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ORIGINAL RESEARCH ARTICLE

Graph attention network and radial basis function neural network-based hybrid framework for epileptic seizure detection from EEG signal

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ABSTRACT

Epileptic seizure is a neurological disorder characterized by recurrent, abrupt behavioral changes attributed to transient shifts in excessive electrical discharges within specific brain cell groups. Electroencephalogram (EEG) signals are the primary modality for capturing seizure activity, offering real-time, computer-assisted detection through long-term monitoring. Over the last decade, extensive experiments through deep learning techniques on EEG signal analysis, and automatic seizure detection. Nevertheless, realizing the full potential of deep neural networks in seizure detection remains a challenge, primarily due to limitations in model architecture design and their capacity to handle time series brain data. The fundamental drawback of current deep learning methods is their struggle to effectively represent physiological EEG recordings; as it is irregular and unstructured in nature, which is difficult to fit into matrix format in traditional methods. Because of this constraint, a significant research gap remains in this research field. In this context, we propose a novel approach to bridge this gap, leveraging the inherent relationships within EEG data. Graph neural networks (GNNs) offer a potential solution, capitalizing on their ability to naturally encapsulate relational data between variables. By representing interacting nodes as entities connected by edges with weights determined by either temporal associations or anatomical connections, GNNs have garnered substantial attention for their potential in configuring brain anatomical systems. In this paper, we introduce a hybrid framework for epileptic seizure detection, combining the Graph Attention Network (GAT) with the Radial Basis Function Neural Network (RBFN) to address the limitations of existing approaches. Unlike traditional graph-based networks, GAT automatically assigns weights to neighbouring nodes, capturing the significance of connections between nodes within the graph. The RBFN supports this by employing linear optimization techniques to provide a globally optimal solution for adjustable weights, optimizing the model in terms of the minimum mean square error (MSE). Power spectral density is used in the proposed method to analyze and extract features from electroencephalogram (EEG) signals because it is naturally simple to analyze, synthesize, and fit into the graph attention network (GAT), which aids in RBFN optimization. The proposed hybrid framework outperforms the state-of-the-art in seizure detection tasks, obtaining an accuracy of 98.74%, F1-score of 96.2%, and Area Under Curve (AUC) of 97.3% in a comprehensive experiment on the publicly available CHB-MIT EEG dataset.

Keywords: graph attention network; radial basis function neural network; hybrid model; CHB-MIT EEG dataset; electroencephalogram signal; seizure detection; RBFN optimization

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1. Introduction

Extensive research has been conducted for centuries on the intricate workings of the human brain, which stands as the central pillar of the neurological system and arguably represents the most vital organ in the human body. A considerable portion of this research has been dedicated to the study of brain disorders. According to a recent comprehensive study, the prevalence of neurologic diseases, including Alzheimer's, meningitis, stroke, dementia, and Parkinson's disease, has shown a significant increase over the past 25 years[1]. Neuroimaging methods are essential for comprehending and identifying neurological conditions. A common tool for examining the anatomical structure of the brain and identifying anomalies is magnetic resonance imaging, or MRI. Prior studies conducted by Jibon et al[2,3]. have significantly advanced the field of MRI-based brain analysis, especially when it comes to the identification of brain tumors. This research focuses on the complementary use of Electroencephalography (EEG) signals for the detection and analysis of epileptic seizures, while acknowledging the significance of MRI. Among these neurological disorders is epilepsy, which comprises a group of complex conditions characterized by seizures. The World Health Organization (WHO) estimates that approximately 65 million people worldwide are affected by epileptic seizures[4]. The neurological disorder known as epilepsy, characterized by abnormal neuronal activity in the human brain, poses a significant threat to the safety and well-being of millions of patients worldwide, impacting their ability to lead normal lives. Individuals with epilepsy often experience distressing symptoms, including uncontrollable jerking movements, loss of consciousness, and other discomforts. Without timely intervention, this condition can potentially lead to fatal outcomes. The analysis of epilepsy is of paramount importance, as it plays a critical role in preventing permanent brain damage resulting from epileptic seizures and the occurrence of recurrent unprovoked episodes[5].

The voltage fluctuations resulting from ion currents within neurons in the brain are measured as an electroencephalogram (EEG). This EEG recording portrays the bioelectrical activity of the brain and encapsulates significant physiological and disease-related information. The EEG signal has emerged as the foremost diagnostic tool for epilepsy due to its capacity to capture changes in the frequency and rhythm of brain activity during seizures[6]. The EEG signals must be captured to localize epileptic seizures and can be utilized to gather important information about neurological diseases. Frequency is one of the key scales used in clinical EEGs to assess abnormalities and cognition. The frequency of an EEG that has been recorded falls between 0.01 and 100 Hz. The frequency content can be separated into five main bands: delta, theta, alpha, beta, and gamma. **Table 1**, contains information on these bands' corresponding frequencies. Patients with epilepsy display aberrant behaviours both during ictal and interictal periods. In contrast to interictal activity, which can be thought of as seizure-free activity, ictal refers to the activity that takes place during an epileptic episode. Ictal signals typically have sharp, spikey, continuous, or unbroken structural waveforms, whereas interictal signals typically have sharp, spikey, transient waveforms. As a result, the dynamic mechanisms causing the seizures can be described, located, and localized using some distinguishing changes in the EEG data that occur after a seizure. Some patients additionally have an intracranial recording to identify the part of the brain that caused the seizure and to assess if implanted devices for treating epilepsy should be placed there[7].

Table 1. Band Frequency of EEG signals[5].

Band	**Frequency (Hz)**
Delta	1–4 Hz
Theta	4–7.5 Hz
Alpha	7.5–13 Hz
Lower Beta	13–16 Hz
Higher Beta	16–30 Hz
Gamma	30–40 Hz

Based on frequency, time, wavelet transforms, and Gabor filters, various approaches have been developed to detect epileptic seizures in EEG recordings. However, because EEG signals are non-stationary, some considerations must be made when using approaches based on extracted frequency or temporal features because they are insufficient for the job[8]. The study of non-stationary signals is made possible by time-frequency (t-f) approaches, which are potent instruments that break down signals like EEGs into both time and frequency. EEG signals can be seen as images by applying various time-frequency distributions, and several features can be extracted directly from the mapped signals. A Power Spectral Density (PSD) typically describes the amplitude of the signal in the frequency domain[9]. There are many ways to compute the PSD, including parametric and non-parametric techniques. This function extracts the statistical characteristics like mean, variance, standard deviation, and root mean square. For the EEG data, the PSD is calculated, and its mean is obtained. The classifiers use statistical features, and the mean of PSD is taken. The classification procedure typically includes a training and testing step. In the training phase, the classifier is first fed with the features and their labels. Also, fresh inputs will be provided to the trained classifier during testing so that it can recognize the appropriate class[10].

