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# Inter-Lead Dependency Modelling for ECG Anomaly Detection Using Graph Neural Network

**Shaik Janbhasha[1*], Venkateswarlu Sunkari [2], Sudheer Benarji P [3], Swetha Pesaru[4],Vishal Namireddy[5], Movva Pavani[6], Aketi Naresh[7], Garigipati Rama Krishna[8]**

[1] Dept. Of Computer Science and Engineering (Data Science),CVR College of Engineering, Ibrahimpatnam, Hyderabad, Telangana, India, Email: afreen.jbasha@gmail.com
[2] Department of Electrical and Computer Engineering,College of Engineering and Architecture, University of Nizwa, Birkat Al Mouz, Nizwa 616, Oman.Email: v.sunkari@unizwa.edu.om
[3] Department Of CSE,VNR Vignana Jyothi Institute of Engineering and Technology, Hyderabad, Telangana, India, Email: sudheerbenarji_p@vnrvjiet.in
[4]Department of Information Technology,Vignana Bharathi Institute of Technology, Ghatkesar, Telangana, Hyderabad, India.Email: swethapesaru2687@gmail.com
[5]Independent Researcher Dallas, TX,USA,75063, Email: vishaljv3@gmail.com
[6]Department of Electronics and Communication Engineering,Nalla Malla Reddy Engineering College, Divyanagar, Hyderabad. Email: drmovvapavani@gmail.com
[7]Dept of CSE,Sri Sai Institute of Technology and Sciences, Rayachoty, Andhra Pradesh, India. Email: pandu5188@gmail.com
[8]Department of Computer Science and Engineering,Koneru Lakshmaiah Education Foundation, Vaddeswaram, Guntur District, Andhra Pradesh, India. Email: umarkcse@gmail.com

**Abstract**
The automated cardiac signal analysis is an important to detect the ECG anomaly at an early stage and diagnose accurately. Conventional methods are likely to treat ECG leads separately, while applied simple fusion rules, failed to explicitly model dependency between recorded leads simultaneously. To confrontation of this problem, we develop a Graph Neural Network (GNN) framework and the ECG leads are considered as nodes and the signal dependency are considered as weighted edges. This graph-based representation enables information from both leads to be learnt jointly and enables more informative representations for binary ECG anomaly detection. Although the graph formulation can be applied to multi-lead ECGs, the present experimental evaluation is carried out using two-lead ECG data where Lead II and Lead V are derived from the MIT-BIH Arrhythmia database. The proposed GNN achieves an accuracy of 99.00%, precision of 98.61%, recall of 99.39%, and F1-score of 99.00%. The ROC-AUC is 98.2%. The results have shown that adding inter-lead dependency information into the ECG anomaly detection for the tested two-lead configuration is feasible.

***Keywords****:* ECG, Anomaly Detection, GNN, Deep Learning, Cardiovascular

## 1. Introduction

Electrocardiography (ECG) is a common non-invasive method of recording electrical activity of the heart and identifying abnormalities in heart signals [1]. Since manual analysis of the large number of ECG records is time consuming, and subject to variation in the morphology and recording, there has been significant research interest in automated ECG analysis [2]. Hence, the automated ECG anomaly detection and classification using deep learning and other computational techniques are studied in recent years [3].

An ECG recording can have a number of leads and each one gives a slightly different view of the electricity of the heart [4]. So, leads that are recorded at the same time can give additional information about the heart signal. In the conventional ECG analysis methods, each lead is often analysed separately, or features are extracted from each lead and fused by conventional fusion methods [5]. These methods may not be a direct representation of ECG lead relationship. Such inter-lead dependencies can be modelled to give a structured representation of the signal and may help to increase the capacity of automated models to differentiate normal from abnormal ECG signals [6].

Graph Neural Networks (GNNs) offer an appropriate framework to represent multiple structured relationships between signal channels [7]. Each lead of the ECG in a graph representation can be used as a node, and relationships or dependencies between leads can be used as an edge [8]. GNNs can then pass information

between neighbouring nodes and train representations that take into account both the characteristics of each signal and the connection relationships among the leads provided. Graph-based learning has been shown to be applicable to the classification of ECG arrhythmias and other physiological signal-analysis problems[9]. The findings of these studies show that graph representations can be used to capture relationships which are not explicitly modelled by the conventional sequence-based approaches [10].

