# SMART EEG Classifier
# for Abnormality Detection

Final Year Project Report

by


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In Partial Fulfillment

Of the Requirements for the degree

Bachelors of Electrical Engineering(BEE)


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# DECLARATION

We hereby declare that this final year project report entitled " Smart EEG Classifier for Abnormality Detection" submitted to the "School of Electrical Engineering and Computer Sciences (SEECS),NUST", is a record of an original work done by us under the guidance of Supervisor "Sir Imran Abeel" and that no part has been plagiarized without citations. Also, this project work is submitted in the partial fulfillment of the requirements for the degree of Bachelor of Electrical Engineering.

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# DEDICATION

We would like to dedicate this work to Almighty Allah, our parents and our respected advisors, Dr. Hassan Aqeel, Dr. Faisal Shafait & Prof. Imran Abeel.

# ACKNOWLEDGEMENTS

We would like to wholeheartedly thank our advisor Prof. Imran Abeel and the co-advisors Dr. Faisal Shafait and Dr. Hassan Aqeel for helping us throughout the course of the final year project. Without their keen guidance and support, it would not have been possible for us to meet the scope of the project in time.

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# ABSTRACT

Electroencephalogram is a test that is used to check the electrical activity of the brain using EEG signals. It can be used for the diagnosis of brain-related diseases like Alzheimer's disease, depression, dementia, epilepsy and migraine. Neurologists have low inter-rater agreement and the process itself is very time consuming and resource hungry. Compared to the prolonged manual analysis, automation of the initial step of EEG diagnosis can ease the task - identify it as normal or abnormal. EEG research can benefit from the recent advances in deep learning. However, the progress in biomedicine is hindered by the lack of diverse properly curated datasets.

Along with the introduction of a new publicly available dataset we are focusing on the temporal localization of EEG records for different patients. Localization of records requires annotated data for training deep learning models. So, we developed our customized tool to visualize the abnormality and thus annotate it by comparing the results with the paid software already used by MH hospital rawalpindi and verifying it from the doctors.

Most of the publically available datasets are from developed countries with state of the art equipment, and Pakistan being a developing country lacks most of these facilities.Thus, an EEG test conducted in a developing country would not relate to the mostly available dataset and hence, our dataset is one of its kind. We address replication crisis or dataset variability by comparing the two datasets. The results obtained are inline with earlier work providing stringent testing for deep learning solutions developed. MH-NUST is being released to increase the diversity of existing datasets and to overcome the scarcity of accurately acquired public datasets for EEG research.

*Chapter 1*

# INTRODUCTION

The electroencephalogram is basically a recording of the electrical activity of the brain. The waveforms that are recorded represent the cortical electrical activity of the brain. All kinds of Neurological disorders are an emerging challenge to healthcare systems all over the world and this challenge is expectedly growing exponentially in low and middle-income countries in the next decade while awareness is expected to increase leading to shorter treatment gaps. From 1990 to 2010, disability due to Neurological disorders increased by 41%. The exact number increased from 182 million to 258 million in these years [2]. Also, recent estimates show that stroke is the second highest cause of infirmity and mortality all over the globe [3].

Electroencephalogram (EEG) is a noninvasive method which is used for recording the electrical activity of the brain over a certain period of time. Signals are collected by mounting a certain number of electrodes (e.g., 32, 64, and 128) on the scalp according to the standard montages [4]. It is used widely in various medical practices as an inexpensive tool for diagnosis/detection of neurological disorders and observing patterns in various medication conditions due to excellent temporal resolution as compared to other brain imaging techniques such as MRI and CT scan. However, the manual classification of an EEG signal is time-consuming and a resource hungry process. The Inter-Rater Agreement (IRA) among the neurologists on average is as low as 55% [5]. It depends upon subtle events like benign variants. Such kinds of ambiguities or asymmetries may lead to incorrect and conflicting interpretations of the same EEG signals.

Here is when machine learning (ML)/Deep Learning approachess for automatic electroencephalogram (EEG) signals analysis jump in. Due to high competition and lack of resources in medical services, especially in clinical diagnostics, this step for automation is very necessary.. EEG diagnosis is being used for neurological rehabilitation [8], diagnosing depression [9] and warning patients of any suspected seizures [10]. Feature extraction techniques for EEG analysis are inspired by speech recognition, and previous works have shown drastic improvements in the process.

We have used two deep learning models, Deep CNN and Chrononet. All of these models are trained on the MH NUST dataset with the annotated files obtained by our customized tool. The results obtained are thoroughly discussed in chapter 6.

Our solution is designed or developed in such a way that it can be broken down into two parts, namely

1. The research-based part which includes amending the approaches using machine

learning models to improve the accuracy in the field of EEG research and locate the abnormality if it is present in the EEG signal. A new dataset (MH-NUST) is used to aid the advances in automation of EEG analysis using the latest machine learning techniques.

2. The Annotation Tool which the EEG researchers can use to perform the following tasks
    - Perform Manual Annotation
    - Draw bounding boxes over desired EEG regions to get the details about that specific region of the EEG.
    - Extract Channel Names and time-stamps.
    - Export multiple labels into a csv file.
    - To Visualize the localized abnormal and normal region in different colors.

## 1.1 PURPOSE

Routine EEGs consist of either brief recordings lasting typically 15–20 min or long-term manual monitoring. This leads us to the EEG yield problem which proposes that the asymmetries of Neurological disorders are not guaranteed to be available or shown up in EEG data during a session. Just 50% of people who have epilepsy manifest interictal epileptiform discharges or IED in their first recording [6]. This leads to large amount of EEG data generation which needs to be explicated by well-trained investigators or Neurologists through visual inspection to obtain reliable results. Neurologists monitor changes in alpha, beta, theta and gamma frequency band to detect anomalies.

Low IRA (Inter-Rater Agreement) as well as the need for reaffirmation by taking more than one recordings for a patient makes it a strenuous process. Long term monitoring (LTM) may require recordings up-to 72 hrs to be monitored, 10 seconds at a time.
Scarcity of trained neurologists make it difficult for health care centers to afford this facility. The global median of the total neurological workforce (including; neurologists, neurosurgeons and child neurologists) is 3.1 per 100 000 population. While in low-income countries a median of 0.1 per 100 000 population is reported by WHO (World Health Organization) [7]. Therefore, a machine-learning based approach for automated EEG diagnosis could make the diagnostics process more widely accessible, can effectively reduce time and effort for clinicians so making diagnosis potentially more accurate.

## 1.2 Product scope

A new dataset named MH-NUST has been introduced to increase the diversity of existing datasets and to overcome the scarcity of accurately acquired public datasets for EEG research. We have compared the results of different models including Chrononet and Deep Convolutional Neural networks, Support Vector Machines on our newly released annotated dataset. We have also created an online web based Annotation Tool which is used to label the files and to visualize the abnormality. This tool is also publicly available and any researcher can use it for analysis of EEG signals in edf format.

## 1.3 EEG Acquisition

The EEG is recorded with the help of an EEG headset which consists of small discs made up of metals usually tin, gold, stainless steel, or covered with a coating of silver chloride. These small discs are put down on the scalp in special arrangements and positions. These special positions are decided according to the International 10/20 system. The placement of electrodes on the head is referred to as a montage. These montages define the signal between two electrodes by subtracting the adjacent channels. This gives the electrical signal residing between the two points. However, artifacts may be introduced by jaw movement such as chewing, or head bobbing.

The location of every electrode is labeled with an alphabetic letter and a numeric number. Alphabatic letter represents the area of the brain underlying particular electrode e.g. Fp denotes Prefrontal lobe of the brain, F denotes Frontal lobe, T denotes Temporal lobe of the brain, C denotes Central lobe, P denotes Parietal lobe, O denotes Occipital lobe, and A denotes Mastoid Process lobe of the brain. Similarly, even numbers and odd numbers represents the right and left side of the head respectively

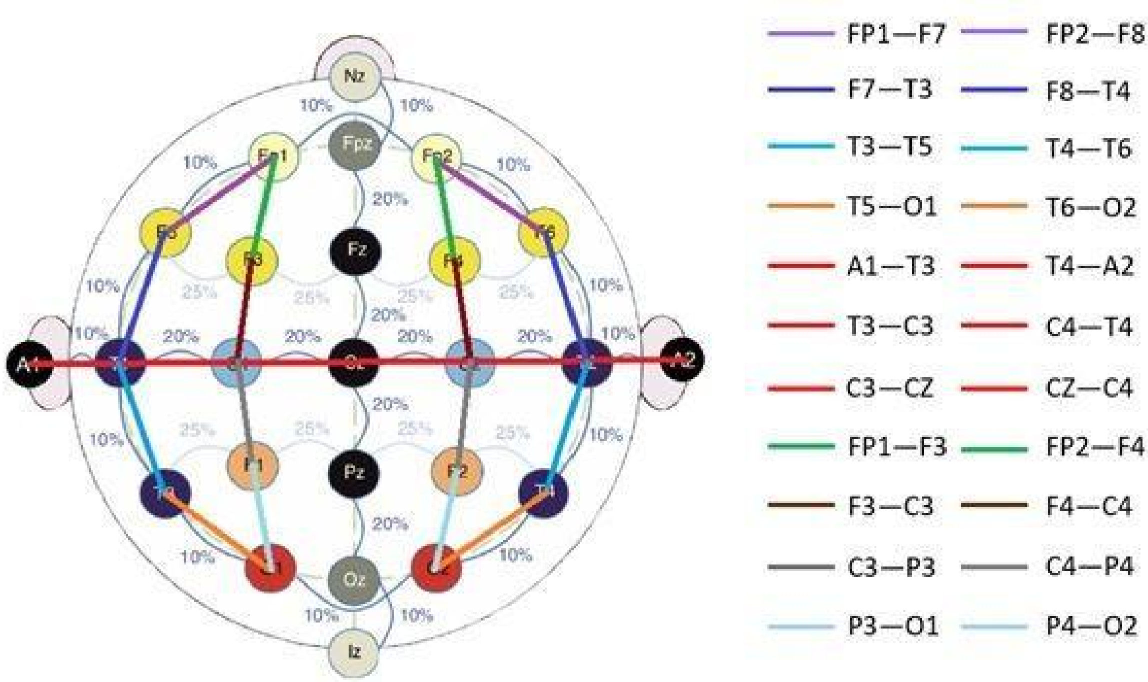



Figure 1. Standard electrode locations for a 10-20 system.