Several machine learning algorithms have been developed to recognize epileptic seizures using statistical, temporal, frequency, time-frequency domain, and nonlinear aspects[11]. In conventional machine learning methods, features and classifiers are selected through a process of trial and error. Machine learning models are excellent for small amounts of data. Due to the growing accessibility of data, machine learning techniques may not be effective in the present era. Modern Deep Learning (DL) techniques have been applied to do this. DL models require a lot of training data, in contrast to conventional machine learning techniques[12]. This is because these models have a large number of feature spaces and overfit when there isn't enough data. Deep neural networks, as opposed to standard neural networks, or so-called shallow networks, are made up of more than two hidden layers. This growth in network size leads to a sharp rise in the number of network parameters, necessitating proper learning strategies as well as precautions against overfitting the taught network. Instead of multiplying a weight vector (matrix), convolutional networks use filters convolved with input patterns, which drastically decreases the number of trainable parameters[13].

Non-Euclidean structured data cannot be processed directly by General Convolutional Neural Network (CNN)-based DL methods because discrete convolution does not preserve the translational invariance of non-Euclidean signals and the fixed convolution kernel cannot capture all of the nodes' neighbourhood information[14]. However, Graph Convolutional Neural Networks (GCNNs) address the relational qualities between nodes, they can easily extract features from such non-Euclidean data and analyse graph-structured signals. The new features generated by GCNNs aid in the distinction of EEG signals and make them more valuable for classification[15]. GCNNs extend the convolution technique to non-Euclidean graph data. The graph convolutional operation seeks to build representations for vertices by combining the features of a given vertex with the features of its neighbours. The relationship-aware representations generated by GCNNs considerably improve the discriminative power of CNN features, and the improved model interpretability can assist physicians in determining, for example, the areas of the brain that are primarily active in one specific task. Graphs automatically capture relationships between things and are thus potentially highly beneficial for these applications to encode relational information between variables. As a result, attention has been put into generalizing graph neural networks (GNN) into non-structural and structural contexts[16]. To investigate the spatial relationship of multi-channel EEG, we consider different channels of the EEG as a model based on Graph Attention Network (GAT). The EEG signals of an item are represented as a graph, with each channel acting as a node in the graph. The attention coefficients between nodes are mapped to the graph's edges. Following that, it computes the attention coefficients between nodes. In general, self-attention will direct attention to all nodes in the graph, resulting in the loss of structural information. GAT incorporates the graph structure by only examining the node's first-order neighbors[17].

Radial Basis Function Neural Networks (RBFNs) have been discovered to be particularly appealing for a wide range of applications in deep learning formulation. RBFNs have the essential virtue of forming a unifying link between many distinct study domains, including function approximation, regularization, noisy interpolation, pattern recognition, and medicine. RBFNs are becoming increasingly popular because of their simple topological structure, locally adjusted neurons, and ability to have a quick learning process when compared to other multilayer feed-forward neural networks. The conventional estimate hypothesis forms the cornerstone of the RBFN organization. It can be widely estimated. Because of its simpler structure and significantly quicker training process, the Radial Basis Function or simply RBF organization is a well-known alternative to the highly effective multilayer perceptron (MLP). The precise addition of a focused information arrangement in a multidimensional space is the root of the RBF arrangement. It can be seen as a particular type of functional connectivity network. To compare the improved results of the integrated approach, the experiment connected across the dataset using an RBFN classifier with and without clustering findings[18]. In the area of epileptic seizure detection, the Radial Basis Function Neural Network (RBFN) offers a promising answer to the problems that currently used algorithms are up against. The choice of Gaussian activation functions, LS (Least Squares) criteria, and a distinctive three-layer architecture, along with RBFN's quick learning capability, make it a potent tool for improving seizure detection's accuracy and timeliness. RBFN offers the ability to address shortcomings in existing algorithms and dramatically improve the diagnosis and management of epileptic seizures by effectively designing complicated EEG data correlations[19].

This study used a state-of-the-art method to preprocess EEG data and extract the information necessary for seizure detection. The power spectral density (PSD) is applied to increase the signal-to-noise ratio and reduce artifact signals. The EEG data is then processed further before being fed into a graph attention network (GAT). The synergy between GAT and RBFN enables the proposed model to effectively capture intricate patterns within the data, offering a level of accuracy and reliability that distinguishes this research from previous efforts. This work's primary contributions can be summed up as follows:

1) This research provides a method for automatically detecting seizures that are based on GAT and RBFN. The suggested method effectively uses computational powers to identify seizures in raw EEG data.

2) We employed power spectral density (PSD) as a preprocessing technique for raw EEG signals. This approach effectively eliminates unwanted signals, enhancing the model's accuracy in detecting seizures.
3) The proposed approach improves state-of-the-art algorithms in seizure detection tasks using the CHB-MIT dataset.

The remaining sections are categorized as follows. Section 2 explains previous research and a comparative analysis of the state-of-the-art on seizure detection. Section 3 demonstrates the proposed methods where data processing, GAT, RBFN architecture, and the paper's system model are included. Section 4 describes the model dataset. Section 5 describes the result and experiment analysis, patient-specific experiments, cross-validation ablation studies, and comparison to other state-of-the-art techniques. Section 6 is the conclusion of the paper.

2. Related work

Seizure detection relies on the premise that the seizure and non-seizure states are qualitatively different. Most epilepsy research nowadays centers on using EEG data to detect seizures.

Shoeb and Guttag[20] presented a study in which they used the Support Vector Machines (SVM) classifier to detect epileptic seizures on a scalp EEG dataset. This method achieved 96% accuracy on test data. Tzallas et al.[21] used the short-time Fourier transform (STFT) to derive the power spectrum density (PSD) of EEG data and extract features associated with the fractional energy of TF (Time Frequency) plane windows. These features were then loaded into an artificial neural network (ANN) to classify epileptic seizures. Birjandtalab et al.[22] extracted data from EEG signals using frequency domain characteristics (normalized in-band power spectral density), and then improved seizure detection precision by using a deep learning method based on a multilayer perceptron. The results reveal that the nonlinear technique can detect seizure and non-seizure episodes easily and automatically, with an F-measure accuracy of roughly 95%. CNN has generated the most interest in seizure detection research using deep learning systems. Because seizure detection studies using CNN often require image data as input, the EEG signal is preprocessed into a two-dimensional format. Zhou et al.[23] employed a convolutional neural network (CNN) to extract features from raw EEG signals. Unfortunately, CNN is unable to extract time features in an efficient manner, which results in information loss at the time level. As a result, Recurrent Neural Network (RNN) was utilized to analyze EEG signals. The long short-term memory (LSTM) neural network was employed in the work to process epileptic EEG information. Before classification, the LSTM model made use of a variety of temporal features to boost seizure detection ability[24]. However, some research combines the CNN and RNN models. Xu et al.[25] proposed a hybrid model of CNN and LSTM for seizure recognition utilizing EEG inputs. Using the public UCI (University of California, Irvine) epileptic seizure recognition data set, the proposed technique achieves high recognition accuracies of 99.39% and 82.00% on the binary and five-class epileptic seizure recognition tasks, respectively. The combination of CNN and LSTM is useful, and the addition of a convolution layer in RNN aids in the discovery of connections in the signal channel space. Although LSTM solves the gradient explosion problem of RNN, it can only create a one-way time series model. BiLSTM (Bidirectional Long Short-Term) can solve this problem. BiLSTM networks[26] can not only overcome the gradient explosion problem of RNNs, but they can also transmit information in both directions, making them ideal for evaluating long-term data sequences. A seizure detection approach based on the BiLSTM network was created[27]. Information transmitted both forward and backward is used. The approach detected seizures with great accuracy. Recently, Geng et al.[28] combined S-transform and BiLSTM to detect seizures. The S-transform is applied to raw EEG segments first, and the resulting matrix is grouped into time-frequency blocks before being submitted to the BiLSTM for feature selection and classification. The moving average filter, threshold assessment, multichannel fusion, and collar method are then utilized in postprocessing to improve detection performance. The experiment has a sensitivity of 98.09% and a specificity of 98.69%. Osman et al.[29] suggested an automatic epileptic seizure detection method based on self-organization maps (SOM) and radial basis function (RBF) neural networks. The SOM technique was used to distinguish between the unknown patterns in the seizure and epilepsy datasets. For the tests to detect and categorize the standard dataset for epilepsy disease, different RBF neural network techniques with integrated SOM algorithms were used. On the UCI epilepsy dataset, the hybrid technique was evaluated. The overall detection accuracy was 97.47% with 10-fold cross-validation. Adeli et al.[30] proposed a novel EEG classifier based on integrated Power Spectral Density (PCA) and cosine RBFN. The two-stage classifier is used with the mixed-band wavelet-chaos technology to provide a precise prediction of electroencephalogram (EEGs) from healthy and epileptic participants into three different categories (healthy, ictal, and interictal). For normal healthy EEGs, interacting EEGs, and ictal EEGs, the suggested technique achieved 98.4%, 97.0%, and 94.8%, respectively.

