Easy Perturbation EEG Algorithm for Spectral Importance (easyPEASI): A Simple Method to Identify Important Spectral Features of EEG in Deep Learning Models

Authors: David Nahmias & Kimberly Kontson (2020)

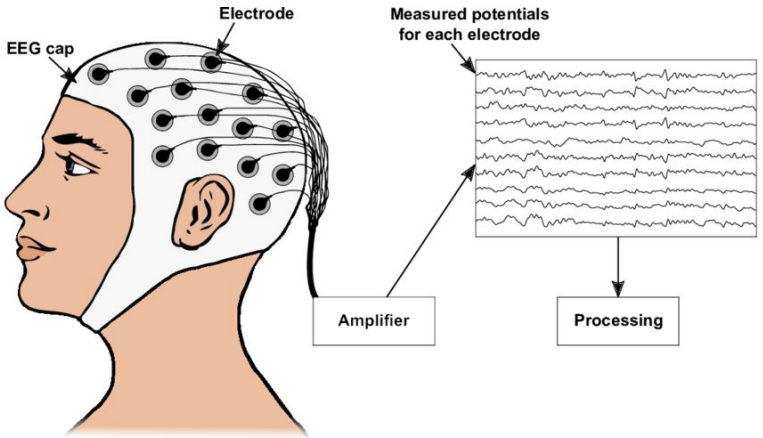
Trial Lecture by: Mohamed Radwan

Agenda

- Discuss core ideas behind the article
- Discuss advantages and flaws in the methods
- Show My attempt to fix those flaws
- Give conclusions of what is the main challenges in the data and reflect what could be possible solutions
  (N.B. My attempts are introducing questions more than answers)

What is EEG?

- Recording of brain activity which sensors are attached to the scalp to measure electrical signals from the brain by introducing stimuli
- Number of electrodes/channels changes per systems
- Low Signal to Noise ratio (Intrinsic, extrinsic)
- Frequency band:
    - delta (1: 4 Hz),
    - theta (4: 8 Hz)
    - alpha (8: 12 Hz)
    - mu (12: 16 Hz)
    - beta (16: 25 Hz)
    - gamma (25: 40 Hz)



Source: Sebastian Nagel, 2019

Frequency Band and Functions

Brainwave Type	Frequency Range (Hz)	State of the brain
Delta (δ)	0.1Hz to 3Hz	Deep, dreamless sleep, non-REM sleep, unconscious
Theta (θ)	4Hz to7Hz	Intuitive, creative, recall, fantasy, imaginary, dream
Alpha (α)	8Hz to12Hz	Relaxed, but not drowsy, tranquil, conscious
Low-range Beta (β)	12Hz to 15Hz	Formerly SMR, relaxed yet focused, integrated
Mid-range Beta (β)	16Hz to 20Hz	Thinking, aware of self & surroundings
High-range Beta (β)	21Hz to 30Hz	Alertness, agitation
Gamma (γ)	30Hz to 100+Hz	Motor Functions, higher mental activity

Source: Sugumar Durai and P. T. Vanathi, 2017

Background and Motivation

- Deep Learning models can achieve state of the art results but it lacks clarity and interpretability.
- Interpretability is critical in medical research
- There are several approaches to measure the effects of features on the prediction of the models
- In Machine Learning, feature importance is done by corrupting one feature and check how the model performs.
- Adding noise to the features is one way (i.e. perturbation)

Objective of the article

- Determining which frequency band is important for the model to make predictions
- This is done by adding random noise to each one feature at a time

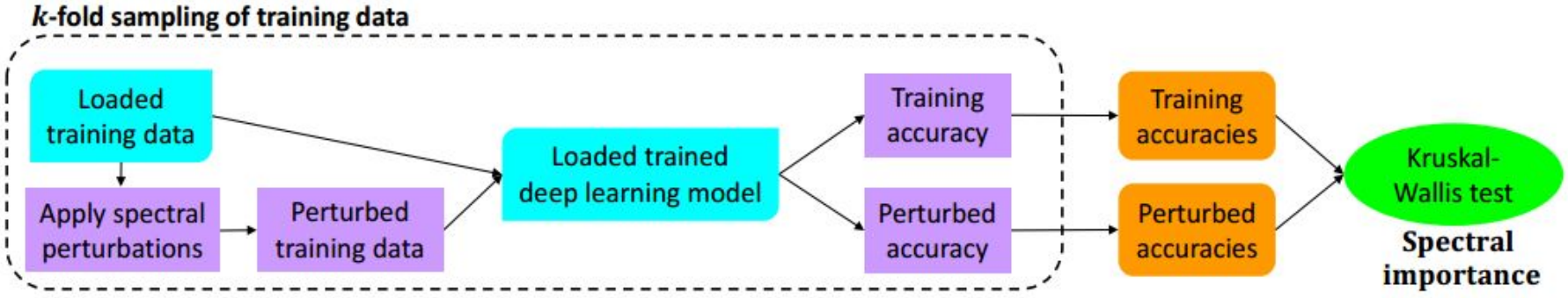
- First Task: Binary classification of each EEG into normal/abnormal
- Second Task: Binary classification of each EEG into for identification of medications

Used Data

- Released by Temple University Hospital (TUH) Neural Engineering Data Consortium (NEDC)
- EEG Corpus 35,370 EEGs spanning the years from 2002 to present. (1.1TB) from approximately 13,486 subjects
- Each record has a report containing clinical impressions and patient characteristics, including age and sex and medications
- Data is annotated as normal/abnormal
- Each sample consists of (#channels, #time steps)
- Reference: https://isip.piconepress.com/

