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LG-TriCapsNet: A lightweight graph capsule framework with nearest neighbor graphs for multi-disease EEG classification

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ABSTRACT

EEG signal classification for neurological disorders is a very critical task in the healthcare field, demanding accuracy and efficiency. Due to the diversity of these disorders and the complexity of the EEG signals, the task of diagnosing these disorders is very challenging. Traditional methods usually cannot capture the intricate relationships between temporal and spatial features, which are inherent in EEG data. To overcome this challenge, the proposed Lightweight Graph Triplet Capsule Networks combined with Nearest Neighbor Graphs effectively leverage both temporal and spatial information in EEG signals. The graph-based representation enhances the spread of information across the network, which thus performs efficient feature extraction and good classification performance. By integrating NNG, the model dynamically captures spatial-temporal dependencies between EEG channels, significantly improving feature discrimination across neurological conditions. The novelty of the approach lies in the combination of graph structures and capsule networks, which particularly makes it suited for handling the complexities of EEG data. LG-TriCapsNet is performing quite well as the F1 score is 98.32 %, accuracy is 98.34 %, sensitivity is 98.30 %, and specificity is 98.40 %, and it also outperforms the current state-of-the-art models, which points to the fact that this framework is really effective for the classification of such a variety of neurological disorders. LG-TriCapsNet, by providing a computationally efficient, real-time solution, holds great potential for advancing clinical decision-making and patient care by offering a robust tool for automated neurological disease detection and diagnosis. At https://github.com/jainshraddha12/LG-TriCapsNet, the source code will be available to the public.

1. Introduction

The primary goal of our study is to develop a new technique for brain diseases detection, aligning it with the World Health Organization's plan in 2022. This involves using EEG data despite their complexity low signal strength and high background noise issues as valuable sources that can provide significant details about brain activity. Our strategy that primarily aims at recognizing and treating common neurological disorders, then fostering efforts towards enhancing quality care with better data collection within WHO initiatives plays a pivotal role in these important fields [1]. The information on brain function and brain disorders is critical as EEG signals are representative of the electrical activity produced by the brain itself [2]. One of the interesting methods in identifying those neurological disorders (like stroke, epileptic seizures, schizophrenia, parkinson) involves the use of spectrogram images. These images show the changes in a visual manner from the time-frequency domain for EEG signals [3]. This technique we used as part of a multi-disease neurological disorder categorization problem addressed in our most recent study; we aim at achieving higher levels of precision and efficiency when it comes to disease categorization task. This application used for deep learning-based feature extraction and classification methods, integrated with the spectrogram images [4].

Recent developments in deep learning and graph-based approaches have greatly enhanced the capability of EEG signal classification. Of these, the most commonly adopted approaches in feature extraction with regards to EEG signals in neurological disease detection are CNNs, RNNs [5], and LSTM networks [6]. Such methods have the ability to learn complex, hierarchical patterns in data but generally tend to be inefficient at capturing the dependencies both in temporal and spatial in EEG signals. Such dependencies are critical to proper diagnosis. Recently, graph-based models such as Graph Convolutional Networks (GCNs) and Graph Neural Networks (GNNs) have emerged as powerful tools for capturing spatial relationships and topological structures in EEG signals, thereby significantly improving the classification accuracy

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for diseases like Alzheimer's, schizophrenia, and epilepsy [7].

Recent developments in EEG-based diagnosis of neurological disorders have led to significant improvements in classification accuracy and disease detection. Such of the developments by Yu et al. [8] include the use of supervised network-based fuzzy learning, as presented in integrating fuzzy logic and supervised learning for the improved classification of EEG signals. This does account for the uncertainty in the EEG data, consequently improving the detection of Alzheimer's disease in terms of its capacity to capture complex, imprecise relationships. Adebisi et al. proposed the rising technique of EEG-based brain functional network analysis for differential identification of dementia-related disorders [9]. This method allows the differentiation of the types of dementia and tracking the onset: based on the analysis of functional connectivity. Besides, the recent developments in graph-based deep learning techniques in medical diagnostics by Ahmedt-Aristizabal et al. [10] have shown promising capabilities to capture complex relationships in EEG data, leading to better diagnosis of neurological disorders. Finally, Yan et al. [11] reviewed how graph theory combined with both EEG and MRI data leads to the ability to diagnose neurological disorders by applying the strengths of both data types for more precise disease detection. These innovations present the growing importance of deep learning and graph-based approaches in the diagnosis and analysis of neurological diseases, especially in terms of EEG signal classification.

Recent advancements in Capsule Networks (CapsNet) and graph-based models have been promising in the analysis of EEG signals for neurological disorder classification. However, these approaches fail to capture both spatial and temporal dependencies between EEG channels effectively. Though CapsNet has been successful in learning hierarchical features from EEG signals, it cannot represent dynamic interactions between brain regions over time. In this work, we put forward a new approach called Lightweight Graph Triplet Capsule Network, or LG-TriCapsNet for short. It's built by integrating NNG with Capsule Networks, enabling the model to capture both spatial and temporal relationships within EEG data. Our approach addresses major limitations to previous methods by modeling intricate brain connectivity patterns effectively and providing superior classification performance in multi-disease classification tasks such as epilepsy, Alzheimer's, or Parkinson's disease.

Apart from these advanced capabilities of feature extraction, the interpretability of graph-based features that arise from the EEG signal is also explored here. Such a feature plays a vital role in unveiling the structural and functional relationships within brain regions. Our graph-based features are compared with traditional EEG analysis methods, such as functional brain networks and modulation of spectral power, which have been widely used in EEG analysis, including studies on acupuncture modulation of brain activity. These comparisons help us to assess the value of the proposed method in capturing brain connectivity more comprehensively. Triplet network design holds the promise of extracting features that are class-separable; there are difficulties in optimizing its performance for classification. Although training for class-separable features is naturally sensitive, there is still a gap in efficiently converting metric loss into concrete classification results [12]. Finding the best classification architecture is made more difficult by inconsistent classification performances throughout training epochs, resulting in the need for a careful examination of feature–classifier combinations. It becomes challenging to identify the root cause of under-performance in the classifier, learns features, or both [13].

We propose LG-TriCapsNet, a multi-disease neurological classification system that integrates Nearest Neighbor Graph (NNG) and Lightweight Graph Triplet Capsule Networks. To extract useful features from complicated neurological data, LG-TriCapsNet utilizes capsule networks and graph-based representation learning [14]. Its main innovation is how it uses Nearest Neighbor Graph (NNG) to extract features from neurological datasets effectively and capture underlying structural links. LG-TriCapsNet also utilized triplet capsule networks to learn hierarchical features and spatial correlations. It reduced constraint on achievable end performance and offers a way to speed up the optimization process [15]. This work focuses on reducing dependency on labelled data by proposing the LG-TriCapsNet architecture. Combining nearest neighbor graph, our approach aims to fill the gap between the scarcity of labelled data and the need for robust and generalizable models in medical time series research. We present comparison research within a challenging patient-independent environment over three baselines from five different datasets.

1.1. Motivation

We introduce a new multi-disease neurological classification framework called LG-TriCapsNet, a novel hybrid model which is a fusion of Nearest Neighbor Graphs (NNG) and Lightweight Graph Triplet Capsule Networks (CapsNet). The proposed model exploits spatiotemporal dependencies of EEG data and maintains hierarchical relations among features. With the integration of graph-based representation, LG-TriCapsNet effectively models local and global structural patterns within EEG signals and mitigates the shortfalls of existing approaches. In LG-TriCapsNet, NNG facilitates efficient extraction of structural and functional correlations among EEG channels, while triplet capsule networks facilitate feature discriminability for enhanced classification performance. The combination addresses the prevalent issue of sparse labelled EEG data by limiting dependence on large datasets and enhancing generalization across diverse neurological disorders. Hierarchical feature extraction through capsule networks guarantees strong representation learning, which is essential to address the complexity of neurological EEG datasets.

EEG signals have spatiotemporal correlations such that brain areas dynamically interact over time. Nonetheless, conventional models such as CNNs and RNNs fail to capture spatial dependencies and hierarchical relations. CapsNet is great at learning hierarchical spatial features but fails to incorporate an explicit mechanism for modeling functional connectivity between EEG channels. To fill this deficit, we incorporate Nearest Neighbor Graphs (NNG) that capture functional connectivity between EEG channels and support feature propagation to achieve effective disease classification. We treat EEG channels as graph nodes and their interactions as weighted edges and utilize NNG to tighten feature relations and improve classification.

The proposed framework for the identification of multiple neurological disorders from EEG signals is summarized in Fig. 1. The process of ensuring an in-depth evaluation of the model's quality to distinguish between neurological disorders is depicted in the diagram in multiple steps.

In this paper, our main work includes:

Our contributions include a complete methodology for the EEG-based classification of neurological diseases:

1. We propose Nearest Neighbor Sparse Inverse Covariance (NNSIC) to represent EEG signals as a graph structure, which can capture the spatiotemporal relationship among EEG channels for the model.
2. We introduce LG-TriCapsNet, an integration of Capsule Networks (CapsNet) with Nearest Neighbor Graphs (NNG). Such an integration enables the model to retain hierarchical relationships of features and at the same time use graph structures to enhance feature extraction.
3. We utilize Graph Routing Algorithms in place of standard pooling methods in order to maintain spatial relationships to better provide for classification accuracy. Adding Triplet Loss Optimization boosts the feature separability further to increase the ability of the model to separate and classify distinct neurological diseases.
4. Our model has 98.34 % accuracy (F1: 98.32 %), outperforming state-of-the-art models such as 1D-CapsNet (97.44 %) and AlexNet + CNN (95.79 %). LG-TriCapsNet is tested on several public EEG datasets and demonstrates excellent generalization ability, even when tested with noisy and missing EEG signals.

