Localization of abnormalities in EEG signal

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Dedication

I dedicate this dissertation to Allah Almighty my creator, my source of inspiration, wisdom, knowledge and understanding. He has been the source of my strength throughout this program and on His wings only have I soared. I also dedicate this work to my parents , who has been a constant source of support and encouragement during the challenges of graduate school and life. To my respected supervisors Dr. Faisal Shafiat and Dr. Hassan Aqeel who have been affected in every way possible by this quest.

Certificate of Originality

I hereby declare that this submission titled " Localization of Abnormalities in EEG signal" is my own work. To the best of my knowledge, it contains no materials previously published or written by another person, nor material which to a substantial extent has been acceptedfor the award of any degree or diploma at NUST SEECS or at any other educational institute, except where due acknowledgement has been made in the thesis. Any contribution made to the research by others, with whom I have worked at NUST SEECS or elsewhere, is explicitly acknowledged in the thesis. I also declare that the intellectual content of this thesis is the product of my own work, except for the assistance from others in the project's design and conception or in style, presentation, and linguistics, which has been acknowledged. I also verified the originality of contents through plagiarism software.

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Date: ____________

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Prof. Dr. Faisal Shafait

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ABSTRACT

Electroencephalogram (EEG) can be used for the diagnosis of neurologist disorders: Alzheimer's disease, depression, dementia, and epilepsy. Manual interpretation of EEG is time consuming and resource hungry process. An automated diagnosis system would help neurologist to interpret EEG in less time. EEG data collected from a local hospital along with channel wise annotations of anomalies created a unique opportunity for the proposed research problem. A hybrid model is proposed to localize anomalies in each channel of EEG record. Proposed architecture is divided into two steps. First, Deep CNN is trained for detecting abnormal channels. Furthermore, to detect anomaly time from abnormal channels Long Short-Term Memory (LSTM) network is trained.

Chapter 1

INTRODUCTION

1.1 PURPOSE

Electroencephalogram (EEG) is a recording that detects electrical activity of the brain along the scalp. The wave forms that are recorded reflect the cortical electrical activities. An EEG is one of the main diagnostic tests for neurological disorders, which 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. According to report 'NEUROLOGICAL DISORDERS public health challenges' published by World Health Organization (WHO) from 1990 and 2015, disability adjusted life-years due to these disorders increased by 41% and is the second highest cause of morbidity and mortality worldwide [1].

Manual interpretation of EEG is expensive and time- consuming process, as only trained experts can interpret them these recordings may last for several days [2]. Therefore, an automated diagnosis system would help neurologist to interpret EEG in less time. Despite having challenges, the potential of artificial intelligence in healthcare systems cannot be denied in modern age.

EEG data collected from a local hospital along with channel wise annotations of anomalies created a unique opportunity for the proposed research problem. A hybrid model is proposed to localize anomalies in each channel of EEG record. Deep CNN is trained for detecting abnormal channels. To extract time of abnormal epochs Long Short-Term Memory (LSTM) networks is used.

1.2 PRODUCT SCOPE

EEG classification is a common research problem but to localize abnormalities in EEG signal is not much addressed. Data corpus MH-NUST is collected from a local hospital, data is annotated channel wise by neurologists and experts. Proposed architecture is divided into two parts: first it detects abnormal channel secondly, abnormal epochs are detected from detected channels. Proposed model detects with significant accuracy and sensitivity. Therefore, it can be utilized by the EEG researchers and healthcare workers.

1.3 EEG ACQUISITION

The EEG is recorded with the help of an EEG headset which consists of small

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.

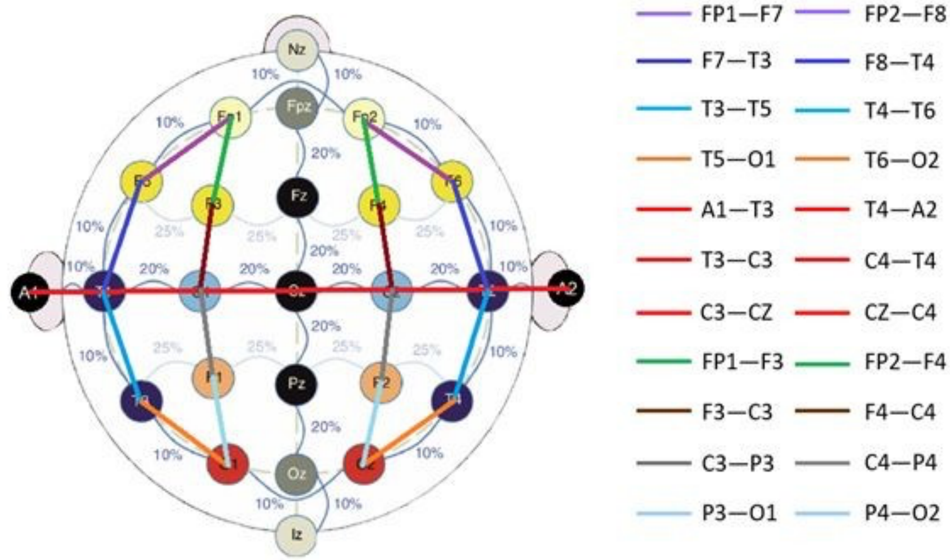

Figure 1. Standard electrode locations for a 10-20 system with a defined 22-channel TCP montage.

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. found in the TUH EEG Corpus: AR (left), LE (right)

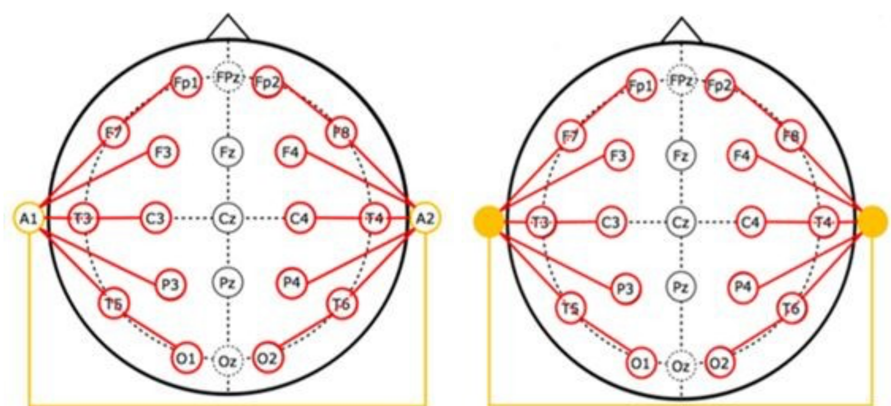

Figure 2. Location information of the electrodes for two montages.

