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DEVELOPMENT OF AN ACCURATE SEIZURE DETECTION SYSTEM USING RANDOM FOREST CLASSIFIER WITH ICA BASED ARTIFACT REMOVAL ON EEG DATA

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Abstract

The creation of a reliable artifact removal and precise epileptic seizure identification system using Seina Scalp EEG data and cutting-edge machine learning techniques is presented in this paper. Random Forest classifier used for seizure classification, and independent component analysis (ICA) is used for artifact removal. Various artifacts, such as eye blinks, muscular activity, and environmental noise, are successfully recognized and removed from the EEG signals using ICA-based artifact removal, increasing the accuracy of the analysis that comes after. A precise distinction between seizure and non-seizure segments is made possible by the Random Forest Classifier, which was created expressly to capture the spatial and temporal patterns associated with epileptic seizures. Experimental evaluation of the Seina Scalp EEG Data demonstrates the excellent accuracy of our approach, achieving a 96% seizure identification rate A potential strategy for improving the accuracy and clinical utility of EEG-based epilepsy diagnosis is the merging of modern signal processing methods and deep learning algorithms.

Keywords: Random forest classifier on EEG, Independent Component Analysis (ICA) epilepsy, Seizure Identification, Artifact Removal, Seizure Detection

1. INTRODUCTION

A non-invasive method for capturing electrical activity in the brain is electroencephalography (EEG). Neurological illnesses like epilepsy, sleep problems, and brain injuries can all be diagnosed and treated using EEG signals, which are frequently employed in clinical practice. However, a variety of artifacts, including eye blinks, muscular movement, and background noise, frequently taint EEG readings. The accuracy of EEG-based diagnosis and treatment may be impacted by these artifacts because they might mask the underlying brain activity.

The process of preparing EEG data for clinical use must include artifact reduction. For the elimination of artifacts, a number of techniques have been suggested, such as independent component analysis (ICA), wavelet denoising, and time-frequency analysis. A blind source separation method called ICA breaks down EEG signals into separate components, some of which might be artifacts. A filtering method called wavelet denoising uses the wavelet coefficients of EEG signals to get rid of noise from the signals. EEG signals are divided into time-frequency components using the signal processing method known as time-frequency analysis. These components can then be filtered according to their power spectra.

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EEG signals can be examined for the detection of epileptic episodes in addition to the elimination of artifacts. Recurrent seizures, which are abrupt and fleeting alterations in the electrical activity of the brain, are the hallmark of the neurological condition epilepsy. Epileptic activity in the brain can frequently be detected and localized using EEG signals. In the EEG signal, epileptic activity is often characterized by spikes or sharp waves that signify aberrant neural activation.

The detection of epileptic activity in EEG signals has been proposed using several methods, including time-domain analysis, frequency-domain analysis, and machine learning. Based on their amplitude, duration, and form, spikes and sharp waves in the EEG data are identified via time-domain analysis. Based on their power spectra, aberrant spectral components in the EEG data are identified by frequency-domain analysis.

Zhang [3] CNN-based method for detecting epileptic spikes in EEG signals had a 92.5% accuracy rate. Similar to this, Daoud [2] reported an RNN-based method with a 94.1% accuracy for detecting epileptic activity in EEG recordings. EEG signals can be examined for the diagnosis of various neurological conditions, such as sleep apnea and attention-deficit hyperactivity disorder (ADHD), in addition to epileptic activity. For instance, Zhen [3] reported a CNN-based method that successfully detected sleep apnea events in 91.6% of EEG signals.

Several seizure prediction model studies have explored the development of seizure prediction models using deep learning architectures. Shahbazi and Aghajan [24] introduced a generalizable model based on a CNN-LSTM architecture for seizure prediction. Ozcan and Erturk [29] investigated the application of 3D convolutional neural networks (CNNs) with an image-based approach for seizure prediction in scalp EEG. These studies highlight the potential of deep learning models in accurately predicting seizures. The relationship between aging and epilepsy has been examined by Beghi and Giussani [25]. They discussed the epidemiology of epilepsy in relation to age, shedding light on the impact of aging on seizure occurrence. Understanding the age-related aspects of epilepsy can contribute to improved management and treatment strategies for different age groups.

The identification of preictal and interictal states is crucial for accurate seizure prediction. Stacey et al. [30] reviewed the present-day EEG evidence for a preictal state, exploring the characteristics and potential markers associated with it. Various studies have investigated feature selection and optimization techniques for seizure prediction. Bandarabadi et al. [27] examined the selection of the preictal period and optimal time frame for detecting pre-seizure patterns. The performance evaluation and comparison of different seizure prediction models have been addressed in the literature. Graph Theory and Network Analysis: Network analysis and graph theory have been applied to investigate brain connectivity and epileptic seizures. Khambhati et al. [31] explored the dynamical network biomarkers for seizure prediction using graph theory-based measures. Their study highlighted the importance of network connectivity patterns in understanding and predicting epileptic seizures.

