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Brain Waves Decoded: Cutting-Edge Seizure Recognition with Graph Fourier and BrainGNN

Dhruvi Thakkar[1], Zankhana Patel[1], Dhruv Dudhat[1], Dr. Rocky Upadhyay[2], Ankita Kothari[3], Dhara Parikh[3]

[1]Student at Krishna School of Emerging Technology and Applied Research, Drs. Kiran & Pallavi Patel Global University, Vadodara-Mumbai NH#8, Varnama, Vadodara-391243, Gujarat, India

[2]HOD & Associate Professor at Krishna School of Emerging Technology and Applied Research, Drs. Kiran & Pallavi Patel Global University, Vadodara-Mumbai NH#8, Varnama, Vadodara-391243, Gujarat, India

[3]Assistant Professor at Krishna School of Emerging Technology and Applied Research, Drs. Kiran & Pallavi Patel Global University, Vadodara-Mumbai NH#8, Varnama, Vadodara-391243, Gujarat, India

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ABSTRACT

For effective therapy, epileptic seizures, which are characterized by sudden electrical disruptions in the brain, must be identified accurately and promptly. Conventional techniques, such feature extraction and EEG signal analysis, have demonstrated limits in terms of robustness and precision. In order to greatly improve seizure recognition, this paper present a novel method that integrates Brain Graph Neural Networks (BrainGNN) and Graph Fourier Transforms (GFT). By transforming brain wave impulses into the frequency domain, the GFT examines brain wave signals and reveals complex patterns associated with epileptic activity. With great accuracy, BrainGNN—which is optimized for graph-structure data—capture the temporal and spatial correlations in these signals to differentiate between seizure and normal states. Our combined GFT and BrainGNN method outperformed conventional technique by a significant margin, achieving outstanding test accuracies of 99.77%. This sophisticated method offers insights into the neural dynamics of seizures to enhancing detection abilities. It also emphasizes the potential of fusing neural network and graph-based techniques to improve neurophysiological disorder diagnostics, which could lead to more potent, non-invasive tools for the management of epilepsy.

Keywords: Brain Graph Neural Networks, Graph Fourier Transforms, EEG Signal Analysis, Neural Dynamics, Non-Invasive Diagnostics, Epileptic Seizures.

Introduction

Millions of people worldwide suffer from epileptic seizures, which can cause everything from mild awareness lapses to severe convulsions. The unpredictable nature an intensity of these seizures can seriously interfere with day-to-day functioning for those who are affected, underscoring the necessity for accurate and prompt detection techniques. Even though conventional methods like feature extraction and EEG signal analysis have improved seizure identification, their accuracy and consistency are still frequently lacking.

This research aims to:

1. Determine the most reliable and efficient way to identify seizure by comparing all available methods in-depth.
2. By including several features into the models being utilized, seizure detection sensitivity and accuracy can be increased.

These goals are meant to help with prompt interventions and give patients individualized treatment regimens. The current investigation is framed by a review of noteworthy achievements and methodologies from earlier research in the second portion of this publication. The research processes and methodologies used for the study are described in Section 3. A thorough summary of the research findings, including experimental data and evaluation criteria, is provided in Section 4. Section 5 offers future research directions in this topic and wraps up with a summary of the findings.

Related Work

Kunekar et al. [1] investigated the use of deep learning (DL) and machine learning (ML) methods for the identification of epileptic episodes from EEG data. They compared the performance of various ML algorithms, including logistic regression, SVM, KNN, ANN, and DL models such as CNN and LSTM. The study found that the LSTM-based model outperformed other approaches, achieving a validation accuracy of 97%. This research underscores the potential of ML and DL to enhance medical diagnostics, particularly in the field of epilepsy, and emphasizes the significance of choosing the right model for improved accuracy in seizure detection.