1.4 OUTLINE OF THE REPORT

This report comprises of eight chapters, each of which focuses on a specific portion of the thesis.

The first chapter explains the practical need of proposed solution, project's purpose, and scope.

The second chapter explains all the related 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.

The fourth chapter explains the proposed methodology for problem statement.

The fifth chapter 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 the implementation and testing details

The seventh chapter discusses the results obtained from the implementation and how they are in accordance with 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

RELATED WORK

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 neurological diagnosis by EEG: i.e., to detect and localize abnormalities channel wise in an EEG signal. EEG diagnosis can be helpful in improving neurological rehabilitation, diagnosing epilepsy and warning patients of upcoming seizures [1,2]. Deep learning techniques inspired by speech recognition are also applied for EEG analysis.[5]

To localize abnormalities in EEG signal largest publicly available data set of EEG recordings is Temple university event corpus (TUEC). Most of the literature available for this problem is tested on TUH data set. [3,6].

When I reviewed at the existing literature of this research problem, A hybrid deep learning architecture is presented in, and the results are reported on TUH Event corpus. In this data set, 359 EEG recordings were used to train algorithm and 159 recordings to evaluate the methodology. Events are annotated into six classes in the data set. Authors applied a three-pass system that is a combination of HMMs and deep learning architectures to automatically analyze EEG signal. The results are evaluated on metrics that are calculated by Any-Overlap Method (OVLP) and delivered a sensitivity above 90% while maintaining a specificity below 5%. However, this hybrid architecture is only able to detect true positives with a very low false positive rate. [4].

EEG and speech signal share some similarities, both contains temporal information. Therefore, a methodology proposed by Picone [5] adapted automatic speech recognition (ASR) tool kits such as HTK and Kaldi for event classification in EEG signal. This methodology was also trained and tested on TUH EEG event corpus. Due to certain factors such as sharp spike in signal and wave discharges which were hard to detect by algorithms used for ASR, delivered low performance as claimed in paper Kaldi delivered 37.5% sensitivity and HTK 57.3% sensitivity on EEG data. [5]

DeepSleepNet, is a deep learning model that use raw single- channel EEG for automatic sleep state scoring in an EEG signal. In this model [9], conventional neural networks (CNN) are used to extract time-invariant features, and bidirectional- long short-term memory (LSTM) to learn transition rules among sleep stages automatically from EEG epochs. Model automatically learned features for sleep stage scoring from raw single-channel EEGs without training model on any hand-engineered features. [9,10] Proposed model performed efficiently, as evaluated on single channel of EEG. Accuracy claimed by authors in paper is 83%. [7]

Similarly, Convolutional Neural Networks (CNN) after acing image related tasks, have successfully been adopted for brain computer interface in [16]. Two Popular CNN models AlexNet [17] and VGG [16] are fine-tuned by AL Hussein 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 [12] 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% to 83%.

Channel wise deep learning models are used for various EEG tasks [8], [10] Classification of Epileptic seizure, Motor Imagery classification and emotion recognition performed well with CW model. Long Short-Term Memory (LSTM) networks are used in epileptic seizure prediction using EEG signals and delivered a significant increase in seizure prediction performance as compared to state of art. A hybrid deep learning model, CNN and RNN, is effectively utilized for emotion recognition based on multi-channel EEG signals. The CNN model co relates information. Whereas RNN model i.e., LSTM is used to learn long term information from sequences. The proposed method has been shown effective in the trial-level emotion recognition task. Proposed model for each time step, with accuracy of 76% [11].

Statistical techniques are used for automatically detecting anomalies in temporal data [19]. There are wide range of applications including decision-making in finance and business, quality process control in industry, management of power flows, risk assessment in medicine that have high accuracy rate in detecting anomalies in time series data. Statistical techniques can also be applied on EEG data as it is also temporal in nature. Seasonal Extreme Studentized Deviate (SESD) use mean and standard deviation. It is well known that these metrics are sensitive to anomalous data. As such, the use of the statistically robust median, and the median absolute deviation (MAD), has been proposed to address these issues [19]. Luminol which detects abnormality by identifying events that do not conform to an expected pattern or data points that deviate from a dataset's normal behavior by calculating anomaly score [20].

Only a limited number of literatures have addressed localization of abnormalities channel wise in EEG signal. Deep learning models has been applied to many EEG problems and gave successful results, including motor imagery, seizure detection, sleep stage scoring, and emotion recognition tasks. The design of these deep network studies varied significantly over input and network design. By reviewing multiple EEG related literature, it has been observed that hybrid CNN/LSTM architecture outperformed other types of deep learning models, such as Hidden Markov Model and MLPNN's with EEG data [9]. Therefore, a novel methodology has been proposed for automatic localization of abnormalities on raw channel wise EEG data, which is different from existing algorithms. A hybrid CNN/LSTM architecture is trained on raw data to detect abnormality channel and time channel wise.

Chapter 3

PROBLEM DEFINATION

3.1 PROBLEM DEFINATION

EEG records electrical activity of the brain using electrodes, which is significant in diagnosing neurological diseases such as epilepsy, brain tumor, brain dysfunction, inflammation of the brain (encephalitis), stroke, and sleep disorders. EEG recordings may last several hours or days moreover it is only interpretable by trained experts and neurologists. 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 [1]. 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, the burden of neurological diseases in developing countries, including Pakistan, is increasing due to rising life expectancy, urbanization of population and better diagnostic facilities.

EEG signals are intrinsically noisy and suffer from channel crosstalk. 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 neurologists who have low IRA as well.

The asymmetries of a disorder are not guaranteed to be present in an 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 highly trained experts. 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.

