# Characterization of EEG signals according to brain regions using machine learning techniques

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# Table of Contents


1. Introduction
2. Theoretical background
3. EEG signals pre-processing
4. Machine learning methods
5. Empirical results
6. Conclusion and future works

# Table of Contents


1. Introduction
2. Theoretical background
3. EEG signals pre-processing
4. Machine learning methods
5. Empirical results
6. Conclusion and future works

# Brain

**Figure 1:** Human brain

# Introduction

- Every vertebrates and most of invertebrates have brain.
- When it works, it generates electrical signal.
- Electroencephalography (EEG) is a method to record the neuraloscillations (often known as "brain waves") of the brain.
- Different region of the brain generates specific type of different signal.

# Problem and Objective

- **Objective:** Characterize brain regions over labeled EEG signal.
- **Why we have to study this?**
  - When some area of the brain is damaged, the brain plasticity provokes other parts. It can be activated and have new functionalities in order of mitigating the impact of brain damages.
  - So here is why:
    1. Analyzing the plasticity of the brain.
    2. How damaged brain provokes changes in their functionality.
- Our goal is to have a general comparison between 2 well-known machine learning techniques LSTM and SVM in classifying brain regions.

# Table of Contents

1. Introduction
2. Theoretical background
3. EEG signals pre-processing
4. Machine learning methods
5. Empirical results
6. Conclusion and future works

# Brain electrical signals

More specific

- Brain is a complex organ, contain over 86 bilions neurons.
- Each neuron connects to thousands of others.
- Communicate over synapses electrical signal.

# Electroencephalography

- Frontal lobe (F) (Red)
- Cerebellum (C) (Cyan)
- Parietal lobe (P) (Yellow)
- Occipital lobe (O) (Emerald)
- Temporal lobe (T) (Green)

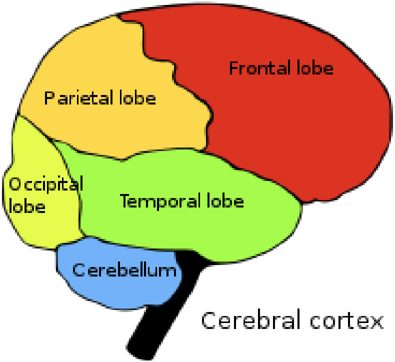


**Figure 2:** Region of the brain

# Electroencephalography

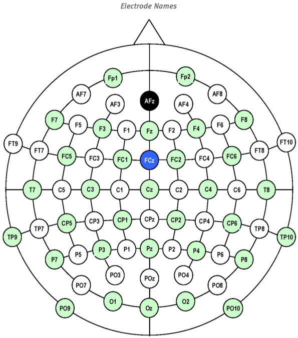


**Figure 3:** full electrode map system

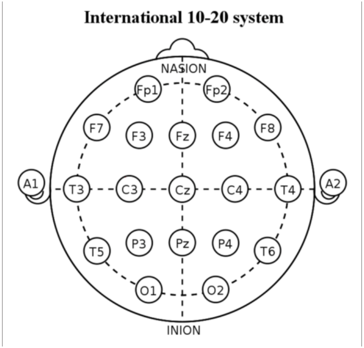


**Figure 4:** 19 electrodes map system

# Electroencephalography

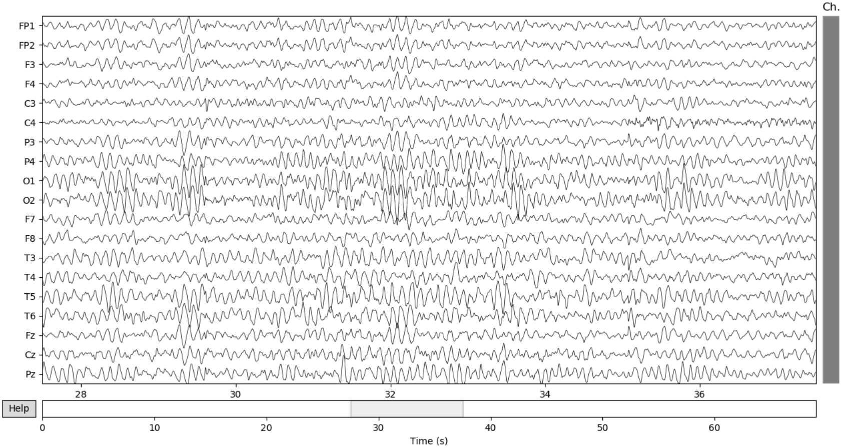


**Figure 5:** 19 EEG signal example

# Table of Contents

1 Introduction

2 Theoretical background

3 EEG signals pre-processing

4 Machine learning methods

5 Empirical results

6 Conclusion and future works

# EEG signals pre-processing

To have the data ready for the machine learning part, we have to get through:

- Noise reduction
- Learning set creation

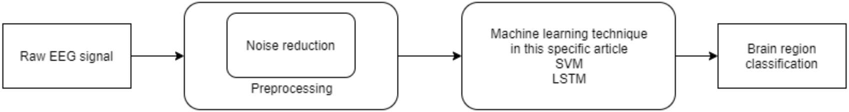


**Figure 6:** Project sequences breakdown

# Noise reduction

The technique that we use to denoise in this study is Z-score.

$$z = \frac{x - \mu}{\sigma}$$

**Why ?**

Because EEG signal very stable. Any significant changes is considered as outliers. In this case, I want to consider around 5% of the data we have is outliers.