Ahmed Omar and Tarek Abd El-Hafeez et al. [5] using deep learning models, a unique method was created to maximize the identification of epileptic seizures. The dataset included EEG recordings from several people, and different preprocessing methods were used to train nine distinct deep learning architectures. With the addition of dropout layers, the study demonstrated the efficacy of a Conv1D and LSTM combination architecture, with a high test accuracy of 99.3%. Strong performance was also demonstrated by other architectures, including LSTM, BiLSTM, and GRU, with corresponding accuracy of 98.6%, 98.3%, and 98.4%. Compared to MinMax scaling, standard scaling greatly enhanced the performance of the GRU and BiLSTM models. Furthermore, the models demonstrated persistent high test accuracy across all Principal Component Analysis (PCA) percentages, especially when 50% and 90% of the features were retained. In order to improve model performance, the study emphasized the significance of feature scaling, PCA, and Chi-square feature selection. The ultimate goal of this effort is to enhance patient outcomes and quality of life by refining deep learning models for the identification of epileptic seizures.

Ilakiyaselvan et al. [6] created a deep learning method employing reconstructed phase space pictures to identify seizures. In order to categorize epileptic EEG data, this study used a hybrid CNN-LSTM method that combined convolutional neural networks (CNN) with long short-term memory (LSTM) networks inside a bidirectional recurrent neural network (BRNN). When the EEG data were first received, the CNN layers extracted the spatial properties, while the LSTM layers extracted the temporal characteristics. For ternary classification, the hybrid model yielded results of 98%, 97.4%, 98.3%, and 96.8% for accuracy, specificity, sensitivity, and ROC, respectively. The solution outperformed existing approaches in binary classification, achieving even greater accuracy rates and doing away with the requirement for manual processes. This method proved very successful in improving identification accuracy, resolving issues with low signal-to-noise ratios in EEG data, and offering a reliable means of diagnosing epilepsy automatically.

Sakorn Mekruksavanich and Anuchit Jitpattanakul et al. [7] utilized deep learning approaches to detect epileptic seizures through EEG signals. In their study, they introduced a novel deep residual model called ResNet-BiGRU-ECA. The model analysed brain activity using EEG data to accurately identify epileptic seizures. The evaluation was conducted using a publicly available epilepsy benchmark dataset, and the proposed model outperformed both basic models and other state-of-the-art deep learning models, achieving an exceptional accuracy rate of 99.8% and an F1-score of 0.998.

Methodology

The study's methodology—which covers data collecting, preprocessing, model construction, and assessment methods—is explained in this section. These methods were applied to 500 patients' EEG data points in order to identify and analyze epileptic episodes.

3.1. Data Set: Epileptic Seizure

One hundred files, each representing a distinct subject or person, are contained in each of the five folders in the original dataset from the reference. A 23.6-second recording of brain activity is included in every file. A sample of 4097 data points are taken from the associated time-series. Each data point represents the EEG recording value at a specific point in time. Each of the 500 individuals contains 4097 data points for a duration of 23.5 seconds.

A total of forty-97 data points were divided and jumbled into twenty-three pieces, each containing 178 data points for a split second. The data points show the values of the EEG recordings at each unique moment. There are now 23 x 500 = 11500 informational rows, with the label y {1,2,3,4,5} displayed in the last column and each row holding 178 data points for a single second (column).

The response variable in the dataset is column 179, or y, and the explanatory variables are features labelled X1, X2..., X178 that are contained in the 178-dimensional input vector. One of five categorical values for the response variable y corresponds to a particular environment for the EEG data:

Table 1: Value of y and their corresponding environment of EEG data

Value of 'y'	Description
1	Captures information about seizures
2	EEG recorded from the tumor region
3	EEG from a healthy brain region (tumor location identified)
4	EEG recorded with the patient's eyes closed
5	EEG recorded with the patient's eyes open

This table provides a clear overview of the different categories associated with the response variable in the dataset. There were training and testing sets inside the dataset. To be more precise, 80 percent of the data were used for training, which allowed the model to gain knowledge from this portion. Twenty percent was reserved for testing, so that evaluation of the model could be done with data that had not yet been seen.