There are two general montages used within the TUH EEG database: (1) Average Reference (AR) and (2) Linked Ears Reference (LE) (Figure 2). The AR montage uses the average of a certain number of given electrodes as the reference electrode position, whereas LE montage uses the (side) electrically quiet ear electrodes as reference.

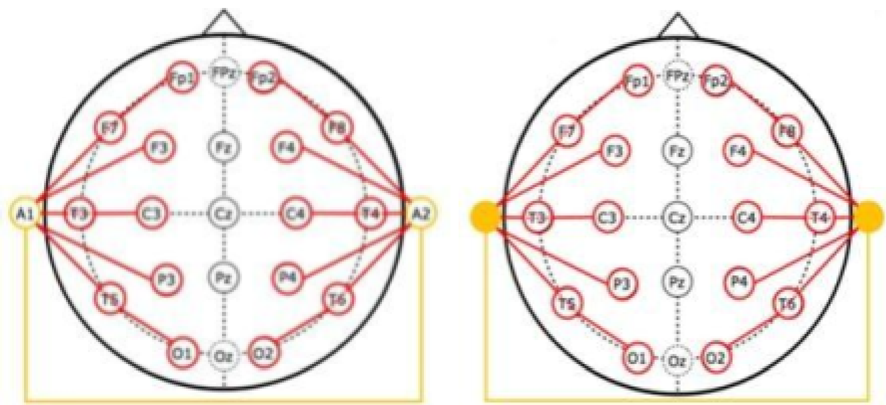



Figure 2. Location information of the electrodes for two montages found in the TUH EEG Corpus: AR (left), LE (right)

## 1.4 OUTLINE OF THE REPORT

This report comprises eight other chapters, each of which focuses on a specific portion of the final year project.

The first chapter explains the unmet need of the society, project's purpose, scope and the customers it targets.

The second chapter explains all the previous research work that has been put into this work and a background knowledge of the related work that has been done and published as journals, papers, websites etc.

The third chapter defines the problem statement in detail, providing all the technical difficulties and problems faced and what solution is being provided in this regard.

Chapter 4 provides the solution to the problem and what methodology has been adopted in developing that suggested solution.

Chapter 5 states all the design constraints and the architecture adopted for developing the solution. This will help the readers to understand the technicalities of the project in a much better way.

The sixth chapter provides the readers with all the implementation and testing details along with the screenshots of the actual implementation and testing done on the application being developed.

Chapter 7 discusses all the results obtained from the implementation and how they are in accordance to the original objective of our project.

The eight chapter discusses all the future aspects and work that can be done to further improve this system and maintain it.

*Chapter 2*

# LITERATURE REVIEW

The prolonged process of EEG diagnosis and lack of neurologists available in Pakistan, the ultimate best solution is to automate this resource-hungry process. Our research provides an automation of the EEG diagnosis. The EEG signal is passed through different classifiers which then classify the signal as either normal or abnormal and can perform temporal localization upto 3 seconds. The automation process also helps to locate the abnormality in the EEG signal. EEG diagnosis can be helpful in improving neurological rehabilitation [8], diagnosing depression [9] and warning patients of upcoming seizures [10]. Many feature extraction techniques inspired by speech recognition are also applied for EEG analysis.

When we look at the earlier stages of this research field, Lopez in [13] concentrated on the TUH EEG Corpus for evaluation purpose and the channel they have used for their study is differential measurement of two electrodes i.e, T5 and O1, which includes in the TCP montage. In this study, they only took the first 60 seconds of the EEG recordings for the feature extraction process. The extracted features use a standard approach which is cepstral coefficient-based and is more similar to Mel Frequency Cepstral Coefficients (MFCCs). MFCCs support feature extraction in 2D array based input signals similar to speech data for the task of speech recognition [23]. First eight cepstral coefficients are used for this process after discarding the 0th coefficient. These features are augmented with a differential energy component giving a 9 dimensional feature vector. Principal Component Analysis, PCA [24] is used to reduce the dimensionality of this feature vector. Research is done for different values of k while the best kNN system was approximately 60% accurate. This suggests a need for improvement as it is not practical to introduce such a low accuracy system for such a serious issue.

In further stages, HMM [11] is adopted by Lopez in [1]. and MFCC in [12] [13] for EEG pathology detection to publish a baseline on feature based classification. After getting their features using MFCCs and applying PCA for feature reduction the same features are fed to the Random Forest. Ensemble and the results are obtained for different numbers of trees. The results for Nt = 50 are shared in their research paper which shows an improved accuracy of 68.3%. Despite the fact that it is a good improvement but still it is not a practical system, there is a lot of room for improvement.

Similarly, Convolutional Neural Networks (CNN) after acing image related tasks, have successfully been adopted for brain computer interface in [14] [15]. Two Popular CNN models AlexNet [16] and VGG [16] are fine tuned by Alhussein on the public dataset - TUH after conversion to frequency domain and filtering [17] to achieve 89% accuracy, 78% sensitivity and 94% specificity. But the problem that rises is that their experiments are neither open source nor fully explained. Leeuwen extended Schirrmeister's work on a private dataset of 8522 regular EEG recordings from Massachusetts General Hospital. This dataset promised utilizing age and sleep stage only to improve slightly [18] i.e. 81% (reproduced on Deep CNN) to 83%.

TABLE I. Related works on pathology decoding using TUH Abnormal EEG Corpus. All approaches rely on ConvNet architectures. Only chronologically oldest publication used handcrafted features. Publications marked with $*$ used pretrained models and additional training data. Publication marked with + did not use TUH Abnormal EEG Corpus.

| Automated Diagnosis | Architecture | Accuracy |
|---|---|---|
| Lopez de Diego (2017) [13] | CNN + MLP | 78.8 |
| Schirrmeister et al. (2017) [14] | Deep CNN | 85.4 |
| Roy et al. (2019) | [19] | 86.6 |
| Amin et al. (2019)$*$ [20] | AlexNet + SVM | 87.3 |
| Alhussein et al. (2019)$*$ [17] | 3 x AlexNet + MLP | 89.1 |
| Van Leeuwen et al.+ (2018) [18] | Deep CNN | 82.0 |

We compare results with the MH-NUST dataset on shallow and deep CNNs [19] and Chrononet [20] . We validated Deep Convolutional Neural Network adopted from Schirrmeister [19] to learn representations for overlapping crops of EEG recording in spatio-temporal representation, followed by an LSTM on sequence of these representations to classify EEG into abnormal or normal. Using the TUH Abnormal Corpus, a sensitivity of 0.83 and specificity 0.87 is achieved, using this technique for removing the need for use of pseudo-labels assigned to crops as used in earlier works [19]. This way distance from clinically accepted sensitivity of 0.90 and specificity of 0.95 is reduced. Further, the model is trained and tested on MH-NUST localized dataset to compare the results of public dataset with local health care center i.e MH Rawalpindi to observe training accuracy of 80.54% on unlocalized dataset and 87.07% with localization

*Chapter 3*

# PROBLEM DEFINITION

EEG diagnosis is a time-consuming and resource hungry task which requires neurologists to constantly observe the patterns in the EEG signal to diagnose any abnormality. There are only 150 neurologists in Pakistan according to [25]. According to this report, 33% of Pakistani population above the age of 45 years are estimated to be suffering from hypertension. Around one-third of them were unaware of their disease. Dr. Wasay in this report said that the burden of neurological diseases in developing countries, including Pakistan, was increasing due to rising life expectancy, urbanisation of population and better diagnostic facilities. Mapping of EEG signals is non-trivial and replicating human analysis has a number of challenges to overcome before it is commercially accepted. EEG signals are noisy and also suffer from channel cross-talk. EEG signals not only have low signal to noise ratio but also high interpersonal variability. EEG signal varies from time-to-time depending on age, sleep-stage, medication and other unclear reasons. High dimensionality of the data makes it computationally challenging to design an end-to-end solution. Thus, this time-consuming process must be automated to reduce the burden off of neurologists who have low IRA as well.

The datasets available publicly are from developed countries, with state-of-the-art equipment. Hence, there is a need for EEG datasets from developing countries like Pakistan. This would help observe the trends of neurological diseases in such countries. So, we are publicly releasing a properly curated new dataset with age and gender labels, to aid the on-going research in the field of automated EEG analysis.

EEG yield problem is one of the important points covered in our research. EEG yield problem states that the asymmetries of Neurological disorders are not guaranteed to be available/present in EEG data recording. Just 50% of people who have epilepsy manifest interictal epileptiform discharges or IED in their first recording [6]. So, such a phenomenon leads to the large amount of data generation for manual interpretation by experts Neurologists.. Neurologists monitor changes in alpha, beta, theta and gamma frequency band to detect anomalies. EEG is usually manually and visually inspected which is a highly time-consuming as well as a  resource hungry process.

A platform where an EEG signal could be identified as normal or abnormal upto 3 seconds temporal localized window, to perform an initial screening for the neurologists is much needed. This platform would help to classify live acquisition of EEG data in real-time

Moreover, the accuracy for machine learning models to classify a sensitive piece of information on which a person's life is dependent, must be improved. In this case, state of the art machine learning (ML) models are looked into. And with experimental amendments, sensitivity and accuracy are relatively improved along with temporal localization.

*Chapter 4*

# MATERIAL AND METHODS

## 4.1 DATASET

A major hurdle in machine learning (ML) models development for different medical applications is the lack of large datasets available to the research community for supporting training of deep learning models. We introduce MH NUST Dataset for this purpose. It includes the prescription from neurologists and demographic information about all the patients such as age and gender along with annotated files in csv format to represent abnormality in small regions. However, we believe that the diversity of datasets is vital to enhance the research opportunities in automation of EEG diagnosis. This is the reason to introduce MH-NUST to the researchers.