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Integrating multiple data modalities has shown promise in improving seizure prediction accuracy. By leveraging complementary information from different modalities, the study demonstrated enhanced prediction performance. Deep transfer learning techniques have been employed to improve seizure prediction models. Acharya et al. [10] introduced a transfer learning-based approach for multi-class seizure prediction using EEG signals. By transferring knowledge from pre-trained models, their method achieved improved prediction accuracy. Nonlinear Dynamics and Chaos Theory: Nonlinear dynamics and chaos theory have been applied to analyze EEG signals for seizure prediction.

Overall, the detection and treatment of neurological illnesses have demonstrated promising outcomes using EEG-based artifact reduction and epilepsy detection methods. These methods are constantly changing as new machine learning and signal processing algorithms are created. Better patient outcomes can result from the application of these approaches in clinical practice, which can increase the precision and dependability of EEG-based diagnosis and treatment.

2. MATERIAL AND METHODS

Complete classification procedure including the artifact removal of EOG and ECG along with ICA is described in figure 1 below. Time and frequency domain features are extracted and visually explained in the later part of the paper.

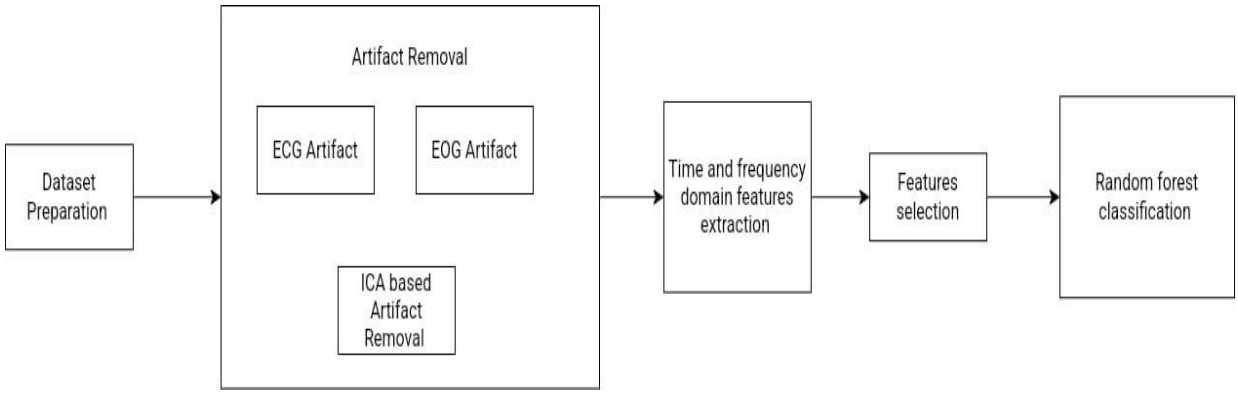

Figure 1: EEG classification procedure block diagram

2.1. Dataset description

Both interictal (between seizures) and ictal (during seizures) EEG recordings are included in the collection. A 21-channel EEG system with electrode placement based on the International 10-20 method was used to obtain the recordings and 1-2 EKG recordings are also there to support removal of artifacts. The EEG signals were stored in EDF format and recorded at a sampling rate of 512 Hz. Reusable silver and goldcups electrodes are used with EB Neuro and Natus Quantum LTM amplifiers for fetching the data. Each recording in the dataset comes with a metadata file that contains details about the patient, the length of the recording, and the patient's clinical background. The metadata also contains details on the patient's particular type and frequency of

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seizures. Researchers interested in creating machine learning algorithms and other computational techniques for the epilepsy diagnosis and treatment will benefit greatly from the dataset. The database is having 14 folders each consisting of one patient file with 5 different 2.11GB of data files each with a descriptive text file that informs about seizure location. [33]

2.2. Preprocessing

2.2.1 Filtering

In the artifact identification process, bandpass filtering is an essential step for reducing DC offset and powerline noise. In this method, the EEG signals are subjected to a bandpass FIR filter with a frequency range of 0.5 to 30 Hz. Based on the characteristics of neuronal activity linked to epilepsy and the reduction of undesired noise sources, this particular frequency range was selected. The retention of low-frequency elements associated with slow wave activity and prospective seizure patterns is made possible by the 0.5 Hz cutoff frequency, which can be a useful tool for epilepsy identification. In contrast, the 30 Hz upper cutoff frequency is chosen to keep the relevant brain activity while excluding higher frequency noise and artifacts. Employing a bandpass FIR filter with a tailored frequency range, the methodology aims to enhance the signal quality, improve the accuracy of subsequent analysis, and enable the identification of epileptic patterns within the EEG data. The same is represented in Figure 2 where raw plot channel-wise representation after application of bandpass filter.

