Automated EEG Pathology detection

Final Year Project Report

by

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DECLARATION

We hereby declare that this project report entitled “DEEG - Automated EEG Pathology Detection” submitted to the “School of Electrical Engineering and Computer Sciences (SEECS)”, is a record of an original work done by us under the guidance of Supervisor “Dr. Hassan Aqeel” 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 Computer Science.

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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 & Dr. Adnan Malik.

ACKNOWLEDGEMENTS

We would like to wholeheartedly thank our advisor Dr. Hassan Aqeel and the co-advisors Dr. Faisal Shafait and Dr. Adnan Malik 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 (EEG) 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.

We have introduced a new dataset for EEG research: MH-NUST. We are publicly releasing an open source EEG dataset consisting of 625 hours of 2500 session recordings from unique participants with an average duration of 15 minutes each. Moreover, it consists of demographic information about the patient such as gender and age. A comparative analysis of the performance of existing deep learning algorithms is presented on the released dataset. Performance of these algorithms on MH-NUST is also compared to existing publicly available EEG dataset released by Temple University Hospital named EEG Abnormal Corpus TUAB (v2.0.0) [1]. 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. Moreover, we have created an API for the classification of EEG recordings using the Deep CNN model.

Chapter 1

INTRODUCTION

The electroencephalogram (EEG) is a recording of the electrical activity of the brain along the scalp. The waveforms that are recorded reflect the cortical electrical activity. Neurological disorders are an emerging challenge to healthcare systems globally. The neurological burden of disease is expected to grow exponentially in low and middle-income countries in the next decade while awareness is expected to increase leading to shorter treatment gaps. Between 1990 and 2010, disability adjusted life-years due to these disorders increased by 41%. The figure went from 182 million to 258 million [2]. The most recent estimates show that stroke is the second highest cause of morbidity and mortality worldwide [3].

Electroencephalogram(EEG) is a noninvasive method used to record the brain's spontaneous electrical activity over a period of time. Signals are collected by mounting a certain number of electrodes (e.g., 32, 64, 128) on the scalp according to the standard montages [4]. It is used widely in medical practice as an inexpensive tool for diagnosis of neurological disorders and observing patterns in various medication conditions due to excellent temporal resolution as compared to other brain imaging techniques such as magnetic resonance imaging (MRI) and computed tomography (CT). 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. Asymmetries of the EEG background similarly range from obvious to subtle. Such ambiguities may lead to incorrect and inconsistent interpretations of the same EEG signal.

Here is when machine learning (ML) methods for automatic electroencephalogram (EEG) analysis jump in. Due to high competition and lack of resources in medical services, especially in the domain of 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 compare results with the MH-NUST and TUH datasets on shallow and deep CNNs [14] and Chrononet [20] . Our contribution in the field of deep learning is that we validated Deep Convolutional Neural Network adopted from Schirrmeister [14] to learn representations for overlapping crops of EEG recording in spatio-temporal representation, followed by an LSTM on sequence of these representations (features) to classify EEG into abnormal or normal.

On the TUH Abnormal Corpus, a sensitivity of 0.83 and specificity 0.87 is achieved by using this technique. We also eradicated the need for use of pseudo-labels assigned to crops as used in earlier works [14]. In this way, distance from clinically expected sensitivity of 0.90 and specificity of 0.95 is reduced. Further, the model is trained and tested on MH-NUST dataset to compare the results of public dataset with a local health care center to observe sensitivity of 0.81 and specificity of 0.84. Moreover, the results were reproduced using the Chrononet model on both datasets. A comparison among the deep learning models is discussed in Chapter 6.

Our solution is designed in such a way that it can be easily 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, comparing their results on different datasets and introducing a new dataset (MH-NUST) to aid the advances in automation of EEG analysis using the latest machine learning techniques.
2. The Application Programming Interface which the EEG researchers and product developers can potentially use to test the sample EEG signals once a reliable and affordable headset is developed.

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 a disorder are not guaranteed to be present in EEG data during a session. Only 50% of epileptic patients show interictal epileptiform discharges (IED) in their first recording [6]. This leads to the generation of a large amount of EEG data which needs to be interpreted by well-trained investigators 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 approach that supports the diagnostic process could make EEG diagnosis more widely accessible, reduce time and effort for clinicians and potentially make diagnosis 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 Convolutional Neural networks) on our newly released dataset and a publicly available data set i.e. Temple University Hospital named EEG Abnormal Corpus TUAB(v2.0.0) [1].

We have also created an Application Programming Interface (API) to create an interface to our model with the best accuracy and sensitivity, so that the EEG researchers and healthcare workers can use it to automatically go through the first step of EEG analysis; classify the EEG signal as Normal or Abnormal.

1.3 EEG Acquisition

The EEG is recorded with the help of an EEG headset which consists of small metal discs usually made of stainless steel, tin, gold or silver covered with a silver chloride coating. These discs are placed on the scalp as nodes in special positions. These positions are officially specified using 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.

Each electrode location is labeled with a letter and a number. The letter refers to the area of the brain underlying the electrode e.g. Fp denotes Prefrontal lobe, F denotes Frontal lobe, T denotes Temporal lobe, C denotes Central lobe, P denotes Parietal lobe, O denotes Occipital lobe, and A denotes Mastoid Process lobe. Similarly, even numbers denote the right side of the head and odd numbers the left side of the head.

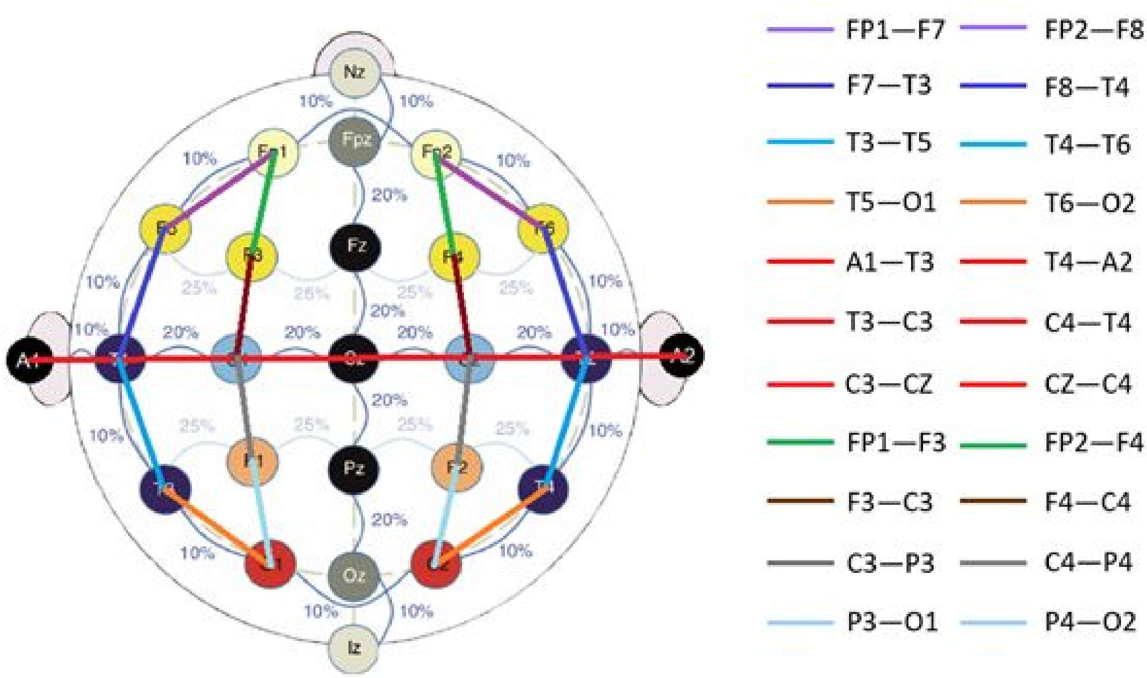


Figure 1. Standard electrode locations for a 10-20 system with a defined 22-channel TCP montage.