Methods

- Train binary classification models on the original data (10 models using KFolds)
- Perturb one feature at a time from the original data and check the model performance
- Run Kruskal Wallis test to see if there are significant changes in accuracies



Source:[David Nahmias and Kimberly Kontson, 2020]

Algorithm

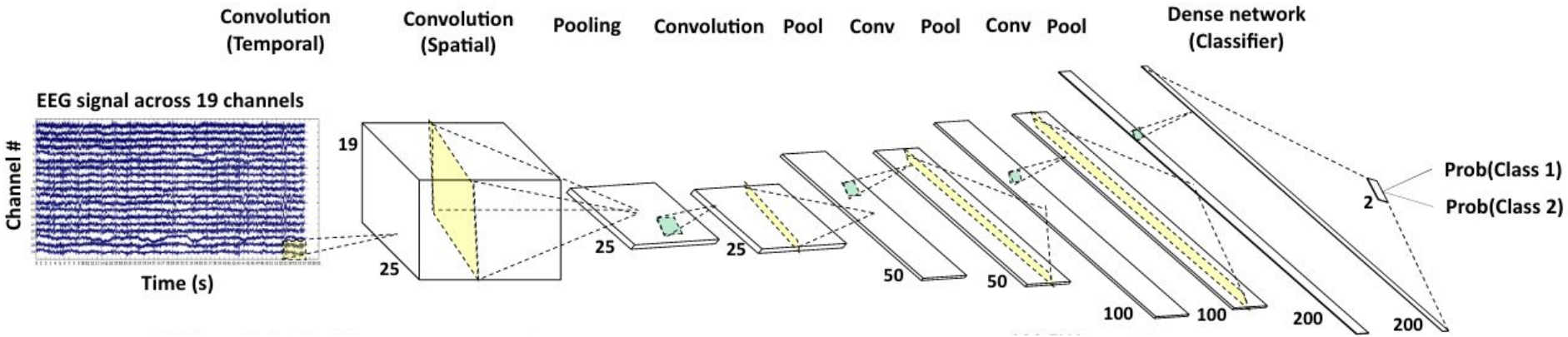
Source:[David Nahmias and Kimberly Kontson, 2020]

Algorithm easyPEASI: Easy perturbation EEG algorithm for spectral importance

```
function PerturbEEGBands(EEG,F_Low,F_High)
    for channel ∈ EEG do
        Ω ← rFFT(EEG[channel])
        μ ← Mean(Ω[F_Low,F_High])
        σ ← SD(Ω[F_Low,F_High])
        Ω[F_Low,F_High] ← N(μ, σ)
        EEG[channel] ← irFFT(Ω)
    return EEG
function BandImportance(k,F_Low,F_High)
    for i ← 0 to k − 1 do
        EEG, Labels ← LoadTrainData(i)
        Model ← LoadTrainedDeepModel(i)
        PerturbedEEG ← PerturbEEGBands(EEG,F_Low,F_High)
        TrainAcc[i] ← EvalModel(Model,EEG,Labels)
        PerturbAcc[i] ← EvalModel(Model,PerturbedEEG,Labels)
    P ← KruskalWallisTest(TrainAcc,PerturbAcc)
    Δ ← ||Mean(TrainAcc) − Mean(PerturbAcc)||
    return P, Δ
procedure easyPEASI( )
    k ← 10                                          ▷ k-fold samplings
    BandFreqLim ← [1,4,8,16,25,40]                  ▷ Hz
    for b ← 0 to length(BandFreqLim)−2 do
        F_Low ← BandFreqLim[b]
        F_High ← BandFreqLim[b+1]
        P, Δ ← BandImportance(k,F_Low,F_High)       ▷ Results
```

Used Neural Networks (DCNN)

- Traditional CNN with convolution and pooling layers



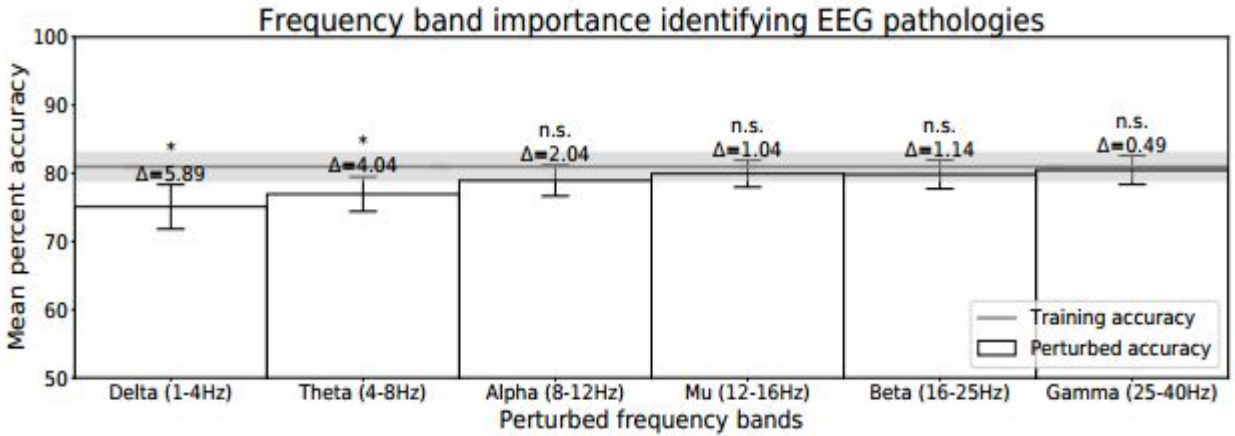
Source: [David Nahmias, Eugene Civillico and Kimberly Kontson, 2020]

