Software Requirements Specification

for

A reinforcement learning based for seizure detection

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1. Introduction

1.1 Introduction

The word epilepsy originates from the Latin and Greek word ‘epilepsia’; which means ‘seizure’ or ‘to seize upon’. It is a neurological disorder with unique characteristics, tending of recurrent seizures. The context of epilepsy. Found in the Babylonian text on medicine, it was written over 3000 years ago. This disease is not limited to human beings,but extends to cover all species does not give any type of clues about the cause of or severity of the seizures. It is remarkable and uniformly distributed around the world.

Reinforcement learning algorithms enable an agent to learn an optimal behavior when letting it interact with some unknown environment and learn from its obtained rewards. An RL agent uses a policy to control its behavior, where the policy is a mapping from obtained inputs to actions. Reinforcement learning is quite different from supervised learning where an input is mapped to a desired output by using a dataset of labeled training instances. One of the main differences is that the RL agent is never told the optimal action, instead it receives an evaluation signal indicating the goodness of the selected action.

In this paper we have presented a method of electroencephalogram (EEG) signal classification using a reinforcement learning (RL) model. So, there are two parametres ictal and non-ictal, that are given as inputs to train our model for classification using the Deep Reinforcement Learning approach. Firstly we have performed a 6th order low pass Butterworth filter having a sampling frequency of 45.12 Hz for preprocessing our data then after extracting the 92 features from our preprocessed data and reducing it into a single feature using Dimensionality Reduction Technique. For each correct action, the model will be awarded with a positive number and with a negative number for wrong answer. Model will try to get maximum positive reward by applying the Deep Q Network algorithm.

1.2 Importance

Epilepsy is a neurological disorder characterized by epileptic seizures [1][2], which are episodes of vigorous shaking. Each shaking episode can last from brief to long periods and it can result in physical injuries. In epilepsy, seizures tend to recur without warning or any immediate underlying cause; for this reason, people with epilepsy experience varying degrees of discomfort in their social life due to their condition

Approximately 50 million people currently live with epilepsy worldwide, which corresponds to about 0.65% of the world population. Globally, an estimated 2.4 million people are diagnosed with epilepsy each year. This chronic disorder of the brain affects people of all ages and it is one of the most common neurological diseases globally. Approximately 30% of people with epilepsy have a drug-resistant form, which corresponds to about 15 million of people.

1.3 Application

Nowadays, there exist machine learning techniques that could be applied to improve the everyday-life quality of people suffering from drug-resistant epilepsy. Research on the application of machine learning to epilepsy could also lead to a possible contribution for a study in the medical field in order to better understand the causes of epileptic seizures.

In the case of epileptic seizures, machine learning can be very useful if used for seizure prediction. Indeed, the ability to predict epileptic seizures could be essential mainly for two types of applications: the notification of the incoming seizure to the patient, or the anticipation of the seizure using neurostimulation in order to avoid it.

In the first case, we could think about a case scenario in which a person suffering from epilepsy receives a notification on his phone warning him of an incoming seizure in 10 minutes. By being alerted by a notification, the person has the time to put himself in a safe state before the start of the seizure, in order to avoid any subsequent injury. This is an example in which machine learning does not help avoiding the actual problem, but it is very helpful in order to contain the subsequent damages.

In the second case, the application of seizure prediction is even more interesting, because it is able to avoid the actual seizure occurrence. Indeed, some medical researches [15] have proved the effectiveness of neurostimulation in the treatment of epilepsy: there exist devices that can provide stimulation to the entire brain or to specific areas of the brain (the ones responsible for the seizures) in order to reduce the number of seizures over the years or to actually avoid the seizure. If applied to the seizure focus in advance, the neurostimulation is able to "block" a single occurrence of shaking; therefore the ability to predict a seizure some seconds before its beginning could allow the device to intervene in time and to avoid the episode [16].

1.4 Challenges and Gaps

One of the most significant and decisive steps is to select suitable statistical features because each channel or electrode implanted on the brain provides different statistical measures. Undoubtedly, earlier researchers made their consistent efforts to find the best features.

Class imbalance is one of the serious problems [140] in machine learning and the majority is seen in medical datasets [141], particularly in EEG signals. This is because the duration of EEG recording is long, time-consuming and seizure duration is for a few seconds, which results in being prone to errors [91]. As a result, the dataset becomes highly imbalanced.