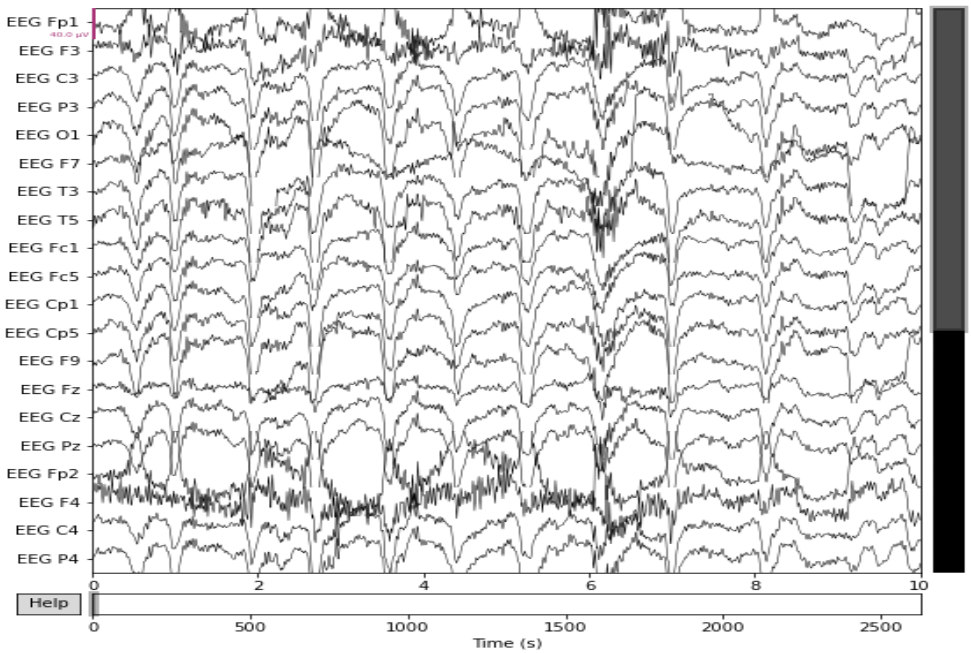

Figure 2: EEG data after application of Bandpass filter

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2.2.2 Electrooculogram - EOG artifact detection

A particular set of parameters is used in the artifact detection methods provided in the Kaggle code to create EOG epochs using a finite impulse response (FIR) filter. The lower passband edge of the FIR filter is set at 1 Hz, and the upper passband edge is set at 10 Hz. The 5120-sample filter length is chosen. There are 112 notable peaks found after filtering.

These peaks reflect EOG-active epochs, which can offer important details for later artifact removal and detection procedures. It is easier to separate EOG-related artifacts from other sources of noise and interference when these strong peaks are noticed in the EEG data.

By utilizing the FIR filter with the specified parameters, the methodology aims to effectively extract EOG epochs, enabling further analysis and identification of artifacts originating from eye movements and blinks.

Figure 3 shows the EOG – Eye blink pattern effect on EEG signal which is mostly affected by all the channels. This step contributes to the overall accuracy and reliability of the artifact detection system, facilitating the subsequent processing and identification of other types of artifacts in the EEG data.