Most EEG datasets available are from developed countries, from hospitals and labs generally equipped with state-of-the-art, well-maintained test equipment, rigorous training of medical staff, and continuously updated procedures. Pakistan, being a developing country, lacks in one or more of these areas. Thus, an EEG test conducted in a hospital in Pakistan could possibly have shortcomings that are not present in a test conducted in a developed country. With a load of 1 trained neurologist for a population of 1 million, Pakistan is critically short on experts who can read and interpret EEG reliably. It is thus of paramount importance that an automated screening system be developed which is capable of separating pathological from healthy recordings. Any system developed for this purpose must be tested on a dataset that is acquired under use-case conditions, with all the possible shortcomings and artifacts of the testing setup. This dataset is acquired in a hospital which has a good reputation, and none of the shortcomings and artifacts, if any at all, have been artificially introduced in the dataset. This makes it a representative dataset of recordings that a neurologist would come across in a decent hospital of Pakistan.

### 4.1.1 MILITARY HOSPITAL DATASET

A database of 2500 routine EEGs from the Department of Neurology in Military Hospital Rawalpindi was collected from 2016 to 2020. The raw signals obtained from the recordings varies in channel numbers from 20 to 128, sampled at 250 Hz frequency. The Partners Institutional committee approved anonymous analysis of the EEG dataset without requiring additional consent for its use in this study. All EEG recordings uses the standard international 10–20 EEG system. Recordings consist of Aver-age referenced channel signals in European Data Format (EDF) exported from a proprietary eeg format using available utility. There is an average of 15 minutes of EEG data per recording while the age of patients is 24 years on average (see Fig. 4). The label "normal" or "abnormal" is assigned by trained neurologists and used as target labels for each small region to be predicted for our study. EEG files are annotated using our customized Online Web Based tool by trained neurologists and corresponding csv files are exported. Subject characteristics are summarized in Table II. MH Abnormal corpus represents an accurate characterization of clinical conditions.

TABLE II. Socio-demographics of MH Dataset

| Age | Files |
|---|---|
| $<$ 1 year | 148 |
| Between 1-5 year | 356 |
| Between 5-12 year | 411 |
| Between 13-50 year | 1421 |
| Between 51-90 year | 325 |

| Gender | Files |
|---|---|
| Female | 886 |
| Male | 1775 |

TABLE III. MH Abnormal corpus 1.0.0 Statistics

| MH Abnormal EEG Data | Abnormal | Normal |
|---|---|---|
| Train | 410 | 1905 |
| Test | 90 | 95 |


Fig. 3. Gender distribution in MH Abnormal

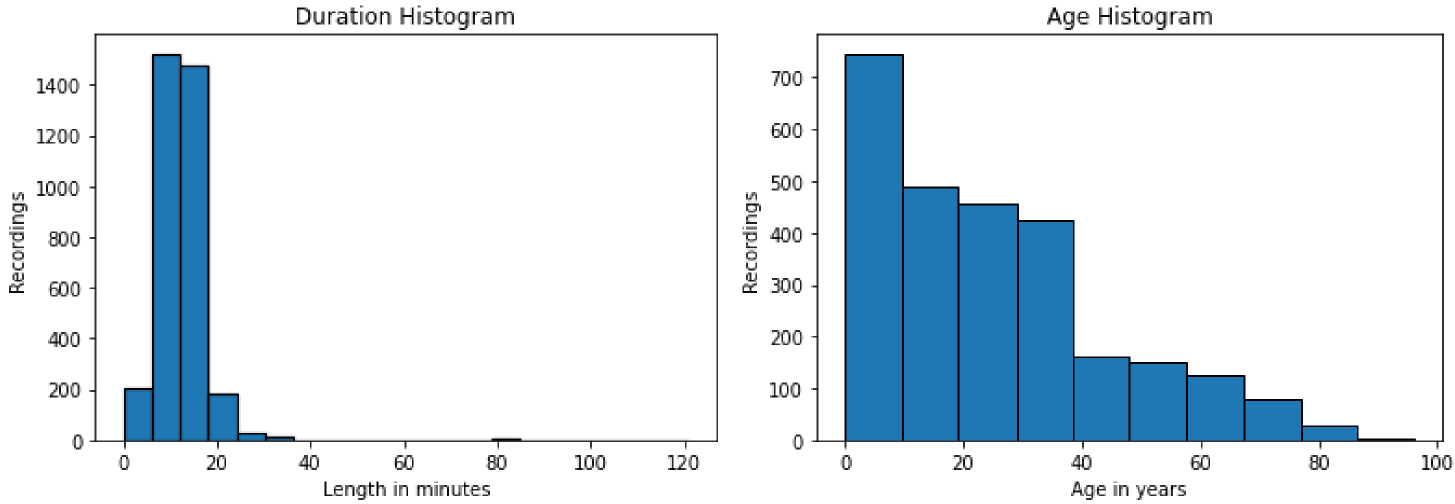



Fig. 4. Number of files in MH dataset for different lengths of recordings in minutes and age group

An imbalance between two classes in MH dataset can be observed in table III. This is a reflection of the clinical situation in neurology practice. We use oversampling from abnormal classes during training for solving the problem of classification bias.

## 4.2 EXPERIMENTS

We evaluate two models i.e Chrononet and Deep CNN on localized MH dataset which proves the dataset variability problem. So we fine-tune the model trained for MH data to study the effect. We also attempt to reproduce Chrononet (roy et.al 2019) results followed by evaluation on MH dataset. Finally we use a novel technique in an attempt to solve the EEG Yield problem which involves features from Deep CNN to make a sequence of crop features. These sequences are classified using LSTM. The preprocessing and design choices for models are discussed in detail in this chapter.

### 4.2.1 Data Preprocessing

### 4.2.2 Channel Selection

Researchers suggest that some electrodes play a greater part in decision making for particular tasks, for example T5_O1 of Temporal Central Parasagittal(TCP) was selected by Obeid et.al(2017) for feature extraction due to better performance on detection of abnormal EEGs. Similarly changes in Delta and Theta bands in temporal channels are found effective by Schirrmeister et.al(2018) in perturbation visualizations. However, the end-to-end training model is expected to learn these relations from the dataset. Montage is kept the same throughout the dataset for consistency and 21 average referenced channels are used for CNN models so the results are comparable with Schrimmeister et. al(2017) and 22 TCP channels are used for the chrononet model for similar analysis.

### 4.2.3 Neural Network Architecture

We used different neural network based deep learning architectures including deep ConvNets and Chrononet to detect the abnormality from the EEG recordings. Firstly, we used a four-layered deep ConvNet architecture called Deep CNN as already introduced by Schirrmeister et al. (2017). The BD-Deep4 neural network based architecture [Figure 5] has an initial separated convolution where the first layer is temporal and other one is spatial. It is a rather general architecture and has already proven to generalize well for several other EEG decoding tasks such as motor imagery decoding(schrimmeister et.al, 2017).

#### A. Deep and Shallow Convolutional Neural Network (CNN)

Deep and shallow CNN architecture of convnet provided state of the art accuracy on EEG analysis e.g. decoding information from EEG. The performance of deep and shallow ConvNet which is end-to-end trained is relatively comparable to that of those algorithms where hand-engineered features are extracted first. While Deep CNN is generic, shallow CNN is tailored to learn band-power features. Braindecode(BD)

[21] by Schrimmeister et.al includes detailed implementation of both architectures. The authors used spatial filters followed by temporal filters which in case of shallow CNN are

equivalent to filter bank common spatial patterns (FBCSP)(Ang et al., 2008). Alternating layers of convolution with pooling layers are used like most EEG classification models and exponential linear units are used as activation functions. Maximum overlapping crops are used for capturing time dependencies.The ConvNet parameters are optimized using stochastic gradient descent with the Adam optimizer. Cropwise training (Schirrmeister et.al, 2018) forces models to learn the anomalies rigorously and have shown to be effective by the authors. We have trained these deep and shallow cnn models on our NUST-MH dataset

