Harmful Brain Activity Classification

Classifying seizures and other patterns of harmful brain activity in critically ill patients

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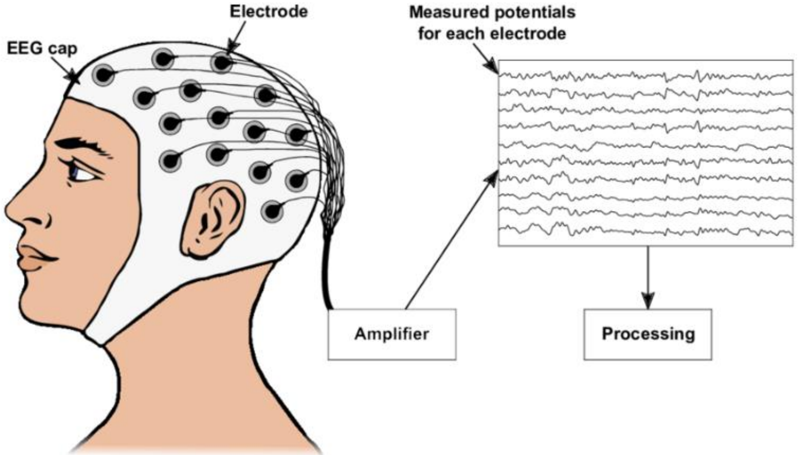
Detecting Harmful Brain Activity

- Chronic Brain Disorders like Epilepsy can lead to Seizures and other activity that show up on electroencephalograms (EEGs).

- EEGs are tests that **measure electrical activity** in the brain using small, metal discs (electrodes) attached to the scalp.

- They can be used as **raw signals** to **extract several features** that represent brain activity. This is what we are using for classification.[1]



Sketch of how to record an Electroencephalogram.

Nagel, Sebastian. (2019). Towards a home-use BCI: fast asynchronous control and robust non-control state detection. 10.15496/publikation-37739.

[1] Britton JW, Frey LC, Hopp JLet al., authors; St. Louis EK, Frey LC, editors. "Electroencephalography (EEG): An Introductory Text and Atlas of Normal and Abnormal Findings in Adults", 2016. https://www.ncbi.nlm.nih.gov/books/NBK390358/

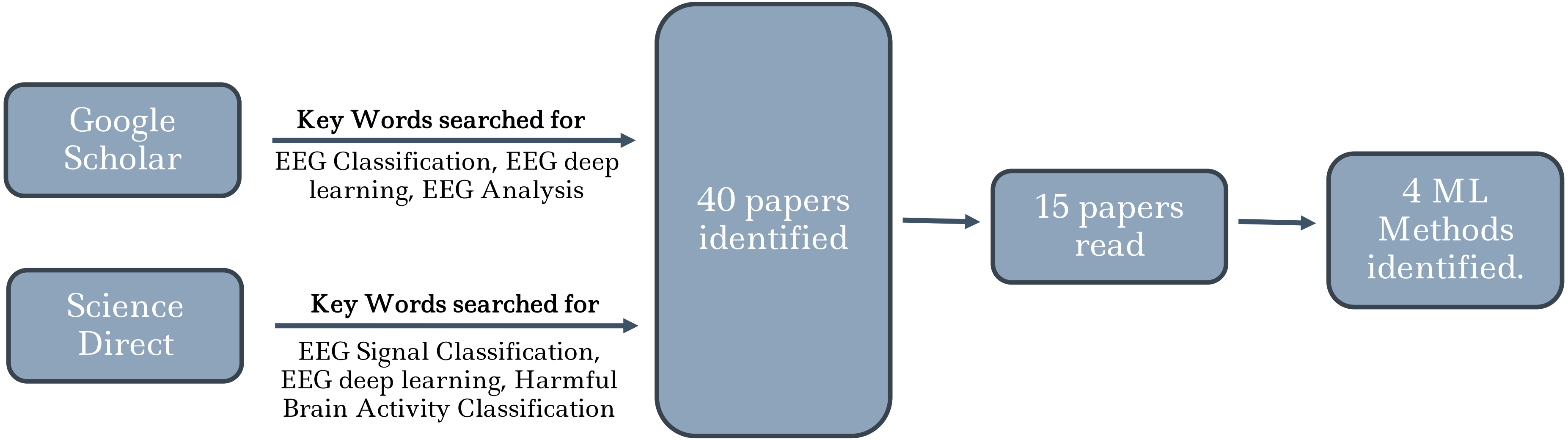
The Problem

- Detecting Harmful Brain Activity using EEGs relies solely on **slow, error-prone manual analysis** by specialized neurologists. This can be un-reliable.

- As a solution, we aim to classify EEG data into six classes:

  Seizures (SZ), **Generalized Periodic Discharges** (GPD), **Lateralized Periodic Discharges** (LPD), **Lateralized Rhythmic Delta Activity** (LRDA) and **Generalized Rhythmic Delta Activity** (GRDA) and **Others.**

Literature Survey



Literature Survey

WaveNet-based Architecture[2]

- Use of increasing dilation of each convolutional layer, which gives it ability to capture long-term dependencies.
- Evaluated on the TUH abnormal EEG Corpus V.2.0.0, divided into five distinct classes.
- 97.45% accuracy for binary classification between normal and abnormal EEG recordings.

SVM[3]

- Uses **mean**, **max**, **min** and **standard deviation** of **256 wavelet coefficients** and **128 Lyapunov exponents**. The dataset also had 5 classes, but only had single-channel EEGs.
- The input dataset consisted of 100 single-channel EEG signals. 98% accuracy for five class classification problem.

[2] Albaqami, H., Hassan, G. M., & Datta, A. (2023). Automatic Detection of Abnormal EEG Signals Using WaveNet and LSTM. Sensors (Basel, Switzerland), 23(13), 5960. https://doi.org/10.3390/s23135960
[3] I. Guler and E. D. Ubeyli, "Multiclass Support Vector Machines for EEG-Signals Classification," IEEE Transactions on Information Technology in Biomedicine, vol. 11, no. 2, pp. 117-126, Mar. 2007.

Literature Survey

DenseNet with FAM[4]

- Uses dense convolutional blocks (DCB), feature attention modules (FAM) and residual blocks (RB).
- Evaluated on the University of Bonn EEG dataset, divided into five distinct classes.
- 99.96% accuracy in classifying the five-class problem.

Transfer Learning Techniques

- **ResNet[5]**

Binary classification model giving accuracy 99.7% over RGB features of EEG data. RGB features were from University of Bonn dataset.

