ETH zürich | ALMA MATER STUDIORUM UNIVERSITÀ DI BOLOGNA

Pruning and Fine-tuning Foundational Models for EEG Classification

Semester Project Final Presentation - 2025.02.06
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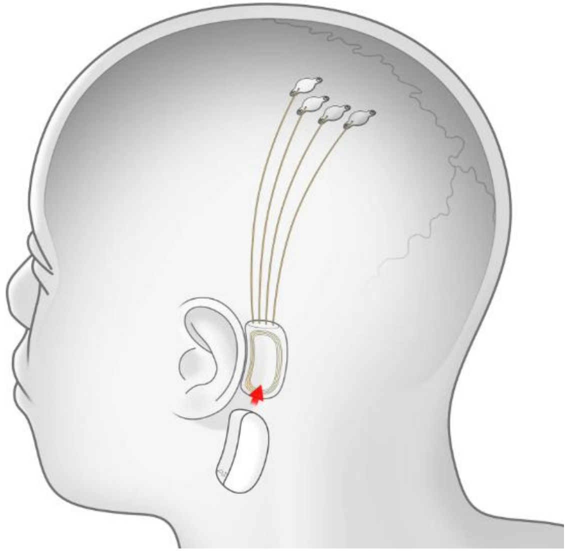
Introduction and Motivation

Why try to understand and classify EEG data?

- EEG data plays a critical role in neuroscience.



Problem and Potential Solution

Why explore the use of foundation models for this task?

- EEG data is difficult to interpret.
- Foundation models are highly successful in other fields.
- Removes the need for designing one model per task.

Downsides:

- Large datasets + size.
- Difficult to hyperparametrize.

Goals

1. Fine-tune the pretrained foundation model MEST on 4 datasets:

- EEG-ImageNet 2024 [1].
- EEG-ImageNet 2020 [2].
- Sleep Deprivation [3].
- Sleep Stage Classification [4].

2. Reduce the model in size while maintaining accuracy.

- Mainly using pruning techniques.

Background (1)

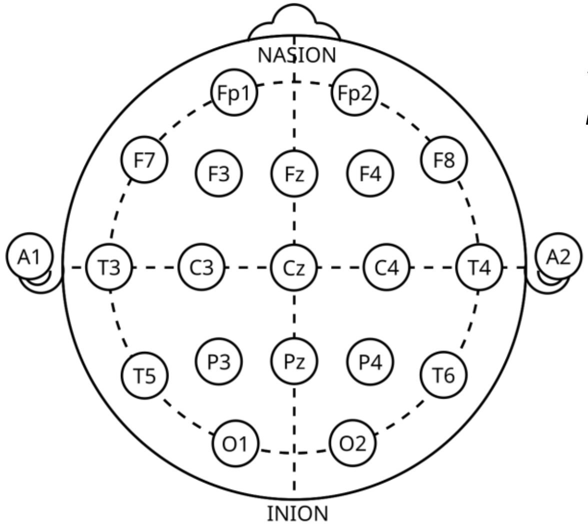


Fig 1: Illustration of electrode placement in 10-20 system [5].

EEG (Electroencephalography) data:

- Invasive vs non-invasive recording.
- Channels follow the 10-20 system.
- Amplitude/time signal.
- Different sampling frequencies.

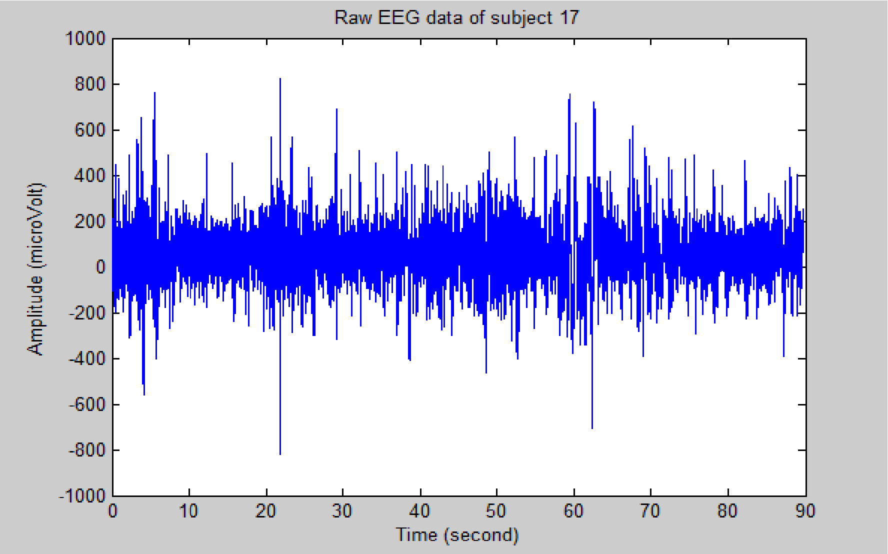


Fig 2: Example of an EEG signal (single channel) [6].

