The Interpretable Graph Neural Network of ECG Beat Classification

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Abstract

Cardiovascular disease is the leading cause of death in the world. Cardiac arrhythmia is detected based on the electrocardiogram (ECG), which is related to cardiovascular disease. The automatic diagnosis of ECG improves efficiency for doctors and assists people who would likely learn some relative knowledge. The Graph Neural Network obtains the correlations between nodes via the node embedding and the graph networks. Therefore, this work develops a novel Graph Neural Network to classify cardiac arrhythmia based on the ECG beat. The 'BlackBox' characteristics make some people doubt the trustworthiness of models, so one interpretable method in the models that produce the visual graph is designed. The learning layer of the ECG time series was proposed. In this paper, a visual analysis of the ECG will be conducted, which increases the confidence level of this model. In this article, a visual analysis of the electrocardiogram will be performed, which increases the confidence of the model, and the classification results will be compared with three classic machine learning techniques, with the model achieving a classification accuracy of up to 98.65%. The selected features in the model were also explicitly studied in a visual method.

Keywords: BlackBox, Electrocardiogram, Graph Neural Network, Cardiac arrhythmia

1 Introduction

Cardiovascular disease ranks first [1, 25] in the cause of death worldwide: more people die each year from cardiovascular disease than any other cause. Of the 17 million deaths under 70 due to noncommunicable diseases, 82% occurred in low-income and middle-income countries, and 37% were caused by cardiovascular disease.

An Electrocardiogram (ECG) [2] was used as an essential medical basis for preventing and diagnosing cardiovascular diseases. Therefore, classifying the electrocardiogram is of the utmost significance. ECG is a kind of graph that uses an electrocardiograph to record the electrical activity changes generated by each cardiac cycle of the heart from the body's surface. Doctors use the electrocardiogram to diagnose essential diseases, such as arrhythmia, myocardial infarction, etc. Doctors could judge abnormal heartbeat through ECG. The automatic diagnosis of ECG efficiently saves the expert's time and energy and aids the doctor in learning some expert knowledge concerning some relevant fields.

Recently, deep learning and meta-heuristic algorithm has made substantial progress in many fields [3-4], such as medical classification [5], Economic Load Dispatch Problem [6], Natural language processing (NLP) [7] and Wireless Sensor Networks [8]. The traditional manual ECG automatic diagnosis technology has shortcomings, such as manual diagnosis errors, low timeliness, and so on. The existing ECG automatic diagnosis technology includes machine and deep learning methods [9]. The algorithm design based on machine learning includes two processes. The first process is the feature of manual extraction, such as wavelet transform [10], Fourier transforms [11], and principal component analysis [12]. Then it builds a classifier to classify these features. Considerable areas employed deep learning techniques such as Wind power prediction [13], Image classification [14], and power load prediction [15]. The abstract and deep features [16] could be obtained via deep learning techniques. Moreover, deep learning techniques realize end-to-end classification of ECG, such as 1D Convolution Neural Network (CNN), Long Short-Term Memory Network (LSTM) [17], and Deep Neural Network (DNN). Many studies have proved that deep learning has excellent prospects in various fields, such as bionics [18] and medicine [19]. Deep learning models with the optimal network architecture [20] enhance efficiency and lessens the complexity of model training. In [21], Huang et al. presented a novel network architecture of 2D convolution combined with a short-time Fourier transform. It transforms the ECG signals into an image suitable for CNN. They first process the ECG data from the MIT-BIH database with a short-time Fourier transform. Then the spatial locality was obtained by pooling and convolutional layers. Yıldırım et al. [22] proposed one end-to-end neural network structure based on long-duration ECG classification. It designed a new 1D CNN which was conducted on mobile devices. In [23], Dokur and Ölmez devised intersecting spheres neural network for ECG classification. It optimizes the first layer parameter using

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Genetic Algorithms (GA). Codewords in the next layer adjusted the weight. ECG signals were transformed into 2D images via Recurrence plots in [24]. Then Mathunjwa et al. divided the classification process into two stages. In the first process, the ventricular fibrillation and others were differentiated using the classifier. In the second stage, the other four arrhythmias were separated.