- **EfficientNet[6]**

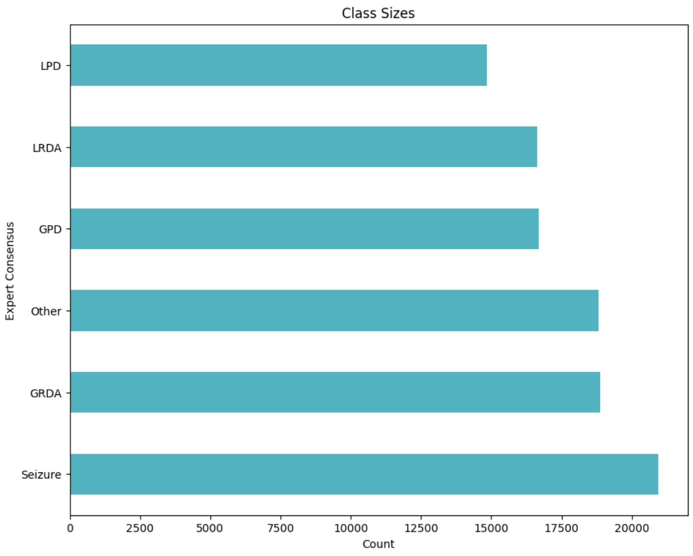
The model uses Transfer Learning with EfficientNet to do seizure classification and obtain an accuracy of 95.25. The University of Bonn dataset was used.

[4] Islam, M. S., Thapa, K., & Yang, S. H. (2022). Epileptic-Net: An Improved Epileptic Seizure Detection System Using Dense Convolutional Block with Attention Network from EEG. Sensors (Basel, Switzerland), 22(3), 728.
[5] A. Agrawal, G. C. Jana and P. Gupta, "A Deep Transfer Learning Approach for Seizure Detection Using RGB Features of Epileptic Electroencephalogram Signals," (Sydney, NSW, Australia, 2019, pp. 367-373, doi: 10.1109/CloudCom.2019.00063.
[6]Xiong, Z., Wang, H., Zhang, L., Fan, T., Shen, J., Zhao, Y., Liu, Y., & Wu, Q. (2021). A Study on Seizure Detection of EEG Signals Represented in 2D. Sensors (Basel, Switzerland), 21(15), 5145. https://doi.org/10.3390/s21155145

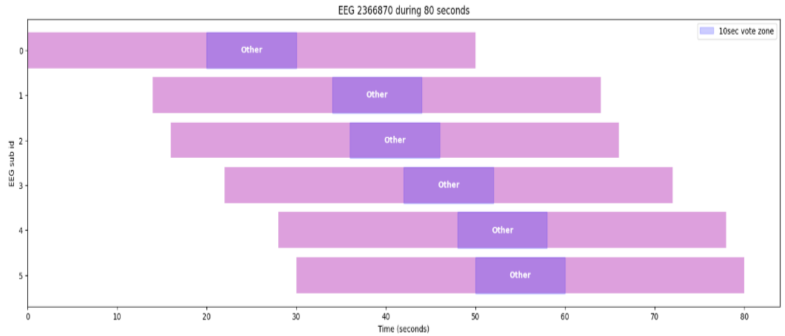
Dataset and Features Preprocessing

Understanding our Dataset

- The data is collected by Kaggle for the competition. The labels are annotated by experts from the **Critical Care EEG Monitoring Research Consortium (CCEMRC)**.
- The dataset does not contain any data for gender or age. This limits our study into biases.



This plot for train data demonstrates that we have balanced data.



	eeg_id	eeg_sub_id	eeg_label_offset_seconds	spectrogram_id	spectrogram_sub_id	spectrogram_label_offset_seconds
0	2366870	0	0.0	1232582129	0	0.0
1	2366870	1	14.0	1232582129	1	14.0
2	2366870	2	16.0	1232582129	2	16.0
3	2366870	3	22.0	1232582129	3	22.0
4	2366870	4	28.0	1232582129	4	28.0
5	2366870	5	30.0	1232582129	5	30.0

This plot showcases the overlapping time windows of eeg_subs.

Understanding our Dataset

- There can be multiple **`eeg_ids`** for one **`patient_id`** → one patient has donated more than one sample.
- The IDs have subsamples. Each **`eeg_sub`** is a dataframe (stored as .parquet), with 20 channels (19 EEG and 1 EKG). The sampling frequency is **200 Hz**, and the duration of one subsample is 50 seconds.

Ground truth data can be extracted using many strategies, such as, **Votes** (using SoftMax of the all the votes columns):

- Choosing only one random subsample or middle subsample
- Choosing the subsample with the highest number of total votes
- Average of all the subsamples.

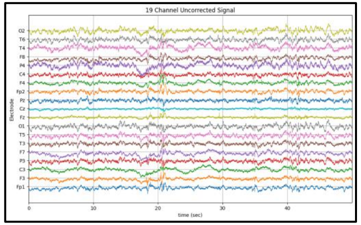
Introduction to our Loss Function

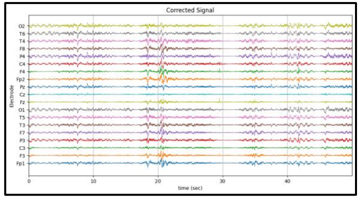
KL Divergence

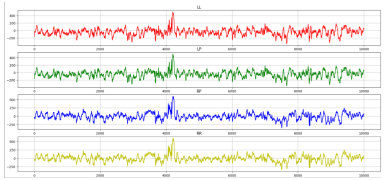
- Kullback-Leibler (KL) divergence, is a metric used to compare two data probability distributions.
- KL divergence is defined as the number of bits required to convert one distribution into another.
- A lower KL divergence score indicates better performance.
- We have two discrete probability distributions, P and Q, with a common sample space E. In the case of our project, let P represent the solution (ground truth) and let Q represent the submission (model output).

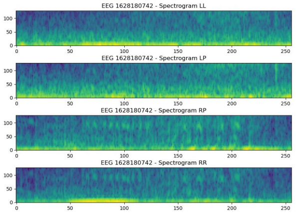
$$\mathrm{KL}(\mathbf{P},\mathbf{Q}) = \sum_{x\in E} p(x)\ln\left(\frac{p(x)}{q(x)}\right)$$

Input Types









Raw EEG Time Series Data

↓

Cleaning and Scrubbing

↓

Montaged EEG Time Series Data → DenseNet
WaveNet

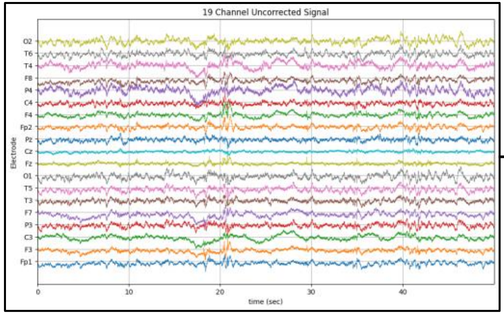
↓

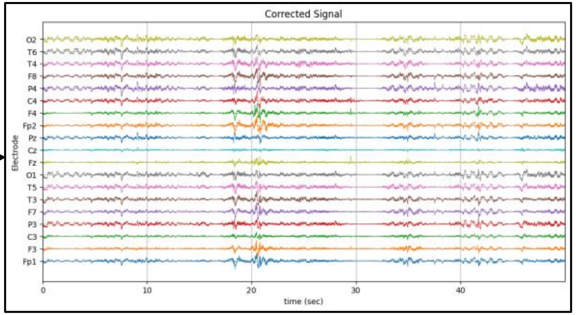
2D Spectrogram Images → TL with EfficientNet
TL with ResNet101