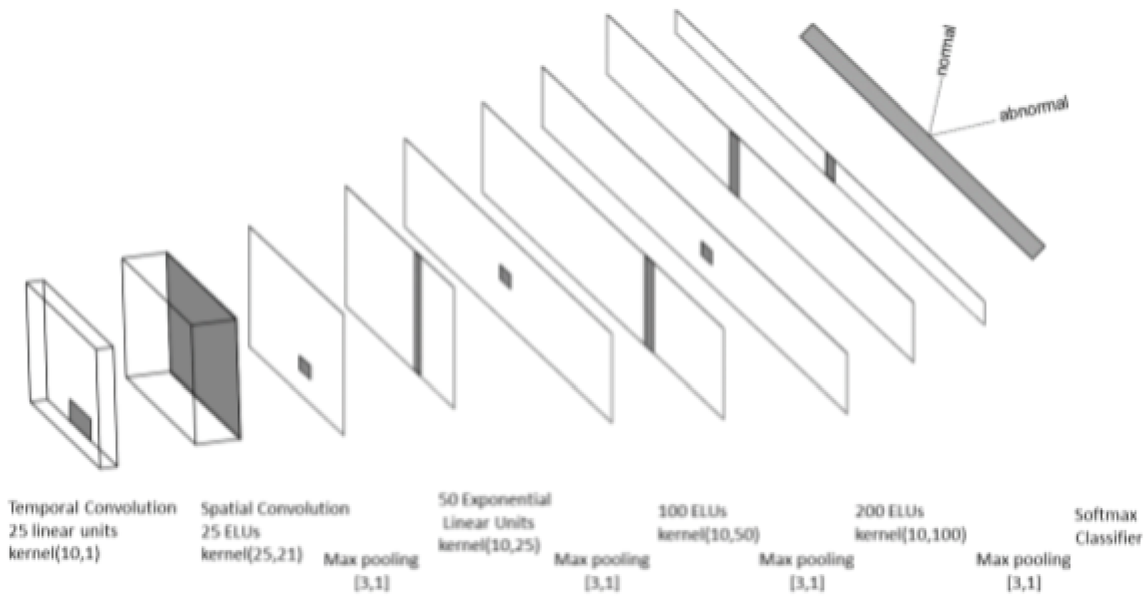



Figure 5. Deep ConvNet architecture with four conv-pool Block

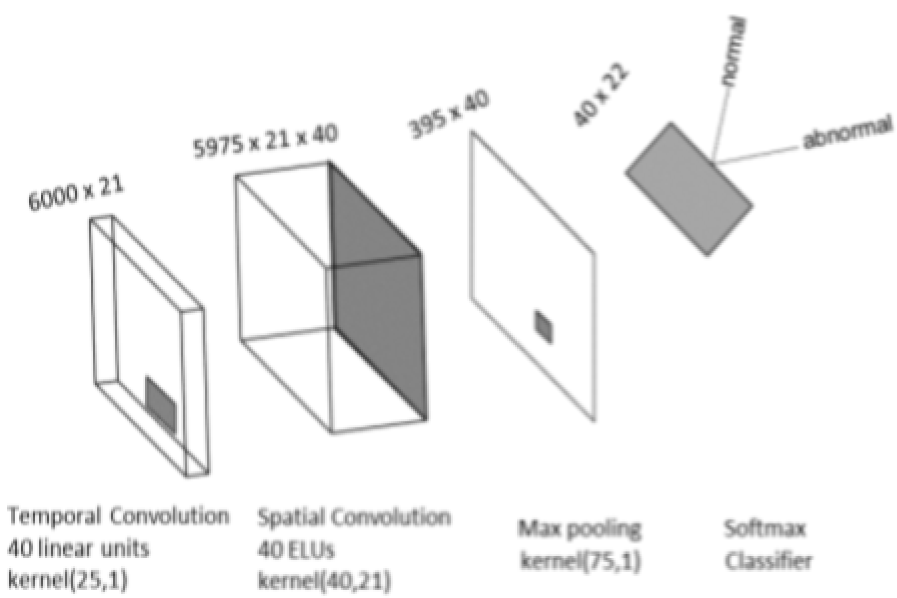



Figure 6. Shallow ConvNet architecture with one conv-pool Block

without localization and then with our localize data to see improved performance in terms of abnormality detection.

### B. Chrononet Architecture

Chrononet is a deep architecture which uses recurrent neural networks (RNN), inspired by the state of the art image classification techniques and is designed in such a way it works efficiently with EEG signals data. It uses inception layers along with given exponentially varying kernel lengths for 1 dimensional convolutional layers along with densely connected recurrent layers.

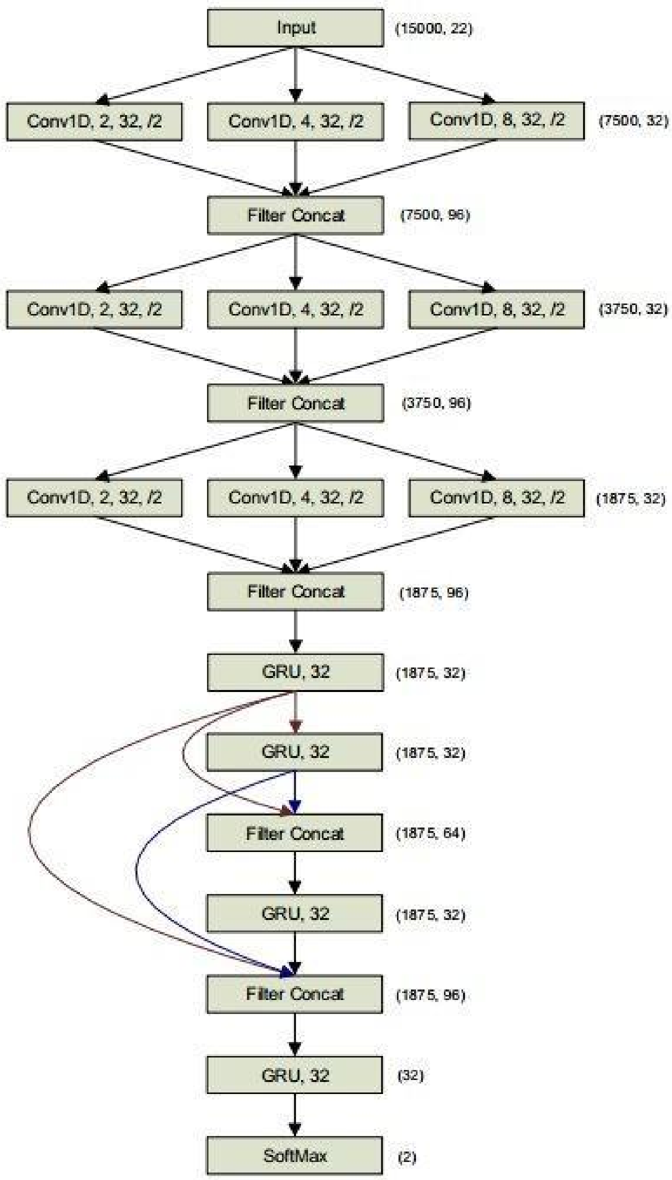



Figure 7. Chrononet: Densely Connected Gated Recurrent Neural Network based architecture

We trained Chrononet on max-normalized multichannel EEG signals as 2D matrix after converting average referenced recordings of NUST-MH dataset to Temporal Central Parasagittal(TCP) montage shown in figure 1 to reproduced result on dataset augmented by using the technique proposed by authors [19]. We reproduced the results to achieve accuracy of 81%, compared to reported 86% [19]. Then, temporal localization was performed upto 3 seconds and the model is trained with localized data to get improved results along with temporal localized abnormality detection.

*Chapter 5*

# IMPLEMENTATION

## 5.1 TOOLS AND TECHNOLOGIES

The tools used for this project are as follows:

1. HTML/CSS
2. JavaScript
3. PyTorch and Keras
4. Torchvision
5. Numpy
6. Braindecode
7. MNE
8. MATLAB
9. Tkinter

**HTML/CSS** are used for front end development of visualization tool, it dictates how the elements will appear on the webpage.

**Javascript** is used to make the web application dynamic and create interactive and a better experience for the user.

**PyTorch**, **Keras**, **Torchvision**, **Numpy**, **Braindecode, mne** and **Pillow** are the python libraries that were used for development of the deep learning model.

**Matlab** is used for some pre-processing of all EEG files to clean the data.

**Tkinter** is used for creating GUI for generating predictions

### 5.1.1 IMPLEMENTATION

#### 5.1.1.1 Annotation Tool

The annotation tool is designed to let the users to label the EEG files which are present in the edf format. At first, the user uploads the file. The uploaded file then can be seen on the screen. The user can use multiple features that comes within this tool. Some features of this tool include uploading the file, getting information about the signal by draw bounding boxes, commenting about the abnormality, saving the file etc. The complete guide to this tool is explained in the steps mentioned below.

#### 5.1.1.2 A WALK-THROUGH THE ANNOTATION TOOL

Annotation tool is a tool that is used to label the data files. A screenshot of the tool is shown in the figure below.

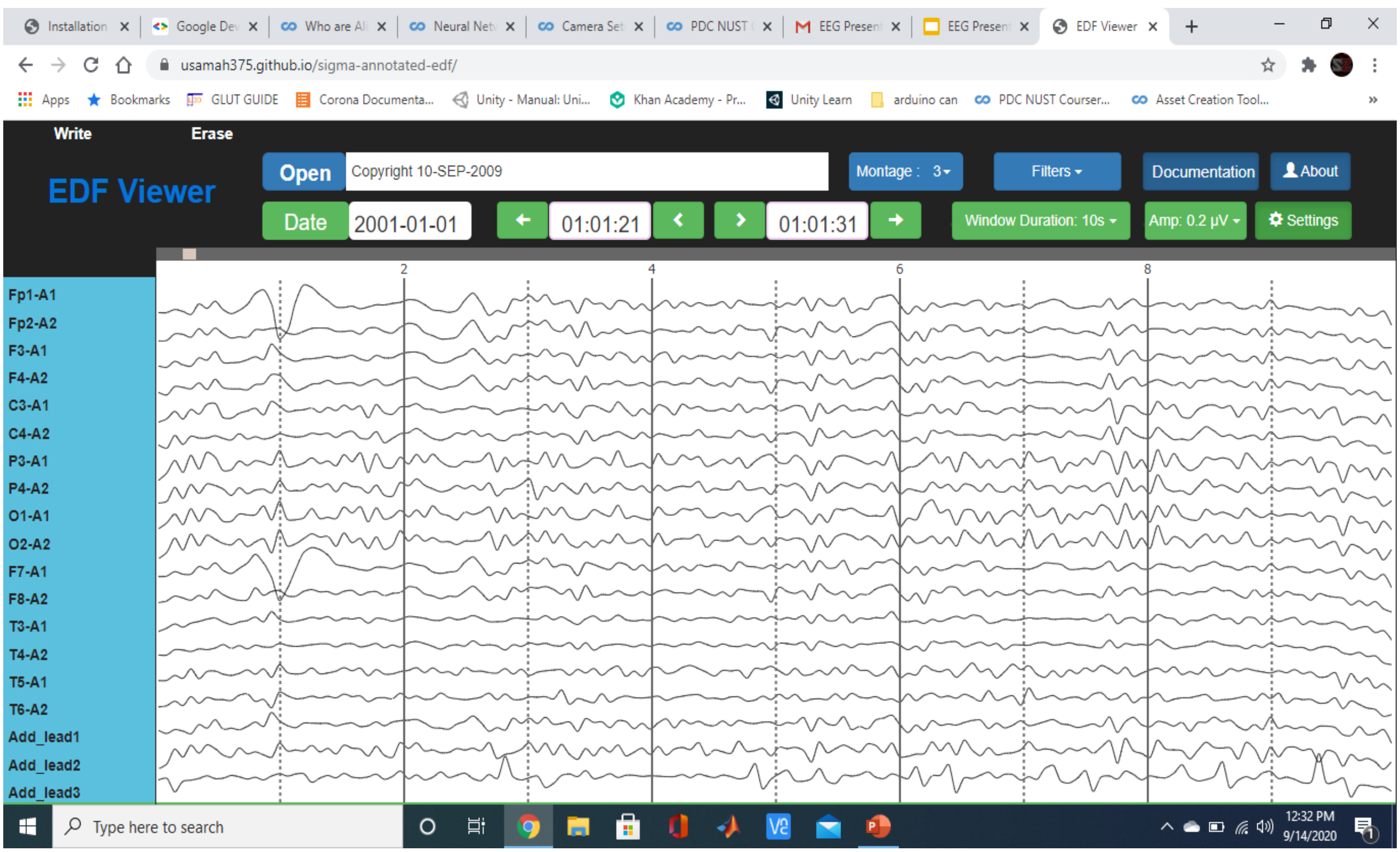



Figure 8. Annotation Tool

The user can select the edf file by clicking on the open tab. It is shown in the following image.

