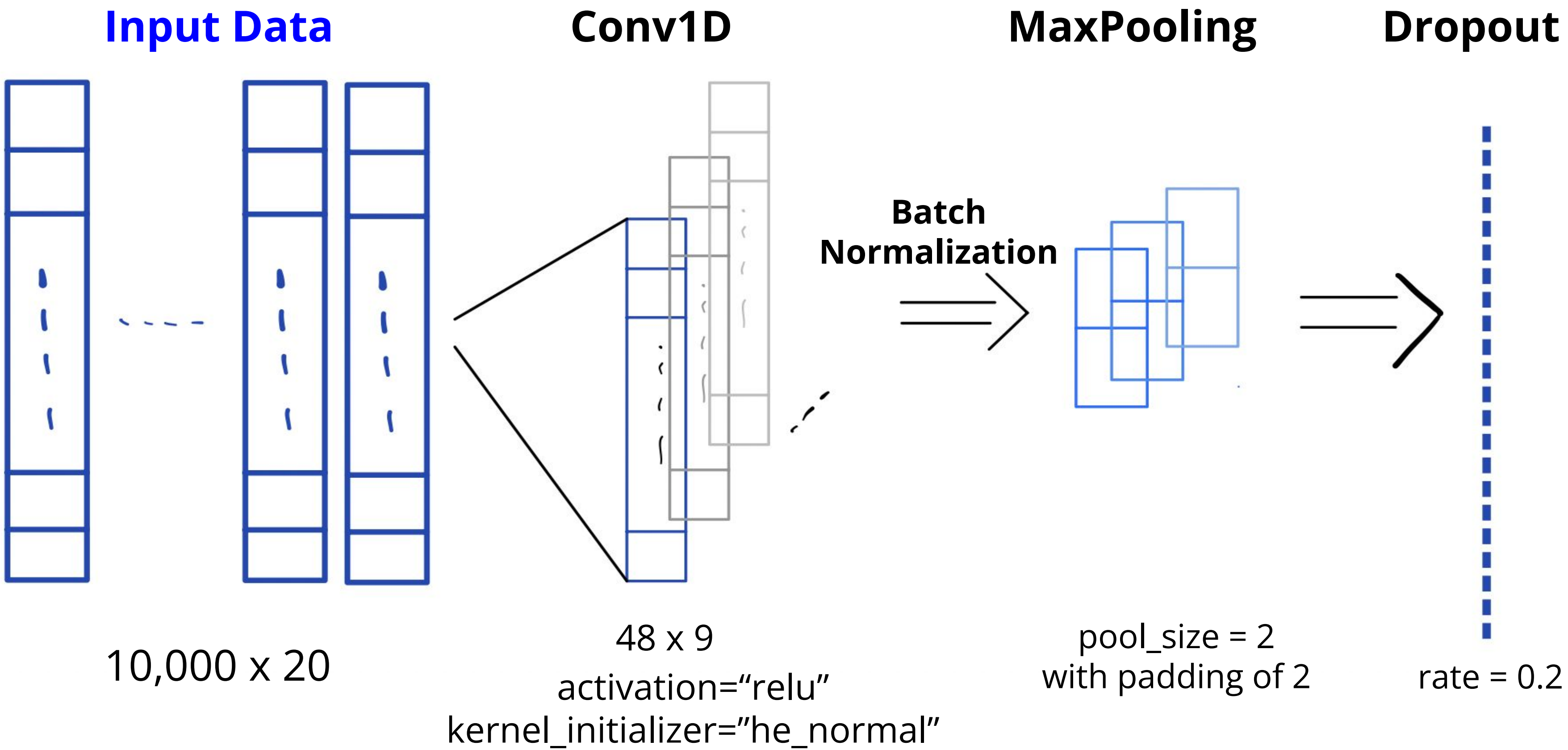
Building the Model

Model Selection and Implementation

CNN1D

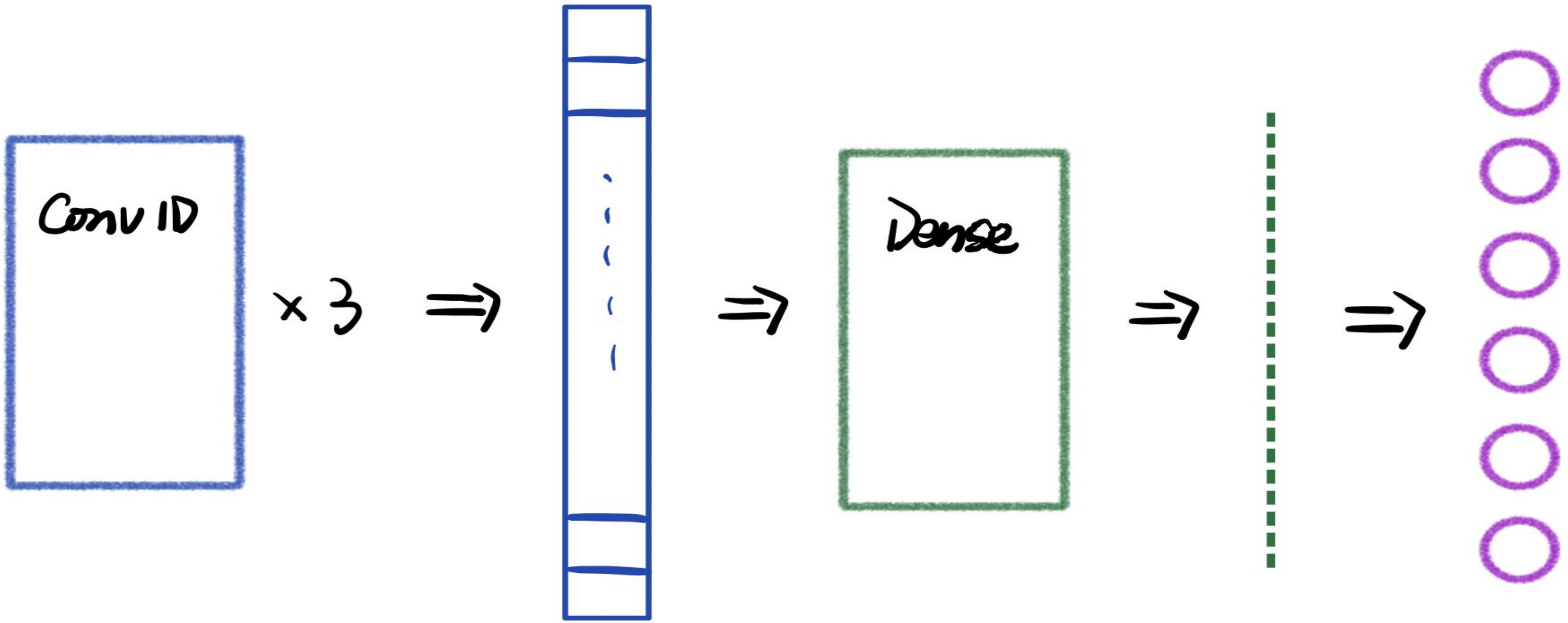
- Convolutional Neural Networks (CNNs) are a class of deep learning models extensively used for processing images.
- 1D because EEGs are time-series data, which is sequential in nature.
- We used the same model for both EEG and spectrogram to compare which data is more suitable for training CNN1D model.