Data Cleaning

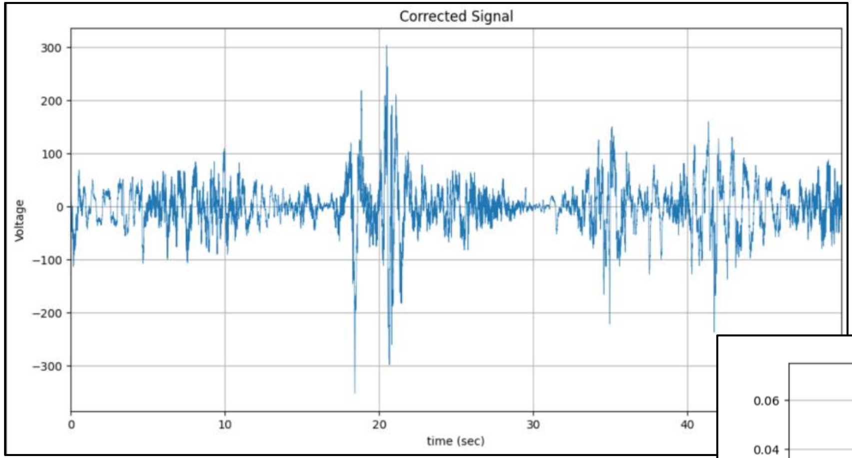
- Raw EEG signal data can contain artifacts due to **muscle movement**, **breathing** or **cardiac movement**.
- We identified that these artifacts can be removed using techniques such as **ATAR** and **ICA**. Out of these, ICA is used across more papers [3].
- We applied ICA using the extended-infomax algorithm [4] on **all 19 EEG channels**. Before ICA we applied a high-pass filter. This process takes 31.4s to run per subsample.

High-pass filter frequency band: **70 Hz**
ICA parameters: **kurtosis threshold = 2** and **correlation threshold = 0.8**.



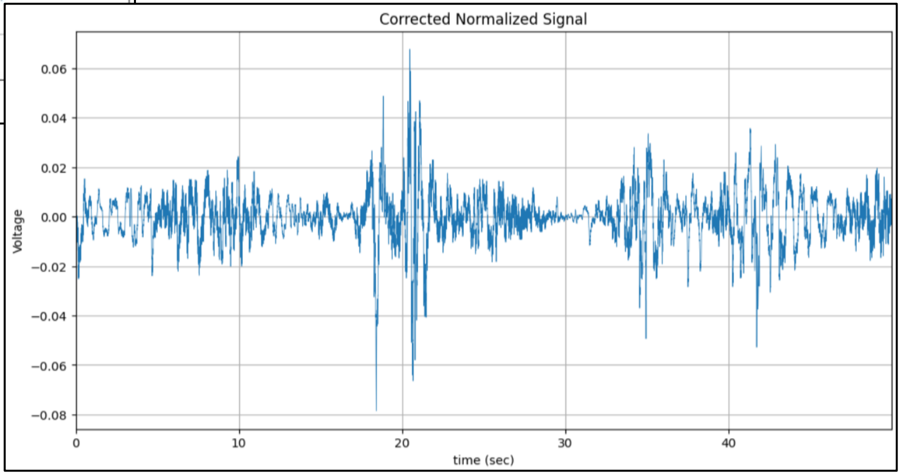


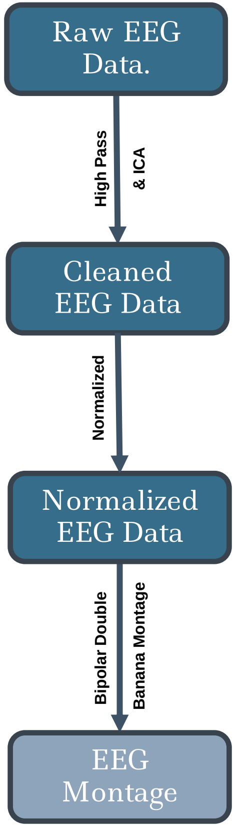
Normalization of Cleaned Signal

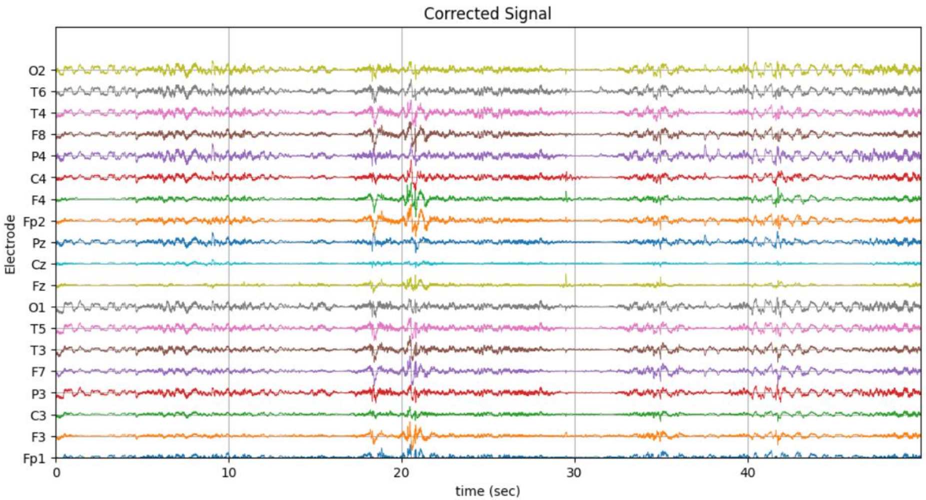


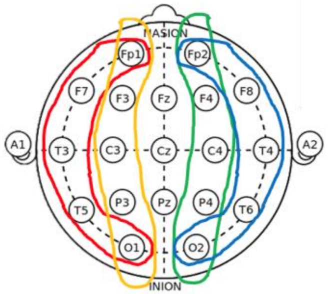
We used **Normalization** on the cleaned data to ensure the model converges faster.

This was done on 19 EEG channels.



