Segment Based Abnormality Detection in EEG Recordings

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Abstract*—Electroencephalograms or EEGs are essential tests employed to diagnose any abnormalities in the brain waves that can be related to numerous brain disorders. These EEG recordings are ordered for a minimum length of 20 minutes and can go up to an hour or more, which makes the process of analysing it cumbersome and time consuming for medical professionals, and makes diagnosis very subjective. The aim of this paper is to aid in diagnosing EEG recordings with higher efficiency and accuracy. This is achieved by flagging segments of the recording into different classes that need special attention. This includes normal sleep wave patterns like POSTS, vertex waves and spindles, artifacts like ECG artifacts and Eyes open/close artifacts which can lead to misdiagnosis, and abnormal waveforms like spikes and slow waves. Most of the existing literature focuses on classifying the entire EEG as either abnormal or normal. However, in practice, a medical professional interprets the EEGs by looking at only particular sections of the recording. Therefore, our approach is to have individual segments classified instead. EEG signals, owing to their highly dynamic nature, are difficult for machine learning models to process and analyze effectively. To achieve this, we explore different methods of signal decomposition, feature elimination and classification, and find the best combination of these for the annotation task. Our combination of Empirical Wavelet Transform (EWT) for signal decomposition, Recursive Feature Elimination and Linear SVM model for classification, achieved an accuracy of 70% on the Temple University dataset and 90.78% on a private dataset.

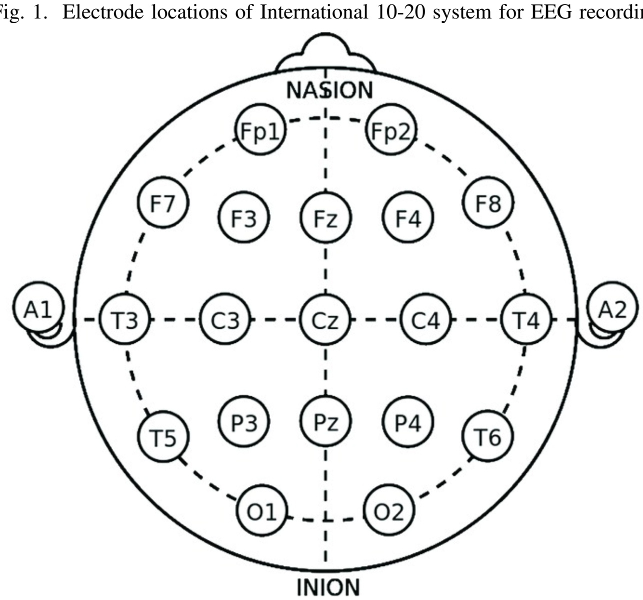
***Index Terms*—EWT, Empirical Mode Decomposition, SVC-RFE, RBF SVM, XGBoost, Spectral Features, MLP, TUH**

I. INTRODUCTION

Electroencephalography or an EEG is a way of measuring the electrical activity of the brain. EEG recordings help medical professionals diagnose many neurological disorders that influence brain activity like epilepsy, encephalopathies, along with multiple brain related attributes such as depth of anaesthesia, coma and even brain death. Thus, accurately reading and analysing an EEG is an important skill for any neurologist.

During the procedure, electrodes are placed across various sections of the scalp. Each electrode has a name and location as specified by the 10-20 international electrode system as seen in Fig.I. These electrodes pick up the feeble electrical impulses between neurons present in the brain. Each electrode is attached to an amplifier as the inherently feeble signals need to pass through layers of bone, skin and hair before they are picked up by the electrode. The signal is amplified to about 1000 to 100000 times its original amplitude and passed through an analog to digital converter. The result is a digital signal that can be read and processed on the computer to generate an EEG report. In case of abnormalities, they present themselves in multiple ways. Asymmetrical recordings

Fig. 1. Electrode locations of International 10-20 system for EEG recording



of the left and right hemispheres of the brain are indicative of abnormalities if the patient is asleep. The presence of slow waves in the EEG recording of an awake adult patient is indicative of abnormalities. Artifacts like eye blinks, muscle movements and ECG interference, if recorded, could contribute to incorrect diagnoses.

After capturing the EEG, the doctor goes through the complete recording and identifies areas of the EEG that might indicate abnormality to come up with a diagnosis.

