Deep Learning for Generalized EEG-based Image Visualization

6 May 2021

11-785

EEG-Vision:
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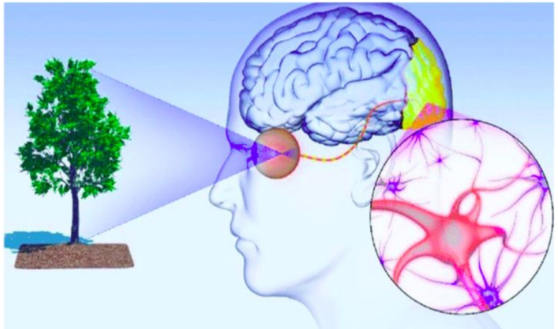
Problem



How do we know that this is a tree?

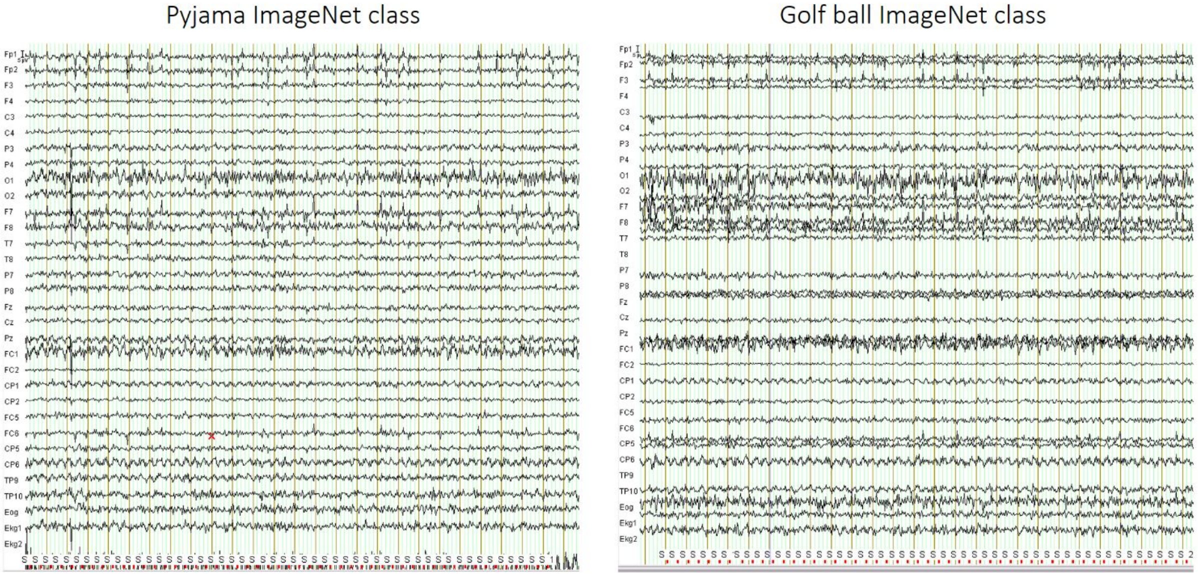


Figure 1. Examples of brain signals evoked by visual stimuli of two different ImageNet object classes.

Spampinato et al. (2017)

Previous Research vs Our Research

- All previous research propose models to classify EEG signals into the class of the Image that the viewer was shown (40 classes)
    - Spampinato et al. (2017) → test accuracy: 21.8%
    - Palazzo et al. (2018) → test accuracy: 60.4%

- Their model are bound to the number of Image classes chosen for training

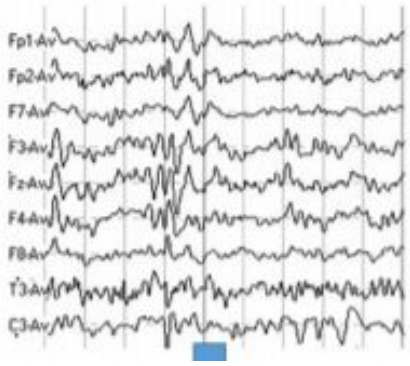
- We want to create a system that classifies and identifies an image that is from a set of images, whose classes are not used in training
  → generalization increases usability and scalability

Datasets

EEG Dataset

- Collection: 6 participants were shown images from ImageNet dataset, their brain activity was recorded using EEG cap
- 128-channel EEG recordings at 1000Hz
- 40 image classes with 50 images each
- Dataset shape = (12000 x 128 x 500)
- No explicit data transformation was applied

