Epilepsy Detection using EEG Signals

Enrollment Nos	17103070, 17103071, 17103076
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Dec - 2020

Submitted in partial fulfillment of the

Degree of Bachelor of Technology

in

Computer Science Engineering

DEPARTMENT OF COMPUTER SCIENCE ENGINEERING &

INFORMATION TECHNOLOGY

DECLARATION

We hereby declare that this submission is our own work and that, to the best of our knowledge and belief, it contains no material previously published or written by another person nor material which has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text.

Place: Noida

Date: 5 December, 2020

Signature: …………………….

Name: **Siddharth Batra, Sunny Dhama, Parth Chandna**

Enrollment Nos: **17103070, 17103071, 17103076**

CERTIFICATE

This is to certify that the work titled "**Real time Epilepsy detection using Electroencephalogram(EEG) Signals**" submitted by "**Siddharth Batra (17103070), Sunny Dhama (17103071), Parth Chandna (17103076)**" in partial fulfillment for the award of degree of **Bachelor of Technology** of **Jaypee Institute of Information Technology, Noida** has been carried out under my supervision. This work has not been submitted partially or wholly to any other University or Institute for the award of this or any other degree or diploma.

Signature of Supervisor	…………………….
Name of Supervisor:	**Dr. Pawan Kumar Upadhyay**
Designation:	Associate Professor
Date:	8 December, 2020

(IV)

ACKNOWLEDGEMENT

We thank our mentor **Dr. Pawan Kumar Upadhyay , Department of CSE, Jaypee Institute of Information Technology, Sector-62, Noida**. We express our sincere gratitude towards her, as her guidance, encouragement, suggestions and constructive criticism have contributed immensely to the evolution of ideas on the project.

Turning this idea into a project wouldn't have been possible if he hadn't provided us with the knowledge he possesses and helped us to get the best conclusion possible.

Signature of the Student(s): ……………………

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Date: 5 December, 2020

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SUMMARY

Epilepsy is a neurological disorder that affects approximately 50 million people according to the World Health Organization. While electroencephalography (EEG) plays important roles in monitoring the brain activity of patients with epilepsy and diagnosing epilepsy, an expert is needed to analyze all EEG recordings to detect epileptic activity. This method is obviously time-consuming and tedious, and a timely and accurate diagnosis of epilepsy is essential to initiate antiepileptic drug therapy and subsequently reduce the risk of future seizures and seizure-related complications. We intent to propose a very scalable and efficient solution which can be distributed to masses and can help in detecting epilepsy using the electroencephalogram(EEG) signal.

The various studies given in section I helps us achieve the goal. A details analysis and summary of all the papers is given in the sections below. These papers proved to be quite helpful while drawing out the plan of action towards the project. Many recent papers used the recent technologies and methods which we intend to use in our project. These papers also gave us a detailed review of all the datasets that can be used for making the project successful.

Motivation of the Project:

Epilepsy is a central nervous system (neurological) disorder in which brain activity becomes abnormal, causing seizures or periods of unusual behavior, sensations, and sometimes loss of awareness. Anyone can develop epilepsy. Epilepsy affects both males and females of all races, ethnic backgrounds and ages. Globally, an estimated five million people are diagnosed with epilepsy each year. The current model for detection of epilepsy is not that robust or automated. It could lead to slower start of anti-epileptic drugs. Making this system automated would actually help the doctors start the treatment early and observe for a longer time to where this epilepsy is leading.

Chapter 1: Introduction:

1.1 General introduction

Human brain consists of millions of neurons which are playing an important role for controlling behavior of the human body with respect to internal/external motor/sensory stimuli. These neurons will act as information carriers between the human body and brain. Understanding cognitive behaviour of the brain can be done by analyzing either signals or images from the brain. Human behaviour can be visualized in terms of motor and sensory states such as, eye movement, lip movement, remembrance, attention, hand clenching etc. These states are related with specific signal frequency which helps to understand functional behavior of complex brain structure. Electroencephalography (EEG) is an efficient modality which helps to acquire brain signals corresponding to various states from the scalp surface area. These signals are generally categorized as delta, theta, alpha, beta and gamma based on signal frequencies ranges from 0.1 Hz to more than 100 Hz. This paper primarily focuses on EEG signals and its characterization with respect to various states of the human body. It also deals with experimental setup used in EEG analysis.

Electroencephalography (EEG) is an electrophysiological monitoring method to record electrical activity of the brain. It is typically noninvasive, with the electrodes placed along the scalp, although invasive electrodes are sometimes used, as in electrocorticography, sometimes called intracranial EEG.

EEG analysis is exploiting mathematical signal analysis methods and computer technology to extract information from electroencephalography (EEG) signals. The targets of EEG analysis are to help researchers gain a better understanding of the brain; assist physicians in diagnosis and treatment choices; and to boost brain-computer interface (BCI) technology. There are many ways to roughly categorize EEG analysis methods. If a mathematical model is exploited to fit the sampled EEG signals,[1] the method can be categorized as parametric, otherwise, it is a non-parametric method. Traditionally, most EEG analysis methods fall into four categories: time domain, frequency domain, time-frequency domain, and nonlinear methods. There are also later methods including deep neural networks (DNNs).

XGBoost is a decision-tree-based ensemble Machine Learning algorithm that uses a gradient boosting framework. In prediction problems involving unstructured data (images, text, etc.) artificial neural networks tend to outperform all other algorithms or frameworks. However, when it comes to small-to-medium structured/tabular data, decision tree based algorithms are considered best-in-class right now. Please see the chart below for the evolution of tree-based algorithms over the years.

1.2 Problem statement

Studies in the field have shown great advancements in the designing algorithms that hampers the raw input resulting in misclassified objects. Researches have shown how these algorithms play with arcade games like Atari, etc and hamper the condition as always win. Keeping these vulnerabilities in minds, we came up with the following objectives to achieve

- Study the cause and effect of such adversaries.
- Identify the winners in the adversarial category.
- Implement a tool to demonstrate live attacks on models.
- Study the defense mechanism that can help defend the subject.