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 electrodes as the reference, whereas the LE montage uses the (side) electrically quiet ear electrodes as reference.

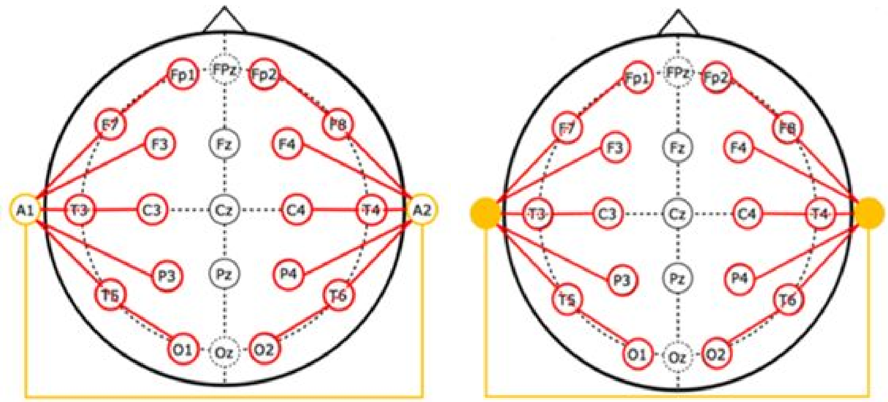


Figure 2. Location information of the electrodes for two montages found in the TUH EEG Corpus: AR (left), LE (right)

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 initial step of EEG diagnosis; i.e. to classify the EEG signal as normal or abnormal. 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] focused on the TUH EEG Corpus for evaluation and the channel they have used for their study is differential measurement of T5 and O1, which is part of the popular 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 cepstral coefficient-based approach which is 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 of 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 and TUH datasets 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 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 dataset to compare the results of public dataset with local health care center i.e MH Rawalpindi to observe sensitivity of 0.81 and specificity of 0.84.

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 intrinsically noisy and 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 a disorder are not guaranteed to be present in EEG data during a session. Only 50% of epileptic patients show interictal epileptiform discharges (IED) in their first recording [6]. This phenomenon leads to the generation of a large amount of data that then needs to be manually interpreted by expert investigators such as 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 time-consuming and resource-hungry process.

A platform where an EEG signal could be identified as normal or abnormal, to perform an initial screening for the neurologists is much needed. This platform would help 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 models are looked into. And with experimental amendments, sensitivity and accuracy are relatively improved.

Chapter 4

MATERIAL AND METHODS

4.1 DATASET

A critical obstacle in the development of machine learning (ML) technology for medical applications is the lack of big data resources available to the research community for supporting training of complex deep learning systems. TUHAbnormal Corpus [1] is the only existing publicly available dataset of its kind. Along with the EEG data, it includes the prescription from neurologist and demographic information about the patient such as age and gender. 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. The data has been collected from South Asian demographic, and is unique to its kind. [23]

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 ofNeurology in Military Hospital Rawalpindi was collected from2016 to 2019. The raw signals obtained from the recording vary between 20 to 128 channels, sampled at 250Hz frequency. The Partners Institutional committee approved anonymous analysis of the dataset without requiring additional consent for its use in this study. All EEG recordings were recorded using 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 to be predicted for our study. 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

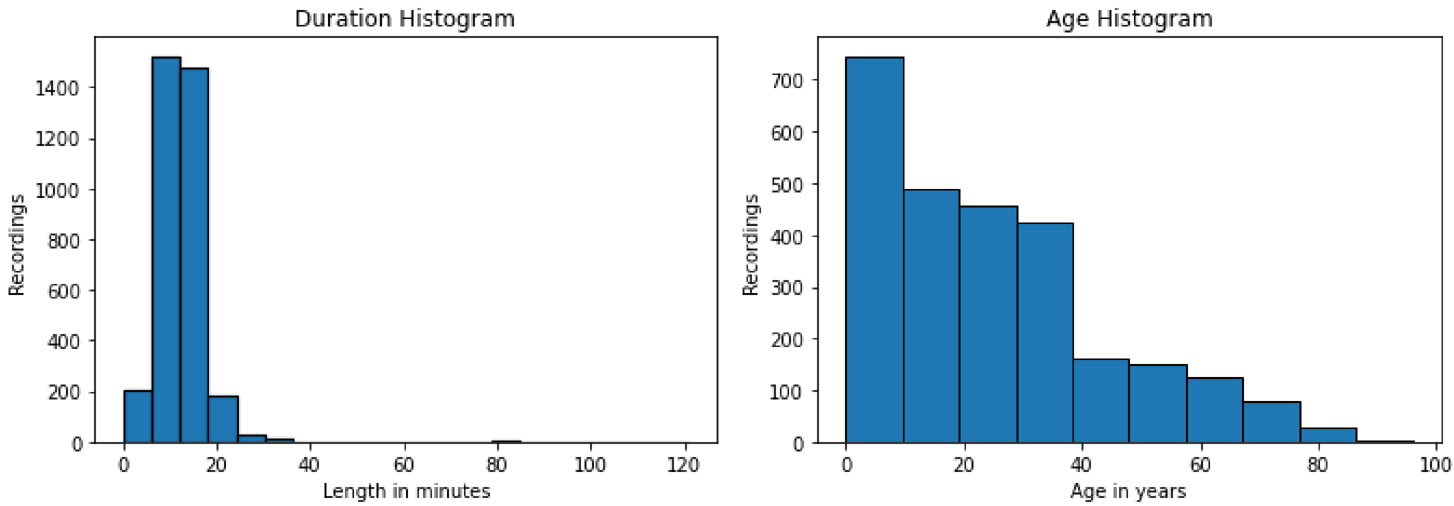
Gender	Files
Female	886
Male	1775

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 clinical situation in neurology practice. We use oversampling from abnormal class during training for solving the problem of classification bias.

4.1.2 Temple University Hospital Dataset

The Temple University Hospital (TUH) EEG Data Corpus[24] is the largest publicly available dataset of raw EEGwith medical reports from certified neurologists. It contains over 16000 clinical recordings of more than 10000 subjects from over 12 years. We are using a manually labeled subsetTUAB. The Abnormal Corpus contains 2,978 recordings, 1506 of which were labeled normal and 1472 of which were labeled pathological. The Corpus was split into a training and evaluation set, see Table IV below

TABLE IV. TUH Abnormal Corpus 2.0.0 Statistics

TUH Abnormal EEG Data	Abnormal	Normal
Train	1379	1361
Test	126	150

4.2 EXPERIMENTS

We first establish the baseline by reproducing results on the TUH data set for Deep and shallow CNN as discussed above . Next we evaluate the two models on MH dataset which proves the dataset variability problem. So we fine-tune the model trained on TUH for MH data to study the effect of using two datasets. 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

Typically minimal preprocessing of raw EEG is performed for end-to-end classification methods. For Deep CNN and Shallow CNN(Schirrmeister et.al, 2018) we perform clipping, normalization and downsampling of signals from all the channels as mentioned by Schirrmeister et.al(2018). Downsampling has been proved to have minimal effect on pathology detection and increase computational efficiency. Further, EEG recordings are cropped into overlapping crops of a minute each to achieve data augmentation by almost ten times. We represent the input as a 2D-array with the number of time steps as the width and the number of electrodes as the height.

In our pilot experiments,we studied the effect of Montage on detection of pathology and found no direct correlation between the two. However for Chrononet (Roy et.al,2019) we used Temporal Central Parasagittal(TCP) montage as mentioned by the authors. As the effect of more data is commonly greater than the effect of more elaborate algorithms(Halevy et al. (2009), EEG Signals are normalized and split into crops for training the huge model. Pseudo Labels are generated for each crop and by assigning the same label as for the trial. However this computational feasibility affects another interest that is EEG yield. EEG yield is greater for more time of recorded EEG and some abnormalities may not appear in a short crop of one minute. However studies on automated detection have focused on background EEG as a sufficient indicator of anomalies for models considering professional experience from neurologists.