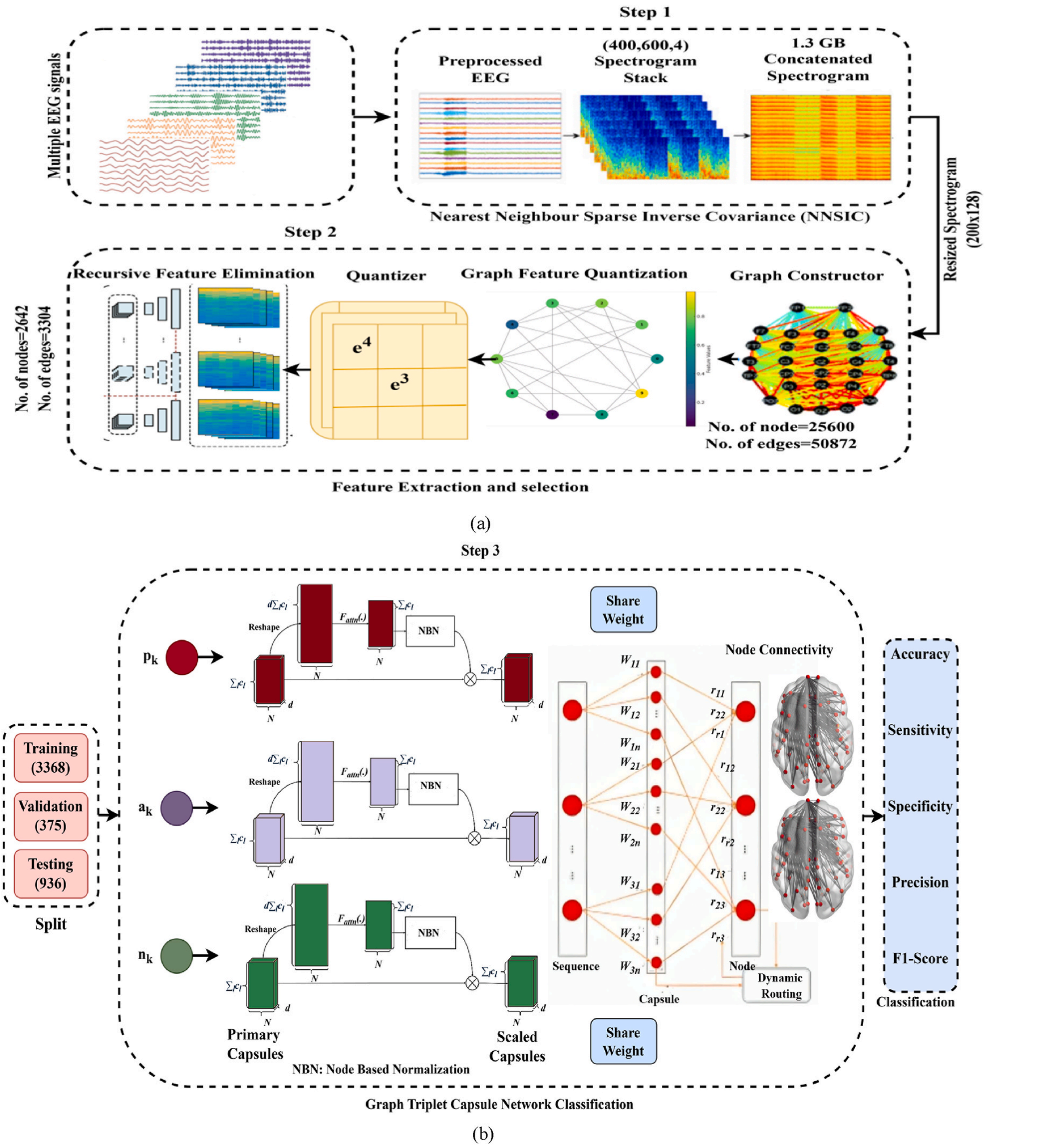


Fig. 1. Block diagram of the proposed LG-TriCapsNet framework (a) EEG signal preprocessing, spectrogram generation, feature extraction, and graph construction pipeline. (b) Graph Triplet Capsule Network architecture for multi-disease EEG classification including training-validation-testing split and performance metrics.

2. Related works

Recent advancements in EEG classification have explored Capsule Networks (CapsNet) for hierarchical feature learning. However, standard CapsNet models primarily function as local feature extractors and do not model spatiotemporal interconnections among brain regions. Meanwhile, Graph Neural Networks (GNNs) and functional connectivity methods capture global brain correlations but often lack fine-grained feature extraction required for disease classification.

To address these limitations, we introduce a novel fusion of Capsule Networks and Nearest Neighbor Graphs (NNG) in our LG-TriCapsNet model. This integration ensures both hierarchical feature learning and structural connectivity modeling of EEG signals, enhancing classification accuracy for multiple neurological disorders.

2.1. Graph-based representation learning for classifying neurological disorders

The classification of neurological diseases has become popular with techniques that use graph-based representation learning such as RGNN, MT-MVGCN, and Co-GCN. The use of Graph Neural Networks has been able to enhance the analysis of the brain's connectivity by learning and representing reasoning networks from large datasets [16]. The spatial techniques used in GNNs aggregate information from neighboring brain regions, and the spectrum-based techniques use spectrum filters for Fourier domain convolutions. The update equation of the node in the spatial GNNs can be given by

$$h_i^{(l+1)} = \sigma\left(W_1^l h_i^l + \sum_{j\epsilon N(Vi)} W_2^l h_j^l e_{ji}\right) \quad (1)$$

Here, h_i is the node embedding vector, and σ is the activation function, W is the learnable parameter matrix, N(Vi) is the neighborhood of the node Vi, and e_{ji} is the edge weight [17]. On the contrary, the spectral GNNs perform convolution operations in the spectral domain through operations such as Graph Signal Processing (GSP) and Graph Fourier Transform (GFT) [18]. However, while spectral GNNs provide interpreted capability, spatial GNNs are by far more adaptive for EEG classification tasks with better scalability and ability to adjust better for the inputs structured with irregularity [19,20]. In general, GNNs are very flexible frameworks for identifying complex correlations in EEG data for enhancing diagnostic and disease comprehension of neurological diseases. So, These GNN-based approaches are missing hierarchical feature learning, which is important for dealing with fine-grained EEG variations. It is to overcome this that we combine NNG with Capsule Networks to provide both spatial and hierarchical feature preservation.

2.2. Brain connectivity using nearest neighbor graph (NNG)

In this point, it would be appropriate to perform dynamic analysis in EEG connectivity for understanding the dynamical topology of the brain network over time. Dynamic connection approaches account for the temporal variations of the topology of the brain network, but the static functional connectivity is instrumental for the classic graph-based models [21]. These methods can provide a more comprehensive view of brain dynamics because they consider the shifting connections among the different regions of the brain. The current approaches often presume a static graph topology, missing the dynamic character of brain connectivity. The validation requirements for dynamic EEG connectivity analysis are formulated with closest neighbor (NN) graph [22].

Recall that given a set of feature-value pairings {(X1, V1), (X2, V2) … } and a query for an unknown value (Xq,Vq), the probability p(Vq = v|Xq) is estimated from the nearest neighbors of X q within a fixed radius r q. The following expression then corresponds to the above estimate:

$$p(V_q = v|X_q) = \frac{1}{|N_{\underset{rq}{q,}}|}\sum_{i\epsilon N_{\underset{rq}{q,}}} I(V_i = v) \quad (2)$$

Where, V_q is the value to be estimated and X_q is the query point with some unknown value. The symbol v is any specific value and it could be a value for discrete class labels C or continuous responses R. $N_{q,rq}$ is the neighbors in a radius rq of the query point Xq. The indicator function I (Vi = v) equals 1 if the value V_i of the ith neighbor is equal to v, and 0 otherwise. This adaptive connectivity modeling is especially helpful in EEG-based neurological classification, where brain areas have dynamic interactions that change over time and conditions. NNG learns these relations dynamically, in contrast to static connectivity graphs that cannot reflect real-time changes. Such elements are of paramount importance for the implementation and use of the NNG-based estimation methods, more so in cases, such as, for instance, in the analysis of dynamic EEG connectivity [23]. In theory, an increase of k for rq = d q,k should enhance the confidence in the estimate since by the law of large numbers the estimation error upper bound is decreasing [24]. However, this also increases the risk of including samples not belonging to p(Vq| Xq). How to select the correct value for r q or for k is a problem still under research and it is usually optimized by different ways other than the cross-validation. Neural networks are, therefore, very powerful non-parametric tools for deep learning feature analysis within the nonlinear framework.

2.3. Capsule and triplet network for EEG signal classification

By using capsules that can describe the instantiation parameters—such as pose (position, size)—of an entity, capsule networks allow for the existence of hierarchical relations in this sense between lower-level and higher-level entities. This paper extends the recently proposed CNN with capsules to generalizing the use of capsules to models based on graphs by utilizing higher-order statistical moments in GCAPS-CNN. However, it does not consider that graphs are inherently hierarchical [25]. To address this, CapsGNN constructs graph capsules with multiple GNN channels, although without local structure data. Compared to the use of transformation matrices, our approach is more memory efficient since we use transformation GNNs to determine the pose of every higher-level entity [26]. The length of the capsule, denoting a probability that an entity exists, is determined using the following formulation:

$$p(V_q = v|X_q) = \sum\nolimits_{i\epsilon N_{\underset{rq}{q,}}} I(V_i = v) \quad (3)$$

With respect to a neural network, V_q is the value to be estimated and X_q is the query that has an unknown value [27]. We will also use the symbol v to represent a specific value: a discrete class label C or a continuous response R. The set of neighbors of the query point X_q in a radius rq is represented as $N_{q,rq}$.

The indicator function I(Vi = v) returns the value 1 if the ith neighbor's value, V_i, matches v, and 0 otherwise.