Since it is a qualitative analysis, the accuracy often depends upon the experience and the skill of the doctor analysing the EEG. Hence, there is bound to be a level of human error that comes into play, therefore, the diagnoses usually differ from doctor to doctor for the same scan. Some scans can also clock up to a tens of hours, which naturally causes the accuracy of the diagnosis to reduce.

Motivated by this problem, this research is aimed towards finding an effective solution which can automatically flag segments of the EEG that require further reviewing by medical professionals. These labels include normal sleep wave patterns like POSTS, vertex waves and spindles, artifacts like ECG artifacts and Eyes open/close artifacts, and abnormal waveforms like spikes and slow waves.

II. Review of Literature

The literature survey is broken down into the different stages corresponding to our implementation.

A. Decomposition Methods

Reference [1] state that Adaptive Decomposition methods are more successful than Fourier Transforms for decomposing EEG signals as they are more suited to deal with non linear and non stationary data. The paper describes 5 methods out of which we picked 2. Empirical Mode Decomposition (EMD) transforms the incoming non-stationary signal into intrinsic mode functions (IMF). Empirical Wavelet Transform (EWT) transforms the signal into a predefined number of modes. Once the modes/ IMFs are generated, features that quantify the continuity and complexity of the signal are extracted from them. The paper also describes various parameters that can be extracted from the signals and elimination techniques such as Fischer Score.

Reference [2] present a comparative analysis between decomposition methods. It is mentioned that EMD can accommodate non-stationary as well as non linear signals. The issue with EMD is that when it is applied to multi-channel signals, they can be non uniform, and the nature of IMFs vary. In this method, the signal is projected in various directions in an n-dimensional space with these directions being selected in a uniform manner. By doing so, an envelope is obtained in each of the directions that the signal has been projected in. These envelopes are then averaged and interpolated by employing a cubic spline function and thereby the local n-dimensional mean is calculated. An important feature of EMD that the paper mentions is that the bands in the resultant IMFs can be associated with a corresponding brain activity when EMD separation is achieved.

B. Feature Elimination

Reference [3] discuss Recursive Feature Elimination (RFE) as a wrapper-based feature selection method used to find the most important features. This is done to reduce complexity and negate the curse of dimensionality. Support Vector Machine with a linear kernel is the model used for the RFE. In RFE, one feature is eliminated in each iteration until only a subset of the original features remain. For the classification task, the best results are obtained when SVM, either with a linear or rbf kernel, is used as the classification model after applying RFE.

Reference [4] discuss how Fisher Score can be employed for feature elimination. In this method, each feature is assigned a score independently. The authors also introduce a General Fisher Score that outperforms the normal Fisher Score.

C. Classification

There are mainly 2 approaches to the classification task; one using feature based machine learning models supported by decomposition methods, and the other methods employing end-to-end artificial neural networks and their modifications.

1) Feature Based Machine Learning Approach: Reference [5] describe two methods of classification, namely, k-nearest neighbours (kNN) and random forest ensemble learning. They used a subset of TUH's EEG dataset consisting of 400 EEGs. Only 1 channel (T5-O1 channel) was considered over which Principal Component Analysis was done for the feature elimination step. The authors mention that the first minute of the recording is sufficient to classify the entire EEG. Hence, they use only the first 60 seconds of the EEG from which spectral features are extracted. They arrived at an overall error rate of 31.7%.

Reference [6] discuss a supervised method of classification (kNN) along with an unsupervised approach to classification of graphoelements (k-means). All the channels of the EEG are first made to undergo adaptive segmentation. For each of the segments, a total of 16 features are extracted after which they are normalized. For the classification using k-means clustering, the number of classes was chosen to be 7. Whereas, for the kNN classification, the choice of classes was handled by the doctor. The number of classes was set to 15 and k was chosen to be 5. Based on their experiment, the authors concluded that kNN was more suitable since the classes had graphoelements with higher homogeneity than those obtained using K-means classification.

2) Artificial Neural Network Approach: Reference [7] used a 23 layered, one-dimensional Convolutional Neural Network (CNN) to classify a single channel signal from the temporal to the occipital lobe. They employed an end-to-end model; hence, the preprocessing stage didn't require any form of decomposition. They did, however, have to segment the data into 60 seconds intervals, which resulted in each input having 15000 samples, as the EEGs were recorded at a sampling rate of 250Hz. The Deep Neural Network had 23 layers, which were determined by brute force. These layers included a one dimensional convolutional layer, a layer which implemented

MaxPooling, a dropout layer, followed by a layer which implemented batch normalization, and finally, some dense layers.