4.2.2 Channel Selection

Researches suggest that some electrodes play a greater part in decision 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 architectures including ConvNets and Chrononet to decode the pathology from the EEG recordings. First, we used a four-layered ConvNet architecture called Deep CNN as previously introduced by Schirrmeister et al. (2017). The BD-Deep4 architecture [Figure 2] has an initial separated convolution (first temporal, then spatial). It is a rather general architecture that has proven to generalize well to several EEG decoding tasks such as motor (imagery) decoding(schrimmeister et.al, 2017).

A. Deep and Shallow Convolutional Neural Network (CNN)

Deep and shallow CNN provided state of the art accuracy on EEG analysis e.g. decoding task-related information from EEG. The performance of deep and shallow ConvNet trained end-to-end is comparable to that of algorithms using hand-engineered features. 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.

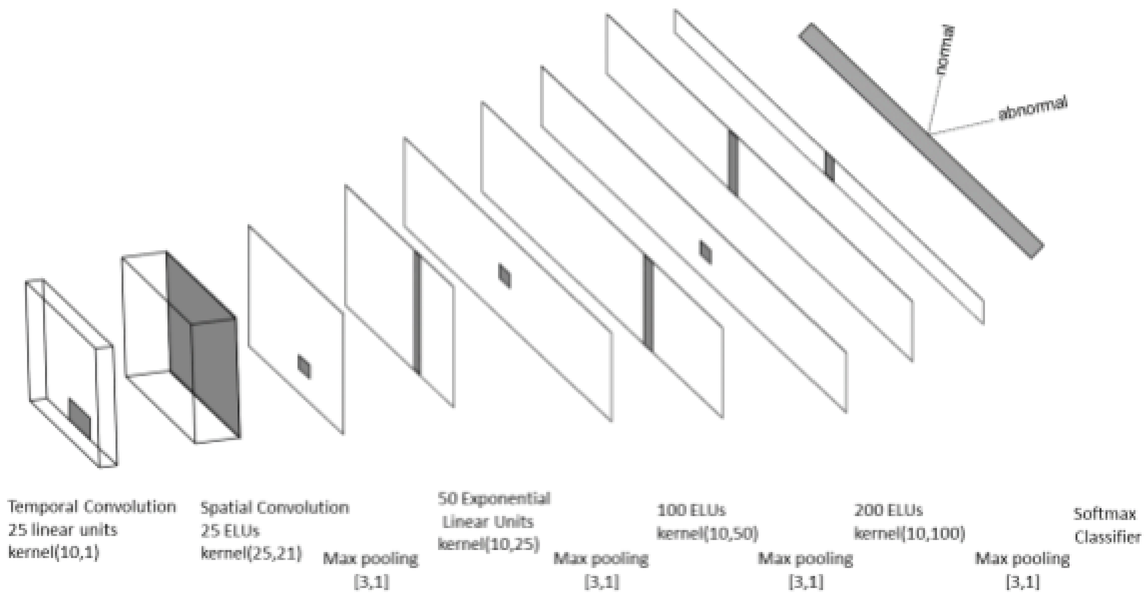


Figure 5. Deep ConvNet architecture with four conv-pool Block

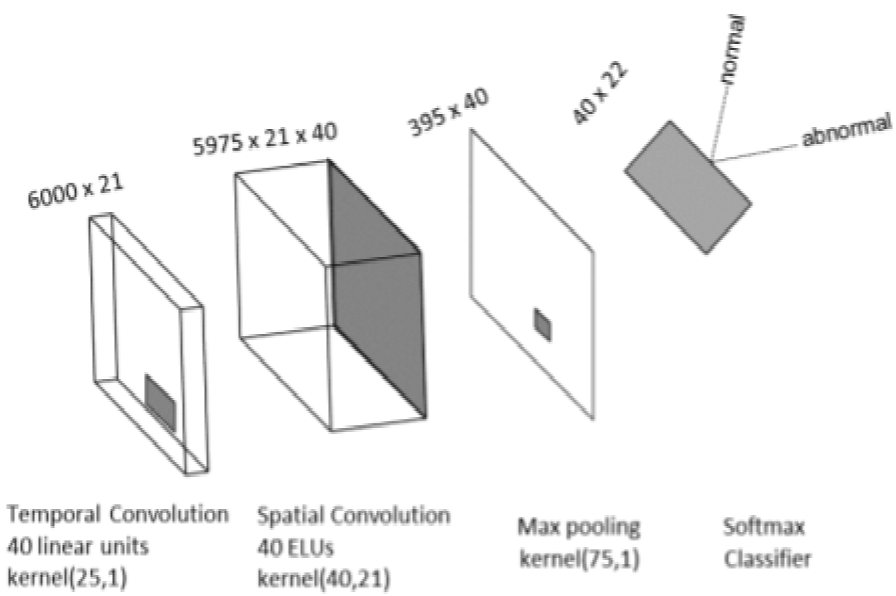


Figure 6. Shallow ConvNet architecture with one conv-pool Block

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 to work efficiently with EEG data. It uses inception layers with exponentially varying kernel lengths for 1D convolution layers in combination with densely connected recurrent layers.

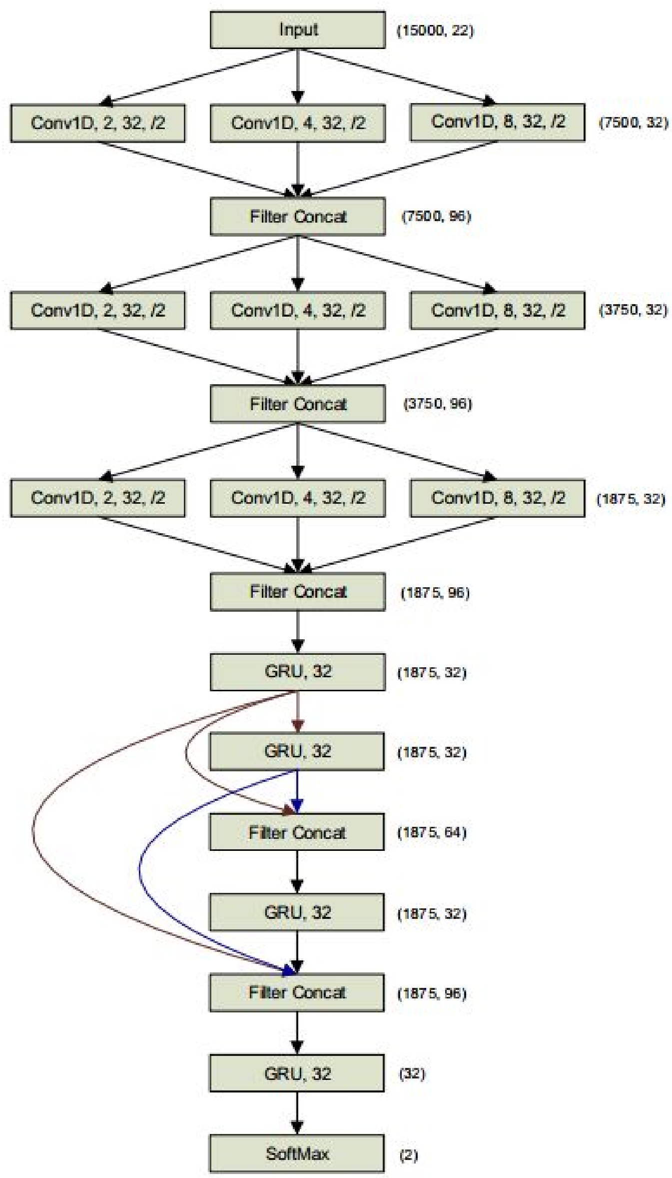


Figure 7. Chrononet: Inception Convolutional Densely Connected Gated Recurrent Neural Network

We trained Chrononet on max-normalized multichannelEEG signals as 2D matrix after converting average referenced recordings of TUH 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].