Many great deep neural network categorization models have been proposed by researchers as deep learning has progressed[31]. Recent advancements in machine learning techniques have improved seizure onset zone localization for epilepsy patients, using functional networks from EEG recordings and graph neural networks and attention mechanisms. A Generalized Neural Network (GNN) was utilized by Grattarola et al.[32] to identify brain areas connected with individual electrodes in the interictal and ictal phases. Without prior seizure onset zone knowledge, the GNN's attention-based layer identified critical locations. The research was expanded to include human patients and brain activity simulators, proving its resilience and potential clinical utility. Li et al.[33] propose a new graph-generative neural network (GGN) model for identifying brain functional connectivity based on a study of scalp electroencephalogram (EEG) signals. The GGN model correctly recognized seven different types of epileptic seizure episodes 91% of the time. To identify seizures and categorize different seizure types, Zeng et al.[34] used hierarchical GCN. Chen et al.[35] introduced the E-GCN model, a graph convolutional network, to mine more extensive data sets and investigate potential relationships between signals. A hybrid framework of GAT and Bi-directional LSTM (BiLSTM) for seizure detection was used. GAT is employed as the front end for spatial feature extraction, making full use of the EEG channel topology[36]. The back end is the BiLSTM network, which mines time relations and makes a final choice based on prior and future states. The CHB-MIT dataset is used as the basis for experiments. The seizure detection accuracy, sensitivity, and specificity are 98.74%, 94.74%, and 97.89%, respectively. To automate the identification of neonatal seizures, Raeisi et al.[37] developed a unique deep-learning model based on graph convolutional neural networks. Included are EEG features collected from the EEG signals in the temporal and frequency domains, as well as consideration of long-range spatial information and interdependencies between EEG signals. The spatial data is portrayed as either functional links between individual EEG channels or as distance maps in Euclidean space. Using a public dataset of 39 continuous EEG signals from newborns (AUC90), the area under the curve (AUC) and AUC for specificity values of more than 90% were used to judge how well the model worked. In our earlier work on epileptic seizure detection from electroencephalogram (EEG) signals, we proposed a novel hybrid framework combining a Linear Graph Convolutional Network (LGCN) and a DenseNet architecture[38]. This framework exhibited promising results in capturing complex spatiotemporal features from EEG data for improved seizure detection accuracy.

3. Proposed method

This paper proposed a hybrid deep learning method for the EEG signal of epileptic seizure patients so as to automatically detect seizure with high efficiency. In this section, we demonstrate all components of our comprehensive model which will give a clear understanding about proposed method.

Figure 1 illustrates the major points of the proposed approach. The raw EEG data is segmented into samples first. Then, the adjacency matrix created after applying power spectral density and the graph structure data encoding the link between signal data information and channels is incorporated into the GAT model. The retrieved features are then supplied into the RBFN portion of the algorithm, and the classification is completed by the sigmoid function.

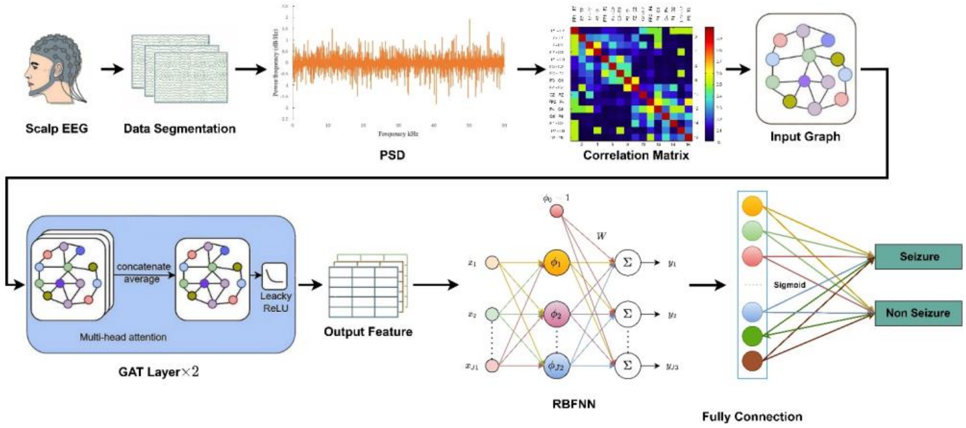

Figure 1. The system model of proposed method.

3.1. Data preparation

In this study, continuous data is assumed to include a lengthy era to guarantee a sufficient quantity of experimental data. That's why long-term EEG data will be broken down into a large number of smaller fragments. After data segmentation, it breaks down into a number of distinct time periods using a sliding window with a period of 1 s and an overlap rate of 0.5. For instance, an EEG signal of 60 s in duration and a sampling frequency of 1 Hz would be represented as a vector 60 s in length. There will be 100 epochs. Once the data has been partitioned the suggested method examines and categorizes the labels of various periods in a linear pattern. Thus, seizures in 60 s EEG recordings are automatically localized based on labels obtained.

3.1.1. Preprocessing

Raw EEG data collected from the scalp is extremely dynamic and non-stationary. Seizures cause a loss of awareness and limb movements, both of which are very sensitive to external elements such as the acquiring environment, eye movement, heart activity, and sweat[39]. So, there is typically some degree of randomness in scalp EEG. To remove unwanted frequency and noise, power spectral density (PSD) is applied to identify and remove irrelevant frequency components in the EEG signal that relate to artifacts or noise while retaining frequency components in the EEG signal that are relevant.

3.1.2. Power spectral density (PSD)

Several scholars, notably Norbert Wiener and John Tukey, made substantial contributions to the development of PSD in the 1950s[40].