The triplet networks thus consist of a comparator network and three identical extractors that share parameters in the process of metric learning. Feature vectors of the samples in the same class are pulled together, all separated from the samples in a different class by some predetermined margin [28]. Organizing input data into triplets implies selecting an anchor sample and combining with it a positive sample from the same class and a negative sample from a different class to enlarge the data set. Better classification performance is achieved in the settings where only a limited amount of data is available, since with the increase of the number of input samples, the overall number of triplets in the data set enlarges quadratically. The Triplet Loss function, Ltri, is

$$L_{tri} = max(0, D_{a,p} - D_{a,n+m}) \quad (4)$$

In triplet networks, we have the definition $D_{a,p} = ||X_a - X_p||^2$, representing the Euclidean distance between the feature vectors of the anchor sample X_a and the positive sample X_p. We define the Euclidean distance between the feature vectors of the anchor sample X_a and the negative sample X_n to be $D_{a,n} = ||Xa - Xn||^2$. The fixed-margin m ensures that in the feature space samples from different classes are separated by a large margin [29]. The triplet dataset is then expanded using:

$$T_p + T_n = n^2p - np^2 \quad (5)$$

The triplet number generated from samples of the positive class is denoted by T_p in triplet network architecture, and the one generated from the negative class is shown as Tn. Triplet loss in EEG classification keeps feature embeddings of the same neurological disorder close to each other and pushes away those from various disorders. This increases class separability and minimizes misclassification errors in LG-TriCapsNet. Also, the total number of input samples is denoted as n, and the number of samples from the positive class is denoted by p [30]. It is clear that these parameters are further used to divide the data into triplets that are instrumental in allowing the network to learn feature representations of the data required for classification. By combining NNG with Capsule Networks, we obtain the best of both worlds: NNG learns dynamic spatial dependencies in EEG signals, and CapsNet enforces hierarchical feature learning. This synergy retains both local and global EEG structure, resulting in more accurate neurological disease classification.

3. Methodology

Integration of Nearest Neighbor Graph (NNG) with Capsule Networks (CapsNet) is the novel contribution for EEG-based classification of neurological disorders. NNG allows the model to capture spatial-temporal dependencies between EEG channels that have not been fully captured by previous methods. Although traditional CapsNet learns hierarchical feature representations, it generally doesn't consider the complex interactions of brain regions over time. We can better model the connectivity between different EEG channels by incorporating NNG into the network. The graph-based representation propagates node-level EEG features through adaptive edge weighting, enabling hierarchical feature aggregation while preserving local connectivity patterns.

3.1. Nearest Neighbor Sparse Inverse Covariance (NNSIC)

We proposed a preprocessing methodology that enhances raw EEG signal analysis in datasets of neurological disorders through the Nearest Neighbor Sparse Inverse Covariance (NNSIC) technique [31]. The preprocessing methodology starts with the careful cleansing and normalization of EEG signals in order to preserve data integrity. Following the preprocessing, spectrograms are calculated for each EEG recording [32]. In Fig. 2 makes the dimensions of the structured dataset become 400 (which equals the number of channels) by 600 (which equals the number of frequency bins) by 4 (which equals the number of time-steps). It brings the conversion into clarity, whereby the EEG data is transformed to a time-frequency domain.

Finally, for all these stacks of spectrograms, the sparse inverse covariance matrices are computed using the nearest neighbor graph. NNSIC combines the available data points from neighboring data points to harden the covariance estimation for sharp analysis. Spectrogram stacks are combined into one dataset during the NNSIC processing [33]. Here, scaling techniques are applied to bring the appended spectrogram down to a manageable 200 × 128 partly as a method to overcome memory limitations and partly because of computational overload. Some of the advantages with NNSIC in the workflow of preprocessing include greater scalability, noise removal, better features extraction, and accurate estimation of covariance. These are instrumental improvements that are necessary in order to maintain computing efficiency while discriminating different neurological states. The spectrograms were drawn to scale, and then plotted to obtain a graph with around 25,600 nodes and 50,872 edges. The following algorithm summarizes the estimation process of the sparse inverse covariance matrix from NNSIC and its ensuing steps of processing for the analysis of continuous EEG data:

Algorithm 1. Nearest Neighbor Sparse Inverse Covariance (NNSIC) Algorithm for Sparse Inverse Covariance.

Input:

Raw EEG recording X, number of nearest neighbor's k, regularization parameter α

Output:

Concatenated sparse inverse covariance matrix Σ

1. X is cleaned and normalized.
2. Compute spectrograms for every EEG recording, where S is the spectrogram value at channel i, time step j, and frequency bin k.
3. For every stack of a given spectrogram S, we construct a graph G= (V,E) of the nearest neighbors where V denotes nodes and E edges.
4. NNSIC For each G:

$$\sum_i = argmin_{\Sigma}(Tr(S_i\Sigma) - log\ det(\Sigma) + \alpha\|\Sigma\|1)$$

Compute $\sum$ using NNSIC: $\sum = || \sum ||1$. and Tr(.) is a trace of matrix. log det(.) is a logarithm of determinant. ||.|| is $l_{1\ \text{-norm}}$. α is regularization parameter.

5. Concatenate Σ into single data.

$$\Sigma = [\Sigma 1, \Sigma 2, \ldots, \Sigma n]$$

6.Scale down using scaling techniques:

$$Scaled_{Spectrogram} = S(\Sigma)$$

7. Graphically represent scaled spectrograms through the use of nodes and edges.

Graph = G(Scaled_Spectrogram)

To improve robustness, we incorporate data augmentation methods like Gaussian noise injection, time-warping, and frequency perturbation. These artificially augment data diversity and mimic real-world noise conditions, enhancing generalization to clinical environments. NNSIC preprocessing is also used to eliminate artifacts, while wavelet filtering and ICA are used to eliminate background noise, providing cleaner EEG inputs.

3.2. Feature extraction and selection

To analyze the features we made use of Graph Joint Feature

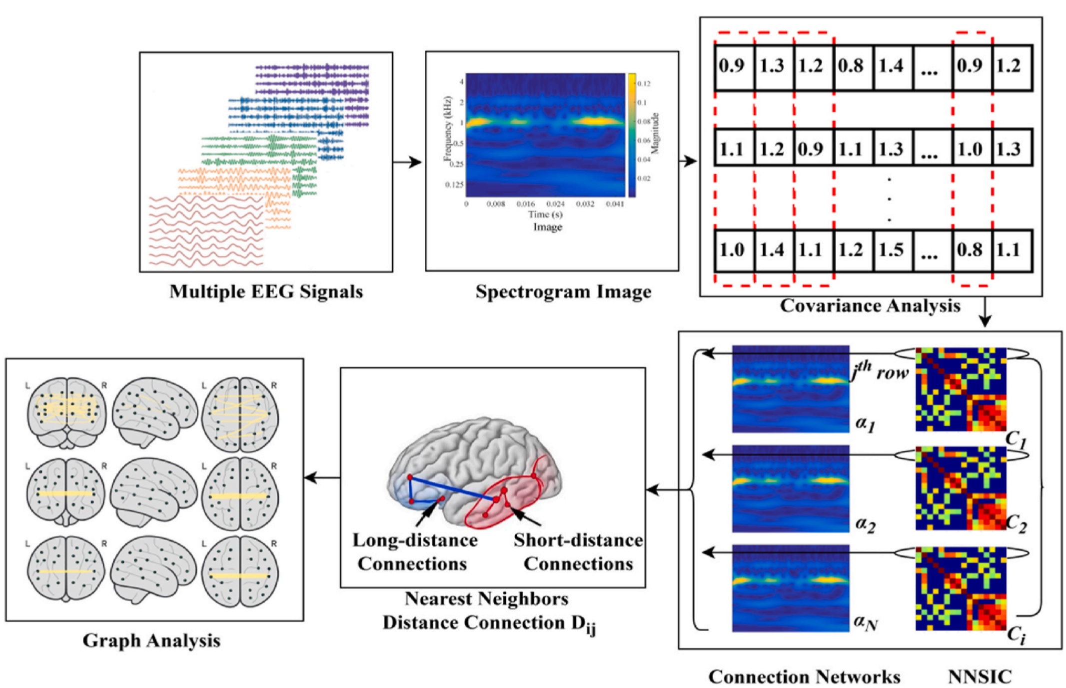


Fig. 2. Pre-processing workflow with NNSIC for EEG signal Analysis.

Quantization (GJFQ) to harness the potential of data in representing graph-based relationships. Our method exploits Graph Joint Feature Quantization (GJFQ) that enables the feature extraction process and presents a host of benefits. Majorly GJFQ is useful in retrieving complex graph-based interactions [34] from data and therefore building succinct but important feature representations. By quantizing the graph features GJFQ condenses the underlying structural information present in the data resulting in meaningful feature representations. In addition GJFQ provides an efficient means of feature extraction permitting the handling of large-scale graph data with minimal computational cost [35]. Furthermore the robustness of GJFQ against noise and variations in the input data facilitates the extraction of consistent and distinctive features even when dealing with noisy or incomplete graphs.

To enhance the interpretability of the extracted features, we use Nearest Neighbor Graph (NNG) as a representation of the spatial and temporal relationships between the EEG channels. Such representations can be visualized or analyzed for functional connectivity relationships between different brain regions; the network structure will thus pick up finer details on information exchange between the brains not captured by traditional methods, for example, spectral power modulation and functional connectivity. Graph theory-based features have the advantage of giving a direct mapping of how the functional and structural regions in the brain are connected. This gives a view of neurological disorders like epilepsy, Alzheimer's, and Parkinson's disease. In Fig. 3 shows better interpretability increases the clinical utility of the features extracted as healthcare professionals would better understand the underlying dynamics of the brain associated with the disorders.

The primary objective is to preserve the essential data necessary for reconstructing the limited segment UKc of the noisy plot signal Gx. This process involves converting the signal into a digital form with a finite number of bits through both sampling and quantization assuming that the structure of the graph signal and its spectral support represented by UK are already identified. The initial step is to sample the graph signal using a transformation matrix φ , resulting in a sampled signal $y = \varphi$ x. This sampled signal y is then discretized using collaborative feature quantizers to generate a finite-bit representation xn from QMn. The main aim is to minimize the mean squared error (MSE) between the approximations of the UKc component based on the compressed representation Q(y) [36].

$$min_{\varphi,Q}E[\|UK_c - E\{UK_c|Q(\varphi_X)\}\|^2] \tag{6}$$

According to the limitation $\sum_{i=1}^{p} log_2 M_i \le log_2 M$ (7)

The maximum capacity is denoted as M while M_i signifies the allocation of bits per joint characteristic quantizer. By utilizing Graph Joint Feature Quantization (GJFQ) intricate graph-based interactions can be efficiently extracted resulting in strong and concise feature representations that enhance the analysis and comprehension of vast graph datasets.

