A Machine Learning Based Classification System for Brain Signals: An Animal Model Application.

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Abstract

EEG signals have seen an increase in usage within both research and clinical applications through the improvement of cheaper non-invasive neural signal collection. Both data collection and feature extracted differentiate between temporal, spectral and statistical data dependant upon the domain of interest. A variety of both machine learning and deep learning architectures have seen an increase in use for this type of multi-channelled data, providing insight into neurological trends given a particular stimulus; alongside this is the use of a variety of different feature extraction methods that depend upon the given scenario.

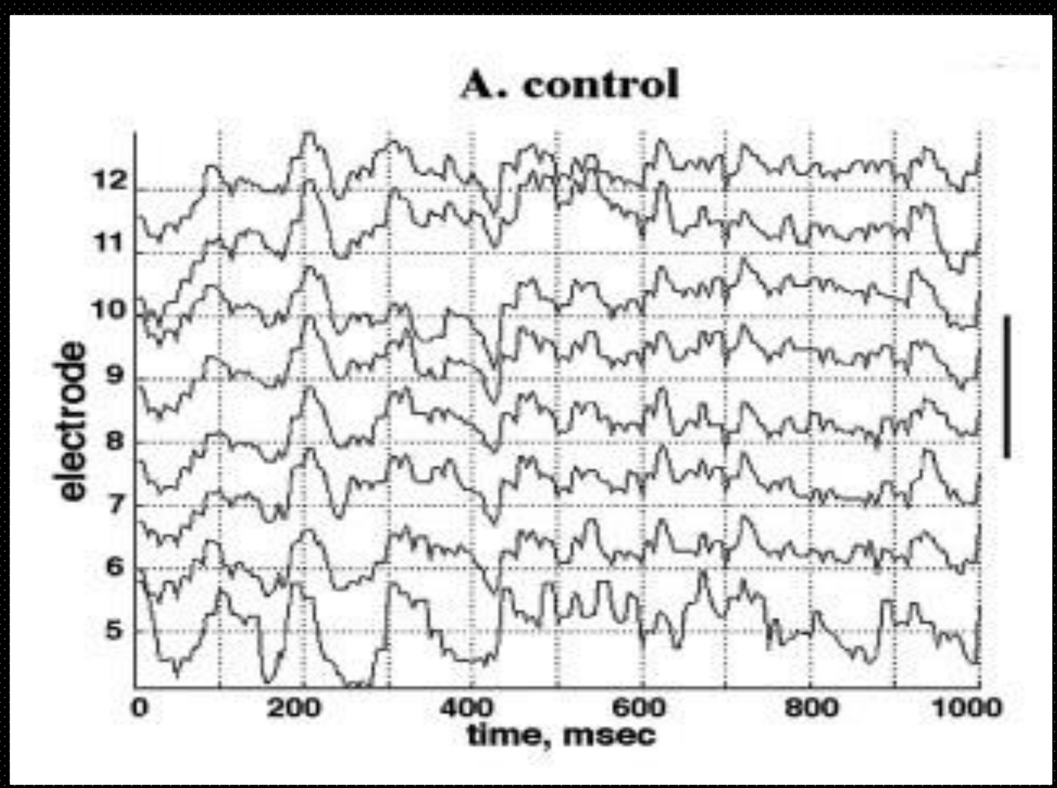

Figure 1. Raw EEG data over several channels for a single subject [1]

Introduction

Electroencephalogram (EEG) signals [Fig. 1] are produced as electrical potentials in the brain, which can recorded by precision electrode based hardware. These Signals differ depending upon the area of the scalp that the electrode is monitoring [Fig. 2] presenting a multi-channeled data analytics problem. Signal analysis has several comparable aspects across domains not only including the medical domain; one such example is seismic data being comparable to EEG data in terms of event classification. Making use of existing machine learning [2] and deep learning [3] data analysis techniques that have been applied within several functional applications, including both animal and human subjects, then applying them to a single problem for comparability of classification is the main aim of this project.

Aims and Objectives

Aim – produce a functional classification of events found within scalp EEG data via feature extraction and machine learning techniques.