It is very important to see the different statistical perspectives of each brain signal by analyzing the statistical properties of the features such as entropy, energy, and skewness. And we must not focus on taking irrelevant feature(s) as such since it will unnecessarily increase the dataset size.Therefore, we should select those potential features that can provide logical results. Hence, it is advisable to select a group of features to avoid a burden to the machine learning classifiers and to get help in related knowledge discovery.

Each classifier has its own merits and demerits, depending on the dataset attributes and requirements [138]. In general, it is very difficult to point out which classifier was the most effective for brain datasets. To identify the capable classifier, several classifiers have been tested on EEG datasets and their performance has been evaluated, and the one which performs well is to be considered in solving seizure detection and imparting knowledge discovery.

2. Literature Survey

2.1 Literature Review

Epilepsy is commonly known as the seizure disorder. If a patient has 2 or more seizures without any type of medical illness or reason being a cause of it, the patient is diagnosed with epilepsy. It is a common misconception to think that if someone has seizures they have epilepsy. The other reason can be as simple as hyperglycemia. Patients with epilepsy are normal characterised by having abnormal EEG apart from getting seizures on a regular basis. The regularity varies from person to person. It can be anywhere from a few lasting for a couple of hours to a double digit number lasting for only a few minutes each day.

50 million people worldwide suffer from epilepsy and for approximately 30% of them the disease cannot be sufficiently controlled by medication. Only 50% of the patients who undergo respective surgery keep seizure free. For all remaining patients the uncertainty and unpredictability of seizures belongs to the most severe disabilities. Although seizures cannot be completely prevented, a reliable forecast of their occurrence would help to overcome the helplessness of affected patients and would significantly improve their quality of life.

Overview of existing work on seizure detection using—machine learning classifiers, features, performance score, performance metrics, datasets, and Authors

Classifier(s)	Feature(s)	Performance (%)	Performance metrics	Dataset	Authors
SVM	Vector	96	Sensitivity (Sen)	CHB-MIT	Shoeb and Guttag [41]
Random forest	Time and frequency	93.8	Senstivity	EPILEPSIAE	Donos et al. [44]
ANN	Line length	99.6	Classification accuracy (Class Acc)	BONN	Guo et al. [69]
Burst detection algo	Line length	84.27, 84,85.7	Acc, Sen, Specificity (Spec)	NICU, Belgium	Koolen et al. [70]
Normalization	Line length	52	ROC	CHB-MIT	Logesparan et al. [71]
ELM and BPNN	SE	95.6	Class Accuracy	BONN	Song and Lio [72]
SVM and ELM	AE and SE	95.58	Class Accuracy	BCI Lab, Colarodo	Zhang et al. [73]
SVM	DWT	94.8	Avg Accuracy	CHB-MIT	Ahmad et al. [74]
GMM	Spectral, hybrid, temporal	87.58	Avg Accuracy	CHB-MIT	Gill et al. [75]
Random forest	PCA, STF, Moving Max	97.12, 99.29, 0.77/h	Sen, Spec, FPR	CHB-MIT	Orellana and Cerqueira

Seizure detection based on statistical features and deep reinforcement learning classifiers:-

The seizure detection using statistical features,classifiers-black box and non-black-box.
The black-box classifiers are those which provide the accuracy without mentioning the reasons behind the results such as ANN and SVM. They are unable to explain their classification steps. Whereas,non-black-box classifiers such as decision forest and random forest are able to explain each step of the processing which is human-understandable.It helps in human- interpretable knowledge with high accuracy.

Seizure detection based on black box classifiers:

Shoeb and Guttag [41] performed seizure detection on their arranged dataset of Child Hospital Boston, MIT (CHB-MIT) [60] using SVM with the vector feature and achieved the estimated accuracy of 96%. Dorai and Ponnambalam [42] came up with an idea of the epoch, which means dividing the dataset into smaller time frames. Further, they applied an ensemble of four 'black-box' approaches—LDA, KNN, CVE, and SVM on these epoch EEG datasets. This approach provides the prediction of onset seizures 65 s earlier. Classifying the EEG data into two classes ' 'seizure" and"non-seizure', Birjandtalab et al. [117] used a Gaussian mixture model

