A Case Study of Epilepsy Seizure Prediction

Capstone Project report

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Acknowledgement

We would like to use this opportunity to express our gratitude to everyone who supported us throughout this capstone project. We are thankful for their aspiring guidance, invaluably constructive feedback and advice during the project work. We are sincerely grateful to them for sharing their truthful and illuminating views on a number of issues related to the project.

We express our warm regards to **Professor Dr. Shailesh**, for his support and guidance throughout the project, his support and guidance has been pivotal for the success of this project.

We would also like to thank our client mentor **Dr. Govind** and our project co-ordinator Reema Gupta for their continuous support throughout the project.

Last but not the least we would like to thank Mr Bhoopathi Rapolu from Cyient for showing faith in us and giving us this opportunity.

Motivation

Epilepsy afflicts nearly 1% of the world's population, and is characterized by the occurrence of spontaneous seizures. For many patients, anticonvulsant medications can be given at sufficiently high doses to prevent seizures, but patients frequently suffer side effects. For 20-40% of patients with epilepsy, medications are not effective -- and even after surgical removal of epilepsy-causing brain tissue, many patients continue to experience spontaneous seizures. Despite the fact that seizures occur infrequently, patients with epilepsy experience persistent anxiety due to the possibility of a seizure occurring.

“Seizure forecasting systems hold promise for improving the quality of life for patients with epilepsy”

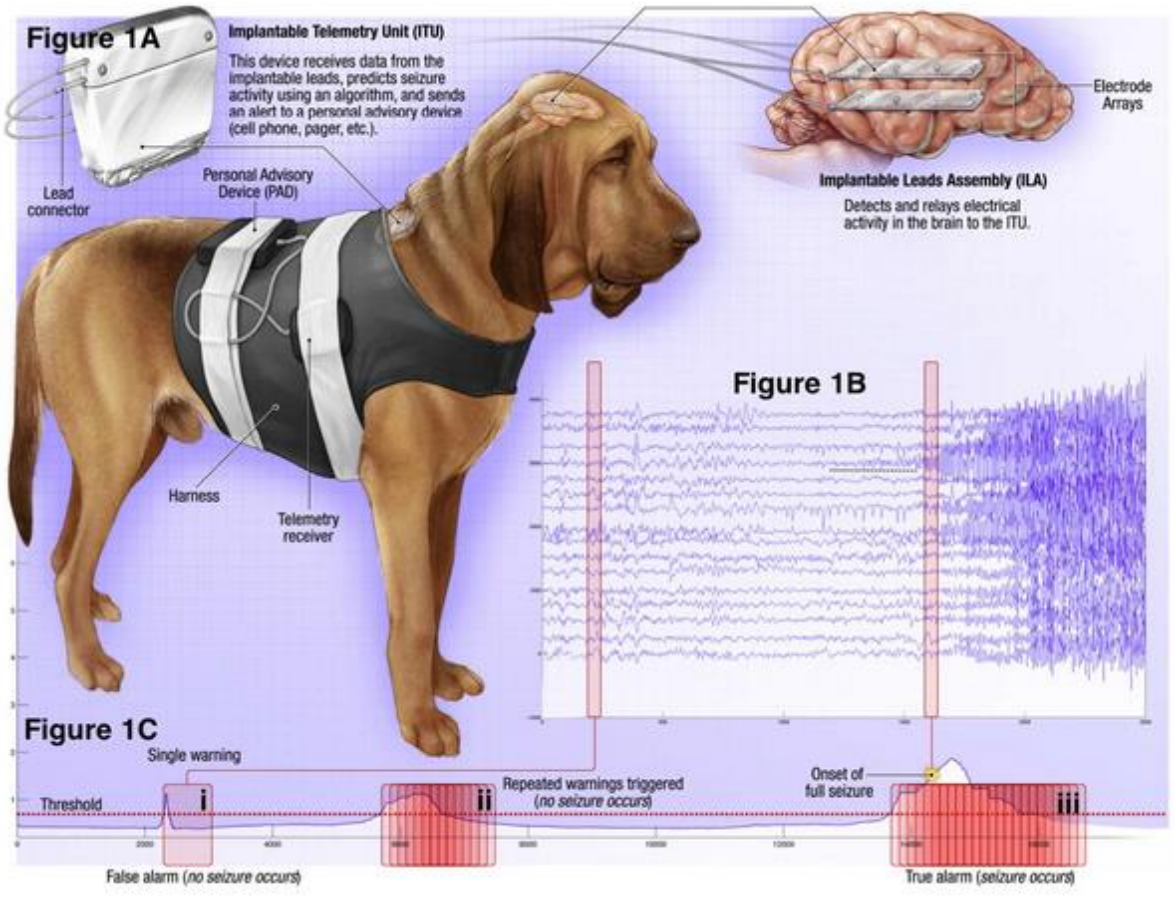
Project Goal

There is emerging evidence that the temporal dynamics of brain activity can be classified into 4 states: Interictal (between seizures, or baseline), Preictal (prior to seizure), Ictal (seizure), and Post-ictal (after seizures). Seizure forecasting requires the ability to reliably identify a preictal state that can be differentiated from the interictal, ictal, and postictal state. The primary challenge in seizure forecasting is differentiating between the preictal and interictal states. The goal of the competition is to demonstrate the existence and accurate classification of the preictal brain state in dogs and humans with naturally occurring epilepsy.

Project Description

Intracranial EEG was recorded from dogs with naturally occurring epilepsy using an ambulatory monitoring system. EEG was sampled from 16 electrodes at 400 Hz, and recorded voltages were referenced to the group average. These are long duration recordings, spanning multiple months up to a year and recording up to a hundred seizures in some dogs.
In addition, datasets from patients with epilepsy undergoing intracranial EEG monitoring to identify a region of brain that can be resected to prevent future seizures are included in the contest. These datasets have varying numbers of electrodes and are sampled at 5000 Hz, with recorded voltages referenced to an electrode outside the brain.

The goal is to distinguish between ten minute long data clips covering an hour prior to a seizure, and ten minute iEEG clips of interictal activity. Seizures are known to cluster, or occur in groups. Patients who typically have seizure clusters receive little benefit from forecasting follow-on seizures. For this project only lead seizures, defined here as seizures occurring four hours or more after another seizure, are included in the training and testing data sets. In order to avoid any potential contamination between interictal, preictal, and post-ictal EEG signals interictal segments in the canine training and test data were restricted to be at least one week before or after any seizure. In the human data, where the entire monitoring session may last less than one week, interictal data segments were restricted to be at least four hours before or after any seizure. Interictal data segments were chosen at random within these restrictions for both canine and human subjects.



The project is to build a predictive model which can accurately forecast Seizures for patients.

Project implications - Industry perspective

Seizure forecasting systems have the potential to help patients with epilepsy lead more normal lives. In order for EEG-based seizure forecasting systems to work effectively, computational algorithms must reliably identify periods of increased probability of seizure occurrence. If these seizure-permissive brain states can be identified, devices designed to warn patients of impeding seizures would be possible. Patients could avoid potentially dangerous activities like driving or swimming, and medications could be administered only when needed to prevent impending seizures, reducing overall side effects.

Domain perspective - what is epilepsy?

- Epilepsy is the fourth most common neurological disorder and affects people of all ages
- Epilepsy means the same thing as "seizure disorders"
- Epilepsy is characterized by unpredictable seizures and can cause other health problems
- Epilepsy is a spectrum condition with a wide range of seizure types and control varying from person-to-person

Epilepsy is a chronic disorder, the hallmark of which is recurrent, unprovoked seizures. Many people with epilepsy have more than one type of seizure and may have other symptoms of neurological problems as well.
Sometimes EEG testing, clinical history, family history and outlook are similar among a group of people with epilepsy. In these situations, their condition can be defined as a specific epilepsy syndrome.
The human brain is the source of human epilepsy. Although the symptoms of a seizure may affect any part of the body, the electrical events that produce the symptoms occur in the brain. The location of that event, how it spreads and how much of the brain is affected, and how long it lasts all have profound effects. These factors determine the character of a seizure and its impact on the individual.
Having seizures and epilepsy also can also affect one's safety, relationships, work, driving and so much more. How epilepsy is perceived or how people are treated (stigma) often is a bigger problem than the seizures.

Classification of epilepsy	Epilepsy syndromes
1.Partial seizures	1.Infantile spasms and myoclonic epilepsy syndromes
2.Primary generalized seizures	2.Epileptic encephalopathy
3.Absence seizures	
4.Myoclonic and atonic seizures	
5.Tonic-clonic and tonic seizures	

Difference between Seizure and Epilepsy

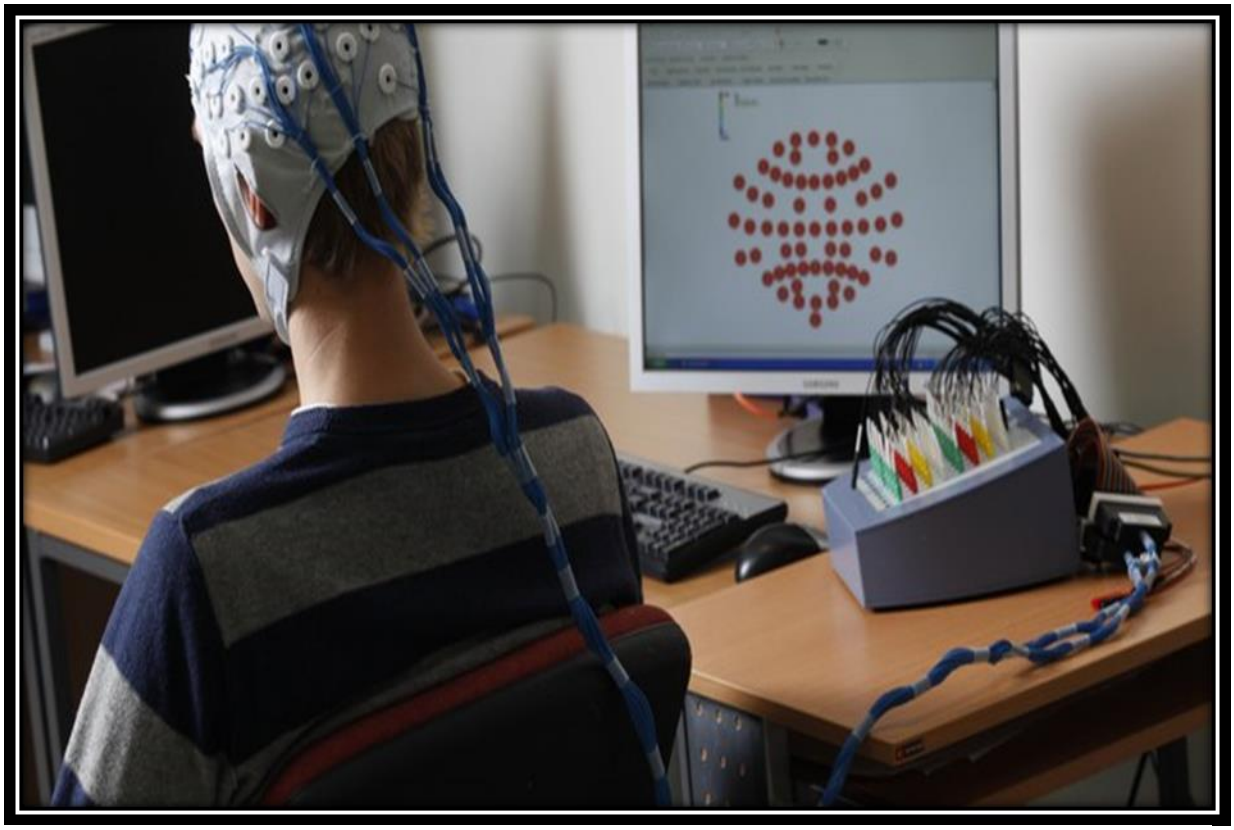
Seizures and epilepsy are not the same. An epileptic seizure is a transient occurrence of signs and/or symptoms due to abnormal excessive or synchronous neuronal activity in the brain. Epilepsy is a disease characterized by an enduring predisposition to generate epileptic seizures and by the neurobiological, cognitive, psychological, and social consequences of this condition. Translation: a seizure is an event and epilepsy is the disease involving recurrent unprovoked seizures.

The above definitions were created in a document generated by a task force of the International League Against Epilepsy (ILAE) in 2005. The definitions were conceptual, (theoretical) and not sufficiently detailed to indicate in individual cases whether a person did or did not have epilepsy. Therefore, the ILAE commissioned a second task force to develop a practical (operational) definition of epilepsy, designed for use by doctors and patients. The results of several years of deliberations on this issue have now been published (Fisher RS et al. A practical clinical definition of epilepsy, Epilepsia 2014; 55:475-482) and adopted as a position of the ILAE.
A commonly used definition of epilepsy heretofore has been two unprovoked seizures more than 24 hours apart. This definition has many positive features, but also a few limitations. This definition does not allow the possibility of "outgrowing" epilepsy. Inclusion of the word "provoked" seems to imply that people who have photosensitive seizures provoked by flashing lights or patterns do not have epilepsy; whereas, most people think that they do. Some individuals who have had only one unprovoked seizure have other risk factors that

make it very likely that they will have another seizure. Many clinicians consider and treat such individuals as though they have epilepsy after one seizure. Finally, some people can have what is called an epilepsy syndrome and these individuals should meet the definition for having epilepsy even after just one seizure. You should not have an epilepsy syndrome but not epilepsy. The new definition of epilepsy addresses each of these points.

A person is considered to have epilepsy if they meet any of the following conditions.

1. At least two unprovoked (or reflex) seizures occurring greater than 24 hours apart.
2. One unprovoked (or reflex) seizure and a probability of further seizures similar to the general recurrence risk (at least 60%) after two unprovoked seizures, occurring over the next 10 years.
3. Diagnosis of an epilepsy syndrome - Epilepsy is considered to be resolved for individuals who had an age-dependent epilepsy syndrome but are now past the applicable age or those who have remained seizure-free for the last 10 years, with no seizure medicines for the last 5 years.



In the definition, epilepsy is now called a disease, rather than a disorder. This was a decision of the Executive Committees of the ILAE and the International Bureau for Epilepsy. Even though epilepsy is a heterogeneous condition, so is cancer or heart disease, and those are called diseases. The word "disease" better connotes the seriousness of epilepsy to the public.
Item 1 of the revised definition is the same as the old definition of epilepsy. Item 2 allows a condition to be considered epilepsy after one seizure if there is a high risk of having another seizure. Often, the risk will not precisely be known and so the old definition will be employed, i.e., waiting for a second seizure before diagnosing epilepsy. Item 3 refers to

epilepsy syndromes such as benign epilepsy with central-temporal spikes, previously known as benign rolandic epilepsy, which is usually outgrown by age 16 and always by age 21. If a person is past the age of the syndrome, then epilepsy is resolved. If a person has been seizure-free for at least 10 years with the most recent 5 years off all anti-seizure medications, then their epilepsy also may be considered resolved. Being resolved does not guarantee that epilepsy will not return, but it means the chances are small and the person has a right to consider that she or he is free from epilepsy. This is a big potential benefit of the new definition.