Accuracy of identifying EEG pathologies

Classification	*n*-train (*n*-test)	Train accuracy (%) (Test accuracy (%))
Normal EEG vs. Abnormal EEG	10,802 (1,200)	80.99 ± 2.22 (80.40 ± 2.41)

Source:David Nahmias and Kimberly Kontson, 2020

Frequency bands for identifying EEG pathologies



Source:[David Nahmias and Kimberly Kontson, 2020]

Accuracy of identifying medications

Classification	*n*-train (*n*-test)	Train accuracy (%) (Test accuracy (%))
Dilantin vs. Keppra with Normal EEG	316 (34)	80.19 ± 13.86 (59.12 ± 7.49)
Dilantin vs. Keppra with Abnormal EEG	476 (52)	83.91 ± 3.48 (60.39 ± 5.03)

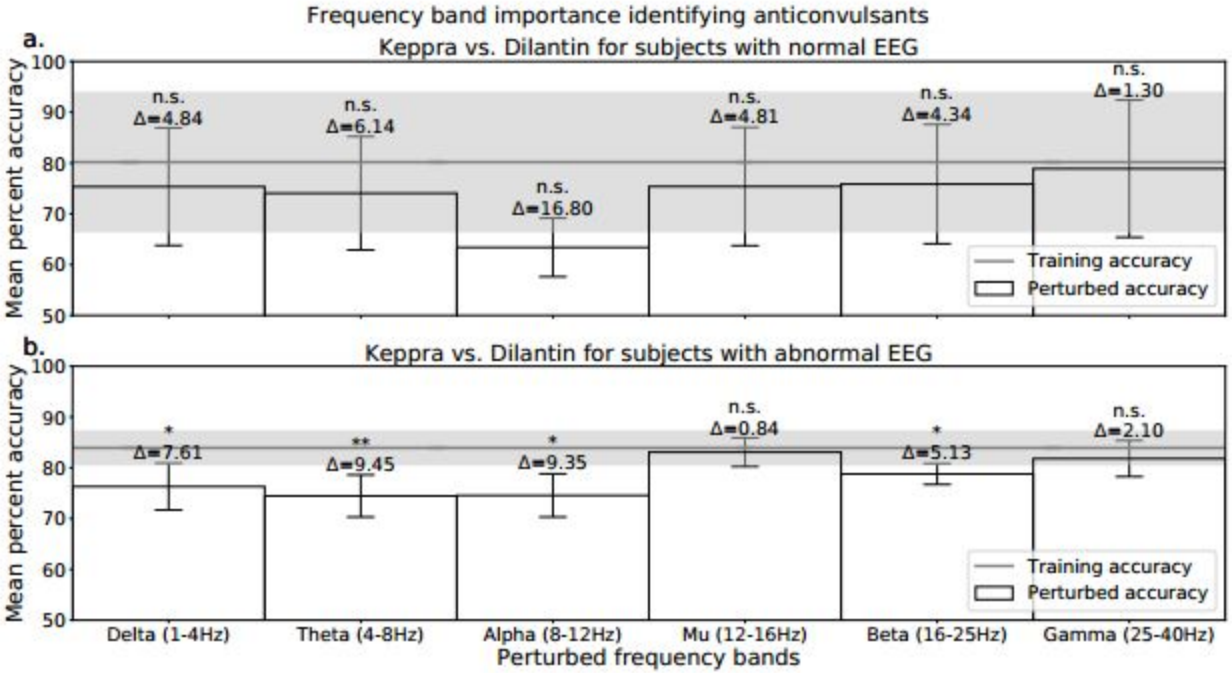
Source:David Nahmias and Kimberly Kontson, 2020

Identifying medications (From subsequent study by same authors)