(GMM) before detecting the seizure, and obtained 90% accuracy with 85.1% F-measure. They also raised the issue of class imbalance in their dataset. Tzallas et al. [103] used time–frequency-domain features with ANN for the EEG dataset and obtained 100% accuracy for the ‘seizure’ and ‘non-seizure’ classification problem; with epochs’ datasets the accuracy is 97.7% from (A, B, C, and D) for ‘non-seizure’ and set E for ‘seizure’ epoch classes. Amin et al. [79] extracted relative energy features from the DWT method, and four classifiers—SVM, MLP, KNN, and Naïve Bayes—were applied for the classification purpose; the result shows 98% of SVM accuracy, which outperforms remaining classifiers. A framework had been proposed by K. Abualsaud et al. [118] using the ensemble of ‘black-box’ classifiers for automated seizure detection on noisy EEG signals, and the reported classification accuracy is 95%. However, the ensemble approach did not provide good accuracy as desired because all four classifiers were ‘black-box’.

Seizure detection based on non-black-box classifiers:

Chen et al. [119] first introduced the decision tree to the EEG dataset for seizure detection. Kemal and Saleh [120] used a C5.0 decision tree [121] algorithm to explore the logic rules for seizure detection, with an average accuracy of 75%. When the same C5.0 was applied to the same dataset processed by Fourier transformation the obtained accuracy with cross-validation was, however, 98.62%. A few related works have been available, where only a decision tree method is applied seizure detection because of less accuracy and a *limited number of patterns* obtained from the logic rules of a decision tree [122]. As a result, both knowledge discovery and accuracy suffer. However, this gap can be filled by applying decision forest approaches instead [51, 57, 123].

Seizure detection based on black-box and non-black-box deep reinforcement learning classifiers:-

Acharya et al. [111] used the ensemble of seven different classifiers—Fuzzy surgeon classifier (FSC), SVM, KNN, Probabilistic neural network, GMM, decision tree and Naïve Bayes for distinguishing the three states of a patient as ‘normal, ‘pre-ictal’ and ‘ictal’. The overall accuracy is 98.1%. Fergus et al. [83] also used distinct classifiers such as linear discriminant analysis (LDA), quadratic discriminant classifier (QDC), logistic classifier, uncorrelated normal density-based classifier (UDC), polynomial classifier, KNN, PARZEN, SVM, and decision tree on the processed data with seven features such as entropy, RMS, skewness, and variance. They contributed that the detected patient is suffering from a ‘Generalized seizure’ (means affecting whole brain region) across different patients without prior information about the seizure focal points. Mursalin et al. [101] proposed a method to reduce the data size, a statistical sampling technique called optimal sample allocation technique, and to reduce the features they developed a feature selection algorithm. The analysis was done on the combination of five classifiers—SVM, KNN, NB, Logistic Model Trees (LMT) and Random forest.

The dataset is made up of EEG data of 13 subjects, and we performed a 13-folds test. We compared the performances of the following versions of models: (1) temporal 1D convolution (baseline model): 1 dimensional convolutional network , (2) LSTM (baseline model): LSTM network , (3) parallel mix: convolutional LSTM network , (4) expectation of (1)-(3) models: (“Average model” in Table 1), and (5) the proposed model. The proposed model achieved a better test accuracy (90.30%) than the average model accuracy (89.98%), and the performance is comparable to that of LSTM. Calculation of all methods, as average or ensemble, required the heaviest computational load.

2.2 Methods

In this paper, we mainly focus on preprocessing and feature extraction by applying a sixth order low pass Butterworth filter with normalized cutoff frequency of 45.12 Hz in our time series data for reducing the noise such as power line interference, muscle movement and eye blinking for preprocessing. Then applying Linear Discriminant Analysis algorithms using Dimensionality Reduction Technique for extracting the features transform the data from a high-dimensional space into a low-dimensional space so that the low-dimensional representation retains some meaningful properties of the original data.