C. Hybrid Architecture

A hybrid model is designed to solve EEG yield problem using features learned from Deep CNN for classifying temporal sequences of features using Long Short Term Memory(LSTM) units. This eliminates the use of pseudo labels for crops and instead classifies a sequence based on actual labels. Feature extraction is done by removing the final softmax layer and features from all one minute crops are concatenated to form a sequence of features of a recording for classification. As shown in the figure 8.

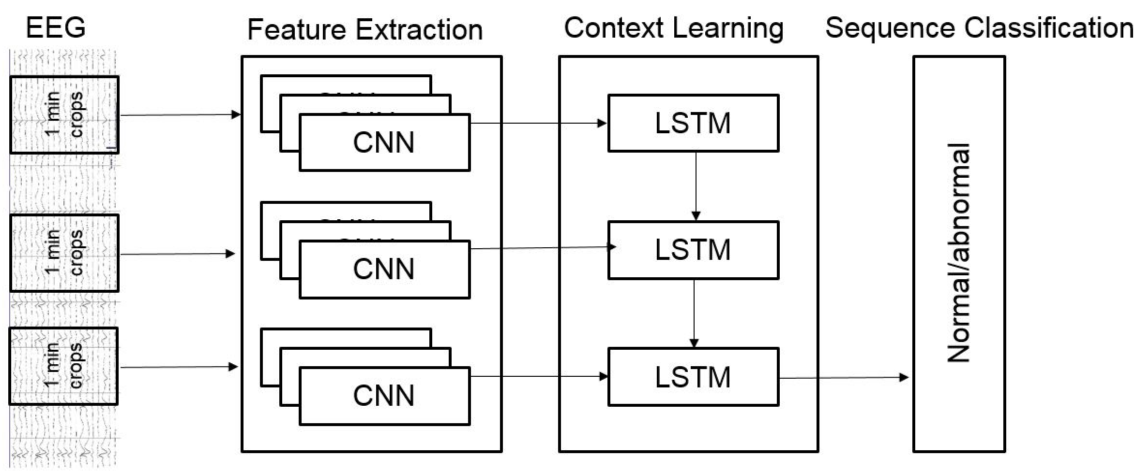


Figure 8. Design of Hybrid Architecture using Deep CNN for Feature Extraction

The results for both datasets on the models above are further discussed in chapter 6 on performance evaluation.

Chapter 5

IMPLEMENTATION

5.1 EEG Predictor Web Application

The significance of EEG Predictor Web application is that it provides a user-friendly interface to the lab technicians or anyone who wants to analyze their recorded EEG file. Since the neurologists have to invest a humongous amount of time into analyzing the signal for any abnormality, this web application provides the facility of initial screening for them. It can classify the EEG signal into normal or abnormal class and saves the time of the medical experts, and the lab-technicians as well. So, you the neurologist only has to dive deeply into the problem if there is an initial suspect in the recorded EEG signal. This user-friendly application helps save the precious time of the neurologists and the patient himself.

5.1.1 Tools and technologies

The tools used for this web application are as follows:

1. Anaconda Navigator (Editor: VSCode)
2. Flask
3. HTML/CSS
4. Javascript
5. PyTorch and keras
6. Torchvision
7. Numpy
8. Pillow
9. gunicorn

Since the system has been developed by focusing on the designing and user-friendly features in the application, the tools specific to Flask application development were Anaconda and VSCode editor, for deploying the deep learning model to the web application. Also, after the final design was confirmed, the implementation of the design in the final working application was easily carried out on a local server using Flask framework.

Flask is a web application framework that is written in Python. It provides inbuilt automation for details like protocol management, thread management, etc.

VSCode through Anaconda Navigator is used as the IDE (Integrated Development Environment) for web application development.

HTML/CSS are used for front end development, 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**, and **Pillow** are the python libraries that were used for development of the deep learning model.

Gunicorn is a Python Web Server Gateway Interface for the HTTP server.

5.1.2 IMPLEMENTATION

5.1.2.1 FLASK WEB APPLICATION

The Flask web application has been completely developed in Python, HTML/CSS and Javascript. The platform used for the purpose has been VSCode using Anaconda Navigator. The interface development has been done in HTML/CSS and Javascript whereas the rest of the back-end functionality has been coded using Python. The implementation phase began by first developing the main structure of the web application. This included the designing and the development of the front-end development activities. And then the deep learning model was integrated into the front end using the Flask framework.

Using the prototypes developed in the Requirements Analysis and design phase, the screens for various functionalities of this component were developed. The input field and the selection buttons were selected keeping in mind the user’s ease of use and interaction with the application. Keeping it as minimal as possible. An About page was also created to emphasize the importance of the project. The web application design theme and color scheme was chosen with care so that the user does not get annoyed when using the web application. The logo of the application was developed and designed using an online logo designer.

Once the front-end of the android application was complete, the second phase i.e. the back-end development began. The deep learning model was developed and integrated into the web application using the Flask framework and was hosted on a local server.

5.1.2.2 A WALK-THROUGH THE APPLICATION

EEG Predictor is a web application that allows the user to input an EEG file (must be in .edf format). Figure 9 shows the landing page for the web application.

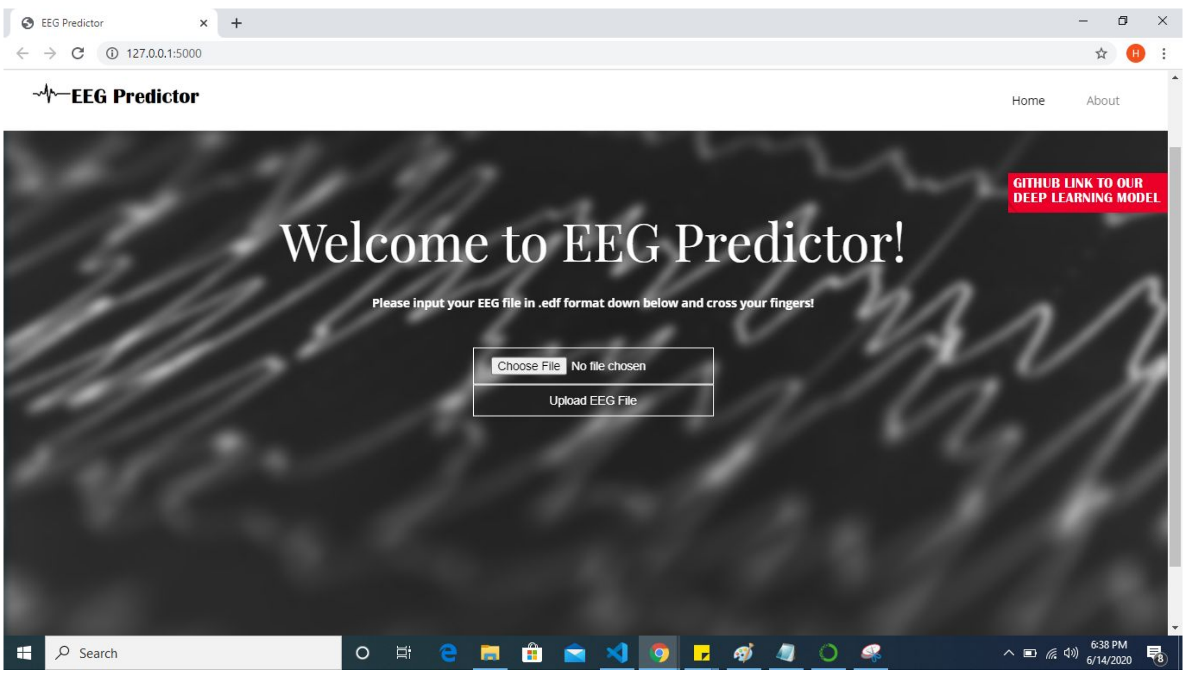


Figure 9. Main Landing page

The user can input the .edf file, Figure 10 shows input from the user and then he clicks on the Upload EEG file button.