Classification	*n*-total (n-test)	Feature-based methods			Network-based methods			
		SVM % (*P*-value)	kSVM % (*P*-value)	RF % (*P*-value)	LNN % (*P*-value)	SCNN % (*P*-value)	DCNN % (*P*-value)	EEGNet % (*P*-value)
Dilantin vs. Keppra with Normal EEG	350 (34)	51.18 ± 6.47 ($P < .939$)	58.23 ± 5.23 * ($P < .004$)	**58.53 ± 4.25** ($P < .013$)	51.47 ± 7.70 ($P < .699$)	53.24 ± 7.94 ($P < .117$)	55.59 ± 8.77 ($P < .466$)	49.12 ± 8.63 ($P < .074$)
Dilantin vs. Keppra with Abnormal EEG	528 (52)	57.50 ± 3.69 * ($P < .009$)	57.88 ± 5.99 * ($P < .009$)	**64.23 ± 6.58** * ($P < .006$)	50.77 ± 6.09 ($P < .704$)	56.35 ± 6.02 * ($P < .003$)	60.19 ± 4.94 ($P < .046$)	39.42 ± 8.21 ($P < .062$)
Dilantin vs. No medications with Normal EEG	358 (34)	58.61 ± 5.75 * ($P < .004$)	59.17 ± 6.34 ($P < .011$)	61.94 ± 6.58 * ($P < .006$)	47.94 ± 8.43 ($P < .877$)	60.00 ± 7.69 * ($P < .008$)	**66.76 ± 6.58** ** ($P < .001$)	54.12 ± 5.61 ($P < .378$)
Dilantin vs. No medications with Abnormal EEG	640 (64)	66.72 ± 6.78 ** ($P < .001$)	**70.78 ± 3.28** ** ($P < .001$)	70.00 ± 2.95 ** ($P < .001$)	52.66 ± 3.05 ($P < .638$)	64.53 ± 5.68 ** ($P < .001$)	68.59 ± 6.11 ** ($P < .001$)	45.00 ± 3.81 ($P < .493$)
Keppra vs. No medications with Normal EEG	350 (34)	55.59 ± 4.45 ($P < .023$)	56.47 ± 8.50 ($P < .120$)	57.65 ± 7.69 ($P < .339$)	51.18 ± 6.20 ($P < .702$)	55.88 ± 6.44 ($P < .065$)	**62.94 ± 6.34** ** ($P < .001$)	49.12 ± 8.22 ($P < .646$)
Keppra vs. No medications with Abnormal EEG	528 (52)	71.54 ± 5.76 ** ($P < .001$)	**73.46 ± 3.92** ** ($P < .001$)	70.00 ± 4.80 ** ($P < .001$)	48.84 ± 5.17 ($P < .820$)	70.77 ± 3.42 ** ($P < .001$)	68.65 ± 6.66 ** ($P < .001$)	51.92 ± 7.60 ($P < .704$)

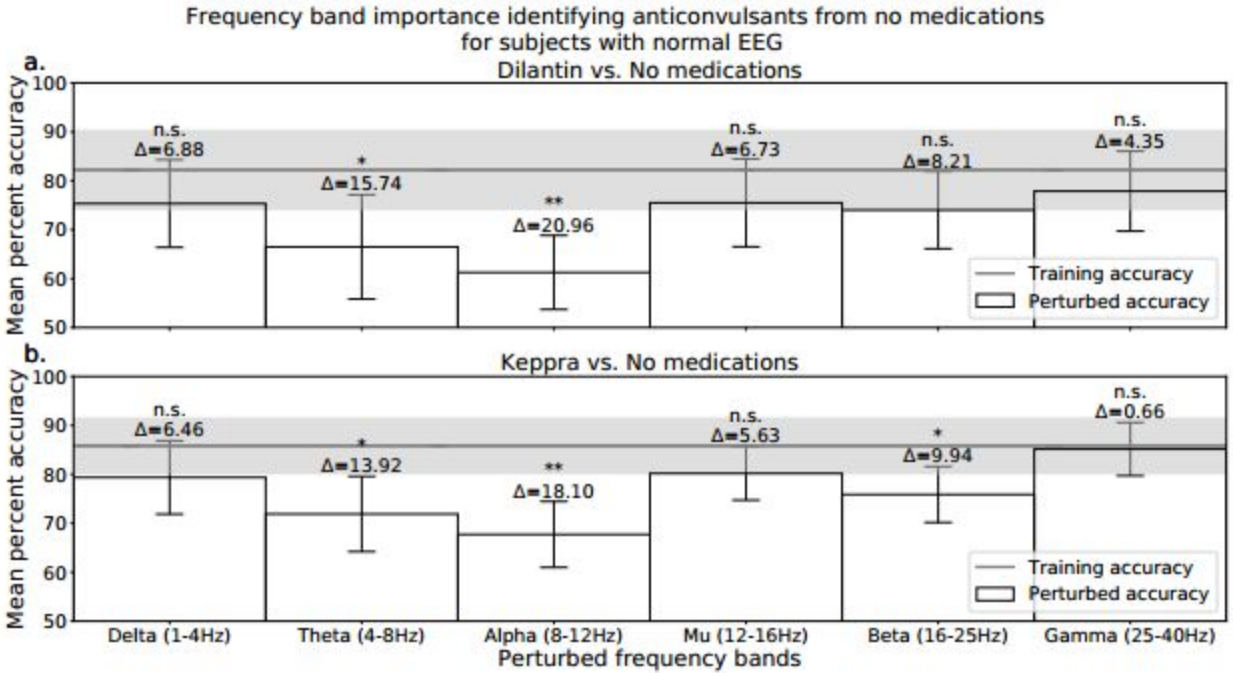
Source: David Nahmias, Eugene Civillico, Kimberly Kontson, 2020

Frequency bands for identifying medications (Keppra vs Dilantin)