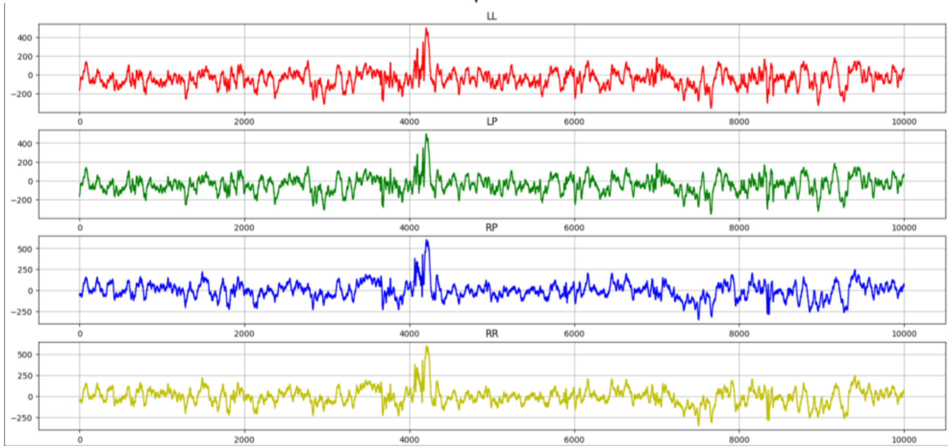






KEY

- LL - Left Temporal Chain
- LP - Left Parasagittal Chain
- RP - Right Parasagittal Chain
- RR - Right Temporal Chain



We use the "**Bipolar Double Banana Montage**" system to create 4 montage features out of 19 features.

A.I.
Methodology

Regularization Techniques

Optimizers

- **Adam**

An algorithm for gradient based optimization. Weight decay is linked to learning rate.

- **AdamW**

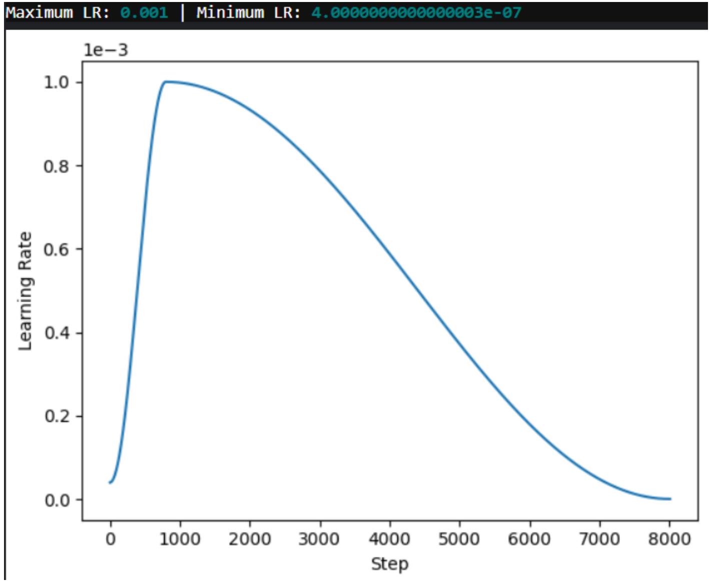
Weight decay and learning rate are separated.

Learning Rate Schedulers

- Learning Rate Schedulers adjust the learning rate during training.

- **Cosine Learning Rate Scheduler**

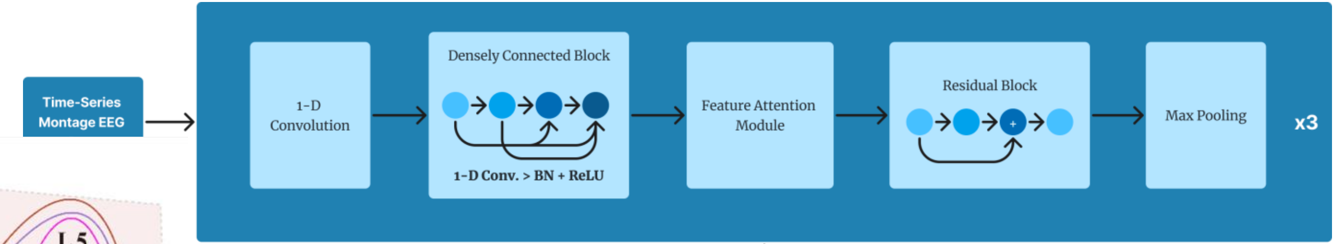
The cosine schedule for learning rate is a type of schedule that starts with a large learning rate that first rapidly decreases to a minimum and then increases again.



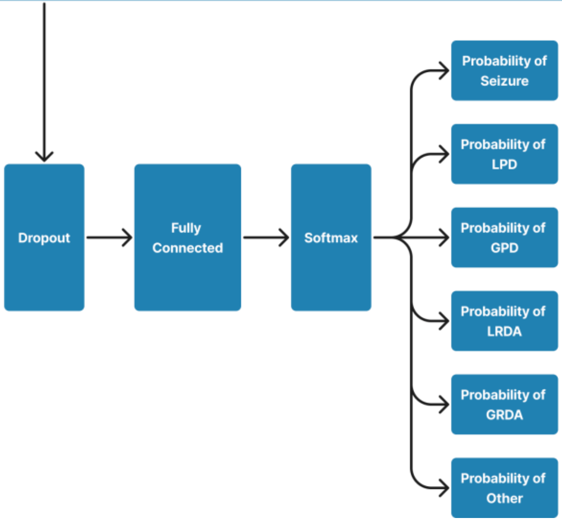
1D EEG Signals as Input

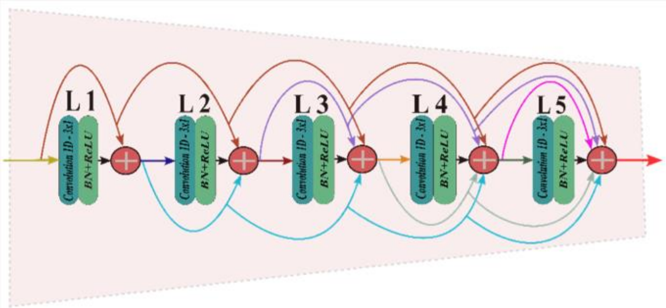
Dense convolutional networks (DenseNet) With FAM

Type of deep convolutional neural network that connect each layer to every other layer in a feed-forward fashion.

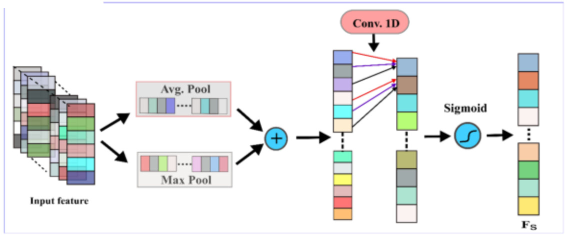


Model Architecture





Dense Block



Feature Attention Module (FAM)

