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ECG Heartbeat Classification Using CNN

Mayank Chourasia, Anurag Thakur, Shresth Gupta, Anurag Singh
International Institute of Information Technology
Naya Raipur, India
{mayankc18100, anurag18101, shresth, anurag}@iiitnr.edu.in

***Abstract*—Electrocardiogram(ECG) is a valuable clinical signal, which is widely used to identify the cardiovascular diseases. However, it remains a cumbersome process to manually evaluate the ECG signals because of smaller variations in its physiological features in normal and abnormal cases that too when there are a huge number of cardiac patients to examine. In such a scenario, automatic classification of ECG signals can provide an ease to the doctors to make a correct diagnosis of a particular disease. This work proposes a classification model to classify the ECG in five different classes based on their morphological features. Instead of using manually designed features as most of the existing ECG classification works do, we have extracted data-driven non-linear features using convolutional neural network. The 1D-CNN model architecture is based on three convolutional, max pooling and dense layers which automatically extracts distinguishable non-linear features from the ECG signals and automatically classify them into five different classes: Non-ectopic beats (Normal Beat), Supraventricular ectopic beats, Ventricular ectopic beats, Fusion Beats and Unknown Beats. The proposed algorithm was assessed using open-source database of MIT-BIH, which is based on 47 subjects. After 5-fold cross-validation, the presented algorithm achieves an accuracy of 97.36% and f1 score of 99.83%. It is a simple yet fast performing model that is implementable on e-healthcare-based devices for remote heart diagnosis of patients.**

***Index Terms*—ECG, 1D CNN, ReLU, Heart disease, Deep learning, Automatic diagnosis**

I. Introduction

Electrocardiography (ECG) is the most popular and easy-to-use tool for diagnosing cardiac arrhythmia also known as heart rhythm disorders. It is a non-prying method that records the electrical activity of heart and hence suitable for prior diagnosis of cardiovascular diseases. Prevention of cardiovascular diseases is a vital task of any health care organization in any country as, on an average, around 50 million people are at risk of heart diseases like arrhythmia in the world [1]. When introduced into health care centres, auto diagnosis of heartbeat can be an appurtenance aid to assist the cardiologists in observing the ECG signals. Implementation of this model in cardiac-clinics to remotely scan an extensive volume of ECG scans will reduce the diagnosis time, the workload of doctors and the expense of ECG signal inspection in the cardiac hospitals.

From past decades number of researchers had put immense efforts into the automatic diagnosis of heart diseases. Most of them have utilized the dataset from MIT-BIH as it is a standard publicly available arrhythmia database. Amongst the two major steps in a standard machine learning-based classification problem i.e feature extraction and classification, many works are based on handcrafted or manual feature extraction methods utilizing the morphological features and time-varying dynamics of ECG. Sayadi et al. [2] utilized Kalman filter and Bayesian filtering approach for classification with high accuracy but limited to only two classes i.e. binary classification. Osowaski [3] utilized beat by beat analysis strategy with class-oriented scheme and used SVM classifier with Hermite transform coefficients, although the achieved accuracy and classification was good but needed manual descriptors. Hu et al. [4] used MOEs for ECG classification. Taken fourteen sample points on both sides of the R peak of ECG and trained the global classifier based on the number of patients and also combined local classifiers to develop a patient featured Mixture of experts classifier model. High accuracy is obtained, but the classification was not generalized. Researchers also developed some generic and automatic ECG classification based on various signal processing techniques, like frequency domain analysis [5], filter banks, wavelet methods [6]. Many approaches like statistical, support vector machines [7], and heuristic approaches were used to improve the precise classifications. Artificial neural network models and mixture-of-experts method are remarkable works, but they have not performed good in real time environment due to inter-patient variations of the ECG signals, and thus, fails in validations of new ECG data [8]. Imbalanced class of data and inaccuracy in validation proves them not to be fruitful for clinical applications. Even the CAD models are framed and tested using the above approaches often undergoes over-fitting and show degraded performance when verified in some different dataset [9].

The recent era introduces deep learning techniques which are getting wide popularity in all walks of engineering applications due to their ability to solve any practical classification/detection problem with intelligence at par with the human being. The deep learning-based approaches have also gained popularity in the biomedical area for automatic diagnosis applications. The deep-Convolutional neural network model and deep belief neural nets have become very useful in ECG multi-class classifications [10]. In this paper we proposed a CNN model that is not dependent on any look-up table, descriptor or handcrafted features. Instead it automatically deduces the patterns or intrinsic features from the ECG signal in its own and delivers the improved classified results.

