Epileptic Seizure Identification using Deep Metric Learning with Attention via EEG

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Introduction: EEG Signals

- An electroencephalogram (EEG) is a recording of brain activity.
- Measures voltage fluctuations from ionic current flows in neurons and fundamental tool in neurology for diagnosing brain disorders
- Characterized by different frequency bands (delta, theta, alpha, beta, gamma)
- Recorded using electrodes on scalp, interpreted by experts for abnormalities
- Varied applications: sleep studies, cognitive neuroscience, epilepsy diagnosis

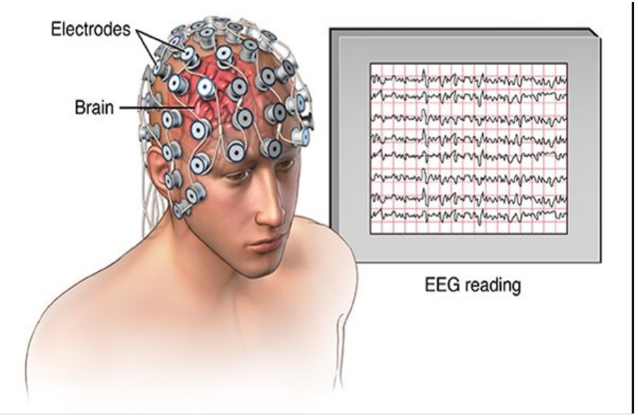


Image source - https://sipl.eelabs.technion.ac.il/projects/examination-of-tms-effect-using-eeg-signal/

Introduction : Epileptic Seizures

- Epilepsy is a disorder of the brain characterized by repeated seizures. A seizure is usually defined as a sudden alteration of behavior due to a temporary change in the electrical functioning of the brain.

- Why treatment is necessary -
  - The risk of premature death in people with epilepsy is up to three times higher than for the general population
  - Uncontrolled seizures can affect cognitive functions, including memory and learning. They can also contribute to psychological issues such as depression and anxiety.

Why automatic epileptic seizure detection ?

- Very less experts worldwide in detection and treatment for the epilepsy.
- AI systems can continuously monitor patients, providing round-the-clock surveillance.
- AI-driven systems can be deployed widely, including in remote or underserved areas where specialized medical practitioners might not be available.
- AI can process and interpret EEG data much faster than a human practitioner.

Dataset

- The proposed model was trained and evaluated using the largest available EEG epilepsy database, the Temple University Hospital EEG Seizure Corpus, TUSZ v2.0.3[1].

- Two classes -
  - **Background** (Baseline/non-interesting events)
  - **Seizure** (Common seizure class which can include all types of seizure)

- This corpus has EEG signals that have been manually annotated data for seizure events (start time, stop, channel and seizure type).

1. Shah, V., von Weltin, E., Lopez. S., McHugh, J., Veloso, L., Golmohammadi, M., Obeid, I., and Picone, J. (2018). The Temple University Hospital Seizure Detection Corpus. Frontiers in Neuroinformatics. 12:83.doi: 10.3389/fninf.2018.00083

Dataset

- Duration of Seizure and background events -
  - Train
    - Seizure ~ 44 hours
    - Background ~ 560 hours
  - Validation
    - Seizure ~ 18 hours
    - Background ~ 37 hours
  - Test
    - Seizure ~ 7.56 hours
    - Background ~ 0.17 hours

Selected only a subset of background data in training to ensure balanced dataset.

Feature Extraction

For extracting features we computed Fast-Fourier transform (FFT) of the signals which have been reported to be effective in analysing EEG signals.

Fast-Fourier Transform (FFT) transforms a signal from the time domain into the frequency domain.

We applied Fast Fourier Transform (FFT) to each 1 seconds of clip having 0.5 seconds overlap across all EEG channels.