After feature extraction Recursive Feature Elimination (RFE) was employed to identify the most advantageous features while discarding less significant ones [37]. This process resulted in a reduction of 2642 nodes and 3304 edges resulting in a refined set of features ready for classification analysis. The preprocessed dataset was split into three subsets: training, testing, and validation after feature selection. The training subset has 3368 samples, which is a huge amount of data for training the model. Within this dataset, the underlying patterns were identified, and model parameters were optimized. The testing set, with 936 samples, is an independent dataset used to evaluate the performance of the trained model. We can test the capacity of the model to generalize and ensure it can classify neurological diseases in new EEG recordings by running it on data that has not been seen in the testing set. For further tuning of the model hyperparameters and preventing overfitting, a validation set of 375 samples is used.

3.3. Lightweight Graph Triplet Capsule Network (LGTriCapsNet) for classification

We proposed Lightweight Graph Triplet Capsule Network (LG-TriCapsNet) for Multi-Disease Neurological Classification provides a novel method for efficiently classifying neurological disorders by utilizing spectrogram images as input data [38]. Fig. 4 showcases the overall architecture of LG-TriCapsNet incorporating specialized components such as graph routing algorithms triplet networks lightweight processing approaches and loss functions to achieve o achieve highly accurate neurological disorder classification.

The first step in the graph-based classification process of LG-TriCapsNet is the ChannelTrans module a lightweight processing unit placed after the initial graph analysis layer [39]. This module employs a 1×1 convolutional layer to reduce feature maps from the input graph to 128 dimensions maintaining important characteristics while enhancing non-linearity and receptive field through ReLU activation and normalization. The ResidualBlock module is further used to improve the classification accuracy by eliminating vanishing gradients. To deal with the different types of graph data, and enhance the accuracy, Instance Normalization (IN) replaces the commonly used Batch Normalization

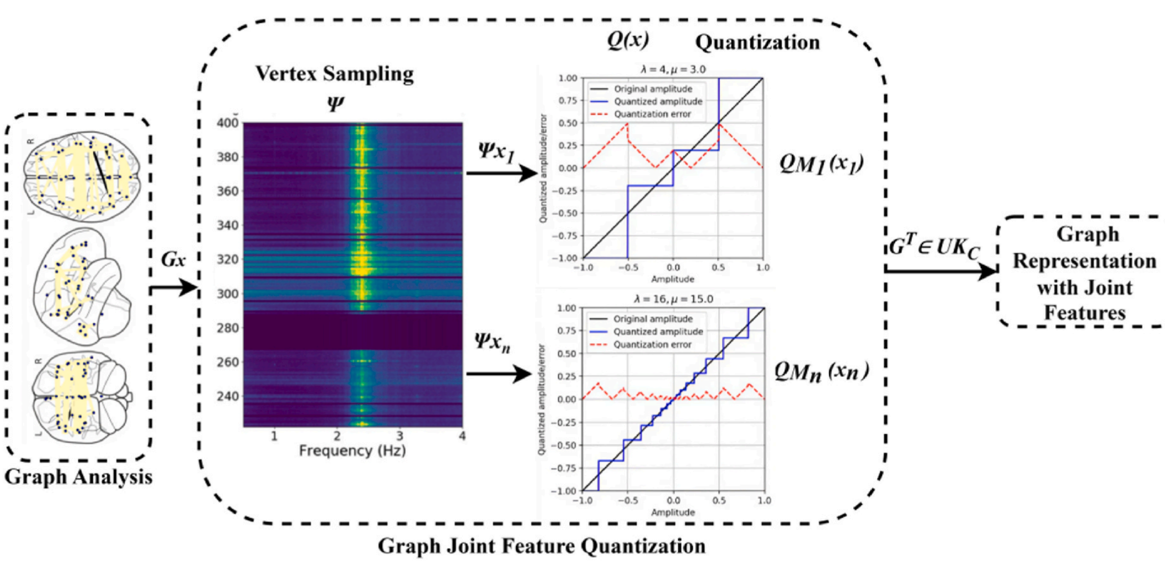


Fig. 3. GJFQ feature Extraction.

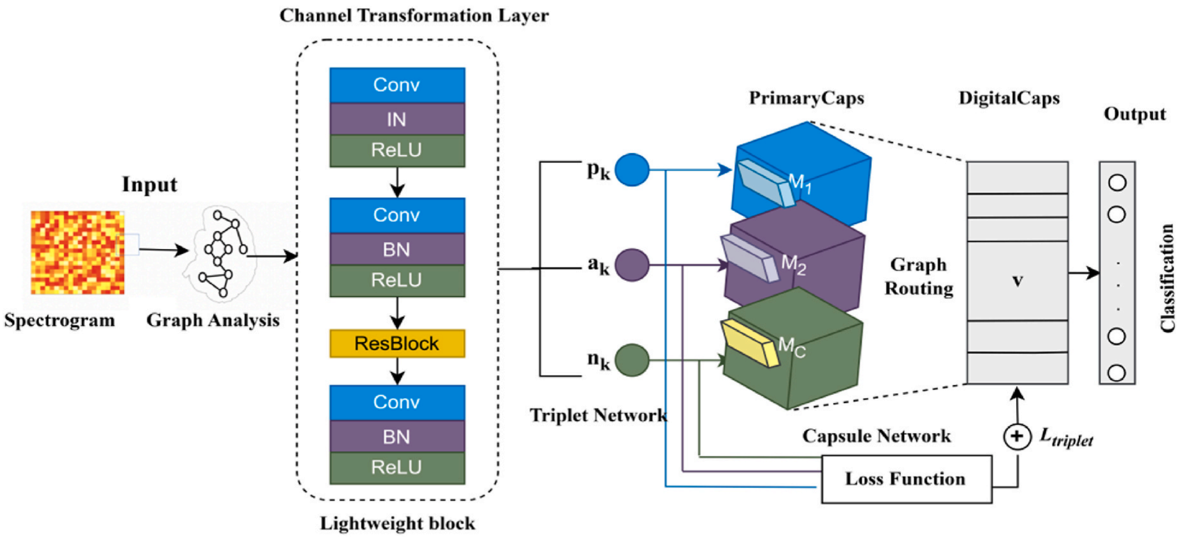


Fig. 4. Classification using LG-TriCapsNet.

(BN). The use of ReLU activation introduces non-linearity that results in more stable outcomes [40]. In summary, the ChannelTrans module significantly contributes to the precision and efficiency of LG-TriCapsNet in classifying neurological disorders. For extracting discriminative representations from the processed graph data, it uses the triplet network component after the ChannelTrans module. These networks select an anchor sample with a couple of positive and negative samples to optimize the feature space and increase classification accuracy. By leveraging the similarities and differences among these samples robust representations are developed [41].

The PrimaryCaps are the base capsule layer that extracts feature data from the processed graph data, and they play a significant role in the design of LG-TriCapsNet. Each PrimaryCap contains several capsule units assigned to capture particular patterns or features that exist in the graph data, allowing the extraction of structured information encoded within the data [42]. The use of graph routing algorithms further enhances the discriminative features essential for precise classification in graph-based tasks by establishing connections between capsules and refining feature representations obtained from PrimaryCaps. Once graph routing is complete the feature vectors are fed into the DigitalCaps layer where dynamic routing algorithms further improve the features and encode them into capsules corresponding to distinct categories [43]. Lastly the output capsules along with the loss function (which typically includes the triplet loss and additional regularization terms) guide the network towards acquiring discriminative features by comparing model predictions with ground truth labels. These feature representations are then used by the classification process to predict the class labels of the input graph data as depicted in Algorithm 2.

Algorithm 2. LG-TriCapsNet for Graph-Based Classification

1. **Input:** Network G containing attributes anchor instances a_i positive instances p_i negative instances n_i regularization value λ margin value α iterations N.
2. **ChannelTrans Module:** $X_{out} = \text{ReLU}(\text{Norm}(\text{Conv1}(\text{ReLU}(\text{Norm}(\text{Conv2}(X))))))$
   Apply normalizing and ReLU activation methods on the outcome of Convolution layers 1 and 2 denoted as X_{out}.
3. Triplet Network:
   $L_{triplet} = \sum_{i=1}^{N}\left[\|f(a_i) - f(p_i)\|^2 - \|f(a_i) - f(n_i)\|^2 + \alpha\right]^+$
4. **PrimaryCaps Layer:** $vi = \text{Squash}(\text{Conv}(X_{out}))$
   Apply the squashing activation function to the output of the convolutional layer.
5. **Graph Routing:** Initialize coupling coefficients c_{ij}.
   $c_{ij} = \text{Softmax}(b_{ij})$
   Compute output capsules s_j:
   $s_j = Squash(i\sum c_{ij}vj)$
6. **Loss Function:** Compute the total loss function:

(continued on next column)

(continued)

$L_{total} = L_{triplet} + \lambda R$
Where R represents a regularization term.
7. **Backpropagation:** Compute gradients of the loss function with respect to the model parameters.
8. **Optimization:** Update the model parameters using an optimization algorithm (e.g., SGD, Adam) to minimize the loss.
9. **Repeat:** Repeat steps 2–8 for multiple epochs until convergence or a stopping criterion is met.

i) Considerations for Integrating NNG and CapsNet:

To improve efficiency, robustness, and scalability, some optimizations were made in LG-TriCapsNet:

1 **Minimizing Computational Overhead:** One of the key challenges in EEG-based classification is the handling of high-dimensional EEG signals while ensuring real-time performance. To ensure this, we introduced:
   - ➢ 1 × 1 Convolutional Layers: The layers down-sample feature map dimensions prior to graph operations, eliminating redundant computations and increasing efficiency.
   - ➢ Instance Normalization (IN) rather than Batch Normalization (BN): Differently from BN, IN is a sample-level operation that eliminates computational complexity and enhances suitability for low-power and real-time applications.