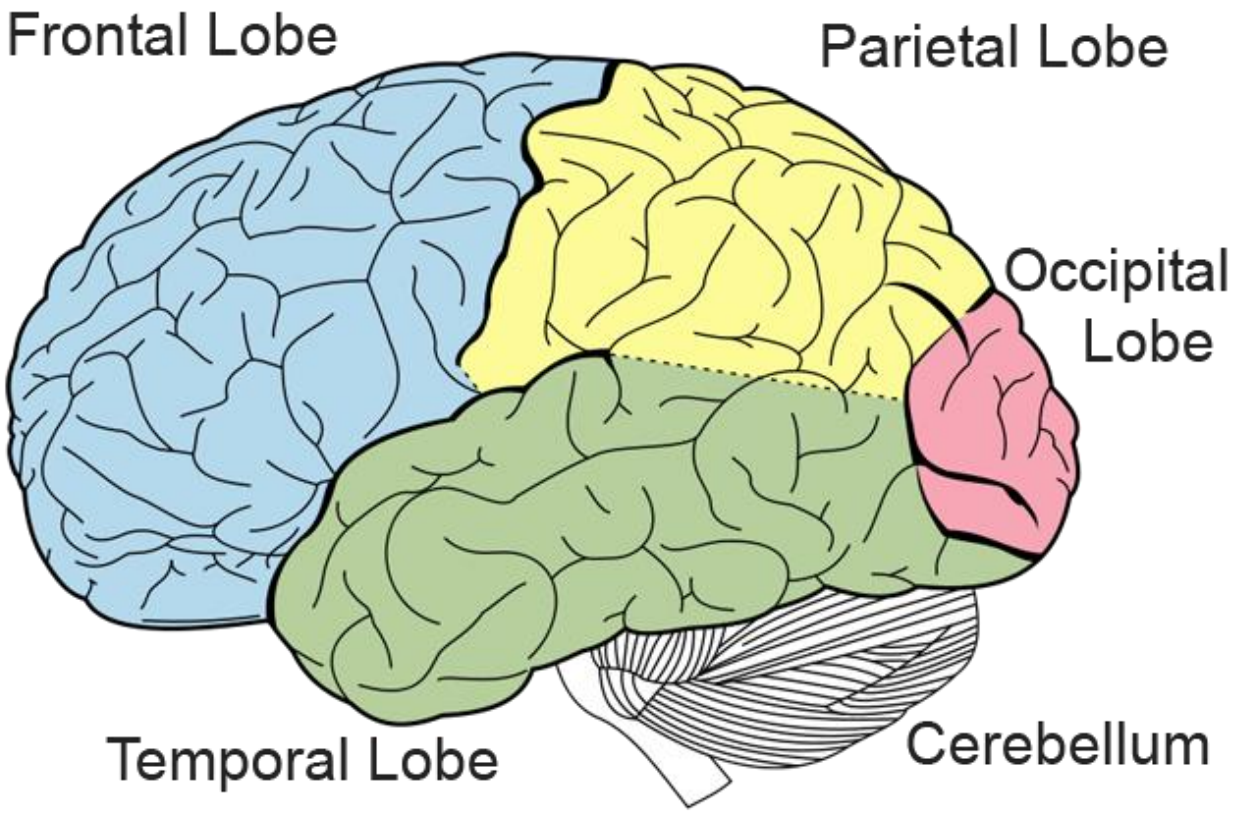
What will change as the result of this new definition? Although revision of the definition has generated some controversy, it is likely that real-world changes will be fairly minor. Some people will be able to say their epilepsy is resolved. Others may encounter the problems and stigma of being told that they have epilepsy after one seizure in some circumstances, rather than after two seizures. The definition might stimulate research on how likely another seizure is after a first seizure in various clinical circumstances. Governments and regulatory agencies, people who do therapeutic trials for epilepsy, insurance companies and other third-party payers might have to adjust some of their definitions. One reason changes will be small is that individuals with one seizure and a high risk for another are currently practically thought of as having epilepsy by many treating physicians. This process simply formalizes that thinking.

Making a diagnosis of epilepsy is not the same as deciding to treat. Some seizures are minor; some patients choose to avoid the side effects of medications. Treatment decisions will be individualized between a person with epilepsy and a physician. Sometimes, information is incomplete; for example, a possible seizure may not have been observed. In these conditions it can be impossible to confidently diagnose epilepsy using any definition. Clinicians will apply best judgment when faced with such incomplete information and often will wait for future developments.

This practical definition is designed for clinical use. Researchers, statistically-minded epidemiologists and other specialized groups may choose to use the older definition or a definition of their own devising. Doing so is perfectly allowable, so long as it is clear what definition is being used. In the process of developing the revised definition of epilepsy, consensus was reached by forging opinions of 19 co-authors of the publication, while accounting for criticisms by five anonymous journal reviewers and over 300 public commenters on the ILAE website. The revised definition is not perfect. It will become more useful over time as we gain better information on seizure recurrence risks. But for now, the new definition better reflects the way clinicians think about epilepsy.

What happens in the brain during a seizure?

Based on the brain temporal dynamics seizures were classified into 4 states



1.	Inter-ictal	Baseline Seizures
2.	Pre-Ictal state (ictogenic state)	Prior to Seizures
3.	Ictal	Seizures
4.	Post Ictal	After Seizures

- The electrical activity is caused by complex chemical changes that occur in nerve cells.
- Brain cells either excite or inhibit (stop) other brain cells from sending messages. Usually there is a balance of cells that excite and those that can stop these messages. However, when a seizure occurs, there may be too much or too little activity, causing an imbalance between exciting and stopping activity. The chemical changes can lead to surges of electrical activity that cause seizures.
- Seizures are not a disease in themselves. Instead, they are a symptom of many different disorders that can affect the brain. Some seizures can hardly be noticed, while others are totally disabling.

Project selection criterion – Sponsor's criterion

Through this pilot project Invanti (A data Science Company) wants to cultivate it's expertise and gain knowledge in area of signal processing. Another major reason is that the data being provided in this competition by Kaggle is already cleaned to a great extent. Noise has been removed and the data set is ready for analysis and model building. This helps in following three ways.

- Provides a reliable dataset to start working with
- Removes the pain of data collection cleansing and validation
- Acts as a platform to cultivate a predictive modeling approach in field of signal processing/Streaming data

Project stakeholders

Name of the Client	**Cyient Insights**
Project Title	**American Epilepsy Society Seizure Prediction Challenge**
Project Team	**Amit Kumar** **Immanuvel Vasanth** **Gopi Chand Parupalli** **Laxmi Nageswari**
Client Mentor	**Dr. Govind – Mentor**
Faculty Advisor	**Dr. Shailesh Kumar**
Project_Team contact Details	**Amit Kumar - 9740162299 - amit_kumar_2014@cba.isb.edu** **Immanuvel Vasanth - 7674879090 - Immanuvel_vasanth_2014@ cba.isb.edu** **Gopi Parupalli – 9849590920 - parupalli_chand_2014@cba.isb.edu** **Laxmi Nageswari -9542691920-Laxmi_varanasi_2014@cba.isb.edu**
Client_Mentor Contact Details	**Dr. Govind** **Personal Email: Govind.Nidigattu@invati-insights.com** **Phone number – 07702374733; 04040111292**
Faculty Advisor Contact Details	**Prof. Dr. Shailesh Kumar** **Personal Email : skumar.0127@gmail.com**

Data Source & Attributes

Data is available on Kaggle website for 5 canine subjects and two human subjects.

American Epilepsy Society Seizure Prediction Challenge

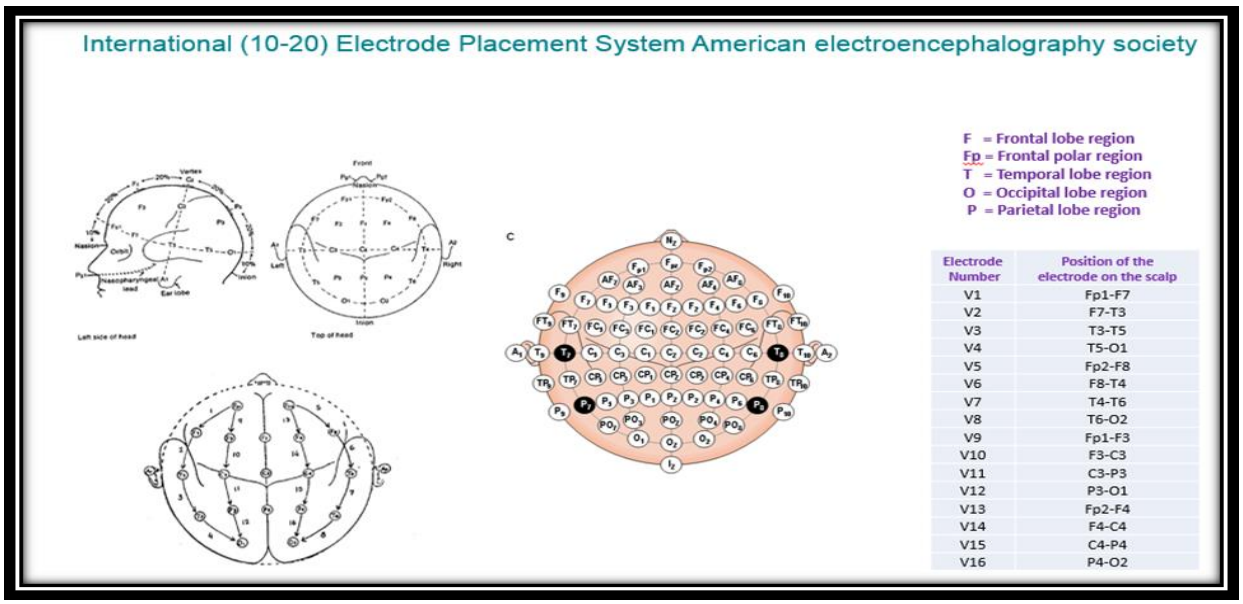
Mon 25 Aug 2014 – Mon 17 Nov 2014 (3 months ago)

Competition Details » Get the Data » Make a submission

Data Files

File Name	Available Formats
Dog_1.tar	.gz (3.81 gb)
Dog_2.tar	.gz (5.89 gb)
Dog_3.tar	.gz (9.46 gb)
Dog_4.tar	.gz (9.32 gb)
Dog_5.tar	.gz (2.60 gb)
Patient_1.tar	.gz (13.73 gb)
Patient_2.tar	.gz (14.83 gb)

Data Description - Intracranial EEG was recorded from dogs with naturally occurring epilepsy using an ambulatory monitoring system. EEG was sampled from 16 electrodes at 400 Hz, and recorded voltages were referenced to the group average. These are long duration recordings, spanning multiple months up to a year and recording up to a hundred seizures in some dogs.



In addition, datasets from patients with epilepsy undergoing intracranial EEG monitoring to identify a region of brain that can be resected to prevent future seizures are included in the contest. These datasets have varying numbers of electrodes and are sampled at 5000 Hz, with recorded voltages referenced to an electrode outside the brain. The challenge is to distinguish between ten minute long data clips covering an hour prior to a seizure, and ten minute iEEG clips of interictal activity.

No, Additional data collection was not required.

Data Limitations

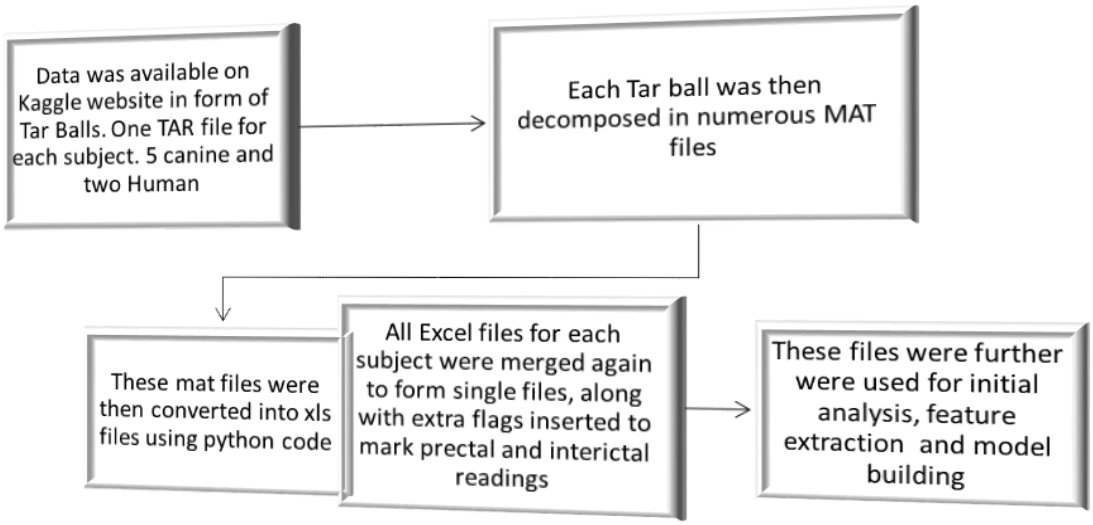
No there was no limitation in terms of availability of data, but due to the size and nature of data set we needed to extract features from the data set to prepare the model.

Benefit for Company

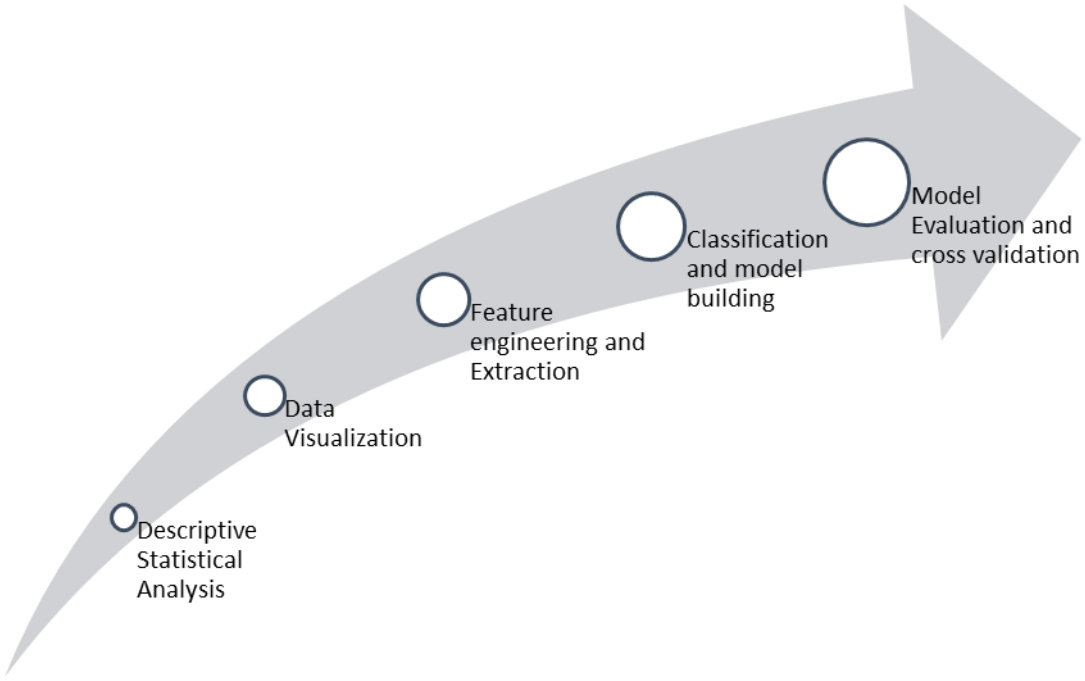
The project output is a detailed report which describes a step by step approach about how to tackle a signal processing data science problem. The learnings from this approach will help Invanti nurture it's capabilities in field of signal processing. This project can act as a showcase of work to show capability and expertise in this emerging area.

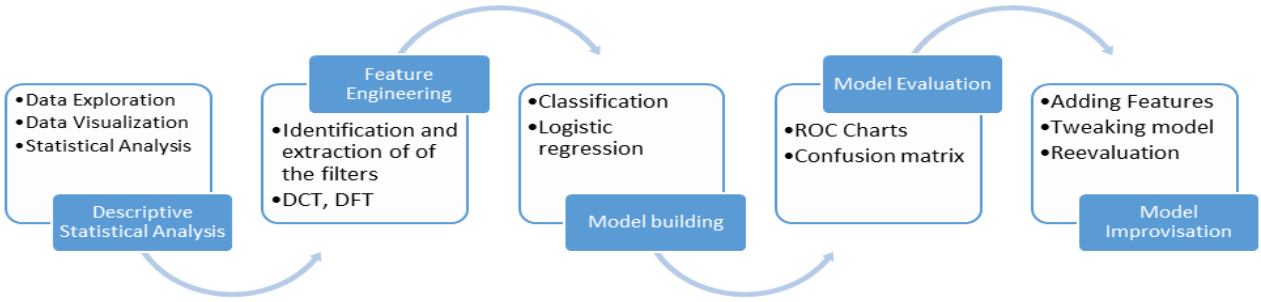
Data collection, Data exploration, Data cleaning

Data collection part was not involved in this project as we got the data directly from Kaggle site in form of Tar balls. But for data Exploration part we did some data manipulation. As data was in form of Tar balls so we needed to extract the same and extracted files were chunk of mat files corresponding to each tar ball. Once we extracted the files we further added some flags for aid of interpretation during data exploration. We added interictal and preectal flags while converting the mat files in csv format and merging the separate files in one csv file per tar ball. The process can be summarized as follows.