The input file goes through pre-processing techniques and then through the deep convolutional neural network, and then the classifier classifies it into either of two class labels 0 or 1. 0 represents the normal recorded EEG whereas 1 represents abnormality in the EEG.

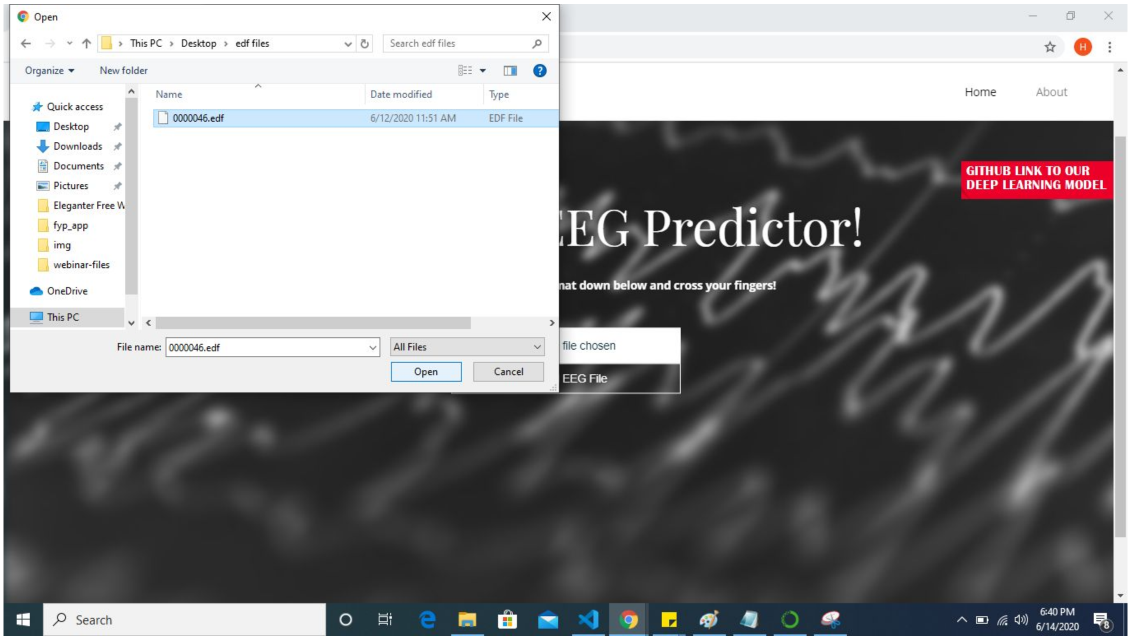


Figure 10. Input from the User

The abnormality alerts the user to contact his respective neurologist for further assistance. The following screenshot Figure 11 shows behind the scenes from VSCode, the print statements while the deep CNN model is running on the input file.

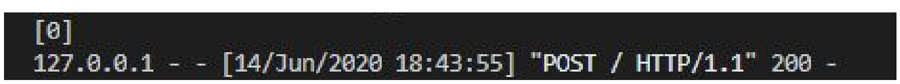


Figure 11. Model script running on input file

Based on the predicted label, the user is redirected to a result page where a description of his input EEG file is shown, Figure 12 shows the respective result page.

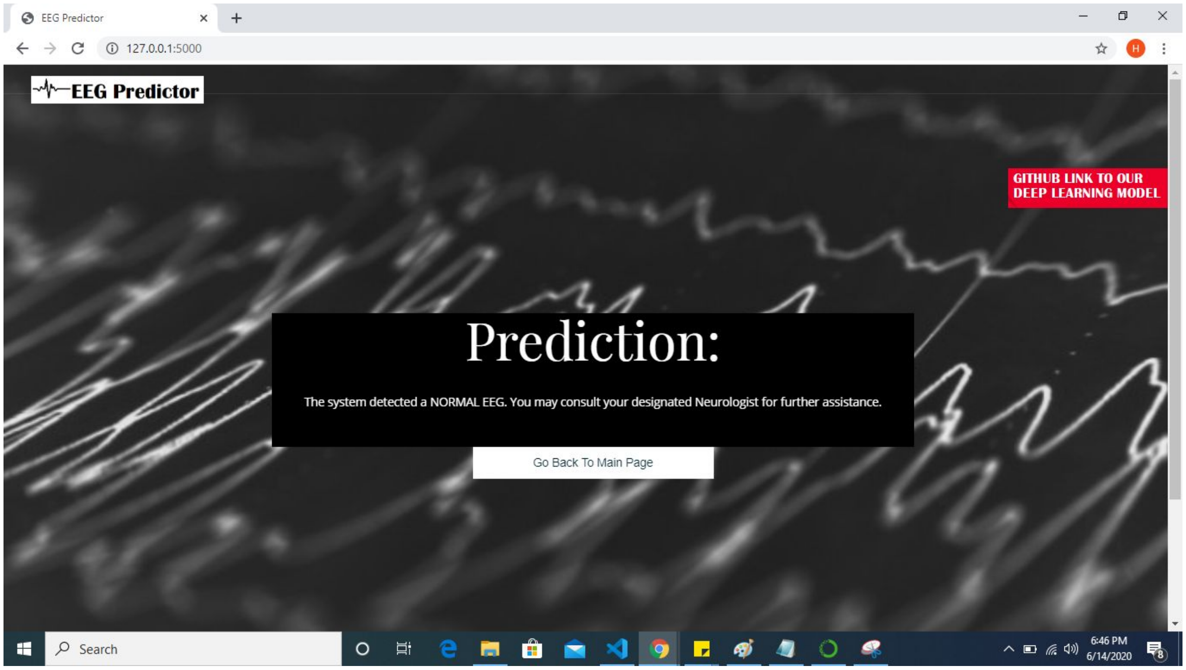


Figure 12. Predicted result page

The user can navigate back to the main page to further test any more files. The user can also access the about page, which signifies the importance of this web application. Figure 13 shows the respective About page.

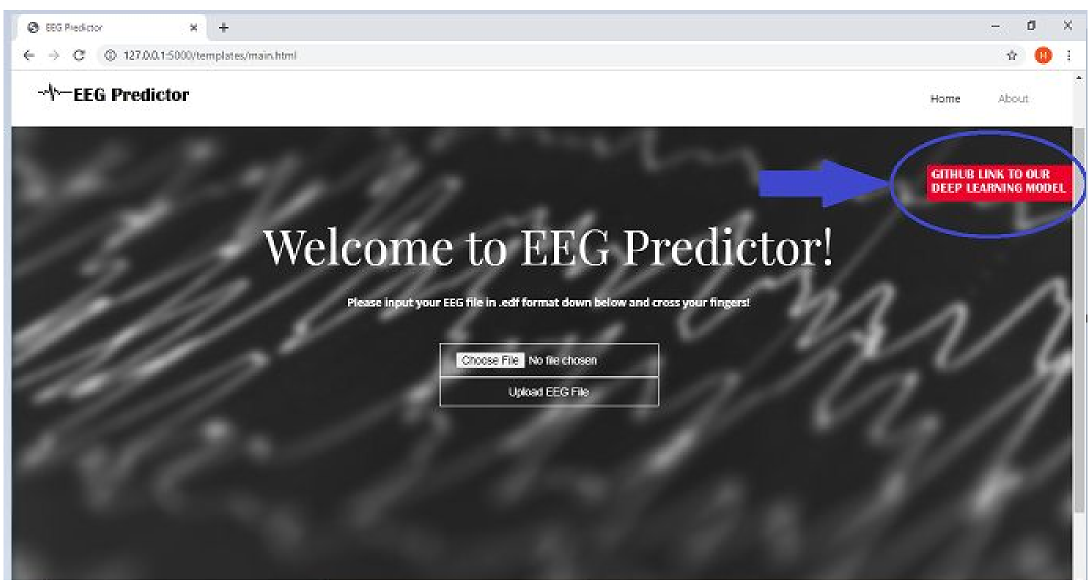


Figure 13. About page for EEG predictor

The user can also access the code and documentation to our deep learning model with the github link label present on the main page. This part is usable for the EEG researchers who might want to reproduce or improve our model.