In the view of the above observations, we successfully designed a tool that can help us understand the effect of such adversaries on real-world objects and identify the shortcomings to serve the defense.

- Implement different kinds of attacks on similar models to help understand the scale of damage.
- Implement a tool to serve input into the model and automate the process of testing and processing.
- Show the proper cause of misclassification of the models.
- Visualize the before and after results of perturbation attacking.

With every neural network, there are some policies associated that parameterise the neural network. Our target is to identify the policies and make use of them to implement functions which verify the researchers studied and are successful in adding noise to images which leads to successful misclassification. Broader perspectives regarding the algorithms and implementations will be discussed later.

1.3 Significance/Novelty of the problem

The purpose of the problem statement is :

- To introduce the patient to a real time monitoring tool for their epileptic attacks.
- To alert the family members when their dear one is in need.
- To collect patients data and provide it to the doctors for further study of the case.
- To collect metadata for further study of medical abnormalities that can be analysed through brainwave signals like Alzeihmers.

1.3 Comparisons of existing approaches to the problem framed

Earlier there were not so user friendly products

Chapter 2: Literature Review:

[1]Automated EEG Analysis of epilepsy:

In this Paper, the main discussion is around feature extraction and the results of different automated epilepsy stage detection in detail. There is also a brief discussion about challenges faced when all of this is implemented in a clinical setting.

[2] A Bayesian Approach to Introducing Anatomo-Functional Priors in the EEG/MEG Inverse Problem:

Their study represents a new approach to the recovery of dipole magnitudes in a distributed source model for magnetoencephalographic and electroencephalographic imaging. Results from EEG simulations of this method are presented and compared with those of classical quadratic regularization and a now popular generalized minimum-norm technique called low-resolution electromagnetic tomography.

[3] Generic Head Models for Atlas-Based EEG Source Analysis:

The purpose of this study is to produce a method to use Generic Head Model, to produce EEG source localizations. Functional Magnetic Resonance Imaging is a widely used and inexpensive method to determine functional problems in the brain. The measured electric potential difference can be used to determine the location of neural current sources. EEG studies are often performed without accompanying scans, In this study it is described as a stereotactic atlas-based procedure in which surface landmarks are used to warp an atlas to the subject's scalp morphology.

[4] A review of channel selection algorithms for EEG signal processing:

Processing of EEG signals is very important and has variety of uses. Some of them are - seizure detection/prediction, sleep state classification, and motor imagery classification.

With so many uses, this paper revolves around using the perfect algorithm for the respective application of the EEG signals. In this study, the recent EEG developments have been summarised along with their applications and classification according to evaluation approach.

[5] Application of adaptive Savitzky—Golay filter for EEG signal processing:

EEG signals consist of artefacts and noise which are filtered out by different types of filters in the pre-processing stage. A Savitzky Golay filter is highly used in filtering noise especially in the field of biomedical signal processing.. Mostly, a random hit-and-trial method or prior experience is required to determine the suitable values of design parameters. However, this study on adaptive Savitzky Golay filter focuses on providing a generic framework for optimal design of filter the order and frame size of the filter. Savitzky Golay filter is successfully tested for EEG signal processing.

[6] EEG Signal-Processing Framework to Obtain High-Quality Brain Waves from an Off-the-Shelf Wearable EEG Device:

Capturing high-quality EEG signals from such a device can be very challenging. To solve this issue, this study proposes an EEG signal-processing framework that can acquire high-quality EEG signals using a wearable EEG device. Understanding brain waves collected by an electroencephalogram can be useful in understanding human conditions such as stress, emotional exhaustion, burnout, and mental fatigue.

[7] Review of Sparse Representation Based Classification Methods on EEG Signal Processing for Epilepsy Detection, Brain-Computer Interface and Cognitive Impairment Dong:

The sparse representation-based classification (SRC) has become an important approach in electroencephalograph (EEG) signal analysis. SRC methods are used to analyze the EEG signals of epilepsy, cognitive impairment and brain computer interface (BCI),as they provide improvement in computational accuracy, efficiency and robustness. This study explores the good parts as well as bad parts about SRC methods.

[8] A Deep Learning Approach for Motor Imagery EEG Signal Classification:

The use of electroencephalography (EEG) signals for motor imagery based brain-computer interface (MI-BCI) has gained widespread attention.Deep learning has been rarely used for MI EEG signal classification. In this study, a deep learning approach for classification of MI-BCI is presented.

[9] Noise robustness analysis of sparse representation based classification method for non-stationary EEG signal classification:

This study aims to analyze noise robustness of the SRC method to evaluate the capability of the SRC for non-stationary EEG signal classification. The classification performance of the SRC and support vector machine is compared. SRC has an inherent adaptive classification mechanism that makes it suitable for time-varying EEG signal classification.

[10] Sleep Stage Classification Using EEG Signal Analysis: A Comprehensive Survey and New Investigation:

Sleep makes the individual either partially or completely unconscious and makes the brain a very less complicated network. This study identifies various stages of sleep. This further helps the physicians to have a better look at sleep related ailments. The motive is to survey the progress and challenges in various existing Electroencephalogram (EEG) signal-based methods.

[11] Detection of neonatal seizures through computerized EEG analysis:

Neonatal seizures or convulsions are the epileptic fits or seizures occuring from birth to neonatal period. This period is the most vulnerable period of all the periods of life for developing seizure. This study used autocorrelation analysis to distinguish seizures from the background of electrocerebral activity. Their method

SAM(Scored Autocorrelation Moment) was successful in distinguishing EEG signals with epilepsy to without epilepsy.

[12] Machine learning for real-time single-trial EEG-analysis: From brain–computer interfacing to mental state monitoring:

This paper showed us a real time experiment with six different subjects that were chosen to perform different tasks. Their brain waves were recorded and were analysed for every action they performed.