Reference [8] approached the problem with a Long Short Term Memory (LSTM) Recurrent Neural Network (RNN) as they highlighted that a CNN model fails to classify the EGG accurately when the EEG has well defined spectral and clinical correlations. However, the training of an RNN has high complexity when it comes to the computation required and the results can often suffer from exploding and vanishing gradients. The latter problem is solved by using an LSTM as opposed to a plain RNN model. The LSTM model has very similar results, comparable to the CNN model, with the additional benefit that the LSTM allows the visualization of the decisions taken during classification.

III. Data

For our work, we mainly explored 2 datasets which were labelled segment-wise by medical professionals at Manipal Hospitals, Bangalore. The first dataset was the TUH (Temple University Hospital) EEG Dataset. This is a publicly available dataset that has been used by most of the state-of-the-art research papers [5], [7], [9]–[11]. The major issue that we faced with the TUH Dataset was its lack of variety in the abnormalities recorded and the quantity of abnormalities per EEG file. To circumvent this issue, we used Manipal Hospitals' inhouse data along with their expertise in regard to the different labels that they deemed important and would be beneficial to the doctors in practice. This was done by 1 technician and 2 neurologists who worked both individually and collaboratively, by going through every EEG they sampled. In addition to this, the data itself had a higher chance of being labelled accurately as it is being done by the same medical professionals who collected it, whereas the TUH data is relatively foreign to them and could have led to less accurate labelling on their end. It also provides us a better representation of data collected by Indian hospitals as compared to the TUH Data.

Following is a brief description of the above mentioned datasets:

TUH EEG Abnormal Corpus: It has 1488 abnormal and 1529 normal EEG sessions. For the ease of the evaluation of automated systems, it has been further divided into a train set (1361 abnormal/1379 normal samples), and a test set (127 abnormal/150 normal samples). We used a subset of the abnormal sessions, comprising 21 files for the model, as abnormal recordings have both normal and abnormal segments in the same file. The entire corpus is approximately 25,200 one-second segments.

- Number of Channels: 24-36 channels
- Display Montage: Referencial
- Filters applied: None - Raw Data

Manipal Hospitals Corpus: This corpus contains a total of 14 files. Each file is 20-120 minutes in length containing annotations for various classes. After segmentation, the entire corpus comprises 28,000 one-second segments.

- Number of Channels: 21 channels
- Display Montage: Bipolar
- Filters applied: 1 Hz High Pass Filter, 70Hz Low Pass Filter

IV. Proposed Methodology

The implementation is broken down into 3 modules namely,

- Preprocessing
- Feature Extraction and Feature Elimination
- Classification and Annotation

The entire pipeline of execution is explained in Fig.II. The first objective of our work was to find the best combination of signal decomposition, feature elimination and classification algorithms which give us the best performance metrics. Our Classification module, instead of classifying the entire EEG as either normal or abnormal, classifies each one second segment into various classes. This requires our dataset to have labels for each segment. Professionals at Manipal Hospitals manually labelled their own inhouse data as well as the TUH Corpus.

As the TUH Corpus was not very populated with different kinds of abnormalities, the annotation labels were restricted to spikes, slow waves and normal wave patterns. Manipal Hospitals, on the other hand, had a very rich dataset and therefore we could include many more labels; the first set was related to sleep characteristics: POSTS or Positive Occipital Sharp Transients of Sleep, Vertex waves and Spindles. Sleep characteristics play a major role as the diagnosis of normal vs abnormal waves varies with respect to the sleep state of the patient. Second set of labels were related to artifacts. Despite passing the EEG through low-pass and high-pass filters, many artifacts remain that may lead to misinterpretations [12], [13]. These labels include: ECG artifact, eye open and eye close artifacts. The last set of labels contained the abnormal wave patterns: Spikes and Slow waves. Including the Normal label, this makes a total of 9 labels compared to the 3 labels for the TUH data.