The explanation of the model of ECG classification is of great importance. It benefits experts to describe the cause of the disease to patients. Ribeiro et al. [25] presented one explainable method called local interpretable model-agnostic Explanations (LIME) about any classifier. It takes a non-redundant process to get classical personal predictions and their explanations. In [26], Koh and Liang explain the Black Box by introducing empirical risk, which takes Perturbing as a training input. It values the influence function by Conjugate gradients and Stochastic estimation. In [27], Zhou et al. explain the Convolutional Neural Network (CNN) with class activation mapping (CAM). Owing to employing the global average pooling, this method may change the designed neural network architecture. One new visualization explanation technique concerning the medium layers was presented in [28]. The process of feature changes was shown in this architecture. To obtain the continuous path to the origin space, Zeiler and Fergus put deconvnet into each layer. In [29], inputs' personal and mutual contributions were explained. Its innovation originated in the fish diversity in the lake. From the perspective of statistics, the weight's influence and input features were analyzed. In [30], the semantic explanation of the CNN architecture was presented. Bau et al. conducted scored semantic information concerning each possible hidden layer in the CNN, which was labeled in potential areas. This could give semantic information to corresponding units. Few deep learning methods can explain the network structure's black-box nature concerning ECG classification. Therefore, this paper proposes a Graph Neural Network (GNN) structure that can explain the basis for classifying ECG heartbeats. This interpretable network architecture benefits doctors in explaining abnormal cardiac fluctuations such as atrial fibrillation and ventricular premature beats. This significantly improves the work efficiency of doctors.

Recently, more and more researchers have focused on the GNN [31], a deep network architecture in graph structure fields. The complex non-Euclidean data could be processed via GNN, which captures the data's internal spatial structure and dependencies. The GNN takes graph-structured data as input and performs classification and regression of nodes, sub-graphs, and whole graphs. Numerous classes of Graph Neural Network exists, including Graph Attention Network (GAT) [32], Graph Convolution Network (GCN) [33], Graph Recurrent Network (GRN) [34], and so on. In [35], Gao et al. presented a new neural network, integrating Convolution and Graph Convolution Neural Network, to categorize Breast Histopathological. They presented one new GCN to reason the graph embedding efficiently. It obtains the superficial feature embedding by CNN and reasons the spatial correlations between histopathological pictures. In [36], the application in bioinformatics was investigated in detail on Graph Neural Network. The molecular structure and biological information can be modeled by graph embedding. The GNN could conform to the node-level, edge-level, and graph-level prediction about the biological structure data. Therefore, this paper proposes a graph-based network structure for ECG classification and visual analysis of abnormal heartbeats. The main contributions of this paper are as follows.

1. This paper developed a new Graph Neural Network architecture for diagnosing ECG waveforms.
2. A new graph learning layer of ECG beat waveforms be presented.
3. A method for enhancing the clinical interpretability graph Pooling Layer was devised.
4. This paper presents a visual interpretability analysis of abnormal ECG beats.

2 Problem Formulation

This section reviews the ECG classification work and relevant explanation models. Owing to the relevance of our work and the GNN, we conclude the two classical models of GNN, including the Graph Convolution Network (GCN) and the Graph Attention Network (GAT).

2.1 The Graph Convolution Network (GCN)

The updated procedure of GCN was introduced first. The node mode, which varies by the method of information propagation, is influenced by its neighbor statements on one entire graph. The iteration formula can be expressed as Eq. (1). H^{t+1} represents all node statements of the t+1 layer. X refers to the inputs which have N nodes and D-dimension features. The Graph Convolution Network (GCN) iterates via Eq. (2).

$$H^{t+1} = F(H^t, X) \tag{1}$$

$$H^{t+1} = \delta(LH^t W^t) \tag{2}$$

where $L = \tilde{D} - A$. $\tilde{D}$ is equivalent to the degree matrix; A is the adjacency matrix. The GCN mainly incorporates two classes: spectral decomposition and spatial structure. We primarily introduce the GCN based on spectral decomposition. In [37], the convolution operation in the fourier frequency domain was presented. Bruna et al. update the node information propagation by calculating the Eigendecomposition of the Laplacian matrix. The Laplacian matrix was shown as follows.