5.1.2.3 DEVELOPMENT SCREENSHOTS

fyp_app > test.py > hello_world

```python
import os
from flask import Flask, flash, request, redirect, url_for, render_template
from werkzeug.utils import secure_filename
from commons import get_model

UPLOAD_FOLDER = 'uploads'
ALLOWED_EXTENSIONS = {'edf'}

app = Flask(__name__)
app.config['UPLOAD_FOLDER'] = UPLOAD_FOLDER

def allowed_file(filename):
    return '.' in filename and \
            filename.rsplit('.', 1)[1].lower() in ALLOWED_EXTENSIONS

@app.route('/', methods=['GET', 'POST'])
def hello_world():
    if request.method == 'GET':
        return render_template('main.html')
    if request.method == 'POST':
        if 'file' not in request.files:
            flash('No file part')
            return redirect(request.url)
        file = request.files['file']

        # if user does not select file, browser also
        # submit an empty part without filename
```

Figure 15. Flask Application interface to handle queries from the user

test.py | commons.py | main.html | about.html | result.html

fyp_app > commons.py > get_model

```python
cuda = False
def get_info_with_mne(file_path):
    """ read info from the edf file without loading the data. loading data is done in multiprocessing since it takes
    some time. getting info is done before because some files had corrupted headers or weird sampling frequencies
    that caused the multiprocessing workers to crash. therefore get and check e.g. sampling frequency and duration
    beforehand
    :param file_path: path of the recording file
    :return: file name, sampling frequency, number of samples, number of signals, signal names, duration of the rec
    """
    try:
        if True:
            edf_file = mne.io.read_raw_edf(file_path, montage = None, eog = ['FP1', 'FP2', 'F3', 'F4',
                                                                              'C3', 'C4',  'P3', 'P4','O1', 'O2','F7', 'F8',
                                                                              'T3', 'T4', 'T5', 'T6','PZ','FZ', 'CZ','A1', '
        else:
            edf_file = mne.io.read_raw_edf(file_path, verbose='error')
    except ValueError:
        return None, None, None, None, None, None
        # fix_header(file_path)
        # try:
        #     edf_file = mne.io.read_raw_edf(file_path, verbose='error')
        #     logging.warning("Fixed it!")
        # except ValueError:
        #     return None, None, None, None, None, None

    # some recordings have a very weird sampling frequency. check twice before skipping the file
    sampling_frequency = int(edf_file.info['sfreq'])
```

Figure 16. Model preprocessing and algorithm implementation, prediction based on pickle file 'deep.pt' and label numpy array

test.py | commons.py | main.html | about.html | result.html

fyp_app > templates > main.html > html > body.size-1140 > main

```html
<!DOCTYPE html>
<html lang="en-US">
  <head>
    <meta charset="UTF-8">
    <meta name="viewport" content="width=device-width, initial-scale=1.0" />
    <title>EEG Predictor</title>
    <link rel="stylesheet" href="{{ url_for('static', filename='css/components.css') }} ">
    <link rel="stylesheet" href="{{ url_for('static', filename='css/icons.css') }} ">
    <link rel="stylesheet" href="{{ url_for('static', filename='css/responsee.css') }} ">
    <link rel="stylesheet" href="{{ url_for('static', filename='owl-carousel/owl.carousel.css') }} ">
    <link rel="stylesheet" href="{{ url_for('static', filename='owl-carousel/owl.theme.css') }} ">
    <link rel="stylesheet" href="{{ url_for('static', filename='css/template-style.css') }} ">
    <link href='https://fonts.googleapis.com/css?family=Playfair+Display&subset=latin,latin-ext' rel='stylesheet' type='tex
    <link href='https://fonts.googleapis.com/css?family=Open+Sans:400,300,700,800&subset=latin,latin-ext' rel='stylesheet'
    <script type="text/javascript" src="{{ url_for('static', filename='js/jquery-1.8.3.min.js') }} "></script>
    <script type="text/javascript" src="{{ url_for('static', filename='js/jquery-ui.min.js') }} "></script>


  </head>

  <body class="size-1140">
    <!-- PREMIUM FEATURES BUTTON -->
    <a target="_blank" class="hide-s" href="https://github.com/rahatUlAin/diagnoseeg" style="position:fixed;top:120px;right
    <!-- HEADER -->
    <header role="banner" class="position-absolute">
      <!-- Top Navigation -->
      <nav class="background-transparent background-transparent-hightlight full-width sticky">
```

Figure 17. HTML home page with CSS and Javascript integrated.

About and result pages were also created using HTML/CSS and Javascript in a similar manner.

5.1.3 Overview of the EEG predictor architecture

Deep Convolutional Neural Network trained on MH-NUST is saved at a checkpoint named ‘deep.pt’, which is a pickle data format file. The labels for classification are stored in a numpy array 0 and 1. 0 represents the normal EEG whereas 1 represents abnormality in the EEG. Flask is a python framework that provides scalable and maintainable production of web applications. It provides inbuilt automation for details like protocol management, thread management, etc. It helps route the POST and GET request from the user. Once a user inputs an edf file through the interface, the flask application routes the request and calls the deep learning model. This model performs pre-processing techniques on the edf file and then classifies the file based on the labels into either normal or abnormal. This flask application is hosted on a local host i.e 127.0.0.1/5000. Once the EEG file is classified into either of the classes, the flask application redirects the user to a result page showing an explanation about the predicted results. An overview of the model is shown in figure 18.