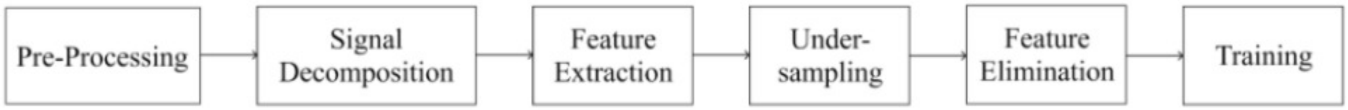
A. *Preprocessing*

For the preprocessing module, we applied low-pass and high pass filters of 70Hz and 1Hz [11], [19] respectively to the entire EEG file. We segmented our EEG into 1 second segments [8], [10] for more localized and accurate results, as abnormalities like spikes occur for a time period of 70-200 milliseconds.

As some of the channels in the data were not explicitly EEG channels, to reduce noise in our data [16], we eliminated the following channels: ECG/EKG, Photic Stimulation and EMG.

As the occurrence of abnormal segments in an abnormal EEG is very sparse when compared to normal segments, we were left with an imbalanced dataset. To negate this, we employed undersampling, where the data samples in the majority labels are reduced. This was implemented using One-Sided Selection (OSS), which is a combination of Tomek Links and Condensed Nearest Neighbor (CNN) methods of undersampling [17]. Tomek links are points on the boundary of the classes present in majority which are randomly selected

Fig. 2. Proposed Architecture for EEG Classification

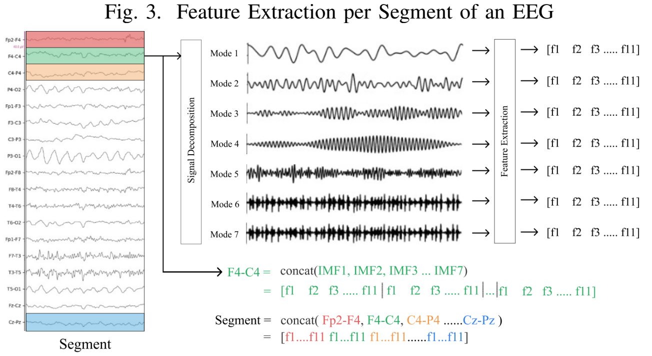


and removed. CNN then removes points of the majority class that are not close to the class boundary.

B. Signal Decomposition

As EEG data is non-stationary and non-linear, decomposition methods like Fourier Transform and wavelet decomposition do not perform well [8]. Furthermore, the above mentioned techniques do not provide accurate time-frequency representations of the original data owing to the Heisenberg uncertainty principle [17]. Hence we have adopted two approaches for signal decomposition: Empirical Mode Decomposition (EMD) and Empirical Wavelet Transform (EWT) [18]. These are used to decompose each channel in every segment into modes/IMFs. The process for signal decomposition per channel for every segment is outlined in Fig.III.

Fig. 3. Feature Extraction per Segment of an EEG



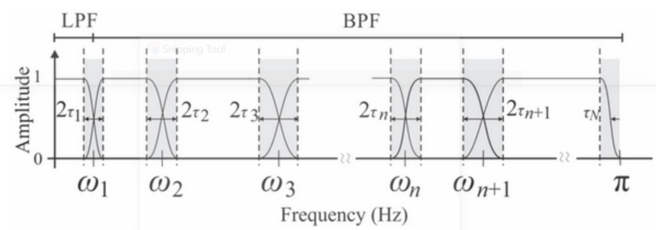
1) Empirical Mode Decomposition (EMD) [1], [2], [19]: EMD is an adaptive analysis method used specifically for temporal data to process signals that are non-linear and non-stationary. EMD breaks the original signal into a specified number of Intrinsic Mode Functions (IMFs) without leaving the time domain. The decomposition is as follows [20]:

$$I(n) = \sum_{m=1}^{M} IMF_m(n) + Res_M(n) \tag{1}$$

Here, I represents the original signal and Res represents the residue for the M^{th} IMF.

2) Empirical Wavelet Transform (EWT) [21], [22]: EWT adapts some of the wavelet formalisations by designing wavelet filter banks. This is followed by performing adaptive decomposition on a signal and splitting it into a specified number of modes. In contrast to traditional wavelet transforms, the support of the filters used in EWT are derived from the spectral distribution of the signal.

Fig. 4. [27] EWT basis construction



The wavelets in EWT are determined by one low pass filter (that is shown in Fig.IV as LPF) $\phi_n(\omega)$ that corresponds to the approximation and N-1 band pass filters (that are shown in Fig.IV as BPF) $\phi_n(\omega)$ that correspond to the details components [27].

