Pod: Fukuiraptor_Saba
Group B: Vahid, Zahra, Saba, Kiarash

2023-07-13, Thursday

Data type: ECoG
Dataset: BCI competition IV: https://www.bbci.de/competition/iv/desc_4.pdf
Task:
- Options:
  - Finger classification
  - Finger trajectory prediction

Literature Review Doc: Group B - Papers

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Meeting with John
Other datasets for motor imagery:
- BCI Datasets
- Korea University Dataset http://deepbci.korea.ac.kr/opensource/opendb/

Epilepsy dataset:
- TUH epilepsy corpus

-> Can think of out-of-the-box ideas :-)
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Rethinking dataset:
- Use another motor imagery dataset that has more subjects

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2023-07-14, Friday

Other EEG MI dataset: http://bnci-horizon-2020.eu/database/data-sets
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DL Ideas to extend simple classification and come up with more specific questions:
> subject-independent (Generalize to other subjects)
> Generalize to other datasets
> online learning
> Use multiple models

Useful resource: This paper seems helpful in giving us a general overview of the field since we don't have much time for a full literature review: Deep learning techniques for classification of electroencephalogram (EEG) motor imagery (MI) signals: a review (2023)
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Meeting with Sudhakar
Q: How to choose the dataset?
A: The criteria is your question/application/goal. For example, if our goal is to help paralyzed people with can go with motor imagery tasks in which people go in four directions. (Wheelchair control)

> Idea: Do generalization/adaptation/transfer learning.

- After doing simple classification, use one or more other datasets to check the generalization.
- Use it on datasets with subjects with a problem (epilepsy, paralysis, etc.) with a transfer learning technique. E.g. train on normal subjects, fix the parameters and train the last layer with the other dataset.

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2023-07-16 - Sunday (Friday cont.)

Final Datasets:

- Normal MI (Source dataset): https://physionet.org/content/eegmmidb/1.0.0/
  - Paperswithcode: https://paperswithcode.com/dataset/physionet-mmi
- Stroke MI (Target dataset): https://figshare.com/articles/dataset/EEG_datasets_of_stroke_patients/21679035/3

Task: Classify whether the brain signal corresponds to the left or right hand
Method: Transfer learning
Question ideas:

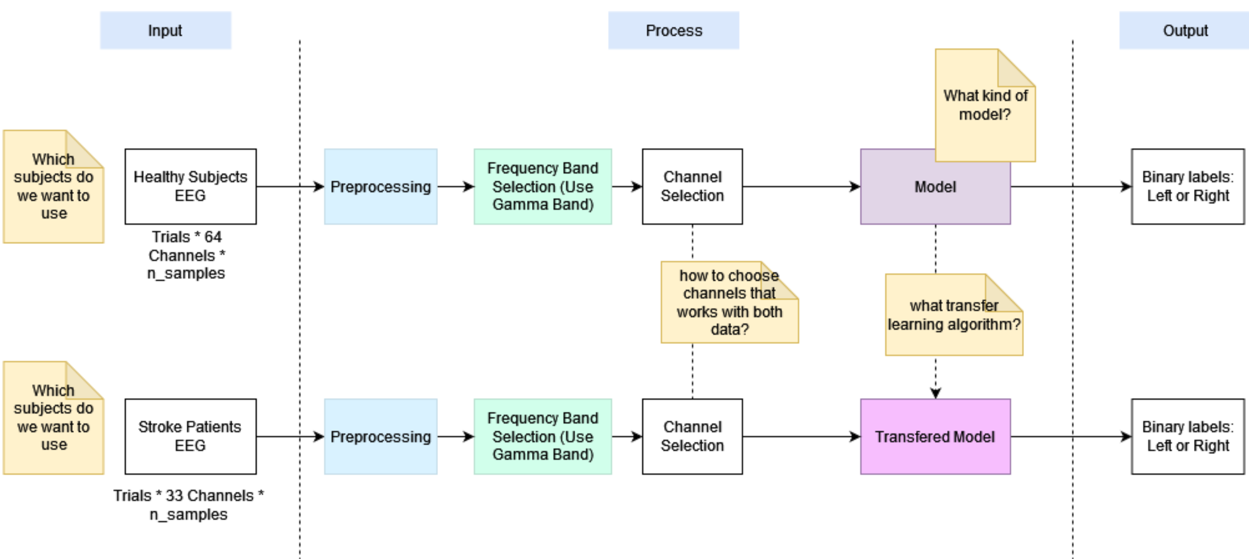
1. Can we improve motor imagery classification in stroke patients by using data from healthy people?
2. Can we use data from healthy people to restore stroke patients' movement?
3. Can we use data from healthy people to improve the detection of stroke patients' movement?
4. Does stroke patient motor imagery function have a significant difference from healthy people?
5. Do Channel or Frequency band selection algorithms improve the motor imagery detection model?
6. Can we implement a motor imagery classification model in stroke patients by using data from healthy people?
7. Can we use a model trained for healthy people, for stroke patients?
8. Can a model trained on healthy people's data improve the detection of stroke patients' movement?
9. Can a model trained for healthy people be helpful for stroke patients?
10. Can a model trained for healthy people be helpful in overcoming the shortage of stroke patient data in motor imagery detection?