[13] Deep Convolutional Neural Network-Based Epileptic Electroencephalogram (EEG) Signal Classification:

Electroencephalogram (EEG) signals contain vital information on the electrical activities of the brain and are widely used to aid epilepsy analysis. A challenging element of epilepsy diagnosis, accurate classification of different epileptic states, is of particular interest and has been extensively investigated. A new deep learning-based classification methodology, namely epileptic EEG signal classification (EESC), is proposed in this paper. This methodology first transforms epileptic EEG signals to power spectrum density energy diagrams (PSDEDs), then applies deep convolutional neural networks (DCNNs) and transfer learning to automatically extract features from the PSDED, and finally classifies four categories of epileptic states (interictal, preictal duration to 30 min, preictal duration to 10 min, and seizure).

[14] EEG signal classification using principal component analysis with neural network in brain computer interface applications:
Brain Computer Interface (BCI) is the method of communicating the human brain with an external device. People who are incapable to communicate conventionally due to spinal cord injury are in need of Brain Computer Interface. Brain Computer Interface uses the brain signals to take actions, control, actuate and communicate with the world directly using brain integration with peripheral devices and systems. Brain waves are necessary to eradicate noises and to extract the valuable features.

Artificial Neural Network (ANN) is a functional pattern classification technique which is trained all the way through the error Back-Propagation algorithm.

[15] EEG signal classification using principal component analysis and wavelet transform with neural network:

This study is based on classification of electroencephalogram signals. This study uses an open source dataset which is publicly available and has been used in various other papers. They propose a system which includes wavelet transformation, principal component analysis and a neural network model. The study suggests that principal component analysis along with neural networks is far superior than wavelet transformation with neural networks.

[16] Deep Learning With Convolutional Neural Networks for EEG Decoding and Visualization.

Deep Learning with Convolutional Neural Networks has given a new insight to computer vision through end to end learning(learning from raw data). In this paper, we studied deep ConvNets with a range of different architectures, designed for decoding imagined or executed tasks from raw EEG. The results of this study that recent advances from the machine learning field, including batch normalization and exponential linear units, together with a cropped training strategy, boosted the deep ConvNets decoding performance, reaching at least as good performance as the widely used filter bank common spatial patterns (FBCSP) algorithm (mean decoding accuracies 82.1% FBCSP, 84.0% deep ConvNets). ConvNets indeed learned to use spectral power modulations in the alpha, beta, and high gamma frequencies, and proved useful for spatially

[17] Multilevel Weighted Feature Fusion Using Convolutional Neural Networks for EEG Motor Imagery Classification

Convolutional Neural Networks are very successful in computer vision tasks. Extracting relevant information from CNN features is one of the key reasons behind the success of the CNN-based deep learning models. In this paper, we studied about the use of the EEG motor imagery data to uncover the benefits of extracting and fusing multilevel convolutional features from different CNN layers, which are abstract representations of the input at various levels. It demonstrates that multilevel feature fusion outperforms the models that use features only from the last layer. The results are better than the state of the art for EEG decoding and classification.

[18] Robust EEG-based cross-site and cross-protocol classification of states of consciousness.

Patients suffering from disorders of consciousness (DOC) demonstrate that it is possible to be awake in the absence of behavioural evidence of consciousness . Despite best efforts for consistency, current diagnostic procedures rely on human interaction and are, therefore, error-prone. The degree of misdiagnosis in patients with DOC may exceed 40% when relying on the clinician's judgement without standardized behavioural assessments.
Following recent trends in neuroimaging, the increasing number of neural markers of consciousness is likely to be best approached with multivariate pattern analysis (MVPA). Indeed, machine learning algorithms can be trained to best predict the medical status of individual patients from unknown combinations of physiological markers.

[19] EEG-based brain-computer interfaces using motor-imagery: Techniques and challenges

This paper reviews state-of-the-art signal processing techniques for MI EEG-based BCIs, with a particular focus on the feature extraction, feature selection and classification techniques used. It also summarizes the main applications of EEG-based BCIs, particularly those based on MI data, and finally presents a detailed discussion of the most prevalent challenges impeding the development and commercialization of EEG-based BCIs. One of the biggest leaps in commercialization of BCIs is adapting the interfaces used in the lab for use in the wider world. Although BCIs hold potential to be applied to various areas including home automation, prosthetics, rehabilitation, gaming, transport, education, VR, artistic computing, and possibly even virtual assistants based on affective computing, the leap to creating viable products involves considering several factors. These factors mainly include: (i) choice of technology, (ii) general appeal, (iii) intuitivism, (iv) usability and reliability and (v) cost

[20] A novel deep learning approach for classification of EEG motor imagery signals.

Summary: Signal classification is a relevant issue in brain computer interface (BCI) systems. Deep learning has been used successfully in many recent studies to learn the features and classification of a variety of data. However, the number of studies that revolve around these approaches on BCI applications is very limited. This study is aimed to use deep learning methods to improve classification performance of EEG motor imagery signals. The datasets that are used in this study include recordings from three electrodes (C3, Cz and C4) during left/right hand MI task. These electrodes are located in the motor area of the brain. Short time Fourier transform (STFT) was applied on the time series for each 2 s long trial. In the case of a 250 Hz signal this is corresponding to 500 samples. STFT was performed with window size equal to 64 and time lapses equal to 14. Starting from sample 1 toward sample 500, STFT is computed for 32 windows over 498 samples and the last 2 samples, remaining at the end, are simply ignored. This leads to a 257 × 32 image where 257 and 32 are the number of samples along the frequency and time axes respectively. Then we extracted mu and beta frequency bands from the output spectrum. The frequency bands between 6–13 and 17–30 were considered to represent mu and beta bands.