We set the number of modes/IMFs as 7 after experimentation with different values. Signal decomposition is applied on every channel in a segment. If an EEG is 20 minutes long, with N channels (varies with the dataset), there will be 20*60 segments, each with N channels. The number of modes/IMFs per segment will then be: N*7.

C. Feature Extraction

The modes/IMFs that were extracted using the decomposition methods were subjected to feature extraction, where 11 spectral features were extracted [6], [18], [23], [24] per mode/IMF. The features extracted were: AM and BM bandwidths, Spectral Entropy, Spectral Power, Frequency Centroid, Peak Amplitude, Peak Frequency, Skew, Kurtosis, Hjorth Mobility and Hjorth Complexity. This makes the number of features per segment: N*7*11. All the features extracted from each decomposed channel per segment were flattened to form a one dimensional array as outlined in Fig.III. These features were then normalised using Standard Scalar (which has zero mean and standard deviation equal to one [12], [18]) as these features have a very wide range of values.

D. Feature Elimination

Extracting features per mode/IMF resulted in an explosion of the dimensions of our dataset. The total features per segment is in the order of N*7*11 per segment, where N lies between 18-32. Therefore, we performed feature elimination, where we tested SVC-RFE and Fisher Score [18]. We chose the number of features to be selected using a heuristic: 20*N [18].

1) Support Vector Classifier - Recursive Feature Elimination (SVC-RFE) [3]: RFE employs the process of backward elimination, which sequentially reduces the number of features considered. It selects a subset of the features and evaluates it by training it on an estimator, in our case, SVC. The main goal is to search the entire feature space to find the most optimal subset.

2) Fisher-Score based elimination [4]: Fisher Score works by assigning a score according to the Fisher criterion. The main aim of the fisher score is to maximize the distance between data points belonging to different classes while minimizing the distance between the data points belonging to the same class. For the i^{th} feature, the fischer score (S_i) is calculated as follows [27]:

$$S_i = \frac{\sum n_j(\mu_{ij} - \mu_i)^2}{\sum n_j * \rho_{ij}^2} \tag{2}$$

Here, n_j is the number of samples in the j^{th} class, μ_{ij} is the mean of the i^{th} feature in the j^{th} class, μ_i is the mean of the i^{th} feature and ρ_{ij} is the variance of the i^{th} feature in the j^{th} class.

E. Classification

After subjecting the data to feature elimination we are left with a set of selected features and labels that are ready to be sent to the classifier. We have considered the following models as they offer a range of different algorithms [18].

1) k - Nearest Neighbors (k-NN) [3], [5], [22]: Parameters: k = 3, Weights = Uniform, Algorithm = Auto, Metric = Minkowski distance.

2) Linear Support Vector Machine (Linear SVM) [3], [10], [22]: Parameters: C (regularization parameter) = 0.1, Gamma = 1, Class Weight = None.

3) Radial Basis Function Support Vector Machine (RBF-SVM) [3], [10], [22]: Parameters: C (regularization parameter) = 1, Gamma = scale, Class Weight = None.

4) XGBoost: XGBoost is an algorithm that has recently been dominating machine learning applications with structured data. It is a decision tree based ensemble model that uses a gradient boosting framework [9]. Parameters: booster = gbtree, num_feature = automatically set, max_depth = 6, gamma = 0, lambda (L2 - regularization) = 1, alpha (L1 - regularization) = 0.

5) Multi Layer Perceptron (MLP) [3], [11], [26]: Parameters: activation = ReLU, alpha (regularization) = 0.05, Learning Rate = adaptive, solver = adam, hidden_layer_sizes = 100.

Grid search was employed for both MLP and SVM as they were our best performing models in order to find the optimised parameters.

V. Results and Discussion

The first phase of our work was to find the best combination of decomposition, feature elimination and classification methods. For decomposition, EMD and EWT gave similar performances, however, EWT was chosen as EMD was more computationally expensive [18]. With respect to the feature elimination step, SVC-RFE was chosen as it was outperforming Fisher Score for both datasets across all classifiers. The performance metrics that we used to assess the models were accuracy, precision, recall, specificity and F-Score [7], [18].

These results were obtained after performing 10 fold Cross-Validation [10] on each model, and the mean of each metric over the 10-folds was reported.