$$L^{sym} = \tilde{D}^{-\frac{1}{2}} \tilde{A} \tilde{D}^{-\frac{1}{2}} \tag{3}$$

$$= \tilde{D}^{-\frac{1}{2}} (\tilde{D} - A) \tilde{D}^{-\frac{1}{2}} \tag{4}$$

$$= I_n - \tilde{D}^{-\frac{1}{2}} A \tilde{D}^{-\frac{1}{2}} \tag{5}$$

$$= U \Lambda U^T \tag{6}$$

where Λ refers to the diagonal matrix; I_n represents the $n \times n$ identity matrix. The update of node information via Eq. (7).

$$H^{t+1} = \delta(U \Lambda U^T H^t W^t) \quad \textbf{(7)}$$

In [38], Kipf and Welling presented the controlled parameter θ and the renormalization function, simplifying the spectral decomposition. The signal matrix is shown in Eq. (8).

$$Z = \tilde{D}^{-\frac{1}{2}} \tilde{A} \tilde{D}^{-\frac{1}{2}} X \Theta \quad \textbf{(8)}$$

Where $\Theta \in R^{C \times F}$ and $Z \in R^{N \times F}$. $\tilde{A} = A + I_n$. The update of node information via Eq. (9).

$$H^{t+1} = \delta(\tilde{D}^{-\frac{1}{2}} \tilde{A} \tilde{D}^{-\frac{1}{2}} H^t W^t) \quad \textbf{(9)}$$

2.2 The Graph Attention Network (GAT)

We first introduce the development of the attention mechanism, which was first proposed in the 90s and applied in the image fields. In 2014 [39], Google Mind successfully combined the recurrent models with attention, which were performed to classify images. In [40], the attention model was first applied in Natural Language Processing (NLP). Bahdanau et al., employing the attention mode to machine translation, conducted the translation and aligned simultaneously. In 2015 [41], Xu et al. successfully performed the attention mechanism to the image caption. In 2017 [42], Vaswani et al. trained text embedding via the self-attention mechanism, which employed simply the attention modes. In 2017 [43], one Graph Attention Network type called GAT was presented. It incorporates the attention mechanism during the information propagation process, which takes the self-attention method. The aggregation formula of node information could be expressed as follows.

$$H_i = \sigma\left(\sum_{j \in N(i)} \alpha(i,j) W x_j\right) \quad \textbf{(10)}$$

where t is the iteration times; i represents the node number. $\alpha(i, j)$ represents the attention coefficients $N(i) = \{j|A(i, j) = 1\}$ refers to the set of neighbors of the i-th node. $\alpha(i, j)$ can be calculated by equations as follows.

$$h_i = W x_i \quad \textbf{(11)}$$

$$relation(i,j) = LeakyReLU\left(\alpha^T \left(h_i \,\|\, h_j\right)\right) \quad \textbf{(12)}$$

$$\alpha\left(i,j\right) = \frac{\exp(relation(i,j)}{\sum_{k \in N(i) \cup i} \exp(relation(i,k))} \quad \textbf{(13)}$$

where $h = \{h_1, h_2, \ldots, h_N\}$ represents the input features of the node set; W refers to the weight matrix of linear transformation based on each node. $\|$ is the concatenation function, and $\alpha \in R^{2 \times F}$ is the weight vector that maps the input features to R. The graph attention layer utilizes a multi-head attention mechanism to stable the training process, which calculates the hidden state via K independent attention mechanism. The multi-head attention mechanism was expressed as follows.

$$H_i = \|_{k=1}^{K} \, \delta\left(\sum_{j \in N(i)} \alpha^k(i,j) W^k x_j\right) \quad \textbf{(14)}$$

2.3 The Electrocardiogram (ECG) Classification

Numerous deep learning models have superficial classical performance in cardiac arrhythmias based on ECG. However, owing to the ‘Black Box’ of the neural network models, the explanation is insufficient for the classification of ECG. This will lead to a trust crisis in the model. In [44], a deep 1D CNN model was proposed to sort the cardiac arrhythmias based on the 2018 China Physiological Signal Challenge [45]. Zhang et al. employed the Shapley value (SHAP) method to conduct the interpretable analysis based on the population and patient level. Mousavi et al. [46] presented a bi-directional Recurrent Neural Network that utilized the hierarchical attention mechanism to categorize Atrial fibrillation. These attention modes, detecting the important signal features, increased the interpretability of ECG classification. In [47], the temporal dependency of the ECG sequence was increased. Neves et al. employed Permutation Feature Importance (PFI), Local Interpretable Model-agnostic explanations (LIME), and SHAP to value the interpretability.