We built a classifier that can classify the ECG signals in mainly five categories, namely Non-ectopic beats (Normal Beat), Supraventricular ectopic beats, Ventricular ectopic beats, Fusion Beats and Unknown Beats (shown in Fig.1 and Fig. 2). For this, we made a 1D CNN model with ReLU (Rectifier Linear Unit) as activation function, max-pooling, and dense layer as hidden layers. The proposed 1D CNN architecture is able to automatically learn and extract intrinsic features and classify ECG signals into their respective five classes. The proposed approach performs better than many existing custom-built feature extraction and manual feature selection-based methods. One of the major contribution in this work is the analytical handling of data imbalance problem. As the data includes different classes of ECG which are highly imbalanced in terms of different samples and they needs to be leveled with the same number of samples corresponding to each class for a fair training justice by CNN. The rest of the paper is arranged in different sections as follows: Section II describes the database taken in this study with comprehensive details. Section III outlines the methodology of the work including architecture and workflow. Section IV includes the performance summary of the result along with a brief discussion and comparison with previous progressive works. Finally, section V narrates the conclusion of this paper.

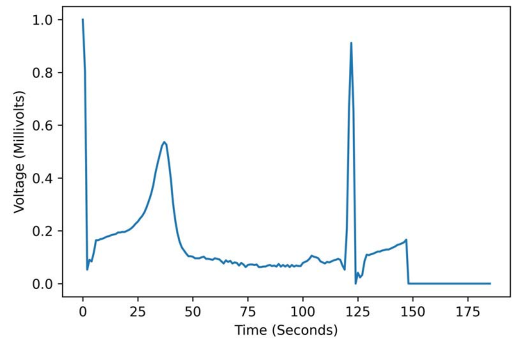

Figure 1. Normal beat

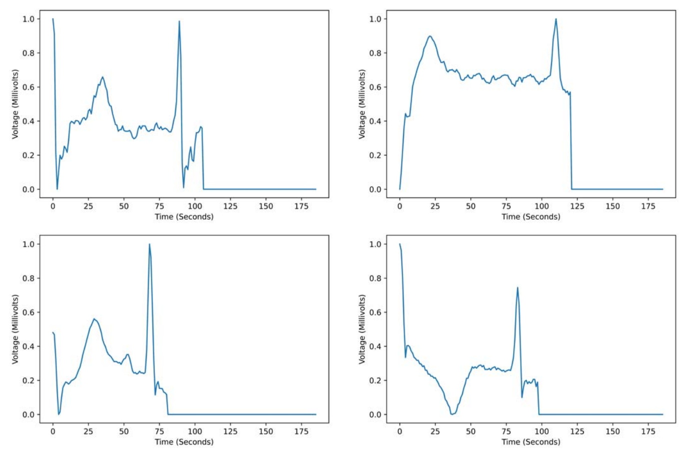

Figure 2. (a) Supra ventricular ectopic beats(top left) (b) Ventricular ectopic beats(bottom left)(c) Unknown beats(top right) (d) Fusion beats (bottom right)

II. Database

The data-set is fetched from the open-source MIT-BIH Arrhythmia database [11] hosted by physionet. It has multiple classes of heartbeat types and five amongst them containing significant samples are symbolized as N, S, V, F, Q indexed 0, 1, 2, 3, 4 respectively. N being normal beats, S being Supraventricular ectopic beats, V being Ventricular ectopic beats, Q being unknown beats and F being Fusion Beats. The dataset was sampled at 125Hz.A collection of 109,446 ECG beats are fetched for this work (see Table I) and the corresponding waveforms are shown in Fig. 1 and Fig. 2.