128

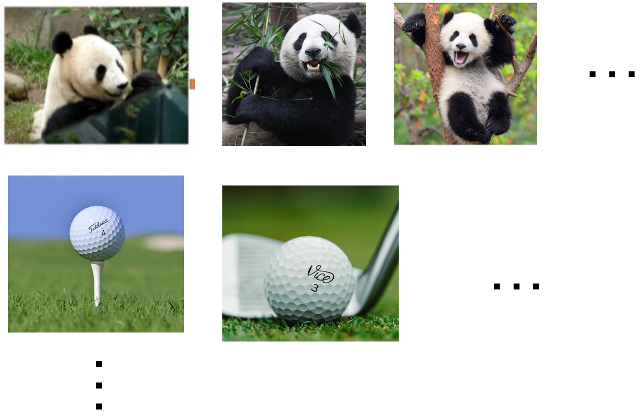


500

Image Dataset

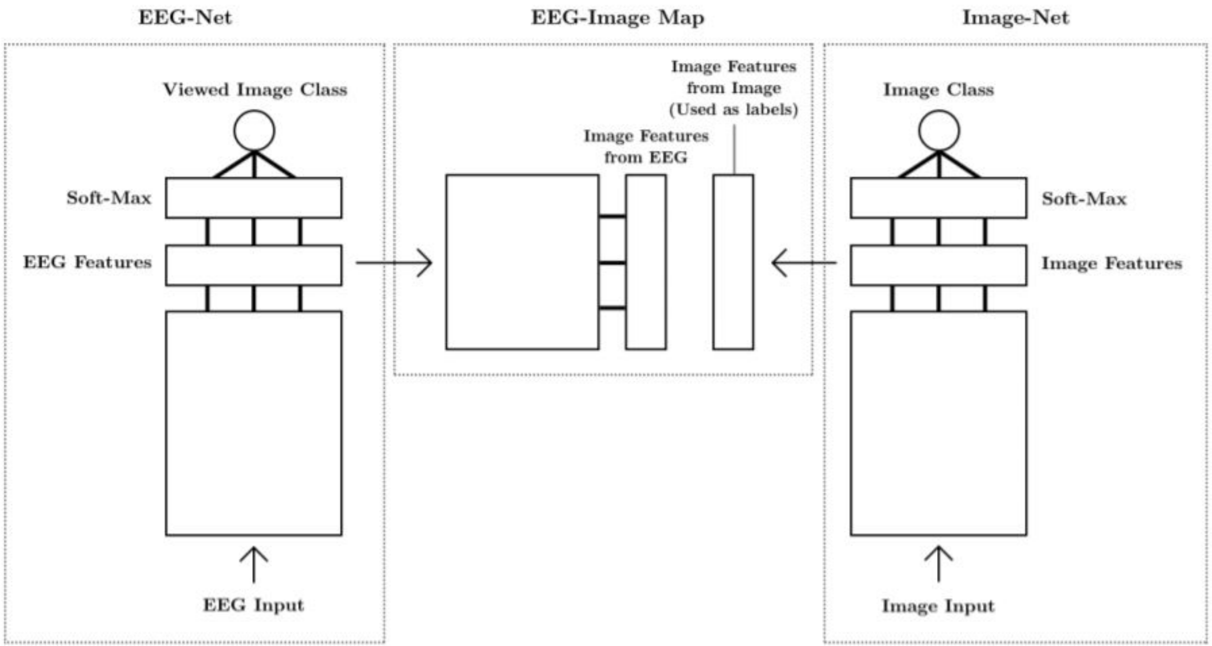
- Sampled images that were used in the EEG dataset from publicly available ImageNet database