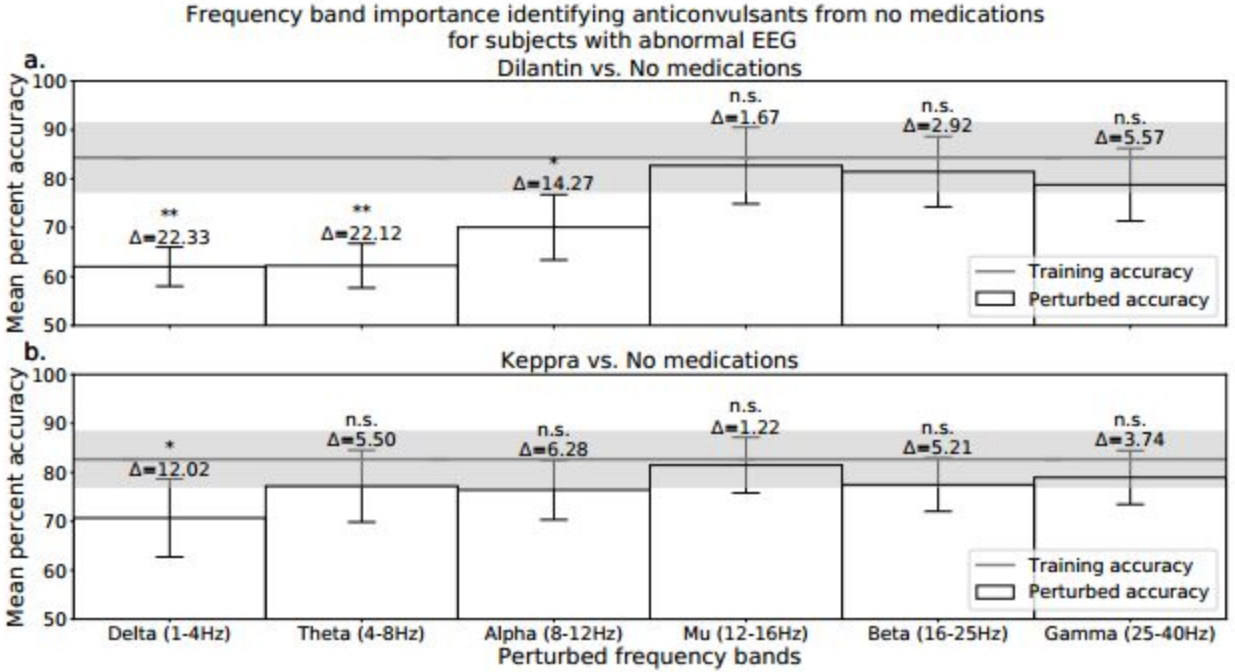
Source:[David Nahmias and Kimberly Kontson, 2020]

Frequency bands for identifying medications (medications vs no medications for normal pathology)



Source:[David Nahmias and Kimberly Kontson, 2020]

Frequency bands for identifying medications (medication vs no medication for abnormal pathology)



Source:[David Nahmias and Kimberly Kontson, 2020]

Advantages

- The methods are simple and straightforward: The authors combined several simple building blocks to make a novel methods

- The methods follow the standard workflow of machine learning in terms of train test split, KFold cross validation and handling imbalanced data (but with a few flaws).

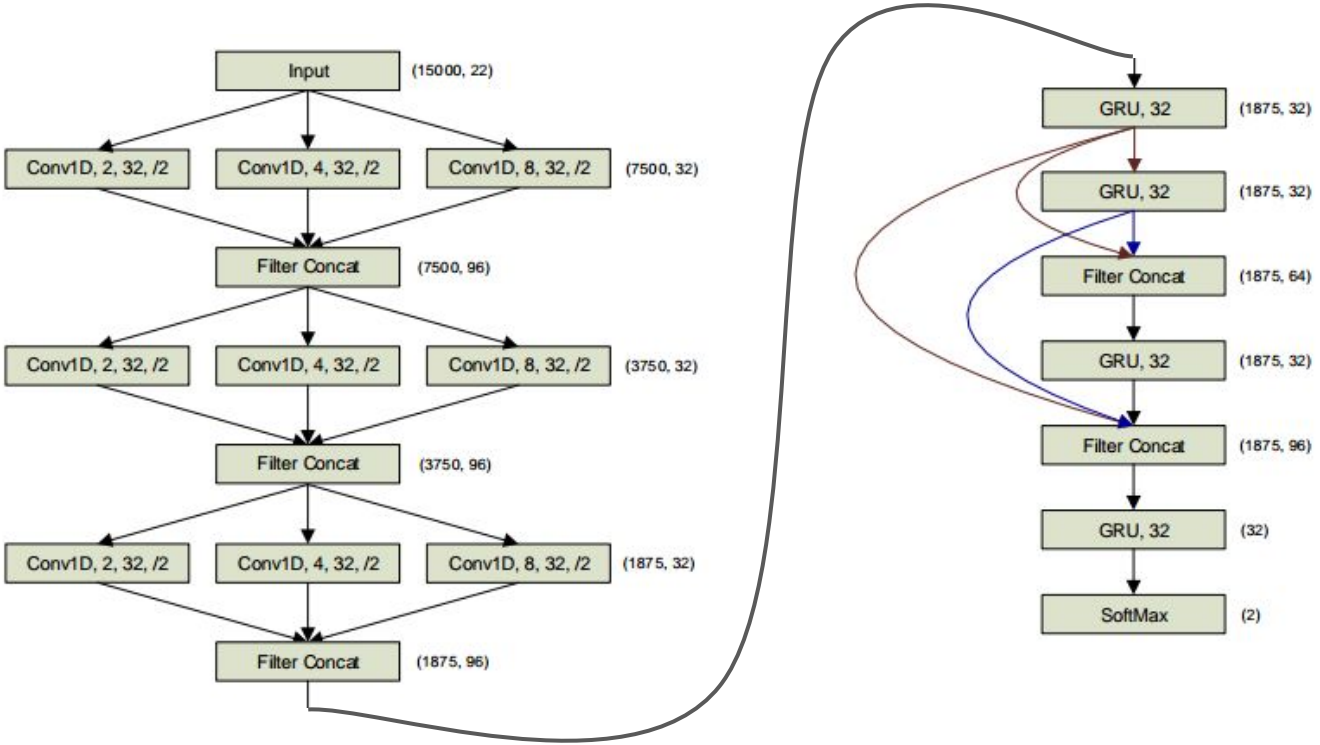
Flaws

- The authors used training accuracies for comparisons ?
- The data is HUGE which makes almost any model will work and give acceptable accuracies. This means that the model will not generalize to different smaller set of data.