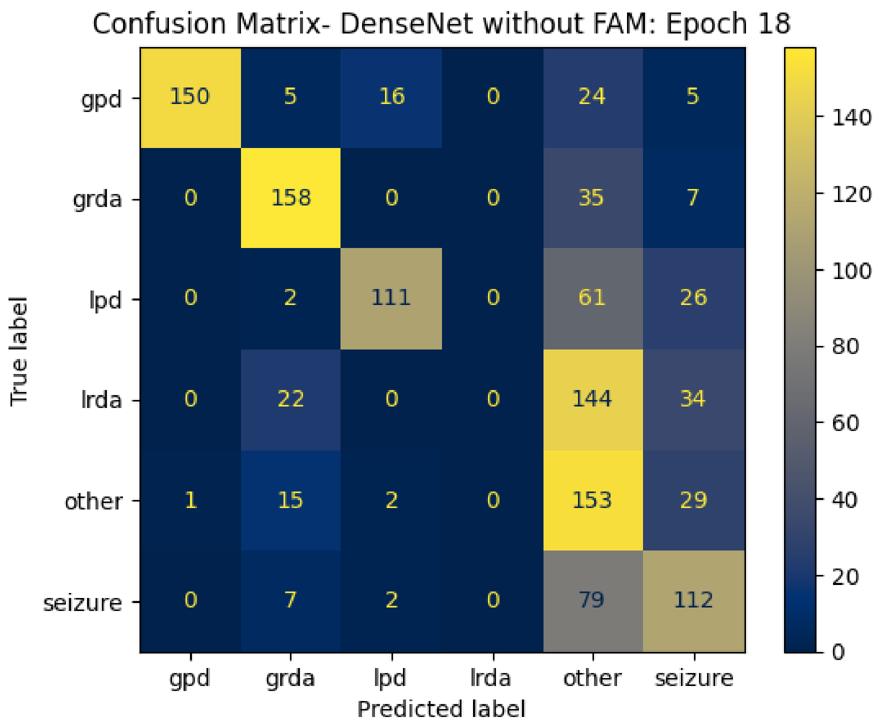
Islam, M. S., Thapa, K., & Yang, S. H. (2022). Epileptic-Net: An Improved Epileptic Seizure Detection System Using Dense Convolutional Block with Attention Network from EEG. *Sensors (Basel, Switzerland)*, *22*(3), 728. https://doi.org/10.3390/s22030728

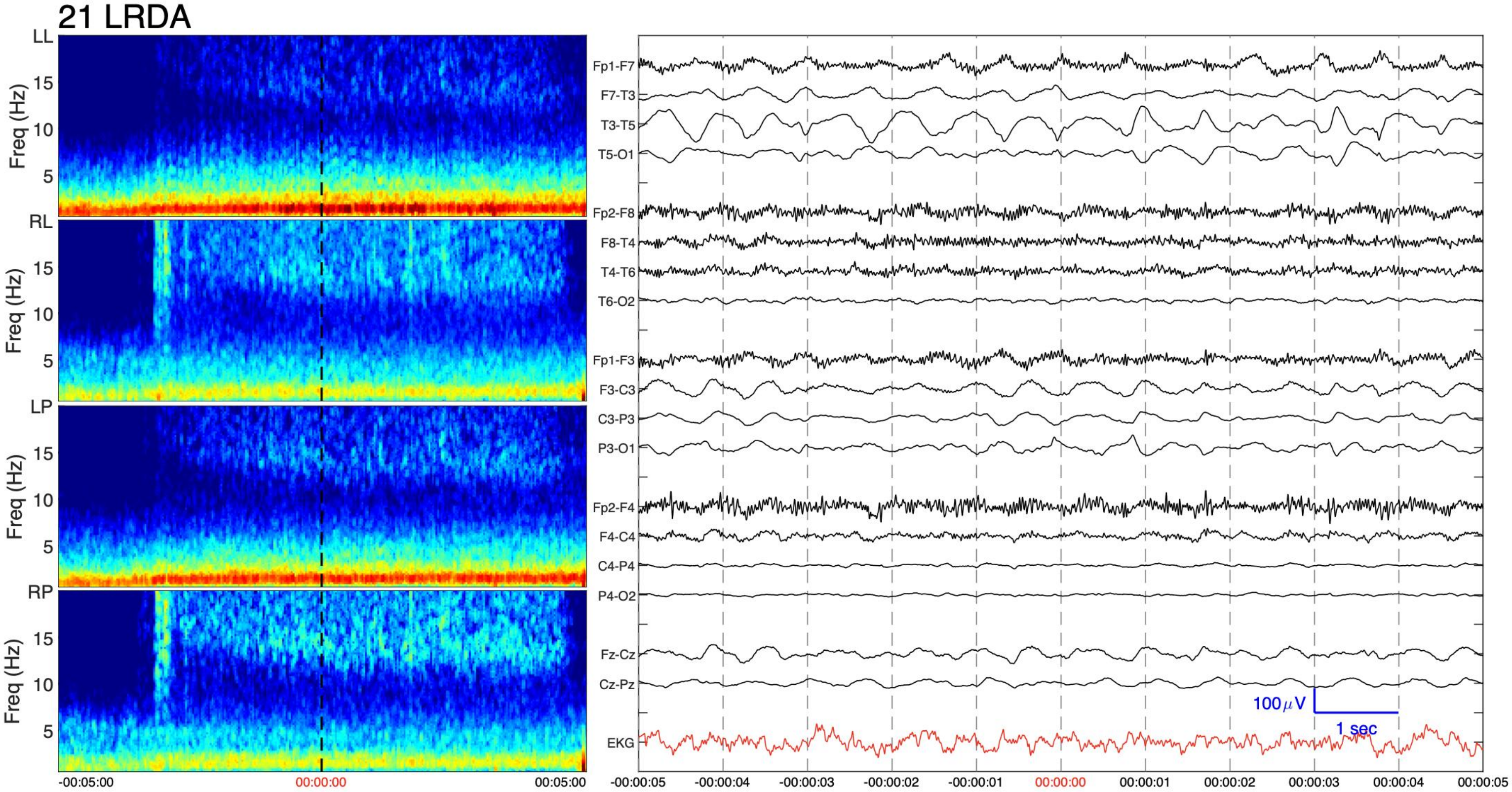
DenseNet Metrics

	precision	recall	f1-score	support
gpd	0.99	0.75	0.85	200
grda	0.76	0.79	0.77	200
lpd	0.85	0.56	0.67	200
lrda	0.00	0.00	0.00	200
other	0.31	0.77	0.44	200
seizure	0.53	0.56	0.54	200
accuracy			0.57	1200
macro avg	0.57	0.57	0.55	1200
weighted avg	0.57	0.57	0.55	1200