40 classes



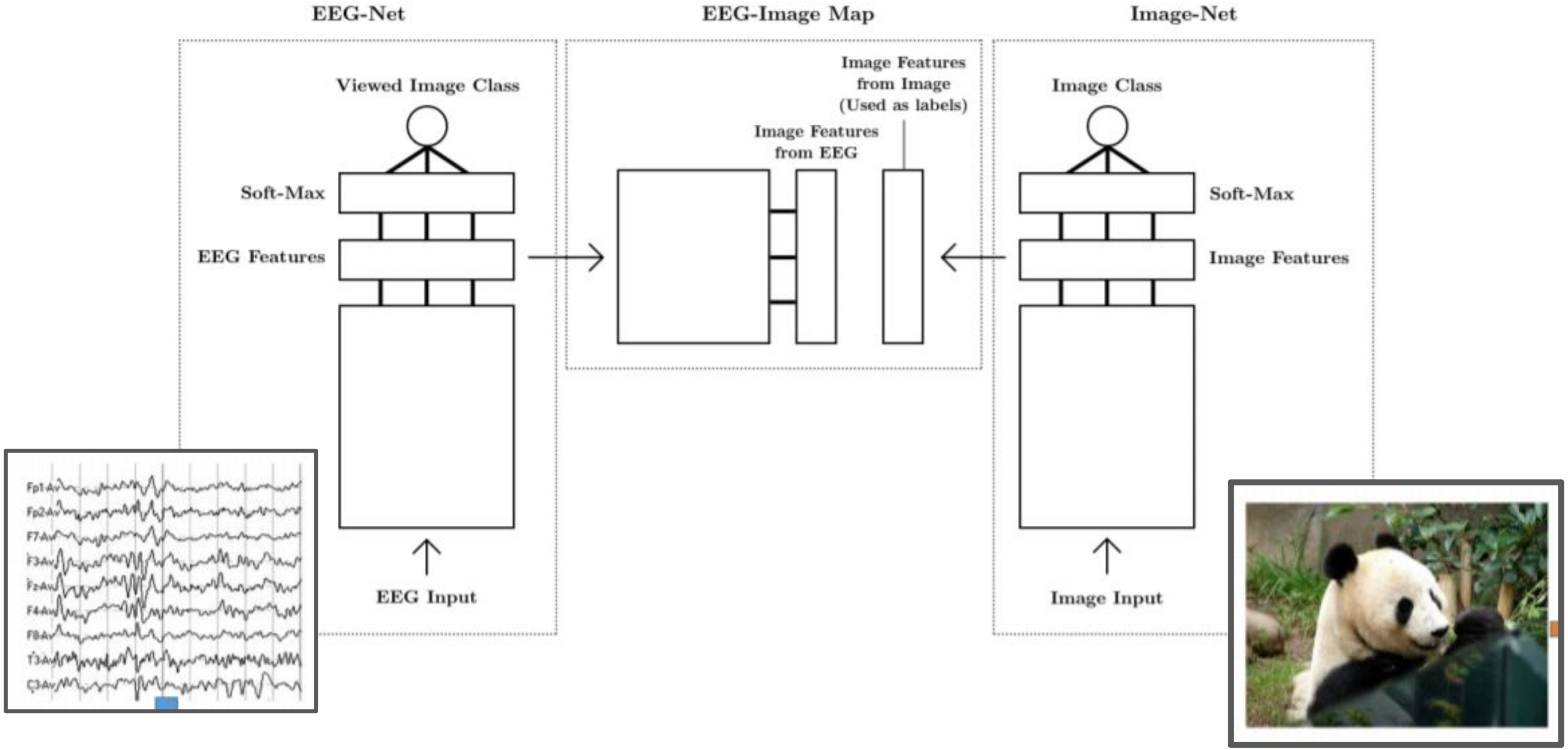
50 images/class

Task

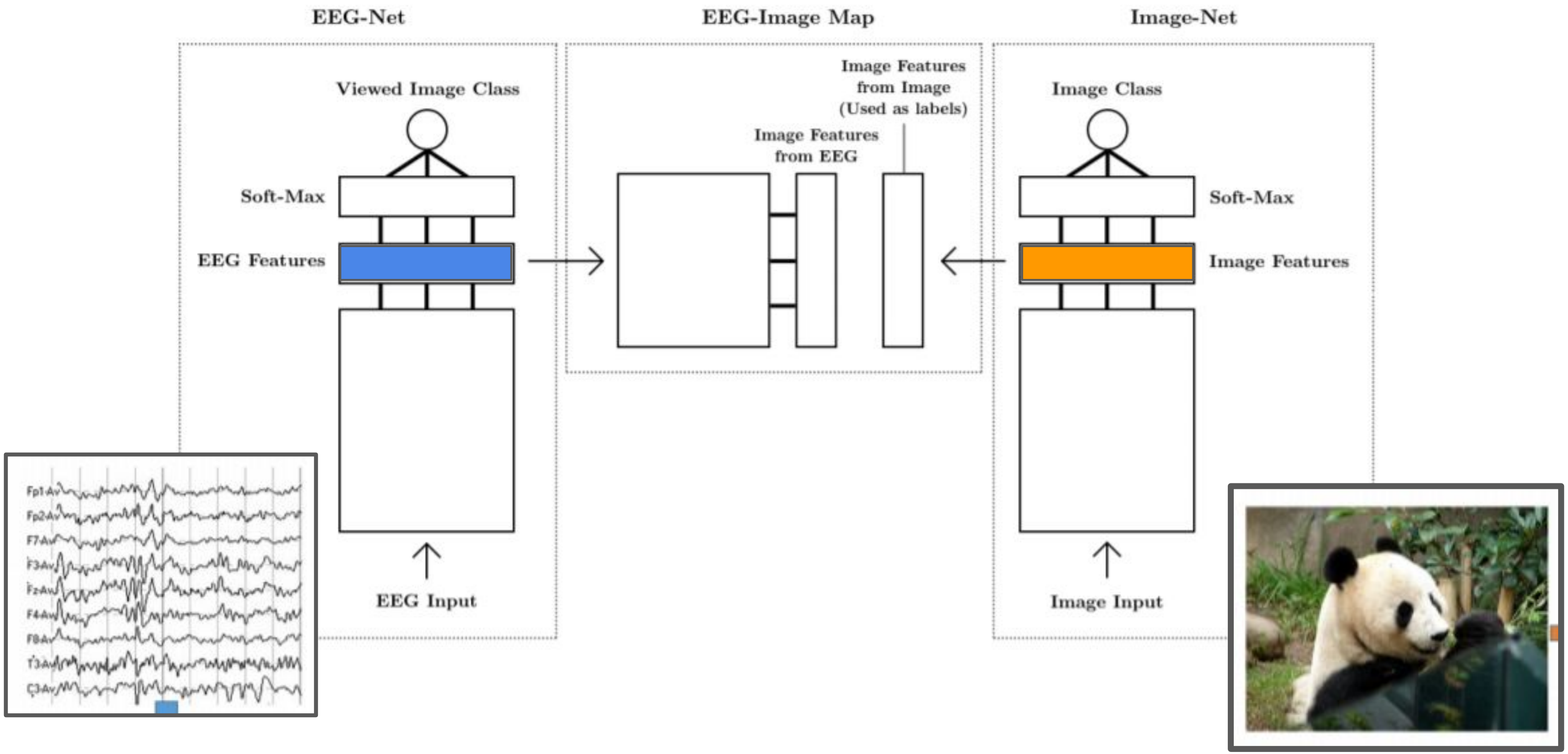


- EEG-Net: improved reimplementation (BiLSTM)
- Image-Net: fine-tuned pretrained model (Inception-v3)
- EEG-Image-Map: our experimental implementation