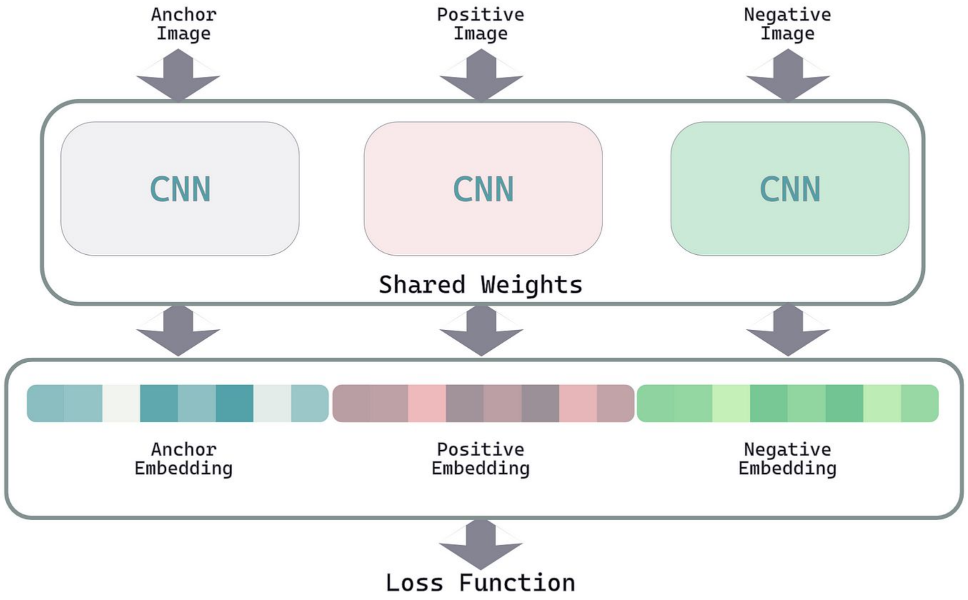
Next, we took $log_{10}()$ of the magnitudes of frequencies in the range $1 - f_{max}$ (where f_{max} = 126 Hz) .

After this operation, the dimension of each training sample becomes (N,125) where N is the number of EEG channels (20 in our case).

1. Roy, S., Asif, U., Tang, J., & Harrer, S. (2019). Machine learning for seizure type classification: setting the benchmark. arXiv preprint arXiv:1902.01012.

Image Embeddings

Image Dimension - (20, 125)



Triplet loss - $$\sum_{i}^{N} \left[\|f(x_i^a) - f(x_i^p)\|_2^2 - \|f(x_i^a) - f(x_i^n)\|_2^2 + \alpha \right]$$

We are using siamese network for learning embeddings for images of seizure and background class.

Triplet loss minimizes the distance between same class images (Anchor, Positive) and maximizes the distance between different class (Anchor, Negative).