Classifier(s)	**Accuracy (%)**	**Dataset**	**Authors**
SVM	93.8	CHB-MIT	Shoeb and Guttag
ANN	96.4	BONN	Guo et al.
Random forest	93.8	EPILEPSIAE	Donos et al.
Logistic Regression	95	CHB-MIT	Our Project
Reinforcement Learning	94	CHB-MIT	Our Project

2.3 Future Scope

Overall, it is believed that the brain solves problems through reinforcement learning and neural networks organized as hierarchical processing systems. The field of AI has been trying to adopt and implement this strategy in computers, notable progress has been seen recently due to better understanding about learning systems, decline of computing costs, and increase of computational power and the seamless integration of different technologies and technical breakthroughs. There are still some situations where these methods fail, underperform against traditional methods and therefore must be improved.

For example the shortcomings of the current techniques and existing open research challenges, and speculate about some future perspectives that will facilitate further development and advancement of the field.

The combined computational capability and flexibility provided by the two prominent ML methods (i.e. DL and RL) also have limitations. Both these methods require heavy computing power and memory, and hence are not worthy of being applied to moderate size data sets. Representing action-value pairs in RL is not possible to use all nonlinear approximators which may cause instability or even divergence in some cases. Also bootstrapping makes many of the RL algorithms hard and inapplicable to real-time application, as they are too slow to converge and in some cases too dangerous(e.g. autonomous driving).. Very few existing techniques support harnessing the potential power of distributed and parallel combination through cloud computing.

The problems pertaining to observability of RL are yet to be completely solved, and optimal action selection is still a huge challenge. But there are timely opportunities to employ deep RL in biological data mining, for example, deriving dynamic information from biological data coming from multiple levels to reduce data redundancy and discover novel biomarkers for disease detection and prevention. Also, new unsupervised learning for deep RL methods is required to shrink the necessity of large sets of labeled data at the training phase.

3.1 Problem Statement

The focus of this report is on the problem of seizure prediction, of which we are going to analyze in order to have a clearer and more complete idea of the machine learning models potentialities on epileptic seizures data.

The problem of epileptic seizure prediction can be identified as a classification task. Classification is the process of predicting the target associated with each sample in the data. In other words, the classification task consists in finding a mapping function from the input sample's features to the discrete output targets. This task is usually associated with data that can be assigned to a certain number of categories, which correspond to the targets to predict. When the data needs to be assigned to only two categories, we talk about binary classification. In this project, the problem of epileptic seizure (as described in Section 2.2) can be considered a binary classification task, since we want to classify the time steps in two classes, which are the seizure class and the non-seizure class.

3.2 Objectives

In brief, the main objectives of this paper are as follows:

1. We have done the review according to five main dimensions. First, researchers who adopted the EEG, ECoG or both for seizure detection; second, significant features; third, machine learning classifiers; fourth, the performance of the classifier during a seizure, and last, knowledge discovery (e.g., seizure localization).

2. Through study, our aim is to select the suitable statistical features and machine learning classifiers to take less computation time as the dataset has a high volume with a high dimension.
3. Another objective of this research is accurate seizure detection on imbalanced datasets of long duration EEG recording datasets.
4. Whilst selecting the machine classifier it should be kept in mind that the classifier does not miss any necessary EEG channel/electrode.
5. Quick seizure detection on long-hour EEG recording.
6. This study will help the researchers with their data science backgrounds to identify which statistical and machine learning classifiers are more relevant for further improvement to the existing methods for seizure detection.
7. The study will also help the readers for understanding about the publicly available epilepsy datasets.
8. In the end, we have provided our observations by the current review and suggestions for future research in this area.

4. Proposed Methodologies

Reinforcement learning is a type of machine learning method where an intelligent agent (computer program) interacts with the environment and learns to act within that." How a Robotics dog learns the movement of his arms is an example of a reinforcement learning Agent learns to behave in an environment by performing the actions and seeing the results of actions. For each good action, the agent gets the reward positive feedback, and for each bad action, the agent gets negative feedback or penalty. It is a core part of Artificial Intelligence, and all AI agents work on the concept of reinforcement learning.Here we do not need to pre-program the agent, as it learns from its own experience without any human intervention.

Now we discuss the Deep Reinforcement Learning (DRL) approach which we are going to use in our model which is a combination of deep learning and reinforcement learning. In DRL, value and policy can be expressed by a neural network, which allows it to deal with a continuous state or action. In recent years, deep reinforcement learning has been successfully applied to computer games, robots controlling. Here, a deep reinforcement learning approach is used for eliminating noisy data and learning better features, which made a great improvement in classification performance.