[21] Classification for EEG report generation and epilepsy detection

Signal classification is a relevant issue in brain computer interface (BCI) systems. Deep learning has been used successfully in many recent studies to learn the features and classification of a variety of data. However, the number of studies that revolve around these approaches on BCI applications is very limited. This study is aimed to use deep learning methods to improve classification performance of EEG motor imagery signals. An automatic generation of medical report method (AGMedRep) was proposed in order to process electroencephalogram (EEG) segments using machine learning (ML) to generate textual reports for epilepsy detection. This method is applied in two phases: (1) predictive model building, and (2) automatic generation of medical reports. In the first phase, 90 signal segments for each class were selected for feature extraction and classifier building. In the second phase, the 50 remaining EEG segments were equally distributed, randomly, into ten folders in order to simulate individual EEG exams.

[22] Epileptic seizure detection in EEGs using time--frequency analysis

The analysis is performed in three stages: 1) t-f analysis and calculation of the PSD of each EEG segment; 2) feature extraction, measuring the signal segment fractional energy on specific t-f windows; and 3) classification of the EEG segment (existence of epileptic seizure or not), using artificial neural networks. The methods are evaluated using three classification problems obtained from a benchmark EEG dataset. The analysis is performed in three stages: 1) t-f analysis and calculation of the PSD of each EEG segment; 2) feature extraction, measuring the signal segment fractional energy on specific t-f windows; and 3) classification of the EEG segment (existence of epileptic seizure or not), using artificial neural networks. The methods are evaluated using three classification problems obtained from a benchmark EEG dataset.

[23] Real-time epileptic seizure detection using EEG

This paper revolves around proposing a novel patient-specific real-time automatic epileptic seizure onset detection, using both scalp and intracranial EEG. The proposed study obtains harmonic multiresolution and self-similarity-based fractal features from EEG for robust seizure onset detection. A fast wavelet decomposition method, known as harmonic wavelet packet transform (HWPT), is computed based on Fourier transform to achieve higher frequency resolutions without the help of recursive calculations. Fractal dimension (FD) estimates are obtained to capture self-similar repetitive patterns in the EEG signal. Both FD and HWPT energy features across all EEG channels at each epoch are organized following the spatial information due to electrode placement on the skull. Then finally, the feature vector combines feature configurations of each epoch within the specified moving window to reflect the temporal information of EEG. Finally, Relevance Vector Machine (RVM) is used for the classification of the feature vectors due to its efficiency in classifying sparse, yet high dimensional datasets.

[24] Epileptic seizure detection based on EEG signals and CNN.

This study is focused on a specific category of methods based on analyses of the spatial properties of EEG signals in the time and frequency domains. These methods have been applied to both interictal and ictal recordings and share the common objective of localizing the subsets of brain structures involved in both types of paroxysmal activity. First of all, original signals based on the time or frequency domain were directly input into the convolutional neural network (CNN) instead of extracting all feature types and then this method was tested on the intracranial Freiburg database and the scalp CHB-MIT database and then this study detects binary epilepsy scenarios, e.g., interictal vs. ictal and interictal vs. preictal, but also verifies the ability of this method to classify a ternary case, e.g., interictal vs. ictal vs. preictal. And then it compares the different performances between the time and frequency domain signals using CNN as a classifier.

[25] Detection of epilepsy using MFCC-based features and XGBoost.

This study brings a MFCC-based feature for detection of epilepsy. This study is inspired by some methods in speech signal processing, and tests the reliability of the feature through experiments. In this study, a valid feature was obtained for epilepsy detection by analyzing the MFCCs of EEG. XGBoost is used as a classifier for epilepsy detection, a model that performs better than traditional classifiers.

[26] Classification of epileptiform EEG using a hybrid system based on decision tree classifier and fast Fourier transform.

The aim of this study is to detect epileptic seizure in EEG signals using a hybrid system based on decision tree classifier and fast Fourier transform (FFT). The present study proposes a hybrid system with two stages: feature extraction using FFT and decision making using decision tree classifier. The detection of epileptiform discharges in the electroencephalogram (EEG) is an important part in the diagnosis of epilepsy.

[27] Motor imagery EEG classification based on decision tree framework and Riemannian geometry

This study proposes a novel classification framework and a novel data reduction method to distinguish multiclass motor imagery (MI) electroencephalography (EEG) for brain computer interface (BCI) based on the manifold of covariance matrices in a Riemannian perspective.

[28] Xgboost: A scalable tree boosting system

Tree boosting is a highly effective and widely used machine learning method. This study describes a scalable end to-end tree boosting system called XGBoost, which is used widely by data scientists to achieve state-of-the-art results on many machine learning challenges. This paper proposes a novel sparsity-aware algorithm for sparse data and weighted quantile sketch for approximate tree learning.

[29] Continuous EEG findings in patients with COVID-19 infection admitted to a New York academic hospital system.

There is evidence for central nervous system complications of coronavirus disease 2019 (COVID-19) infection, including encephalopathy. Encephalopathy caused by or arising from seizures, especially nonconvulsive seizures (NCS), often requires electroencephalography (EEG) monitoring for diagnosis. The prevalence of seizures and other EEG abnormalities among COVID-19-infected patients is unknown.

[30] Detecting Epileptic Seizures in EEG Signals with Complementary Ensemble Empirical Mode Decomposition and Extreme Gradient Boosting.

To overcome the existing weaknesses and enhance the classification performance, this study develops a detection approach of epileptic seizures using CEEMD and XGBoost, named CEEMD-XGBoost, for epileptic seizure detection. y. The main novelty of this study includes three aspects. Firstly, a novel epileptic seizure detection model that combined CEEMD with XGBoost was developed. Secondly, experiments were performed on the Bonn EEG dataset and the CHB-MIT database. Lastly, this study evaluates some characteristics of the proposed CEEMD-XGBoost, including the impact of CEEMD and feature importance.