Classification report

Type	Kaggle Score
Without FAM	1.483
FAM	1.717
FAM with 10 seconds	2.6227





21 LRDA
LL
RL
LP
RP
Freq (Hz)
5
10
15
-00:05:00
00:00:00
00:05:00
Fp1-F7
F7-T3
T3-T5
T5-O1
Fp2-F8
F8-T4
T4-T6
T6-O2
Fp1-F3
F3-C3
C3-P3
P3-O1
Fp2-F4
F4-C4
C4-P4
P4-O2
Fz-Cz
Cz-Pz
EKG
100μV
1 sec
-00:00:05
-00:00:04
-00:00:03
-00:00:02
-00:00:01
00:00:00
00:00:01
00:00:02
00:00:03
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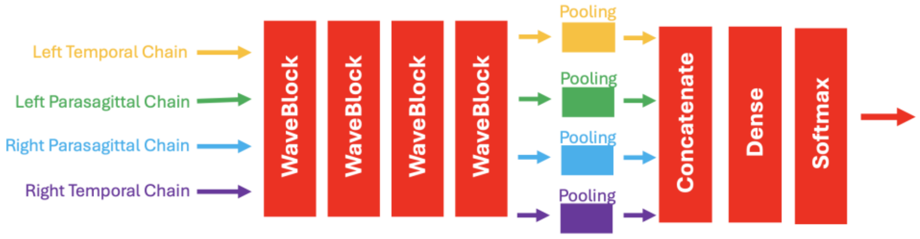
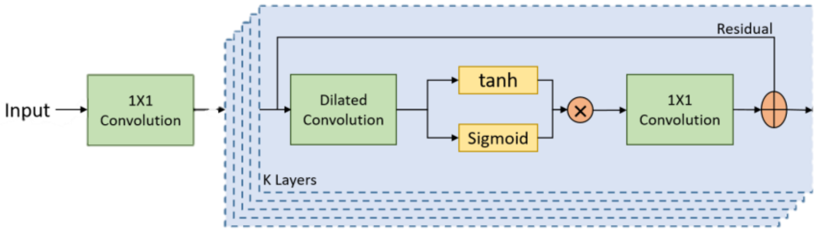
WaveNet

Description

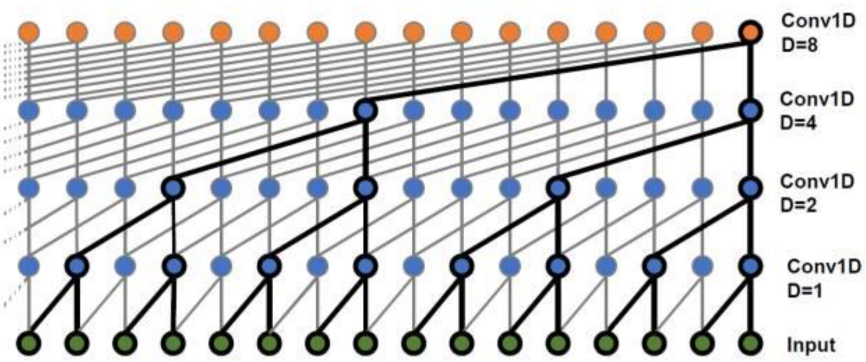
A deep learning architecture developed by Google DeepMind in 2015. By increasing the dilation factor of each convolutional layer, its receptive field can grow exponentially.



WaveNet



Wave Block



Dilated convolution

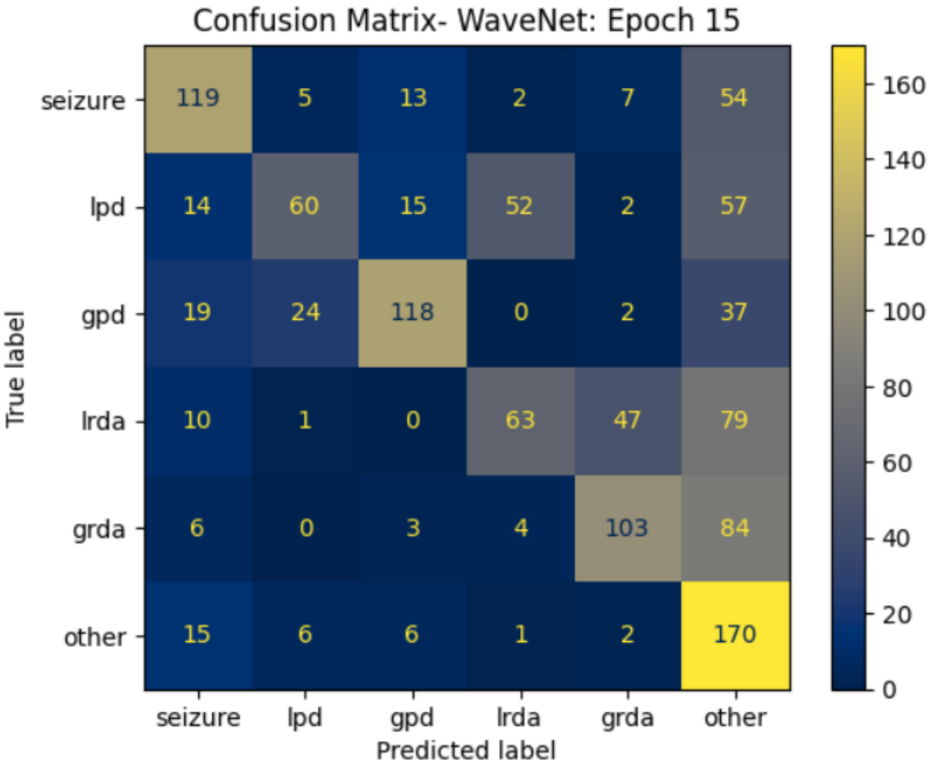
Albaqami, H., Hassan, G. M., & Datta, A. (2023). Automatic Detection of Abnormal EEG Signals Using WaveNet and LSTM. Sensors (Basel, Switzerland), 23(13), 5960. https://doi.org/10.3390/s23135960

WaveNet Metrics

	precision	recall	f1-score	support
seizure	0.65	0.59	0.62	200
lpd	0.62	0.30	0.41	200
gpd	0.76	0.59	0.66	200
lrda	0.52	0.32	0.39	200
grda	0.63	0.52	0.57	200
other	0.35	0.85	0.50	200
accuracy			0.53	1200
macro avg	0.59	0.53	0.52	1200
weighted avg	0.59	0.53	0.52	1200

Classification report

Type	Kaggle Score
Version - 1	0.5031
Version – 2 (more dilation with dropout)	0.5138
Version – 3 (Increased epochs and complexity)	0.4396 Kaggle Leaderboard Rank - 1267



2D Spectrogram Creation

Feature Extraction for CNN-based models

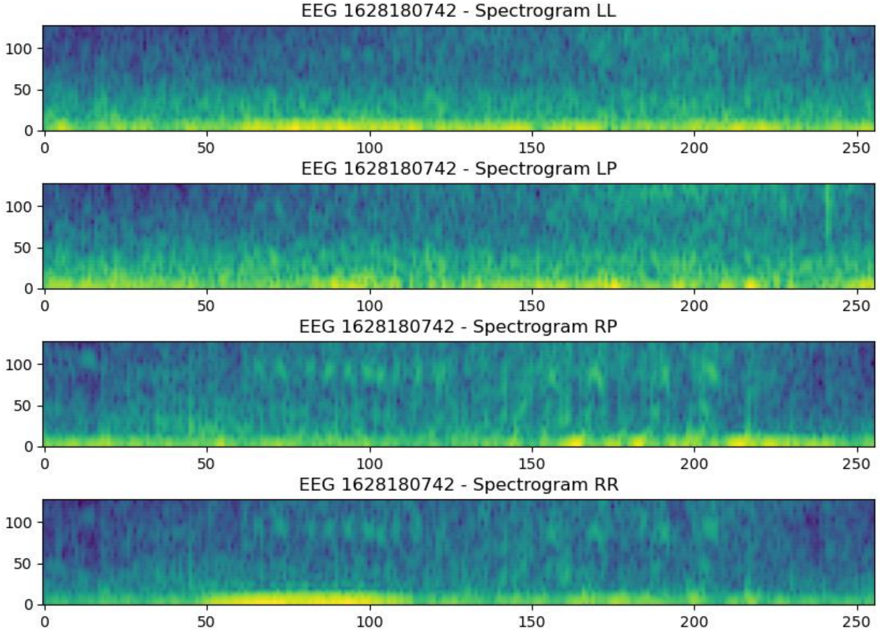
For things like Transfer Learning with Efficient Net, ResNet101 and more...