Objectives

- Obtain EEG data
- Research and select a number of relevant channels from the data to reduce problem dimensionality
- Extract and label significant features from data
- Choose best features and models based upon features
- Train traditional machine learning models
- Train deep learning models from features

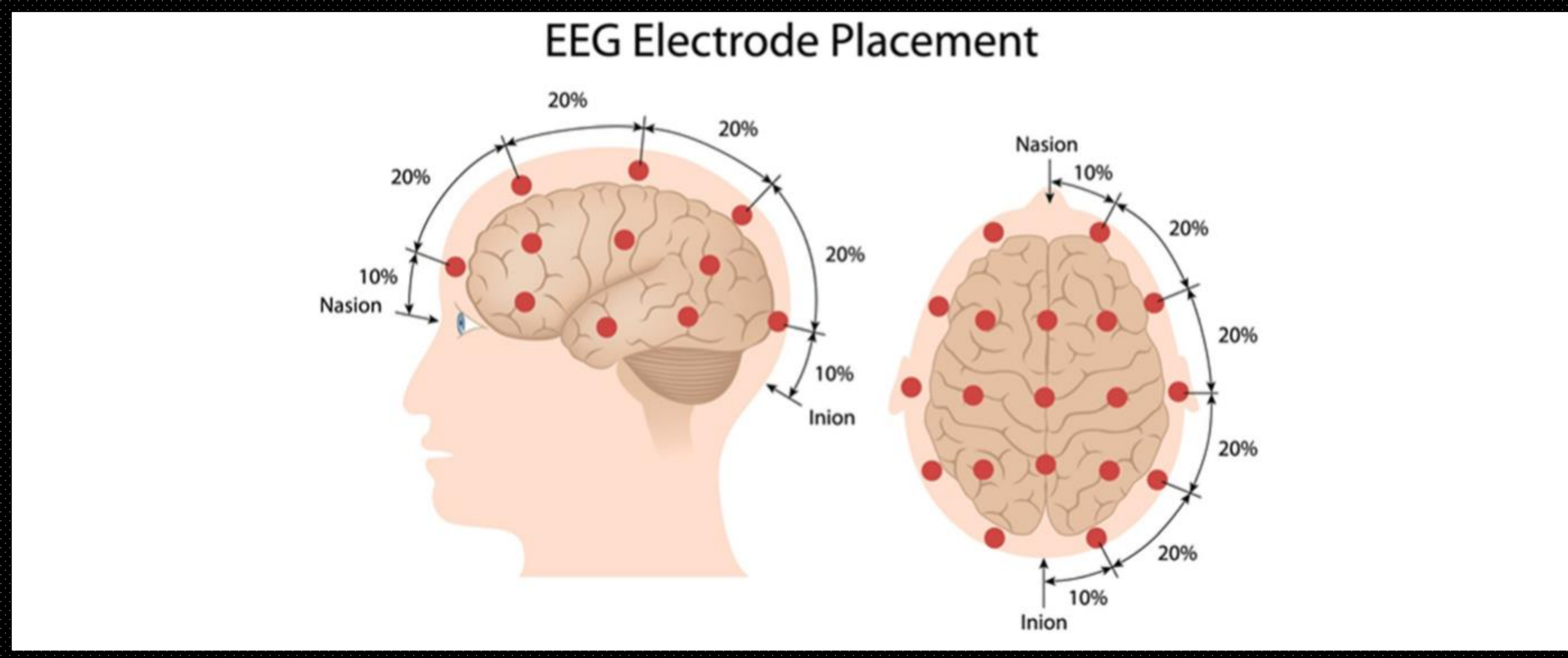

Figure 2. The international 10-20 system, each segment split into 20% of the skull with the exception of front and back of the head where the segments are at 10% of skull width apart. [4]

Research Methods

Research will be based upon the agile methodology which will have specific requirements set, the algorithm parameters and features decided upon and the architectures used based upon those within existing literature as the design; subsequent implementation will involve the following steps:

- Feature extraction techniques.
- Application of traditional machine learning techniques.
- Application of Deep learning techniques.

After the implementation of the proposed methods will be an evaluation and comparison of the techniques compared to those within existing literature.