Approach - Analytical methods and Technology used

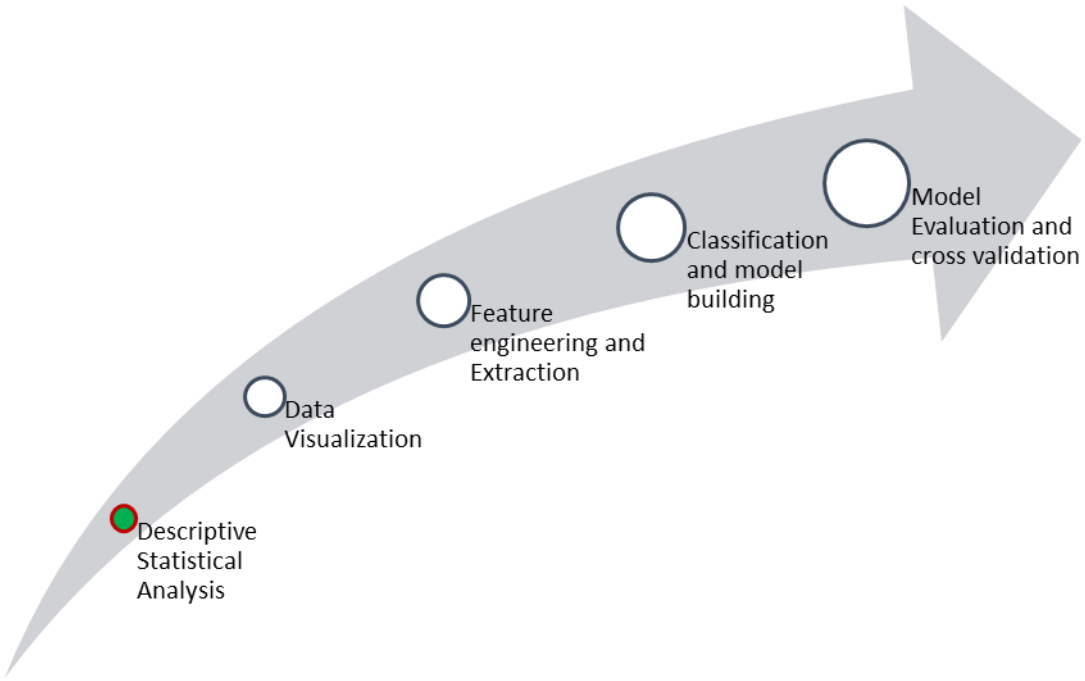




Tools/Languages Used

- **R – Statistical Programming And model building**
- **SAS – Data Transformation and model evaluation**
- **Python – Data Transformation**
- **Tableau - Visualization**

Descriptive Statistical Analysis



```
Rows Read: 500000, Total Rows Processed: 120500000, Total Chunk Time: 0.312 seconds
Rows Read: 342064, Total Rows Processed: 120842064, Total Chunk Time: 0.237 seconds
Computation time: 73.212 seconds.
> rxGetInfo(outputFile, getVarInfo=TRUE)
File name: C:\Users\admin\AppData\Local\Temp\Rtmpsn63Kb\dog_1_both_marked.xdf
Number of observations: 120842064
Number of variables: 19
Number of blocks: 242
Compression type: zlib
Variable information:
Var 1: V1, Type: integer, Low/High: (1, 115087680)
Var 2: V2, Type: character
Var 3: V3, Type: numeric, Storage: float32, Low/High: (-1666.0000, 913.0000)
Var 4: V4, Type: numeric, Storage: float32, Low/High: (-1936.0000, 464.0000)
Var 5: V5, Type: numeric, Storage: float32, Low/High: (-490.0000, 607.0000)
Var 6: V6, Type: numeric, Storage: float32, Low/High: (-717.0000, 1043.0000)
Var 7: V7, Type: numeric, Storage: float32, Low/High: (-1889.0000, 672.0000)
Var 8: V8, Type: numeric, Storage: float32, Low/High: (-2122.0000, 584.0000)
Var 9: V9, Type: numeric, Storage: float32, Low/High: (-602.0000, 1151.0000)
Var 10: V10, Type: numeric, Storage: float32, Low/High: (-911.0000, 1265.0000)
Var 11: V11, Type: numeric, Storage: float32, Low/High: (-2068.0000, 719.0000)
Var 12: V12, Type: numeric, Storage: float32, Low/High: (-618.0000, 532.0000)
Var 13: V13, Type: numeric, Storage: float32, Low/High: (-1221.0000, 580.0000)
Var 14: V14, Type: numeric, Storage: float32, Low/High: (-503.0000, 1586.0000)
Var 15: V15, Type: numeric, Storage: float32, Low/High: (-1387.0000, 1186.0000)
Var 16: V16, Type: numeric, Storage: float32, Low/High: (-1350.0000, 636.0000)
Var 17: V17, Type: numeric, Storage: float32, Low/High: (-1352.0000, 1352.0000)
Var 18: V18, Type: numeric, Storage: float32, Low/High: (-2044.0000, 2028.0000)
Var 19: V19, Type: integer, Low/High: (0, 1)
```

```
> rxGetInfo("interictal", getVarInfo=TRUE)
File name: C:\Users\admin\AppData\interictal.xdf
Number of observations: 5754384
Number of variables: 19
Number of blocks: 12
Compression type: zlib
Variable information:
Var 1: V1, Type: integer, Low/High: (1, 1438596)
Var 2: V2, Type: character
Var 3: V3, Type: numeric, Storage: float32, Low/High: (-641.0000, 882.0000)
Var 4: V4, Type: numeric, Storage: float32, Low/High: (-621.0000, 393.0000)
Var 5: V5, Type: numeric, Storage: float32, Low/High: (-432.0000, 223.0000)
Var 6: V6, Type: numeric, Storage: float32, Low/High: (-328.0000, 283.0000)
Var 7: V7, Type: numeric, Storage: float32, Low/High: (-788.0000, 571.0000)
Var 8: V8, Type: numeric, Storage: float32, Low/High: (-375.0000, 290.0000)
Var 9: V9, Type: numeric, Storage: float32, Low/High: (-354.0000, 441.0000)
Var 10: V10, Type: numeric, Storage: float32, Low/High: (-357.0000, 355.0000)
Var 11: V11, Type: numeric, Storage: float32, Low/High: (-609.0000, 397.0000)
Var 12: V12, Type: numeric, Storage: float32, Low/High: (-352.0000, 230.0000)
Var 13: V13, Type: numeric, Storage: float32, Low/High: (-175.0000, 266.0000)
Var 14: V14, Type: numeric, Storage: float32, Low/High: (-198.0000, 263.0000)
Var 15: V15, Type: numeric, Storage: float32, Low/High: (-641.0000, 538.0000)
Var 16: V16, Type: numeric, Storage: float32, Low/High: (-264.0000, 247.0000)
Var 17: V17, Type: numeric, Storage: float32, Low/High: (-344.0000, 238.0000)
Var 18: V18, Type: numeric, Storage: float32, Low/High: (-289.0000, 271.0000)
Var 19: V19, Type: integer, Low/High: (1, 1)
```

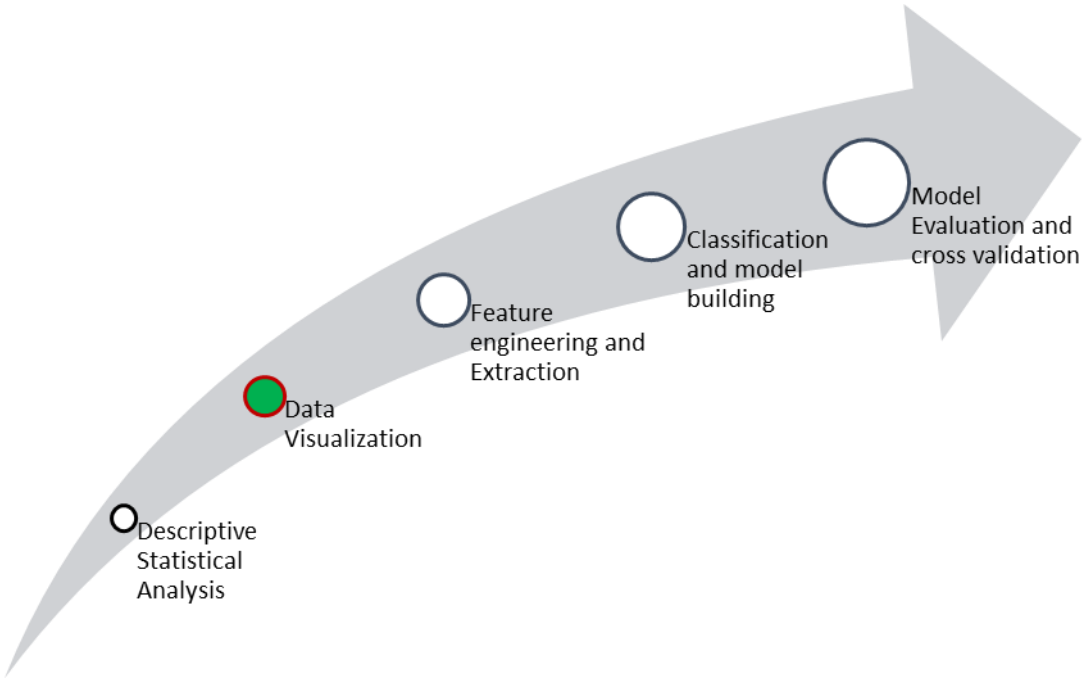
```
Time to read data file: 1.44 secs.
Time to convert to data frame: less than .001 secs.
> myData
   V1                 V2 V3  V4  V5  V6 V7 V8  V9 V10 V11 V12 V13 V14 V15 V16
1   1 preictal_segment_1  7  -1   2  12 15  2 -10   1  -7   8   4  -5  -7  -7
2   2 preictal_segment_1 12 -17  -9 -14 20 -3 -15 -15  13  18   6  -1  32  -4
3   3 preictal_segment_1 17 -28 -17 -20 21  1 -13 -18  10  13  -2 -12  44   1
4   4 preictal_segment_1 35   2  -5  -3 44 24  -3 -10  16  -2  -9 -14 -41 -10
5   5 preictal_segment_1 49  23  -3   4 57 24 -10 -18  15   0 -11 -19 -31 -15
6   6 preictal_segment_1 39  18   2  10 44 24  -3 -10  13   0 -16 -25 -23  -6
7   7 preictal_segment_1 21  18   6  -2 37 28  -1  -8  13   3  -8 -28 -18   3
8   8 preictal_segment_1 -5   5  12  -7 19 13  -7  -9   8   7   6 -13   7  10
9   9 preictal_segment_1 -3   4   7  -6 23 15 -13 -19   8  -1   1  -9  23   5
10 10 preictal_segment_1  6   7   8   6 18 12  -9 -13  -3 -14   1   2 -34  13
   V17 V18 V19
1   -3 -13   1
2   -9  -4   1
3  -12  -2   1
4  -21 -17   1
5  -36 -33   1
6  -36 -25   1
7  -37 -31   1
8  -13 -21   1
9   -7 -23   1
10   8  -6   1
> myData <- rxReadXdf("interictal", startRow=1)

Rows Processed: 5754384
Time to read data file: 50.05 secs.
Time to convert to data frame: 27.99 secs.
```

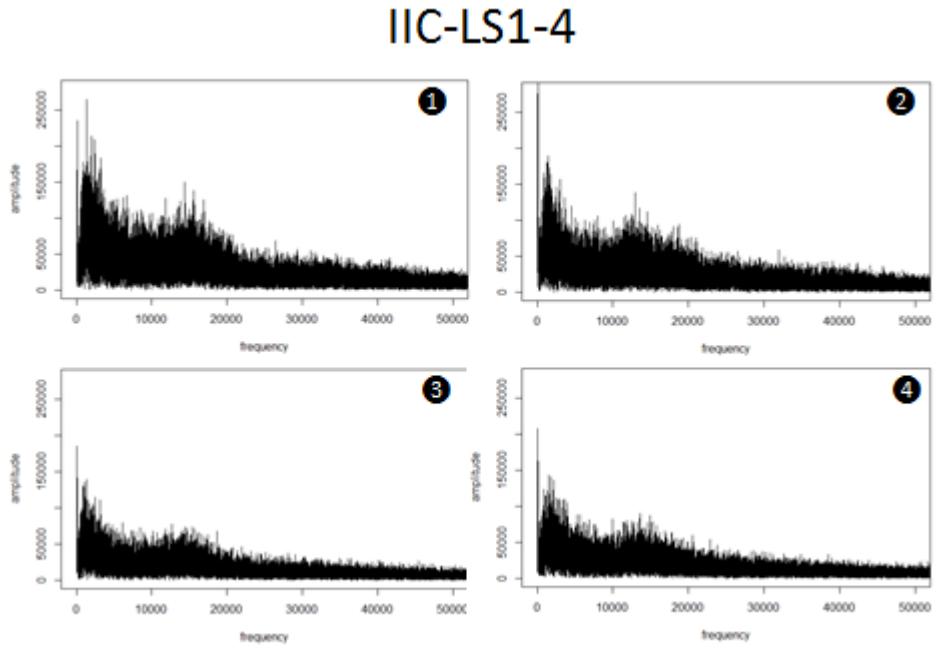
```
> myData <- rxReadXdf("interictal", startRow=1)

Rows Processed: 5754384
Time to read data file: 50.05 secs.
Time to convert to data frame: 27.99 secs.
> nrow(myData)
[1] 5754384
> ncol(myData)
[1] 19
> head(myData)
  V1                 V2 V3  V4  V5  V6 V7 V8  V9 V10 V11 V12 V13 V14 V15 V16
1  1 preictal_segment_1  7  -1   2  12 15  2 -10   1  -7   8   4  -5  -7  -7
2  2 preictal_segment_1 12 -17  -9 -14 20 -3 -15 -15  13  18   6  -1  32  -4
3  3 preictal_segment_1 17 -28 -17 -20 21  1 -13 -18  10  13  -2 -12  44   1
4  4 preictal_segment_1 35   2  -5  -3 44 24  -3 -10  16  -2  -9 -14 -41 -10
5  5 preictal_segment_1 49  23  -3   4 57 24 -10 -18  15   0 -11 -19 -31 -15
6  6 preictal_segment_1 39  18   2  10 44 24  -3 -10  13   0 -16 -25 -23  -6
  V17 V18 V19
1  -3 -13   1
2  -9  -4   1
3 -12  -2   1
4 -21 -17   1
5 -36 -33   1
6 -36 -25   1
```