S. No.	*Methods*	*Dataset*	*Results*	*Remarks*
[1]	The onset of epileptic seizures can be predicted on the basis of pre-ictal EEG signals. Such prediction requires real time classification of EEG segments into three cases along with post processing, previous data and history.	Pre-ictal or interictal EEG samples are taken from an epilepsy patient when there is no seizure. The ictal EEG data is recorded during the seizure.	The results of this study verify that EEG signals can be used to study the mental states and problems related to the brain	This paper tells us briefly about the approach we need to follow to detect mental disorders using EEG.
[2]	This study used LORETA to overcome shortcomings of Quadratic Regularization.	-Not Used-	This study tells that for the treatment of real data sets, realistic world models should be used in EEG, together with an effective collaboration procedure between MRI images—so as to draw a fine patchwork—and another functional imaging to isolate very probable active brain areas	This paper shows us the efficiency of LORETA and also tells us how LORETA is better than conventional Quadratic Regularization.
[3]	First of all the 3D coordinates are measured in the real world and Thin Plate Spline(TPS) is performed and then Finite Element Method (FEM) is used to determine the numerical solution of the forward problem.	Ictal dataset was used for this study which is available for public download.	EEG-based dipole localization using a forward model based on a TPS warped atlas performs a lot better than the widely used three-shell sphere model and also outperforms a generic model that uses an affine transformation of the individual electrode positions.	This study told us to properly process the EEG signals. It provides us with the best possible way to do that.
[4]	This study summarises about the different algorithms and	Ictal dataset was used for this study which is	The study explained about the basic	This study helped us to identify which algorithm should be

	how to use them. It also provides us with the efficient steps to be followed to process the EEG signals properly	available for public download.	notations and procedures of the channel selection process. It presents a description of channel selection approaches for a variety of applications	used for a particular task for maximum efficiency.
[5]	EEG signal is obtained as an arithmetic sum of different sinusoids is used to implement the 'adaptive' S—Golay filtering technique. This simulation is performed for seven epochs and the signal is used as the base signal for correlation with the filtered signal at a later stage	-Not Used-	The filtered signal, apart from removing the noise, retains the features of the original signal efficiently. This proves that adaptive S—Golay filtering algorithm can also be applied on real time signals. The adaptive SG filtering technique takes the place of the heuristic or trial and error process.	This study tells that by employing S_Golay filtering we can further improve the efficiency of the results we obtain after processing the EEG signal.
[6]	Emotiv EPOC+ (EMOTIV, San Francisco, California) was used to record subjects' brain waves in 14 channels. Data was recorded with sequential sampling internally at 2,048 Hz at a rate of 128 Hz deliverable	A wearable headset was used by some people who helped in this study, the data from that headset was used.	This study demonstrates the capability of the proposed signal processing framework to produce high-quality EEG signals from wearables. It provides a standardized process for dealing with both intrinsic and extrinsic artifacts.	This study showed us the real world usage of EEG signals and showed us one of their practical uses.
[7]	Three perspectives of SRC methods used in epileptic detection, which includes reconstruction rules and residual error classifications on the whole classification stage, overcomplete	Z(ictal) and S(Healthy) dataset is used which is publicly available.	Improving the current SRC methods by combining SR with Common Spatial Pattern (CSP) will largely increase the	This study tells us about how we can employ the SRC methods to get the best out of them.

	dictionary on the preprocessing stage, and wavelet based sparse functional linear model on the feature extraction stage.		classification accuracy and efficiency.	
[8]	In this paper, the first step was to divide the dataset into two parts, test data and train data and then after passing both the test and train data through appropriate layers, we got our classification.	The public benchmark Dataset IVa from BCI competition III provided by Fraunhofer FIRST (intelligent data analysis group) have been used.	The framework described in the study is well suited to applications such as wearable devices that require algorithms that are computationally less expensive and can last longer when powered using batteries.	This study also showed us one of the practical approaches. It was inclined towards making the wearables more efficient.
[9]	To compare the classification accuracy of the SRC and SVM methods, the study used the leave-one-out cross-validation,	Noisy test signals and real online-experimental dataset	The classification accuracy of the SRC method is consistently better than the SVM methods regardless of their feature dimension.	This method provides us with the working use of SRC methods and it also tells us how they should be employed to be consistently better than the older SVM techniques.
[10]	The process starts with decomposing the signal and then two statistical parameters were introduced and then several machine learning algorithms were used to classify sleep stages.	PhysioNet Sleep European Data Format (EDF) Database	This study proves that the breakdown process of the single-channel EEG signal tells that digital filters that have an easy-to-use transfer function when used on digital signal processors.	This paper showed us the statistical approach towards analysing the waveforms and base of ML algorithms.
[11]	This paper used several steps for autocorrelation of the different parts of the signals for classifying the EEG signals for identifying neonatal seizures.	Electroencephalogram signals of 14 different infants were used. 11 scalp electrodes were implanted which gave 12 channel bipolar electrocerebral activity.	Their approach showed distinguished periodicity of neonatal seizures as compared to the normal spectral analysis. Their specificity was 98%	Their approach showed us the internals of how the different components interact with each other and how are they co related to each other.

			with sensitivity of about 84%.	
[12]	Six different subjects were chosen and were asked to perform different tasks. Their brain waves were noted and used for classifications.	The data was captured from 6 different persons with 118 different electrodes mounted on the scalp.	This experiment showed significant results with 5 out the 6 subjects discriminable brain signals where the average task length was 3 seconds.	This paper showed an approach towards real life experiment of data generation and how EEG signals are different for different tasks.
[13]	This paper, epileptic EEG signal classification methodology based on deep convolutional neural networks is proposed to classify four critical epileptic states	Epileptic EEG signal data in the CHB-MIT database	A Neural Network has been applied to the BCI problem. In order to improve accuracy of mental task classification.	This paper helped us to understand how to apply neural networks to classify the EEG signals.
[14]	The brain signals obtained from the electrodes serves to be the input for the neural network model. This paper also shows how to use the PCA to preprocess the data for neural network.	The EEG data used is collected from the Colorado state University website .	This paper showed that PCA plus neural networks are superior in classifying the EEG signals.	This paper provided us with the information on how to use the PCA with neural networks to classify the EEG signal
[15]	This study involved the use of three main components which are used in classification of electroencephalogram signals. These three main components are Wavelet transform, Principal component analyser and Neural Network.	The data used in this paper has been taken from (Andrzejak et al., 2001), is publicly available.	This study uses a lot of soft computing techniques to draw out a conclusion that PCA + Neural Networks are more accurate in classifying an EEG Signal.	This paper gave us a brief idea how to handle the waveform and preprocess the data for the neural network.