3 Methodology

3.1 Problem Formulation

In this work, the goal is to classify the ECG beat and visualize the sequence relation. The training data is the time sequence from many different ECG beats. Each series is equal to $X = \{x_1, x_2, \ldots, x_N\}$ in which x_i have the same amount of data points, divided into many nodes with some fixable length sample points. One entire graph represents one sample data that denotes $G = V, Adj$. V is equal to X, and Adj represents the adjacency matrix in which $Adj(i, j)$ = 1 refers to the one-directional edge that exists between i and j.

The learning result of the model is a set of T one-hot labels and the relation graph that implies which node is vital to this label. This one-hot labels represents $Result(t) \in C^4$ where $C \in \{0, 1\}$.

3.2 Model

The proposed mode’s purpose is to categorize the ECG beat and visualize the classification characteristics. The ECG beat from MIT-BIH Arrhythmia Database should be fed into the model. The final output is the one-hot labels and the interpretable graph where the user and experts study the ECG knowledge. The first step is preprocessing training data in which the noise and uneven baseline should be processed to obtain standard data. Secondly, the model learns the node embedding through the graph learning layer, which can efficiently optimize the relation between nodes and the linear transformation. The similarity should be high between nodes in which the temporal dependency exists during the process of another linear space. Next, the graph network layer consists of the Graph Convolution Layer, which captures the spatial links between nodes, and the Graph Attention Layer, where the correlation of whether solid or weak is learned. Finally, the node with a much higher contribution to the classification was selected in the Pooling layer. Figure 1 describes the proposed model overview, including the graph learning, attention, and pooling layers.

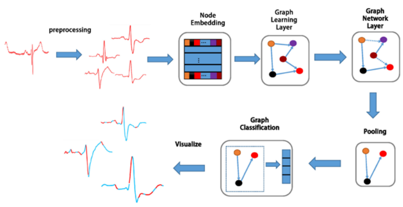

Figure 1. This is the network frame figure of the proposed model

3.2.1 The Graph Learning Layer

The principal motive of the model is to obtain the temporal connections between short ECG beat series in the graph learning layer. The directed graph will be employed to represent the relation between nodes whose edges store the temporal relation. One edge from one node to another suggests that the second node has temporal dependency from the first. The directed graph is used because the time-based dependency between nodes is not symmetric. This paper exerts the adjacency matrix Adj serving as a directed graph, where $Adj(p, q) = 1$ expresses the existence of an edge between p and q node.

The set of temporal correlations $Neighbors_p$ designates the prior knowledge between data samples which can be expressed as follows.

$$Neighbors_p \in \{SET_1, SET_2, ..., SET_n\} \tag{15}$$

$$SET_j \subseteq \{1, 2, \cdots N\} \setminus \{j\} \tag{16}$$

This model first conducts the initial edge process where each node connects all nodes except itself. This paper presents one new similarity formula which computes the temporal dependency between node embedding vectors in another linear space, so the update of adjacency matrix Adj was processed via the following formula.

$$N_1 = \tanh(\beta N_1 \theta_1) \tag{17}$$

$$N_2 = \tanh(\beta N_2 \theta_2) \tag{18}$$

$$A = ELU\left(\tanh\left(\beta\left(N_1 N_2^T\right)\right)\right) \tag{19}$$

$$A_{ix} = topk(A) \tag{20}$$

where β is the saturate rate of the activation function. N_1 and N_2 are the node embedding vectors that can be optimized through the training process. θ_1 and θ_2 are model parameters. $topk(A)$ returns the selected index matrix that stores top k index of nodes existing the temporal dependency with each node. The adjacency matrix, which will be fed to the model, will update via $topk(A)$.