In this work, we explore an ECG-GNN framework for explicit modelling of inter-lead dependency. Each ECG segment is modelled as a graph where the possible ECG leads are considered as graph nodes, and the dependency between the leads is modelled as graph edges. The nodes level features are extracted from time domain and frequency domain features of the ECG and morphological features. The obtained graph representation is then fed to the GNN for performing binary classification of ECG segments as normal or abnormal.

The primary novelty of this study lies in the formulation and assessment of an inter-lead graph representation for the two-lead ECG signals.The proposed approach consists of building a graph for each ECG segment, extracting representative signal features for each of the leads and graph-based message passing to learn relationships between Lead II and Lead V. Standard classification metrics such as accuracy, precision, recall, F1-score and ROC-AUC are used to assess the performance of the proposed framework. Results are analyzed in terms of the ability of the computation to detect anomalies rather than as evidence of clinical diagnosis or clinical decision-support ability.

The remaining part of this paper is classified as section 2 Literature survey, section3 Proposed methodology, section 4 result and analysis followed by conclusion.

## 2. Literature Review

In Recent years, graph-based deep learning has been found to be useful in ECG analysis as there are complex relationships between the features of the signal, the cardiac leads, and the different classes of arrhythmias. In contrast to conventional deep learning methods which typically treat ECG signals as sequences in Euclidean space, graph-based methods offer a way to explicitly represent the relationship between components of the signal. Hence, various works have explored the building of graphs and Graph Neural Networks (GNNs) in the context of ECG classification and anomaly detection.

The author presented an arrhythmia classification method with the help of GNN and the correlation matrix. In this approach, the extracted ECG features were utilized to form a correlation matrix that was then adopted to build the adjacency matrix for graph-based learning. Then the GNN was used to classify various arrhythmia categories. The results reported indicated that the precision and recall for all the arrhythmia classes considered were above 50%, which showed that correlation-based graph representations are viable for classification of arrhythmia. The graph in this study, however, was built on correlations between the features extracted from the ECG signal and not explicitly representing the dependency between simultaneously recorded ECG leads [11].

This work proposed combining edge detection with Graph Neural Networks to classify ECG signals. The study proposed graph-based ECG classification framework and tested it on different ECG datasets such as MIT-BIH and PTB-related data. The work illustrates the applicability of GNNs to learn graph-structured representations of ECG signals and yielded promising classification results on the studied datasets. Their approach is based on graph representations and graph information extraction to classify the ECG, while the graph nodes in the present study are the available ECG leads and the dependency between them is modelled [12].

This work introduced EGCNet, a hierarchical Graph Convolutional Network for the classification of ECG. The approach uses a one-dimensional residual convolution (1D-RC) to extract features and a hierarchical graph network (HGN) to model inter-class dependency among arrhythmias. The authors tested EGCNet on the publicly available ECG data from the PhysioNet/Computing in Cardiology Challenge 2020[20]. For the 24-label classification experiment, EGCNet obtained 0.753 precision and 0.722 F1-score. The study also takes into account the cross-lead dependency while extracting features and inter-class dependency through hierarchical graph learning. While this work shows the benefit of using graph-based dependency modelling, the nodes of the graph in this case are features/classes related to arrhythmia, but not the two ECG leads simultaneously recorded and explored in the present study [13].

In this work proposed a graph-based approach for cardiac arrhythmia classification based on a single lead ECG profile. This method converts the ECG time series into graphs by applying a visibility-graph approach and then extracts features from graphs for classification. The MIT-BIH Arrhythmia Database was used in the study and six classes were taken into consideration (normal, left bundle branch block, right bundle branch block, premature ventricular contraction, atrial premature contraction, fusion beat). Three classifiers, namely GCN, multilayer perceptron (MLP), and random forest were explored. The average accuracy on the MLP was 99.02% and average accuracy on random forest was 98.94%. This work shows good results in encoding the morphology of the ECG into a graph, but it is different from the present study, as this method builds a visibility graph from only one lead of the ECG and does not model the relations between two simultaneously available leads [15].

Conv-RGNN, a Convolutional Residual Graph Neural Network for ECG classification, was proposed [16]. The framework partitions a 12-lead ECG into the individual ECG lead signals, maps each lead to a node in the graph and maps the spatial relationships between leads to graph edges. Temporal information is learned via a convolutional network with position attention whereas spatial information across the ECG leads is learned by

the residual graph neural-network blocks. The authors tested the method on two multi-label and one single-label datasets, and provided competitive classification performance, parameter efficiency, inference speed, and robustness. Both are closely related with the current study as they model the relationship between ECG leads explicitly. Conv-RGNN, however, is developed for classification of 12 lead ECG and the present work considers an experimental two-lead ECG Lead II, Lead V [18].