They created the concept of spectral analysis, which is the act of employing the PSD to translate a time-domain signal into the frequency domain. Power Spectral Density (PSD) is a statistical representation of the amount of power present in a time-domain signal as a function of frequency. It is used to characterize the power distribution in a signal across frequency. In general, a PSD describes the amplitude of a signal in the frequency domain[41]. The PSD of EEG data can be used to investigate variations in brain activity linked with attention and mental state.

First, we must filter the EEG signal to eliminate any undesirable high-frequency or low-frequency noise and, if necessary, perform an artifact correction procedure. The EEG signal is then divided into smaller segments or windows, and a window function (e.g., Hanning, Blackman, etc.) is applied to each window to reduce edge effects. The Hanning window is defined as follows:

$$W(n) = \frac{1}{2}\left(1 - \left(cos\frac{2\pi n}{N-1}\right)\right) \tag{1}$$

where *N* denotes the number of data points in the window. Then to acquire the frequency spectrum, we apply the Fast Fourier Transform (FFT) to each windowed segment of the EEG data. Afterward, we have to calculate the magnitude squared of each FFT coefficient and average the magnitude squared across the windows to determine the PSD of the EEG signal. Subsequently, plot the PSD estimate as a function of frequency to visualize the EEG signal's power content across multiple frequency bands. The discrete version of a one-dimensional,

Power spectrum (PS) is written as:

$$PS(v) = \frac{|U_T(v)|^2}{N^2} \tag{2}$$

where $|U_T(v)|^2$ denotes the discrete Fourier transform of the signal $u_T(t)$. As a result, the crucial result is that a Fourier transform of the signal is all that is required to compute the power spectrum. After that, the PSD is just:

$$PSD(v) = \frac{PS(v)}{\Delta v} \tag{3}$$

It has amplitude squared units per frequency unit. *N* is the total number of sample points in these equations, and Δv is the data point spacing in frequency space.

PSD expressions in two dimensions, both continuous and discrete, can be written (with a convenient change to spatial coordinates).

$$U(V_{X,}V_y) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} u(x,y)e^{i2\pi(v_x x + v_y y)}\,dx\,dy \tag{4}$$

$$U(v_x, v_y) = \sum_{n_x=0}^{N_x-1}\sum_{n_y=0}^{N_y-1} u(x,y)e^{i2\pi(\frac{v_x x}{N_x} + v_y y/N_y)}\Delta v_x \Delta v_y \tag{5}$$

$$PS(v_x, v_y) = \frac{|U(v_x, v_y)|^2}{N_x^2 N_y^2} \tag{6}$$

$$PSD(v_x, v_y) = \frac{PS(v_x, v_y)}{\Delta v_x \Delta v_y} \tag{7}$$

In these Equations (4)–(7), $\Delta v_x \; and \; \Delta v_y$ are frequency variables, $\Delta v_x \Delta v_y$ are frequency space data point spacings, and $N_x \; and \; N_y$ are the total number of sample points in each domain.

It is a well-known and widely utilized signal-processing approach. The distribution of signal power across frequencies is characterized as power spectral density[42]. **Figure 2** shows the signal density of the frequency components. It depicts the energy's intensity as a function of frequency. It is used to extract features from signals in a variety of domains, including audio, pictures, and time series. It can give information on the frequency content of signals and can be used to train machine learning models to make predictions or categorize signals. Using power spectral density (PSD) analysis, important features were extracted from the raw EEG data during preprocessing. The power spectrum, which captures the distribution of signal power across different frequency bands, is the result of the PSD analysis, which converted the time-domain EEG signals into the frequency domain. These PSD representations were then used as inputs for our Graph Attention Network (GAT), which used the frequency-domain data to enable the network to recognize complex connections and relationships in the EEG data.

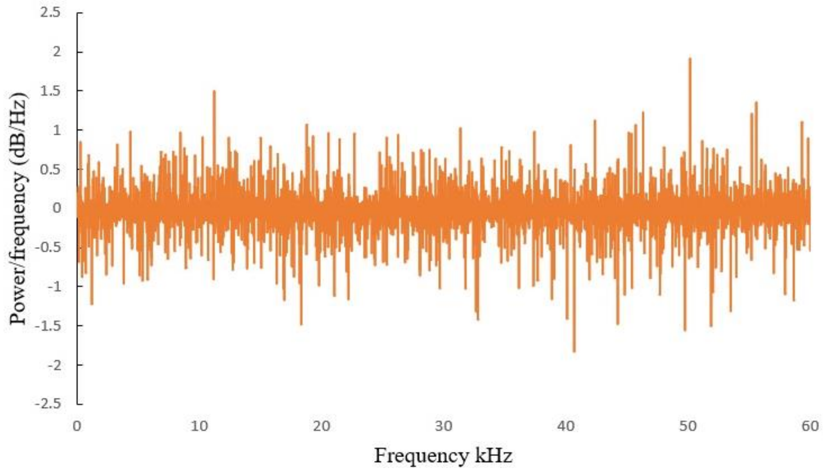

Figure 2. Power spectral density of a signal with two frequency components.

3.2. Graph attention network (GAT)

Consider the various EEG channels as a model based on GAT to thoroughly explore the spatial relationship of multi-channel EEG. Each channel of an object's EEG signals is viewed as a node in a graph that represents the EEG signals as an object. The edges of the graph are mapped by the attention coefficients between nodes.

Assume that there are objects P = {p_1, p_2, …, p_0}. Each object is represented by $p_i \in R^{M \times F}$, where M is the number of channels for each object and F is the feature dimension for each channel. The GAT module accepts a node feature vector set $K = \{k_1, k_2, \ldots, k_M\},\ k_i \epsilon R^F$ as input. To improve the representative power of the learned features, a linear mapping with a shared weight matrix $W \in R^{F \times F'}$ is applied to each node. After transformation, the features are concatenated. After concatenating, the high-level feature is mapped to a real number. The self-attention coefficients e with its neighbors are computed for each node i. The preceding procedure can be expressed as follows:

$$e_{ij} = g\left(Wk_i, Wk_j\right) \tag{8}$$

where g is the mapping of $R^F \times R^{F'} \rightarrow R$. i, j represents any two nodes.

Following that, we compute the attention coefficients between nodes. In general, self-attention will direct attention to all nodes in the graph, causing structural information to be lost. We incorporate the graph structure by only considering i node's first-order neighbors. The attention coefficients α are computed as follows:

$$\alpha_{ij} = softmax_j\left(e_{ij}\right) = \frac{exp\ (e_{ij})}{\sum_{r \in v_i} exp\ (e_{ir})} \tag{9}$$

where i, j, and r are any nodes, V_i is the set of neighbors of i. When fully expanded, the leaky ReLU activation function can be used to calculate the attention coefficient as:

$$\alpha_{ij} = \frac{exp\ (LeakyReLU(a^T[Wk_i \parallel Wk_j]))}{\sum_{r \in V_i} exp\ (LeakyReLU(a^T[Wk_i \parallel Wk_r]))} \tag{10}$$

where, || is used to concatenate, leaky ReLU is the non-linear activation function, and ($a^T \in R^{2F}$) is the parameter for feed-forward neural networks.