We have used the **MelSpec** function of the library **Librosa** which computes a mel-scaled spectrogram to convert our montaged EEG data to Spectrogram values. We then pass these values directly to CNN models.

The above steps are done for each of the 4 montages we created, and the 4 montages are stacked to create a 4-channel output spectrogram image.

We added a Convolutional layer that takes 4-channel input and creates 3-channel output before our pre-trained models.

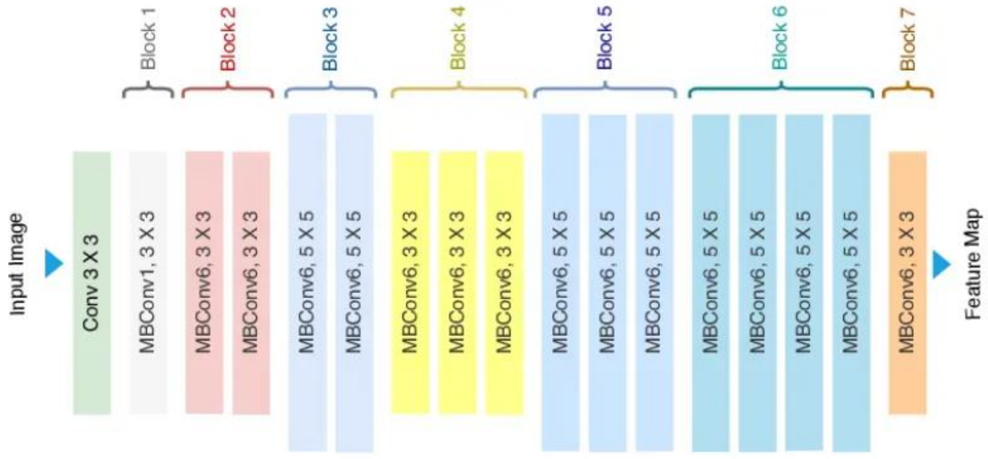
Spectrograms in the Frequency Domain



Transfer Learning with EfficientNet

Description
EfficientNet is a convolutional neural network built upon a concept called **compound scaling**. The idea behind compound scaling is to scale three essential dimensions of a neural network: width, depth, and resolution.

MBConv layer is inspired by inverted residual blocks from MobileNetV2 but with some modifications. It starts with a depth wise convolution followed by two 1x1 convolutions to expand the number of channels and then reduce them back to original, respectively.



EfficientNet Architecture. Source

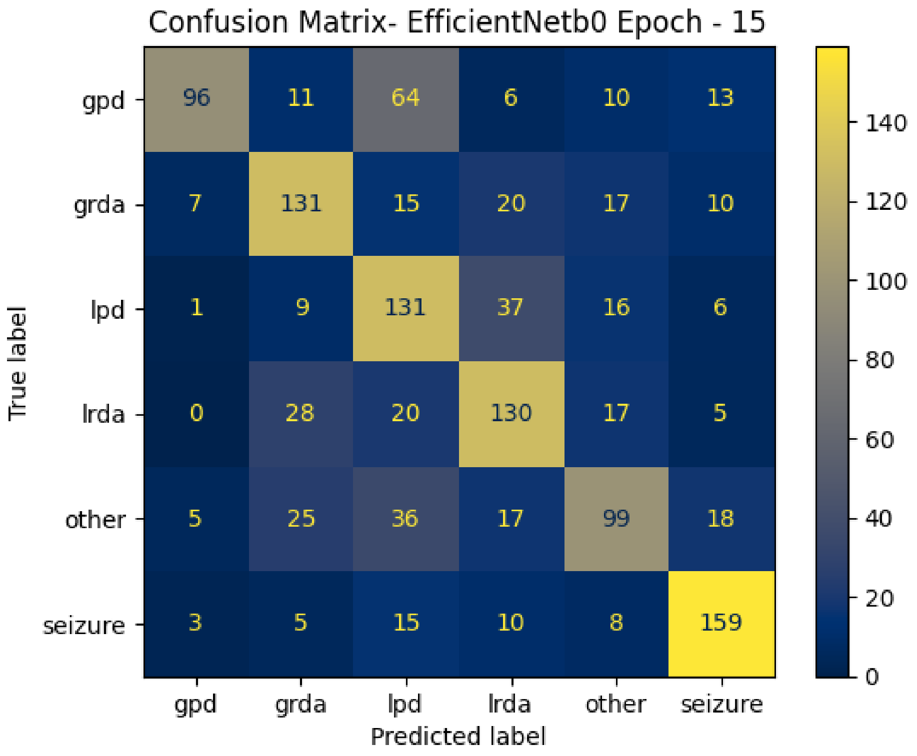
Xiong, Z., Wang, H., Zhang, L., Fan, T., Shen, J., Zhao, Y., Liu, Y., & Wu, Q. (2021). A Study on Seizure Detection of EEG Signals Represented in 2D. Sensors (Basel, Switzerland), 21(15), 5145. https://doi.org/10.3390/s21155145

EfficientNet Metrics

	precision	recall	f1-score	support
gpd	0.86	0.48	0.62	200
grda	0.63	0.66	0.64	200
lpd	0.47	0.66	0.54	200
lrda	0.59	0.65	0.62	200
other	0.59	0.49	0.54	200
seizure	0.75	0.80	0.77	200
accuracy			0.62	1200
macro avg	0.65	0.62	0.62	1200
weighted avg	0.65	0.62	0.62	1200

Classification report

Type	Kaggle Score
Version - 1	0.7761



Transfer Learning with ResNet-50

Description

- 50 layers deep CNN pretrained on ImageNet.
- Works on ‘skip connections' principle because it is easier for it to learn residual than the desired output.
- Residual block is conv layers stacked with batch normalization and ReLU activation layers.