Research Plan

A pseudo-agile style methodology for this project is outlined in figure 3 (without a defined maintenance stage).

Requirements are created at each of the major stages and evaluation is completed throughout the duration of the project. The total timescale and breakdown shown in figure 4.

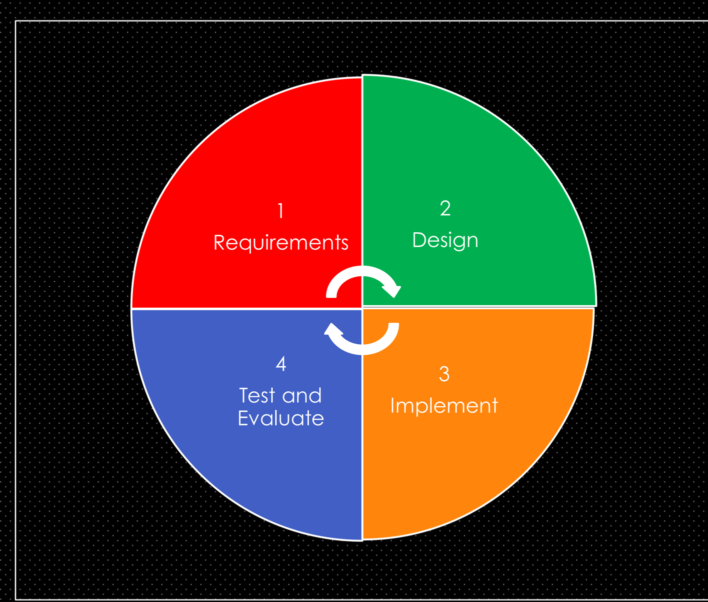

Figure 3. structure of the planned Pseudo-agile methodology.

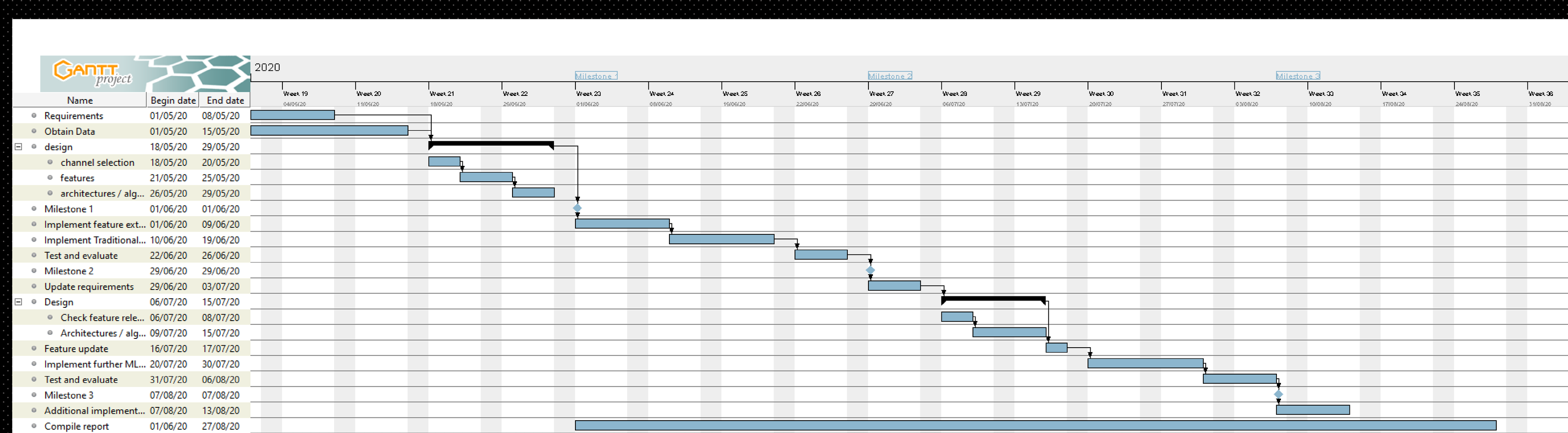

Figure 4. Gantt chart for the project outline, with milestones after each major achievement or section that can be applied to the report.

References

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