[16]	The principles of both filter bank common spatial patterns (FBCSP), the established baseline decoding method referred to throughout this study, and of convolutional neural networks (ConvNets). Next, it describes the ConvNets developed for this study in detail, including the design choices. Afterward, the training of the ConvNets, including two training strategies, is described. Then two novel visualizations of trained ConvNets are presented.	BCI competition IV datasets 2a and 2b	Band power topographies show event related "desynchronization/synchronization" typical for motor tasks Input-feature unit-output. Correlation maps show learning progression through the ConvNet layers Input-perturbation network-prediction correlation maps show causal effect of spatially localized band power features on ConvNet predictions.	This paper mostly discusses the depth of ConvNets.
[17]	EEG signals are a multiple channel thus, we split the first convolution layer into two. Therefore, the first convolution is performed over time samples for each electrode, and the second is conducted on all electrodes or channels. The EEG input is stored as a 2D array that has time across channels.Thereafter, we have the max pooling layer; the second, third, and fourth convolution max pooling block; and the dense softmax layer.	MI dataset.	The study shows that deep CNNs when pretrained with similar EEG data can aid CNN to learn small-sized datasets. The results are better than those of the state of the art for EEG MI classification on the same dataset.	This study tells us about the results of using CNN on small-sized datasets an MI dataset.

[18]	This study chose the Extra-Trees algorithm whose non-parametric design facilitates robust classification. To complement insights from univariate classification, we extracted the so-called variable importance metric from the Extra-Trees following best practice recommendations for enhanced interpretability.	The Coma Science Group, the family of the patient gave their informed consent for participation in the study.	The DOC-Forest classifier exhibited an average performance of AUC = 0.75 (SD = 0.014) and performed better and more robustly than most other markers did individually.) but was already strong with 16 sensors and 5% of epochs. Importantly, using the full EEG configuration, the performance closely resembled previous results reported by Sitt et al. (2014) and beat any other marker.	This study helped us to explore extra trees algorithm for EEG.
[19]	This paper reviews state-of-the-art signal processing techniques for MI EEG-based BCIs, with a particular focus on the feature extraction, feature selection and classification techniques used. It also summarizes the main applications of EEG-based BCIs, particularly those based on MI data, and finally presents a detailed discussion of the most prevalent challenges impeding the development and commercialization of EEG-based BCIs.	Data set number 4 from the Brain/neural computer interaction (BNCI) Horizon 2020 site.	One of the biggest leaps in commercialization of BCIs is adapting the interfaces used in the lab for use in the wider world. Although BCIs hold potential to be applied to various areas including home automation, prosthetics, rehabilitation, gaming, transport, education, VR, artistic computing, and possibly even virtual assistants based on affective computing, the leap to creating viable products involves considering several factors. These factors mainly include: (i) choice of technology, (ii) general appeal, (iii) intuitivism, (iv)	

			usability and reliability and (v) cost	
[20]	Starting from sample 1 toward sample 500, STFT is computed for 32 windows over 498 samples and the last 2 samples, remaining at the end, are simply ignored. This leads to a 257 × 32 image where 257 and 32 are the number of samples along the frequency and time axes respectively. Then we extracted mu and beta frequency bands from the output spectrum. The frequency bands between 6–13 and 17–30 were considered to represent mu and beta bands.	Dataset III from BCI Competition II and training set of Dataset 2b from BCI Competition IV.	The results of this study show that deep learning methods provide better classification performance compared to other state of art approaches. These methods can be applied successfully to BCI systems where the amount of data is large due to daily recording.	
[21]	This method is applied in two phases: (1) predictive model building, and (2) automatic generation of medical reports. In the first phase, 90 signal segments for each class were selected for feature extraction and classifier building. In the second phase, the 50 remaining EEG segments were equally distributed, randomly, into ten folders in order to simulate individual EEG exams.	The public available EEG dataset.	The chosen classifier was computed in each examination to construct textual reports. As a result, the 1NN model reached an average of 84% accuracy in the report generation. Differentiation among EEG segments from five different classes. Comparison among 75 predictive models built by five well known machine learning techniques.	

[22]	The analysis is performed in three stages: 1) t-f analysis and calculation of the PSD of each EEG segment; 2) feature extraction, measuring the signal segment fractional energy on specific t-f windows; and 3) classification of the EEG segment (existence of epileptic seizure or not), using artificial neural networks. The methods are evaluated using three classification problems obtained from a benchmark EEG dataset.	The public available EEG dataset.	This study presents a comparison of using STFT and other 12 well known TFDs to access the nonstationary properties of the EEG signal with respect to epileptic seizure detection. This paper utilized an approach based on t-f analysis and extraction of features reflecting the distribution of the signal's energy over the t-f plane. Both of these aspects have not been employed for epileptic seizure detection, while the results obtained using a publicly available dataset demonstrate the added value of the proposed approach.	
[23]	Fractal dimension (FD) estimates are obtained to capture self-similar repetitive patterns in the EEG signal. Both FD and HWPT energy features across all EEG channels at each epoch are organized following the spatial information due to electrode placement on the skull. Then finally, the feature vector combines feature configurations of each epoch within the specified moving window to reflect the temporal information of EEG. Finally, Relevance	Publicly available long term scalp EEG (dataset A) and short-term intracranial and scalp EEG (dataset B) databases.	The proposed study is effective in seizure onset detection with 96% sensitivity, 0.1 per hour median false detection rate and 1.89 s average detection latency respectively. Results obtained from analyzing the short term data offer 99.8% classification accuracy. These results demonstrate that the proposed method is effective with both short and long-term EEG signal analyzes recorded	