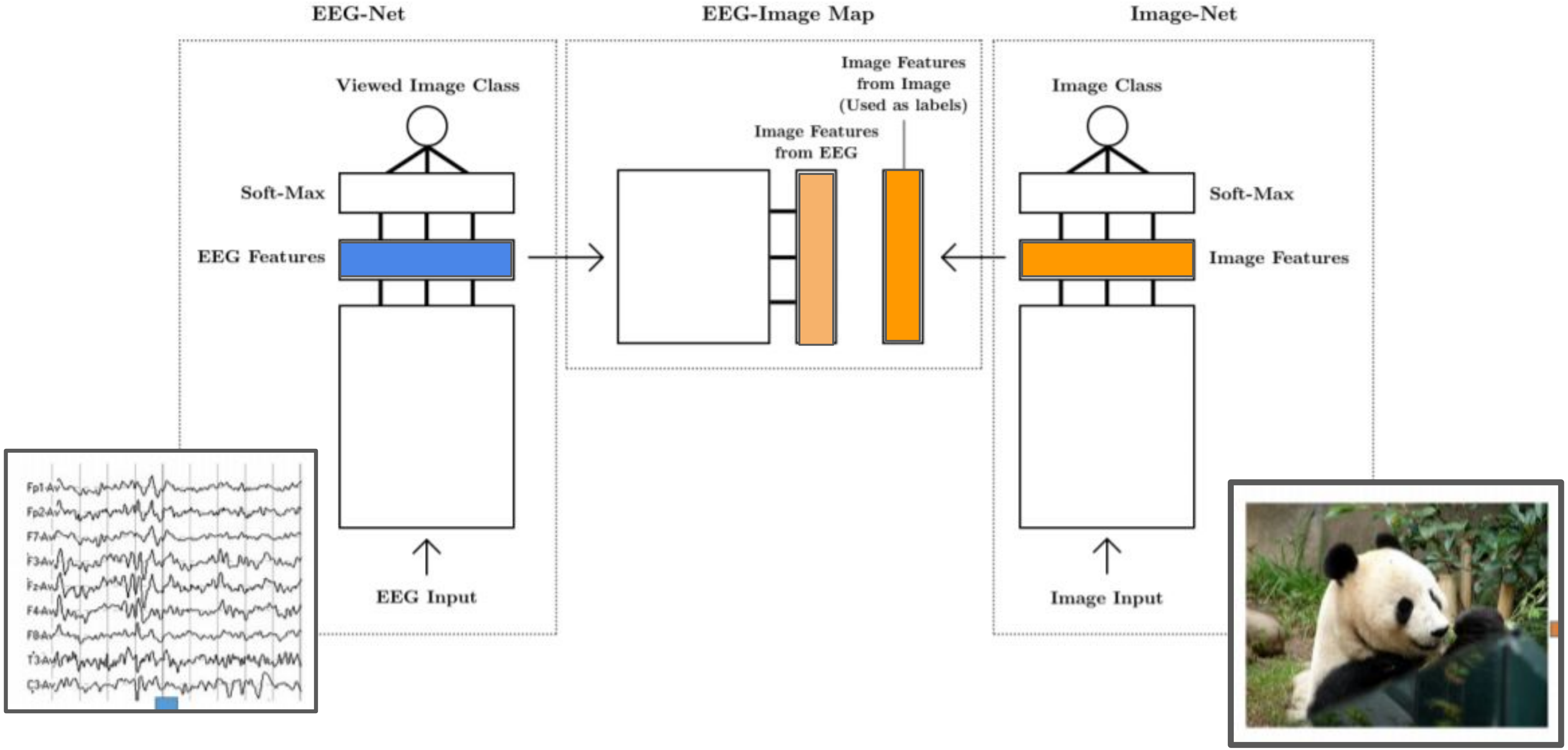
Model Pipeline



Model Pipeline



Model Pipeline



EEG-Net

- Reimplementation of Fares et al. (2018)

- Used a Bi-directional LSTM because it is able to extract temporal data from the EEG signals since the full signal is available

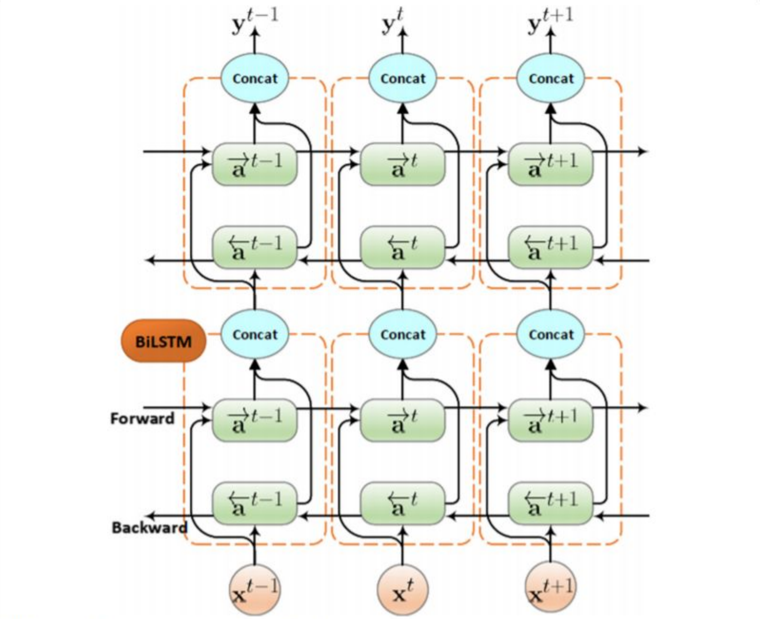
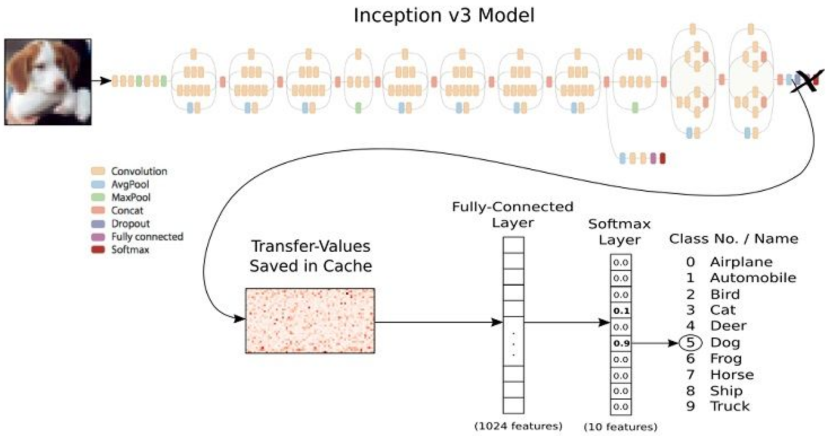