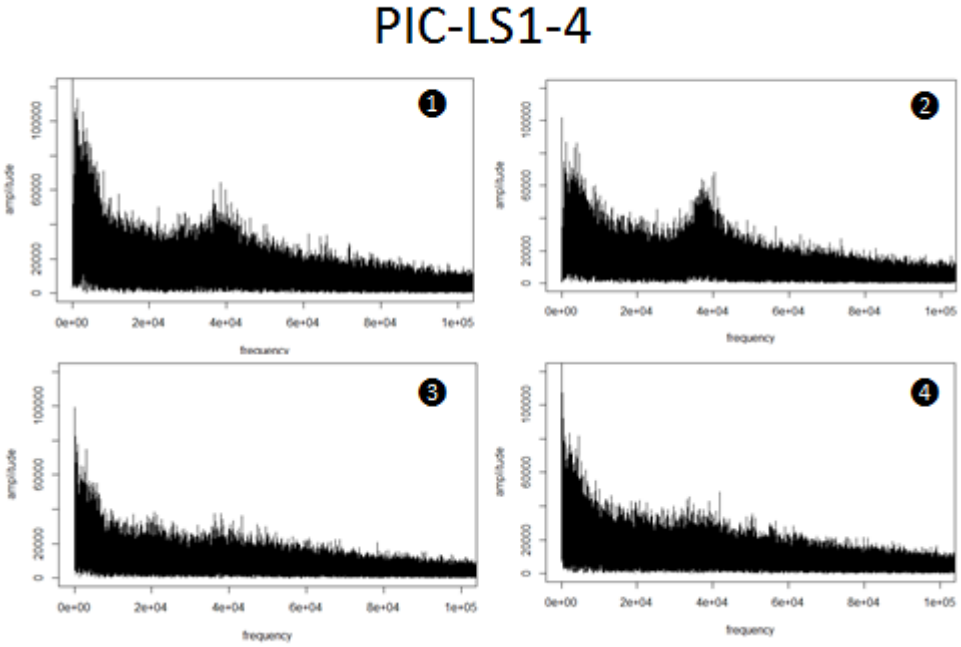
Data Visualization



Interictal Frequency Amplitude Chart

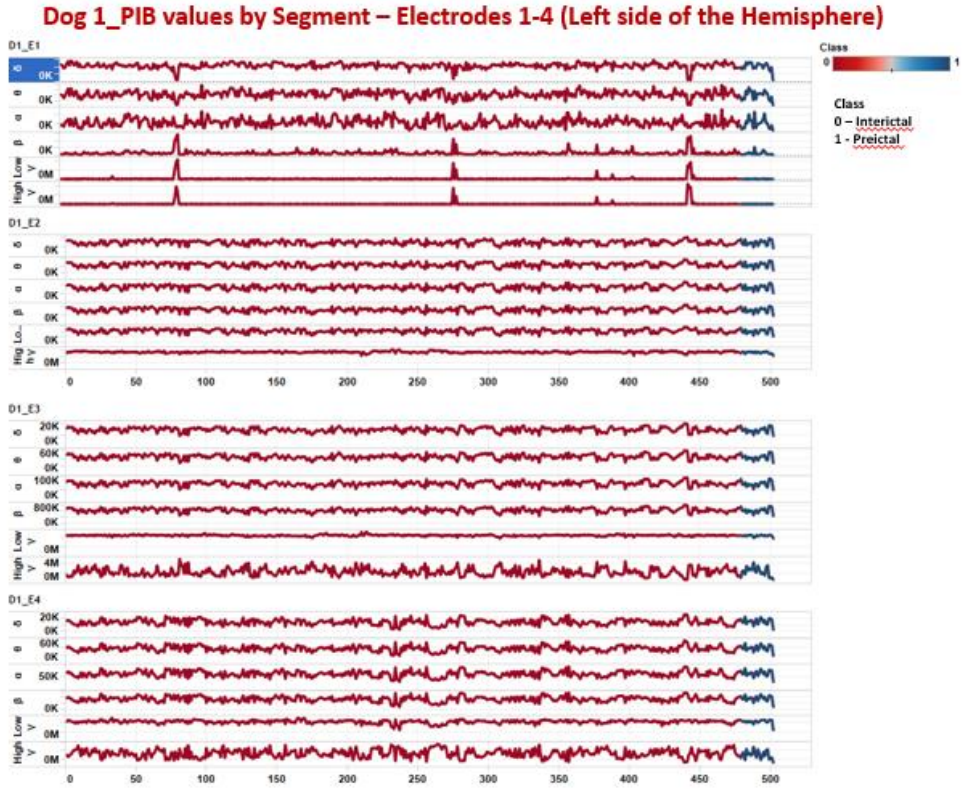


Preictal Frequency Amplitude Chart

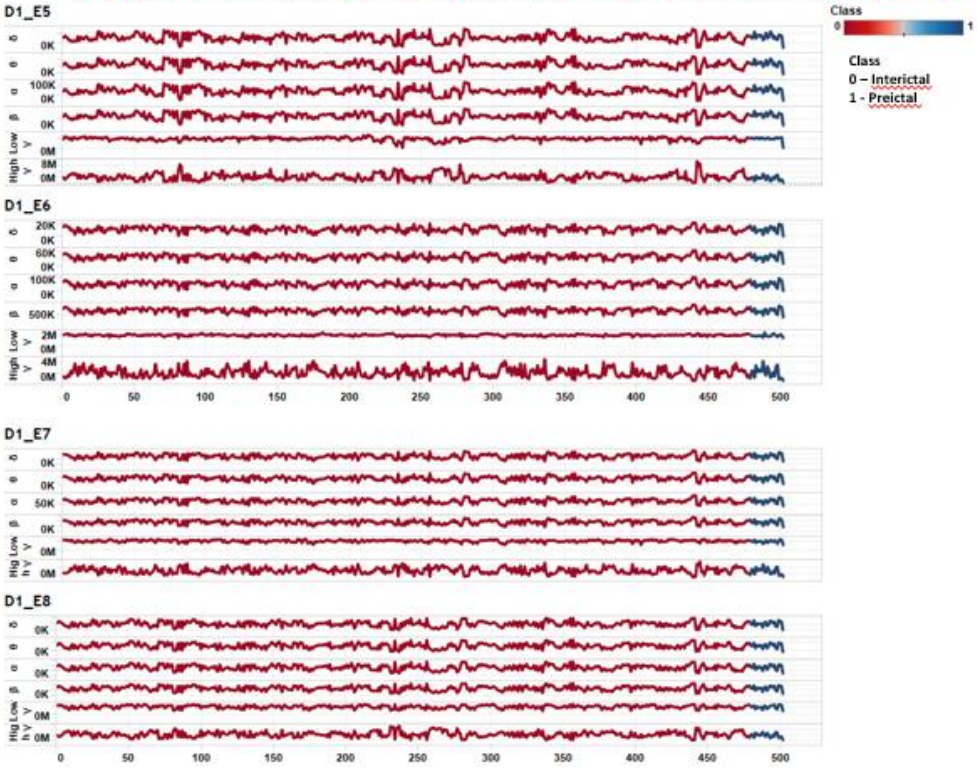


Power in Band values by Segments

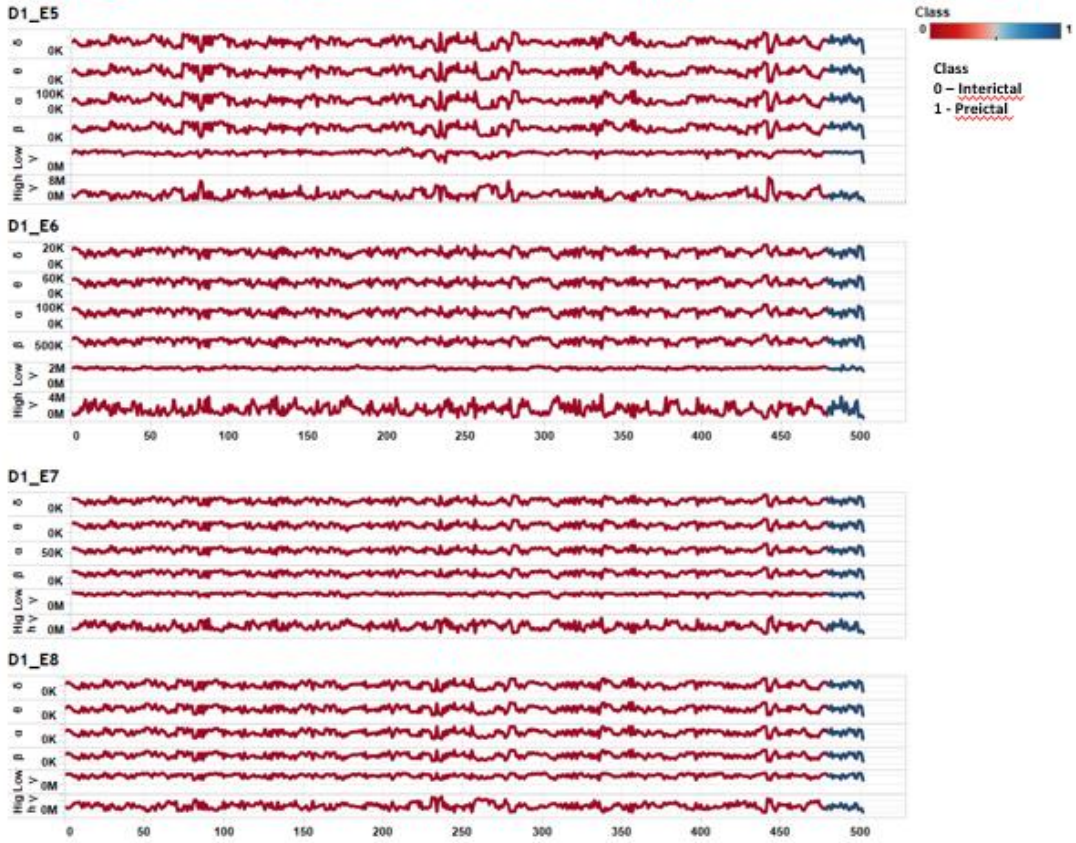
The below chart describes the power in bandfor 6 different frequncy bands for each electrodes.
0 stands for interictal where there is no seizure and 1 stands for preictal which stands for seizure condition. However, each electrode interictal states does show abnormal spikes in multiple segments. This indicates that such spikes are false positive alams. The below charts are to be viewed for visualization purpose only.

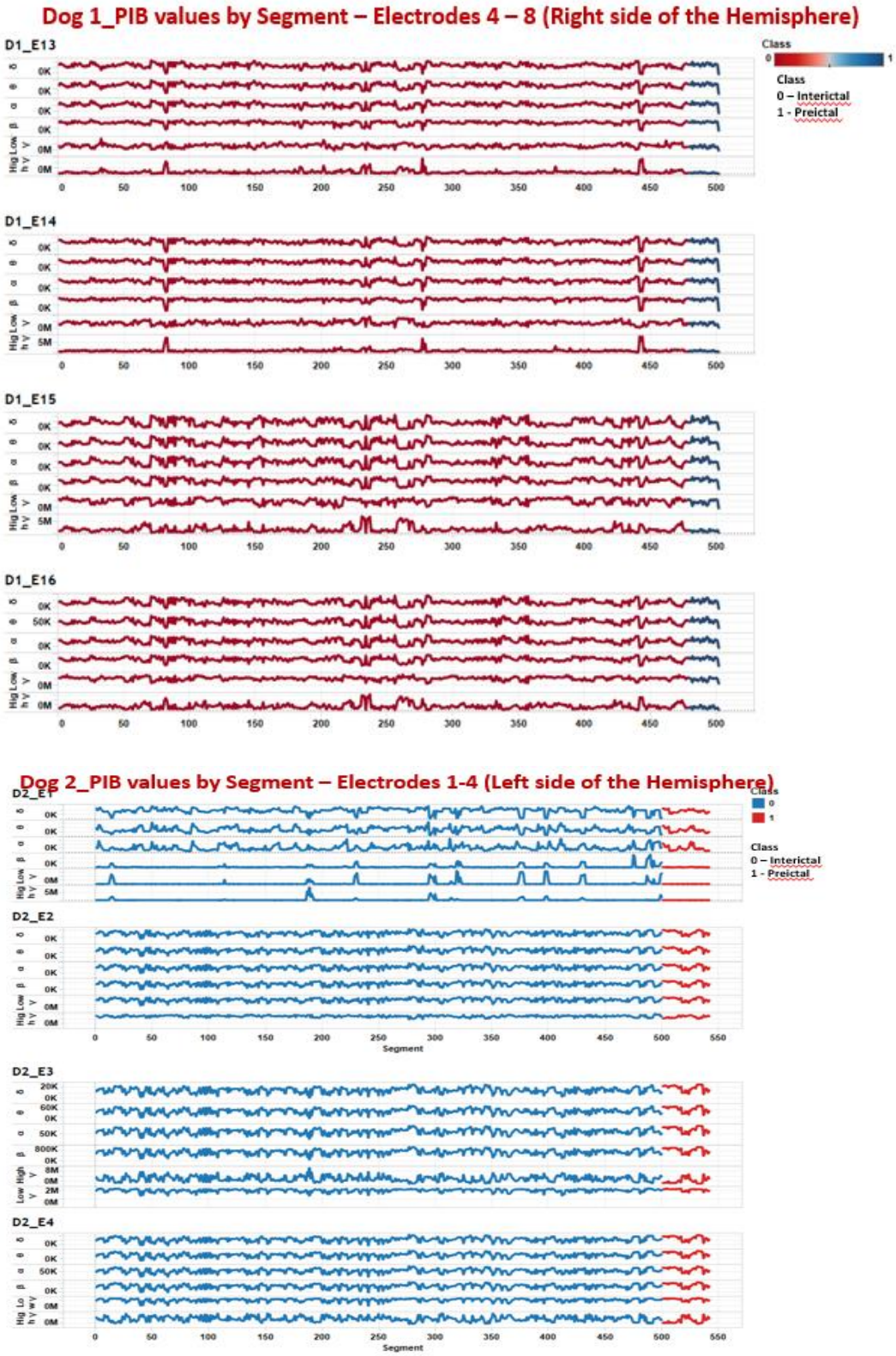


Dog 1_PIB values by Segment – Electrodes 5 –8 (Left side of the Hemisphere)



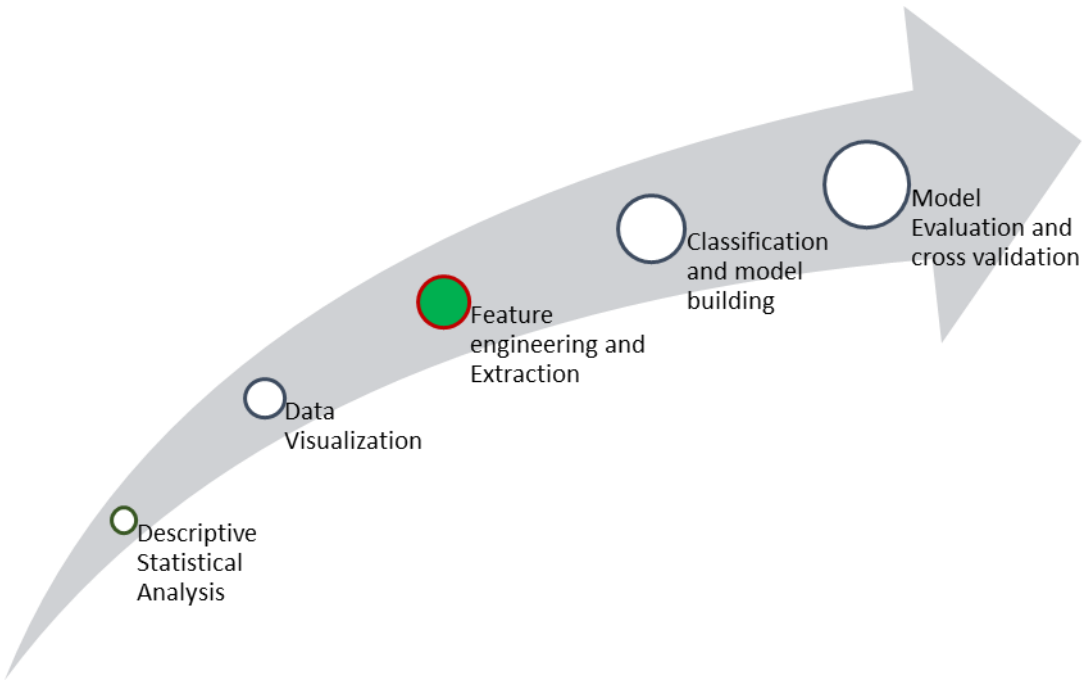
Dog 1_PIB values by Segment – Electrodes 1 - 4 (Right side of the Hemisphere)





Please refer to the attached Appendix for Data visualization outputs and interpretations for further details.

Feature Engineering



Mathematical transformations are applied to signals to obtain further information from that signal that is not readily available in the raw signal. The Time-domain signal which is a raw signal and it gets "transformed" by any of the available mathematical transformations as a processed signal.

Most of the signals in practice **are Time-Domain** signals in their raw format. That is, whatever that signal is measuring, is a function of time. In other words, when we plot the signal one of the axes is time (independent variable), and the other (dependent variable) is usually the amplitude. When we plot time-domain signals, we obtain a **time-amplitude representation** of the signal. This representation is not always the best representation of the signal for most signal processing related applications. In many cases, the most distinguished information is hidden in the frequency content of the signal. The **frequency SPECTRUM** of a signal is basically the frequency components (spectral components) of that signal. The frequency spectrum of a signal shows what frequencies exist in the signal.