Table I
Dataset info: A summary table of the classes of beats

Type	Annotation	No. of beats
Normal beats	N	90592
Supra ventricular ectopic beats	S	2781
Ventricular ectopic beats	V	7235
Unknown beats	Q	8039
Fusion beats	F	802

III. Methodology

This CNN model is a complete sequential framework for classification. However, no denoising is done with the ECG data and used in raw form to match the real-world scenario. As seen in the previous section, the data used for evaluation is imbalanced in nature. In order to handle the minority classes having fewer data, resampling is done with the dataset to overcome the data imbalance problem. This step helped us in improving the overall performance of the 1D CNN model drastically. The dataset is then divided into training dataset and testing dataset in the ratio 78.2% and 21.8%. The overall steps involved in the proposed approach is demonstrated in the form of a flowchart in Fig. 4.

A. Pre-processing

The samples in the dataset (109449 initially) were not balanced i.e. different categories had different no. of samples corresponding to them e.g. there were more data points corresponding to normal beats as compared to fusion beats. So, to balance all the classes, we resampled the dataset and matched the sample levels by duplicating the pattern of samples of minority class to equalize the sample data of each class and got 100,000 samples every fifth of which belonged to the same category i.e. 20,000 samples per class. The sampling frequency used was 125Hz. Out of all the samples, 21.8% were reserved for testing and the rest were utilized for training the model.

B. Features Extraction

In this paper, we used learning-oriented feature extraction in the architecture using 1D CNN. Learning-based feature extraction depicts fine and deeper features of the signals. In other words, the model takes a batch of input and try to extract the inherent data-driven features of the ECG signal. Further iteration makes more accurate extraction and learning of these features from the input. Our CNN model comprises of convolutional, max pooling and dense layers. The convolution layer of CNN helps in capturing spatio-temporal features, while ReLu helps in extracting non-linear features out of the input ECG data. Max pooling layers are responsible for dimensionality reduction of the