Hard Triplet Mining

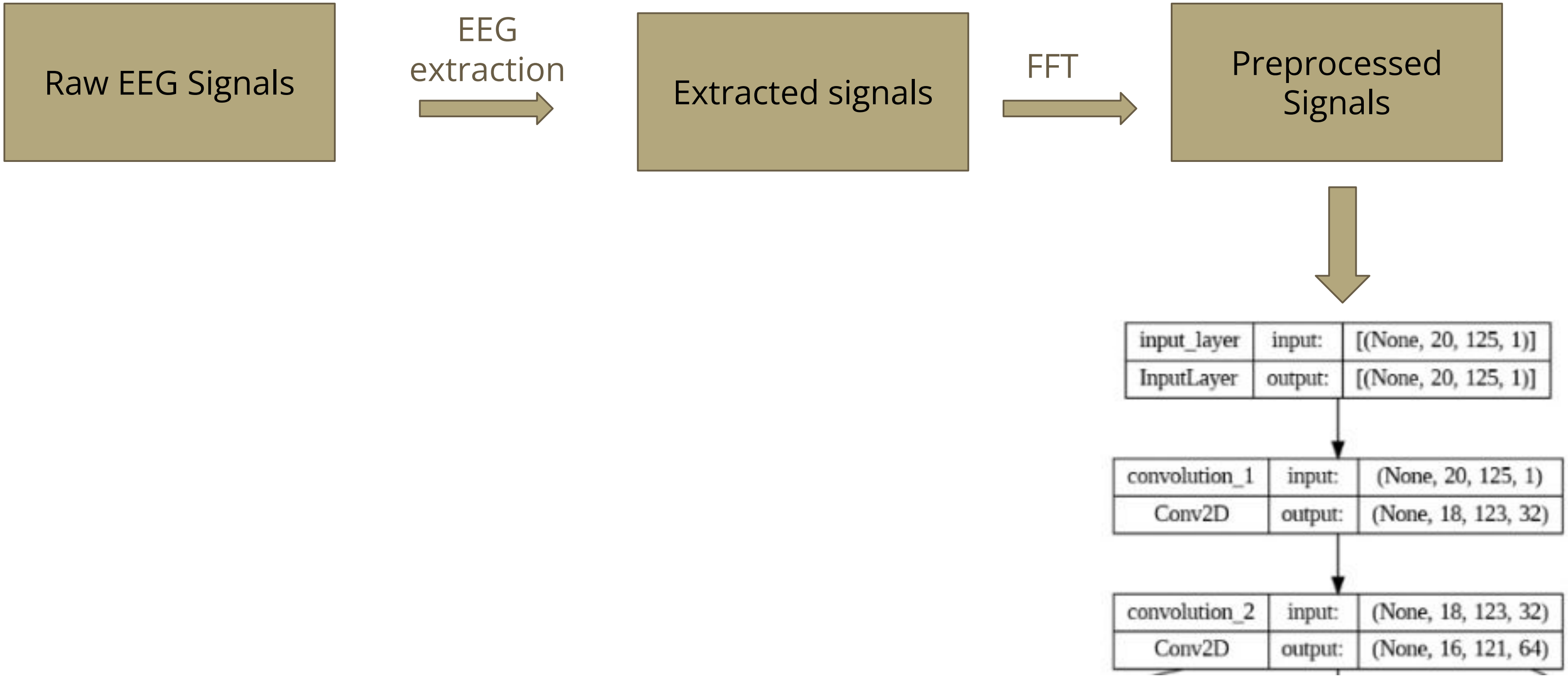
The effectiveness of the triplet loss depends significantly on the selection of triplets. Hard triplet mining focuses on selecting triplets that are difficult for the network to distinguish, which can accelerate training and improve performance.

Hard Positive: A positive sample (P) that is farthest from the anchor (A) but still belongs to the same class.

Hard Negative: A negative sample (N) that is closest to the anchor (A) but belongs to a different class.

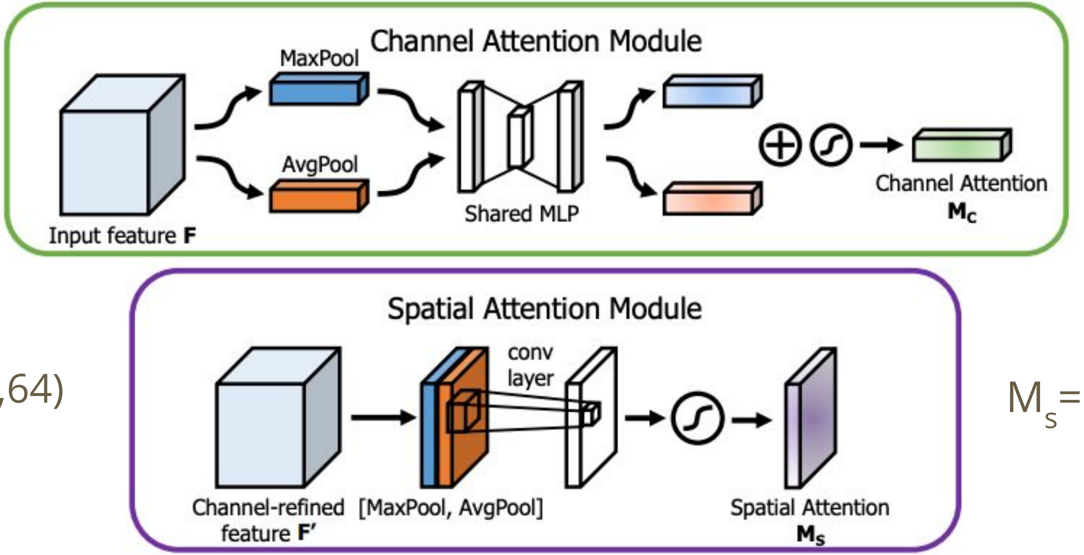
To train the model more robustly , we are calculating the distance matrix for all image embeddings in a batch and selecting only hard triplets to calculate the loss.