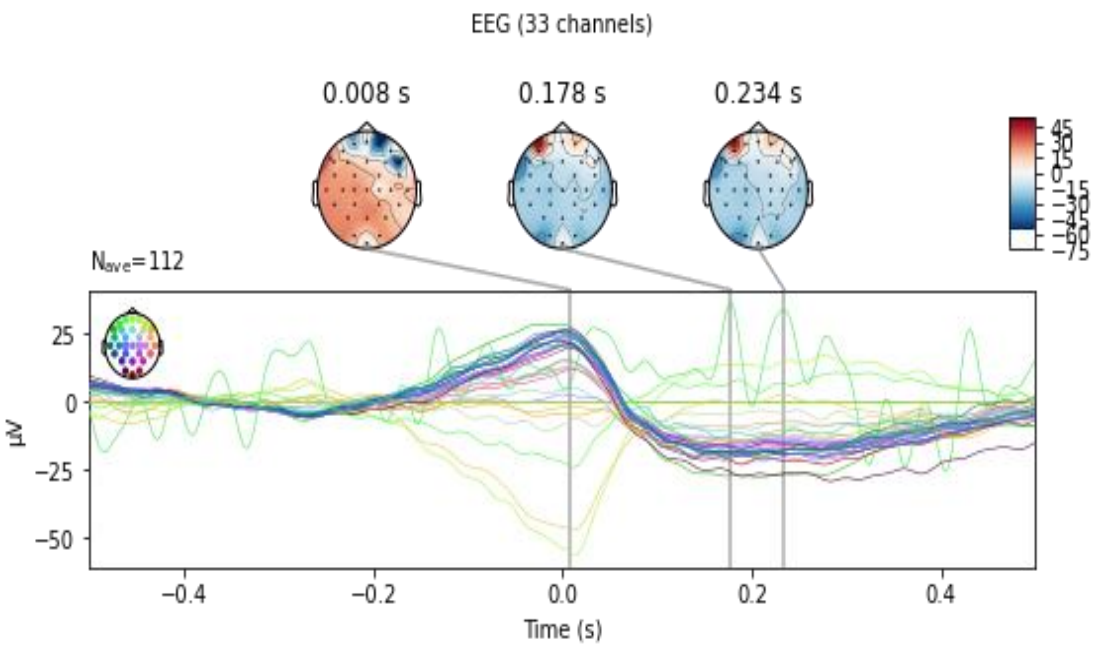

Figure 3: **EEG Signal capture on EOG artifact detection**

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2.2.3. Electrocardiogram - ECG artifact detection:

To obtain EOG (Electrooculogram) epochs using a finite impulse response (FIR) filter in the artifact detection methodology described in the Kaggle code, a specific set of parameters is employed. The FIR filter is designed with a lower passband edge of 8Hz and an upper passband edge of 16Hz. The filter length is set to 5120 samples.

During the filtering process, 2710 significant peaks are identified. These peaks generally known as R peaks represent epochs containing ECG activity, which can provide valuable information for subsequent artifact detection and removal steps. Figure 4 represents the ECG – Heartbeat pattern effect on EEG signal and its relevance with the channels. The identification of these significant peaks' aids in distinguishing ECG-related artifacts from other sources of noise and interference present in the EEG data.

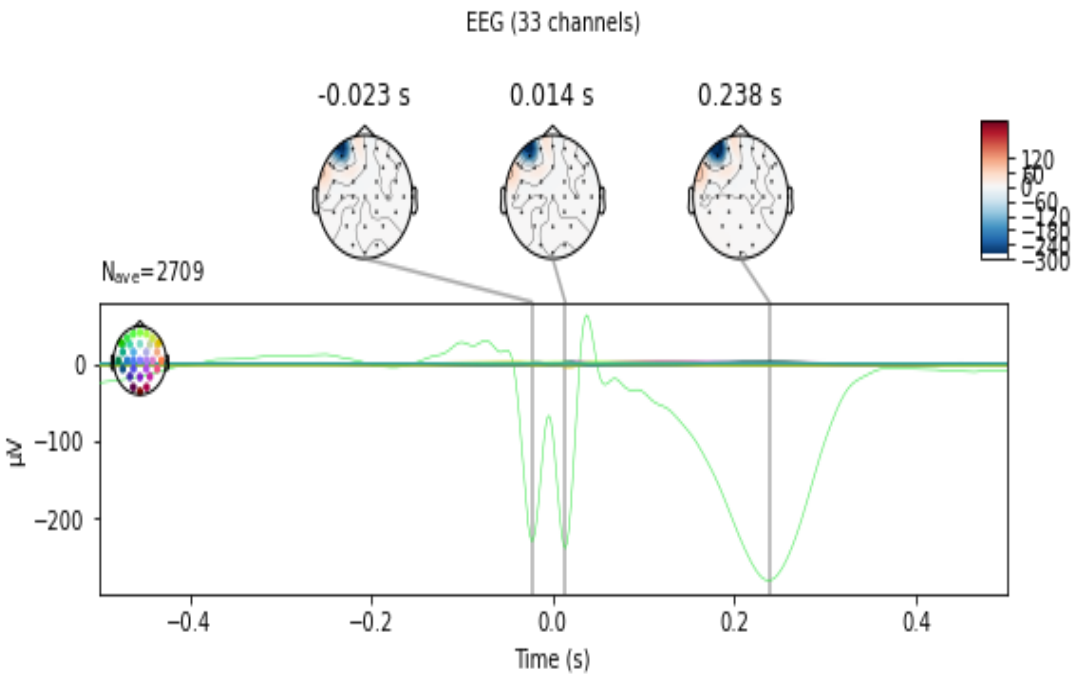

Figure 4: EEG Signal capture on ECG artifact detection

2.2.4. Artifact Detection and Removal using independent component analysis:

For artifact detection using ICA same as the above two artifact detection methods first filters are applied, FIR filter parameters are one-pass, zero-phase, non-causal high pass filter, Windowed time-domain design (firwin) method, Hamming window with 0.0194 passband ripple and 53 dB stopband attenuation, Lower passband edge: 1.00, Lower transition bandwidth: 1.00 Hz (-6 dB cutoff frequency: 0.50 Hz), Filter length: 1691 samples (3.303 sec). ICA fits to all 33 channels and