3.2.1 The Graph Learning Layer

The Graph Network Layer mainly consists of GCN optimizing the node embedding vectors and GAT, where the temporal relations were updated. The GCN layers take node embedding vectors from the Graph Learning Layer, and the sample data $X = \{x_1, x_2, \ldots, x_n\}$ as the input. Employing Eq. (9) aggregates the information from the node's neighbors, which acquires the information from its neighbors, and the edge information. The GCN utilizes 'Mean' as the aggregate function. The laplacian smoothing was used to enhance the similarity between nodes in the set of neighbors. The output of GCN is embedding vectors and edge sets. This information will be fed into the GAT. The adjacency matrix will be updated via the GAT layer. This paper employed the multi-head attention mechanism to represent the node embedding vectors and the series-based temporal correlations. Adding the self-connection will be processed in the GAT, which enhances the representation ability of the node embedding vectors. Eq. (13) will be rewritten as Eq. (21) The output of the multi-head attention layer applied RELU as the activation function. So Eq. (15) will be rewritten as Eq. (22).

$$h_i = x_i \,|\, Wx_i \tag{21}$$

$$H_i = RELU\left(\frac{1}{K}\sum_{k=1}^{K}\sum_{j\in N(i)} \alpha^k(i,j) W^k x_j\right) \tag{22}$$

3.2.2 The Graph Pooling Layer

In the Convolution Neural Network (CNN), the pooling layer, which implements the subsample function and the maintenance of the apparent features, is often followed by the convolution layers. In [48], the top-k mode was proposed to calculate the importance of nodes. Lee et al. [49] improved the top-k mechanism via the self-attention mode and one-layer GCN. The attention score and the node embedding vectors from GCN will be entered in the Graph Pooling Layer as Eq. (23). Meanwhile, this layer conducted the calculation score of nodes which aggregates its neighbors and the edge information via GCN. Calculating the score will enhance this model's interpretability, where each node's contribution to this model can be computed. From the perspective of the scoring mechanism, this paper explains the classification evidence-based the concrete sample data. The multi-layer linear transformation will be followed by the Graph Pooling Layer. The RELU activation function was utilized as the output activation function. The formula of this pooling layer was expressed as Eq. (24) and (25).

$$X^t = E^t \otimes s^t \tag{23}$$

$$H^{t+1} = RELU\left(\tilde{D}^{-\frac{1}{2}}\tilde{A}\tilde{D}^{-\frac{1}{2}}X^t W^t\right) \tag{24}$$

$$ix = top\_\boldsymbol{rank}\left(H^{t+1}, [r * N]\right) \tag{25}$$

where E^l refers to the embedding vectors of the l layer; s^l represents the self-attention score and the neighbor score. This layer employed one layer of GCN to compute the scores of all nodes. The index of the top r node was obtained via Eq.(25), where r is the rate of selected nodes. Each node represents the short time series in which the feature can be visualized. This work will introduce the visualization section in detail.

4 The ECG Classification Results and its Visual Analysis

In this section, we first introduce the ECG datasets from MIH-BIT [50]. Next, this work compared the classification results with some classical models, including Multi-Layer Perceptron (MLP), Logistic Regression (LR), and Long Short-Term Memory Network (LSTM). Finally, this paper conducted an innovative visual analysis concerning cardiac arrhythmia.

4.1 Datasets

This database [51] includes 48 half of one-hour excerpts of double-channel fixed ECG recordings where M1 lead data were selected. The sample data were recorded in 360hz with 11-bit resolution over a ten mV range. Extracting 1h ECG recordings from the database will be utilized in the experiment. The noise and uneven baseline were wiped out in this study via the wavelet transform. The ECG data were divided into 6800 ECG beat segments, including four classes, which will be fed into the proposed models. R peak located in the center of the ECG beat with 301 sample points. These processed data samples have four classes, including Normal Sinus Rhythm beat (NSR), Left Bundle Branch Block beat (LBBB), Right Bundle Branch Block beat (RBBB), and Premature Ventricular Contraction (PVC).