Model Architecture



Attention

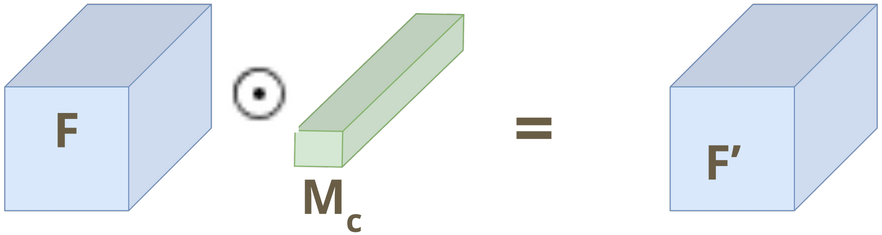
F = (16,121,64)



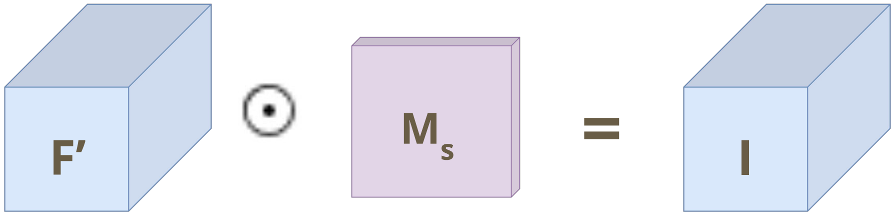
M_c = (1, 1, 64)

F′ = (16,121,64)

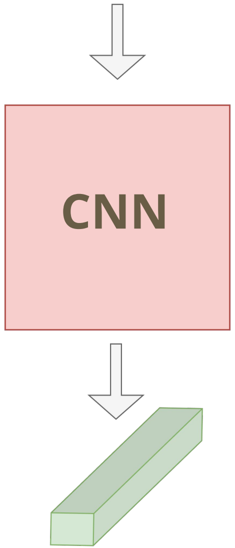
M_s= (16, 121, 1)