Automatic classification of EEG records is quite a common research problem now with multiple methods and high accuracy reported. Whereas, localizing abnormalities channel wise did not got much attention. An automated platform where abnormalities in an EEG record could be localized would help interpret EEG much efficiently. Channel wise abnormality annotation of MH-NUST dataset by trained experts created a unique opportunity for the proposed research problem.

Localization of abnormalities in EEG signals is referred to detect abnormality time window, epoch in each channel of an EEG record. Automated detection would reduce cost and resources used. A hybrid CNN-LSTM model is proposed to localize anomalies in each channel of EEG record. Proposed architecture is divided into two steps first a deep CNN model is trained for detecting abnormal channels in an EEG record. Moreover, to detect time of abnormal epochs a Long Short-Term Memory (LSTM) networks is trained.

Chapter 4

MATERIAL & METHODS

4.1 DATA:MH EEG CORPUS

A critical obstacle in the development of artificial intelligence technology for medical applications is the lack of data resources available to the research community. Huge amount of data is required for training of deep learning systems. TUH event Corpus [2] is the only existing publicly available data set in which anomalies are annotated channel wise. Along with the EEG data, it includes the anomaly annotations from neurologist and demographic information about the patient such as age and gender. However, to enhance the diversity of automatic EEG diagnosis data from local hospital is collected along with EEG data anomalies are annotated channel wise. A database of 2500 routine EEG's from the Department of Neurology in Military Hospital Rawalpindi, Pakistan was collected from 2016 to 2020.Out of 2500 EEG records 450 abnormal records are annotated channel wise.

Table 1 shows corpus details.

TABLE I *Data Set*

MH dataset	**Abnormal**	**Normal**
Train Set	355	1876
Test Set	90	94

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 Average referenced channel signals in European Data Format

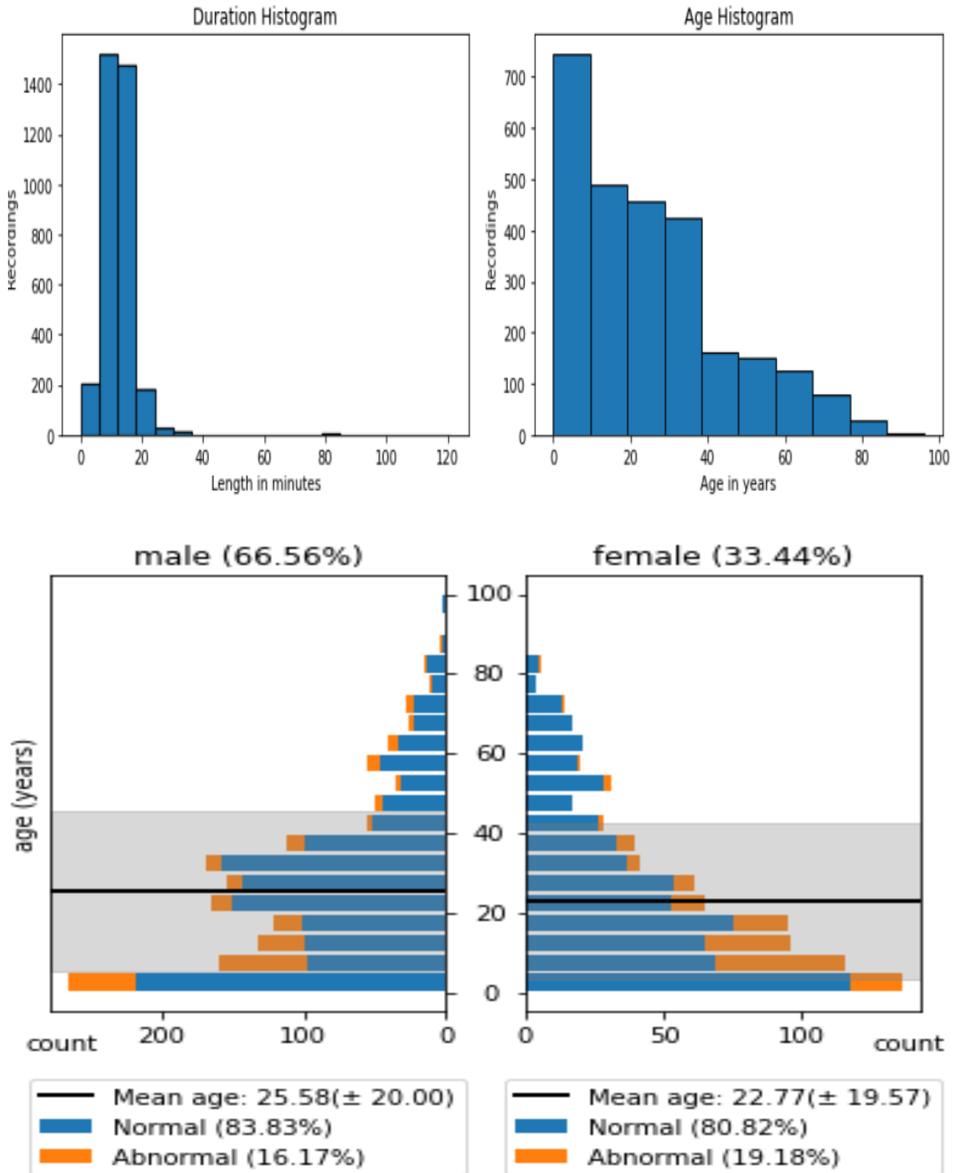

Figure 3. Statistics of MH dataset

(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. The annotations of abnormal epochs are assigned by trained neurologists and used as target labels to be predicted for research. Statistics of dataset are represented in figure 3.

MH Abnormal corpus represents an accurate characterization of clinical conditions. An imbalance between two classes in MH data set can be observed in table I. This reflects clinical situation in neurology practice. I have used oversampling from abnormal class during training for solving the problem of classification bias.

A team of neurologist and experts collaborated to annotate abnormal data channel wise into types of abnormalities [2]. Data annotations included channel and time where anomaly is observed which are considered most relevant for EEG diagnosis according to neurologists. The annotations were created on a channel basis—the specific channels on which an event was observed were annotated. Sample annotation of MH-NUST dataset is demonstrated in Figure 4. Box on image represent abnormalities channel-wise.