Fig. 2 Two stacked layer structure in bi-directional LSTM with three consecutive time steps

Image-Net

- Used a pretrained Inception-v3

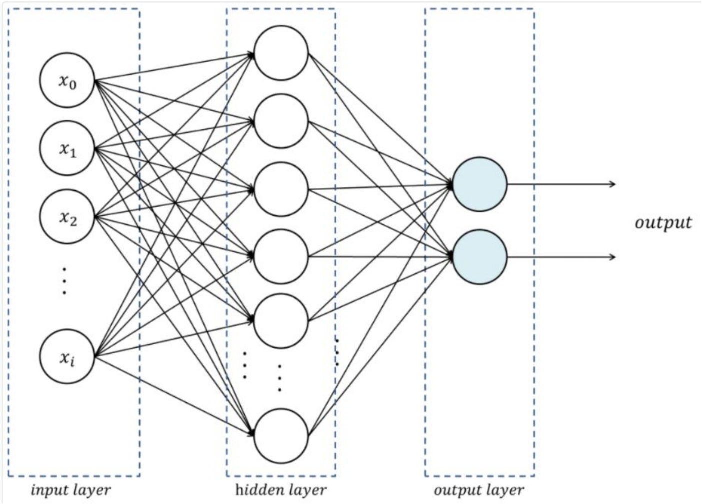
- Added a layer for feature embeddings
- Changed final output layer dimension to match the number of classes from the EEG dataset



EEG-Image-Map

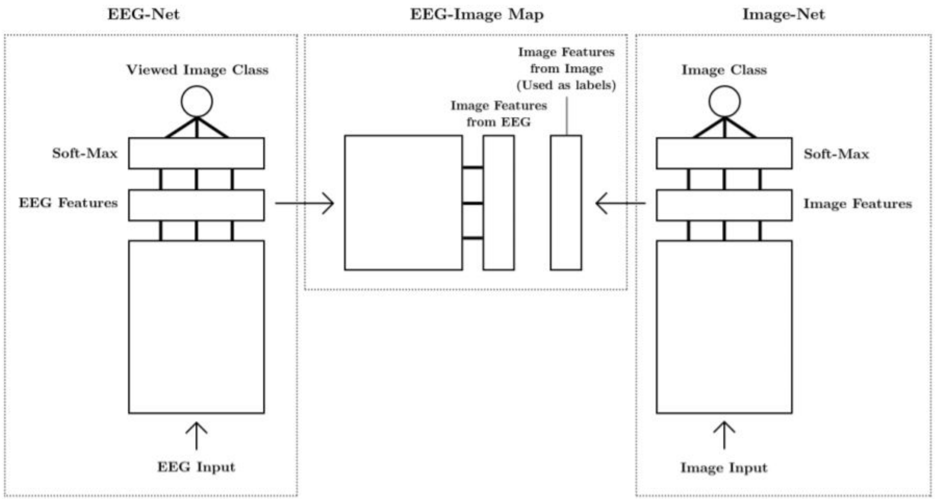
- Experimented with MLP and LSTM
- Input: EEG feature embedding
- Output: Image feature embedding
- Loss function: CosineEmbeddingLoss

<u>Hypothesis: if output embedding can match corresponding Image feature embedding, then our system will classify/identify well for image of any class</u>