We have used Discrete Cosine Transform (DCT) to transform a time domain signal into a frequency domain to obtain frequency-amplitude representation of that signal. Discrete cosine transform (DCT) transforms is a real transform that transforms a sequence of real data points into its real spectrum and therefore avoids the problem of redundancy.

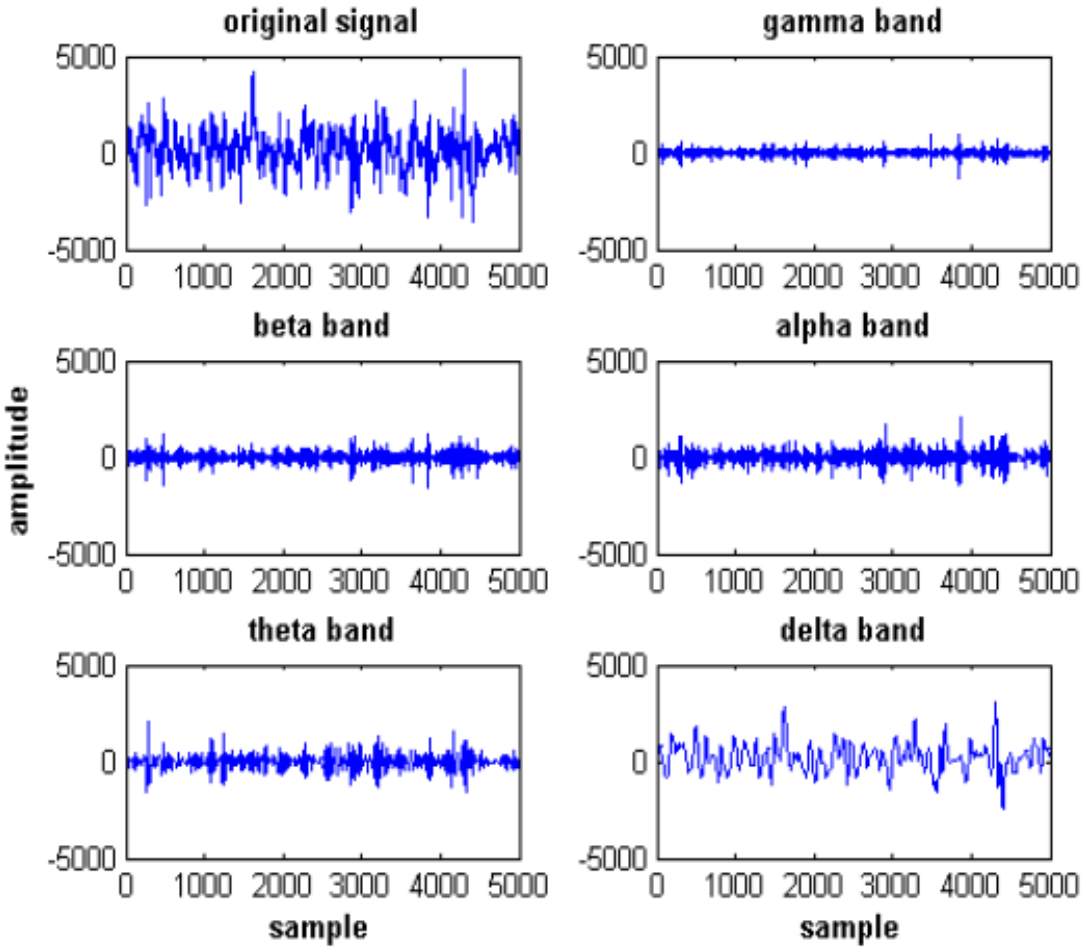
Feature Extraction from EEG Signals

EEG signals are recorded from 16 channels and studied during several mental and motor tasks. Features are extracted from those signals using several methods: Time Analysis, Frequency Analysis, Time-Frequency Analysis and Time-Frequency-Space Analysis. Extracted EEG features are classified using Logistic Regression classifier.

v1_delta	v1_theta	v1_alpha	v1_beta	v1_lowGamma	v1_highGamma
v2_delta	v2_theta	v2_alpha	v2_beta	v2_lowGamma	v2_highGamma
v3_delta	v3_theta	v3_alpha	v3_beta	v3_lowGamma	v3_highGamma
v4_delta	v4_theta	v4_alpha	v4_beta	v4_lowGamma	v4_highGamma
v5_delta	v5_theta	v5_alpha	v5_beta	v5_lowGamma	v5_highGamma
v6_delta	v6_theta	v6_alpha	v6_beta	v6_lowGamma	v6_highGamma
v7_delta	v7_theta	v7_alpha	v7_beta	v7_lowGamma	v7_highGamma
v8_delta	v8_theta	v8_alpha	v8_beta	v8_lowGamma	v8_highGamma
v9_delta	v9_theta	v9_alpha	v9_beta	v9_lowGamma	v9_highGamma
v10_delta	v10_theta	v10_alpha	v10_beta	v10_lowGamma	v10_highGamma
v11_delta	v11_theta	v11_alpha	v11_beta	v11_lowGamma	v11_highGamma
v12_delta	v12_theta	v12_alpha	v12_beta	v12_lowGamma	v12_highGamma
v13_delta	v13_theta	v13_alpha	v13_beta	v13_lowGamma	v13_highGamma
v14_delta	v14_theta	v14_alpha	v14_beta	v14_lowGamma	v14_highGamma
v15_delta	v15_theta	v15_alpha	v15_beta	v15_lowGamma	v15_highGamma
v16_delta	v16_theta	v16_alpha	v16_beta	v16_lowGamma	v16_highGamma

Alpha	**Waves occur at a frequency of 8 to 13 cycles per second.**
Beta	Waves occur at a frequency of 13 to 30 cycles per second.
Theta	Waves occur at a frequency of 4 to 8 cycles per second.
Delta	Waves occur at a frequency of 0.1 to 5 cycles per second.
Gamma	Low gamma waves occur at a frequency of 30 to 70 cycles per second and high gamma waves occur at a frequency of 70 to 180 cycles per second.

There are five major brain waves distinguished by their different frequency ranges [4]: Delta waves lie within the range of 0.5 to 4 Hz, Theta waves lie within the range of 4 to 7 Hz, with an amplitude usually greater than 20 μ V, Alpha with a rate of change lies between 8 and 13 Hz, with 30-50 μV amplitude, Beta, the rate of change lies between 13 and 30 Hz, and usually has a low voltage between 5-30 μV. Beta is the brain wave usually associated with active thinking, active attention, focus on the outside world or solving concrete problems and finally the Gamma waves which lie within the range of 35Hz and up. It is thought that this band reflects the mechanism of consciousness. Theta, alpha and beta frequencies are used in our work to classify the mental tasks.



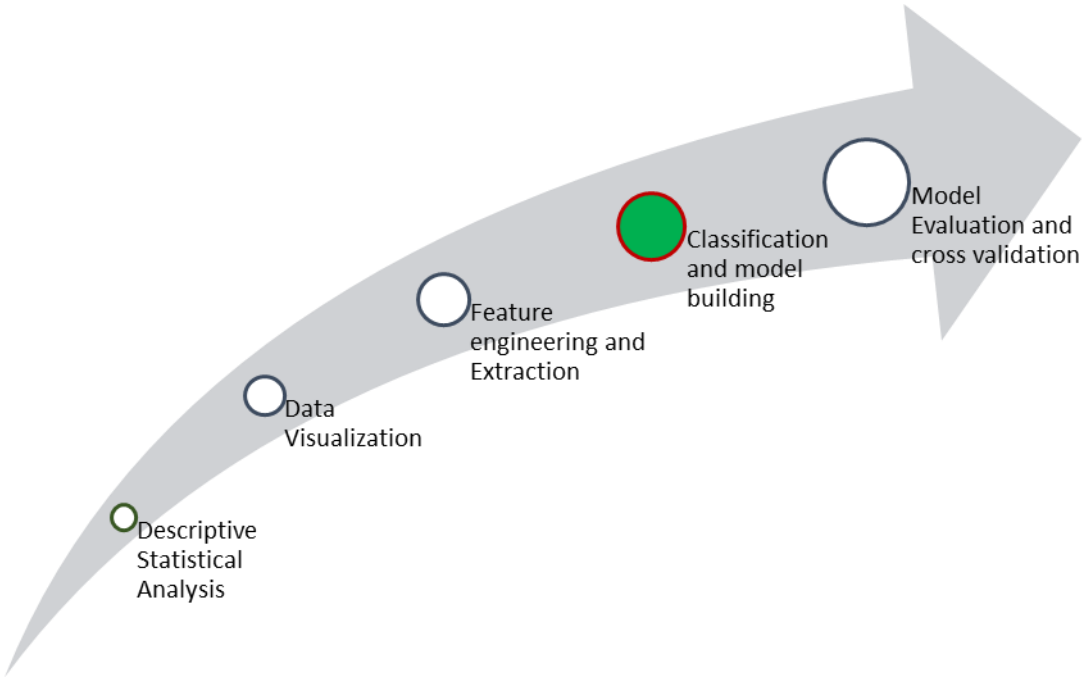
Power in Band

Power in band measures the total power within any specified frequency range or band. Power in band is characterized by the following equation:

$$Power\ in\ Band = \sum_{f_l}^{f_h} X(f)$$

where X is the input power spectrum from a specified band, fl is the low bound of the frequency band, and fh is the high bound of the frequency band. The low and high bounds of this band can be determined from the centre frequency.

Classification & Model Building



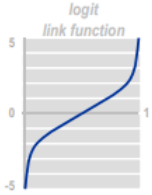
We used logistic Regression for classification and our model building. Logistic regression is done if the target variable is a discrete variable. In logistic regression the model predicts the probability of a particular level(s) of the target variable at the given values of the input variables. Because the predictions are probabilities, which are bounded by 0 and 1 and are not linear in this space, the probabilities must be transformed in order to be adequately modeled. The most common transformation for a binary target is the logit transformation.

Logistic Regression Prediction Formula

$$\log\left(\frac{\hat{p}}{1-\hat{p}}\right) = \hat{w}_0 + \hat{w}_1 x_1 + \hat{w}_2 x_2$$ *logit scores*

Logit Link Function

$$\log\left(\frac{\hat{p}}{1-\hat{p}}\right) = \hat{w}_0 + \hat{w}_1 x_1 + \hat{w}_2 x_2$$ *logit scores*



The logit link function transforms probabilities (between 0 and 1) to logit scores (between −∞ and +∞).

Logit Link Function

$$\log\left(\frac{\hat{p}}{1-\hat{p}}\right) = \hat{w}_0 + \hat{w}_1 x_1 + \hat{w}_2 x_2 = \text{logit}(\hat{p})$$

$$\hat{p} = \frac{1}{1 + e^{-\text{logit}(\hat{p})}}$$

To obtain prediction estimates, the logit equation is solved for $\hat{p}$.

Parameter estimates are obtained by maximum likelihood estimation. These estimates were used in logistic equation to obtain predictions.

Logistic regression classifiers were trained to discriminate labeled pre-ictal and inter-ictal blocks using combinations of PIB features. For training purposes, blocks between 90 minutes preceding a seizure and the seizure itself were given a pre-ictal label, and all other blocks were labeled as inter-ictal. When applied to test data, the output of the trained classifier was a relative seizure risk for each test block on a continuous scale between 0 and 1.

Logistic regression consolidated data (dogs 1-4) Interpretation

The simplest diagnostic test is where the result of an investigation, such as an EEG examination is used to classify both interictal and preictal states in to two groups. Confusion matrix table shows the relation between the results of a test of an EEG of interictal (normal state) and preictal state (abnormal state). The proportions of segments with no seizure and seizure are correctly classified from the EEG data. The terms positive and negative refers to the presence and absence of seizures. Thus, there are 369 true negatives and 323 true positives. The proportions of these two groups that were correctly classified by the EEG data is (217/369) = 0.58 and (200/323) = 0.61 respectively.

Sensitivity is the proportions of true positives that are correctly identified by the test. Specificity is the proportions of true negatives that are correctly identified by the test. From this analysis we could expect 58% of those shown no seizure conditions (negative) while 61% of those with seizure condition (positive). Sensitivity and Specificity are one approach to quantify the no seizure and seizure status of the test. In health care practice you want to know how good the test is at predicting seizure status and what proportions of test with seizure and no seizure results are truly seizures.

The whole point of a diagnostic test is to use it to make a seizure status so we need to know the probability that the test will give the correct seizure status. The sensitivity and specificity do not give complete information instead we must approach the data from the test results using predicted values. Positive predictive value is the proportion of cases with positive test results which are correctly classified.

We know that the 217 of 340 cases with normal seizure status giving the proportion of correct classification as 217/340 = 0.63. Among 352 cases with seizure status the proportion of correct classification of true seizures is 200/352= 0.56.

Logistic Regression Models

<table>
<tr><th></th><th>Logistic Regression - Model Test</th><th>Logistic Regression - Model Validation</th></tr>
<tr><td>Accuracy</td><td>60.26</td><td>58.17</td></tr>
<tr><td>Specificity</td><td>0.619</td><td>0.619</td></tr>
<tr><td>Sensitivity</td><td>0.588076</td><td>0.61747</td></tr>
<tr><td>Area of ROC Curve</td><td>0.645</td><td>0.616</td></tr>
<tr><td>Confusion Matrix</td><td>
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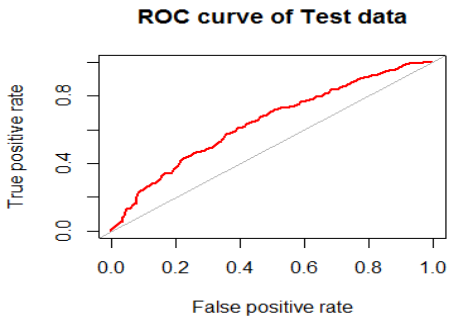
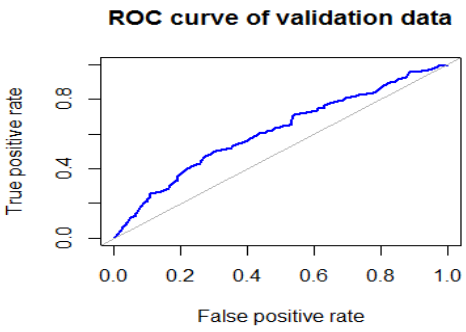
<tr><td></td><td> 
</td><td> 
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Figure 1: Logistic regression analysis for consolidated dogs data (dogs 1-4)

Dog 1

<table>
<tr><td></td><td>Logistic Regression - Model Test</td><td>Logistic Regression - Model Validation</td></tr>
<tr><td>Accuracy</td><td>0.65346</td><td>0.64</td></tr>
<tr><td>Specificity</td><td>O.27907</td><td>0.375</td></tr>
<tr><td>Sensitivity</td><td>0.57407</td><td>0.625</td></tr>
<tr><td>Area of ROC Curve</td><td>0.62</td><td>0.67</td></tr>
<tr><td>Confusion Matrix</td><td>
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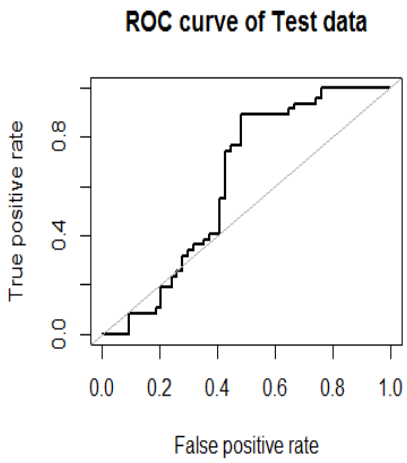
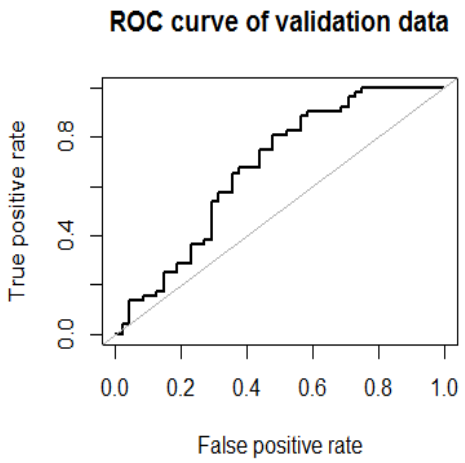
<tr><td></td><td> 
</td><td> 
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Figure 2: Logistic regression analysis for dog1 data