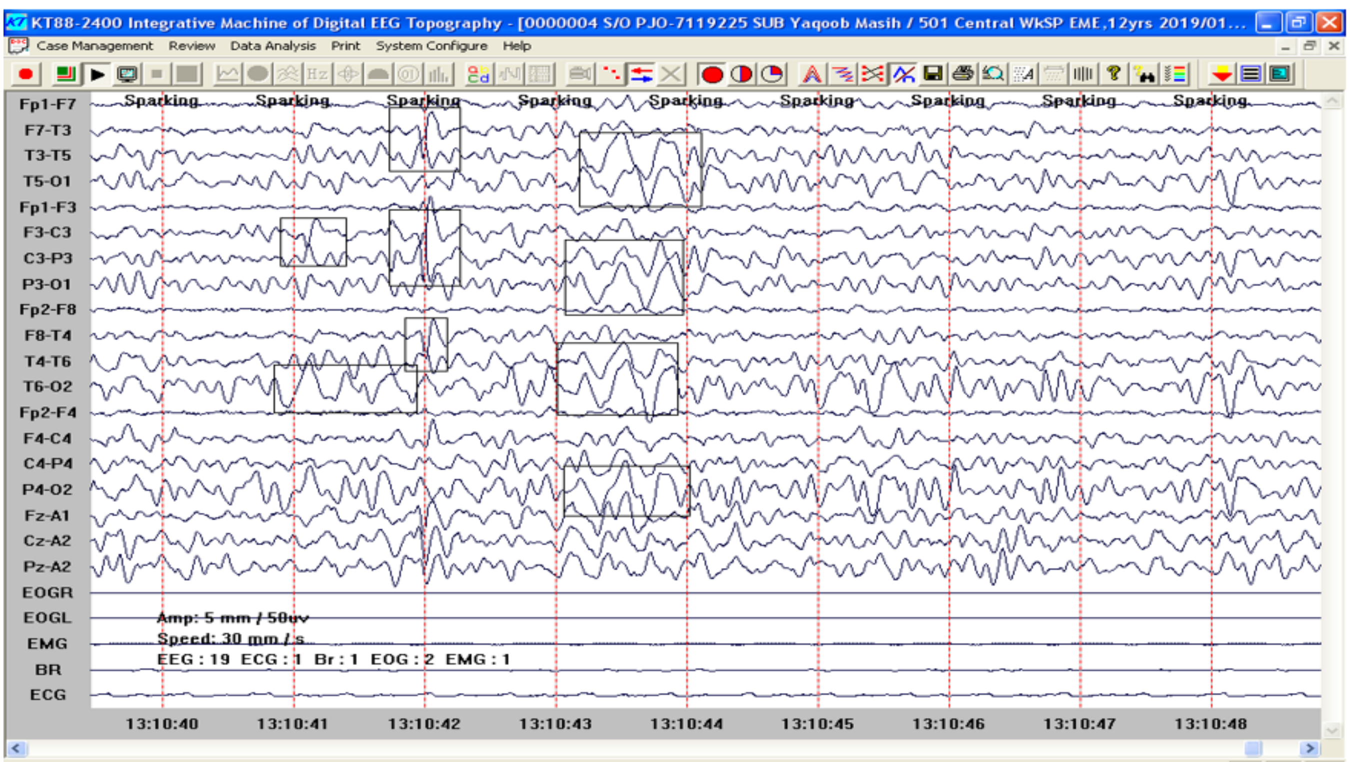

Figure 4. Channel-wise annotations of abnormalities.

Abnormal patterns in EEG signal are certain patterns that deviate in frequency, distribution from normal patterns Type of anomalies annotated are stated in table 2.

TABLE II: Abnormality type annotations

Sr #	Abnormality type
1.	Rolandic spikes
2.	Triphasic waves
3.	Poly spikes
4.	Sharp waves
5.	Delta Focal slow waves
6.	Generalized paroxysmal delta slow waves
7.	Spike and Focal wave discharge
8.	Generalized paroxysmal spike and wave discharge
9.	Low Voltage Waves
10.	Polyspikes and wave
11.	Fragmented spike and wave discharge

Four most commonly occurring abnormalities in dataset are defined below.

- **Spike/sharp waves**: Abrupt increase in the amplitude of sharply contoured wave forms are referred as sharp/spike waves. Spikes are fast electrical waves. Generally, each spike lasts less than 1/12th of a second and may be followed by slow waves. Spikes clearly stand out from other brain activity on the EEG are observed during epileptic seizures. Figure 5 shows sharp waves in an EEG record.

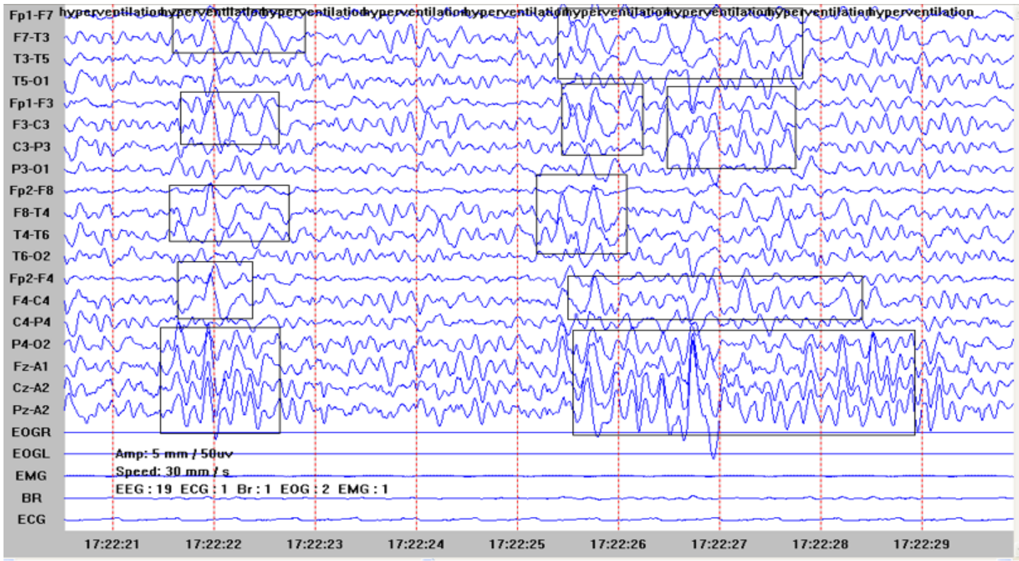

Figure 5 Spike waves can be observed at 17:22:22 and 17:22:26

- **Polyspikes**: are a series of spikes that happen quickly. Polyspikes are observed in generalized epilepsy and less commonly in focal epilepsy. Polyspike and wave discharges have a frequency ranging from 3.5 Hz to 5 Hz. Figure 6 shows polyspikes in an EEG record.