The ECG sequence modelling can be achieved by transformer-based approaches as a complementary direction. DeepECG-Net [26] was proposed to detect anomalies in ECG, using a hybrid approach of CNN and Transformer. The model comprises of the CNN + multi-head self-attention layering, which facilitates local signal features and long-range dependencies. The reported results include 98.2% accuracy, 98.2% precision, 96.8% recall, and 97.5% F1-score and AUC 98%. The study also presented a memory usage of around 30 MB, and sub-50-ms latency on a Raspberry Pi 4B, which illustrated the computational properties of the proposed implementation. DeepECG-Net, on the other hand, mainly treats ECG information as a temporal sequence and uses self-attention to capture temporal dependencies, instead of explicitly modeling the relationships between ECG leads as graph edges [19].

Multi-lead ECG anomaly detection has been further explored with the use of attention mechanisms implemented in transformer-based studies [21]. The author introduced TranECG, a multi-lead ECG anomaly-detection framework based on Transformer. The method combines Transformer-based representation learning with reconstruction-based anomaly detection and attention information to locate the regions of anomaly [22]. The author explored the same direction by introducing Transformer-based anomaly detection for ECG monitoring [23] and proposed ECG-TransCovNet, a model combining convolutional feature extraction with Transformer-based sequence modelling for arrhythmia detection [24]. ECG-TransCovNet was tested using benchmark ECG datasets and achieved a 98.6% detection accuracy. Both of these studies have proven effective in using temporal and attention-based representations to analyse an ECG and offer an adequate sequence-learning context in which to assess graph-based representations [25].

The literature survey shows that there are several methods to encode ECG relationships such as feature-correlation graphs [11], classification of ECG using graphs [12], hierarchical graph modelling between classes [13], visibility graphs of single-lead ECG signals [15], spatial graph modelling of multi-lead ECG signals [16] and learning temporal dependency using Transformer [17] and [19]. But these are not the same techniques as those used in the experimental environment of the current study.

The proposed work is centered on the explicit representation of the two leads ECG Lead II and ECG Lead V of the ECG as graph nodes, and modelling their signal dependency through an edge for binary normal/abnormal ECG anomaly detection. It is not the introduction of GNNs to ECG analysis, as has been done previously in the literature, but the evaluation of an explicit two-lead inter-lead dependency representation with the MIT-BIH-derived data set used in the experiments presented here that is the contribution. The current experimental set-up is for the 2-lead application only.

## 3. Proposed Methodology

The proposed methodology figure 1 outlines the framework which has been developed for the ECG anomaly detection system, which is based on the inter-lead graph-based learning approach. Preprocessing of the ECG signals is needed to smooth out the noise and to provide a uniform representation of the signal. To extract features from the processed Lead II and Lead V signals, they are subsequently converted into a graph representation and dependency modelling. Lastly the extracted features are taken as input under the proposed GNN model and classified as normal and abnormal.

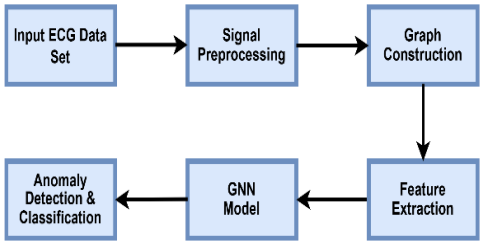


**Figure 1.** Proposed Inter-Lead GNN Model

### 3.1 ECG Data Set:

The dataset of ECG to use for experimental evaluation is from a Kaggle provided ECG Arrhythmia Classification dataset based on the MIT-BIH Arrhythmia Database [14]. The reported experiments employ a two-lead ECG Lead II and Lead V. The experimental data set includes 87,644 ECG samples, includes two ECG leads – Lead II and Lead V. The data is split into the training and the testing sets with a ratio of 80:20 which means 70,115 samples are used for training and 17,529 samples are used for testing. The underlying MIT-BIH data base has 48 recordings from 47 patients which are sampled at 360 Hz, but the experimental data are obtained through a secondary redistribution via the Kaggle platform.