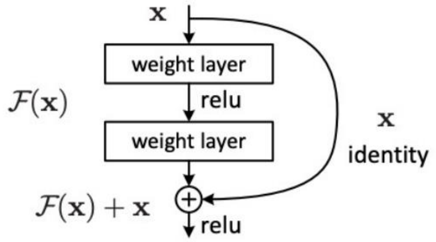
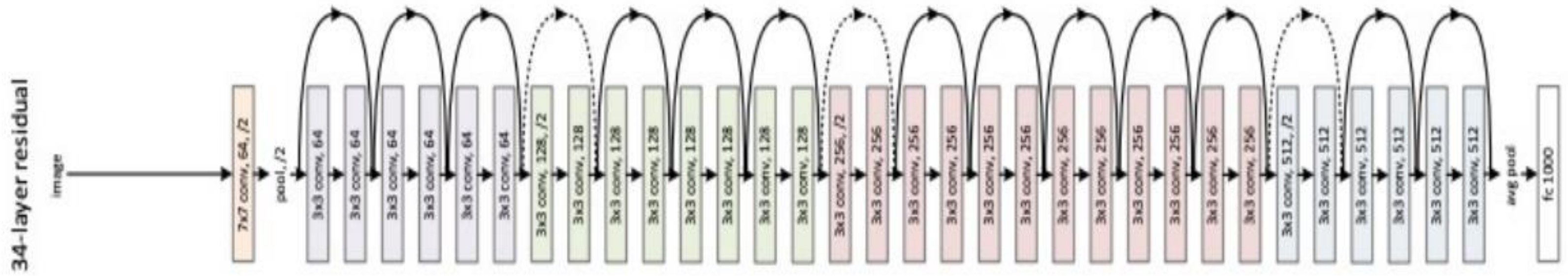


Figure 2. Residual learning: a building block.



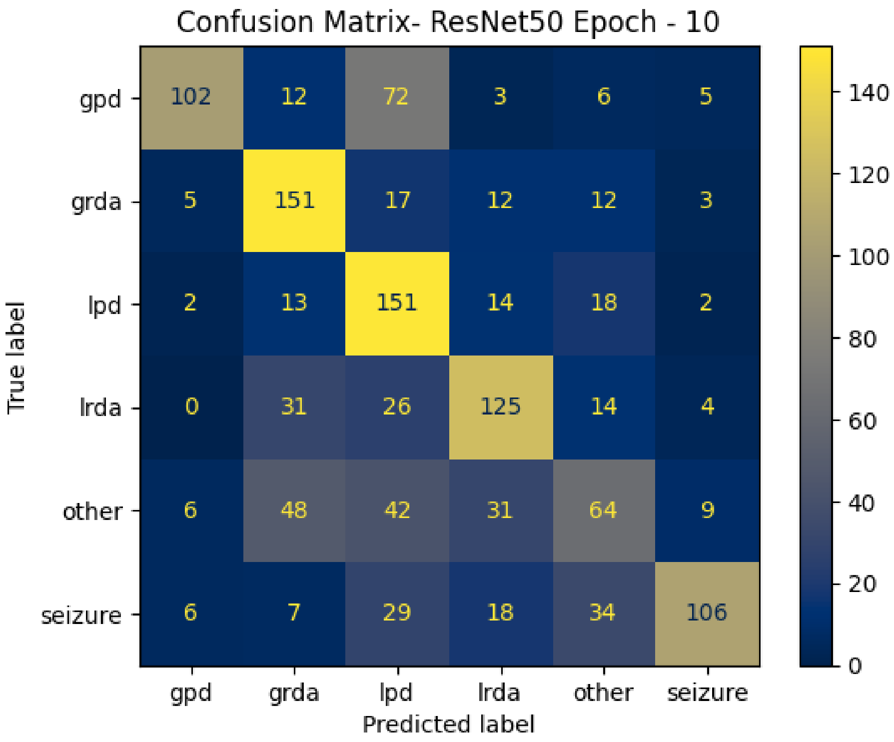
Model Architecture

A. Agrawal, G. C. Jana and P. Gupta, "A Deep Transfer Learning Approach for Seizure Detection Using RGB Features of Epileptic Electroencephalogram Signals," (Sydney, NSW, Australia, 2019, pp. 367-373, doi: 10.1109/CloudCom.2019.00063.

ResNet Metrics

	precision	recall	f1-score	support
gpd	0.84	0.51	0.64	200
grda	0.58	0.76	0.65	200
lpd	0.45	0.76	0.56	200
lrda	0.62	0.62	0.62	200
other	0.43	0.32	0.37	200
seizure	0.82	0.53	0.64	200
accuracy			0.58	1200
macro avg	0.62	0.58	0.58	1200
weighted avg	0.62	0.58	0.58	1200

Classification report



Type	Kaggle Score
Version - 1	0.9112

Challenges Faced

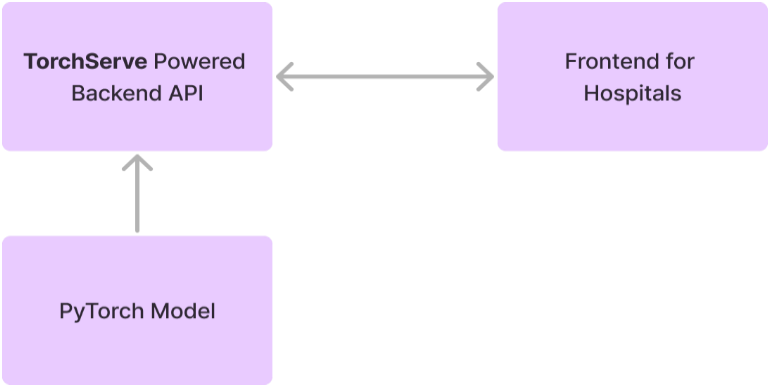
- Handling the massive dataset (**26.4 GB**) was challenging. This requires large memory capacity.
- Time complexity increases since the training needs to use a **smaller batch size** (due to memory limits). The complex nature of the models also increases complexity.
- Since time to train the model is high, it is harder for us to judge which features are truly increasing accuracy. The model's explainability is reduced.
- Kaggle's loss function was different than what we used in our models.
- Transfer learning models take 3-channel images, but we had 4-channel.
- Some classes like LRDA are hard to classify because of very noisy patterns.
- We couldn't run SVM on full dataset because we didn't have enough RAM and traditional SVM doesn't support batches.

Deploying

Deploy-ability

Deployment Process

- Model is packaged using TorchServe.
- It is then deployed across on-premise servers and cloud platforms.
- This ensures that the runtime environment is isolated from the underlying system.



Flow post deployment

- EEG data of the patient is acquired.
- It is sent as an inference request to TorchServe exposed RESTful API hosting the deployed model.
- The approx. inference time for this will be 30 seconds.
- Then the doctor can further investigate and analyze the results.

Ethical Consideration

- **Data Privacy and Security:** EEG data is highly sensitive information. Robust data privacy and security in compliance with regulations like HIPAA.

- **Bias and Fairness:** AI system can amplify the biases present in the training data. It is crucial to ensure that the model is free from biases that could lead to unfair decisions based on factors such as gender, age or ethinicity.

Bibliography

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Thank You