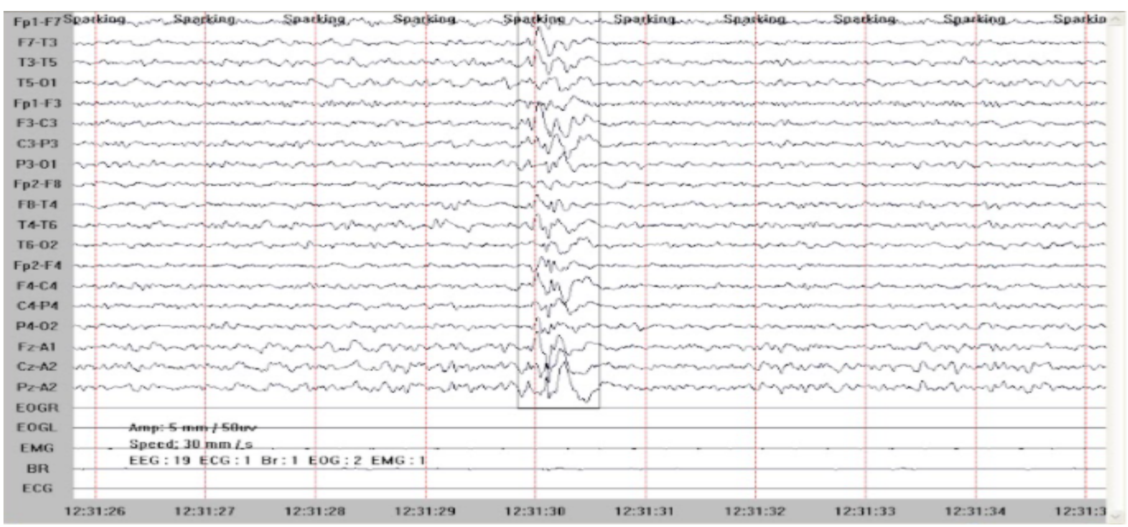

Figure 6 Polyspike waves can be observed at 12:31:30

- **Periodic lateralized epileptiform discharges (PLED):** patterns defined as repetitive periodic, focal, or hemispheric epileptiform usually recurring every 1 to 2 seconds, usually seen in patients with serial seizures and acute structural brain lesions. Figure 7 shows Periodic lateralized epileptiform discharges in an EEG record.

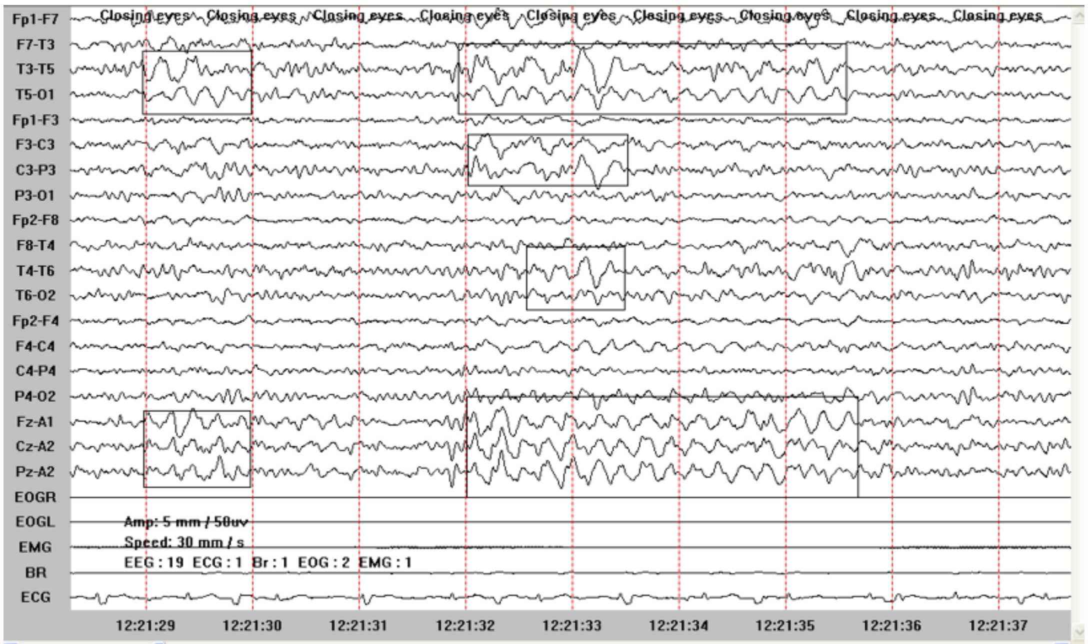

Figure 7 Periodic lateralized epileptiform discharges can be observed at 12:21:32

- **Slow waves:** are bilaterally synchronous discharges occur in the symptomatic generalized epilepsies. The frequency of these discharges is commonly in the range of 1 Hz to 2.5 Hz. Figure 8 shows slow waves in an EEG record.