Dog 2

<table>
<tr><td></td><td>Logistic Regression - Model Test</td><td>Logistic Regression - Model Validation</td></tr>
<tr><td>Accuracy</td><td>0.712963</td><td>0.62037</td></tr>
<tr><td>Specificity</td><td>0.254545</td><td>0.326531</td></tr>
<tr><td>Sensitivity</td><td>0.706897</td><td>0.568966</td></tr>
<tr><td>Area of ROC Curve</td><td>0.670</td><td>0.67</td></tr>
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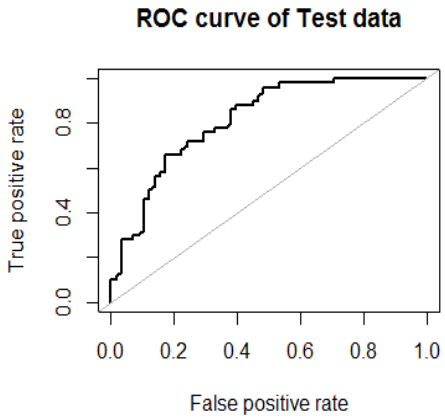
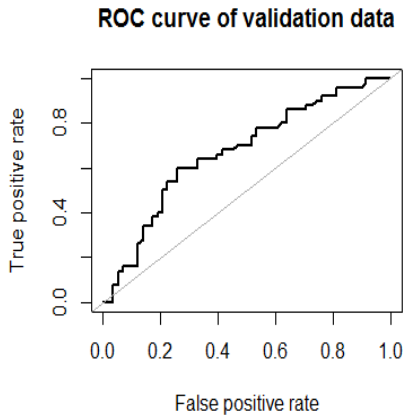
<tr><td>ROC Curve</td><td> 
</td><td> 
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Figure 3: Logistic regression analysis for dog2 data

Dog 3

<table>
<tr><td></td><td>Logistic Regression - Model Test</td><td>Logistic Regression - Model Validation</td></tr>
<tr><td>Accuracy</td><td>0.642384</td><td>0.622517</td></tr>
<tr><td>Specificity</td><td>0.357143</td><td>0.33333</td></tr>
<tr><td>Sensitivity</td><td>0.5625</td><td>0.575</td></tr>
<tr><td>Area of ROC Curve</td><td>0.67</td><td>0.66</td></tr>
<tr><td>Confusion Matrix</td><td>
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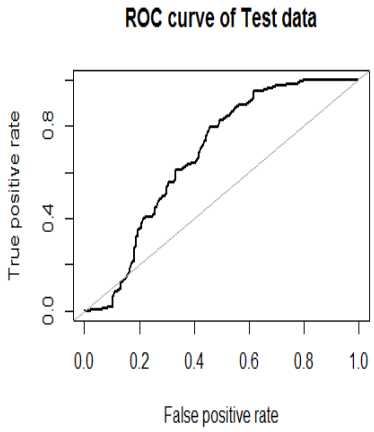
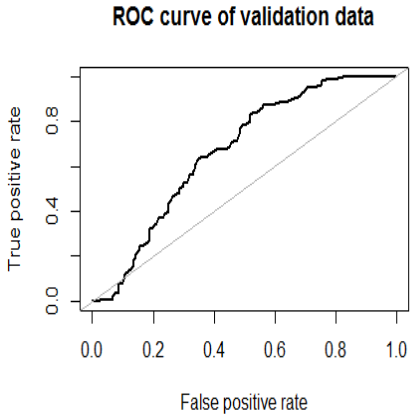
<tr><td></td><td> 
</td><td> 
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Figure 4: Logistic regression analysis for dog3 data

Dog 4

<table>
<tr><th></th><th>Logistic Regression - Model Test</th><th>Logistic Regression - Model Validation</th></tr>
<tr><td>Accuracy</td><td>0.666667</td><td>0.627778</td></tr>
<tr><td>Specificity</td><td>0.292683</td><td>0.31861</td></tr>
<tr><td>Sensitivity</td><td>0.617021</td><td>0.62</td></tr>
<tr><td>Area of ROC Curve</td><td>0.73</td><td>0.69</td></tr>
<tr><td>Confusion Matrix</td><td>
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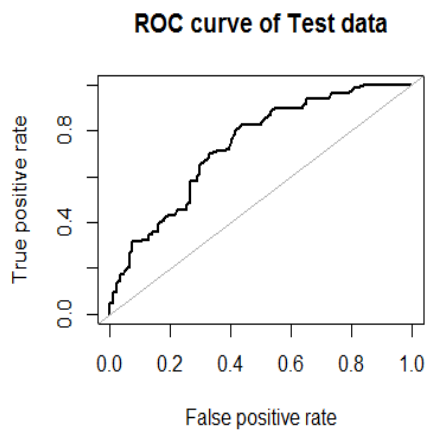
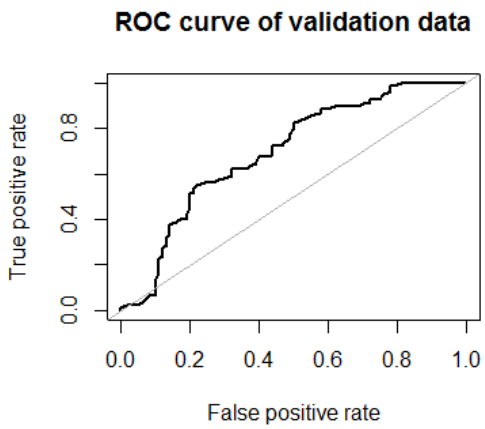
<tr><td></td><td> 
</td><td> 
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Figure 5: Logistic regression analysis for dog4 data

Figure 6: Logistic regression analysis for dog5 data

<table>
<tr><td></td><td>Logistic Regression - Model Test</td><td>Logistic Regression - Model Validation</td></tr>
<tr><td>Accuracy</td><td>0.708333</td><td>0.708333</td></tr>
<tr><td>Specificity</td><td>0.190476</td><td>0.236842</td></tr>
<tr><td>Sensitivity</td><td>0.62963</td><td>0.604167</td></tr>
<tr><td>Area of ROC Curve</td><td>0.71</td><td>0.73</td></tr>
<tr><td>Confusion Matrix</td><td>
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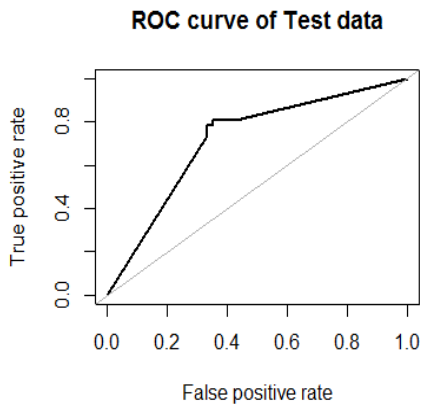
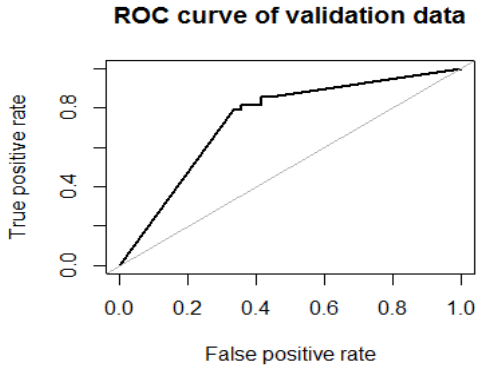
<tr><td></td><td> 
</td><td> 
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The confusion matrix

The performance of a classification model, we are interested in the model's ability to correctly predict or separate the classes. When looking at the errors made by a classification model, the confusion matrix gives the full picture. A predictive model may result in the confusion matrix when tested on independent data.

The confusion matrix shows how the predictions are made by the model. The rows correspond to the known class of the data. The columns correspond to the predictions made by the model. The value of each of element in the matrix is the number of predictions made with the class corresponding to the column for examples with the correct value as represented by the row. Thus, the diagonal elements show the number of correct classifications made for each class, and the off-diagonal elements show the errors made.

The confusion matrix is the rightmost section in the statistics table displayed for classification models.

Performance measures

Accuracy - Accuracy is the overall correctness of the model and is calculated as the sum of correct classifications divided by the total number of classifications.

Precision

Precision is a measure of the accuracy provided that a specific class has been predicted. It is defined by: Precision = tp/(tp + fp) where tp and fp are the numbers of true positive and false positive predictions for the considered class.

Recall

Recall is a measure of the ability of a prediction model to select instances of a certain class from a data set. It is commonly also called sensitivity, and corresponds to the true positive rate. It is defined by the formula: Recall = Sensitivity = tp/(tp+fn) where tp and fn are the

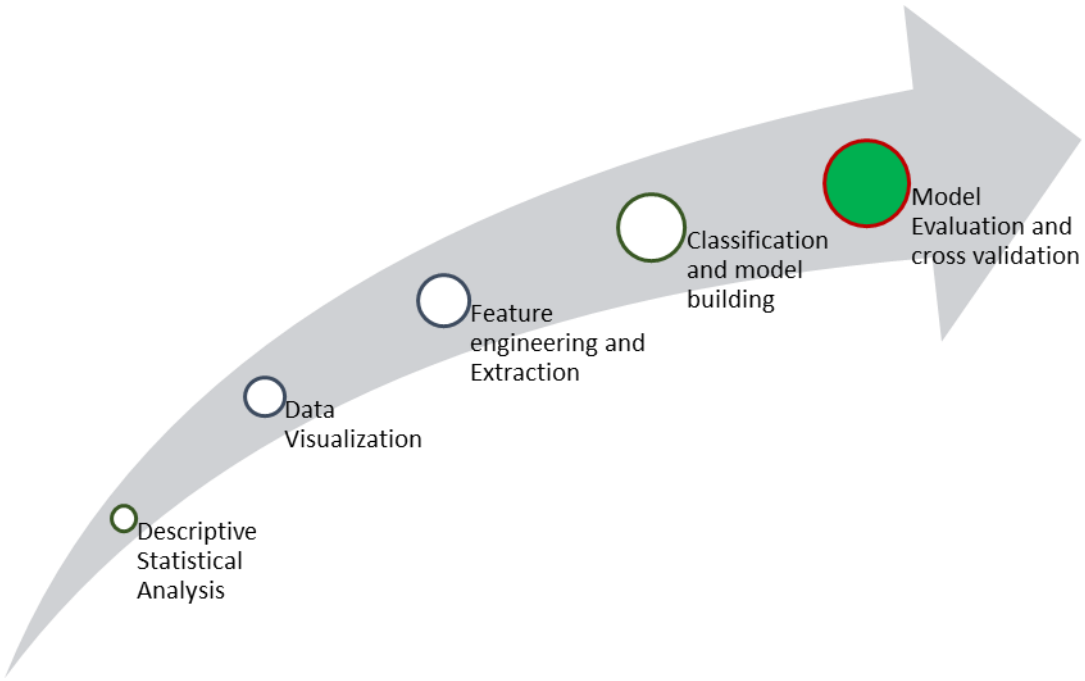
numbers of true positive and false negative predictions for the considered class. tp + fn is the total number of test examples of the considered class.

Specificity

Recall/sensitivity is related to specificity, which is a measure that is commonly used in two class problems where one is more interested in a particular class. Specificity corresponds to the true- negative rate. Specificity = tn/(tn+fp).

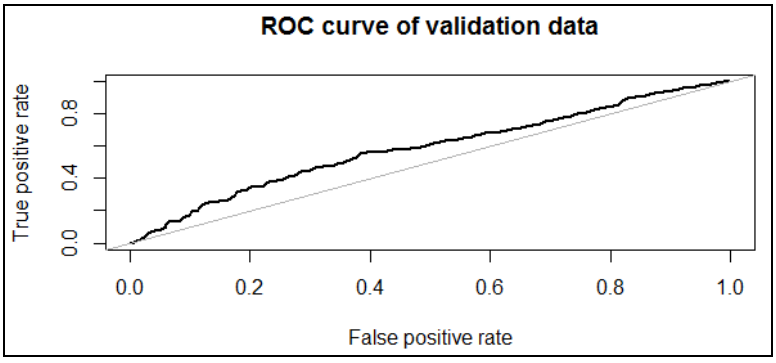
The class probabilities for selecting your cases based on predictions. In order to do this, the Receiver- Operating Characteristic (ROC) curve, and the measure Area under Curve (AUC), are instrumental.

Model Selection - Evaluation & Cross Validation



LOGISTIC REGRESSION – MODEL 1

ITERATION 1			
TEST MODEL		VALIDATION MODEL	
CONFUSION MATRIX		CONFUSION MATRIX	
208	163	197	156
141	180	140	198
Accuracy	0.5607	Accuracy	0.5716
Recall	0.5607	Recall	0.5858
Precision	0.5248	Precision	0.5593
Sensitivity	0.5960	Sensitivity	0.5846
Specificity	0.4394	Specificity	0.4419
AUC - 0.58			

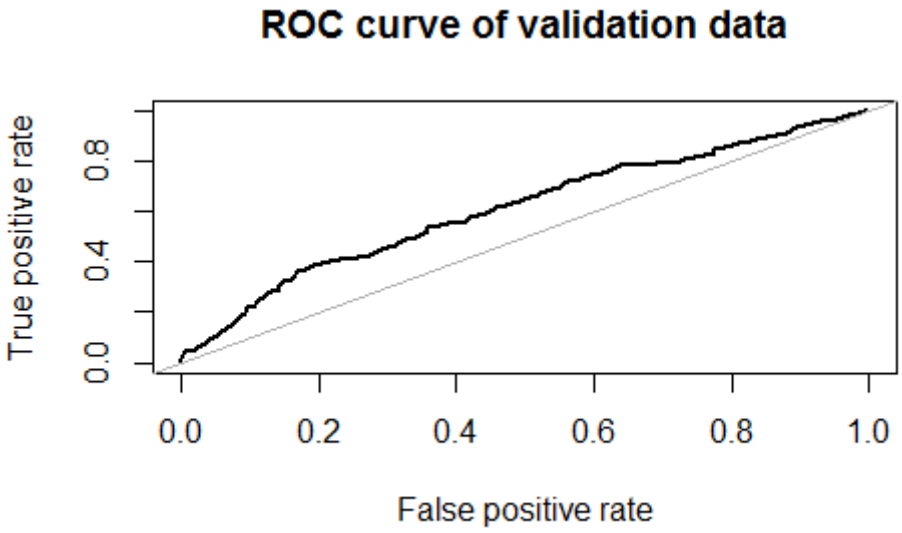


Model 1 Interpretation:

- Model uses all 96 variables and it gives a moderately strong model with 56% accuracy and decent specificity and sensitivity considering a strong model in health care will have 70% accuracy and above.
- ROC curve for validation data set has a decent area under curve.
- However, there are some insignificant variables in the model which we will remove and run another iteration.