3.2. Data Preprocessing:

Throughout the feature extraction process, all columns other than the response variable (y) were designated as features for model training. These features capture different parts of the EEG data. Conversely, the category labels associated with the EEG data are represented by the response variable (y), which was isolated as the target variable for classification purposes. It is ensured that the model will be trained on relevant features using this strategy, and that it will accurately predict the linked categories.

By converting each feature to a comparable scale, data scaling aims to guarantee that each feature contributes equally to the model. For algorithms that rely on feature size, this phase is crucial. In order to attain a zero mean and unit variance, the attributes were scaled using scaling procedures. Because each feature is trained with the same weight thanks to the normalization method, the model converges more smoothly and performs better overall.

In the figure below, the feature distribution of data points of some features is examined before and after Data Scaling.

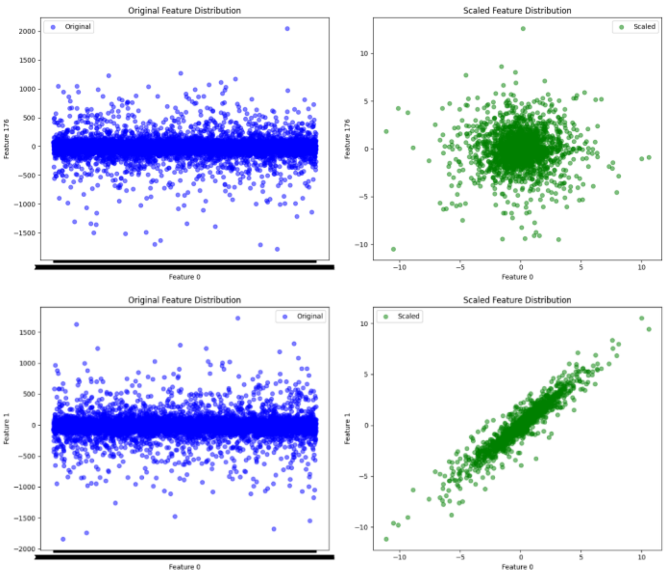

Figure 1: Scatter Plot Visualization of Features Before and After Scaling

Proposed Methodology

4.1. Graph Construction and Graph Fourier Transform (GFT):

Graph creation is the act of transforming data into a representation as a graph, where nodes stand for individual data points and edges indicate relationships or similarity between these points. By converting the scaled features into a graph structure, the goal for EEG data is to effectively capture the intricate relationships and dependencies between the data points. The code provided to generate this graph makes use of the Python Graph Signal Processing package. In this instance, each node is a row in the scaled train feature, and edges are formed according to the degree of similarity between the nodes, which is often assessed using distance metrics or other variables. This graph creation lays the groundwork for further research using graph-based approaches.

Graph Fourier Transform (GFT) is a technique that can be used to study signals described on graph structures by transforming data from the spatial domain into the frequency domain. GFT looks for global patterns and trends in the graph data by determining the frequency components that are present. The GFT of the graph made in the previous stage is computed during the process. The GFT function and the Fourier transform are used to the graph data in order to extract and filter significant frequency components. The data has been transformed so that it can now be represented in the frequency domain as the train frequency domain and the test frequency domain. This makes it easier for the model to recognize patterns and features that are important for outcome prediction and highlights distinct frequency components that are important for the classification tasks.

4.2. Model Definition and Training:

The process of BrainGNN Model Definition and Training comprises configuring a GNN that is intended to process graph-based EEG data representations. The primary objective is to learn from these graph-based data representations in order to create a model that can precisely predict the occurrence of seizures. The initialized parameters of the BrainGNN model are as follows: the number of layers (the number of layers in the network, such as 8 or 10), the learning rate (the rate at which the model updates during training, such as 0.01 or 0.005), the dropout rate (the fraction of neurons dropped to reduce overfitting, such as 0.01 or 0.005), and the hidden dimension (the number of dimensions in the hidden layers, like 512 or 1024). With these values, the model is fitted using the train frequency domain and labels, or training data and labels from the Graph Fourier transform. Labels and training data that have undergone graph Fourier transformation are used to fit the model during training. The model generates verbose output for monitoring, processes batches of samples at once, and iterates across the dataset for a predetermined number of epochs. The test set is used to assess the model's performance after training to determine how well it predicts data that hasn't been seen before.