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resulting plots are shown in Figure 5, Primarily 19 channels ICA are represented in figure which further helps to remove the muscle movement and other artifacts which can create false detections in EEG

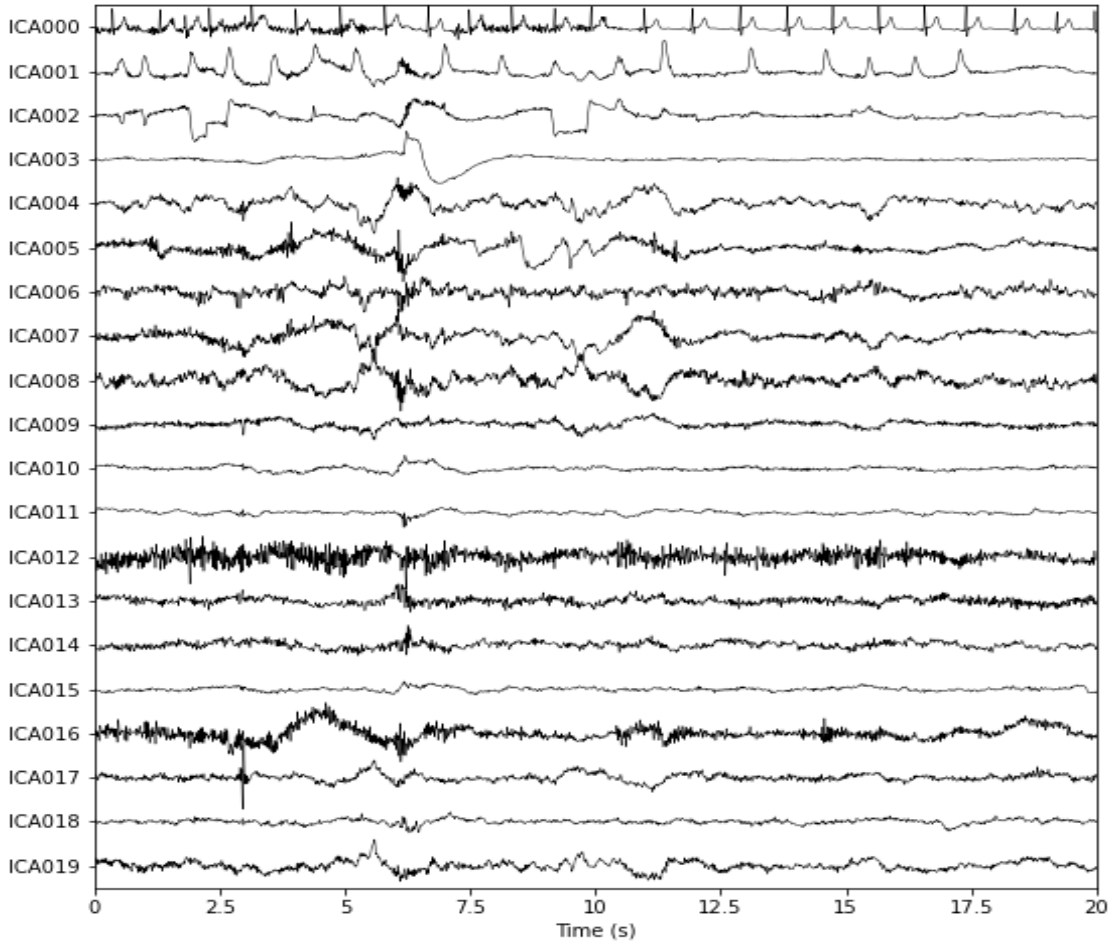

Figure 5: EEG ICA component decomposition view

Figure 6 depicts a topography map illustrating the sensory interface, highlighting the correlation between channels and Independent Component Analysis (ICA) channels.