LOGISTIC REGRESSION – MODEL 2

ITERATION 2				
TEST MODEL			VALIDATION MODEL	
CONFUSION MATRIX			CONFUSION MATRIX	
207	172		220	159
129	184		125	187
Accuracy	0.5650		Accuracy	0.5890
Recall	0.5879		Recall	0.5994
Precision	0.5169		Precision	0.5405
Sensitivity	0.6161		Sensitivity	0.6377
Specificity	0.4538		Specificity	0.4195
AUC - 0.61				

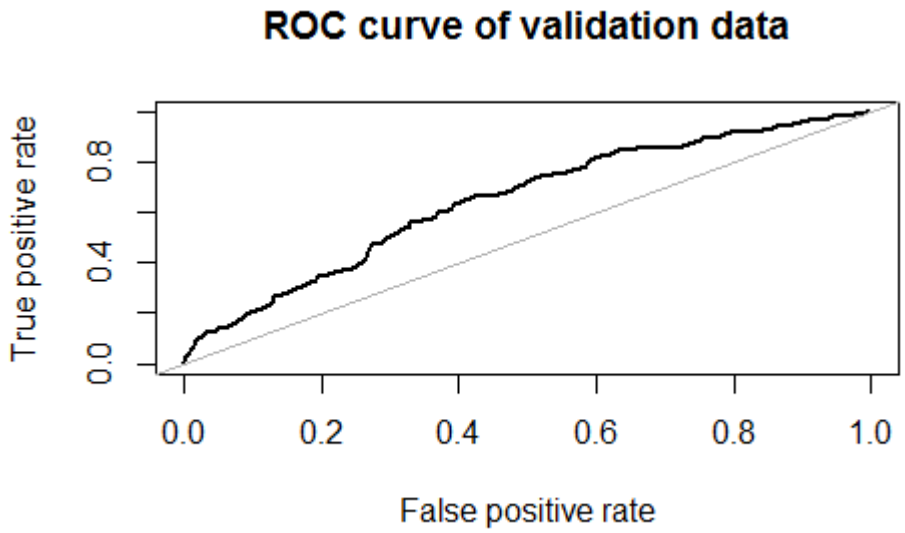


Model 2 Interpretation:

- Following backward selection, eliminating the last insignificant variable it gives a moderately strong model with 56% accuracy which is slightly higher than model 1. There is a proportional increase in specificity and sensitivity
- Area under ROC curve has improved to 61% compared to 58% in model 1.
- However, there are some insignificant variables in the model which we will remove and run another iteration.

LOGISTIC REGRESSION – MODEL 3

ITERATION 3			
TEST MODEL		VALIDATION MODEL	
CONFUSION MATRIX		CONFUSION MATRIX	
209	166	227	132
126	191	133	199
Accuracy	0.5780	Accuracy	0.6165
Recall	0.6025	Recall	0.5994
Precision	0.5350	Precision	0.6012
Sensitivity	0.6239	Sensitivity	0.6306
Specificity	0.4538	Specificity	0.4195
AUC - 0.65			

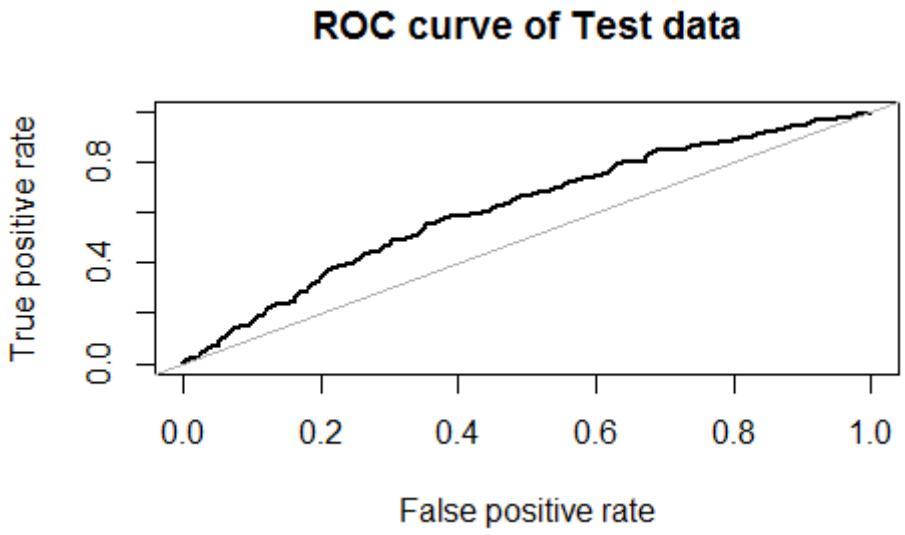


Model 3 Interpretation:

- Following backward selection, eliminating the last 20 insignificant variables it gives better model with 61% accuracy which is significantly better than model 1 and model 2. Better sensitivity and specificity makes this model a strong one.
- Area under ROC curve has improved to 65% compared to 61% in model 2.

LOGISTIC REGRESSION – MODEL 4

ITERATION 4			
TEST MODEL		VALIDATION MODEL	
CONFUSION MATRIX		CONFUSION MATRIX	
204	132	205	146
155	201	146	194
Accuracy	0.5853	Accuracy	0.5774
Recall	0.5646	Recall	0.5706
Precision	0.6036	Precision	0.5706
Sensitivity	0.5682	Sensitivity	0.5840
Specificity	0.4538	Specificity	0.4195
AUC - 0.61			



Model 4 Interpretation:

Compared to Model 3 which is so far the better model, in model 4 the quality of the model drops in terms of sensitivity and specificity. Even the area under ROC has dropped to 58% compared to Model 3 which was 65%.

Model Comparison

	Model 1		Model 2		Model 3		Model 4	
	TEST	VALIDATION	TEST	VALIDATION	TEST	VALIDATION	TEST	VALIDATION
Accuracy	0.5607	0.5716	0.5650	0.5890	0.5780	0.6165	0.5853	0.5774
Recall	0.5607	0.5858	0.5879	0.5994	0.6025	0.5994	0.5646	0.5706
Precision	0.5248	0.5593	0.5169	0.5405	0.5350	0.6012	0.6036	0.5706
Sensitivity	0.5960	0.5846	0.6161	0.6377	0.6239	0.6306	0.5682	0.5840
Specificity	0.4394	0.4419	0.4538	0.4195	0.4538	0.4195	0.4538	0.4195
AUC	0.58		0.61		0.65		0.61	

Individual model performance of supervised learning methods is often assessed using a confusion matrix. The objective, typically, is to increase the number of correct predictions (sensitivity) while maintaining incorrect predictions or the false alarm rate (specificity) at an acceptable level.
As ROC curve represents relationship between True positive rate and false positive rate and the area under ROC curve represents the tradeoff between these two measures. Hence, we have chosen area under ROC as the criteria for selecting a model from multiple models.
Model 3 has the a better area under curve of 0.65 which is a better model compared to the others. Also, it has the better accuracy and precision of 0.61 and 0.60 respectively.

Challenges faced

Multiple Domain Knowledge required – To understand the data and proceed with model building, first challenge that we faced was to gain domain knowledge. Even descriptive analysis was dependent on domain knowledge about Epilepsy and signal processing.

Volume of data – The volume of data was another big challenge. There was roughly around more than 70 GB of data, and that too sheer volume of numbers in just 16 columns. This enormous amount of data made it very challenging to use conventional tools for analysis. For example there were more than 120,000,000 record for one canine subject. We had to look for alternates like revolution analytics R. An enterprise version of R which allows to convert CSV files in XDF format and read it in chunks. So using that we were able to visualize huge volumes of data more effectively.

Feature Engineering – On top of volume our project also required feature engineering, as the mere readings made lesser sense for model building. So to proceed further we needed to extract features (DCT – Discrete Cosine Transform) from the signal values to build the model. It again required us to understand new techniques like DCT (Desecrate Cosine Transform), DFT (Discrete Fourier Transform), and LDA (Fisher Projection) and experiment them with dataset to see which is suitable in our case.

What improvements would you recommend in the Capstone process?

Biggest room in the world is the room for improvement, though there is only that much that we could do in the prescribed time but the model can be further improved by following these steps.

Addition of further features – Addition of any other feature which has promise of improving classification result will add further values by improving results and accuracy

Considering other classification Techniques – We have used only Logistic regression but we can further use other classification tools and can compare them to pick the best one, decision tree, neural networks, random forest are a few to be considered for the same.

Comparing and combining best parts – The reason why many a times ensemble models are best because they pick best pasts of all the models compared. So we should consider ensemble model as well.

Conclusion/Recommendations & Business Impact

This project describes an automated classification of EEG signals for the detection of epileptic seizures using statistical pattern recognition. An overall classification accuracy of 69% was achieved. The results confirmed that the proposed algorithm has a potential in the classification of EEG signals and detection of epileptic seizures, and could thus further improve the diagnosis of epilepsy.

The major strength of the framework is that it is completely flexible and can be adopted according to various other business rules and practices. This model can be used for many other areas of health care and signal processing, and this project report can act as guided approach to solve new problem in field of signal processing and healthcare.

Recommendation implementation - Justification

Yes the implementation of recommendations are quite cost effective and are very well justified by the profit generating potential that they hold.

Challenges - Organizational/process changes required

The model will add the predictive modelling capability for Invanti in field of signal processing, but extracting real meaning from data can be challenging. Bad data, flawed processes, lack of IT support, lack of capability to exploit big data and the misinterpretation of results can yield false positives and negatives, which can lead to inaccurate conclusions and ill-advised business decisions.

Get the necessary IT support - Legacy IT structures may hinder new types of data sourcing, storage, and analysis. Existing IT architecture may prevent the integration of siloed information, and managing unstructured data often remains beyond traditional IT capabilities.

Many legacy systems were built to deliver data in batches, so they can't furnish continuous flows of information for real-time decisions.

Transforming Company's Capabilities - Many companies grapple with such problems, often because of a mismatch between the organization's existing culture and capabilities and the emerging tactics to exploit analytics successfully.

Develop capabilities to exploit big data - Adjusting culture and mind-sets typically requires a multifaceted approach that includes training, role modeling by leaders, and incentives and metrics to reinforce behavior.

Re-evaluation and Re-calibration

The Model can be re-evaluated and Re-calibrated as and when required. Though one good point should be if any time a new features is discovered which has potential of increasing the accuracy of model then that should be included in model and model should be re-evaluated and re-calibrated.

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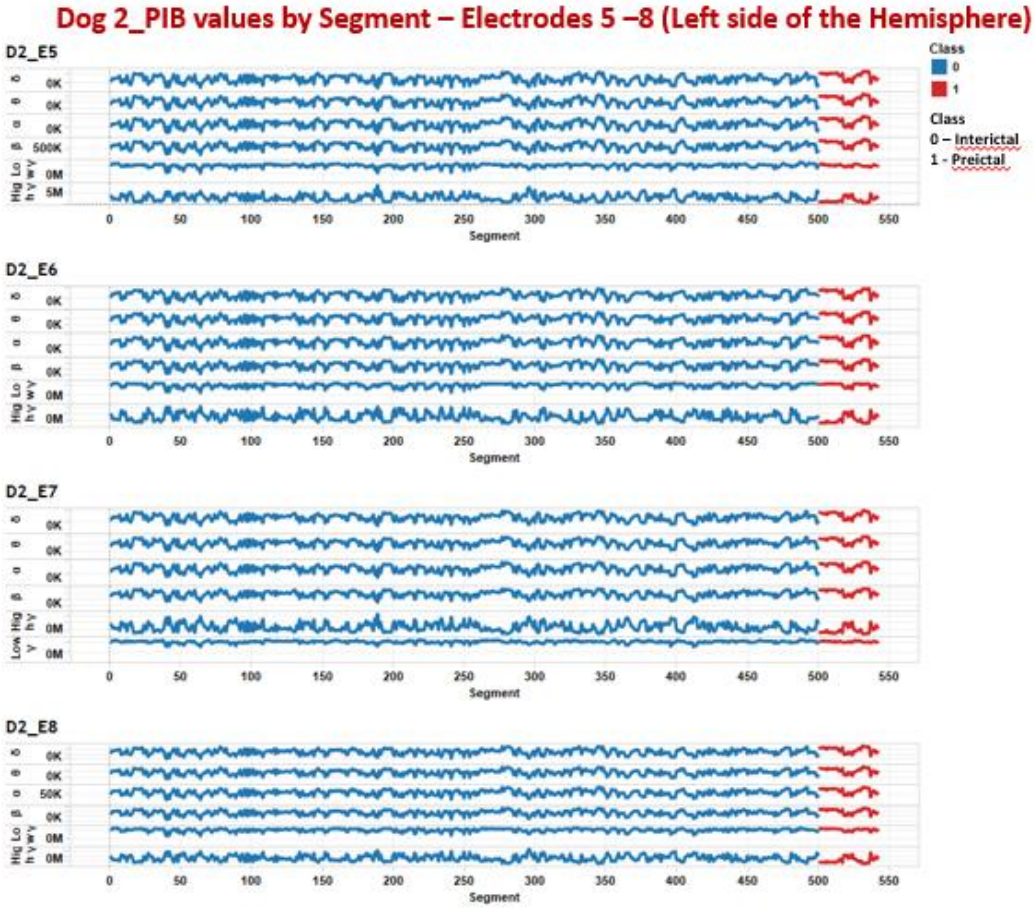
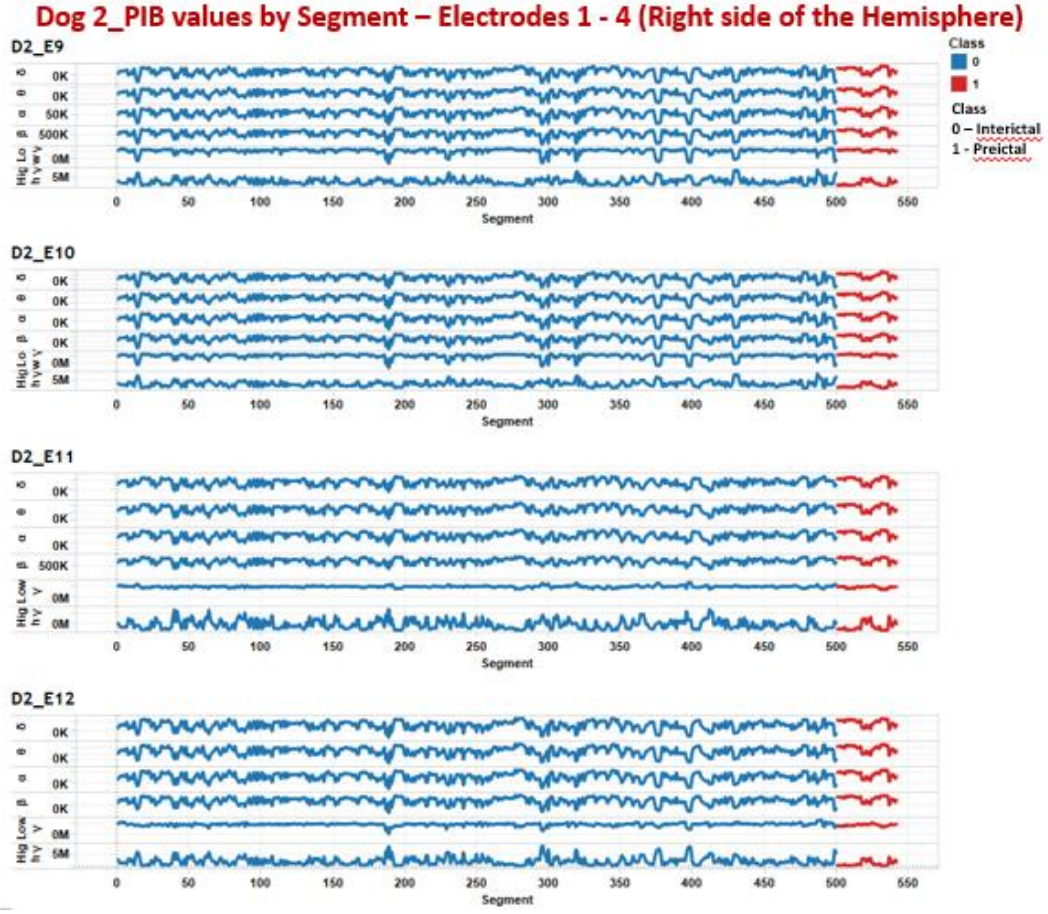
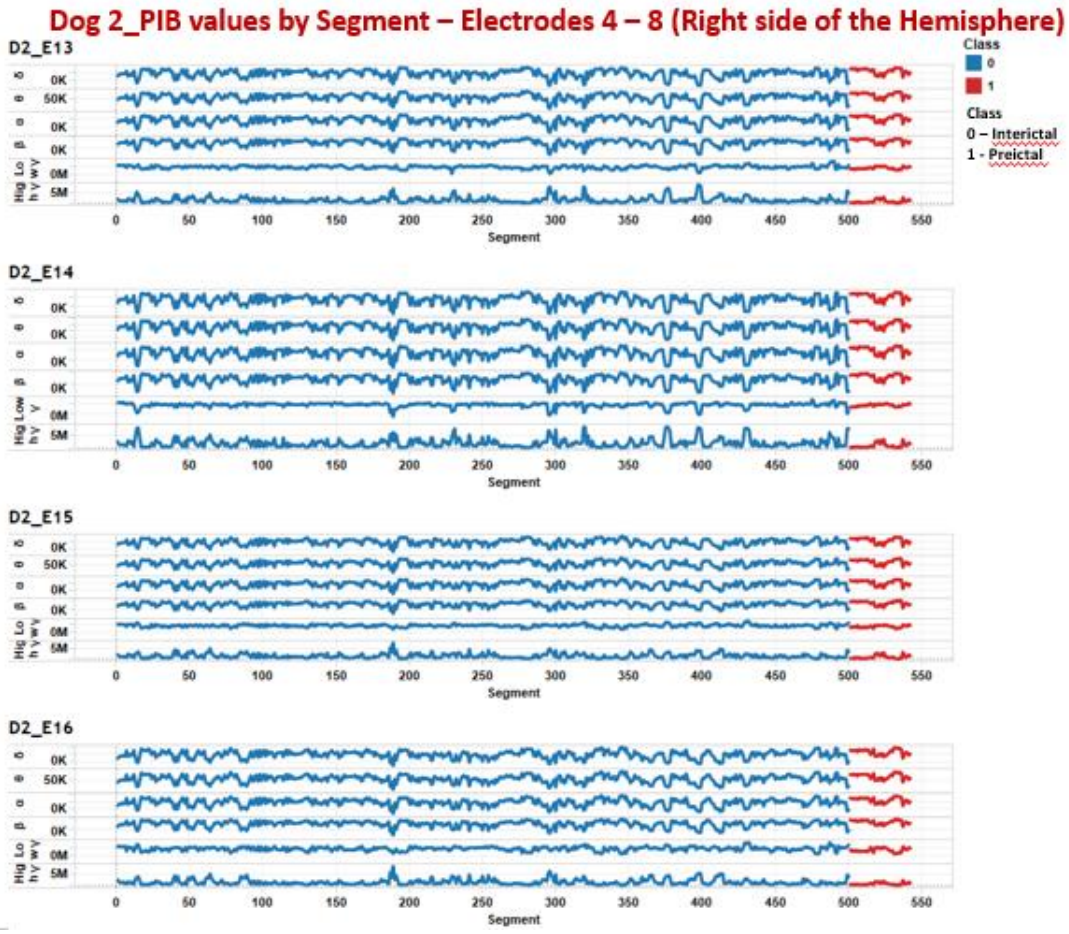
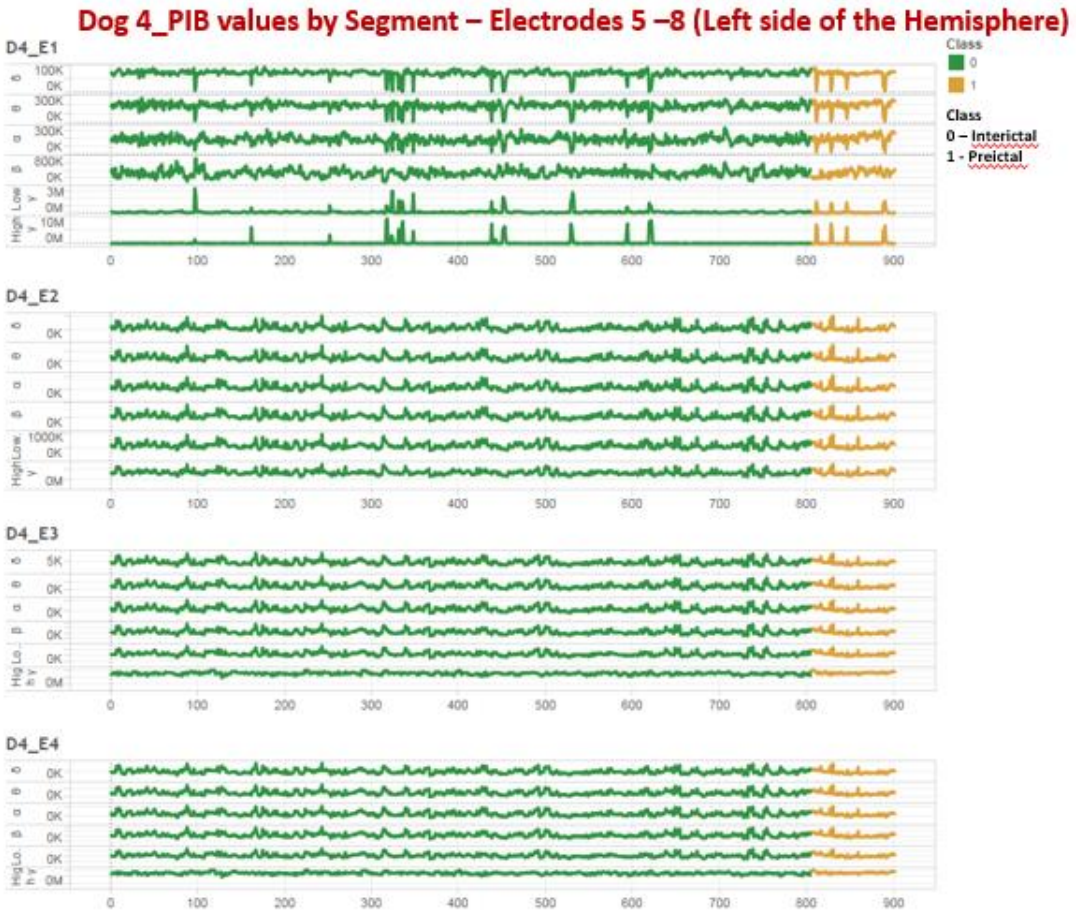
Apendix