Background (2)

Foundation models:

- **Transformer based architecture:**
  - Encoder/Decoder + Multihead self-attention
- **Pre-trained on large datasets.**
- **MEST (Masked EEG Sequential Transformer):**
  - Transformer-based masked-autoencoder model.
  - ~33M parameters
  - TUAB Dataset [7].

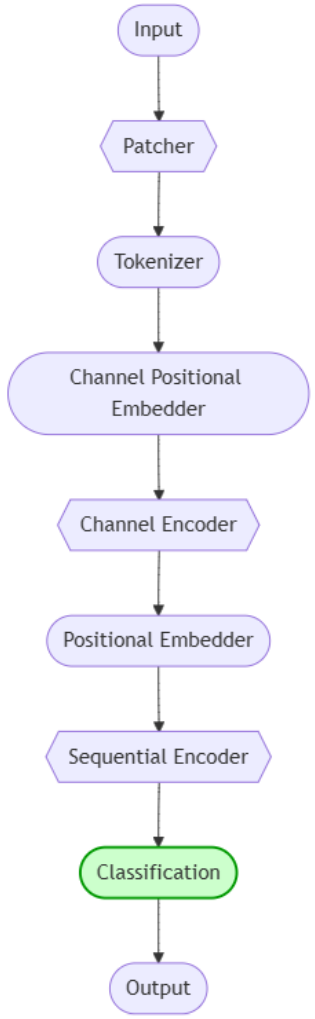


Fig 3: Block Diagram of MEST for fine-tuning.

Background (3)

Pruning techniques:

- Structured: whole layer/channel removal.
- Unstructured: individual weight removal.

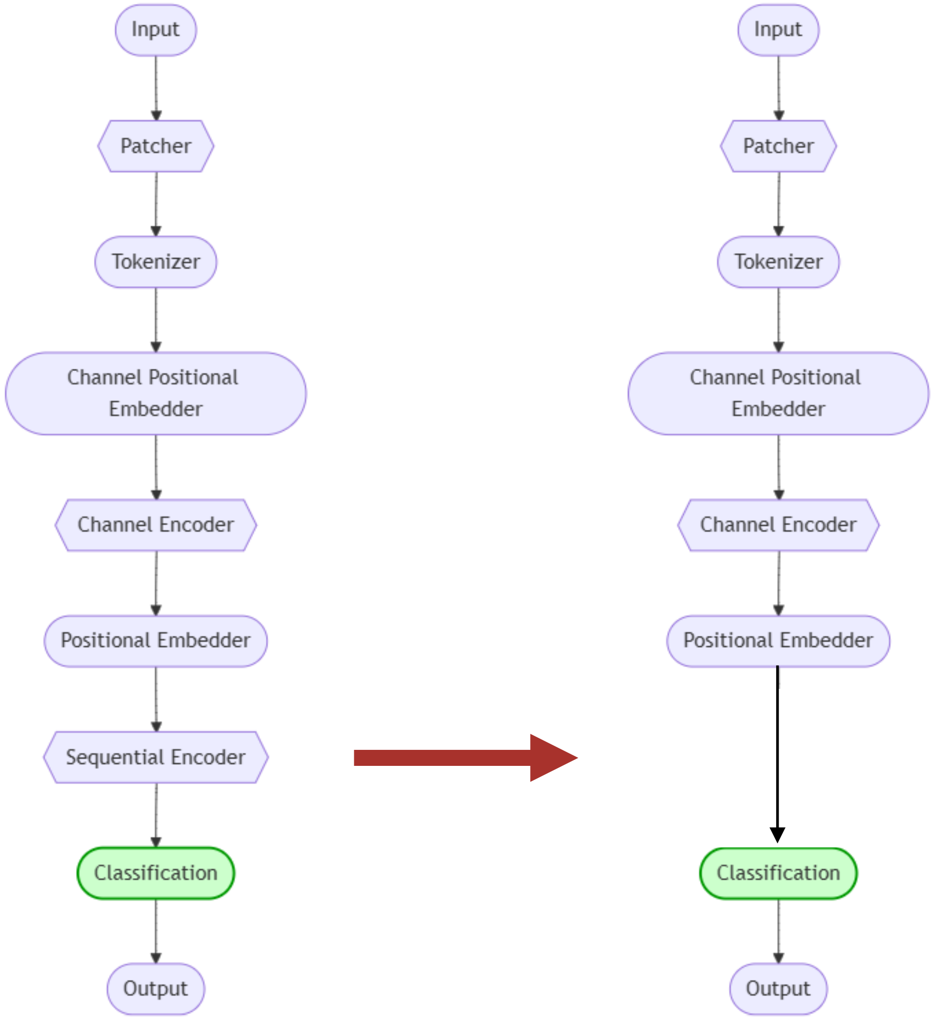


Fig 4: Structured pruning example.

SOTA Work

Dataset	Model	Size	Best Performance
EEG-ImageNet 2024	RGNN [1]	1.2M	40.5%
EEG-ImageNet 2020	NeuroGrasp [8]	9M	93.6%
Sleep Deprivation	BrainWave [9]	120M	69%
Sleep Stage Classification	Brant-X [10]	1B	84.58%

Table 1: Summary of state of the art work for each dataset.