2. **Providing Stability and Robustness:** EEG signals tend to be influenced by noise, missing channels, and inter-subject variability. To improve robustness, we included:
   - ➢ Gaussian Noise Augmentation: Injecting controlled noise into EEG signals, the model learns to cope with real-world signal variability and artifacts (e.g., eye blinks, muscle movements).
   - ➢ Data Imputation Techniques: Interpolation methods are used to reconstruct missing EEG channels, making the model perform well even with incomplete data.
   - ➢ Ablation Study Validation: As demonstrated in our Ablation Study, performance degrades when NNG, Graph Routing, or Triplet Loss is removed, validating the requirement for these elements.

3. Generalization and Scalability: To facilitate deployment of LG-TriCapsNet in diverse clinical settings, we made the model:
   - ➢ Dataset-Agnostic: The model is evaluated on various publicly accessible EEG datasets across diverse neurological diseases to ensure effective generalization.

➢ Lightweight and Deployable: LG-TriCapsNet is computationally lightweight, making it appropriate for real-time clinical settings and wearable EEG systems, supporting feasible usage in real-world diagnosis.

4. Experimentation and results

4.1. Datasets descriptions

This work employs five publicly released EEG datasets covering various neurological disorders to assess the performance and generalizability of LG-TriCapsNet. The datasets are Epilepsy (Ep), Parkinson's Disease (Pd), Alzheimer's Disease (Ad), Schizophrenia (Sz), and Stroke (St), providing a diverse range of brain activity patterns that shows in Table 1. The experiment employs EEG datasets from multiple publicly accessible sources to provide diversity in patient populations, recording environments, and types of neurological disorders. The datasets cover subjects of varying age groups, genders, and clinical histories, making LG-TriCapsNet more generalizable. The datasets come from various research centers and hospitals in different geographic locations, enabling the model to learn from diverse EEG patterns and enhance its robustness for practical use. This diversity is important for creating a robust model that can deal with real-world variations in EEG recordings.

EEG signals are intrinsically noisy because of several factors, such as patient-specific variability (age, gender, neurological condition), inconsistencies in electrode placement, differences in EEG recording devices, and noise artifacts like eye blinks and muscle movements. These fluctuations can impact classification performance in actual clinical environments. To counteract these issues and improve model generalization, we use sophisticated preprocessing methods and data augmentation techniques to clean EEG signals prior to training. Preprocessing pipeline consists of Independent Component Analysis (ICA) for artifact removal, Wavelet Transform Filtering for denoising, and Nearest Neighbor Sparse Inverse Covariance (NNSIC) for extracting functional brain connectivity patterns. Data augmentation methods like Gaussian noise injection, time-warping, and frequency perturbation are also added to mimic real-world EEG variations and enhance robustness. To further test the robustness of LG-TriCapsNet in actual clinical situations, we also simulated noisy EEG conditions by adding Gaussian noise to the dataset. Missing EEG channels were also treated using interpolation methods, which ensure the model still performs well when there is partial data loss. These preprocessing steps enhance generalization and enable improved performance on actual EEG recordings.

All of these datasets are publicly available on the internet, and when the data was being collected, each subjects provided their informed permission for it to be published. Our proposed model outperformed the present state-of-the art methods on five datasets. Performance measures included mean accuracy and total accuracy for the model proposed.

4.2. Hardware and software configuration

We describe here the experimental setting designed for multi-disease neurological categorization using the Lightweight Graph Triplet Capsule Network (LGTriCapsNet). The high-performance computing environment employed for the LGTriCapsNet model features a Dell Precision 7920 workstation, containing an Intel® Xeon® Silver 4114 processor, equipped with 40 cores and a clock rate of 2.20 GHz. This heavy equipment allows complex calculations required for capsule network architecture and graph-based neurological data to be performed in the most efficient way possible. Such a setup is also ideal for our demanding classification exercises, with rich resources like the 8 GB NVIDIA Quadro P4000 for graphics and the processing time, 64 GB DDR4 RAM for very large datasets, and a 3 TB SSD for quick access to data for storage and retrieval.

We employ the Ubuntu 22.04 operating system, renowned for its reliability and efficiency in high-performance computing, to provide support for the software environment. For the reliable simulation and analysis of neurological data using the LGTriCapsNet architecture, the software environment incorporates PyTorch version 1.3.1, a flexible deep learning framework. Our multi-disease neurological classification investigations are carried out seamlessly and are aptly assessed because of this combination of hardware and software resources. In addition, the equipment and software developed can process the EEG data significantly faster and ensure scalability for larger datasets in the future as well as more complex models. In other words, such a foundation would serve well for a scalable future that would be well-supported for deployment in real clinical environments.

4.3. Used hyperparameter and loss function

The proposed new architecture for multi-disease neurological categorization using EEG signals is called Lightweight Graph Triplet Capsule Network (LGTriCapsNet). LGTriCapsNet is highly suitable for real-time analysis as it processes 90 batches or 30 EEG frames per second with excellent efficiency. The framework performs very well in real-time neurological condition analysis and diagnosis as it analyzes up to 1100 EEG frames per second. Moreover, with a low training loss of 0.1306 per epoch, LGTriCapsNet is resistant and can accurately categorize training data in around 3 ms each training step. During training optimization, the learning rate was 0.0001, the proposed LGTriCapsNet was trained for 200 epochs, and the Adam optimizer was used for fast computation. Combining the advanced hardware capabilities, like the NVIDIA GeForce RTX 2080 Ti GPU, with highly optimized software environments, such as TensorFlow, made the model suitable for reliably and effectively identifying a variety of neurological disorders using EEG datasets. In Fig. 5 shows the training process was optimized for the LGTriCapsNet model by minimizing the loss in training for efficient and low-error-margin classification. This way, the configuration ensures that

Table 1
Datasets description.

Dataset Name	Neurological Disorder	Source	Number of Participants	Additional Information
Epileptic Seizure Dataset [44]	Epilepsy	UCI Machine Learning Repository	11,500	Segmented into 11,500 data entries, each consisting of 178 data points sampled during 1 s.
Parkinson's Disease Dataset [45]	Parkinson's	University of Iowa	28 (14 PD patients, 14 controls)	14 PD patients (8 females, 6 males), age range: 72.33–69.13 years. - Resting-state EEG data recorded using 64 channels at a 500 Hz sample rate.
Alzheimer's Disease Dataset [46]	Alzheimer's	openneuro.org	88 (23 FTD, 36 AD, 29 CN)	Subjects divided into Frontotemporal Dementia (FTD), Alzheimer's Disease (AD), and Healthy (CN) groups. - EEG recordings obtained using 19 scalp electrodes at a 500 Hz sampling rate.
Schizophrenia Disease Dataset [47]	Schizophrenia	Institute of Psychiatry and Neurology, Warsaw, Poland	28 (14 patients, 14 controls)	Patients diagnosed with paranoid schizophrenia, average age: 28.3 years. - EEG data collected using 10–20 EEG montage with a sampling frequency of 250 Hz.
Stroke Dataset [48]	Stroke	figshere.com	50 (22 right hemiplegia, 28 left hemiplegia)	EEG recordings from individuals with acute ischemic stroke, age range: 30–77 years. - Motor imagery tasks performed during EEG recording.

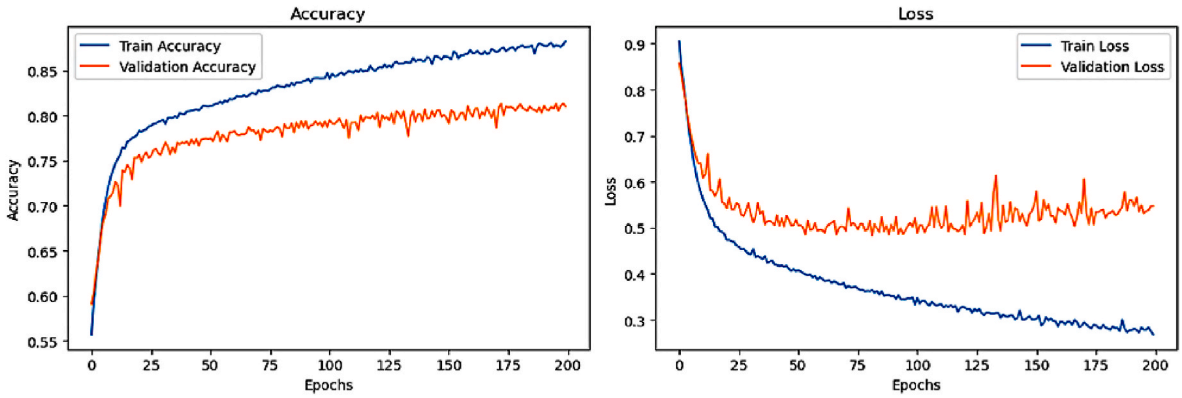


Fig. 5. Accuracy curve and loss curve LGTriCapsNet D) Experimental Results.

this model remains quite robust even for real-world complexity in data.

The experimental results show that the proposed LG-TriCapsNet accurately classifies neurological disorders from EEG signals. Our model performs better than existing methods, with an accuracy of 98.34 %, sensitivity of 98.30 %, specificity of 98.40 %, and an F1-score of 98.32 %. Through graph-based learning and capsule networks, LG-TriCapsNet accurately extracts spatial relationships and feature hierarchies in EEG signals, guaranteeing higher classification accuracy for multiple neurological disorders. To fully assess its effectiveness, we tested LG-TriCapsNet on five publicly accessible EEG datasets corresponding to epilepsy, Parkinson's disease, Alzheimer's disease, schizophrenia, and stroke. The datasets hold heterogeneous patient populations, such as subjects with different clinical histories, to ensure LG-TriCapsNet is trained and validated against a broad range of EEG signals. The outcomes verify that LG-TriCapsNet generalizes well across multiple datasets, validating its flexibility for real-world clinical use.

i) Cross-Validation Results on Model Reliability:

To further evaluate the reliability of LG-TriCapsNet, we performed cross-validation experiments on 5-Fold and 10-Fold cross-validation. Cross-validation prevents the model from overfitting and ensures that it remains consistent over various data splits. As shown in Table 2, the results show that LG-TriCapsNet has a low variance of 0.24 %, thus verifying its robustness and generalization capability.