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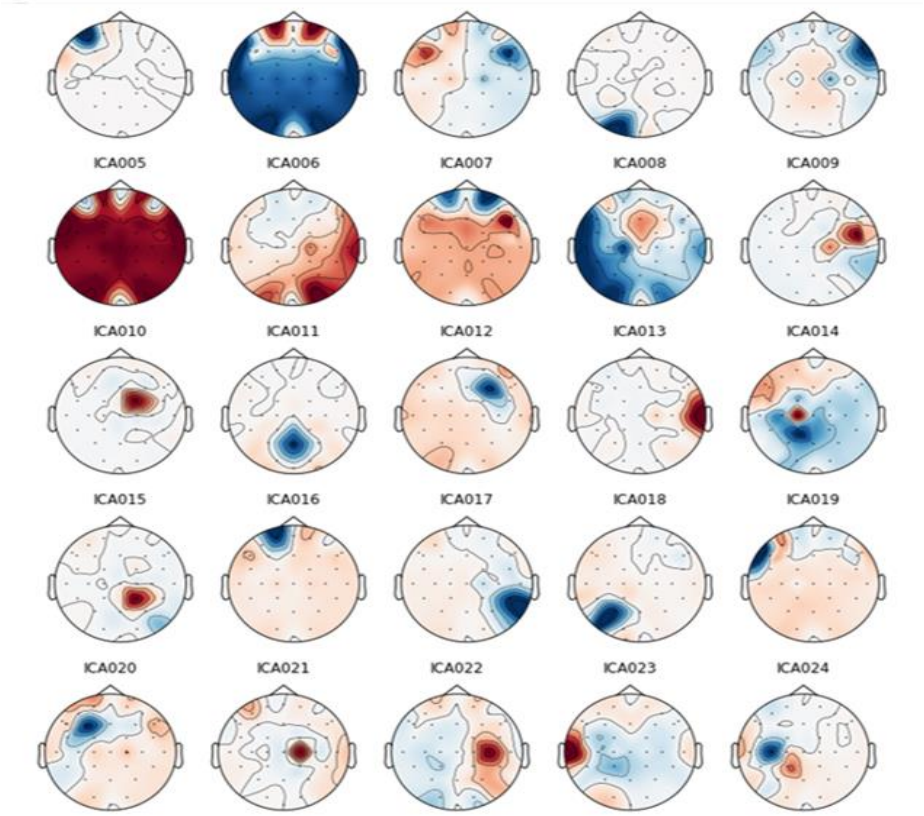

Figure 6: Topography EEG ICA component decomposition view

3. RESULT

The artifact removal effectively reduces the impact of muscular activity, eye blinks, and external interference, resulting in cleaner and more reliable EEG signals. Following artifact removal, the continuous EEG signal is segmented into fixed-length epochs of 5 seconds, with a 1-second overlap between consecutive epochs. This segmentation approach ensures continuity and captures potential transient changes at epoch boundaries. Each epoch is then meticulously labeled as either normal or abnormal, enabling subsequent analysis and interpretation of the EEG data. By adopting this methodology, researchers and clinicians can gain valuable insights into brain activity and detect abnormal patterns that may be indicative of neurological disorders or other abnormalities.

The EEG data used in our study comprises 5-second epochs, sampled at a frequency of 512 Hz, resulting in 2560 samples per epoch. The dataset consists of recordings from 35 channels. Specifically, we focus on seizure data, which spans 50 seconds, resulting in 10 seizure epochs. In contrast, the seizure-free data encompasses 3125 seconds, yielding 643 normal seizure-free epochs. To facilitate analysis, we converted the EEG data into arrays, accompanied by corresponding labels denoting normal and abnormal epochs.

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Following the addition of labels to the complete dataset, comprising both seizure and seizure-free epochs, we proceeded with feature extraction. Our feature extraction process encompassed various time domain features, including mean, standard deviation, peak-to-peak amplitude, variance, minimum and maximum values, along with their respective indexes. Additionally, mean square and root mean square (RMS) values, coupled with absolute differences, were calculated. To capture frequency-related information, we further subdivided the data into specific frequency bands, namely delta (0.5-4.5 Hz), theta (4.5-8.5 Hz), alpha (8.5-11.5 Hz), sigma (11.5-15.5 Hz), beta (15.5-30 Hz), and gamma (30-45 Hz). For each epoch, we measured the power spectral density and appended all the extracted features to a designated array. Furthermore, the seizure data was appropriately labeled for subsequent analysis.

To understand more about selected features and their distribution follow below histogram Figure 7, According to it the outliers can be easily identified and effective distribution of parameters can be selected to improvise the overall performance of the ML algorithm.