My Work

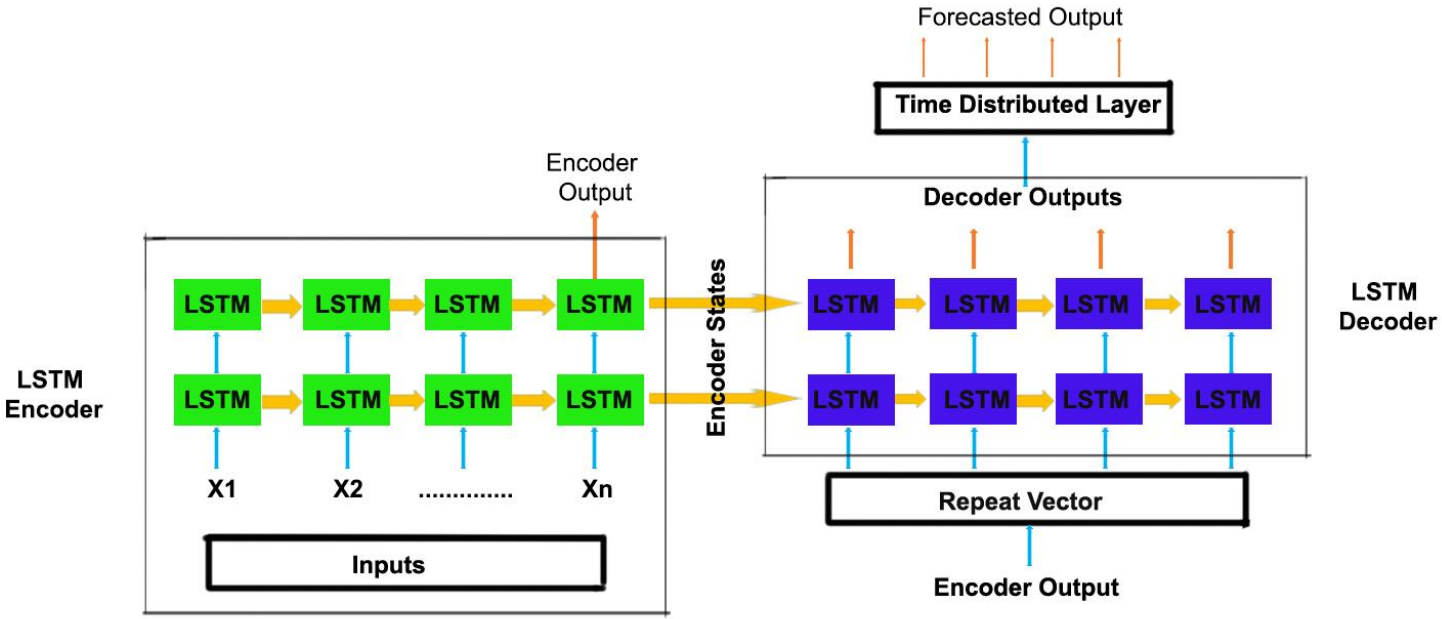
- 1.1TB is not possible to download or saving on disk or using for training using my resources (35,370 EEGs)
- Instead, we use small subset of the data (560 EEGs which is only 12GB).
- Similar workflow was used in terms of data preprocessing
- Some modifications have been made to the workflow
- Tried different models for training instead of DCNN (Using DCNN leads to instability in performance)
- Main Models: DCNN, LSTM, LSTM Autoencoder, ChronoNet
- Data Augmentation such as: filtering and noising.