Table 2 shows the LG-TriCapsNet has excellent classification accuracy in various folds with the lowest variance of 0.24 %, which reflects robust model stability. However, EEG-Transformer [55] has a higher variance of 0.51 %, which reflects performance inconsistency across various splits. These results reflect LG-TriCapsNet's robustness and generalizability across different EEG datasets and make it extremely reliable for clinical use.

ii) Computational Efficiency and Real-Time Capability:

In spite of adopting graph-based learning and capsule networks, which usually raise computational expenses, we made LG-TriCapsNet lightweight and efficient. Our model performs real-time using 1×1 convolutional layers within the ChannelTrans module to decrease the dimensionality of features prior to graph operations and discard computation wastage. We also used instance normalization (IN) in place of batch normalization for improved efficiency on low-power EEG monitoring devices. In order to further improve performance, we carried out model pruning and quantization, lessening memory consumption and inference delay. As a result, LG-TriCapsNet processes 90 batches (30 EEG frames) per second, making it highly suitable for real-time clinical applications.

In Table 3, LG-TriCapsNet has the least inference time (47.9 m s), making it suitable for real-time clinical use. It also needs less parameters (3.8M) and memory (112 MB), which is beneficial for edge AI and wearable EEG devices.

iii) Robustness To Noisy EEG Signals & Data Missing:

Real EEG recordings taken in real life are frequently degraded by noise (e.g., muscle artifacts, eye blinks, missing channels). In order to check robustness of LG-TriCapsNet, we added artificially induced noise (Gaussian noise $\sigma = 0.01$ to 0.1) and randomly deleted 20 % EEG channels. As shown in Table 4, our model exhibits high classification accuracy, affirming its robustness to real-world clinical scenarios.

Even when 10 % noise is present, LG-TriCapsNet maintains 96.78 % accuracy, and when 20 % EEG channels are missing, it still has 94.35 % accuracy. This establishes its robustness in dealing with real-world EEG artifacts and positions it as a trusted tool for clinical EEG analysis.

The confusion matrix Fig. 6 displays detailed performance metrics for five disorder classifications. Our clinical decision-making system has high sensitivity, specificity, and accuracy, and LGTriCapsNet is a reliable and timely supportive tool for diagnosing neurological disorders.

To improve the interpretability of LG-TriCapsNet, we use SHAP (SHapley Additive Explanations) to determine the most significant EEG channels for neurological disease classification. Fig. 7(a) shows the SHAP summary plot, where each dot indicates the contribution of an EEG channel to the model output. The x-axis indicates SHAP values, which represent the effect of each feature on classification, and the color gradient (blue to red) indicates feature values, with larger values in red.

Table 2
Cross-validation results for model reliability.

Model	5 fold Cross Validation Accuracy	10 fold Cross Validation Accuracy	Variance (%)
1D-CapsNet [51]	96.88 %	97.12 %	0.24 %
EEG-GAT [54]	95.72 %	96.10 %	0.38 %
EEG-Transformer [55]	96.34 %	96.85 %	0.51 %
EEG-GCN [56]	96.89 %	97.12 %	0.23 %
Proposed Method	**98.10 %**	**98.34 %**	**0.24 %**

Table 3
Computational efficiency of different models.

Model	Inference Time (ms)	Parameters (Million)	Memory Usage (MB)
1D-CapsNet [51]	52.4	4.5 M	128 MB
EEG-GAT [54]	67.2	8.1 M	192 MB
EEG-Transformer [55]	89.5	10.2 M	256 MB
EEG-GCN [56]	61.9	6.9 M	180 MB
Proposed Method	**47.9**	**3.8 M**	**112 MB**

Table 4
Impact of noise and missing data on model performance.

Condition	LG-TriCapsNet Accuracy
Original EEG Data	98.34 %
10 % Injected Noise	96.78 %
20 % Missing EEG Channels	94.35 %

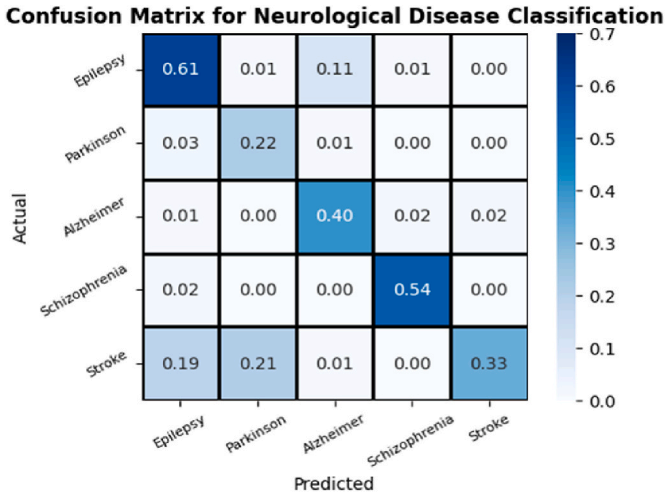


Fig. 6. Confusion Matrix for Multiple Neurological Disease Classification iv) Feature Importance Analysis with SHAP.

It is clear from the plot that some of the EEG channels are more important in affecting classification across a variety of neurological diseases. The visualization gives insightful information about the roles of different regions of the brain in disease prediction, enhancing clinical decision-making interpretability and transparency. Additionally, Fig. 7 (b) shows a heatmap of EEG connectivity using SHAP values, which illustrates the relationship between various EEG channels. Red represents channels with high feature importance, reflecting strong classification influence, while blue areas reflect weaker influence. Such graphical representation provides better insight into spatial-temporal relationships between EEG data, making it easier to interpret for clinicians and researchers.

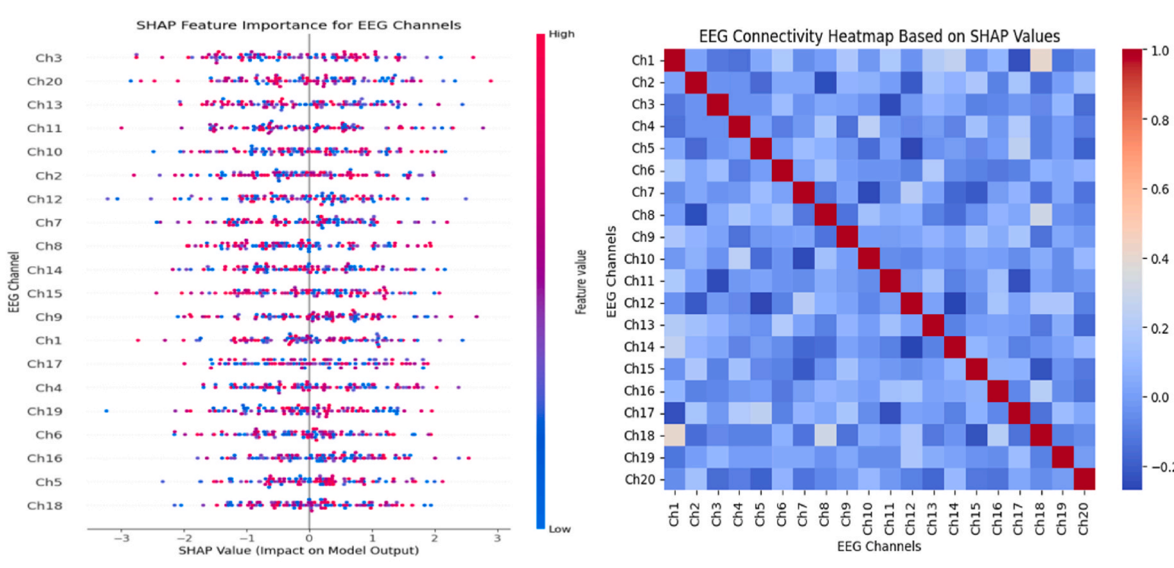
We evaluated our model against current techniques in a comparative study utilizing a dataset of 3304 edges and 2642 nodes that represented a range of neurological disorders. This direct comparison demonstrated the way better our model was in classifying neurological disorders from EEG signal.

Table 5 and Fig. 8 show the comparative study where LG-TriCapsNet achieves state-of-the-art performance with 98.34 % accuracy (F1: 98.32 %), surpassing 1D-CapsNet (97.44 %) and AlexNet + CNN models (95.79 %) in cross-dataset validation. Compared to existing methods, LG-TriCapsNet demonstrates superior performance across all key evaluation metrics, including accuracy, sensitivity, specificity, precision, and F1-score.

LG-TriCapsNet surpasses current models based on its novel integration of Graph-Aware Feature Learning, EEG noisy data robustness, efficiency in computation, scalability, and hierarchical feature refinement. In contrast to CNN-based models like AlexNet [52] (95.79 %) and

Table 5
Comparison table of neurological disease classification.