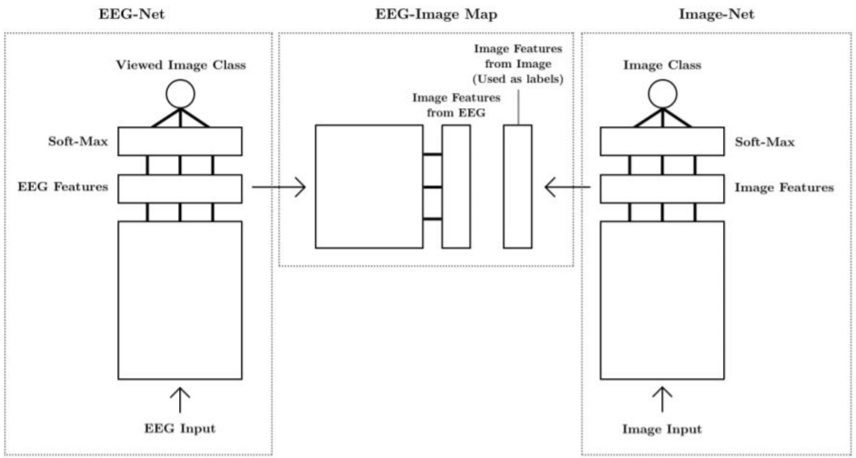
Phase 1 - Training and testing with all 40 classes

```
EEG-Net test  accuracy: 47.9429 %
Image-Net test  accuracy: 99.4975 %
EEG-Image-Map avg test cosine similarity: 0.9178
EEG-Image-Map test classification accuracy: 46.683459 %
EEG-Image-Map test identification accuracy: 1.511335 %
```



Phase 2 - Train, Val: 35 classes, Test: 5 classes

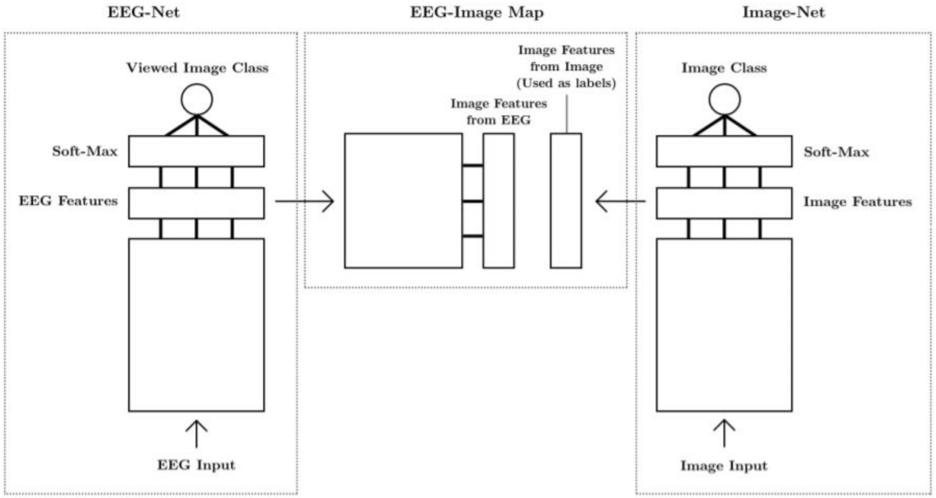
1. Split data into 35 / 5 image classes
2. Make train and val dataset using 35 classes
3. Make test dataset using 5 classes
4. Retrain EEG-Net and EEG-Image-Map
5. Create array of image features from testing set using Image-Net
6. Predict image and image class



Phase 2 - Train, Val: 35 classes, Test: 5 classes

```
EEG-Net val accuracy: 52.7778 %
Image-Net test accuracy: 99.6 %
EEG-Image-Map avg test cosine similarity: 0.8652
EEG-Image-Map test classification accuracy: 20.066667 %
EEG-Image-Map test identification accuracy: 0.066667 %
```

```
EEG-Net val accuracy: 52.7778 %
Image-Net val accuracy: 98.2759 %
EEG-Image-Map avg val cosine similarity: 0.9217
EEG-Image-Map val classification accuracy: 44.636015 %
EEG-Image-Map val identification accuracy: 1.245211 %
```



Conclusions

- EEG-Net has potential to do better, better EEG feature extraction for EEG-Image-Map training

- Mapping EEG features to Image features generalizes well in terms of cosine similarity

- Maximizing feature similarity did not correspond to better classification and identification accuracies (null hypothesis)