4.2 Classification Results and Visual Analysis

Two-layer GCN and GAT were included in the Graph Network Layers. This work runs the experiments on a Ubuntu 20.04 with RTX 3090 GPU, which have 24GB video RAM and 16-core Intel(R) Xeon(R) Platinum 8350C CPU @ 2.60GHz that has 45GB memory. The models were trained in the Adam optimizer, which optimizes the Cross-Entropy Loss. The experiment set the maximum epochs of 50 with a learning rate of 0.003. The dropout rate of each layer was set to 0.3. The mini-batch size of the training data is equivalent to 128 during the initializing process. This paper employs the python language and the Pytorch Frame to conduct the experiments. The setting of these parameters is shown in Table 1. This paper utilizes some indices to validate the classification result of the test data, including accuracy rate, precision rate, F1 score, and recall. Figure 2 shows the accuracy curve of 50 epochs. The accuracy and precision rate is over 0.95%. Moreover, the LBBB, RBBB, and PVC accuracy exceeded 0.95%. The bar chart of comparison with three baselines was expressed as Figure 3.

Table 1. The parameter table

Learning	Optimizer	Epochs	Dropout	Batch
0.003	Adam	50	0.3	128

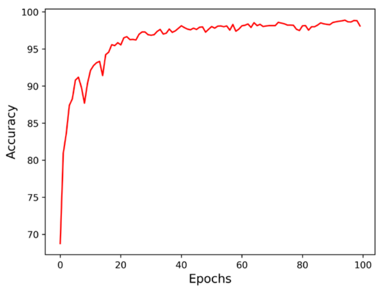

Figure 2. This is the accuracy curve

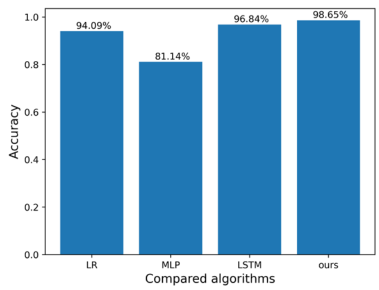

Figure 3. This is a bar chart of classification results

In this section, a precise visual analysis of three classes of cardiac arrhythmia will be performed. Firstly, we introduced the feature changes of SNR. One regular ECG beat consists of five parts, including the P wave, PR interval, QRS waves, ST segments, and T wave. Figure 4 to Figure 7 visualize the beat features of four heart rhythms. An example of SNR is shown in Figure 4, where the P wave emerges early, and the T wave last appears. The P wave has little volatility, less than 120ms, and is generally obtuse and rounded, sometimes with possible tangents. The PR interval refers to the time coming from the start of the P wave to the start of the QRS wave group, which represents the time from the start of atrial depolarization to the start of ventricular depolarization. The PR interval is 0.12-0.20s when the heart rhythm is in the normal range. The QRS wave group is generally upward in its primary wave in the absence of an electrical axis shift. Normal adults have a QRS time of less than 0.12s, with most in the range of 0.06-0.10s. The ST segment is the line between the end of the QRS wave group and the beginning of the T wave, representing the slow repolarisation process of the ventricles. The normal ST-segment is usually the first-potential line, but sometimes there can be a slight shift, but in either lead, the ST-segment shift is usually no more than 0.05mV. The T wave signifies the change in potential during rapid repolarisation of the ventricles.

A premature ventricular contraction (PVC) is an extra heartbeat that starts in one of the two lower pumping chambers (ventricles) of the heart. Premature ventricular beats increase the risk of developing abnormal heart rhythms (arrhythmias) or reduced diastolic forces of the heart muscle (cardiomyopathy). Observing the time interval of QRS waves, the direction of the T wave with QRS waves, and the occurrence time of the P wave could explain whether the patient has PVC. Figure 5 shows the selected features that discriminate the model's ECG beat class. The 'Red' part in the curve represents the selected features with higher scores in the neural network model. These features having more miniature scores were labeled with 'Blue'. The figure has vast QRS waves which exceed 60 sample points (120ms). P wave appears earlier in this image, where the third red part represents these characteristics. The T wave has reversed orientations and shapes with QRS waves based on the last red. According to these analyses, the ECG beat can be classified the PVC.