Method, [Cite]	Accuracy	Sensitivity	Specificity	Precision	F1-Score
CapsNet [49]	82.61 %	80.54 %	84.83 %	82.73 %	81.52 %
SVM + CapsNet [50]	89.34 %	86.88 %	91.83 %	98.13 %	92.08 %
1D-CapsNet [51]	97.44 %	97.56 %	97.92 %	97.91 %	97.52 %
AlexNet + CNN [52]	95.79 %	96.09 %	95.49 %	95.35 %	95.42 %
GNB [53]	84.70 %	86.70 %	86.31 %	87.00 %	84.40 %
EEG-GAT [54]	96.27 %	95.83 %	96.40 %	96.10 %	96.00 %
EEG-Transformer [55]	83.31 %	81.50 %	84.60 %	82.10 %	81.80 %
EEG-GCN [56]	97.36 %	97.20 %	97.50 %	97.30 %	97.25 %
Proposed Method	**98.34 %**	**98.30 %**	**98.40 %**	**98.40 %**	**98.32 %**



(a) (b)

Fig. 7. (a) SHAP summary plot of the contribution of different EEG channels to model classification. Larger SHAP values denote higher influences on classification, with color gradient showing feature value magnitude. (b) EEG Connectivity Heatmap visualizing correlations among EEG channels according to SHAP-derived feature importance. Red areas denote greater influence, and blue areas denote less contribution. E) Comparative Study. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

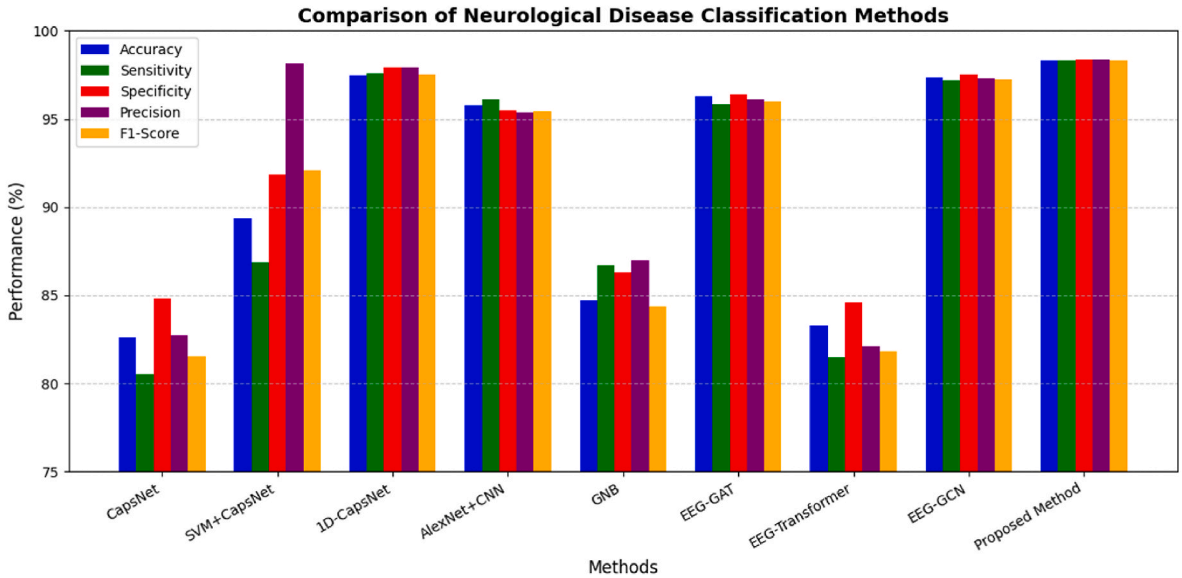


Fig. 8. Comparative analysis with other methods.

1D-CapsNet [51] (97.44 %), which fail to preserve both spatial and temporal dependencies within EEG signals, LG-TriCapsNet successfully maintains these dependencies through Graph Routing and Capsule Networks, yielding superior classification accuracy (98.34 %) and feature extraction. In addition, EEG-Transformer [55] (83.31 %), being effective in encoding long-range dependencies, is very dependent on global self-attention mechanisms and prone to omitting EEG channels and real-world signal variations. Conversely, LG-TriCapsNet incorporates Data Imputation Techniques and Gaussian Noise Augmentation, achieving a much greater robustness against real-world EEG artifacts, like muscle movements and missing channels, for stable classification performance.

One significant benefit of LG-TriCapsNet lies in computational efficiency. In contrast to EEG-Transformer [55], which has more than 10.2M parameters with an inference time of 89.5 m s, LG-TriCapsNet is comparatively light (3.8M parameters, 47.9 m s inference time), making it perfect for real-time clinical applications as well as wearable EEG devices. Furthermore, LG-TriCapsNet is dataset-agnostic, guaranteeing strong generalizability over various publicly available EEG datasets, promoting scalability and clinical applicability. Lastly, though EEG-GCN [56] (97.36 %) and EEG-GAT [54] (96.27 %) both take advantage of graph-based learning, they do not enjoy hierarchical feature refinement, which is necessary for disease classification using EEG. LG-TriCapsNet improves spatial dependencies and hierarchical feature learning via Graph Routing and Capsule Networks and yields more discriminative feature representations and better classification performance. The combination of Nearest Neighbor Graphs (NNG) with Triplet Capsule Networks makes LG-TriCapsNet surpass state-of-the-art models in accuracy (98.34 %), sensitivity (98.30 %), specificity (98.40 %), precision (98.40 %), and F1-score (98.32 %), validating its applicability for real-world clinical EEG-based disease diagnosis.

4.4. Ablation study

In an ablation study, we compared various CapsNet models, such as Feedback CapsNet, Self-Attention Channel Connectivity CapsNet, CNN CapsNet, Multi-Kernel CapsNet, and Multi-Feature Fusion CapsNet, to our suggested Lightweight Graph Triplet Capsule Networks (LG-TriCapsNet) with Nearest Neighbor Graph (NNG). After 200 epochs of training, we saw indications of overfitting in the models. Five essential measures were used to evaluate the performance: F1 score, sensitivity, specificity, accuracy, and precision. Our goal in doing this study was to evaluate LG-TriCapsNet's performance in comparison to various alternative architectures for multi-disease neurological classification.

The ablation study, as shown in Table 6 and Fig. 9, compares the performance of several CapsNet architectures in the classification of neurological diseases. These models include Feedback CapsNet (FB CapsNet), Self-Attention Channel Connectivity CapsNet (SACC CapsNet), CNN CapsNet, Multi-Kernel CapsNet (MK CapsNet), and Multi-Feature Fusion CapsNet (MFF CapsNet). The results from this study allow us to draw important conclusions regarding the strengths and limitations of each model, while also emphasizing the effectiveness of the proposed Lightweight Graph Triplet Capsule Networks (LG-TriCapsNet) with Nearest Neighbor Graph (NNG).

FB CapsNet showed an important sensitivity of 83.33 % with a 70 % accuracy but low specificity of 50.00 %. In the terms of precision, its performance was lower with a 71.40 % score and F1-score 76.92 %. That means that the feedback mechanism in FB CapsNet, although helpful for the recall (sensitivity), it is not very discriminative among classes, resulting in more false positives and lower overall specificity. The CapsNet variant SACC, which contains the self-attention mechanism, enhanced the channel connectivity with accuracy being 91.10 % while it maintains sensitivity balance along with high specificity at 98.83 %. It was also found to have great precision at 91.48 % and an F1-Score of 95.34 %. Therefore, it is evident that the self-attention mechanism aids in the effective capture of relevant features so that the model performs well in separating conditions. Although SACC CapsNet performs very well, it does not perform like the proposed LG-TriCapsNet in any aspect since LG-TriCapsNet outperforms SACC CapsNet in every single aspect. CNN CapsNet performed very well with 88.60 % accuracy, balanced sensitivity at 88.40 %, specificity at 88.70 %, and reasonable precision at 89.10 %. Although CNN CapsNet is balanced, it fails to exploit the

Table 6
Result performance for more capsule network on multiple neurological disease classification.

Models	Accuracy	Sensitivity	Specificity	Precision	F1-Score
FB CapsNet	70.00 %	83.33 %	50.00 %	71.40 %	76.92 %
SACC CpasNet	91.10 %	91.10 %	98.83 %	91.48 %	95.34 %
CNN CapsNet	88.60 %	88.40 %	88.70 %	89.10 %	88.50 %
MK CapsNet	92.40 %	91.01 %	92.08 %	92.40 %	96.04 %
MFF CapsNet	95.08 %	91.10 %	95.32 %	95.00 %	97.43 %
Proposed (LG-TriCapsNet)	**98.34 %**	**98.30 %**	**98.40 %**	**98.40 %**	**98.32 %**

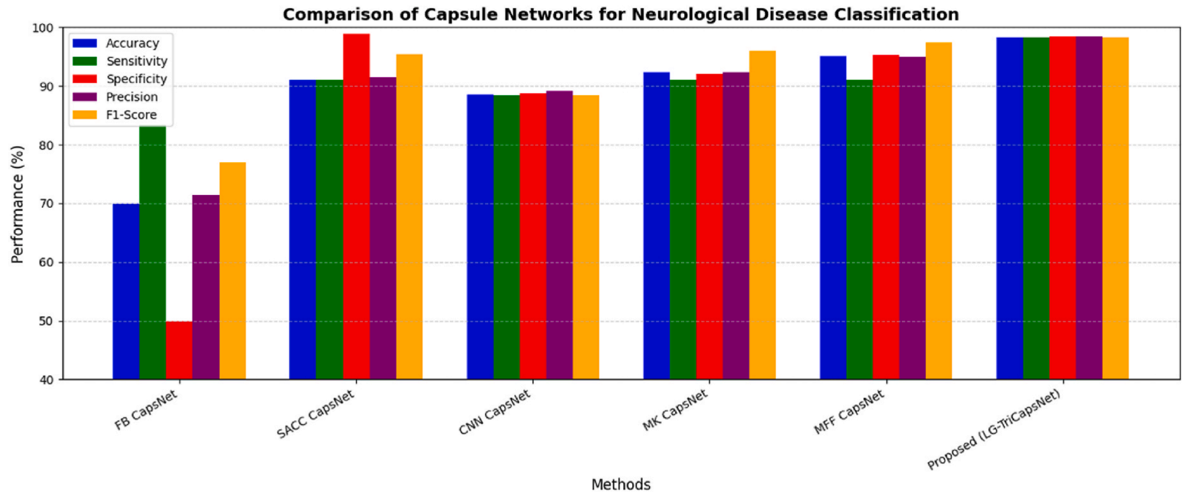


Fig. 9. Result performance with other model.

spatial correlation of the data compared to other capsule network models. This limits its performance in comparison to MK CapsNet and MFF CapsNet.