Now we perform classification tasks using deep Q learning (DQN). Assume that the training data set is $D = \{(x_1, l_1), (x_2, l_2)\text{..........} (x_T, l_T)\}$ where x_i is the ith sample and l_1 is the label of the ith sample. We propose to train a classifier as an agent where state S:

VI. Algorithm:

Training

Input: Training data $D = \{(x_1, l_1), (x_2, l_2)..........(x_T, l_T)\}$Episode number K

Initialize experience replay memory M

Randomly initialize parameters θ

Initialize simulation environment ε

for $episode\ k = 1\ to\ k$ **do**

Shuffle the training data D

Initialize state $s_1 = x_1$

for $t = 1\ to\ T$ **do**

Choose an action based ε-greedy policy:

$a_t = \pi_\theta(s_t)$

$r_t, terminal_t = STEP(a_t, l_t)$

Set $s_{t+1} = x_{t+1}$

Store $(s_t, a_t, r_t, s_{t+1}, terminal_t)$ to M

Randomly sample $(s_j, a_j, r_j, s_{j+1}, terminal_j)$ from M

if $target_j = True$:

Set $y_j = r_j$

else $target_j = False$:

Set $y_j = r_j + \gamma\, max_{a'}\, Q(s_{j+1}, a'\ ; \theta)$,

perform a gradient descent step on $L(\theta)$ w.r.t.θ:

$L(\theta) = (y_j - Q(s_j, a_j; \theta))^2$

if $terminal_t = True$ **then**

break

5. Data Sets

A. Experimental Datasets

we use two publicly available datasets for the experiment, CHB -MIT and Bonn dataset

CHB-MIT: CHB-MIT Dataset, collected at the Children's Hospital Boston, consists of EEG recordings from pediatric subjects with intractable seizures. Subjects were monitored for up to several days following withdrawal of anti-seizure medication in order to characterize their seizures and assess their candidacy for surgical intervention.

Recordings,grouped into 23 cases,were collected from 23 subjects (5 males,ages 3-22;and 17 females,ages 1.5-19).The file named Subject-Info contains the gender and age of each subject.(Case chb24 was added to this collection in December 2010,and is not currently included in SUBJECT-INFO.)

Each case (chb01,chb02,etc) contains between 9 and 42 continuous .edf files from a single subject. Hardware limitations resulted in gaps between consecutively-numbered .edf files ,during which signals were not recorded;in most cases,the gaps are 10 seconds or less,but occasionally there are much longer gaps. In order to protect the privacy of the subjects, all protected health information(PHI) in original .edf files has been replaced with surrogate information in the files provided here.Dates in the original .edf files have been replaced by surrogate dates,but the time relationship between individual files belonging to each case have been preserved.In most cases,the .edf files contains exactly one hour of digitized EEG signals,although those belongings to case chb10 are two hours long,and those belongings to cases chb04,chb06,chb07,chb09,and chb23 are four hours long;occasionally, files in which seizures are recorded are shorter.

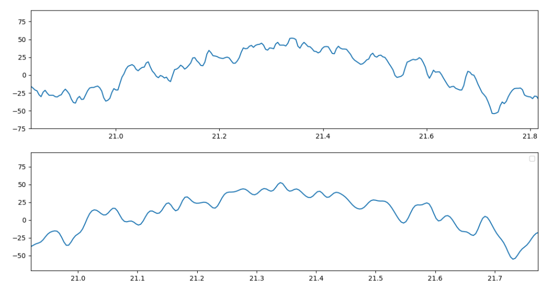
All signals were sampled at 256 samples per second with 16-bit resolution.Most files contain 23 EEG signals(24 or 26 in a few cases). The international 10-20 system of EEG electrode positions and nomenclature was used for these recordings.In a few seconds,other signals are recorded,such as an EEG signal in the last 36 files belonging to case chb04 and a vagal nerve stimulus(VNS) signal in the last 18 files belonging to case chb09.In some cases,up to 5 “dummy” signals were interspersed among EEG signals to obtain an easy to read display format;these dummy signals can be ignored.

The file RECORDS contains a list of all 64 .edf files included in this collection ,and the file RECORDS-WITH-SEIZURES lists the 129 of those files that contain one or more seizures.In all , the records include 198 seizures(182 in the original set of 23 cases); the beginning ([) and the end (]) of each seizure is annotated in the .seizure annotation files that accompany each of the file listed in RECORDS-WITH-SEIZURES.In addition,the files named cnn-summary.txt contain information about the montage used for each recording, and the elapsed time in seconds from beginning of each .edf file to beginning and end of each seizure contained in it.