4.3. Hyperparameter Tuning:

Excessive parameter to optimize the BrainGNN model's performance, a number of crucial parameters must be carefully changed through the tuning process. The BrainGNN model is set up with several hyperparameters: Num layers, which is set to 10, allowing a deeper network to learn complex representations; learning rate, which is set to 0.005, offering a gradual and stable learning rate; and dropout, which is set to 0.005, a low rate to minimize overfitting while preserving most neurons during training. The model is trained with 150 epochs and a batch size of 256, ensuring sufficient iterations to learn from the data while balancing processing resources and training efficiency. This hyperparameter setup aims to maximize the trade-off between learning capacity and overfitting prevention in order to increase the model's accuracy and generalization on the EEG data.

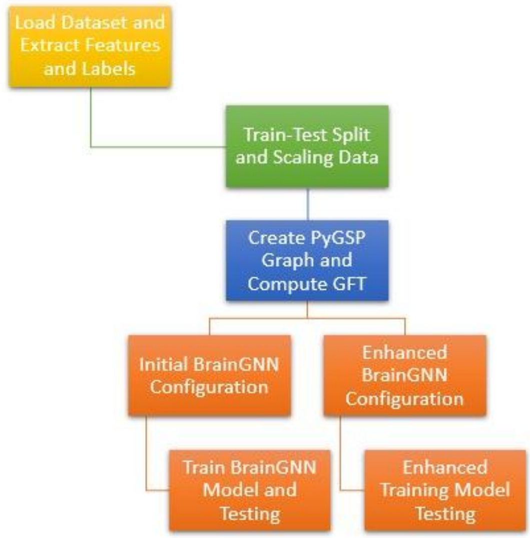

Figure 2: A graphic depiction of the BrainGNN algorithm's use for model training and evaluation, graph creation, Graph Fourier Transform, and data preparation.

Experimental Analysis

In this section, we present the experimental results and provide insights from the graphs, highlighting the implications of our analysis for Epileptic Seizure. The experiment configuration is as follows: Hardware: AMD Ryzen 7, 1.90 GHz (16 GB RAM); Software: Google Colab CPU, T4 GPU; Libraries: Matplotlib, Pandas, Scikit-learn, Brain GNN; Architecture: Brain GNN; Dataset: Epileptic Seizure.

Three basic classification measures were used to evaluate the model's performance: accuracy, precision, and recall. Accuracy evaluated the model's overall correctness, precision evaluated the importance of positive predictions, recall showed the model's ability to properly identify positive cases, and precision measured the recall of the model.

Strict 5-fold cross-validation was employed throughout the hyperparameter adjustment process to increase the robustness of the model assessment and reduce the risk of overfitting. The dataset was divided into five subgroups. The model was trained on four of these subsets, and its performance was evaluated on the fifth. The five iterations of this approach were averaged to provide a comprehensive evaluation of the model's capabilities.

The model's final performance reporting provided a thorough categorization report along with critical parameters including accuracy, precision, and recall. Readers were provided with a comprehensive analysis of the evaluation and particulars on the model's performance across the board in this categorization report. Confusion matrices were also utilized to classify predictions into true positives, true negatives, false positives, and false negatives in order to provide further light on the model's performance.