### 3.2 Signal Preprocessing

To get a coherent representation of the signal, and to reduce unwanted signal components like noise, a pre-processing is performed before the graph construction of the ECG signal. The ECG signals are filtered by using a band-pass filter between 0.5 – 40 Hz. The signals are then filtered and amplitude normalized and split into separate ECG beats or fixed length ECG segments. The preprocessed Lead II and Lead V is then used for feature extraction and creation of a graph.

### 3.3 Graph Construction

The pre-processed segment of the ECG signal is modelled as a graph G= (V, A) with two graph nodes: Lead II and Lead V, are represented as graph nodes v1, v2 respectively, and connecting edge between the two nodes indicates the dependency between the signals as shown in Figure 2.

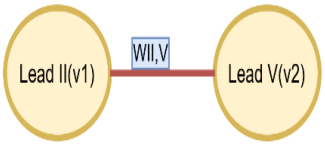


**Figure 2.** Graphical Representation of ECG Leads II and V

The corresponding adjacency matrix $A = \begin{bmatrix} 0 & w_{II,v} \\ w_{v,II} & 0 \end{bmatrix}$

here $w_{II,V}$ and $w_{V,II}$ are the dependency weights between the two leads.

For GNN processing,the adjacency matrix is normalized by using the following equation

$\hat{A} = D^{-1/2}AD^{-1/2}$ Eqn (1)

where D is the degree of the matrix.

The graph is built as per ECG segment, and is not a fixed graph used on all samples, but it is a signal-dependent graph. Because the experimental data set used only Lead II and Lead V, the proposed graph represents the dependency between these two leads that are available.

### 3.4 Feature Extraction

Once the preprocessing has been done, the data is given to feature extraction module to extract the features specific to ECG data from the Lead II and Lead V using NeuroKit2whereas the GNN is able to learn the dependency between Lead II and Lead V using the graph structure. Extracted features include relevant temporal, amplitude, heart-rate and morphological features of each of the leads of the ECG. These features are grouped into node level feature vectors, one of which is for lead II while the other is for lead V. The generated feature vectors are then placed on each node on the graph and fed into the Graph Convolutional Network along with the created inter-lead adjacency matrix.

### 3.5 GNN Model

The proposed GNN model is composed of two layers Graph Convolutional Network (GCN) with 64 hidden dimensions and ReLU activation function, and a global mean pooling layer, and a fully connected binary classification layer. The GCN is fed with the node-level feature vectors extracted with NeuroKit2 from both Lead II and Lead V along with the inter-lead adjacency matrix. The feature representations and the dependency patterns between the two ECG-leads are learned by the GCN layers, and the node representations are aggregated to a graph-level representation by means of global mean pooling. The obtained graph level representation is then fed to the fully connected layer to classify normal/abnormal class. The training is done using the Adam optimizer, learning rate of 0.001, batch size of 64 and 50 training epochs and binary cross-entropy loss is considered as the training objective. All the experiments are performed through Google Collaboratory with an NVIDIA T4 GPU having 16 GB memory.

### 3.6 Anomaly Detection and Classification

Finally, the learnt graph-level representation is used for binary ECG anomaly detection. The GNN classification layer gives the probability value of the abnormal ECG class and each ECG segment will be classified as abnormal or normal depending on the classification threshold value. Therefore, the anomaly-detection task in this study is set up to be a computational binary classification task, instead of dividing the arrhythmia classes into sub-classes and giving the clinical diagnosis. Finally, the evaluation measures such as accuracy, precision, recall, F1 and ROC-AUC are computed based on the predicted labels. The study does not have clinical diagnostic reliability or clinical decision-support capability due to the lack of external clinical validation and medical-expert evaluation.

**Algorithm:** Proposed Inter-Lead GNN

Input: ECG Dataset

Output: Node-Level Feature Vectors and Classified Anomaly Labels.

**Input:** ECG dataset containing Lead II and Lead V

**Output:** Predicted normal/abnormal ECG labels.

**Step 1: Dataset Initialization**

Define the ECG dataset as

$D = \{(X_i, y_i)\}_{i=1}^{N}$ Eqn (2)

Where $X_i$ represents the i-th ECG segment containing lead II and V, $y_i \in \{0,1\}$ represents the corresponding normal or abnormal class label, and N is the number of ECG Segemnts.