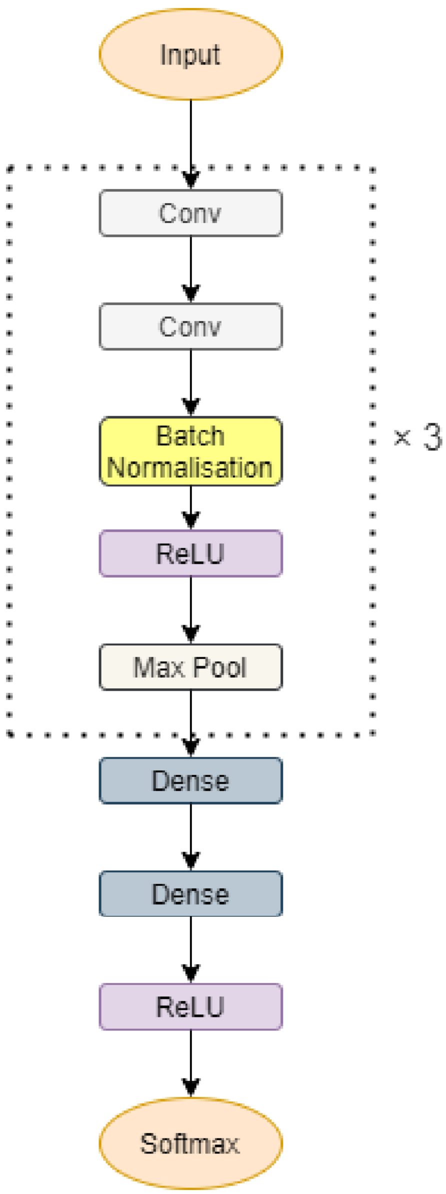

Figure 3. Architectural diagram of the presented 1D-CNN model

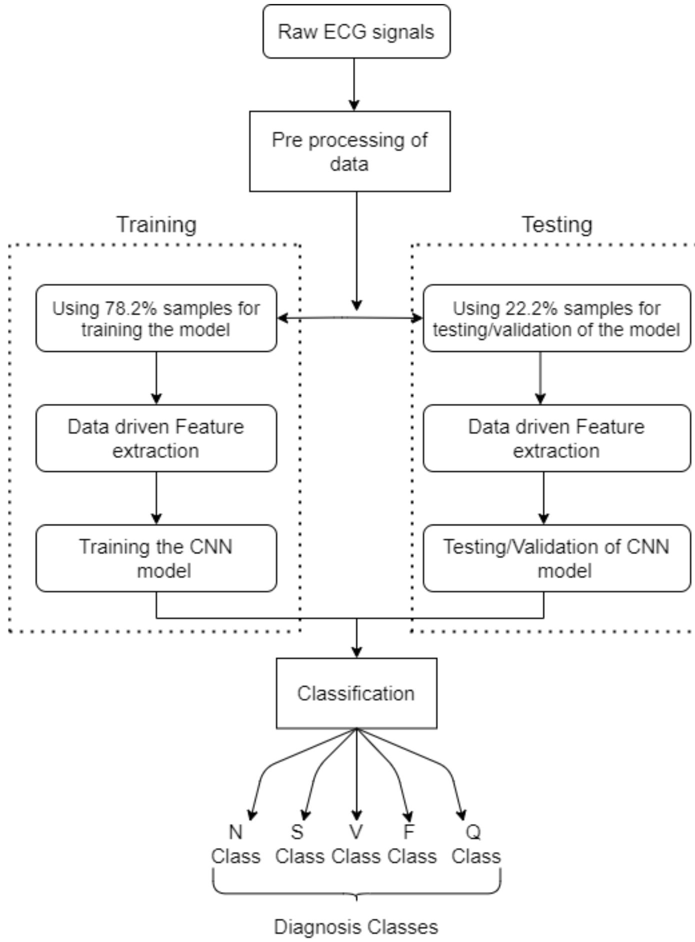

Figure 4. Flowchart of the proposed methodology

C. 1D CNN Model

As ECG signals are 1D signals, we employed a 1D CNN architecture for automatic heart disease classification using ECG signals.CNN is a prime choice in this work to analyse the deviation of time interval and amplitude against their nominal ranges to distinguish between normal and abnormal heartbeat.although a CNN requires a substantial computation and somewhat time consuming scheme for classification of images but a one dimensional signal like ECG is easy to deal with long duration episodes. The details of the CNN model have been discussed in detail in the following subsections.

1) Architecture Details: Our CNN model consists of convolutional, max pooling and dense layers. The batch normalization layer is used between every convolutional layer and max pooling layer. For increasing the accuracy further dense layer, and at last prediction layer for predicting the results. The convolution layer contains 64 filters with a stride of 2. Fully connected layer has 2048 neurons and for prediction layer softmax function is utilized for output in multi-class classification. The CNN is then trained on a training data set and the parameters of the CNN model are set with randomly initialized weights and biases which are lead into the network to train the model. back propagation process is responsible for weight updation of convolutional layers as well as dense layer which reflects the phenomena of auto-learning the features of waveform pattern itself by the neural net. The CNN model is then trained with 100000 sample heartbeats and validated using 21892 heartbeats.

2) ReLU Nonlinearity: In any neural network, the activation function performs the transformation of total added weighted input from the node into the activation of the node. The rectified linear activation function is a piece-wise linear function that will deliver the input directly if finds positive, else, it will reflect zero. It is the most popular activation function for many CNN models because it helps the CNN models attaining ease for training and better performance [10].

3) Pooling Layers: Pooling layers can help us in reducing the proportions of the feature maps. It helps in reducing the number of variables to learn, thus reducing the no of computations required to train the network [12]. There are two popular functions which are commonly used for pooling : Max Pooling: It gives the maximum secured value of each feature map. Average Pooling: To obtain the average value of each feature map, Average pooling is employed.

4) Fully connected Layer: In a neural network, Fully connected layer takes input from the preceding layer and calculates the probability scores of each class and gives the output vector of N-classes, N representing the no. of classes. Fully Connected Layers are commonly called as feed forward neural networks. [12] The input to the fully connected layer is the output obtained from the final Pooling Layer.

5) Optimization algorithm: Adam optimizer can be viewed as a combination of the two ideas of RMSprop and stochastic gradient descent with momentum [13]. The mathematical equation of the adam optimizer is given by the following:

$$\begin{aligned}&\nu_t = \beta_1 * \nu_{t-1} - (1-\beta_1) * g_t\\&s_t = \beta_2 * s_{t-1} - (1-\beta_2) * g_t^2\\&\Delta\omega_t = -\eta \frac{\nu_t}{\sqrt{s_t+\epsilon}} * g_t\\&\omega_{t+1} = \omega_t + \Delta\omega_t\end{aligned}$$

η : Initial Learning Rate of the model
g_t : Gradient at the time instant t along ω^3
v_t : Exponential Average value of gradients along ω_j
s_1 : Exponential average of the squares of gradients along ω_j
β_1, β_2 : Hyperparameters used