In **Figure 3**, the attention mechanism $\alpha(W\overrightarrow{h_i}, W\overrightarrow{h_j})$ used by our model is parameterized by a weight vector a $\vec{a} \epsilon \mathbb{R}^{2F'}$ using a Leaky ReLU activation. And a representation of multihead focus (with $K = 3$ heads) by node 1 in its neighborhood[43]. Different arrow designs and hues signify different attention calculations. Each head's aggregated characteristics are concatenated or averaged to produce $\overrightarrow{h_1'}$.

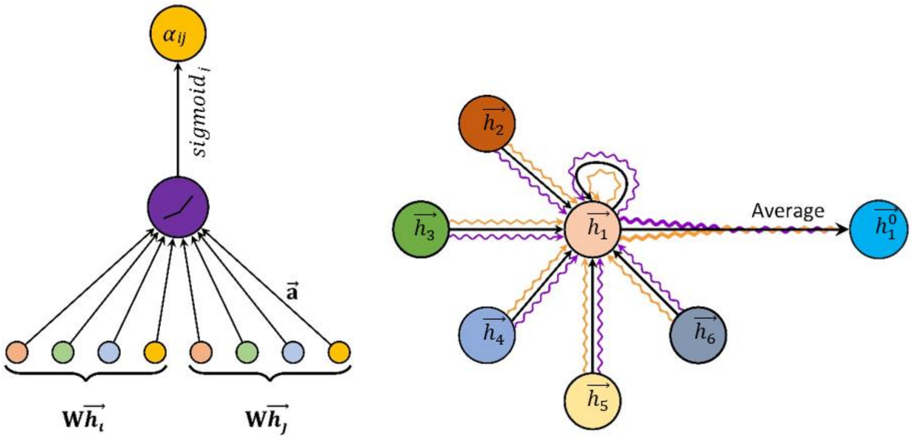

Figure 3. Graph attention network for seizure detection[43].

Khan and Ahmad[44] employ a multi-head attention technique to enhance the model's capacity for fitting. To calculate self-attention specifically, Q attention mechanisms are used, and W is the weight matrix for the head q. The learning properties of each attention mechanism are distinct, and the outcomes of various attention mechanisms are averaged to create a more stable GAT[45]. This leads to the following computation of node *i* as the learned feature for node.

$$k_i' = \sigma(\frac{1}{q}\sum_{q=1}^{k}\sum_{j\epsilon v_i}\alpha_{ij}^{q}W^{q}k_j) \tag{11}$$

where $k_i^{'}$ represents the new feature of GAT output that integrates neighborhood information for each node *i*. The output of the GAT module is a new node feature vector set: $K^{'} = \{k_1^{'}, k_2^{'}, \dots, k_M^{'}\}$, $k_i^{'} \epsilon R^{F^{'}}$, where F' represents the new node feature vector dimension[46].

GAT does not require complicated matrix operations like eigenvalue decomposition, in contrast to GNN[17]. It is capable of automatically allocating weights to nearby nodes. As a result, GAT has a stronger ability to represent information, which can enhance seizure detection performance. After utilizing the Graph Attention Network (GAT) to capture the intricate relationships and dependencies within the feature representations, the resulting data is further processed by feeding it into the Radial Basis Function Neural Network (RBFN) where it will detect epileptic seizures.

3.3. Radial basis function network (RBFN)

Broomhead and Lowe[47] introduced the RBF network framework. It can handle high-dimensional input data, making it ideal for issues with several input features. By reducing the number of parameters and lowering the possibility of overfitting, it can obtain a sparse representation of the input. The RBF organization is a well-known alternative to the exceptional multilayer perceptron (MLP) due to the fact that it has a simpler structure and a significantly more expedient method of preparation. Although the Triangular Basis Function (TBF) is more computationally efficient than other radial basis functions, we choose the Gaussian basis function because of its ability to handle complex data more precisely and its intuitive parameterization. This makes it a popular choice. If the stabilizer is symmetrical, an RBF organizer is made.

The forms of the RBF and TBF basis functions are shown in **Figure 4** respectively. As detailed in the following section, the cosine angular distance and the RBF are chosen because they produce more accurate classifications than the Euclidean distance.

The input layer, hidden layer, and output layer are the three layers, as shown in **Figure 5**, that make up the radial basis function[48]. The RBF serves as the hidden layer's activation function. It is a real-valued function whose value changes depending on how far you are from the origin or center.

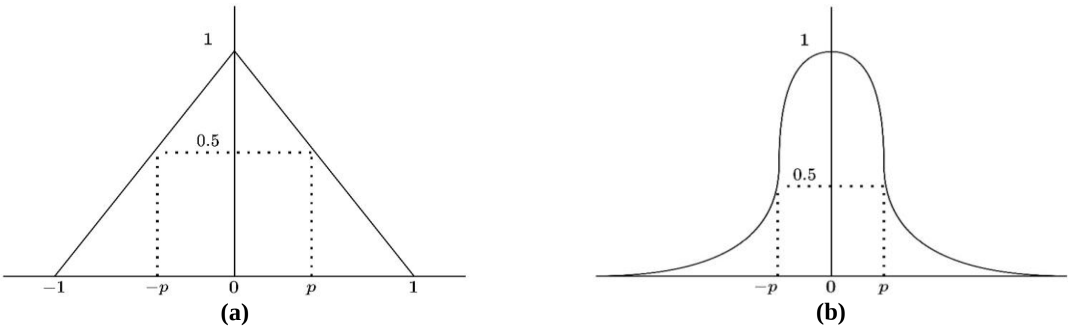

Figure 4. (a) TBF; **(b)** RBF[30].

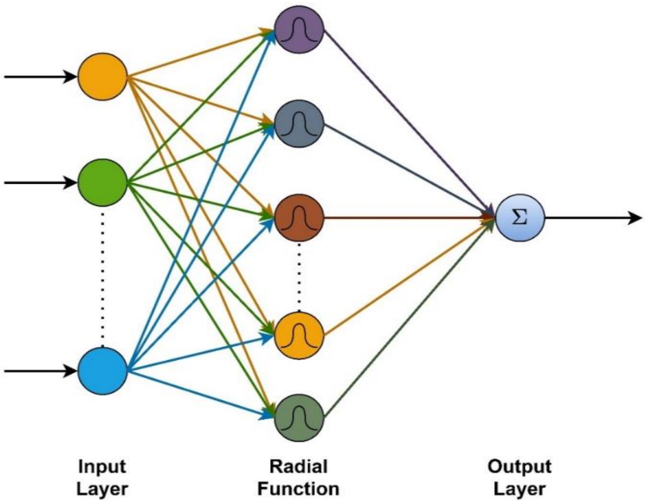

Figure 5. The architecture of RBFN.

Radial basis functions are used by the RBFN to transfer the input data to an output that depends on the separation between the input data and the centers of the radial basis functions. The norm is the Euclidean distance. The following equation can be used to figure out the Euclidean distance between the input vector x and the RBF center c.

$$d(x, c_i) = \|x - c_i\| \tag{12}$$

where $\|x - c_i\|$ is the Euclidean distance between the input vector x and the RBF center c. Here, we employ a Gaussian radial basis function for activation value[49]. The radial basis function is denoted by,

$$\Phi_i(||X - C_i||) = exp\left[-\frac{(||X - C_i||)^2}{2\sigma_i^2}]\right] i = 1,2, \ldots., N \tag{13}$$

where, C_i is the center of the i^{th} RBF and σ_i^2 is the scale of the i^{th} RBF.