**Step 2: Signal Preprocessing**

Apply a 0.5–40 Hz band-pass filter to the ECG signals. Segment the filtered signals into individual ECG beats or fixed-length ECG segments and perform amplitude normalization. The resulting Lead II and Lead V signals are used for feature extraction and graph construction.

The $k$-th segment can be represented as

$S_{i,k} = S_i[t_k : t_k + W]$ Eqn (3)

Where $S_i$ is the i-th ECG Segment, $t_k$is the starting position of the k-th segment, and W is the Segment Length.

**Step 3: Graph Construction**

For each ECG segment, construct a two-node graph

$G_i$=$(V_i, E_i)$ Eqn (4)

Where the two nodes correspond th lead II and V, and the edge represents the their signal dependency.

The adjacency matrix id defined as

$A_i$=$\begin{bmatrix} 0 & w_{II,V} \\ w_{V,II} & 0 \end{bmatrix}$

Where $w_{II,V}, w_{V,II}$represent the dependency weights between Lead II and Lead V.

The normalized adjacency matrix is calculated as

$\hat{A} = D_i^{-1/2} A_i D_i^{-1/2}$Eqn (5)

Where $D_i$ is the corresponding degree matrix.

**Step 4: Feature Extraction**

By usingNeuroKit2, we extracted ECG-related temporal, heart-rate, amplitude, and morphological features from Lead II and Lead V. The node-level feature matrix is represented as

$X_i$=$\begin{bmatrix} x_{II} \\ x_V \end{bmatrix}$

Where $x_{II}$and $x_V$ are the feature vectors associated with Lead II and V, respectively.

**Step 5: GNN Model Learning**

Initialize the node representation as

$H_i^{(0)}$=$X_i$Eqn (6)

And perform graph convolution using

$H_i^{(l+1)}$=Relu($\hat{A}_i H_i^{(l)} W^{(l)}$) Eqn (7)

Where $W^{(l)}$ is the learnable weight matrix of the $l$-th GNN layer.

The proposed model uses two GNN Layers with 64 hidden dimentions and Relu Activation function. Global mean pooling is applied to obtain the graph -level representations:

$Z_i$=$\frac{1}{|V_i|}\sum_{v \in V_i} H_{i,v}^{(L)}$Eqn (8)

The graph level representation is passed to the fully connected binary classificationlayer

$p_i$=$\sigma(W_c Z_i + b_c)$Eqn (9)

$p_i$ is the predicted probability of the abnormal class.

The binary entrophy loss is calculated as

$L$= -$\frac{1}{N}\sum_{i=1}^{N}[y_i log_{(p_i)} + (1 - y_i)\log(1 - p_i)]$ Eqn (10)

The model is trained using adam optimizer , with a learning rate 0.001, batch size of 64, 50 training epochs.

**Step 6: Anomaly Detection and Classification**

The predicted probability is used to classify each ECG segment as normal and abnormal

$\bar{y}_i$=$\begin{cases} 1, p_i \geq \tau_c \\ 0, p_i < \tau_c \end{cases}$Eqn (11)

Where $\tau_c$ is the thrshols value and $\bar{y}_i = 1$ is normal and 0 is abnormal.

**4. Result And Analysis**

This section shows the experimental results of the proposed Inter-Lead GNN for binary classification of ECG anomalies, with the provide Lead II and Lead V signals. The model is tested and evaluated by its classification performance by using accuracy, precision, recall, F1-score and ROC-AUC.

The following Performance metrics are used to calculate the proposed method metrics values

$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$Eqn (12)

$Precision = \frac{TP}{TP+FP}$Eqn (13)

$Recall = \frac{TP}{TP+FN}$Eqn (14)

$F1\ Score$=2*((Precision*Recall)/(Precision+Recall))Eqn (15)

In the above performance metrics TP-True Positives, TN-True Negatives,FP-False Positives, FN-False Negatives

Furthermore, the results are compared with DeepECG-Net to assess the performance of explicitly considering inter-lead relationships by graph-based representation learning.