The results of SVC-RFE feature elimination for Manipal Hospitals Data and TUH Data for each of the different classifiers are illustrated in Table I and Table II and respectively.

The combination of EWT for signal decomposition, SVC-RFE for feature elimination and Linear SVM for classification, gave us the best metrics, which we finalised as our pipeline.

Table I illustrates the results we obtained for classification of the Manipal Hospitals dataset on the labels: Vertex waves, POSTS, Spindles, ECG artifact, Eyes open, Eyes closed, Spikes, Slowing and Normal, per segment for various classification models. Linear SVM performed the best out of all the models with accuracy, precision, recall and specificity of 90.78%, 89.56%, 89.05% and 98.86% respectively.

Table II illustrates the results we obtained for classification of the TUH dataset on the labels: Spikes, Slowing and Normal per segment for various classification models. Linear SVM performed the best out of all the models with accuracy, precision, recall and specificity of 88.48%, 87.35%, 84.21% and 93.13% respectively.

It is observed that the specificity, which measures the ability of the model to correctly identify normal segments, was overall very high. This indicates that the models have classified majority of the normal segments correctly and the segments labelled as abnormal contain only abnormalities, thereby saving the doctors a lot of time during analysis.

According to our literature survey, there is a lack of research on classification of individual segments of EEGs. All the papers involve classification of the entire EEGs as normal or abnormal. Our models classify individual segments of EEGs into various classes, as opposed to this binary classification. In order to perform a comparison, we have compared our results with papers that have done an overall classification of entire EEGs using similar methods of signal decomposition and feature extraction.

Reference [9] reported an accuracy of 87.68%, recall of 83.3% and specificity of 91.33% using their CatBoost model for the classification of the entire EEG. Our Linear-SVM model outperforms their model on a segment level classification using the same dataset as shown in Table II . We achieved better results on our Manipal dataset as shown in Table I.

Reference [11] reported accuracies for binary classification using TUH dataset employing both feature based models and

TABLE I
PERFORMANCE OF DIFFERENT CLASSIFICATION MODELS USING SVC-RFE ON MANIPAL HOSPITALS DATA

Classification Model	Accuracy(%)	Precision(%)	Recall(%)	Specificity(%)	F-Score(%)
Linear SVM	90.78	89.56	89.05	98.86	88.93
MLP	87.78	86.06	85.30	98.48	85.01
RBF-SVM	81.97	79.30	77.72	97.71	76.55
XGBoost	81.05	77.52	77.19	97.64	76.60
k-NN	73.80	72.88	67.97	96.65	70.34

TABLE II
PERFORMANCE OF DIFFERENT CLASSIFICATION MODELS USING SVC-RFE ON TUH DATA

Classification Model	Accuracy(%)	Precision(%)	Recall(%)	Specificity(%)	F-Score(%)
Linear SVM	88.48	87.35	84.21	93.13	85.33
MLP	80.33	77.70	73.62	88.21	74.89
RBF-SVM	73.41	76.77	56.90	82.24	65.36
XGBoost	75.09	76.22	61.58	83.75	68.12
k-NN	62.07	55.40	55.10	79.02	53.17

artificial neural network models in the range of 81 - 86%. Our Linear SVM model for TUH data showed 88.48% accuracy, improving on this state-of-the-art model by at least 2%.

Reference [27] in their study reported an accuracy of 89.13%, recall of 80.16%, and specificity of 96.67% for binary classification on TUH data using their best model which uses features from different temporal segments of the EEG signal. They have pre-trained their model on private data before subjecting their model to TUH data. Hence, we can compare these results with the results we have obtained from our private data. In this aspect, our Linear SVM model, with accuracy, recall and specificity of 90.78%, 89.05% and 98.86% respectively out-performs all of their metrics.

These are the results of our final annotation task. Fig.V shows Eyes open artifacts and Eyes closed artifacts, Fig.VI represents the sleep characteristics: Spindles and Fig.VII and Fig.VIII illustrate the flagging of Spike and Slow waves abnormalities in the EEG after annotation, respectively.