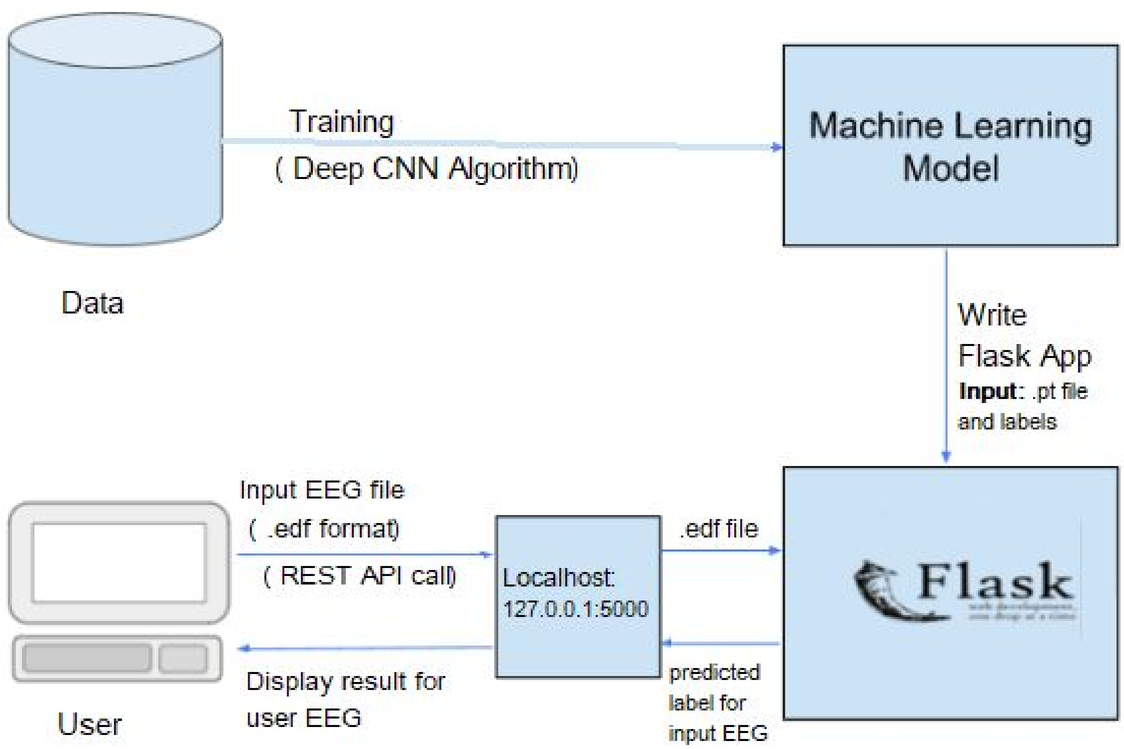


Figure 18. Overview of the EEG Predictor Web Application Architecture

5.1.3 Testing

System testing is performed through a strong testing strategy and the test cases cover all the use cases.

Test no.	Test Case	Test Input	Expected Result	Actual Result	Test Result
1	Checking the format of input file from the user. (with valid input)	0000042.edf	EEG Predictor redirects to result page	EEG Predictor redirects to result page	Pass
2	Checking the format of input file from the user. (with invalid input)	flower.jpg	EEG Predictor shows an input error message on the same page.	EEG Predictor shows an input error message on the same page.	Pass
3	User clicks on "GITHUB LINK TO OUR DEEP LEARNING MODEL"	Mouse click action	EEG Predictor redirects to our deep CNN GitHub repository.	EEG Predictor redirects to our deep CNN GitHub repository.	Pass
4	User clicks on "ABOUT"	Mouse click action	EEG Predictor redirects to its About page.	EEG Predictor redirects to its About page.	Pass

TABLE V. Test cases

Chapter 6

RESULTS AND DISCUSSION

We performed 10-fold cross-validation (CV) on the training set. For final evaluation, we evaluated our models on the unused evaluation set. EEG Classification is a critical diagnosis problem that demands a high sensitivity and specificity solution. As accuracy may not be a true representative of a classifier in some cases, we evaluated EEG classification models based on sensitivity, specificity and F1 Score. We envisioned a representation learned from smaller crops would help classify complete EEG recordings.

6.1 Convolutional Neural Network Classifier Evaluation

6.1.1 Deep CNN and Shallow CNN Training and Fine tuning

Both Deep and Shallow CNN were trained on TUH and Tested on both TUH and MH for evaluation of performance. The accuracy we achieved validate results from schirrmeister et.al while sensitivity and specificity vary greatly compared to 0.78% and 90.5 respectively reported by the authors. According to our intuition it may be due to correction in the dataset version. Confusion matrices for both the models are shown in figure 19 and 20 below.

However evaluation of the models trained on TUH for MH test set and that of Model trained on MH and tested on TUH is only as good as a random classifier (as shown in figure 21) due to acquisition hardware difference and dataset variability problem.

	TUH	Actual pathological	Actual normal	Metrics
predictions	pathological	102	20	*Accuracy: 0.84*
	normal	24	130	*Roc-AUC: 0.92*
	Sensitivity/ Specificity	0.80	0.87	*F1 Score: 0.82*

Figure 19. Confusion matrix for Deep CNN trained on TUH to reproduce results as a baseline

TUH	Actual pathological	Actual normal	Metrics
predictions: pathological	95	10	*Accuracy: 0.85*
predictions: normal	31	140	*Roc-AUC: 0.93*
Sensitivity/ Specificity	0.75	0.93	*F1 Score: 0.82*

Figure 20. Confusion matrix for Shallow CNN trained on TUH to reproduce results as a baseline

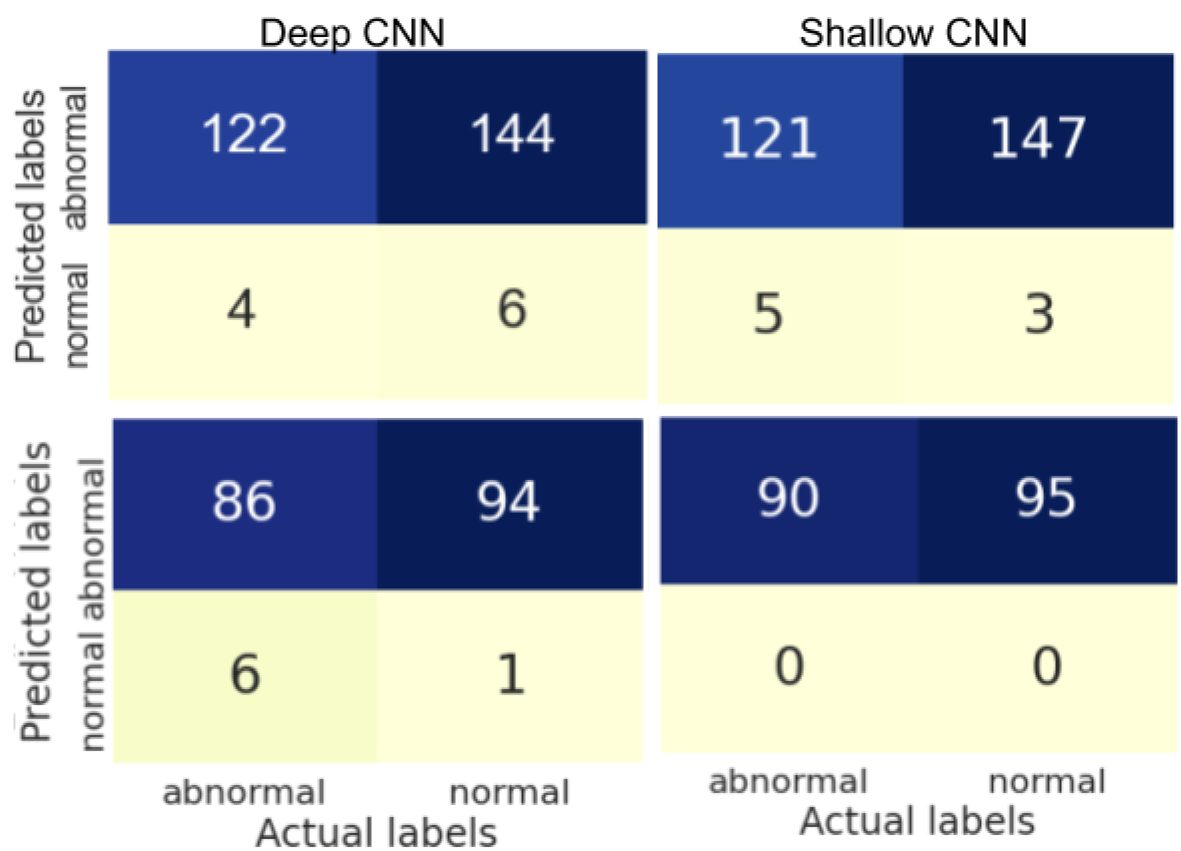


Figure 21. Confusion Matrices for Models trained on TUH and tested on MH(below) and vice versa(above)

Further, We studied the effect of transfer learning from TUH dataset on MH dataset. We finetuned the Deep CNN and Shallow CNN model trained on TUH for MH train set. We trained both models on MH train set and tested on designated testset, as a comparison baseline. The performance metrics show reduced performance for both deep and shallow CNN for the same number of training epochs. The confusion matrices for finetuning(figure 22) and a model trained and tested on MH dataset(figure 23) are shown below.