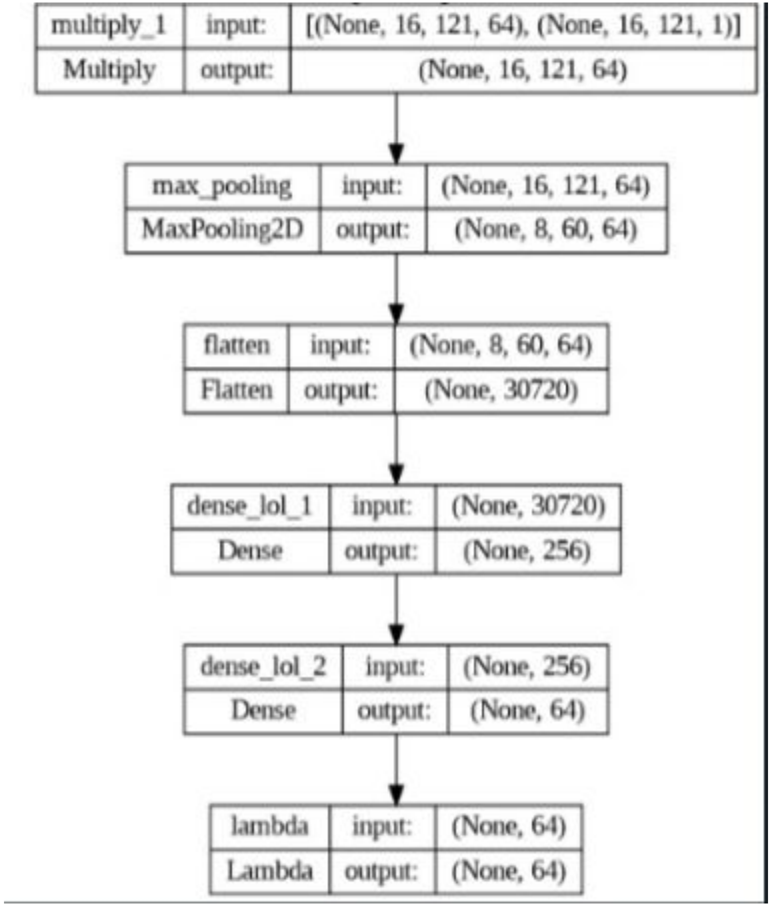
After Attention



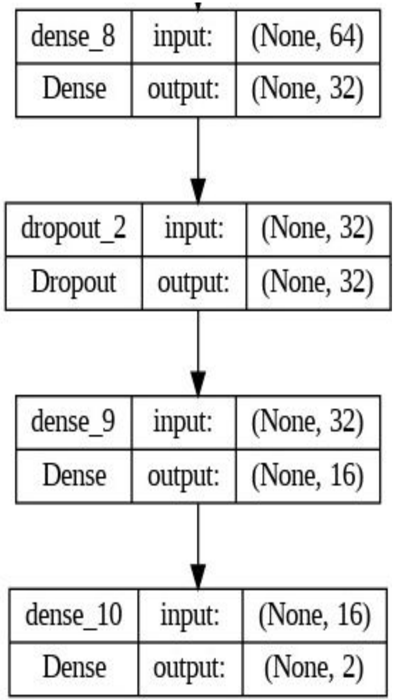
After Attention we passed the input I in CNN to get the embedding of each image.



64-dim

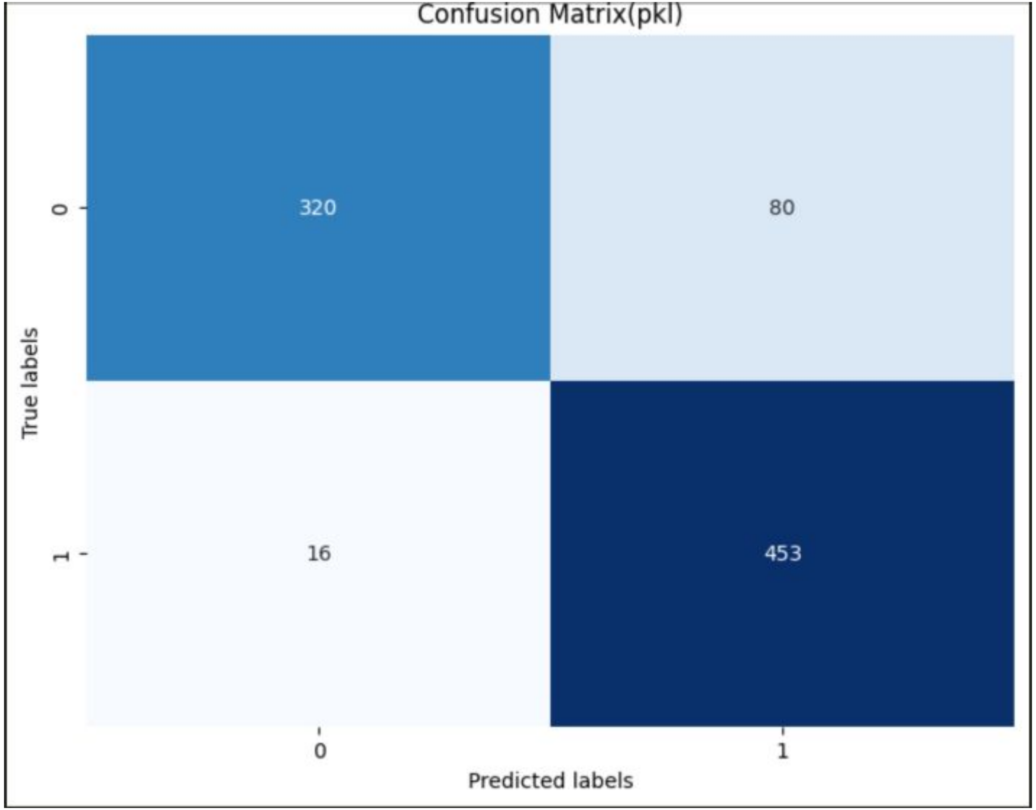


Classification Model Architecture



After classifying each image we have done majority voting to determine if the patient's EEG signal depicts Seizure patterns or not.

Results



	Precision	Recall	F1-Score
0	0.95	0.80	0.87
1	0.85	0.97	0.90

Accuracy - 89 %

Thank You