Bonn-Dataset: Our seizure recognition experiments are conducted using a widely used and publicly available EEG database produced by Bonn university. This database consists of five diverse subsets (set A-E) denoted as Z,O,N,F and S.Sets A and B are composed of surface EEG recordings of healthy volunteers in wakeful state with eyes open and eyes closed, respectively. On the other hand,Sets C,D and E are gathered from patients with epilepsy. There ,Sets C and D were recorded from hippocampal formation of the opposite hemisphere of the brain. Set D was recorded from within the epileptogenic zone.Set E only included seizure activities. Each of these sets contains 100 single-channel recordings of EEG signals with a sampling rate of 173.61 Hz and a duration of 23.6 s. The corresponding time-series is sampled into 4097 data points.Besides, the Rochester Institute of Technology divided every 4097 data points into 23 chunks. Each chunk contains 178 data points for 1 second.To increase the number of samples for training a deep model ,Bonn Dataset in this format is adopted , whose amount of sample increases 22 times.Therefore ,the number of each category has 2300 EEG samples.

B. Dataset & Baseline Methods

In the CHB-MIT dataset ,we extract the region of interest from the recordings or the incident when seizure actually happens in the 71 text files and same for non-seizure.After extraction we conclude 1136640/256 = 4440 sec or 74 min recordings of seizure and same 74 min of non-seizure data for all the 23 patients.
Now for preprocessing, we apply a sixth order low pass butterworth filter with cut off frequency of 45.12 Hz.Our filter will pass only the frequencies having less than cutoff frequency and remove all the frequencies higher than cut off frequency.Here we have shown the figure below where we can clearly see that original signal have been smoothed after applying low pass filter.



Then after, we perform the feature extraction so there are 23 channels in our dataset and recording of 74 *2 = 148 min (8880 sec) for both seizure and non-seizure patients. for each channel, we mainly calculate four features: **variance, standard deviation ,Shannon entropy and kurtosis**.Total 23*4 =92 features will be created for segment of every 10 sec (10*256 = 2560) signal. So 1136640/2560 = 444 rows will be created for 92 features for seizure data..After creating 444*92 matix for seizure and 444*92 for non*seizure, we perform linear discriminant analysis for reducing the 92 features into single features because more input features often make a predictive modelling task more challenging to model, more generally referred to as the curse of dimensionality.

finally features are extracted and Now our agent is ready for training.Here we train our model using Deep Q Network, a standard Deep Reinforcement learning algorithm, a neural network, uses loss function and the predicted (current) Q value, Target Q value, and Observed reward to complete the loss to train the network and thus improve its the predictions.