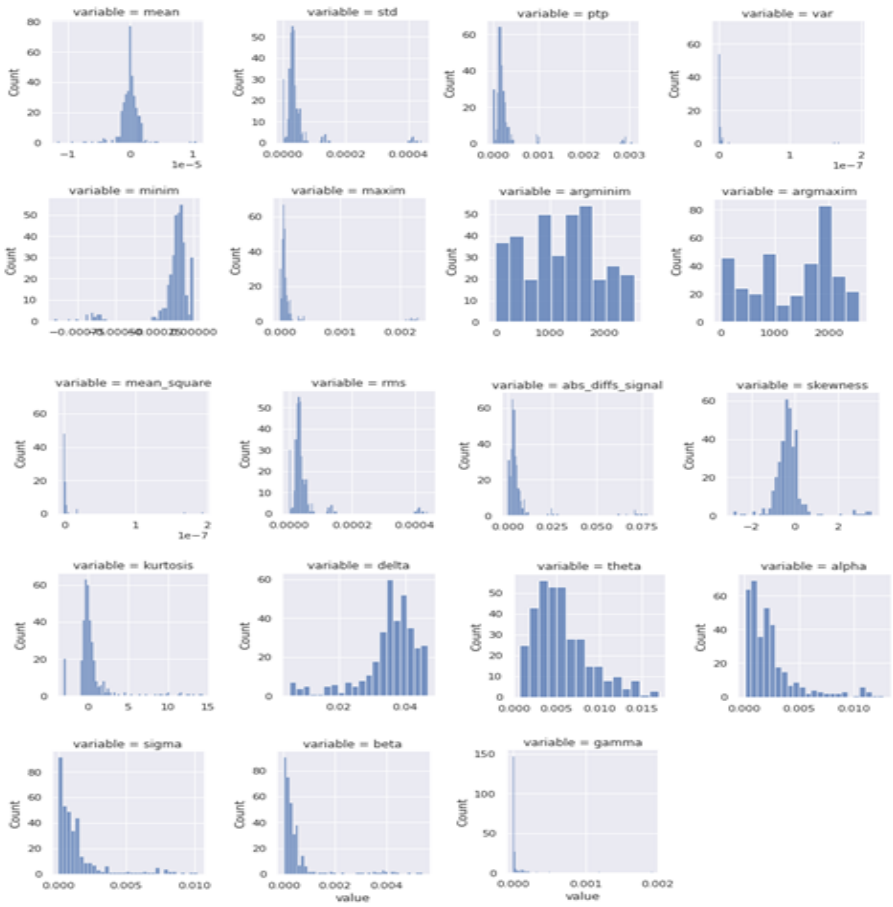

Figure 7: Histogram of distribution of selected features

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The feature listing and their significance are shown in the heatmap below. In Figure 8 alpha, beta, etc are the power spectral density of the epoch.

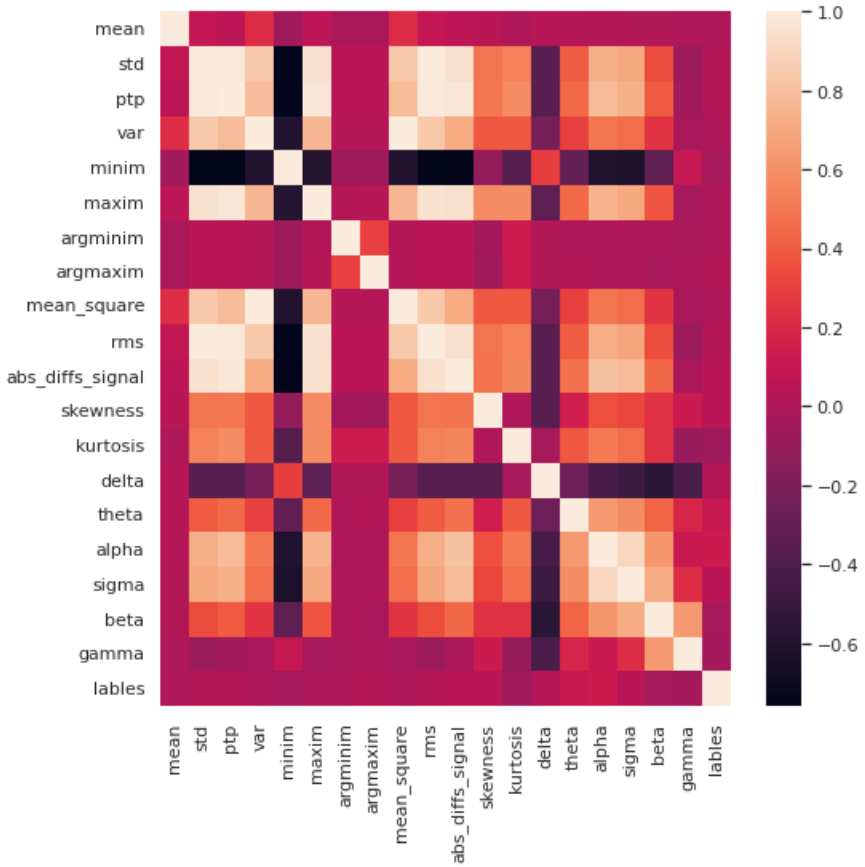

Figure 8: Heatmap of correlation between features

4. DISCUSSION

There is a wealth of ongoing research in this domain, and among them, notable studies have unveiled fascinating insights, Nasseri, M. [34] conducted a study focusing on the development of a seizure forecasting system utilizing a long short-term memory (LSTM) recurrent neural network (RNN) algorithm. The research involved the utilization of a noninvasive wrist-worn research-grade physiological sensor device, resulting in a mean AUC-ROC of 0.80 (with a range of 0.72–0.92). Nahzat, S. & Yağanoğlu, M. (2021) [35] employed a range of classification algorithms, namely Random Forest (RF), K-Nearest Neighbors (KNN), Artificial Neural Network (ANN), Support Vector Machine (SVM), and Decision Tree (DT). These algorithms were applied to predict epilepsy using the dataset, with the additional implementation of the Principal Component Analysis (PCA) feature reduction technique and analyzed the performance of the classifiers both