CNN1D Block Structure



Model Structure

Flatten Dense (128) Dropout **Output**



rate = 0.2 activation = “softmax”

Model Summary

- Trainable Data: 140,000
- Loss Function: Categorical CrossEntropy
    - suitable for multi classification
- Optimization Algorithm: Adam
- Evaluation Matrices: Accuracy
- EarlyStopping: patient = 5

```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d_9 (Conv1D)           (None, 9996, 9)           909

 batch_normalization_9 (Bat  (None, 9996, 9)           36
 chNormalization)

 max_pooling1d_9 (MaxPoolin  (None, 4998, 9)           0
 g1D)

 dropout_12 (Dropout)        (None, 4998, 9)           0

 conv1d_10 (Conv1D)          (None, 4994, 9)           414

 batch_normalization_10 (Ba  (None, 4994, 9)           36
 tchNormalization)

 max_pooling1d_10 (MaxPooli  (None, 2497, 9)           0
 ng1D)

 dropout_13 (Dropout)        (None, 2497, 9)           0

 conv1d_11 (Conv1D)          (None, 2493, 9)           414

 batch_normalization_11 (Ba  (None, 2493, 9)           36
 tchNormalization)

 max_pooling1d_11 (MaxPooli  (None, 1246, 9)           0
 ng1D)

 dropout_14 (Dropout)        (None, 1246, 9)           0

 flatten_3 (Flatten)         (None, 11214)             0

 dense_6 (Dense)             (None, 128)               1435520

 dropout_15 (Dropout)        (None, 128)               0

 dense_7 (Dense)             (None, 6)                 774

=================================================================
Total params: 1438139 (5.49 MB)
Trainable params: 1438085 (5.49 MB)
Non-trainable params: 54 (216.00 Byte)
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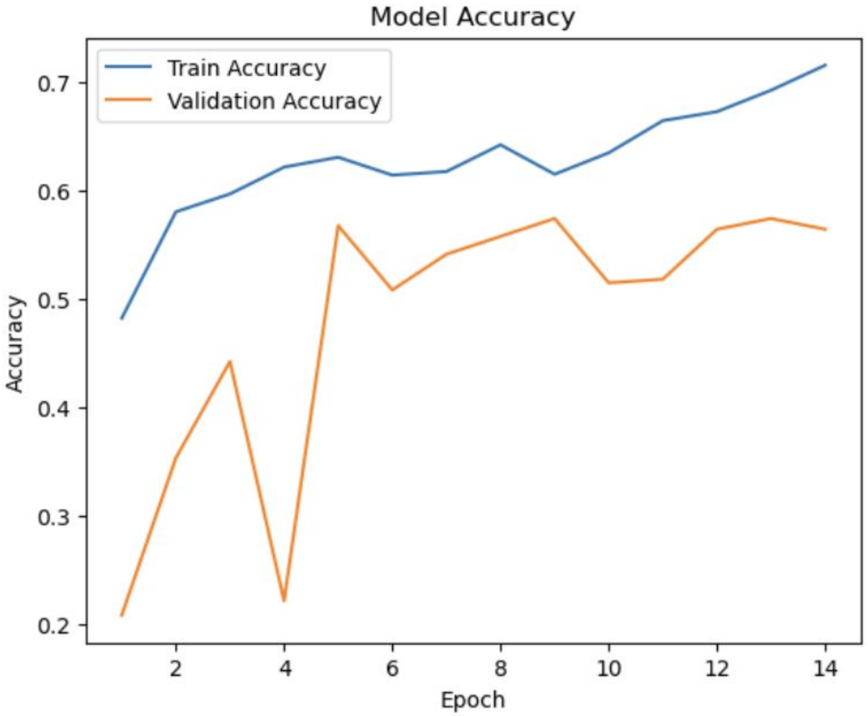
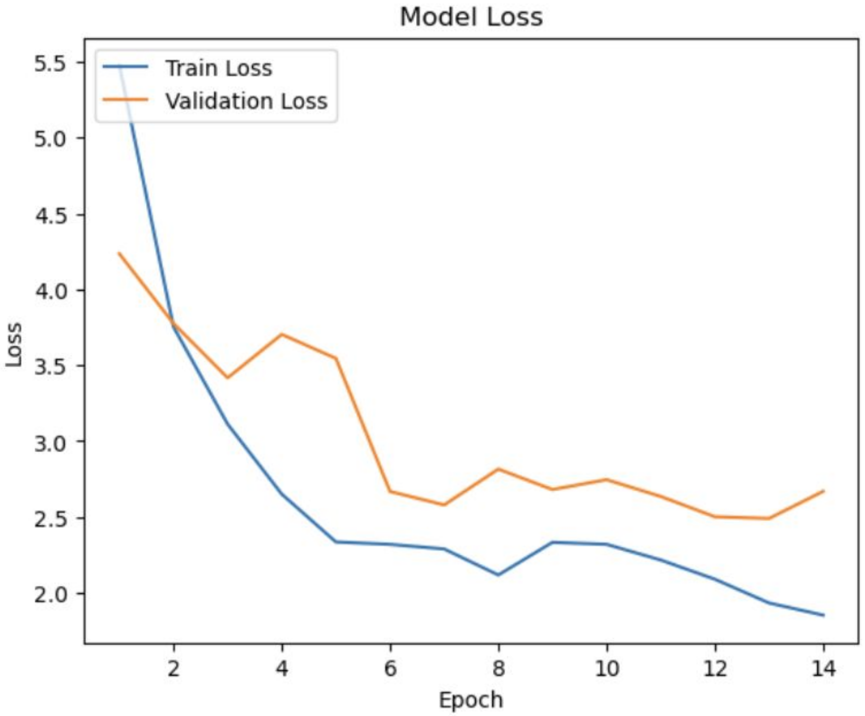
Model Evaluation

EEG Training

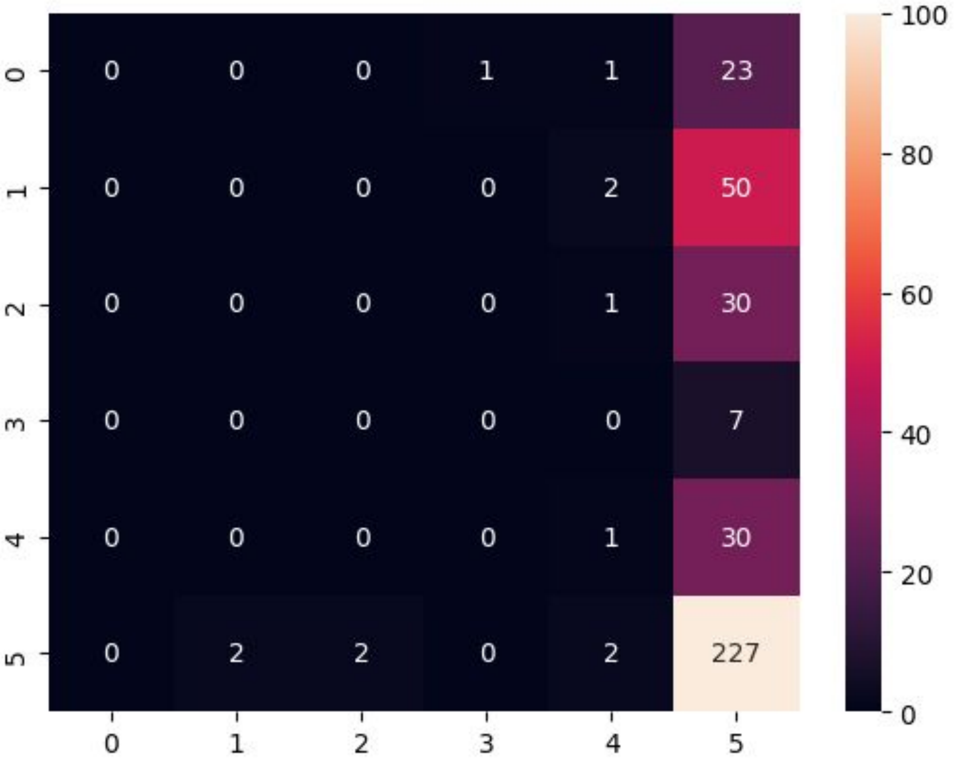




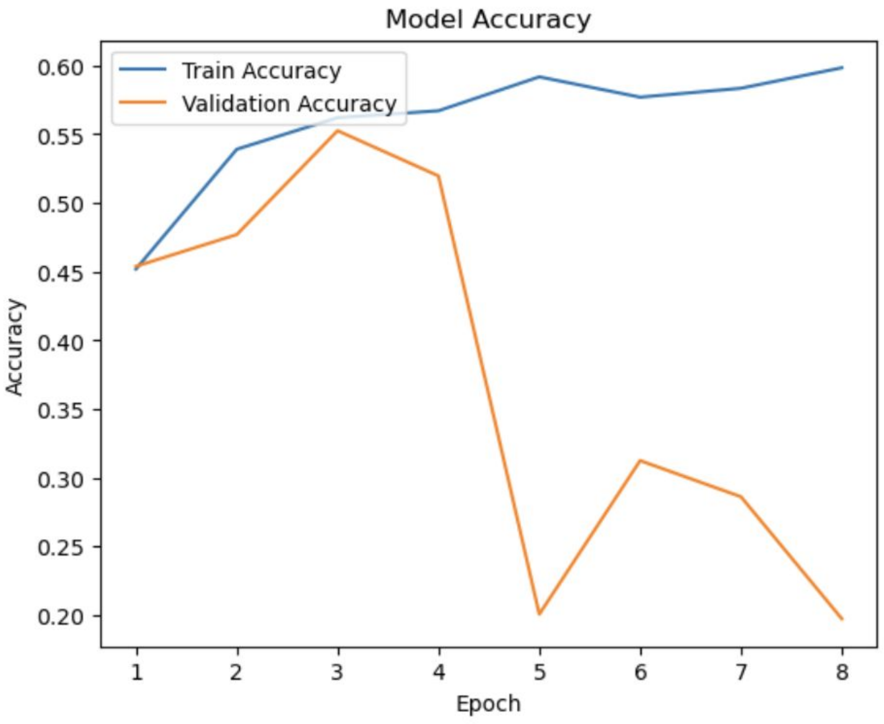