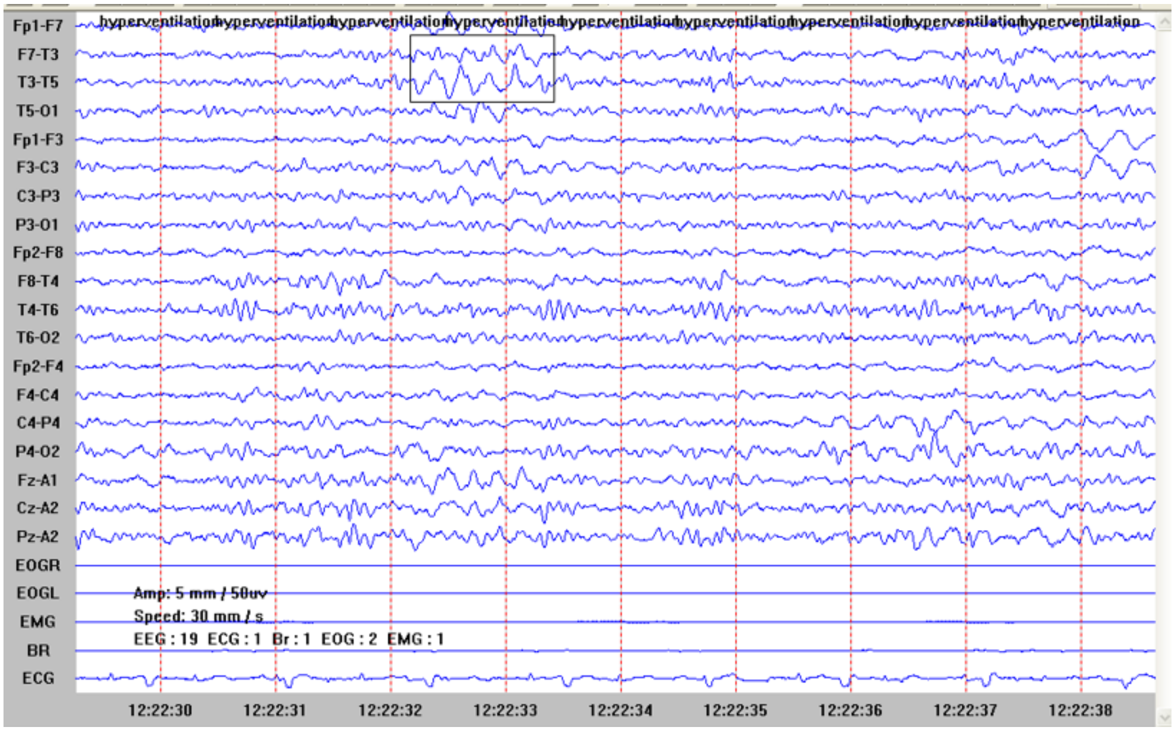

Figure 8 Slow waves can be observed at 12:22:32

4.2 PROPOSED METHODOLOGY

An overview of the proposed architecture consists of two main parts as shown in Figure 8. The first part is detection of abnormal channels, from each of raw channel of EEG record. The second part is anomaly time detection from abnormal channels detected by CNN.

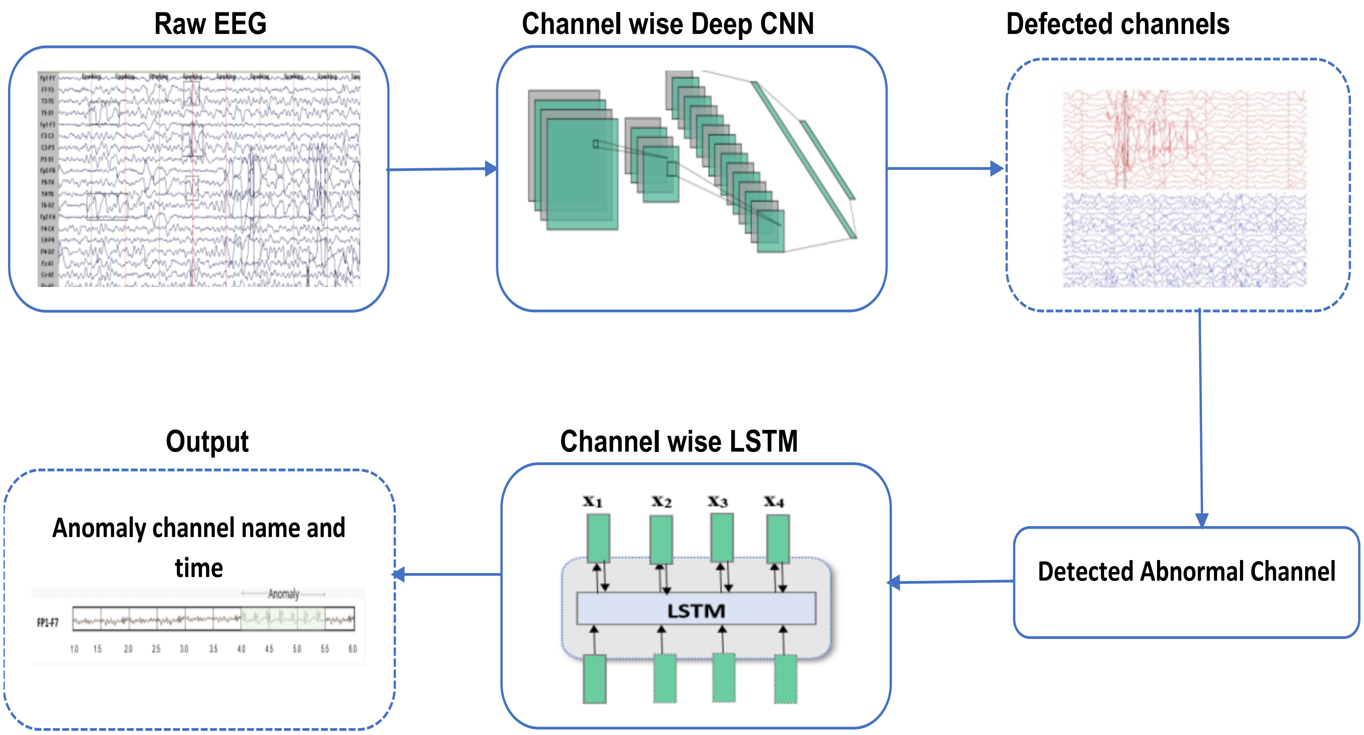

Figure 8. Architecture diagram of proposed methodology.