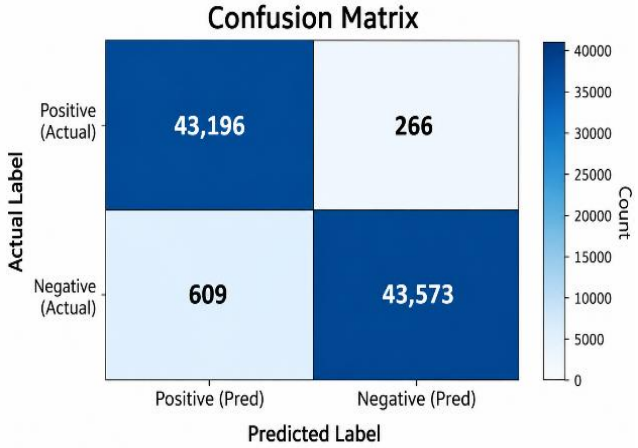


**Figure 3.** Confusion Matrix of Proposed Inter-Lead GNN.

The confusion matrix for the experimental data is evaluated is shown in figure 3. Among the 87,644 samples, 43,196 of the predictions are true and positive, 43,573 are true and negative, 609 are false and positive and 266 are false and negative. The values show that the proposed model is better classification of the binary ECG signal as normal or abnormal.

**Table 1.** Proposed Inter-Lead GNN method performance metrics values

| **S.No** | **Proposed method Performance Metrics** | **% Value** |
|---|---|---|
| 1 | Accuracy | 99.00 |
| 2 | Precision | 98.61 |
| 3 | Recall | 99.39 |
| 4 | F1-score | 99.00 |
| 5 | ROC-AUC | 98.2 |

The performance parameters of the proposed method for ECG classification is enumerated in Table 1. The proposed method shows the overall classification accuracy of 99.00% which is highly accurate. The recall of 99.39% suggest that the model has very low false positive and false negative rates. The F1-score 99.00% further validates a high degree of equilibrium between precision and recall and the ROC-AUC 98.2% proves to be a superb discriminative influence between the considered ECG classes. This high performance is due to the proposed model's capacity to model inter-lead dependence and learn meaningful relations among ECG signals, which enhances the performance in representing the features. In general, the results show that the proposed method achieves reliable and good performance for ECG classification based on the metrics considered.

**Table 2.** Comparison of performance metrics between DeepECG-Net with Proposed Inter-Lead GNN

| S.No | Performance Metric | DeepECG-Net | Proposed Inter-Lead GNN |
|---|---|---|---|
| 1 | Accuracy | 98.20 | 99.00 |
| 2 | Recall | 96.80 | 99.39 |
| 3 | Precision | 98.20 | 98.61 |
| 4 | F1-Score | 97.5 | 99.00 |
| 5 | ROC-AUC | 98.0 | 98.20 |

Table 2 shows the performance of the proposed Inter-Lead GNN model, in comparison with the existing DeepECG-Net, on different evaluation metrics. The results demonstrate that the proposed Inter-Lead GNN outperforms DeepECG-Net on all the metrics evaluated, showing 99.00% accuracy, 98.61% precision, 99.39% recall, 99.00% F1-score and 98.20% ROC-AUC. The proposed model is graph-based, which models the relationship and dependency between the different leads of the ECG signal and makes it perform well. This enables the model to extract important information between the leads of the ECG and the learning of more

discriminative features of the signal. The proposed Inter-Lead GNN can achieve more robust and stable ECG classification performance than the current DeepECG-Net.

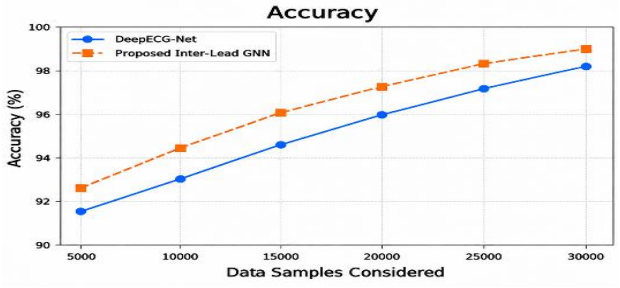


**Figure 4.** Accuracy comparison of DeepECG-Net with Proposed Inter-Lead GNN

The Figure 4represents the accuracy comparison of DeepECG-Net with Proposed Inter-Lead GNN.The proposed Inter-Lead GNN gives an accuracy of 99.00% while DeepECG-Net gives the accuracy of 98.20%. The proposed model outperforms the existing, as it explicitly models the relationship and dependency among ECG leads; instead of treating each signal individually. The graph representation consists of nodes representing ECG leads and edges representing the relationships between the signals, enabling the GNN to sum up data from neighboring leads. This enables the model to learn complementary and correlated patterns in the ECG signals, leading to informative feature representations. Thus, the proposed Inter-Lead GNN's graph-based learning capability also helps to improve its classification accuracy.