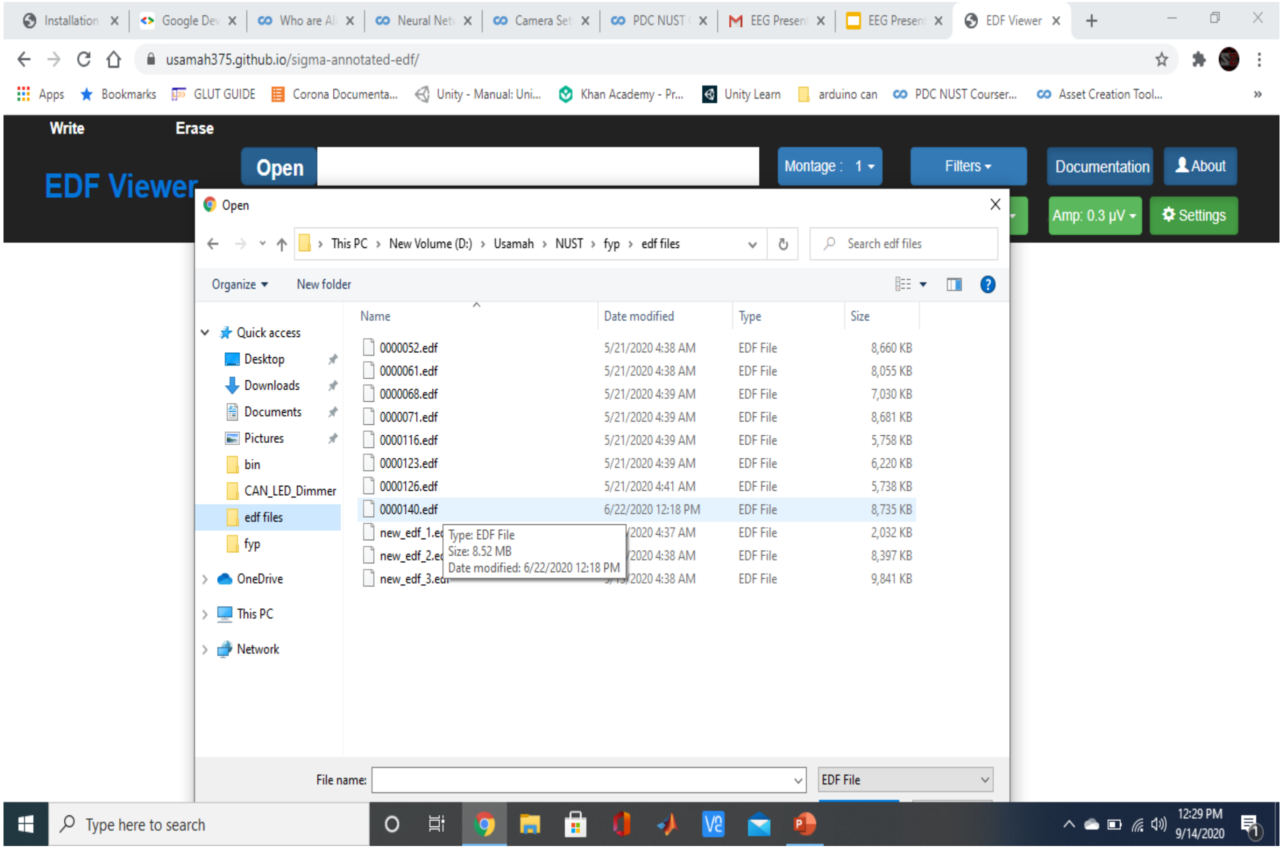



Figure 9. Open File

The user can set the start time of the EEG signal file (edf file) if that is needed. This process is explained in the image shown below.

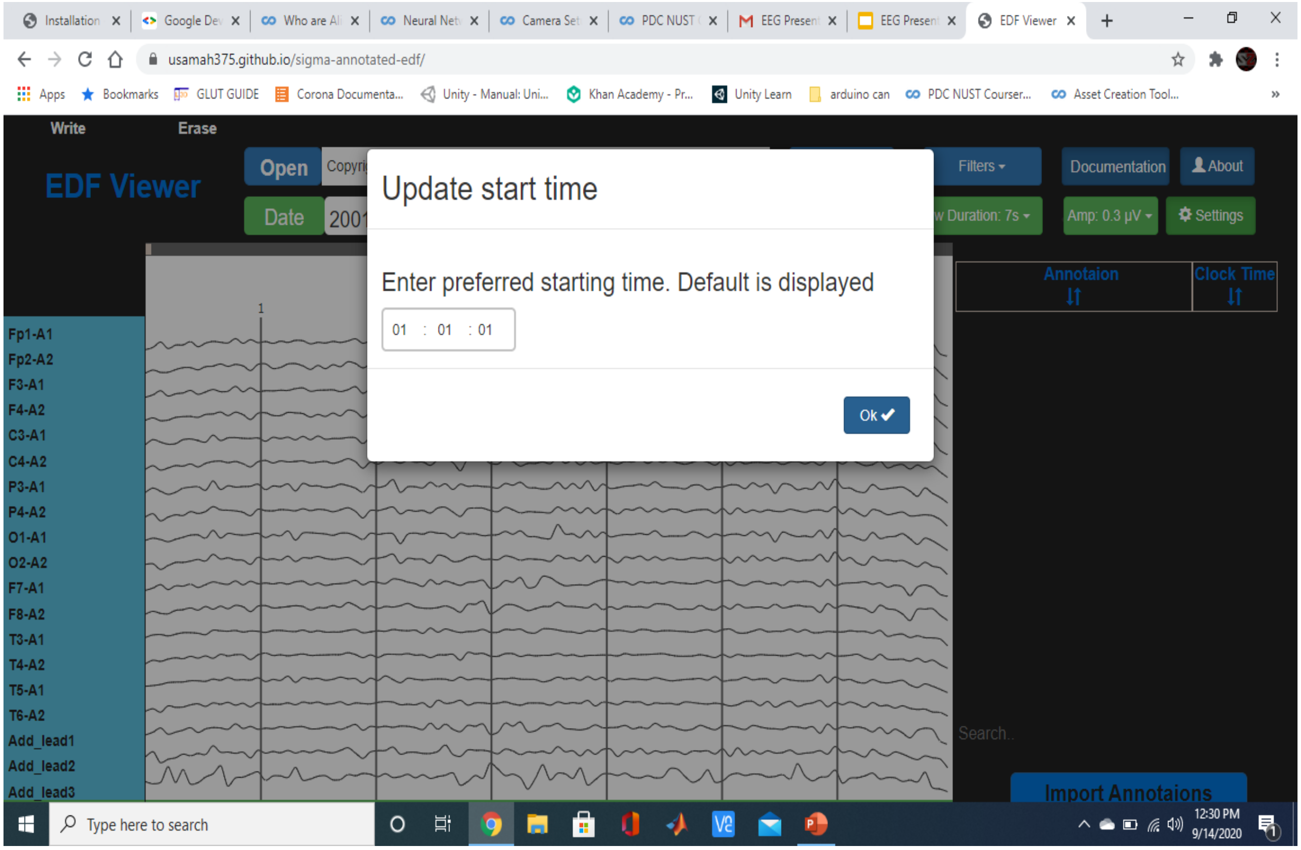



Figure 10. Set Custom Start Time

The user can also draw bounding boxes around the EEG signal with the help of our mouse. If the user drags the mouse click over a certain area of our EEG signal, he will be able to see the details of the selected EEG signal in that certain region. Below is the image which shows this feature of the tool.


Figure 11. Drawing bounding boxes with mouse

The user can comment about the abnormality while labelling the EEG signal. The image shown below explains this step.