A weighted sum of the activation values of the radial basis functions is what the RBFN will produce as its final product. Linear regression is utilized to estimate the output layer weights by using the minimum mean square error (MSE) between the actual and predicted outputs of the RBFN. The linear transformation equation is given as:

$$Y = \sum_{i=1}^{N} \omega_i * \Phi_i(||X - C_i||) + b \tag{14}$$

where the output of the RBF neural network is denoted by Y. N is the number of RBF units that are contained within the hidden layer. ω_i refers to the amount of weight that is linked with the i^{th} RBF unit. C_i is the center of the i^{th} RBF unit and b is the bias term. The output of an RBF neural network is just the weighted sum of the activations of the RBF units since this linear function is typically just the identity function. Using the linear optimization approach, the RBF network obtains a global optimal solution for the adjustable weights in the least mean square error (MSE).

This sequential integration of GAT and RBFN allows for comprehensive feature extraction and modeling, enabling our hybrid framework to effectively analyze and detect epileptic seizures in the electroencephalogram (EEG) data.

4. Dataset

The dataset is taken from Boston Children's Hospital (CHB) and the Massachusetts Institute of Technology (MIT), which is publicly available and contains scalp electroencephalogram (sEEG) data from 23 pediatric subjects[20].

Scalp EEG waves were recorded with 23 electrodes at a sampling rate of 256 Hz. Fixed 23-electrode setups are employed in 15 tests, with some electrode configuration variations in the remaining measurements. The recordings are organized into 24 cases, with most of the 24 cases segmenting the EEG signals into 1-hour epochs, but epochs lasting 2–4 hours can also be found. The overall length of the accessible EEG recordings is around 877.39 h. In all, 877.39 h of EEG data were used in this study, with 2.47 h used for training and 874.92 h used for assessing performance. According to the database's annotation files, most of the 24 cases have frequent changes in the EEG signal recording montage, with channels being added or removed from one epoch to the next during the recording process. 18 channels in total are consistent across all 24 cases, including: "FP1-F7", "F7-T7", "T7-P7", "P7-O1", "FP1-F3", "F3-C3", "C3-P3", "P3-O1", "FP2-F4", "F4-C4", "C4-P4", "P4-O2", "FP2-F8", "F8-T8", "T8-P8", "P8-O2", "FZ-CZ" and "CZ-PZ". This is applicable in all circumstances except Case 24, where the file's start and end times are not stated. The table shows the specifics of this dataset. **Table 2** shows the details of the dataset which contains information on all patients.

Table 2. CHB-MIT dataset.

Case	Gender	Age (years)	Number of seizures	Duration of recordings (hh:mm:ss)
chb01	Female	11	7	40:33:08
chb02	Male	11	3	35:15:59
chb03	Female	14	7	38:00:06
chb04	Male	22	4	156:03:54
chb05	Female	7	5	39:00:10
chb06	Female	1.5	10	66:44:06
chb07	Female	14.5	3	67:03:08
chb08	Male	3.5	5	20:00:23
chb09	Female	10	4	67:52:18
chb10	Male	3	7	50:01:24
chb11	Female	12	3	34:47:37
chb12	Female	2	40	20:41:40
chb13	Female	3	12	33:00:00
chb14	Female	9	8	26:00:00
chb15	Male	16	20	40:00:36
chb16	Female	7	10	19:00:00
chb17	Female	12	3	21:00:24
chb18	Female	18	6	35:38:05
chb19	Female	19	3	29:55:46
chb20	Female	6	8	27:36:06

Table 2. (*Continued*).

Case	Gender	Age (years)	Number of seizures	Duration of recordings (hh:mm:ss)
chb21	Female	13	4	32:49:49
chb22	Female	9	3	31:00:11
chb23	Female	6	7	26:33:30
chb24	Not provided	Not provided	16	21:17:47

5. Experiment and result analysis

In this section we present the details of our experiments and explain the experimental outcomes that clearly establish our proposed method.

5.1. Productive setup

Here we will discuss the setup of our workstations, the hyperparameters of our model of GAT+RBFN, the methods we used to conduct our experiments, and the metrics we used to evaluate our results show that a 32 GB RAM and an Intel Core i7-12700 CPU were utilized. The suggested model was trained on a computer with a GPU (graphics processing unit) from Nvidia's GeForce RTX 3060 Ti series. The software stack being tested consists of Python 3.9, Keras 2.3.1, and Tensorflow 2.6.0. **Table 3** shows the hardware setup and all specific information about it.

As a hyperparameter, the growth rate was set to 32 and the compression factor was set to 0.5, as shown in **Table 4** Additionally, the optimizer that will be utilized is Adam, and the activation function will be Leaky ReLU. The learning rate will be 0.001, and it will be set to that value.

Table 3. Hardware setup.

Software or hardware	Specification	Developer details
CPU	Intel Core i7-12700	
GPU	GeForce RTX 3060 Ti	
RAM	DDR4 32 GB	
Python	3.9	Microsoft researcher Guido van Rossum, University of Amsterdam, The Netherlands
Tensorflow	2.6.0	Google researchers, 1600 Amphitheatre Parkway in Mountain View, California, US
Keras	2.3.1	Google researcher François Chollet, 1600 Amphitheatre Parkway, Mountain View, California, US

Table 4. Hyperparameter setup.

Hyperparameters	Values
Growth rate	32
Compression factor	0.5
Activation function	Leaky ReLU
Optimizer	Adam
Learning rate	0.001

5.2. Procedure

To categorize epileptic EEG data, the processed EEG segments and graph structures are first entered into GAT, and then the retrieved features are entered into RBFN[4]. **Figure 6** shows the detailed version of the process.

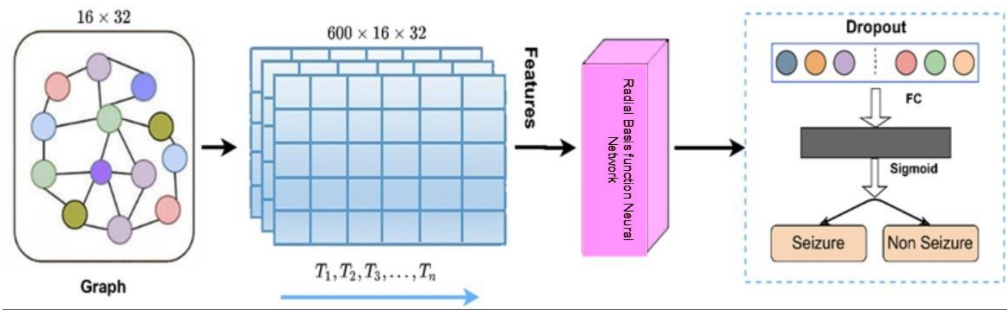

Figure 6. Detailed about of model development.