4.2.2 Preprocessing

In general, preprocessing is the procedure. In EEG data, preprocessing usually refers to removing noise from the data that transforms raw data into a format that is more suitable for further analysis and interpretable for the user. For the proposed methodology clipping, normalization and down sampling of signals from all the channels as mentioned by Schirrmeister (2018) is performed [12]. Down sampling has been proved to have minimal effect on pathology detection and increase computational efficiency. Therefore, Sampling frequency is set to 250Hz.Input signal is transformed into a data frame in python with the number of time steps as the rows and the number of electrodes as the columns. [12]

4.2.3 Channel Selection

Researchers suggest that some electrodes plays a greater role in decision for tasks for example T5 O1 of Temporal Central Parasagittal (TCP) was selected by Obeid [16] for feature extraction due to better performance on detection of abnormal EEG's. Similarly changes in Delta and Theta bands in temporal channels are found effective by Schirrmeister [12] in perturbation visualizations. However, the end-to-end training model is expected to learn these relations from the data set. Montage is kept the same throughout the data set for consistency and 21 average referenced channels are used for CNN and LSTM model. [11]

4.2.4 Abnormal Channel detection

Convolution neural networks has ability to extract features across multiple layers of convolutional transformation and learn to differentiate data classes. CNN has been successfully applied to many EEG tasks, including motor imagery, seizure detection, mental workload, sleep stage scoring, event related potential, and emotion recognition. Generally, CNN's and RNN's outperformed other types of deep networks, such as SAE's and MLPNN's that is because it can extract sequential information from EEG signal.

A four-layered Sequential Deep CNN architecture is trained channel wise [9] to detect anomaly from each channel of an EEG record. CNN model use three dense layers and one dropout layer. Dense layer receives input from all neurons of previous layers that enhance the performance. Dropout is a regularization technique to prevent overfitting that enhance learning of the model. In input layer, raw signals are used as input is convolved in CNN where kernel of feature maps, this removes requirement of feature extraction. Therefore, raw data can be used as an input to the model. This model yields list of abnormal channels from each record and achieved 82% accuracy on true positive cases.

4.2.5 Anomaly Time Detection

EEG data is comprised of a sequence of values over time. Anomaly time detection in an EEG channel refers to the process of identifying epoch of event in a particular channel that do not conform to an expected pattern or data points that deviate from a normal behavior. An auto encoder LSTM is trained supervised anomaly detection algorithm, to extract epoch of anomaly. Long Short-Term Memory (LSTM) networks have been useful for learning sequences in timer series data containing longer term patterns of unknown length, due to their ability to maintain long term memory. [9] This type of modeling is called multi-step multivariate time series. Multi step because model is forecasting next steps, multivariate as model have 22 channels to forecast.LSTM network is proposed in [10] to evaluate seizure prediction, similar approach is used to detect anomaly on raw EEG signal using Long Short-Term Memory (LSTM) units.

Chapter 5

IMPLEMENTATION

5.1 ANOMALY LOCALISATION APPLICATION

EEG recordings may last several hours or days moreover it is only interpretable by trained experts and neurologists. This makes manual interpretation of EEG costly and time consuming. Localization of abnormalities would detect abnormal channel and epoch of each abnormality. Automated detection would reduce cost and resources used. Proposed application can be used for clinical and research purpose.

5.1.1Tools and Technologies

The tools used for this web application are as follows:

1. Anaconda Navigator
2. PyTorch and keras
3. Torchvision
4. Numpy

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

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

The user can input the .edf file. The input file goes through pre-processing techniques and then through the deep convolutional neural network, and then LSTM and returns anomaly channel and time in each channel number of EEG record as shown in figure 9.

```
0000002.edf 0 [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28,
29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39]
0000002.edf 1 [0, 1, 2, 3, 4, 5, 6, 8, 9, 11, 12, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31,
32, 33, 35, 36, 38, 39]
0000002.edf 2 [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28,
29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39]
0000002.edf 3 [0, 1, 2, 3, 4, 5, 6, 11, 12, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 27, 28, 29, 30, 32, 34, 36, 37, 38, 3
9]
0000002.edf 4 [0, 1, 2, 3, 4, 5, 6, 7, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 29, 30,
31, 32, 33, 34, 35, 36, 37, 38, 39]
0000002.edf 5 [0, 1, 2, 3, 4, 5, 6, 7, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 23, 24, 25, 26, 27, 29, 30, 31, 32, 3
4, 35, 36, 38]
```

Figure 9. Output of hybrid architecture

5.1.2 Development of Application

```python
# To Run: python locate_defected_channels.py
import os
import mne
import numpy as np
import pandas as pd
from tensorflow.keras.models import load_model


model_name = 'all_keras_deep_conv_cnn_trained_model.h5'


# read edf file
def read_edf_file(file_path):
    eeg_data, tot_channels_name = read_edf_and_eeg_channels_transformation(file_path)

    #print(eeg_data.shape)

    return eeg_data, tot_channels_name


# read the edf tranform the channels into other montage space
def read_edf_and_eeg_channels_transformation(edf_file_path):
    edf_file = mne.io.read_raw_edf(edf_file_path, eog=['FP1', 'FP2', 'F3', 'F4',
                                                    'C3', 'C4', 'P3', 'P4', 'O1', 'O2', 'F7', 'F8',
                                                    'T3', 'T4', 'T5', 'T6', 'PZ', 'FZ', 'CZ', 'A1', 'A2'
                                                    ],
```

```python

    predicted_defected_channels = []

    raw_data = raw_data.astype('float32')
    for i, channel_data in enumerate(raw_data):
        predict_data = []
        predict_data.append(channel_data)

        predict_data = np.asarray(predict_data, dtype=np.float32)
        #print("ch shape", channel_data, channel_data.shape, np.array(channel_data))

        y_class = model.predict_classes(predict_data[0:1, :])
        print(y_class)

        if y_class[0] == 1:
            predicted_defected_channels.append(total_chann_name[i])
            # print("Defected Channel ", total_chann_name[i])

    return raw_data, predicted_defected_channels


if __name__ == '__main__':

    abnormal_file_to_predict = 'E:/0000002.edf'
    raw_data, total_chann_name = read_edf_file(abnormal_file_to_predict)
    raw_data, total_chann_name = transformed_raw_eeg(raw_data, total_chann_name)
    raw_data, predicted_defected_channels = predict_defected_channels(raw_data, total_chann_name)

    print("For {}, Defected channels are {}:  ".format(abnormal_file_to_predict, predicted_defected_channels))
```