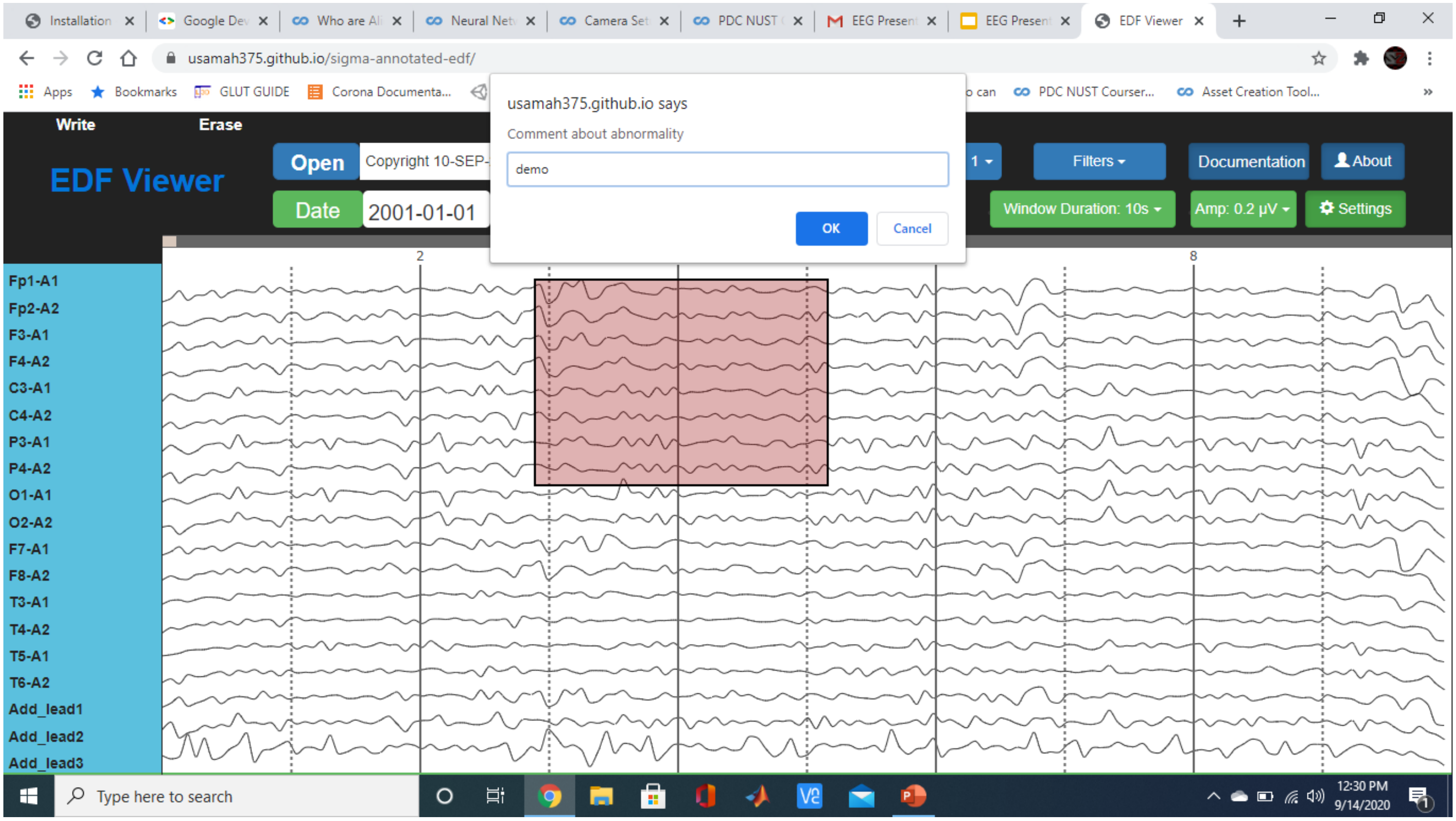



Figure 12. Commenting the Abnormality

The user can adjust the parameters of the EEG signal by clicking on the write button available in the tool. Shown below is the image to describe this process

.

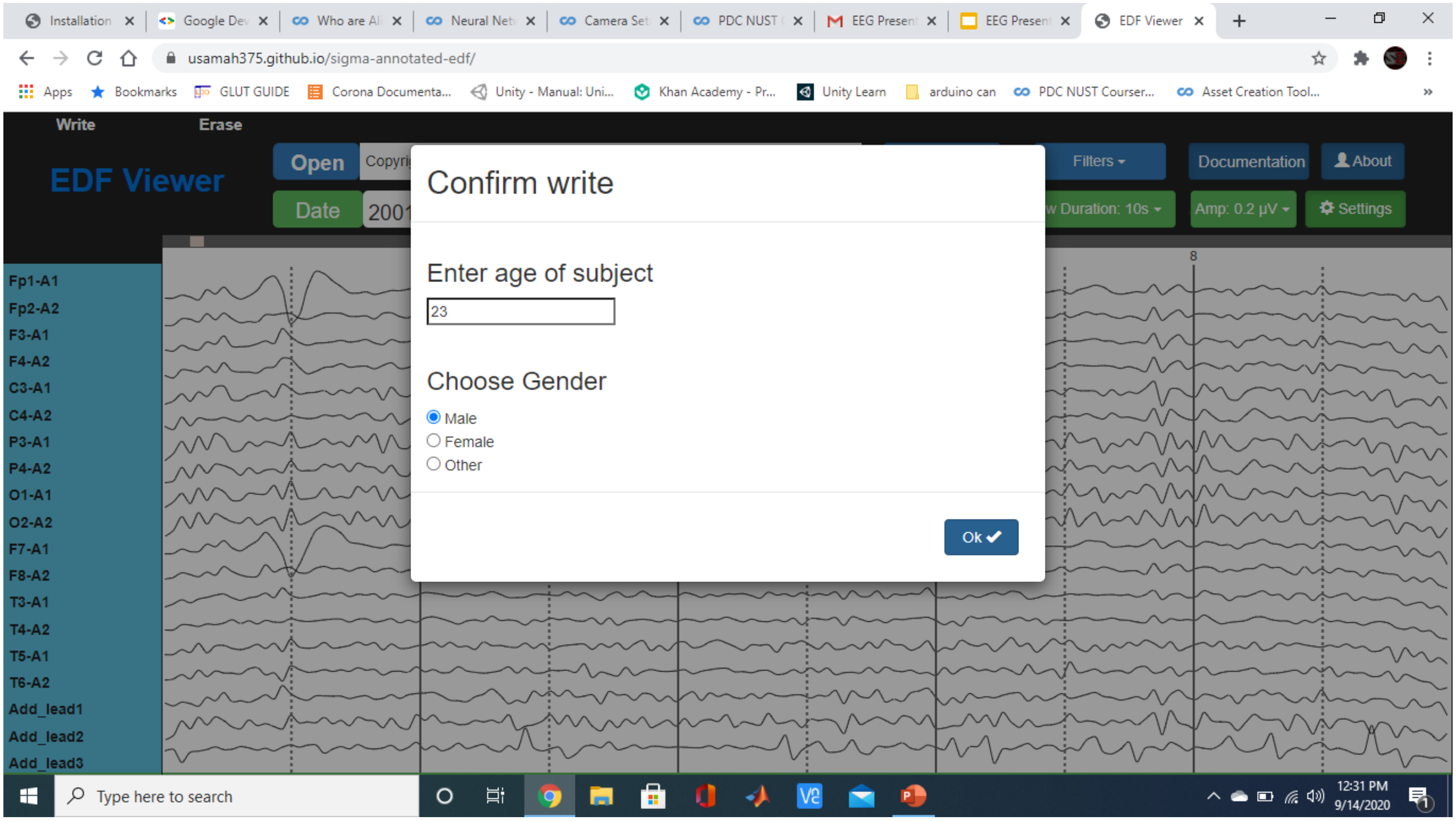



Figure 13. Adjusting the Parameters

Finally, the user can save the file and the saved files can be shown in the images below.

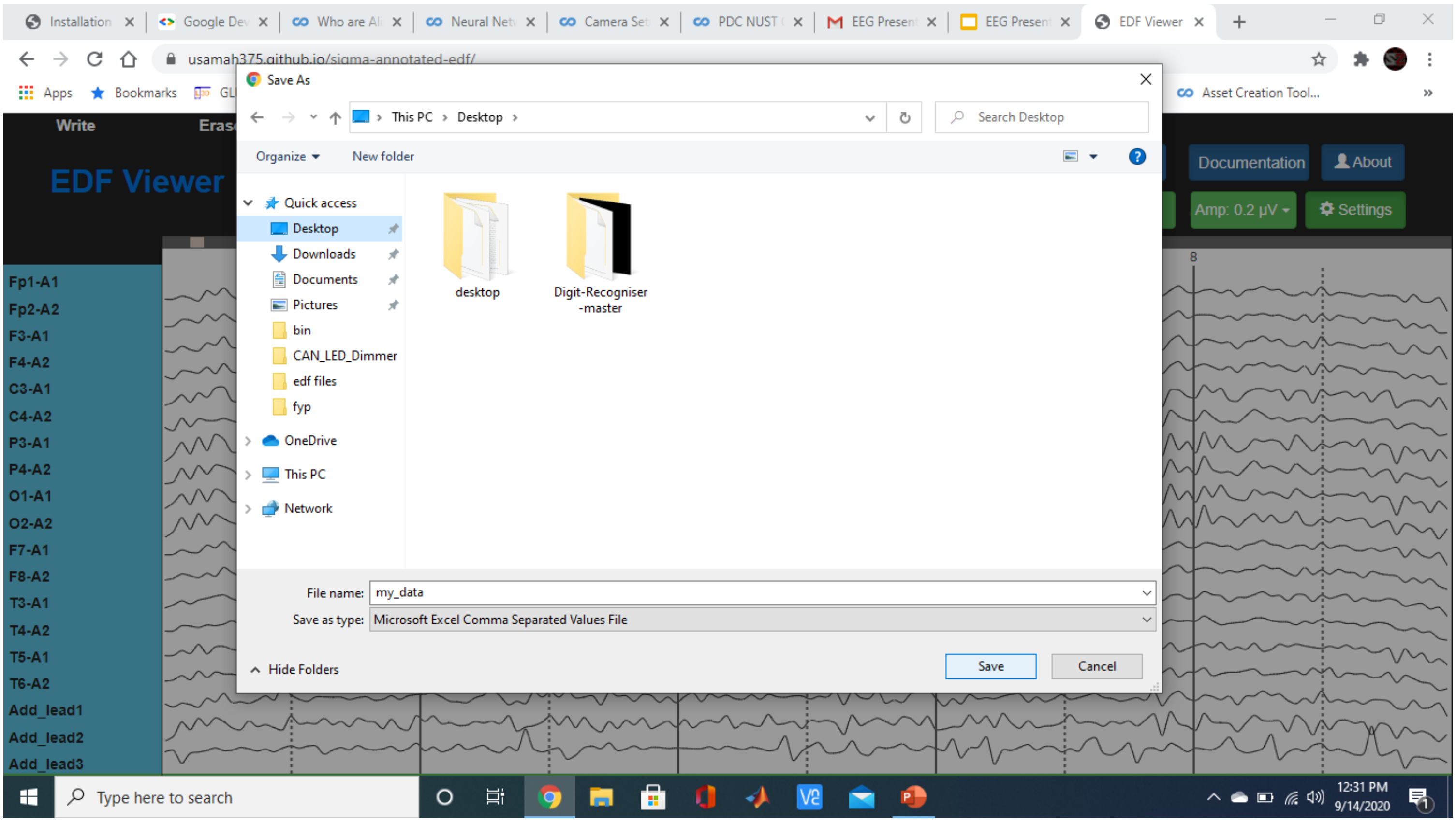
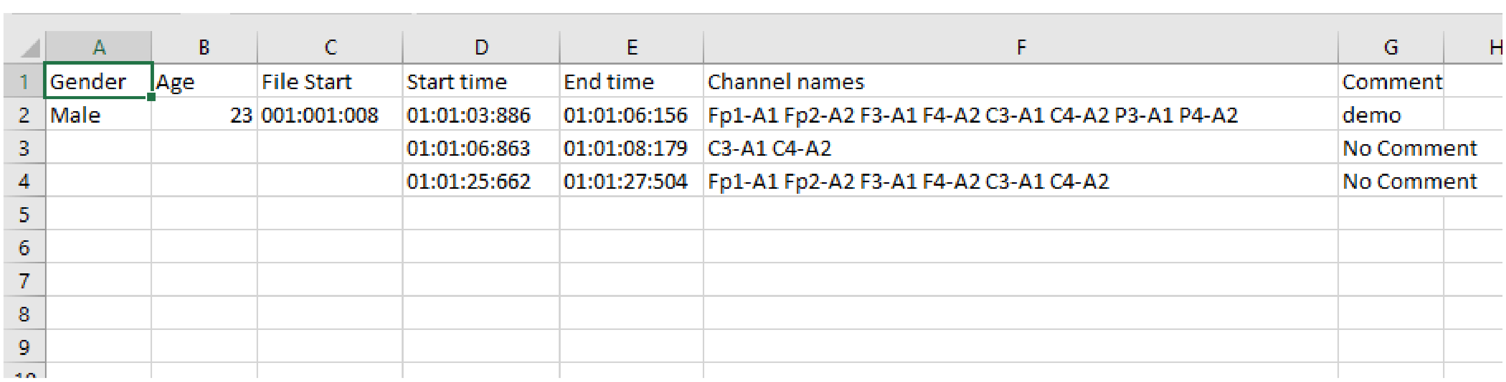