	Vector Machine (RVM) is used for the classification of the feature vectors due to its efficiency in classifying sparse, yet high dimensional datasets.		with either scalp or intracranial modes respectively.	
[24]	This study detects binary epilepsy scenarios, e.g., interictal vs. ictal and interictal vs. preictal, but also verifies the ability of this method to classify a ternary case, e.g., interictal vs. ictal vs. preictal. And then it compares the different performances between the time and frequency domain signals using CNN as a classifier.	1**.** Dataset provided by the Epilepsy Center at the University Hospital of Freiburg, Germany. 2. Open-source EEG database from CHB-MIT.	The mean accuracy of classification between the interictal and preictal signals was 96.7%, and the average sensitivity and specificity values were 96.7 and 96.8%, respectively. s the classification results for time domain signals from patients in the Freiburg database. The average accuracies of the three experiments were 91.1, 83.8, and 85.1%, respectively.	
[25]	Both the EEG signal and the speech signal are time series, the MFCC feature can also be extracted from EEG by a conventional method. This study divided the signal into overlapping frames and then used a set of triangular filters to wrap the power spectrum. To evaluate the performance of XGBoost and the validity of the MFCC-based features, this study divided each EEG sample of the subsets into four samples to increase the total number of samples.	Benchmark dataset made by University of Bonn.	The experimental results show that the method of XGBoost classifier using MFCC-based features can obtain high accuracy on epileptic detection problems.	

[26]	This proposed method consists of two stages: FFT based Welch method and decision tree classifier. This study applied the Welch spectral analysis method to the EEG signals and then 129 features obtained from FFT based Welch method was applied to decision tree classifier to detection of epileptic seizure.	EEG signals of healthy subjects and subjects suffering from epilepsy diseases	The evolution of the proposed system was conducted using k-fold cross-validation, classification accuracy, and sensitivity and specificity values. We have obtained 98.68% and 98.72% classification accuracies using 5- and 10-fold cross-validation.	
[27]	Subject-specific decision tree (SSDT) framework with filter geodesic minimum distance to Riemannian mean (FGMDRM) is designed to identify MI tasks and reduce the classification error in the nonseparable region of FGMDRM. Method 2 includes a feature extraction algorithm and a classification algorithm. The feature extraction algorithm combines semi supervised joint mutual information (semi-JMI) with general discriminant analysis (GDA), namely, SJGSA, to reduce the dimension of vectors in the Riemannian tangent plane	BCI competition IV dataset 2a	The experimental results of method 1 show that the proposed classification framework significantly improves the classification performance of the classifier. The experimental results of method 2 show that the SJGDA algorithm proposed in this paper is superior to GDA and semi-JMI in feature extraction, and method 2 has the highest recognition rate in this study.	
[28]	The most time consuming part of tree learning is to get the data into sorted order. In order to reduce the cost of sorting, this study proposed to store the data in in-memory units, which we called block. Data in each block is stored in the	Higgs 10M dataset.	This study proposed a novel sparsity aware algorithm for handling sparse data and a theoretically justified weighted quantile sketch for approximate learning. This experience shows that	This paper helped us to explore the advantages over other classifiers.

	compressed column (CSC) format, with each column sorted by the corresponding feature value. This input data layout only needs to be computed once before training, and can be reused in later iterations. The block structure also helps when using the approximate algorithms.Collecting statistics for each column can be parallelized, giving us a parallel algorithm for split finding.		cache access patterns, data compression and sharding are essential elements for building a scalable end-to-end system for tree boosting.	
[29]	Medical records and EEG studies of patients hospitalized with confirmed COVID-19 infections over a 2-month period at a single US academic health system (four hospitals) were reviewed to describe the distribution of EEG findings including epileptiform abnormalities (seizures, periodic discharges, or nonperiodic epileptiform discharges).	111 Patients	Of 111 patients monitored, most were male (71%), middle-aged or older (median age 64 years), admitted to an intensive care unit (ICU; 77%), and comatose (70%). Excluding 11 patients monitored after cardiac arrest, the most frequent EEG finding was moderate generalized slowing (57%), but epileptiform findings were observed in 30% and seizures in 7% (4% with NCS). Three patients with EEG seizures did not have epilepsy or evidence of acute or remote brain injury, although all had clinical seizures prior to EEG.	This paper gave us insight into how epilepsy affected Corona Patients.

[30]	Firstly, the decomposition method, CEEMD, which is capable of effectively reducing the influence of mode mixing and end effects, was utilized to divide raw EEG signals into a set of intrinsic mode functions (IMFs) and residues. Secondly, the multi-domain features were extracted from raw signals and the decomposed components, and they were further selected according to the importance scores of the extracted features. Finally, XGBoost was applied to develop the epileptic seizure detection model.	Bonn dataset and the CHB-MIT Dataset.	The extensive experimental results indicated that, compared with some previous EEG classification models, CEEMD-XGBoost can significantly enhance the detection performance of epileptic seizures in terms of sensitivity, specificity, and accuracy.	This study taught us a different approach with the incorporation of XG Boost and CEEMD, which made the prediction more sensitive and accurate.

Chapter 3: Requirement Analysis and Solution Approach

3.1 Overall description of the project

Machine learning is driving rapid innovation and providing new insights into how we can interpret and control complex data and environments. With these advances, adversaries will seek to circumvent their controls and drive systems for their malicious ends. In recognition of this reality, this project aims at visualizing the adversaries which hampers the outcome of a classifier model.

EEG Analysis has been a topic of research for a very long time. Researchers have implemented and followed various approaches to achieve more accuracy and precision in this field. In this project we focussed on creating a product and for that we implemented many classifiers to find out which one is the best for EEG signals.