A bundle branch block is a delay or block in the conduction path of the electrical impulses that stimulate the heart to beat. A block causes the right bundle branch conduction block in the right bundle branch of the heart, which prevents electrical signals from being transmitted to the right ventricle via this route and must be activated by signals from the left ventricle. Analyzing the time interval of QRS waves, the shapes of ST segments, and T wave could reason about whether or not the patient have LBBB. Figure 6 shows the selected features which differentiate the ECG beat label in the proposed model. The last four 'Red' part in the curve represents the ST segments in the ECG beat. These features having smaller scores were labeled with 'Blue'. The figure has extensive QRS waves which exceed 60 sample points (120ms). The directions and shape are contrary between ST segments and the primary waves, which have the same orientations as the T wave. According to these analyses, the ECG beat can classify the LBBB. The time interval of QRS waves, directions, and shapes of ST waves reason about whether or not the patient has RBBB. Figure 7 shows the selected features which differentiate the ECG beat label in the proposed model. The second 'Red' part in the curve represents the T wave in the ECG beat. These features having more minor scores were labeled with 'Blue'. The figure has broad QRS waves which exceed 60 sample points (120ms). S waves have a more deep wave shape than normal S waves. The directions and shape are contrary between ST-T segments and the leading waves. According to these analyses, the ECG beat can classify the RBBB.

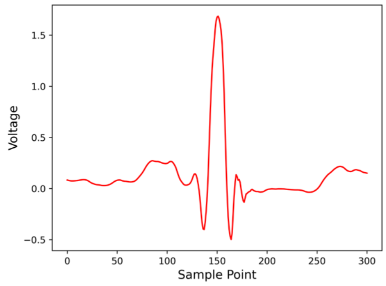

Figure 4. This is a visualize figure of Normal Sinus Rhythm beat

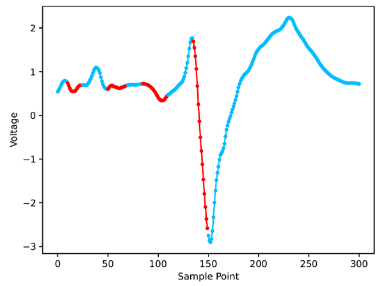

Figure 5. This is a visualize figure of Premature Ventricular Contraction (PVC)

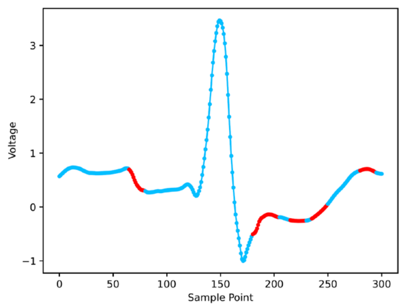

Figure 6. This is a visualize figure of Left Bundle Branch Block beat (LBBB)

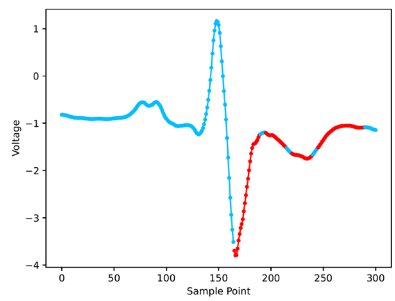

Figure 7. This is a visualize figure of Right Bundle Branch Block beat (RBBB)

5 Conclusion

This paper proposed an interpretable neural network of ECG classification, which produced an interpretable visual graph. The features which has important contribution would be selected via the model. The experts could locate the abnormal ECG beat via this model quickly. The features which have significant contributions would be selected via the model. A visual analysis concerning the four cardiac arrhythmias was presented in this paper. In the future, we will perform the visual explanation of cardiac arrhythmias classification rather than simply LBBB, RBBB, and PVC. This work conducted experiments about double-leads ECG data, limiting the detailed study of many cardiac arrhythmias. Next, we will process the advanced analysis of many leads data rather than two leads. The proposed approach can be further improved by adopting some meta-heuristic optimization algorithms to tune the parameters of the proposed method [52-53].

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