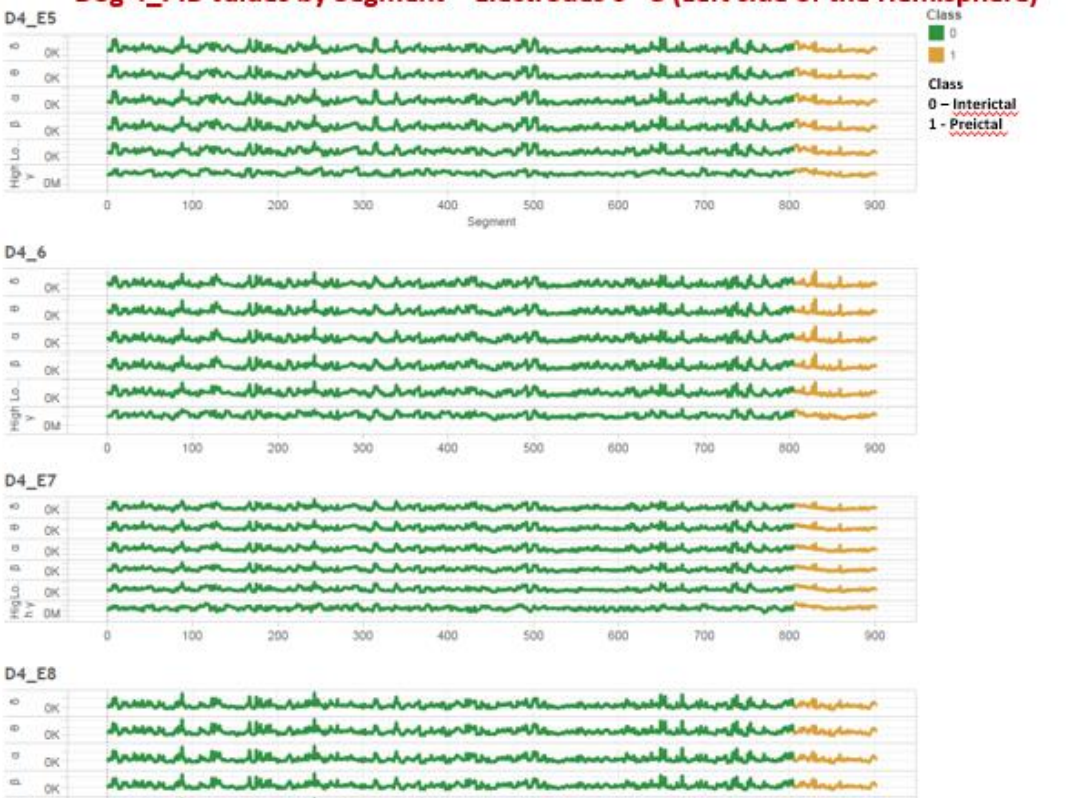

Dog 2_PIB values by Segment – Electrodes 5 –8 (Left side of the Hemisphere)
D2_E5
D2_E6
D2_E7
D2_E8
Class
0
1
Class
0 – Interictal
1 - Preictal
Segment


Dog 2_PIB values by Segment – Electrodes 1 - 4 (Right side of the Hemisphere)
D2_E9
D2_E10
D2_E11
D2_E12
Class
0
1
Class
0 – Interictal
1 - Preictal
Segment

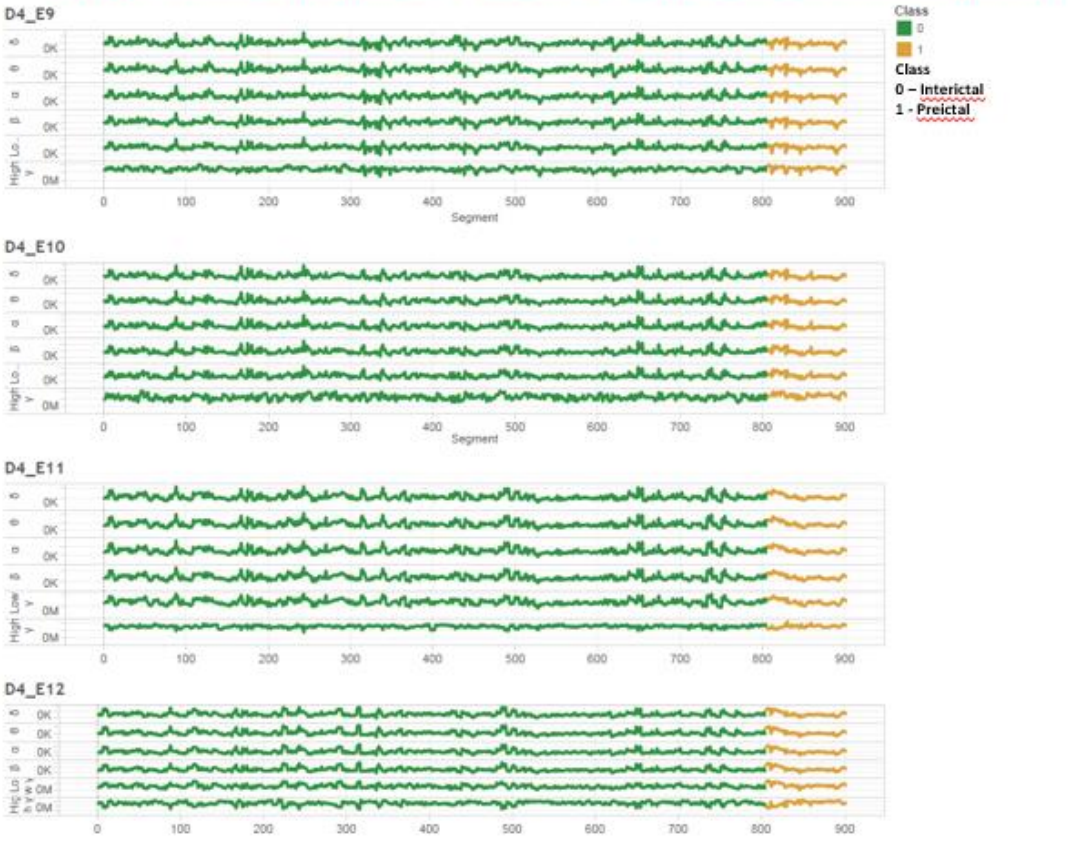

Dog 2_PIB values by Segment – Electrodes 4 – 8 (Right side of the Hemisphere)
D2_E13
D2_E14
D2_E15
D2_E16
Class
0
1
Class
0 – Interictal
1 - Preictal
δ
θ
α
β
Hig h
Lo v
0K
50K
0M
5M
0
50
100
150
200
250
300
350
400
450
500
550
Segment

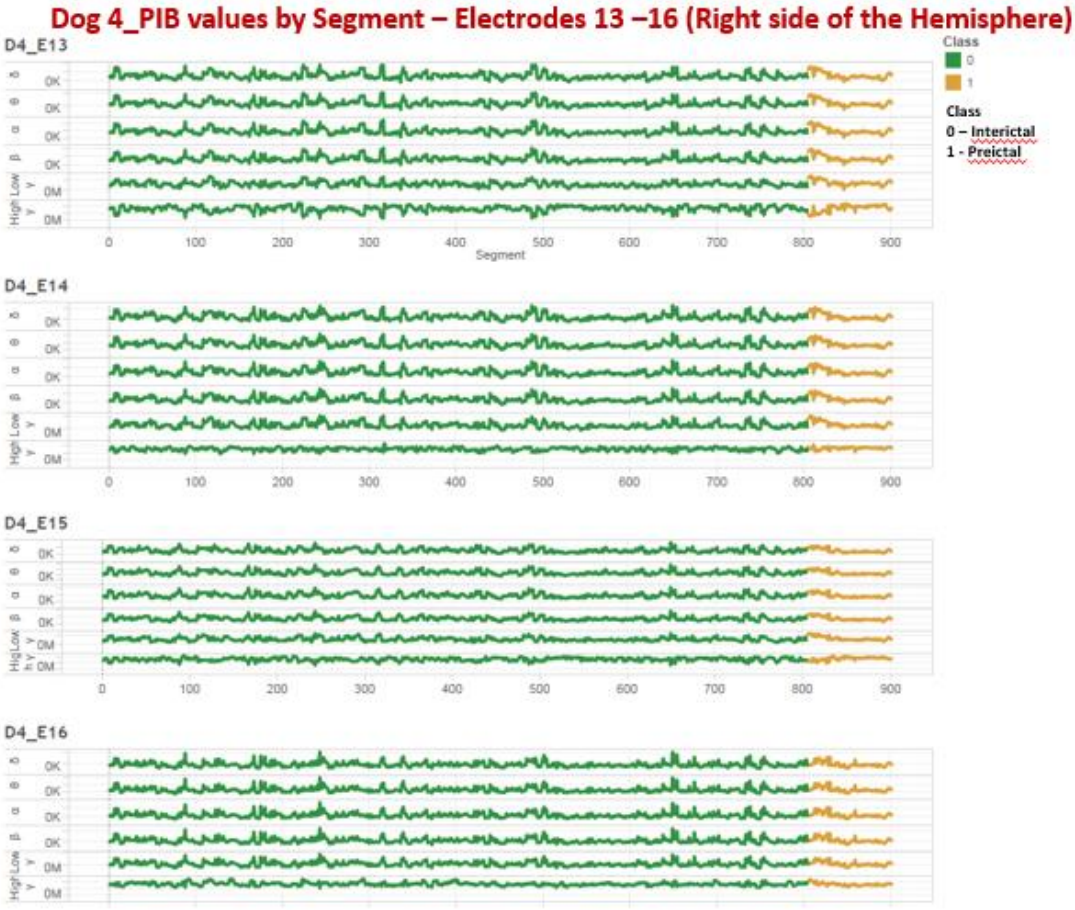

Dog 4_PIB values by Segment – Electrodes 5 –8 (Left side of the Hemisphere)
D4_E1
D4_E2
D4_E3
D4_E4
Class
0
1
Class
0 – Interictal
1 - Preictal

Dog 4_PIB values by Segment – Electrodes 5 –8 (Left side of the Hemisphere)



Dog 4_PIB values by Segment – Electrodes 9 –12 (Right side of the Hemisphere)




Dog 4_PIB values by Segment – Electrodes 13 –16 (Right side of the Hemisphere)
D4_E13
D4_E14
D4_E15
D4_E16
Class
0
1
Class
0 – Interictal
1 - Preictal
Segment
0
100
200
300
400
500
600
700
800
900