6) Hyperparameters: This CNN model was trained using back-propagation technique with a sample size taken as 10. The final hyper-parameter values used for tuning the CNN model are shown in Table III

Table II
DETAILS OF HYPERPARAMETERS USED IN 1D CNN TRAINING

Hyperparameters	**values**
Size of the input layer	(186×1)
Activation used	ReLu
Sample size	10
No. of classes	5
Optimizer used	Adam
Regularization	0.2
Learning rate(λ)	3×10^{-3}
Batch size	30
No. of epochs	20

The hyper-parameters, if chosen precisely, inhibit the over-fitting of data, direct the concurrence of the data, and steer the speed of learning in the process of training.

D. Performance parameters

The effectiveness of CNN model is determined in concerning percentage accuracy along with Precision, recall and F1 scores, which are helpful in performance evaluation in multi-class classification problem. The calculation of these measures are depicted from confusion matrix statistics having true-positive data(Tp), false-positive data (Fp), false-negative data (Fn) and true-negative (Tn) classification data and the whole occurrence ($\sum$) available in the database.

The metrics are defined as follows:

$$\textit{Overall Accuracy} = \frac{T_{p1} + T_{p2} + .. + T_{pN}}{\sum}$$

$$\textit{Recall} = \frac{T_p}{T_p + F_n}$$

$$\textit{Precision} = \frac{T_p}{T_p + F_p}$$

$$\textit{F1 score} = 2 * \frac{Precision * Recall}{Precision + Recall}$$

As we have an uneven class distribution in our dataset, we have up-sampled the data so that all classes present in the database become uniform and the model is not biased towards a particular class. Data augmentation has proven best for improving model accuracy. Accuracy is the best measure if false-positives and false-negatives shows quite similar cost. If there is a large difference reflected in the cost of false-positives and false-negatives, the best way is to see the Precision and Recall measures which in turn produces another measure called F1 score. Its performance is excellent in the case of sparse gradient and poor performance in non-convex optimization of neural networks.

IV. RESULTS AND DISCUSSION

The performance evaluation of the presented approach has been carried out using database from MIT-BIH. We have used 100000 sample heartbeats for training and 21892 heartbeats were used for testing the model. The model is trained with a total of 20 numbers of epochs with batch size as 30. Fig. 5

and Fig. 6 demonstrates the model accuracy curves and loss curves of the model with respect to the number of epochs. These curves show that model is trained properly after the optimal value of network weights has been achieved as the accuracy and loss get saturated. Also, the validation loss appears nearly close to training loss, which reveals the fine optimization of the model with minimum loss. After testing the model with unknown heartbeats, this model has achieved 97.17% overall accuracy. Individual accuracy of each class are also calculated and shown in TABLE III. The model attains a maximum accuracy for the class of non-ectotic beats with 99.3% while the supra ventricular ectopic beats achieve the lowest accuracy of 95.3%. The confusion matrix of the presented CNN model is also obtained and displayed in Fig.7. The confusion matrix summarizes the classification of individual classes. The correctly classified classes are highlighted in the diagonals of the matrix. The class-S and class-F heartbeats have little more miss-classification while the other classes shown better classification results. The comparison of our work with the other standing works is tabulated in Table IV. The compared works include both types of work, manually handcrafted feature extraction and feature selection-based work and deep learning-based works. Acharya et al. [9] presented a similar classification using deep CNN but with poor optimization of parameters which in turn produces the accuracy of only 94.03%. Shadmand et al. [15] have utilized BBNN (block based neural network with Network structure and the weights in which he utilized the particle swarm optimization method and obtained the accuracy of 97% which is marginally low to our work. The proposed work outperforms other machine learning-based approaches [14, 16]. The use of ADAM optimization in our CNN model helped the model to deliver an improved performance. The F1 score of our model is 0.99 (shown in Table III), which clearly shows the robustness and data handling capacity of this model for imbalanced data (under multi-class classification). However, the performance can be further improved using CNN coupled with fast signal processing models that will be robust towards ECG noise.