Implementation

1. **Installation of the environment.**
   - Setting up/familiarizing with the tools
2. **Preprocessing the datasets.**
   - Inspecting all datasets
   - Convert to h5 format
3. **Test experiment using a small model (EEGNet [11]).**
4. **Fine-tuning on MEST.**
   - Tune hyperparameters
5. **Model size reduction with pruning.**

Pruning Results

Fine-tune baseline → baseline accuracy: **78.52%** (**29.9M**)

(on pre-training data)

Model reduction results:

- Remove one encoder layer → **25.9M** → **79.32%**
- Unstructured pruning → **44%** removed → **77.14%**
  - Scheduled random removal across entire network.
- Remove linear layers in encoder → **15.9M** → **79.46%**

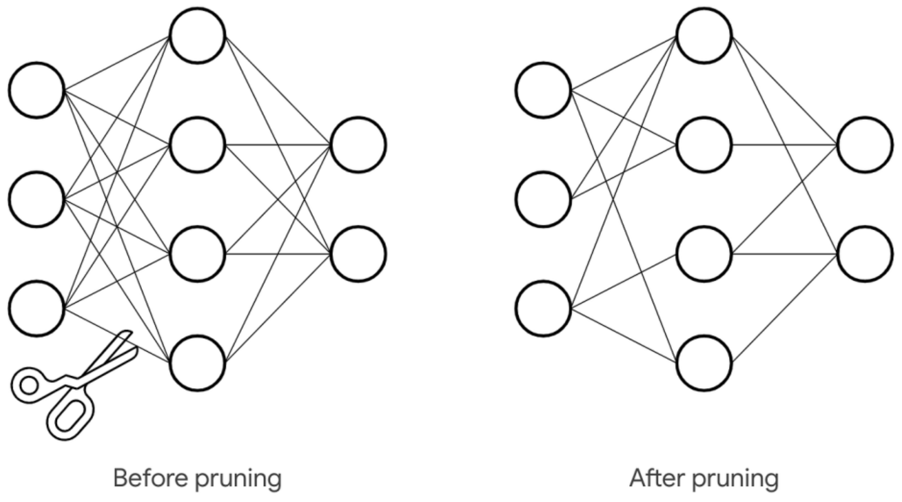


Fig 5: Visual example of unstructured weight pruning.

Discussion

- Maintained accuracy with **~50%** reduction in parameters!
- File size reduction from 135MB to **61MB** in FP-32 precision.
- Next step would have been to perform quantization and observe performance.
- Theoretical file size at int8 quantization → **~16MB → ~128Mbits**

↳ BioGAP [12] → **128Mbits**

Fine-tuning Results (1)

Test-experiment on EEGNet (50k):

Dataset	Accuracy	SOTA
EEG-ImageNet 2024	3.20%	26.04%
EEG-ImageNet 2020	28.43%	31.90%
Sleep Deprivation	68.94%	N/A
Sleep Stage Classification	13.94%	N/A

Table 2: EEGNet performances on each dataset.

Observations:

- EEG-ImageNet 2024 has poor performance.
- Other datasets → model learns.
- Not random classification.

Fine-tuning Results (2)

Fine-tuning results on MEST (33M):

Dataset	Accuracy	SOTA
EEG-ImageNet 2024	4.75%	40.5%
EEG-ImageNet 2020	15%	93.6%
Sleep Deprivation	50%	69%
Sleep Stage Classification	12.5%	84.58%

Table 3: MEST fine-tuning performances for each dataset.

Observations:

- Poor performance close or equal to random classification.
- Worse performance than EEGNet!
- Model does not seem to generalize well to these datasets.

Discussion

Why such low performances?

- **Datasets too different from pre-training data:**
  - Different channels amounts.
  - Different channel positions.
  - Different number of output classes.
- **Did not find suitable hyperparameters.**
- **Classification head not large enough.**
- **Not enough data.**

Potential solutions/paths to explore:

- Format data to try and match pre-training data.
- Pre-train model with different combination of data.

Conclusion & Future Work

- **Great model reduction results:**
    - Paves the way for usability on edge devices.
    - Next → Explore quantized model performance.
- **Poor performance for fine-tuning to specific dataset:**
    - Shows difficulty of generalizing these models.
    - Next → Explore modifying the fine-tuning data to reach proximity with pre-training data.

Thank you for listening!

Q&A

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Extra Dataset Info

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Dataset	Subjects	Images	Classes	Channels	Recording length	Sampling Freq
EEG-ImageNet 2024	16	4000	80	62	500ms/image	1000Hz
EEG-ImageNet 2020	6	2000	40	128	500ms/image	1000Hz
Sleep Deprivation	71	N/A	2	61	2 sessions of 5 min	500Hz
Sleep Stage Classification	98	N/A	8	2	2 whole night recordings	100Hz