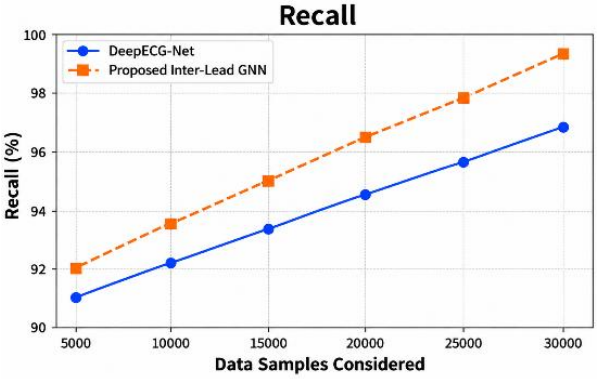


**Figure 5.** Recall comparison of DeepECG-Net with Proposed Inter-Lead GNN

The comparison of the recall performance of DeepECG-Net and the proposed Inter-Lead GNN is shown in Figure 5. The proposed model can be recalled with a 99.39% while DeepECG-Net can be recalled with a 96.80%. The high recall suggests that the proposed model has the ability to correctly identify ECG patterns and minimizes the number of missed abnormal cases. The GNN's capacity to tackle inter-lead relationships, such as representing ECG leads as interconnected nodes and aggregating information across them, to support this performance. The proposed Inter-Lead GNN can learn more informative ECG representations by learning these dependencies, and combine the complementary information from different leads.

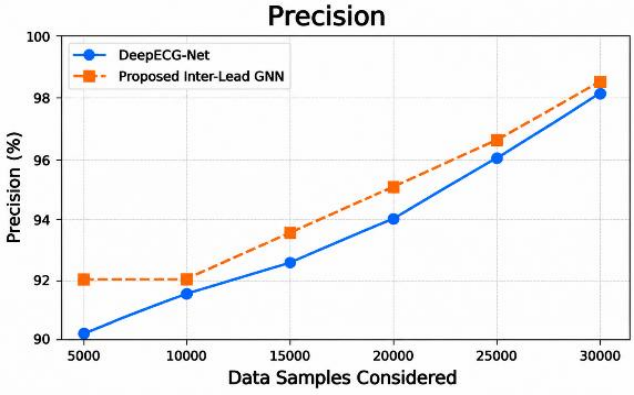


**Figure 6.** Precision comparison of DeepECG-Net with Proposed Inter-Lead GNN

The precision of DeepECG-Net and proposed Inter-Lead GNN is compared in the Figure 6. The proposed model is able to achieve 98.61% precision, which is better than 98.20% of DeepECG-Net. The increased accuracy

suggests that the proposed model can make more accurate predictions in recognizing the ECG pattern with minimal false-positive predictions. This improved performance is primarily attributed to the GNN's ability to model inter-lead dependencies, enabling the GNN to jointly learn information from ECG leads that are connected. The proposed model can gain more discriminative ECG features by using these relationships and yield more reliable classification results.

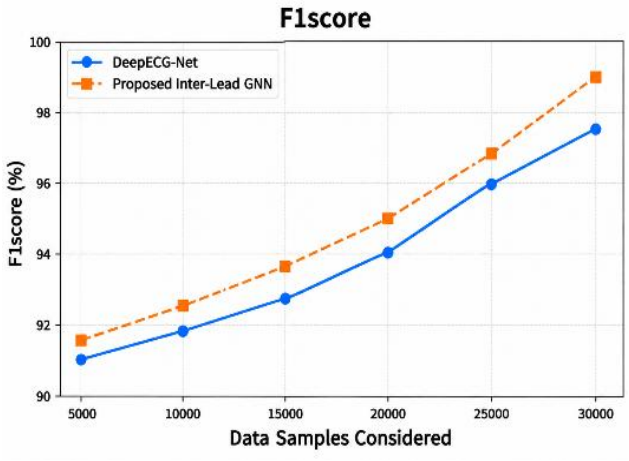


**Figure 7.** F1 score comparison of DeepECG-Net with Proposed Inter-Lead GNN

The comparison of the F1-score of the proposed Inter-Lead GNN and DeepECG-Net is shown in the Figure 7. The proposed model has an F1-score of 99.00% while DeepECG-Net has 97.50%. The proposed model has achieved higher F1-score which shows that the higher value is indicating that the proposed model provides better balance between precision and recall during ECG classification. This improvement is enabled by the GNN, which can learn inter-lead relationships and fuse information from ECG leads that are connected. The proposed Inter-Lead GNN is able to learn these complementary dependencies to obtain more informative representation of ECG, resulting in more reliable overall classification performance.