Figure 14. Saving a File



| | A | B | C | D | E | F | G | H |
|---|---|---|---|---|---|---|---|---|
| 1 | Gender | Age | File Start | Start time | End time | Channel names | Comment | |
| 2 | Male | 23 | 001:001:008 | 01:01:03:886 | 01:01:06:156 | Fp1-A1 Fp2-A2 F3-A1 F4-A2 C3-A1 C4-A2 P3-A1 P4-A2 | demo | |
| 3 | | | | 01:01:06:863 | 01:01:08:179 | C3-A1 C4-A2 | No Comment | |
| 4 | | | | 01:01:25:662 | 01:01:27:504 | Fp1-A1 Fp2-A2 F3-A1 F4-A2 C3-A1 C4-A2 | No Comment | |
| 5 | | | | | | | | |
| 6 | | | | | | | | |
| 7 | | | | | | | | |
| 8 | | | | | | | | |
| 9 | | | | | | | | |

Figure 15. Saved File

Visualizing predictions generated by model:

The prediction scripts output a CSV file containing start and end time for windows of local anomalies for the EDF file passed to it. These, coupled with our modified EDF Viewer can be used to visualize the predictions of our model.

Upload .csv file generated by prediction script:

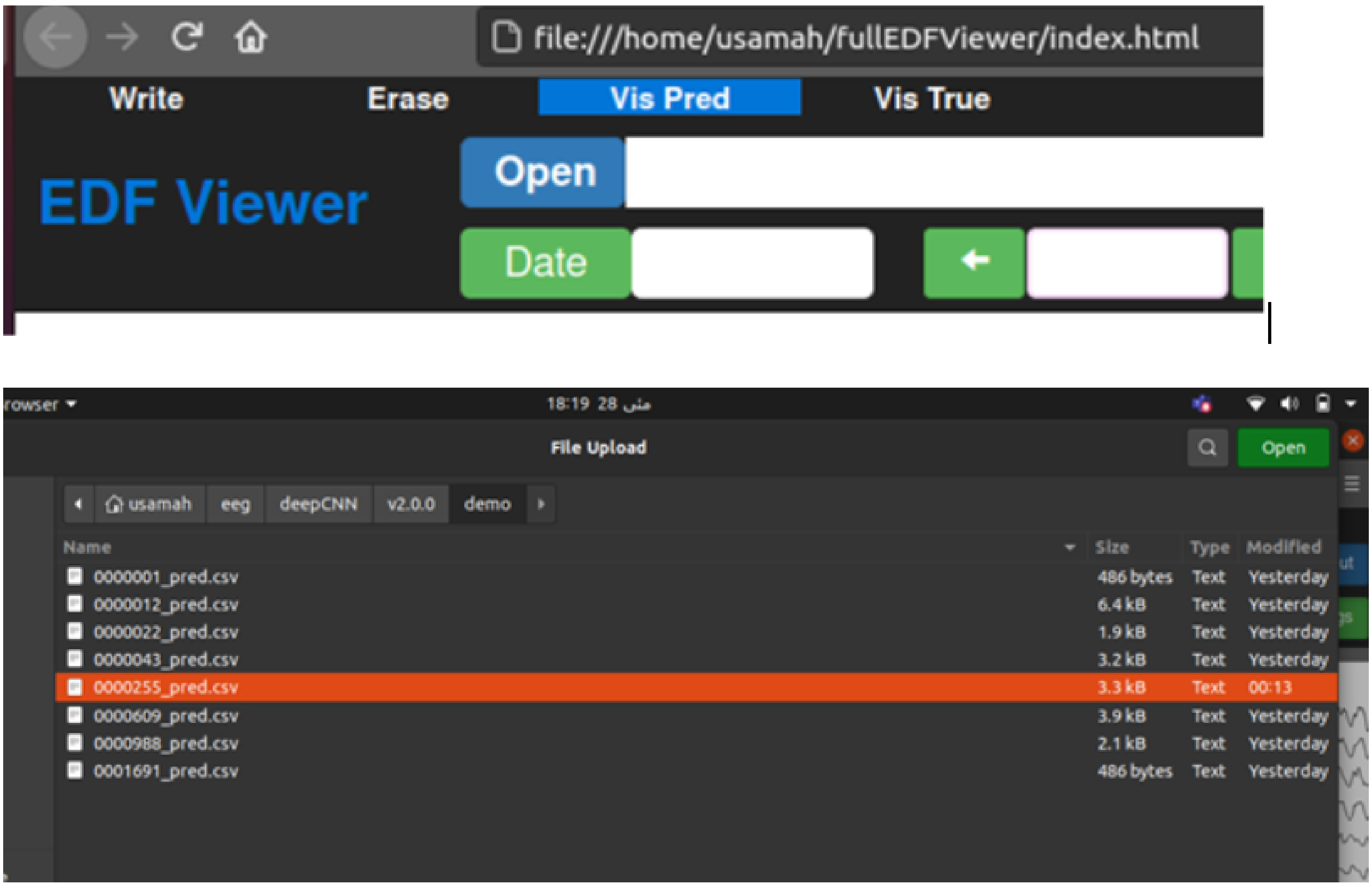



Figure 16. Uploading predictions in csv format


Figure 16. Showing predicted abnormality region

The regions in red represent localized anomalies predicted by our model

If true labels i.e. annotations by expert are available, these can be simultaneously visualized in the Viewer

Upload .csv file containing actual anomalies:

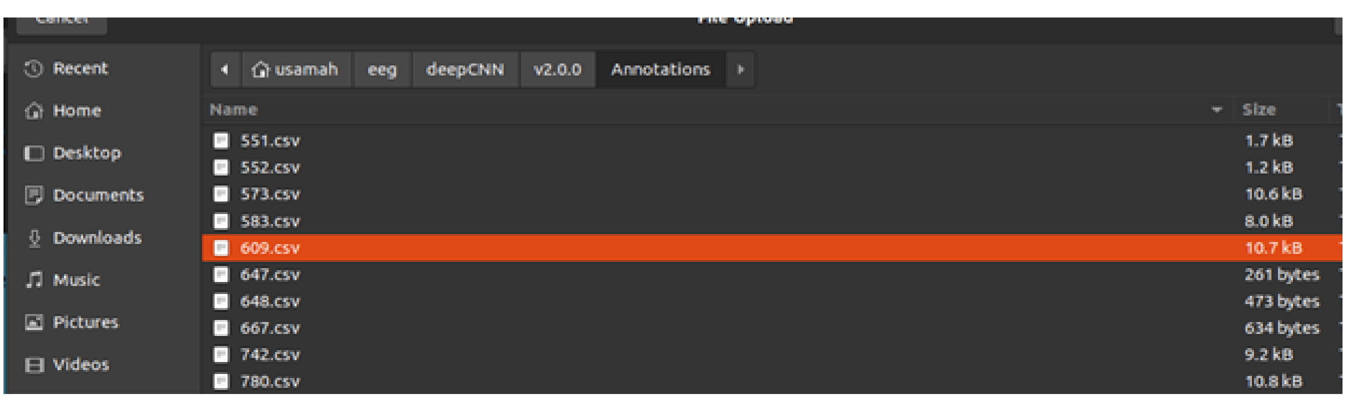



Figure 17. For Uploading True Labels

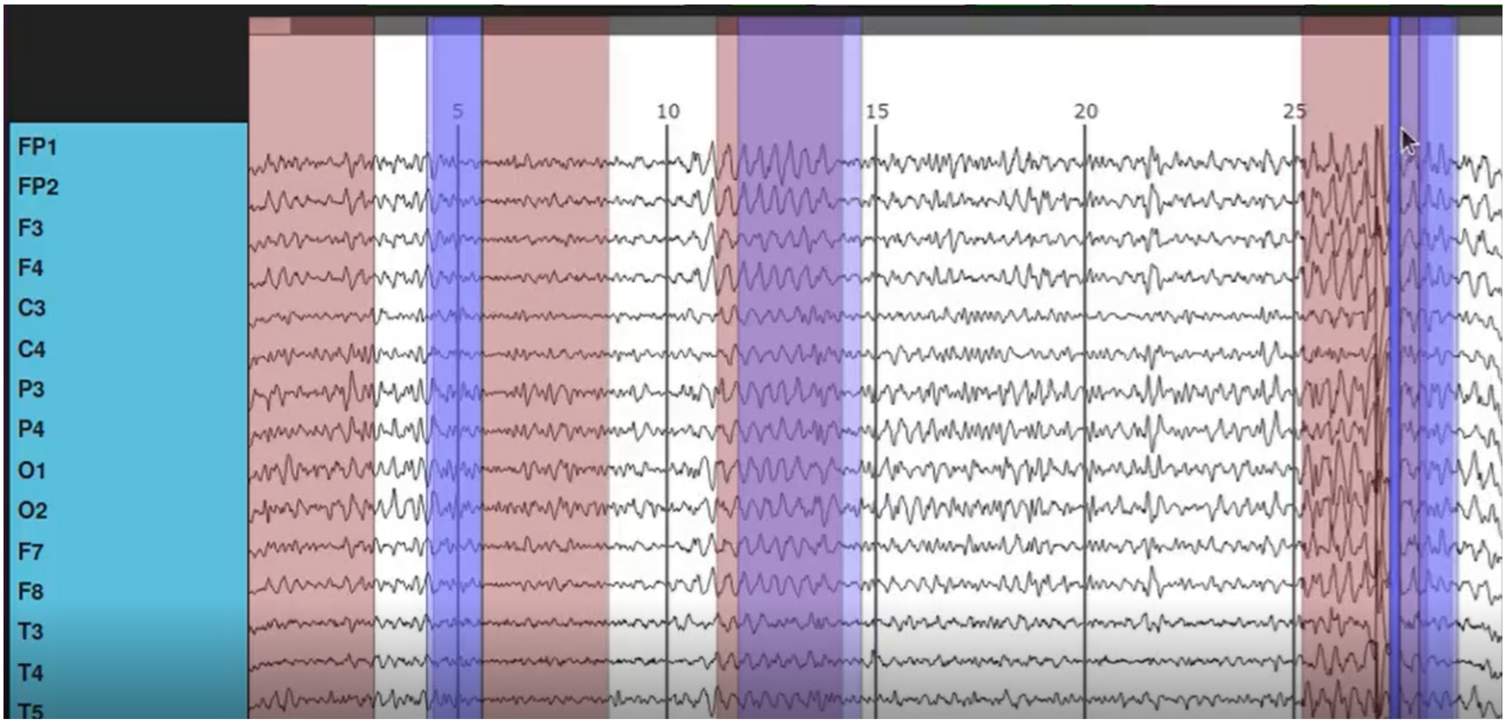



Figure 18. Showing predicted and actual abnormal regions

The regions in blue represent localized anomalies labelled by the expert. By observing overlapping regions of red and blue, we can draw conclusions regarding the performance of our model.

#### 5.1.1.3 Result and Discussion

A simple GUI is created which uses our trained model in the backend and get new edf file for generating predictions normal and abnormal regions in it.

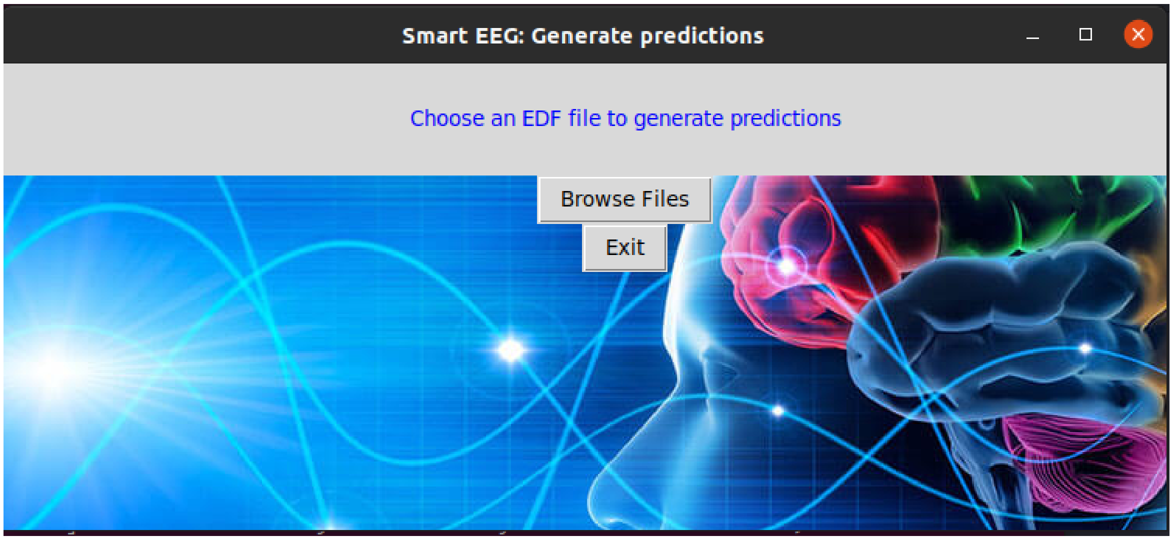



Figure 19. GUI for generating predictions

Comparisons of result of different models we have tried is given below

Table IV :Result for  Chorononet model

| | Training | Validation |
|---|---|---|
| Without Localization | 78.2% | 77.3% |
| With Localization | 95% | 94.3% |

Table V : Result for Deep CNN model

| | Training | Validation |
|---|---|---|
| Without Localization | 80.54% | 81.1% |
| With Localization | 87.07% | 86.03% |

These predictions are then uploaded on our online web based tool for visualising abnormality and comparing with originally labeled files. In this way, in any EEG signal our model can predict abnormality and can be visualized in the tool for verification purposes.

Following file is completely labeled as an abnormal file and our model gives prediction which shows almost all the regions as the abnormal like the given true label for whole file.

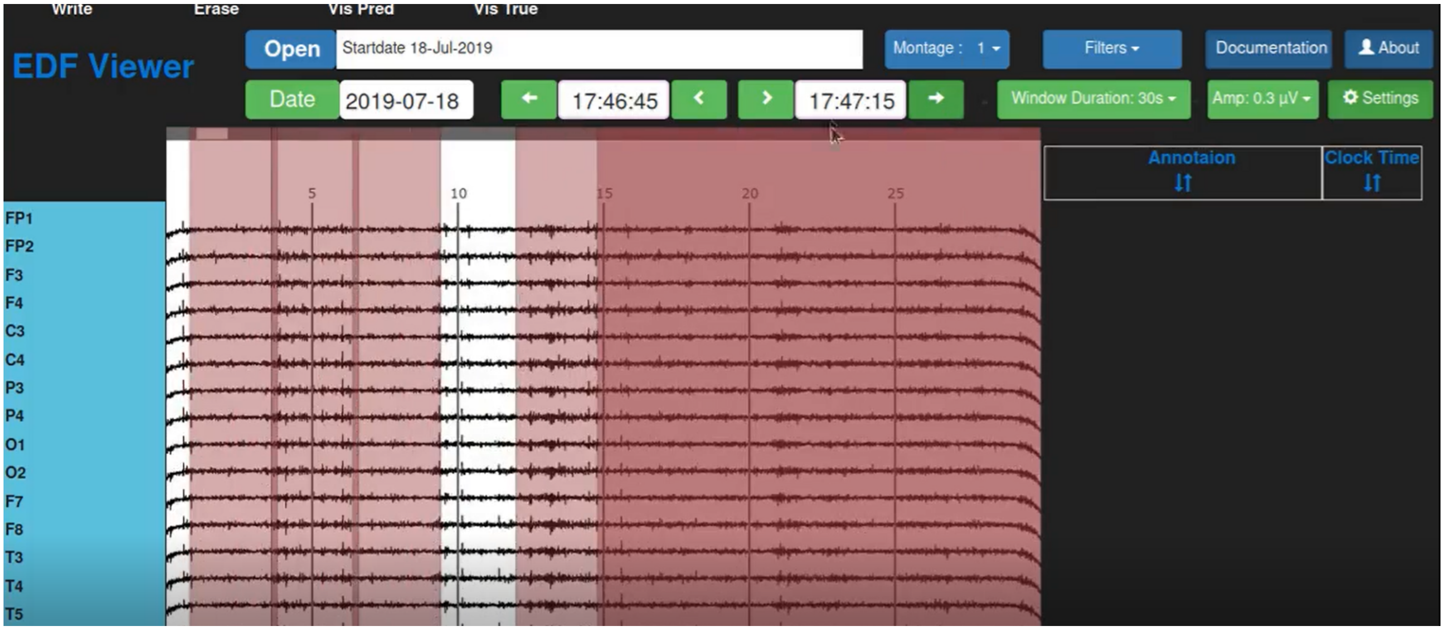



Figure 20.For Complete Abnormal labeled file

For a file which contains some normal and abnormal regions as annotated by a trained professional person from a military hospital. Following picture shows the predicted and actual abnormal regions of the file. Where blue regions shows the actual labeled abnormality and red region shows the predicted abnormality.


Figure 21:File containing some abnormal regions

1.The model has learnt what normal EEG signals mostly look like. This is proven by the fact that most clear regions and normal files have very little red regions.

2. The model can also flag completely erroneous signals, highlighting most of the regions in a corrupted EEG file as abnormal

3. The model does better on dense, large regions of anomalies than sparse, or small regions. Most regions are very close if not completely overlapping

4. Many false negatives/positives can be explained by underlying signal patterns, e.g. lots of fluctuations causing abnormal predictions even though the region is normal.

*Chapter 6*

# Conclusion and Future Work

## 6.1 Conclusion

We worked on cleaning of NUST-MH EEG dataset to increase the research opportunities in this field and also developed an open source online web based annotation tool to label EEG files and to show abnormalities along with different comments.

We also worked to perform temporal localization of EEG abnormality detection using deep learning model and showed useful results in this domain. We tried different state of the art models and compared their performance for given time series sequences of EEG signals.

## 6.2 Future Work

There is always room left for improvement in any solution so is the case for our solution to the problem in the EEG domain for automated abnormality detection. Particularly in ML, an increase in dataset always leads to more accurate results than the architecture design, so one possible approach for this problem is to increase the number of input recordings for improving the inter rater agreement for a given problem in future.

*Chapter 7*

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