Figure 10. Model preprocessing and algorithm implementation

5.1.3 TESTING

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

TABLE III Test cases

	Test Case	**Test input**	**Expected result**	**Actual Result**	**Test Result**
1	Checking format of input file	00000002. edf	process the file	Accept the file	Pass
2	Checking format of input file	00000002. jpg	Does not accept any other format than .edf	Only EDF files are supported by read_raw_edf	Pass
3	Detect defected channels	c	Fp1-F7,F7-T3,T3-T5,T5-O1,Fp1-F3,F3-C3,C3-P3,P3-O1,Fp2-F8,F8-T4,T4-T6,T6-O2,Fp2-F4,F4-C4,C4-P4,P4-O2	For E:/0000002.edf, Defected channels are ['F7-T3', 'F8-T4', 'T3-T5', 'T4-T6', 'T5-O1', 'T6-O2', 'T4-A2', 'CZ-C4', 'FP2-F4', 'F3-C3', 'F4-C4', 'C3-P3', 'C4-P4', 'P3-O1']:	Pass
4	Detect anomaly time	00000002. edf			

Chapter 6

RESULT & ANALYSIS

6.1 RESULT

The most critical evaluation criteria of deep neural network architectures in biomedical system is low false alarm rate. EEG anomaly localization is a critical diagnosis problem that demands a high sensitivity and specificity solution. Evaluation of the proposed hybrid architecture is discussed below.

6.1.1 Abnormal channel detection

To detect abnormal channels, Deep CNN is trained and tested on MH data. Detecting abnormal channel is measured as following:

- True Positives (TP): the number of normal channels detected as normal
- True Negatives (TN): the number of abnormal channels detected as abnormal
- False Positives (FP): the number of abnormal channels detected as normal
- False Negatives (FN): the number of normal channels detected as abnormal

Sensitivity (TP/(TP+FN)) and specificity (TN/(TN+FP)) are calculated from above measures, which are the most used in literature. Confusion matrices for Deep CNN in table 4.

6.1.2 Anomaly time detection

Anomaly in an EEG signal are annotated for every unit of time. EEG data have multi-channel signals, annotating for each unit of time on each channel appropriate since anomalies in an EEG occur on a subset of the channels present in the signal. In speech recognition applications it is practiced to simply score a summary decision per unit of time, such as every 1 sec, that is based on an aggregation of the per- channel inputs. Therefore, to evaluate anomaly time detection, Overlap Method (OVLP) approach is used [6]. True positives are counted when the detected overlaps with the reference annotation. FP’s correspond to situations in which a hypothesis does not overlap with any of the reference annotation. OVLP is a metric that tends to produce much higher sensitivities. If an event is detected near a reference event, the reference event is considered correctly detected. Figure 11,12 illustrates OVLP approach. Confusion matrix for LSTM is illustrated in Table 4.

TABLE IV *Results Reported by Hybrid Architecture*

	Sensitivity	**Specificity**
CNN (Defected channel detection)	78%	81%
LSTM (Abnormality time detection)	63%	71%

Proposed hybrid CNN-LSTM architecture has high sensitivity as well as specificity which is an important for EEG diagnosis. 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.

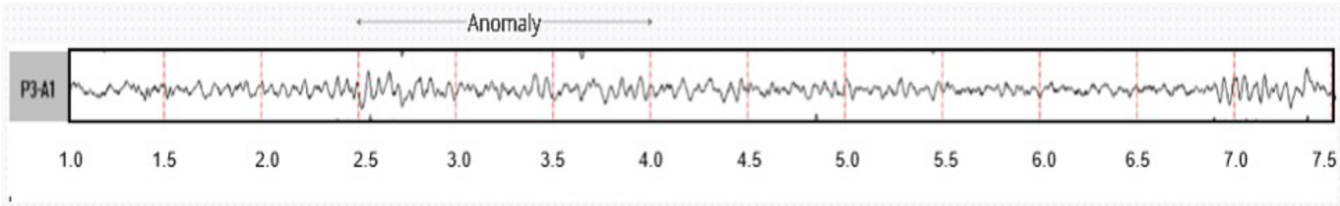

Figure 11. Reference annotation.

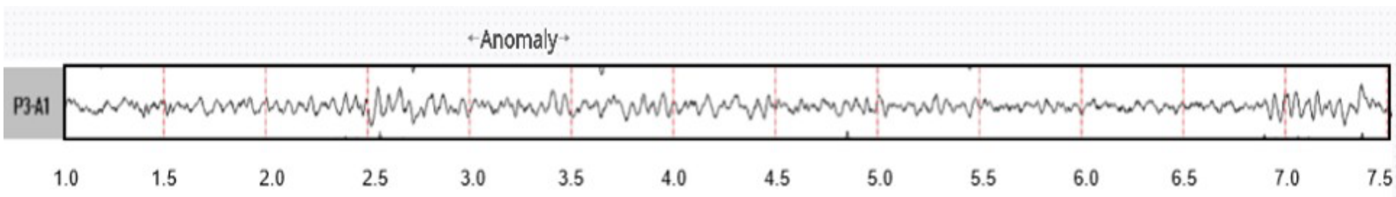

Figure 12. Automatic annotation.

Chapter 7

CONCLUSION AND FUTURE WORK

7.1 Conclusion

To increase diversity of EEG research MH-NUST dataset is annotated channel wise, which includes abnormal channel and abnormality epoch of each record. Automated methodology to localize abnormalities in an EEG record would help neurologist to diagnose neurological disorders by utilizing less resources. A hybrid deep learning model for automatic localization of abnormalities on raw EEG data is proposed. To automate the process proposed architecture is divided into two steps. First a channel wise deep CNN is trained to detect abnormal channels in a EEG record. Secondly, an auto encoder LSTM is trained to detect anomaly time from each defected channel. This architecture delivered significant results.

7.2 Future Work

This research problem is part of ongoing research and proposed architecture can be used to classify detected abnormalities channel wise in an EEG signal. In ML an increase in dataset always leads to more accurate results compared to architecture design. Therefore, we will also increase annotated data which will help further improve the results. Classification of detected abnormalities can further diversify the scope that can make automatic detection system a useful tool for research and clinical practice.

Chapter 8

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