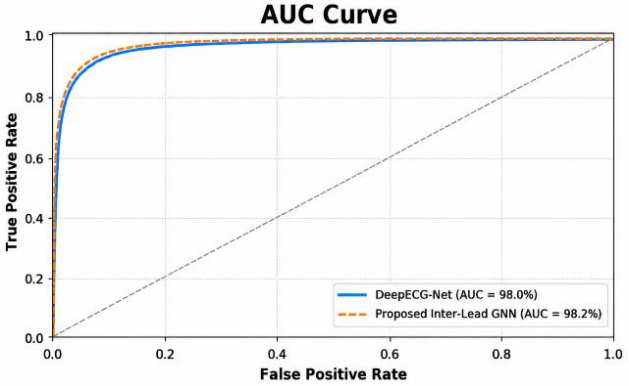


**Figure 8.** ROC-AUC comparison of DeepECG-Net With Proposed Inter-Lead GNN

The Figure 8 curve shows the performance of DeepECG-Net and the proposed Inter-Lead GNN in terms of classification. The model in both cases provided an excellent discrimination of ECG classes with high ROC-AUC of 98.0% for DeepECG-Net and 98.2% for the proposed Inter-Lead GNN. The slightly higher AUC of the proposed model shows that the model can better differentiate the positive and negative ECG patterns at various classification thresholds. This performance is facilitated by the GNN that captures inter-lead dependencies and is capable of combining information from ECG leads that are connected. Thus, the proposed Inter-Lead GNN gives excellent and robust discriminative performance on ECG classification.

**Table 3**.Comparison with Existing ECG Methods

| Method | Lead Configuration | Data Set | Accuracy | Precision | Recall | F1-Score | ROU-AUC |
|---|---|---|---|---|---|---|---|
| Moghaddam et al. [15] | One-lead | MIT-BIH, arrhythmia classification | 99.02 | – | – | – | – |
| Han [11] | ECG feature graph | Arrhythmia classification | >50* | – | >50* | – | – |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| EGCNet [13] | ECG graph | PhysioNet 2020, 24-label classification | – | 75.30 | – | 72.20 | – |
| DeepECG-Net [17] | ECG | Anomaly detection | 98.20 | 98.20 | 96.80 | 97.5 | 98.0 |
| Proposed Inter-Lead GNN | Two-lead: Lead II + Lead V | MIT-BIH | 99.00 | 98.61 | 99.39 | 99.00 | 98.20 |

The proposed Inter-Lead GNN is compared with the existing works in the literature that are based on ECG signals, as shown in Table 3. The proposed model shows a result of 99.00% accuracy, 98.61% precision, 99.39% recall, 99.00% F1-score, and 98.20% ROC-AUC with the configuration of 2-leads (Lead-II and Lead-V). The proposed method has higher values than DeepECG-Net for all the evaluation metrics reported. This good performance is linked to the capability of the GNN in modelling dependencies between the available ECG leads as connected graph nodes. This graph-based representation enables information from both leads to be learnt jointly and enables more informative representations for binary ECG anomaly detection. The comparison shows the usefulness of the proposed inter-lead graph representation in this two-lead scenario.

**5.Conclusion**

This study proposes a novel Inter-Lead Graph Neural Network (GNN) framework to model the dependency between the available ECG leads explicitly for ECG anomaly detection. In this work, we considered the two-lead ECG signals, Lead II and Lead V were the graph nodes and their signal dependency as graph edges. The proposed framework has achieved 99.00% accuracy, 98.61% precision, 99.39% recall, 99.00% F1-score and 98.2% ROC AUC, which is a good performance for the evaluated binary normal/abnormal ECG classification task. The results show that graph representation of inter-lead dependency could be an effective way to learn relation between ECG signals both. This graph-based representation enables information from both leads to be learnt jointly and enables more informative representations for binary ECG anomaly detection. The limitation of our work is only valid for the two-lead setup and it does not prove performance on full 12-lead ECGs or on clinical diagnosis. Future studies will involve testing with original and independent multi-lead ECG data, exploring more adaptive graph-construction methods, and iterative statistical and clinical validation.

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