ChronoNet



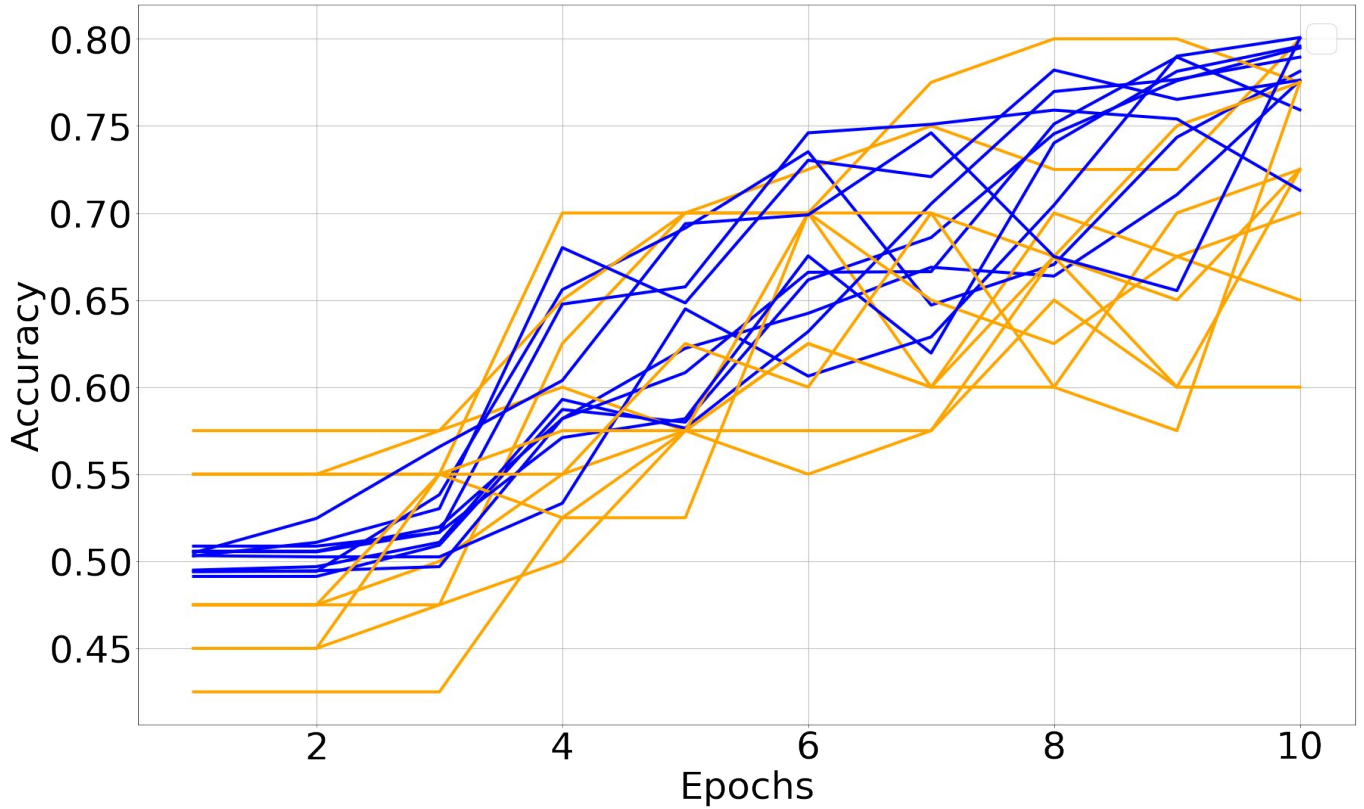
Source: [Subhrajit Roy, etal., 2018]