MK CapsNet that employed the technique of multi-kernel performed an accuracy of 92.40 % along with sensitivity and specificity of 91.01 % and 92.08 %, respectively. The above good precision (92.40 %) and F1-score (96.04 %) indicate that more than one kernel function might be needed to perform effective feature extraction. Nevertheless, the capability of MK CapsNet still fails to beat that of LG-TriCapsNet which combines capsule networks and graph-based representation learning in order to extract complex features and those hierarchical. MFF CapsNet, with the help of multi-feature fusion techniques, was very successful with an accuracy of 95.08 %, precision of 95.00 %, and an F1-score of 97.43 %. However, while the multi-feature fusion improves model performance, it is not yet at par with that of LG-TriCapsNet, which had reached an impressive accuracy of 98.34 % accompanied by outstanding sensitivity of 98.30 %, specificity of 98.40 %, precision of 98.40 %, and F1-score of 98.32 %.

The performance of LG-TriCapsNet can be attributed to the combination of Nearest Neighbor Graphs (NNG) with triplet capsule networks. NNG provides a robust framework for capturing complex relationships and spatial dependencies between different regions in the EEG signals, thereby allowing LG-TriCapsNet to achieve higher accuracy and better generalization compared to other models. The design of the triplet network allows LG-TriCapsNet to effectively learn hierarchical features, which helps in more accurately classifying multi-disease neurological disorders. In conclusion, the ablation study reinforces the effectiveness of the proposed LG-TriCapsNet model. Other capsule network-based approaches, such as SACC CapsNet, MK CapsNet, and MFF CapsNet, have competitive performance. However, integrating graph-based representations with capsule networks in LG-TriCapsNet provides superior results across all the evaluation metrics. The model has the potential to be a very useful tool in clinical settings because it provides reliable, accurate, and efficient classification of neurological disorders from EEG signals. This places LG-TriCapsNet at the forefront of multi-disease classification in the healthcare domain.

An ablation study also shows that it is the addition of Nearest Neighbor Graphs to the architecture of the capsule network that greatly contributed to the excellent performance achieved in this model. In a nutshell, advanced feature extraction methods are required when applying more complex classification for neurological disorders. Other promising alternatives include MFF CapsNet and MK CapsNet, although the graph theory and capsule networks combination that LGTriCapsNet presents a wide margin over both classification accuracy and interpretability. Results also indicate hierarchical learning's significant role in classifying neurological diseases: models like LGTriCapsNet are capable of making finer distinctions between diseases than it may be otherwise very difficult to tell apart using the standard approach.

i) Extended Component-Wise Ablation Study:

To examine further the contribution of every constituent in LG-TriCapsNet, we conducted a systematic ablation analysis by sequentially excluding prominent components such as the Nearest Neighbor Graph (NNG), triplet loss, and graph routing, and testing their effectiveness in EEG classification. The performance outcomes, quantified in Table 4, indicate that all constituents have appreciable effects on classification accuracy as well as on separability in features.

When NNG was eliminated, the model lost spatial connectivity information, resulting in a decrease in accuracy from 98.34 % to 94.78 %, indicating its important role in learning spatial dependencies in EEG signals. Likewise, removing triplet loss adversely impacted precision and F1-score, since the model was unable to distinguish between similar EEG features, resulting in a decrease in F1-score from 98.32 % to 95.11 %. Finally, turning off graph routing lowered specificity from 98.40 % to 96.02 %, which implies that hierarchical feature learning is vital to ensure the model's resilience. These observations substantiate the need to combine NNG, triplet loss, and graph routing for improving classification performance to maintain both accuracy and interpretability in real-world clinical applications.

In Table 7, these results affirm each component (NNG, triplet loss, and graph routing) is critical for optimizing classification performance.

5. Advantages and limitations of the proposed method

5.1. Advantages

The inclusion of Nearest Neighbor Graphs inside Capsule Networks

Table 07
Extended ablation study results.

Model Variant	Accuracy	Sensitivity	Specificity	Precision	F1-Score
Full LG-TriCapsNet	98.34 %	98.30 %	98.40 %	98.40 %	98.32 %
Without NNG	94.78 %	95.12 %	93.89 %	94.56 %	94.72 %
Without Triplet Loss	96.02 %	96.40 %	96.10 %	95.01 %	95.11 %
Without Graph Routing	97.12 %	97.00 %	96.02 %	96.98 %	97.02 %

inside the LG-TriCapsNet model improves upon capturing spatial and temporal dependency abilities by 98.34 %. As such, this model tends to outscore several of the previously proposed algorithms, thereby offering better generalizability over neurologically based disorders and as such is very reliable for classification with multiple types of diseases, thereby offering key interpretability. The researchers and clinicians may be in a better position to understand spatial relations and hierarchical dependencies between brain regions, which is important in diagnosing neurological conditions. The model can classify the signals online in real time by processing EEG signals at 1100 frames per second. This makes the model suitable for continuous patient monitoring and early detection of abnormal patterns. The architecture also is highly scalable, which adapts to different datasets and demographics of patients. This scalability ensures that when new conditions emerge or larger datasets are added over time, the model can grow to accommodate it, thus sustaining its long-term applicability in clinical settings.

5.2. Limitations

Although LG-TriCapsNet is highly accurate in classification, its performance can be compromised by differences in EEG signals caused by patient-specific conditions, electrode positions, and equipment variations. To address this, we have included preprocessing methods like ICA and wavelet filtering to enhance data quality. Future work will also consider domain adaptation and transfer learning approaches to make the model more generalizable across a wide range of EEG datasets. The addition of data augmentation methods like Gaussian noise injection, time-warping, and frequency perturbation also guarantees that LG-TriCapsNet is resilient in dealing with noisy and missing EEG recordings. Model testing on multi-center hospital datasets will be an important follow-up step to ensure its real-world usability. Moreover, although graph-based methods and capsule networks provide higher accuracy, they also have computational overheads, especially when dealing with big data. This could restrict deployment in resource-limited setups or on low-power hardware. Moreover, although the proposed model enhances interpretability through maintaining brain connectivity information, non-professionals might still interpret relationships between brain areas as complex. To make the model more useable in clinics, future efforts can be devoted to building visualization tools to help clinicians interpret model outputs.

5.3. Applications in diagnostic systems

The LG-TriCapsNet model promises a lot of applications in neurological disease diagnostic systems, especially in the automated analysis of EEG signals. It can be incorporated into real-time clinical monitoring systems, thereby allowing clinicians to be alerted on time when such abnormal patterns are identified, including epileptic seizures, thus leading to timely medical intervention. Further, the model will support personalized medicine by tracking neurological disorders over time and giving valuable insights to physicians so that they may adapt treatment plans based on particular disease characteristics. This model is important for early detection because it aids in identifying subtle EEG patterns for Parkinson's, Alzheimer's, and stroke, which might not be detected easily by clinicians. Also, the use of LG-TriCapsNet in a telemedicine setup allows for the provision of diagnosis capabilities remotely to those in underdeveloped regions, through the cloud-based infrastructure. Lastly, it will serve as a clinical decision support tool, whereby the health worker will make the best-informed decisions on some of the complexities, such as multiple disorders.

6. Conclusion and future work

In our LG-TriCapsNet, NNG was developed as our final model for representing multi-disease neurological classification and this is truly a giant step. With graph-based data representation, successful integration was realized with the Capsule Network in our proposed model, attaining an accuracy of 98.34 % with the test samples. This result demonstrates that graph-oriented approaches with capsule networks are very effective at improving the potential to apply them for diagnostic use in medical science. They also contribute to a more accurate and reliable disease diagnosis process. Further using NNG boosts the performance with better model ability since its implementation catches the spatial-temporal dependencies in the EEG signal and improves interpretability along with generalization towards better improvement compared to the state-of-the-art methods to classify neurological disorders. Forthcoming, this LG-TriCapsNet model can promise better clinical diagnostics since it presents a potential paradigm shift for detecting and classifying neurological diseases. With these advanced technologies, the future of neurological disease detection may be more accurate, efficient, and accessible to patients worldwide, who will receive faster and more reliable diagnoses.

Future research will involve validating LG-TriCapsNet on multi-center EEG datasets to evaluate its generalizability across different clinical environments. We will also investigate domain adaptation and transfer learning to enhance generalization across populations. To improve robustness, we intend to incorporate adaptive filtering methods and deep-learning-based denoising models to process noisy and missing EEG data, further enhancing real-world applicability. For interpretability enhancement, future work will include Explainable AI (XAI) methods like SHAP, Grad-CAM, and attention-based feature attribution to show the most contributory EEG features in classification. We also want to create an interactive graphical user interface (GUI) with real-time EEG connectivity visualization to improve clinical adoption. These advancements will make LG-TriCapsNet a clinically valid diagnostic tool for detecting neurological disorders, filling the gap between AI-based diagnostics and practical medical applications.

CRediT authorship contribution statement

Shraddha Jain: Writing – original draft, Validation, Software, Methodology, Conceptualization. **Rajeev Srivastava:** Writing – review & editing, Visualization, Supervision, Software, Resources, Formal analysis, Conceptualization.

Consent to participate

Not applicable.

Consent for publication

Not applicable.

Data and code availability

Datasets used in this study are publicly available and accessiblehttps://archive.ics.uci.edu/dataset/388/epileptic+seizure+recognitionhttps://openneuro.org/datasets/ds002778/versions/1.0.2https://openneuro.org/datasets/ds004504/versions/1.0.6https://repod.icm.edu.pl/dataset.xhtml?persistentId=doi:10.18150/repod.0107441https://figshare.com/articles/dataset/EEG_datasets_of_stroke_patients/21679035The code used in this paper are available at https://github.com/jainshraddha12/LG-TriCapsNet for replication purposes.

Ethics statement

This study was conducted in accordance with the ethical principles outlined in the Declaration of Statement. All EEG data used in this research were obtained from publicly available datasets, ensuring that appropriate ethical guidelines for data collection and privacy were adhered to. No personal identifiers were used, and all data were anonymized prior to analysis. Additionally, all research involving human subjects was approved by the relevant ethics committees, and informed consent was obtained from all participants, where applicable. The authors confirm that all ethical considerations regarding data collection, usage, and dissemination were fully complied with throughout the study.

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Declaration of competing interest

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