For implementation, 16 electrodes were chosen to use for all patients, including "FP1-F7", "F7-T7", "T7-P7", "P7-O1", "FP1-F3", "F3-C3", "C3-P3", "P3-O1", "FP2-F4", "F4-C4", "C4-P4", "P4-O2", "F8-T8", "FZ-CZ", "CZ-PZ," FP2-F8". To begin, we conducted a correlation analysis of the individual EEG channels which is shown in **Figure 7**. To fully exploit the geographical interaction between channels, we model the 16 channels as 16 nodes of the graph and build a graph structure that includes neighborhood information between each channel. To build a multi-tiered graph, we use the GAT model. There are four "head nodes" in the first layer and eight in the next. After being concatenated and weighted averaged, the characteristics represented by the input nodes emerge with a potent capacity for expression, thanks to the multi-head attention mechanism of the two-layer graph. The raw EEG signal is then processed to extract a novel feature that considers the local context. The result of GAT is a collection of node embeddings that reflect the learned characteristics of each graph node. These embeddings will be concatenated to create a feature vector for each time point, which will be fed to the RBFN.

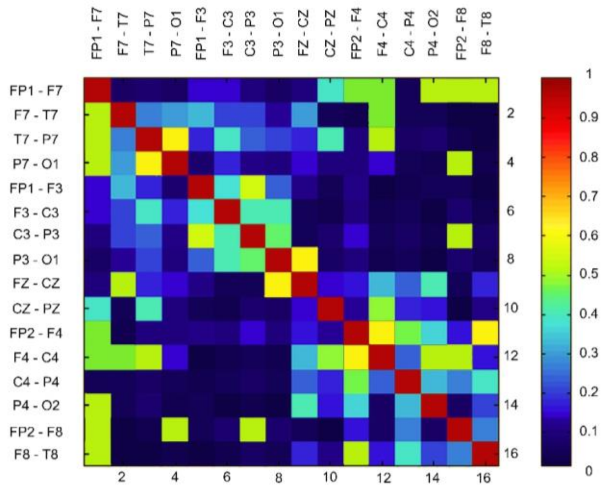

Figure 7. Correlation matrix of EEG signal with 16 channels.

To determine whether the signals represent a seizure or not, we employ the RBFN model. In particular, the feature vector can be created by concatenating the node embeddings for each time point, producing a vector of dimensions (number of time points) × (embedding dimension).

Figure 8 depicts the RBFN model's specifics in depth using GAT data where T represents the number of time points. We set the RBFN input parameters to a sequence length of 600, feature size of 32, and batch size of 16. During training, the RBFN learns mapping between the input feature vector and the matching output label.

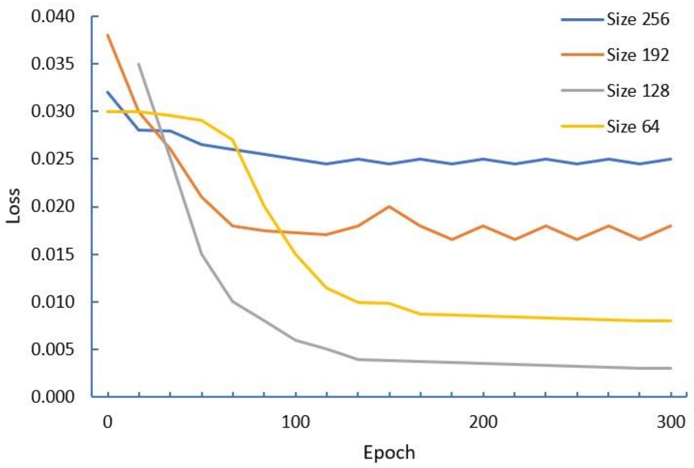

Figure 8. Graph of epoch-loss.

To decrease the gap between the predicted output label and the actual label, the weights and biases of the RBFN are adjusted using an iterative training procedure known as the linear optimization technique. **Figure 6**, depicts this loss in terms of the RBFN cell size. This chart illustrates how the convergence rate of RBFN decreases with decreasing size of the hidden layers. In addition, the loss tends to rise when the hidden layer of RBFN is increased to a depth of more than 128. So, we gave RBFN 128 hidden layers. Additionally, a 20% dropout is implemented for the RBFN to avoid over-fitting.

To conduct our analysis of 16 channels of EEG data, we employ a sliding window of 1 second. Because there aren't a ton of epileptic seizure samples in the CHB-MIT dataset, the data was segmented using the overlapping window approach with a rate of 0.5. In addition, we employ Adam as the optimizer, with parameters of 0.001 for the learning rate, 1e-5 for the weight decay, and 0.2 for the dropout rate.

5.3. Ablation tests

Using the GAT model, the RBFN model, and the suggested GAT+RBFN model, we conduct experimental comparisons to validate the combined contribution of GAT and RBFN in our model. The same model parameters are used throughout all experiments to guarantee consistency and reliability.

Table 2 displays the outcomes. **Table 5** shows that the suggested GAT+RBFN model outperforms the GAT and RBFN models using the same EEG characteristics in three different metrics, demonstrating the robustness and effectiveness of EEG signal processing. Incorporating the best features of both algorithms into a single model greatly enhances its learning capacity.

Table 5. The proposed GAT+RBFN model on CHB-MIT dataset.

Method	Accuracy	Sensitivity	Specificity
GAT	96.12%	91.89%	92.98%
RBFN	93.36%	76.21%	87.23%
GAT+RBFN	98.74%	94.74%	97.89%

5.4. Evaluation metrics

The model's effectiveness is measured in this study using five statistical measures: sensitivity, specificity, accuracy, F1-score, and area under the receiver operating characteristic curve (AUC). The formula for calculating sensitivity is as follows:

$$Sensitivity = \frac{TP}{TP + FN} \tag{15}$$

In this context, TP refers to the total number of correctly detected epileptic seizure pieces. FN is an abbreviation for “false negatives”, which stands for the total number of misidentified seizure items. In all positive cases, sensitivity gives a precise representation of the proportion. The recall number is identical to that one. Accurately determining a target’s specificity requires the following:

$$Specificity = \frac{TN}{TN + FP} \tag{16}$$

TN stands for “true negatives”, which refers to the total number of correctly detected non-epileptic components. The acronym FP, which stands for “false positives”, denotes the number of improperly detected seizure fragments. Precision is the frequency with which erroneous positives are ruled out. We use the following formula to determine accuracy:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FP} \tag{17}$$

This indicates the proportion of valid predictions made throughout the whole set of samples. F1-score and precision may be computed as follows:

$$F1 - Score = \frac{2 \times precision \times recall}{precision + recall} \tag{18}$$

$$Precision = \frac{TP}{TP + FP} \tag{19}$$

The F1-score is a measurement of how accurate a binary classification model is by taking the harmonic mean of the precision and recall values. Precision and recall could be measured on their whole via the use of this approach since both aspects are also included. Precision may be described as the proportion of the actual number of positive samples to the total number of samples that were projected to be positive. The area under the ROC (Receiver Operating Characteristic) curve, often known as the AUC, is a model assessment indicator that is used for classification tasks. The integral value of the ROC curve is the approach that is used to calculate the AUC.