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with and without the utilization of PCA with accuracy levels of the models used in this analysis varied across the algorithms ranges from 92% to 97%.

Along with machine learning techniques other research area explored by Jiang Ximiao, Liu Xiaotong [36] is cross-frequency coupling (CFC) and phase-amplitude coupling (PAC) feature with an interval length of 5 mins and using Random Forest classifier, receiving an accuracy of 85.71% for Seina scalp database to 95.87% in CHB-MIT database. Recent research with deep learning methodology for the feature selection OAOFS-DBNECD (Deep Belief Network for Epileptic Seizure Detection) On CHB-MIT has received an accuracy of 97.81% researchers have applied the algorithm with feature selection and without feature selection and received accuracy in range of 94% to 97%. Figure 9 we have illustrates the comparison between the approach that we have taken with respect to recent deep learning and Neural Network comparison.

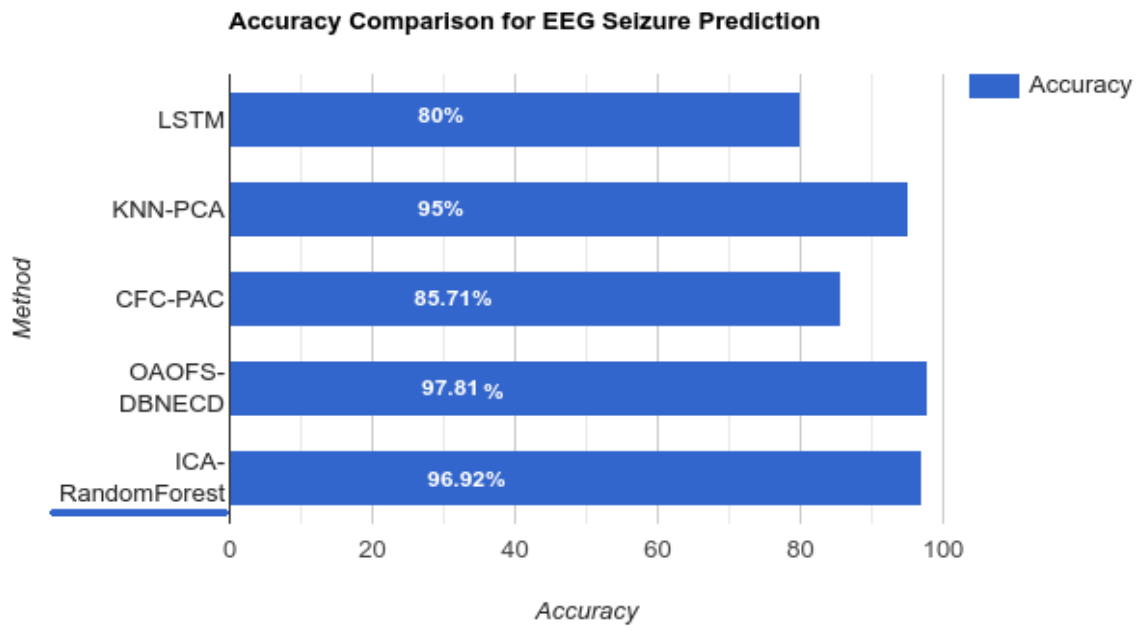

Figure 9: Accuracy comparison of EEG seizure prediction

5. CONCLUSION

Artifact Detection and Removal using Independent Component Analysis, We conducted feature comparison and identified dominant features, specifically the power spectral density of alpha and theta waves, accounting for 10.53% and 11.76% of the discriminative information, respectively. Subsequently, we employed a random forest classifier with selected parameters: 100 n_estimators (the number of decision trees in the forest) and the Gini criterion (used to measure impurity during tree building). The maximum depth of the trees was determined to allow splits until all leaves

contained fewer samples. To determine the best features at each split, the square root of the total number of features was considered. The resulting model achieved an accuracy of 96.92% with a low error rate of 0.094%. The dataset was divided into 80% for training and 20% for testing, and the Python sklearn library was utilized for implementation. Finally, we verified the model's performance on the complete dataset and obtained consistent results.

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