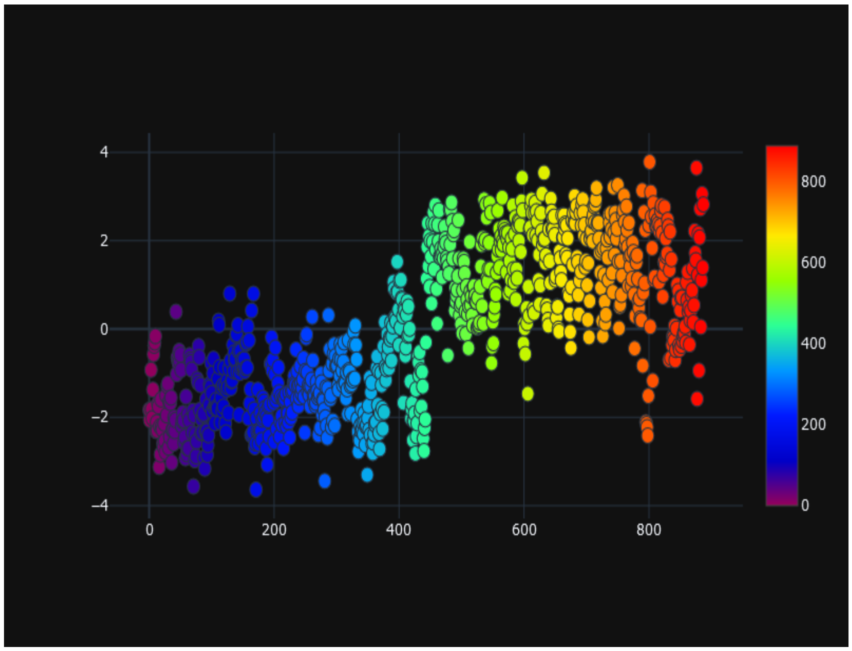
6. Conclusion

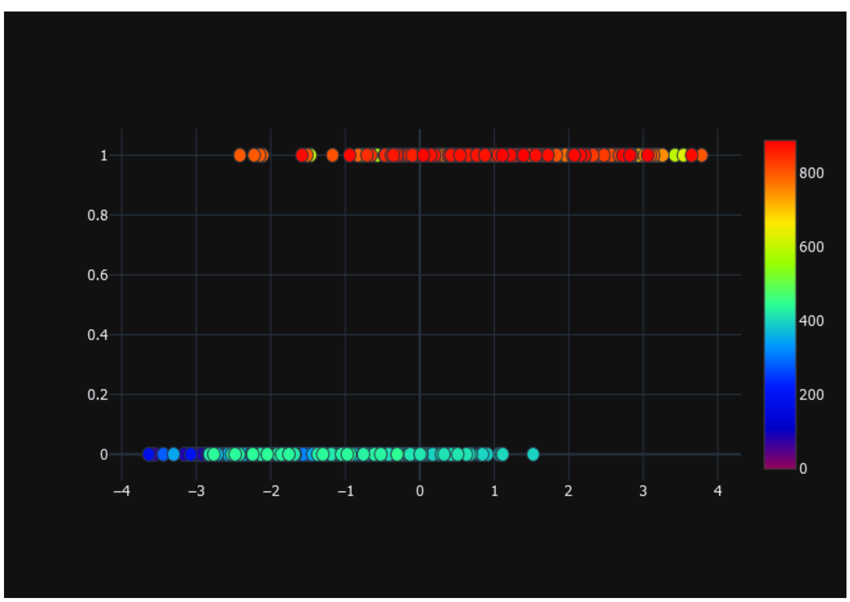
This paper introduces a novel model for classification of seizure(ictal) and non-seizure or seizure free patients using deep reinforcement learning over logistic regression and ANN. The model explians the classification problem as a sequential decision making process.We use mainly deep Q learning algorithms to find the optimal classification policy for sequential decision making process and theoretically analyze the impact of the specific reward function of Q network during the training.

After feature extraction we perform the classification action on a sample at each time step and our model evaluates the classification action and returns a reward to the agent .For each good action agent will be awarded and will be punished for every bad action, try to gain maximum reward as sequential decision making process by applying Deep Q Network (DQN) algorithm.

The results are assessed and deployed when sufficient accuracy is reached. The results depicted that the accuracy is above 94%. Results from other pre-trained networks are also evaluated. Future research can be conducted to test the results by varying the learning rate and other parameters. Extensive work can be performed using other efficient pre-trained networks to improve the capability of transfer learning efficiency.

7. Output Images





	LDA	output
0	-1.832099	0
1	-2.060561	0
2	-1.875726	0
3	-0.923951	0
4	-1.814450	0
...	...	...
883	0.047177	1
884	1.109614	1
885	3.059409	1
886	1.392272	1
887	2.821046	1

888 rows × 2 columns

	0_Variance	0_Std	0_Shannon_entropy	0_Kurtosis	1_Variance
0	719.665414	26.826580	14.187517	0.190072	708.008118
1	924.947826	30.412955	13.743984	1.400555	748.755217
2	1353.019662	36.783416	13.875047	0.846071	1203.869998
3	4600.486414	67.826886	14.078013	0.435332	1695.503603
4	803.552537	28.347002	13.751216	1.388357	822.517711
...	...	...	...	...	...
883	12560.229712	112.072431	12.020829	12.547512	22129.038666
884	29245.599694	171.013449	14.229745	-0.093818	71394.188770
885	29256.911080	171.046517	14.155490	0.016513	22113.090921
886	12449.734759	111.578379	13.208289	3.026988	34982.666337
887	50444.046578	224.597521	14.451390	-0.583072	61106.473636

888 rows × 93 columns

7. References

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