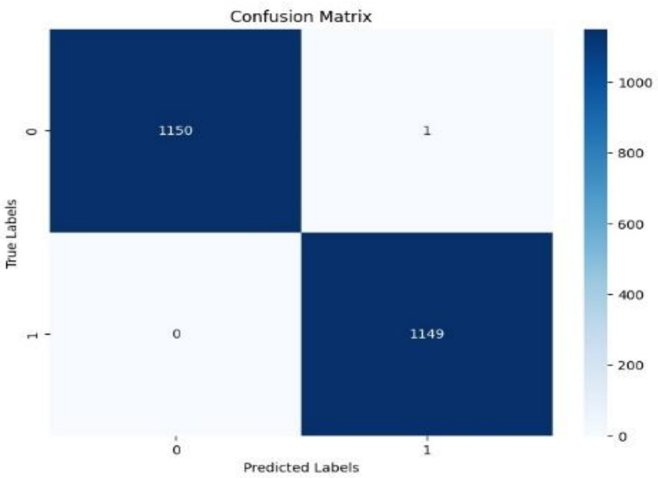

Figure 3: Confusion matrix of BrainGNN

With eight layers, a dropout rate of 0.01, a learning rate of 0.01, and hyperparameters set at hidden dimensions of 512, the BrainGNN model's first configuration produced a noteworthy test accuracy of 99.92%. The accuracy of the model increased to 99.97% after hyperparameter tuning, which changed the parameters to hidden dimensions of 1024, ten layers, a dropout rate of 0.005, and a learning rate of 0.005. This enhancement emphasizes how important fine-tuning is to maximizing model performance.

Classification Report:

	Precision	Recall	F1-score
0	1.00	1.00	1.00
1	0.99	0.99	0.99
Accuracy			0.99
Macro avg	0.99	0.99	0.99
Weighted avg	0.99	0.99	0.99

Figure 4: Comparison of Precision, F1-Score, and Recall across Different Categories

Adjusting the hyperparameters led to a significant increase in accuracy, which highlights how sensitive the model is to these modifications. The BrainGNN was able to identify more intricate patterns in the EEG data by enlarging the hidden dimensions and adding additional layers, which improved classification accuracy. Furthermore, improving learning and dropout rates promoted improved convergence, lessened overfitting, and improved generalization.

One significant drawback that may affect the viability of real-time applications is the high computing requirement linked to these improved hyperparameters. In spite of this, a well-optimized BrainGNN model and sophisticated preprocessing methods reveal a reliable method for identifying epileptic seizures, offering a solid basis for further developments in biomedical signal processing.

Result & Discussion

The experimental findings demonstrate how much more successful the suggested machine learning pipeline is at identifying epileptic seizures. At first, the BrainGNN model with eight layers, a dropout rate of 0.01, a learning rate of 0.01, and hidden dimensions of 512 as hyperparameters produced a remarkable test accuracy of 99.92%. This high accuracy shows how well the model can separate seizure from non-seizure episodes in EEG data. Even better outcomes were obtained by further optimizing the hyperparameters of the model. The model's test accuracy was increased to 99.97% by changing the parameters to hidden dimensions of 1024, ten layers, a dropout rate of 0.005, and a learning rate of 0.005. This enhancement highlights how important fine-tuning is to improving model performance. The improved accuracy illustrates how well the model classifies EEG signals, highlighting the Graph Fourier Transform's (GFT) strong feature extraction capabilities when paired with the BrainGNN architecture. The model's sensitivity to parameter changes is highlighted by the notable improvement in accuracy that occurred after hyperparameter tweaks. The BrainGNN was able to capture more intricate patterns in the graph Fourier coefficients by increasing the number of layers and hidden dimensions, which improved classification accuracy. Furthermore, greater convergence was made possible by adjusting the learning rate and dropout rate, which decreased overfitting and increased generalization. These findings support the usefulness of using graph-based techniques to handle EEG data. With the help of the GFT, the data was successfully converted into a domain in which the BrainGNN could perform better by more completely utilizing underlying patterns and relationships. With an accuracy of 99.97%, the model has proven to be highly reliable and has the potential to be used in real-time seizure detection systems. Overall, the combination of sophisticated preprocessing methods and a fine-tuned BrainGNN model shows great efficacy in identifying epileptic seizures, laying a solid basis for further research and applications in this important area.

Conclusion

The approach described makes good use of sophisticated data processing and analytical techniques to identify epileptic seizures from EEG data. Accurate seizure identification from the raw EEG signals is achieved by merging BrainGNN with graph signal processing. For the analysis of intricate time-series data, like EEG recordings, this approach is reliable. This method's high processing requirement, however, is a drawback that could interfere with real-time applications. In spite of this, the combination of these methods offers a solid basis for further developments in the field of biomedical signal processing.

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