	DEEP CNN	Actual pathological	Actual normal	Metrics
predictions	pathological	73	19	*Accuracy: 0.80*
	normal	17	76	*Roc-AUC: 0.86*
	Sensitivity/ Specificity	0.80	0.81	*F1 Score: 0.80*

	Shallow CNN	Actual pathological	Actual normal	Metrics
predictions	pathological	39	15	*Accuracy: 0.64*
	normal	51	80	*Roc-AUC: 0.78*
	Sensitivity/ Specificity	0.43	.84	*F1 Score: 0.54*

Figure. 22. Confusion matrix for MH testset evaluated on model trained on TUH and finetuned on MH trainset

DEEP CNN		Actual pathological	Actual normal	Metrics
predictions	pathologic al	73	15	*Accuracy: 0.83*
	normal	18	80	*Roc-AUC: 0.89*
	Sensitivity/ Specificity	0.81	0.84	*F1 Score: 0.82*

Shallow CNN		Actual pathological	Actual normal	Metrics
predictions	pathologic al	37	16	*Accuracy: 0.64*
	normal	53	81	*Roc-AUC: 0.66*
	Sensitivity/ Specificity	0.41	0.86	*F1 Score: 0.62*

Figure 23. Confusion matrices for Deep and Shallow CNN trained and tested on MH dataset

6.1.2 Chrononet: Inception Convolutional Densely Connected Gated Recurrent Neural Network

We trained and tested Chrononet for both TUH and MH datasets to study the effect of dataset variability. We were able to only achieve 81% accurate results on TUH dataset compared to reported 86% by authors of chrononet(roy et. al 2019). Sensitivity and specificity were not reported, however, the values achieved are comparable with those achieved with Deep CNN. Similarly We trained and tested chrononet on MH dataset to achieve 78 % accurate results. The confusion matrices are shown in the figure 24 below

	TUH	Actual pathological	Actual normal	Metrics
predictions	pathological	96	22	*Accuracy: 0.81*
	normal	29	127	*Roc-AUC: 0.83*
	Sensitivity/ Specificity	0.77	0.85	*F1 Score: 0.78*

	MH	Actual pathological	Actual normal	Metrics
predictions	pathological	67	20	*Accuracy: 0.76*
	normal	23	75	*Roc-AUC: 0.77*
	Sensitivity/ Specificity	0.74	0.78	*F1 Score: 0.75*

Figure 24. Confusion Matrices for evaluation of chrononet on TUH and MH dataset

6.1.3 Hybrid CNN and LSTM MODEL

We trained a novel hybrid model on TUH dataset to achieve a more sensitive and accurate model as tested on TUH to have 85% accuracy, 83% sensitivity and 87% specificity. The confusion matrix is shown in figure 25 below.

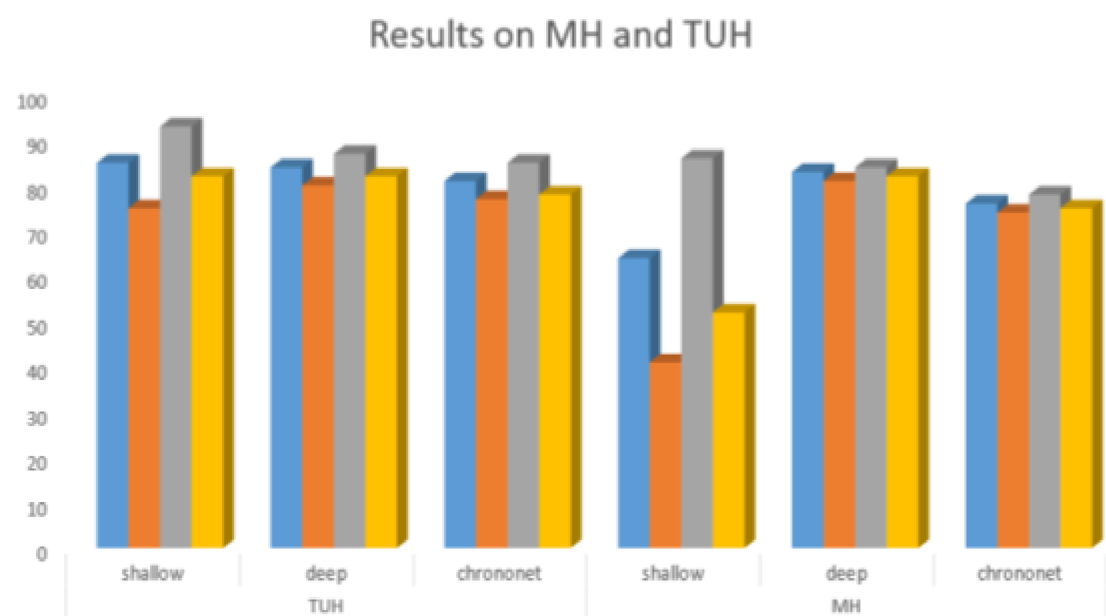
	TUH	Actual pathological	Actual normal	Metrics
predictions	pathological	105	20	*Accuracy: 0.85*
	normal	21	130	*Roc-AUC: 0.94*
	Sensitivity/ Specificity	0.83	0.87	*F1 Score: 0.84*

Figure 25 . Confusion matrix for evaluation of Hybrid model on TUH dataset

6.2 Discussion

We evaluated Deep and Shallow CNN along Chrononet on the two large independent datasets in different configurations to confirm the dataset variability problem. Deep CNN proves to be the most generalizable and robust of the CNN-based approaches. All models reached a specificity of about 84-93% and a sensitivity of about 74-81%. Confusion matrices between the model approaches were very similar.

All our deep learning made more errors on the pathological recordings, as can be seen from Figure 18. This can be caused by dominant regions of normal activity in abnormal recordings. Both shallow and After hybrid CNN+LSTM, deep CNN has high sensitivity as well as specificity which is an important for EEG diagnosis. The proposed system obtained better sensitivity and specificity than did the three others. This performance indicated the success of the proposed system. While we are far from clinically accepted 90 sensitivity and 95% specificity, these results are valuable. This can help EEG diagnostics in developing countries for patients that cannot attend specialized centers for neurology.



	TUH shallow	TUH deep	TUH chrononet	MH shallow	MH deep	MH chrononet
accuracy	85	84	81	64	83	76
senstivity	75	80	77	41	81	74
specificity	93	87	85	86	84	78
F1	82	82	78	52	82	75

Figure 26. Bar plot showing the percentage accuracy, sensitivity, specificity and F1 score for Shallow CNN, Deep CNN and Chrononet on TUH and MH dataset. F1 score is highest for Deep CNN on both datasets i.e 82%

Chapter 7

CONCLUSION AND FUTURE WORK

7.1 CONCLUSION

We introduce a properly curated public dataset MH- NUST, which includes patient's demographic information such as age and gender. Thus, increasing the diversity of EEG datasets for increasing research opportunities in the field.

• we also study a specific medical domain (EEG pathology detection) to show the non-triviality of translating the estimated model's local generalization capabilities into independent external dataset also known as database variability problem [21] by testing model trained on TUH on MH-NUST dataset.

• We attempt to solve the EEG yield problem by training the deep learning model to make decision based on the full length of the EEG signal, instead of an EEG crop.

• We compare the results of different well-known deep learning algorithms on the MH-NUST dataset with the TUH Abnormal Corpus. We also present results and sample code to reproduce the results presented in this paper.

7.2 FUTURE WORK

In the light of experiments performed, there is a need to improve inter rater agreement for datasets to have a stronger ground truth. In ML an increase in dataset always leads to more accurate results compared to architecture design. This is also confirmed in our pilot experiments we performed with a smaller dataset. We aim to update the dataset with more data and improve inter-rater agreement for classification in the future.

Chapter 8

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8.1 CONCLUSION

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