This project focuses on providing the patients and their families a source to rely upon. After finding out the best classifier we created a cross-platform application for the patient to download. The beauty of this app is that it continuously records the EEG signals which have various uses, but the best one is alerting the family members of patients when the patients need help. Some other uses include proper medication by doctor, due to 24*7 analysis and also quick access to connect with doctors.

3.2 Requirement analysis

Table 3.2.1. Model Implementation Requirements

Requirement	**Tool**
Language	Python
Training Environment	Google Colab
Data Set	Publically available EEG dataset
Decision Tree	XG Boost

Table 3.2.2. Web Portal Requirements

Requirement	**Tool**
Language	HTML, CSS, Python, Javascript
Framework (Frontend)	ReactJs
Framework (Backend)	Flask
Route Definition	Axios
Version Control	Git

3.3 Solution approach

The project is divided into a three-staged process. The details of the various stages are provided below:

Stage 1: Identifying the research work.

In this first part, we implemented various classifiers to find out the best one. We compared all those classifiers on various parameters. XGBoost came out to be the best. In this phase we had to read a lot of research papers to back up what we are doing. This phase is the backbone of the product we are trying to create.

Stage 2: Designing a web based and an application based portal

This part was majorly around deciding what features should be there on the application, this was to make sure our product is user friendly and in times of need it works and operates smoothly, to make our application light, we yet again invested a lot of time to not use the custom libraries and implement everything from scratch. This was a great learning experience in terms of Javascript.

Stage 3: Connecting the app and writing down the model.

As in stage1, we already decided that we are going to use XGBoost, so we implemented it and connected it with the cross-platform application we created, after this we added several features in our app based on the data which we were getting from the backend.

Chapter 5: Testing:

Software testing is an important phase in the software development life cycle as it verifies and validates the system under test i.e. whether it works as expected and satisfies the stakeholders' needs. With respect to the text extraction system also, testing & evaluation is significant; as it is important to test the system before deployment. In order to assess the system output, appropriate quality assessment techniques should be adopted for determining the system performance in comparison to the benchmark level or with the quality of the previous version or with similar kinds of different products.

5.1 Testing plan

First of all we tested the models with the few images whose identification were already known to us. Since we are using a pre-trained model and the subject of our study is verifying adversarial attacks, we checked in with the quality of image received and at what kind of images the system works pretty fine and purposefully.

5.2 Component decomposition and type of testing required

The objectives behind the testing of our developed model are:

- Evaluation of Parameters of the developed system
- Calculating accuracy
- Speed of the model
- Evaluation of Complexity in colored images
- User Level Testing

Table 5.2.1. Types of testing

Type of tests	Explanation	Software Component
Requirement Testing	Validation checks were made to ensure that hardware and software specifications meet the minimum requirements. Certain libraries such as Anaconda, Jupyter were required to be specially installed and the minimum CPU/GPU requirements for our architecture were also checked.	VS Code/Anaconda
Performance Testing	Performance testing is the process of determining the speed, accuracy, and consistency of the proposed model. This was achieved by creating, training, and testing the whole image processing based learning system experimenting with varied training methodologies.	VS Code/Anaconda
Experimental Testing	Our model was checked against various experimental tests to fine-tune the hyperparameters in order to ensure the best results. Hardware specification was improved and the hyperparameters were updated increased to improve the specificity and sensitivity of the	VS Code/Anaconda

	prediction	
Unit Testing	The purpose is to validate that each unit of the software performs as designed. The output of the steps within data preprocessing and the result of tumor segmentation was randomly tested in order to ensure valid and consistent results.	VS Code/Anaconda

Chapter 6: Findings, Conclusion and Future Work:

6.1 Findings

From the above study, we learned about the adversarial networks and their working. How they hamper the efficiency of an image classifier and how it is harmful on physical scale. We had the following observation after completing the study on various topics and research papers related to the former subject.

- We were able to understand the logics behind these adversarial vulnerabilities
- We were successfully able to implement four very important ideologies from the field.
- We were able to provide a tool that can be used to significantly understand the effect of adversarial vulnerabilities on image classification.
- We were able to extract the perturbation out of the image for displaying to enhance the understanding of model's working.

6.2 Conclusion

- We learned about the various algorithms which are expected to get replaced by another research topics.
- Various methods describing ideas to analyse the EEG signals have been discussed and it has been found that the majority of the ideas focused on training the training models with all kinds of EEG signals to identify different actions.
- Few studies have shown how the adversarial models hamper the performance of google cloud API and other real world settings.
- Basic implementation of black-box attacks have been perfectly defined in few of the researches.
- We got to know about the future scope of this field of research.
- After implementing the models and testing them on the same image and dataset. We are able to state that One pixel attack is much better attack as it involves minimal distortion, provided the hardware requirements are met.

- Also, we were able to identify that Model4: Basic Iterative Method has been the best at performance as the distortion created was minimal and hardly intriguing. Also, the image generated was tough at comparison and it provided a fairly large set of input parameters.

6.3 Future work

Use of artificial intelligence in medicine in an evolving technology which holds promise for mass screening and perhaps may even help in establishing an accurate diagnosis. The ability of complex computing is to perform pattern recognition by creating complex relationships based on input data and then comparing it with performance standards is a big step. Diabetic retinopathy is an ever-increasing problem. Early screening and timely treatment of the same can reduce the burden of sight threatening retinopathy. Any tool which can aid in quick screening of this disorder and minimize the requirement of trained human resources for the same would probably be a boon for patients and ophthalmologists per capita cost.

This has further increased since the introduction of anti VEGF agents. Very often the disease does not show overt symptoms until it reaches an advanced stage; however, if detected early on, vision impairment can be averted by early intervention which is also the most cost-effective option. In view of the alarming increase in the number of people with diabetes and dearth of trained retinal specialists and ophthalmologists, a computer-based analysis of the fundus images by an automated approach would lessen the burden of the health systems in screening for DR and offer a near ideal system for its management. Therefore, screening will be valuable at any stage of the disease and will also be helpful in avoiding blindness among 90% patients.

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