LSTM Autoencoder

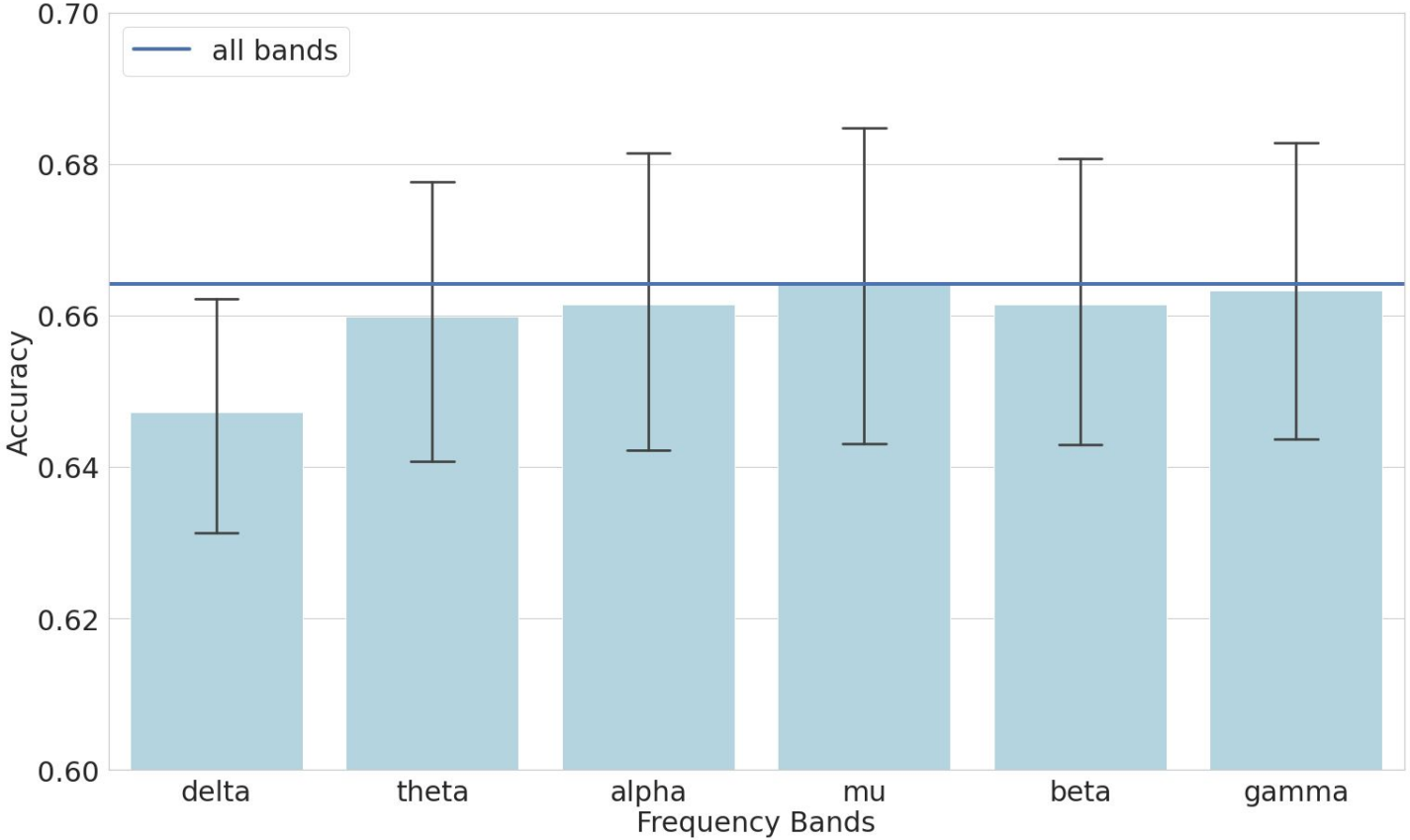


Source: www.analyticsvidhya.com

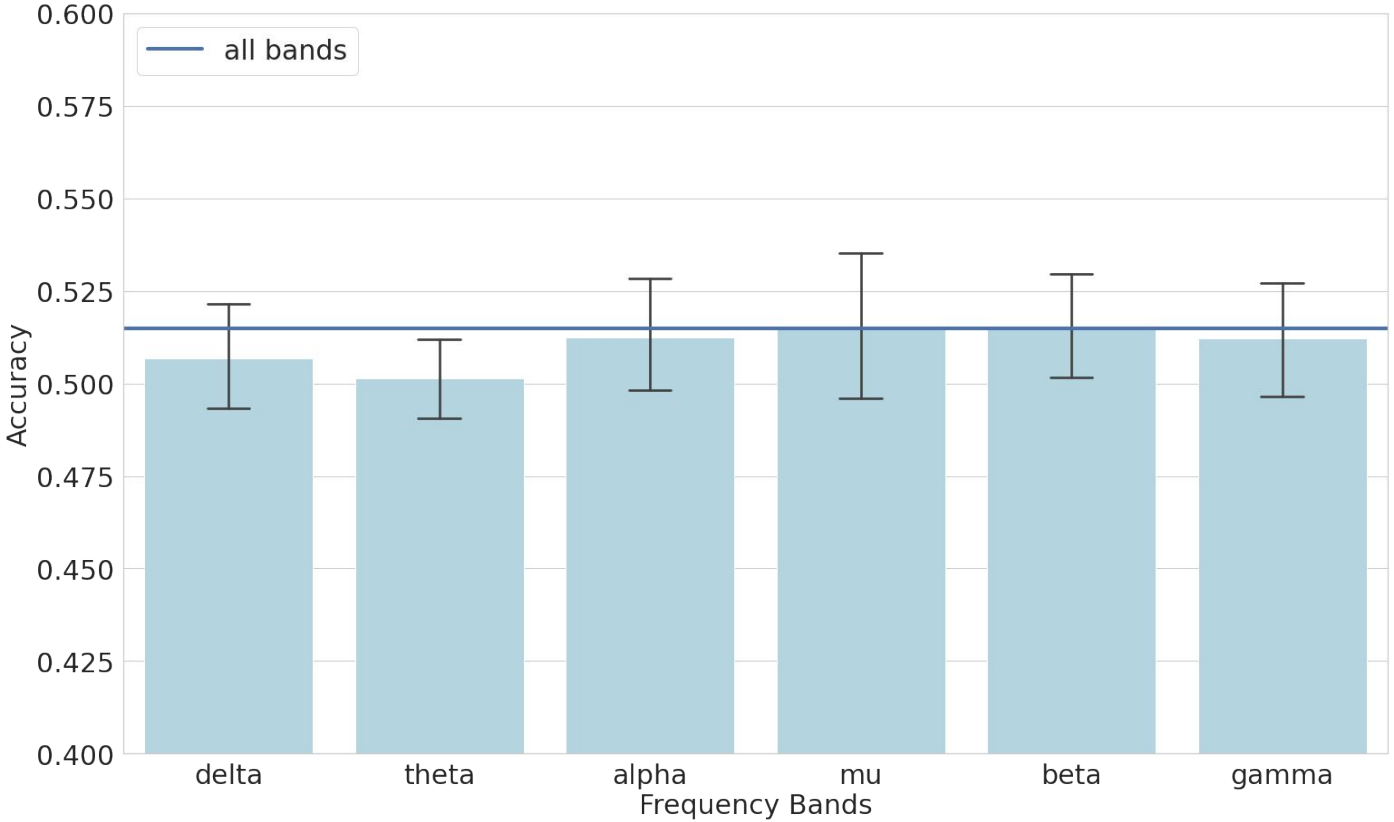
Results: KFold Validation Curve for identifying EEG pathologies



Results: Frequency band importance (Identifying EEG pathologies using ChronoNet)



Results: Frequency Band importance (Identifying medications using DCNN)



Conclusion and Future Work

- Spectral Perturbation is helpful to understand the importance of spectral bands
- The authors used training accuracies to make comparisons (flaw) which we changed in our methods
- The large size of the data is effective in building a robust model, However the model will not generalize or train effectively to a smaller dataset. We are interested in building models that can work in different data sizes.
- Used LSTM, DCNN, ChronoNet, LSTM autoencoder
- Possible Solution: Exploring denoising signal processing methods or Deep Learning methods like denoising Autoencoder to remove intrinsic and extrinsic artifacts

Questions