5.5. Individual patient studies

Through a comparison of the overall accuracy, sensitivity, specificity, and F1-score, the suggested GAT+RBFN architecture’s seizure detection ability is assessed. We performed 5-fold cross-validation to assure consistency in our experiment outcomes. Results for all patients are summarized in 错误!未找到引用源。, shows that this approach has an average accuracy of 98.74%, a sensitivity of 94.74%, and a specificity of 97.89%. Most patients had sensitivities above 98%, with patients #2, #10-12, #15-16, #18, and #23-24 having sensitivities above 100%. The specificity for 20 patients is greater than 90%. Out of all patients, only four had specificities lower than 90%, and that’s just for patient #2 who has a specificity of 100%. The explanation for this is that scalp EEG data are highly influenced by environmental noise, and some individuals experience fewer epileptic episodes than others. As shown by the method’s 96.2% F1-score and 97.3% AUC, it has satisfactory accuracy and stability and can aid in the diagnosis process.

Table 6. Performance of CHB-MIT dataset using the proposed GAT+RBFN architecture.

Patients	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-score (%)	AUC (%)
1	99.73	99.39	99	99.2	99.44
2	100	100	100	100	100
3	99.9	99.8	99.6	99.6	99.7
4	97.37	90.03	95	92.68	96.44
5	98.73	99.38	93	95.77	96.44
6	96.8	89.1	92.45	92.45	90.74
7	98.33	96.6	96	95.05	97.4

Table 6. (*Continued*).

Patients	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-score (%)	AUC (%)
8	98.67	98.94	93	95.88	96.4
9	99.67	99	99	99	99.4
10	99.83	100	99	99.49	99.5
11	99.2	100	95.2	95.2	97.47
12	94.67	100	88	94	91
13	97.47	95.17	88.92	88.92	92.02
14	94.87	85.71	82.76	82.76	84.21
15	99.83	100	99	99.5	99.5
16	99.47	100	96.88	96.88	98.41
7	99.5	98.99	98	98.49	98.9
18	99.83	100	99	99.5	99.5
19	98.44	99.28	91.69	91.69	95.05
20	97.83	96.77	90	93.26	94.7
21	98.56	98.68	92.6	92.6	95.54
22	98.97	99.21	94.57	94.57	96.75
23	99.59	100	97.53	97.53	98.75
24	97.5	100	84	91.03	92
Mean	98.74	94.74	97.89	96.2	97.3

5.6. Discussion

We compare sophisticated machine learning and deep learning algorithms in trials. **Table 6** displays the results. Many of these systems use feature extraction and deep learning to detect seizures, and experimental indications have greatly improved when compared to previous methods. **Figure 9** shows the ROC curve of our model and it suggests that our model has a strong ability to distinguish between the two classes.

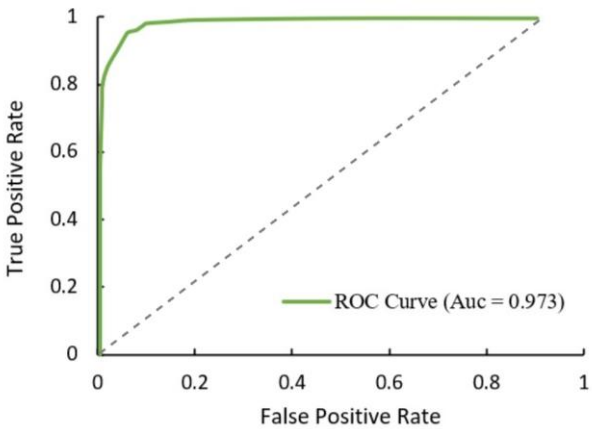

Figure 9. Receiver operating characteristic (ROC curve) of the proposed method.

Unfortunately, few of these techniques consider the interaction between EEG channels. The accuracy and sensitivity of GAT+RBFN are greater than many existing approaches, as shown in **Table 7**. Specifically, our approach is 5.90% more sensitive than BiLSTM[27] and 2.04% more sensitive than CNN[23]. The problem with these methods is that it does not fully extract non-linear relationships between features of EEG signals. This model performs slightly better than GAT+BiLSTM[36] which has similar work to this study (98.74% vs.

98.52%). The reason this model uses radial basis function neural network instead of any variants of RNN is because of its computational efficiency and ability to capture non-linear relationships between features which can be important to complex signals like the EEG data. Improved signal-to-noise ratio in the EEG data is possible through PSD analysis by decreasing background noise and increasing the signal components of interest. Because of computational efficiency, it will be a lot easier to implement this proposed method into real-time applications.

The proposed method is much effective and stable than several other state-of-the-art approaches. Results like these prove that integrating GAT and RBFN for seizure detection works well.

Table 7. Comparison of the proposed method with other state of art.

Author	Method	Accuracy (%)	Sensitivity (%)	Specificity (%)
Zhou et al.[23]	CNN	96.7	95.4	92.3
Hu et al.[27]	BiLSTM	93.61	91.85	92.66
Janjarasjitt[50]	Wavelet+SVM	96.87	72.99	98.13
Hussain et al.[51]	1D-convolutional LSTM	95.75	95.77	95.93
He et al.[36]	GAT+BiLSTM	98.52	97.75	94.34
Proposed method	GAT+RBFN	98.74	94.74	97.89

6. Conclusion

In this research, we present a hybrid model of a GAT+RBFN architecture for detecting epileptic seizures. The proposed model integrates three highly effective methods for deciphering EEG readings: power spectral density, a graph attention network, and a radial basis function neural network. PSD enhances the signal-to-noise ratio and minimizes artifact signals in EEG data. GAT captures both spatial and temporal patterns in EEG data, which is essential for effective seizure detection. RBFN excels in pattern recognition and classification, a critical feature for EEG-based seizure detection. When deciding, this model considers both historical data and information gathered after the present analysis time. In this approach, the benefits of both models are merged. Our result indicates a considerable improvement in the technique used for epileptic seizure identification when compared to earlier research in the field. In order to advance the corpus of knowledge, we meticulously created a cutting-edge method that improves the pre-processing and interpretation of EEG data. It can also streamline and deployable solution with reduced complexity, enhancing its practicality and usability in real-world applications. This technique has an accuracy of 98.74%, sensitivity of 94.74%, specificity of 97.89%, a positive F1-score of 96.2%, and an area under the curve (AUC) of 97.3%. For transfer learning, in which a network is trained on a new task using input and output data that are distinct from the original, this pipeline can be employed in the future. The amount of time and computing power needed to train the models from scratch can be drastically reduced in this way. In real-world applications, where EEG signals are frequently contaminated with noise, the suggested model must be robust to noise and artifacts in the EEG signals. This research offers a significantly simplified approach in terms of computational complexity, paving the way for more efficient and practical epileptic seizure detection.

Author contributions

Conceptualization, FAJ and AT; methodology, FAJ; software, HT; validation, FAJ, AT and HT; formal analysis, FAJ; investigation, FHS, MHM and HHJ; resources, FAJ; data curation, AT; validation: MUK; writing—original draft preparation, AT, NHN and MS; writing—review and editing, MUK, FAJ and AT; visualization, FAJ, MHM, HHJ and AT; supervision, FAJ; project administration, FHS; funding acquisition, MHM and HHJ. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

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