Fig. 5. EEG with flagged eyes open and closed artifacts

VI. CONCLUSION

Electroencephalography or EEGs are used by medical professionals to diagnose diseases or abnormalities related to the

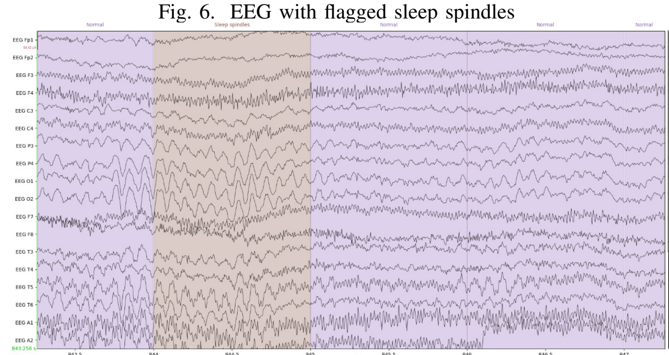


Fig. 6. EEG with flagged sleep spindles

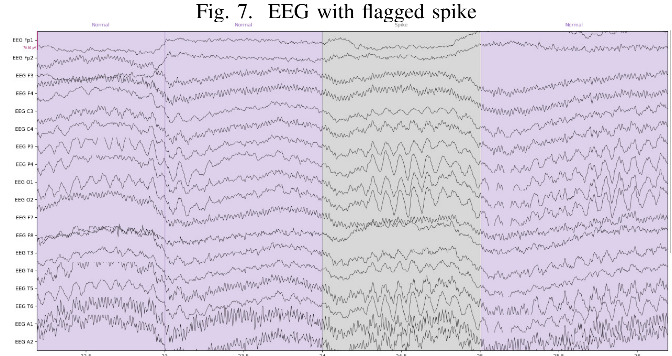
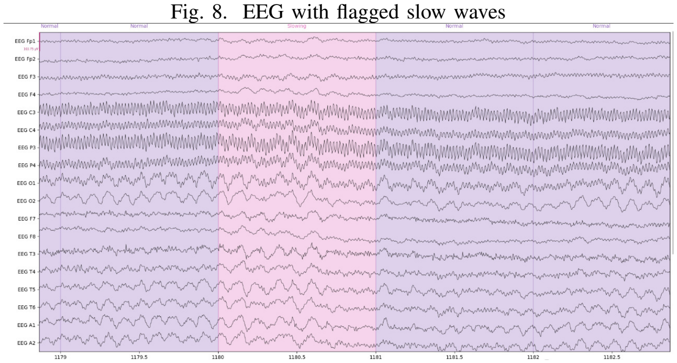


Fig. 7. EEG with flagged spike

brain. Manually analysing these EEG recordings, which can be as long as multiple hours, is a cumbersome process and prone to misdiagnosis as it is very subjective and depends on the individual reading it. Thus automated flagging of segments of EEGs that seem abnormal is very beneficial to the professionals. We proposed a pipeline for this classification consisting of segmentation, followed by signal decomposition using Empirical Wavelet Transform (EWT), Feature extraction, Feature elimination using Recursive Feature Elimination

Fig. 8. EEG with flagged slow waves



(SVC-RFE), followed by classification using Linear Support Vector Machine. This pipeline was finalised after experimenting with multiple signal decomposition, feature elimination and classification methods and models.

We obtained results on an open sourced dataset, from Temple University Hospital, and a private dataset, from Manipal Hospitals. For the TUH Dataset, the accuracy, precision, recall and specificity obtained was 88.48%, 87.35%, 84.21% and 93.13% respectively. For the Manipal dataset the accuracy, precision, recall and specificity obtained was 90.78%, 89.56%, 89.05% and 98.86% respectively. Our models when compared to state-of-the-art models showed better performance. Our work illustrates how technology can aid medical professionals by helping eliminate human error and reducing review time drastically.

VII. Future Work

Our implementation and results obtained are dependent on the medical professionals' experience and expertise to manually label the EEG datasets. Currently, there are no publicly available standardised datasets with individual segments of EEGs classified into multiple classes. An open sourced dataset for the same can be made available.

Our study focuses on two signal decomposition methods, two feature elimination methods and five classification methods. There are many more state-of-the-art signal decomposition methods and machine learning models like CatBoost and LightGBM that can be explored, which could potentially improve the performance of our model.

Our model currently only focuses on highlighting the segments of the EEG which require attention from the diagnostician. Further studies can extrapolate the results of our model to make inferences about disorders as well.

Our models are trained separately for each of our datasets. Future studies could explore the cross data functionality of both the models.

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