# Noise reduction

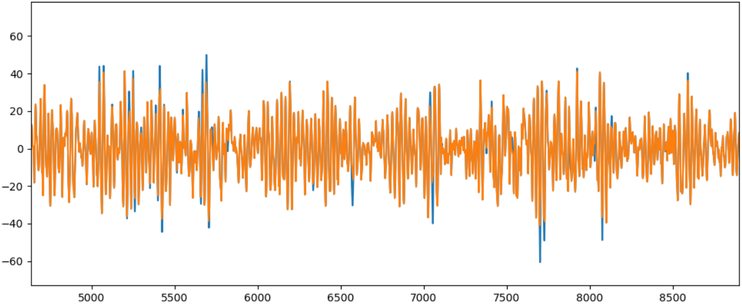


**Figure 7:** FP1 before and after apply Z-score

# Noise reduction

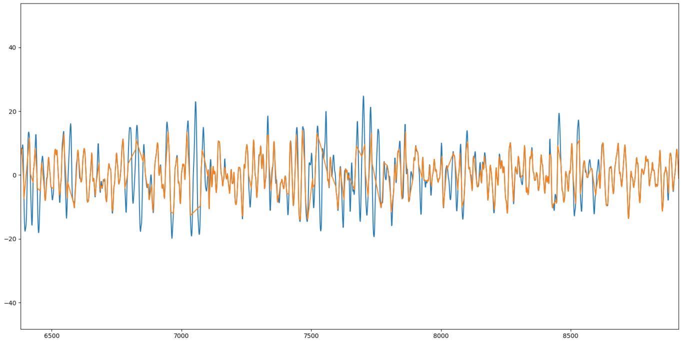


**Figure 8:** Closer look at FP1 before and after apply Z-score

# Learning set creation

- 19 electrodes
- 4 classes:
  1. Class 0: including FP1-AVE, FP2-AVE, F3-AVE, F4-AVE, F7-AVE, F8-AVE, Fz-AVE
  2. Class 1: including C3-AVE, C4-AVE, Cz-AVE
  3. Class 2: including T3-AVE, T4-AVE, T5-AVE, T6-AVE
  4. Class 3: including P3-AVE, P4-AVE, Pz-AVE, O1-AVE, O2-AVE
- 2 datasets with the same signal:
  1. W1: 200 time steps
  2. W2: 400 time steps
- Shuffle whole dataset after divide classes and time windows.

# Learning set creation

2 same datasets with different time window

- W1: 200 time steps each datapoint
- W2: 400 time steps each datapoint

# Table of Contents


1. Introduction
2. Theoretical background
3. EEG signals pre-processing
4. Machine learning methods
5. Empirical results
6. Conclusion and future works

# LSTM-RNN

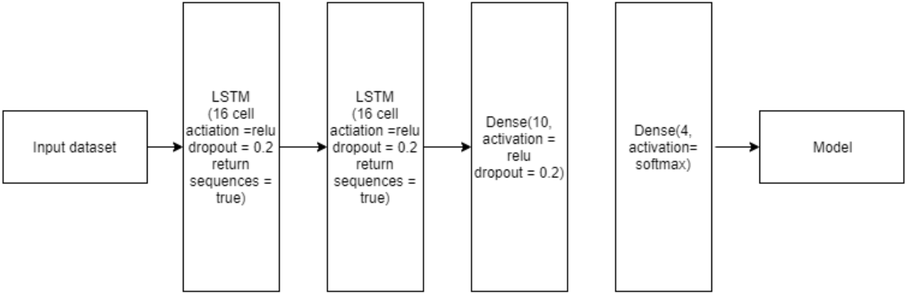


**Figure 9:** LSTM neural network breakdown

# SVM

- Implement SVC in scikit-learn
- Parameter:
    1. Gamma: scale
    2. C: 100

# Table of Contents


1 Introduction

2 Theoretical background

3 EEG signals pre-processing

4 Machine learning methods

5 Empirical results

6 Conclusion and future works

# LSTM-RNN

| | W2 = 400 |
|---|---|
| Epoch 1/2 | acc = 0.3173, val_acc = 0.4255 |
| Epoch 2/2 | acc = 0.3387, val_acc = 0.4326 |

**Table 1:** Accuracy using LSTM with window W2=400 time steps

| | W1 =200 |
|---|---|
| Epoch 1/2 | acc = 0.1941, val_acc = 0.2626 |
| Epoch 2/2 | acc = 0.2662, val_acc = 0.3805 |

**Table 2:** Accuracy using LSTM with window W1=200 time steps

# SVM

| | |
|---|---|
| W2 = 400 | W1 =200 |
| accuracy = 0.72 | accuracy = 0.575 |

**Table 3:** Accuracy using SVM with windows W1=200 and W2=400 time steps

# Table of Contents

1 Introduction

2 Theoretical background

3 EEG signals pre-processing

4 Machine learning methods

5 Empirical results

6 Conclusion and future works

# Conclusion

- SVM has better accuracy than LSTM-RNN.
- window W2 has better accuracy than window W1.
- 0.72 is our best results by far.

# Future works

It is still possible to improve the classifier. We have figured out some of the reasons might affect the result:

- Lack of data.
- ECG and EOG still have not be removed.
- Try to change the filter.