EEG Results

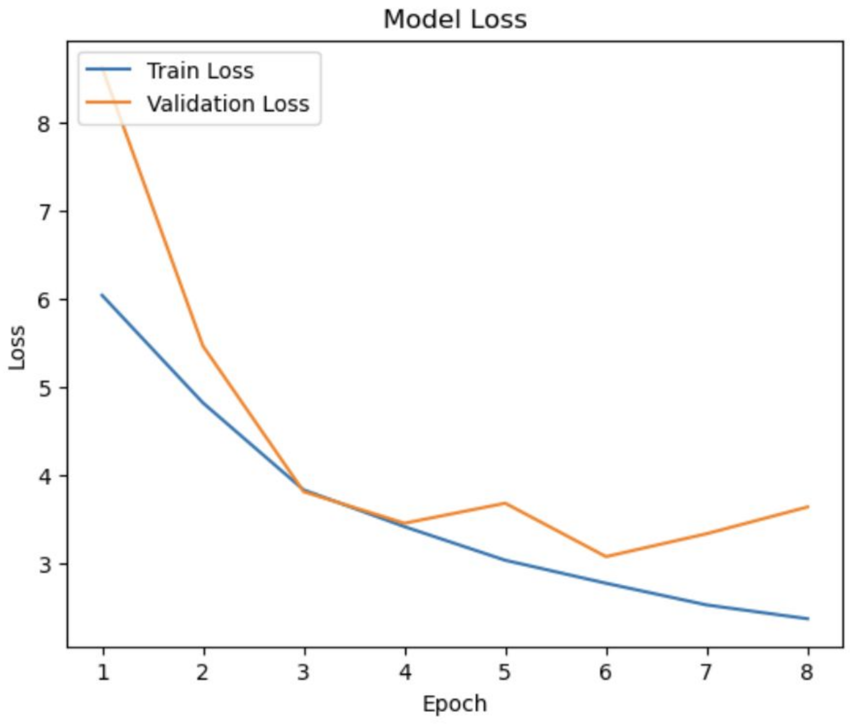
- Test accuracy: 63.1%
- Balanced accuracy score: 17.7%

	precision	recall	f1-score	support
0	0.00	0.00	0.00	25
1	0.00	0.00	0.00	52
2	0.00	0.00	0.00	31
3	0.00	0.00	0.00	7
4	0.14	0.03	0.05	31
5	0.62	0.97	0.76	233
accuracy			0.60	379
macro avg	0.13	0.17	0.13	379
weighted avg	0.39	0.60	0.47	379



Spectrogram Training

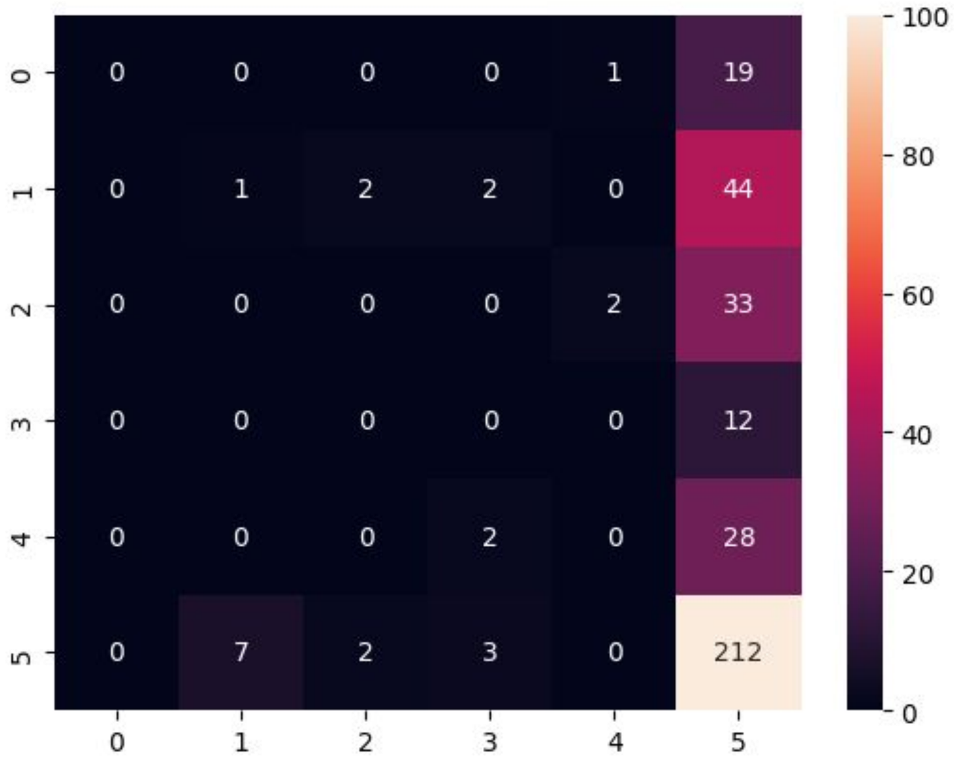




Spectrogram Results

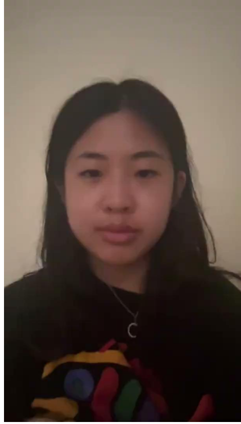
- Test accuracy: 55.5%
- Balanced accuracy score: 17.9%

	precision	recall	f1-score	support
0	0.17	0.07	0.10	27
1	0.29	0.05	0.09	38
2	0.20	0.05	0.08	41
3	0.00	0.00	0.00	15
4	0.00	0.00	0.00	31
5	0.59	0.90	0.71	228
accuracy			0.56	380
macro avg	0.21	0.18	0.16	380
weighted avg	0.42	0.56	0.45	380



Next Steps

- Training on the entire dataset
- After excluding outliers, zero padding remaining data larger than cutoff
- Correct the data distribution by using data augmentation
- Using Scipy packages to convert spectrogram data into images, then use Conv2D for training the model to compare with the result of Conv1D
- Using a pretrained model



Conclusion

The final ideas and takeaways

Resources and Acknowledgements

- **Thank you to Prof. Molontay and our TA Donát Kölleer**
- https://www.kaggle.com/competitions/hms-harmful-brain-activity-classification/overview
- https://www.researchgate.net/publication/353327259_Deep_Learning_Techniques_for_Classification_of_Electroencephalogram_EEG_Motor_Imagery_MI_Signals_A_Review
- https://www.researchgate.net/publication/353327259_Deep_Learning_Techniques_for_Classification_of_Electroencephalogram_EEG_Motor_Imagery_MI_Signals_A_Review
- https://www.researchgate.net/publication/221531473_On_classifiability_of_wavelet_features_for_EEG-based_brain-computer_interfaces