Final questions:

1. Can a Deep Learning model improve motor imagery detection?
2. Do Channel or Frequency band selection algorithms improve the motor imagery detection model?
3. Does stroke patient motor imagery function have a significant difference from healthy people?
4. Can a model trained for healthy people be helpful in overcoming the shortage of stroke patient data in motor imagery detection?
5. Can a model trained on healthy people's data improve the detection of stroke patients' movement?
6. How would the results change if we use 33 channels instead of selecting channels which are just related to the motor cortex of the brain ?

2023-07-17 - Monday

Model Draft:
https://drive.google.com/drive/u/1/folders/1Zl5LNDJ4g4_4J5DPsoO6sNZlAEIncnXP



Version 1.0

Things discussed/to discuss:

- ❖ Discrepancy in channel numbers in datasets (64 vs 33)
  - ➢ Downsample 64 to 33 (simplest approach, but data loss occurs)
  - ➢ Upsample 33 to 64 with
  - ➢ Use dynamic input layer size
  - ➢ Resize so that architecture matches
- ❖ What model should we use?
- ❖ What channel selection technique should we use? Which channels should we select?

        - Pick specific channels from prior knowledge
- What transfer learning algorithm should we use?

Implementation:

- [May be] Useful libraries/codes:
    - General EEG libraries:
        - https://github.com/vlawhern/arl-eegmodels (tensorflow)
        - https://github.com/pbashivan/EEGLearn
            - Pytorch: https://github.com/numediart/EEGLearn-Pytorch
- This paper used the same dataset (Physionet MI/ME), it is in tensorflow but some its functions may be helpful in data loading or preprocessing:
    - **https://github.com/hauke-d/cnn-eeg**
- Final library we settled on:
    - **https://torcheeg.readthedocs.io**

2023-07-18 - Tuesday

Implementation:

- Played around with "edf" data type, trying to load data and events
- Successfully loaded the data and corresponding labels from edf file and extract the trials and segments we were interested
- Divided the data into smaller 2-second windows

Todo tomorrow:

- Talk about splitting the train, validation and test set
- Do preprocessing
- Do frequency band selection
- Save the data

2023-07-19 - Wednesday

Implementation:

- Processed and stored the data in a numpy array
- Did channel selection with prior knowledge
- Did gamma band selection
- Created dataloaders

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Meeting with John

Email: john.thomas3@mcgill.ca

- Channel Selection:
    - Use action potential, plot individual channels

    - Use entropy
    - We can start with all channels and then try these methods
- Preprocessing:
    - Three important things:
        1. Signal Frequency
        2. Remove the electricity notch (some countries have different electricity voltage, etc)
        3. Montage: Common average or bipolar (calculate signal with respect ot sth)
- Frequency band selection:
    - We can try other bands like theta and alpha
- Model:
    - Use EEGNet as baseline and try other models after that
- Augmentation:
    - No need for that but we can try white noise or other methods only on train data
- Cross validation:
    - **Do not put one subject's trials in both test and training**

!! We need to do a literature review for stroke patients and see what has been done.
-> Document our tests and evaluations

2023-07-20 - Thursday

Tasks for today:

1. Fixing data loading and model -> Saba
2. Preprocessing stroke dataset -> Kiarash
3. Do a literature review -> Zahra

Implementations:

- Fix data loaders
- Created an EEGNet model
- Trained the model with data
    - Experiment results Doc: POD 007 - Group B - Runs

Literature Review

2023-07-21 - Friday

Tasks:

1. Complete data loading of stroke patients
2. Improve model and training
3. Find algorithms for transfer learning

    a. Base: Fine Tuning

Implementations:
- Continue with data loading of stroke patients
- Add code for visualizing signals

Todo til Monday:
- Improving model and training
- Looking for transfer learning algorithms

Questions to ask John on Monday:
- Ask about the normalization of data
- Frequency band selection

2023-07-24 - Monday

Meeting with John
- EEG montage
- High-pass filter for stroke (notch filter)
- Modify learning rate
- Do a literature review to compare accuracies

Tasks to be completed:
- Preprocess stroke data again: high pass filter
- Train a model on stroke data and check the accuracy.
- Transfer learning algorithm should be improved.
- Visualize the data first, then decide whether or not to normalize it.

Interesting document about visualizing and preprocessing EEG: https://neuraldatascience.io/7-eeg/introduction.html

2023-07-25 - Tuesday

Todo:
- Write the abstract (From [W3D2](W3D2))
    1. Check out Modeling Steps 10
    2. Check out examples (Step 10 section of deep learning, modeling, and data science)
    3. Answer base questions
    4. Write the first version
    5. Edit abstract individually

6. Put together the final version

- Implementations:
    1. Additional stroke data preprocessing (high pass filter, montage, ICA, artifact removal, etc.)
    2. Visualize the data and compare healthy, stroke, and preprocessed stroke data
    3. Get the base model working for stroke data
    4. Normalize if needed
    5. Perform transfer learning, do fine tuning at different layers, and compare the results
    6. Improve base model
    7. [Bonus] Test the pipeline using all available channels
    8. [Bonus] Finetune model on one subject

Abstract Doc: [Abstract - NMA - POD 007 - Group B]

2023-07-26 - Wednesday

Working on implementation