Table III
SUMMARY OF THE CLASSIFICATION PERFORMANCE

Classes	Precision	Recall	F1 score	Accuracy(%)
Non-ectotic beats	0.99	0.98	0.99	99.3
Supraventricular ectopic beats	0.71	0.84	0.77	95.3
Ventricular ectopic beats	0.92	0.95	0.94	98.4
Fusion beats	0.57	0.89	0.70	96
Unknown beats	0.98	0.99	0.98	99

V. CONCLUSION

A deep residual CNN approach is conferred in this work to perform automatic detection and classification of various types of ECG heartbeats, which holds vital importance in prior identification of cardiovascular diseases. The 1D CNN model

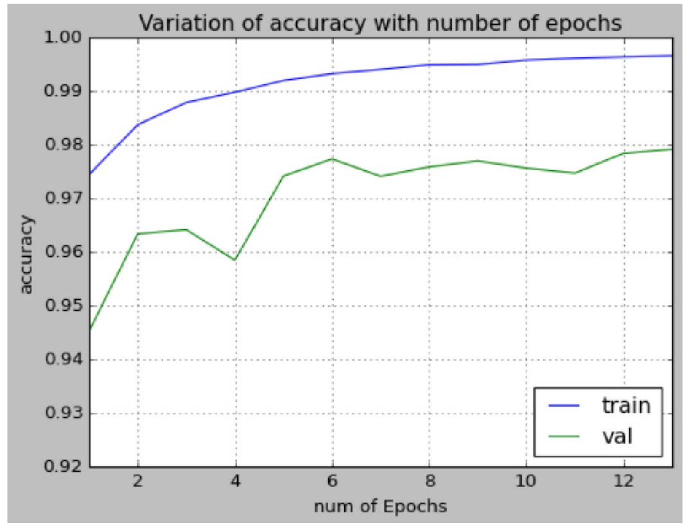

Figure 5. Variation of accuracy with epochs

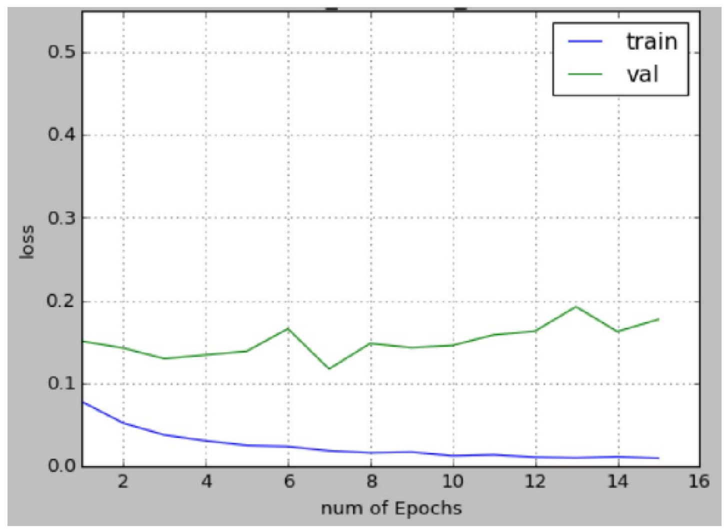

Figure 6. Variation of loss with epochs

Predicted classes-----→

True classes----------↓

	N	S	V	F	Q
N	17718	261	51	62	26
S	76	466	7	6	1
V	33	3	1378	31	3
F	7	0	9	146	0
Q	11	2	1	1	1593

Figure 7. Confusion matrix of the classification model

Table IV
COMPARISON WITH PREVIOUS WORK IN TERMS OF AVERAGE ACCURACY

Work	**Approach**	**Average Accuracy**(%)
Acharya et al. [9]	Augmentation along with CNN	93.5%
Martis et al. [14]	DWT with SVM	93.8%
Li et al. [16]	DWT and random forest	94.6%
Shadmand et al. [15]	BBNN + PSO	97%
This Paper	Deep residual 1D CNN	97.4%

that we employed can easily classify five unique ECG heartbeat classes with relatively better overall accuracy compared to contemporary works. The major highlights of the work are that it is an automatic framework of auto-diagnosis and hence requires no additional handcrafted feature extraction, selection or classification at any stage. moreover the problem of data imbalance is perfectly resolved by re-sampling method. Along with overall accuracy, this model secured a superior F1 score compared to similar works. Since most of the real-time auto-diagnosis in clinical practices deals with imbalanced data and thus a better F1 score metric of the proposed model presents it as a suitable candidate for practical applications. In future we may apply Long Short Term Memory (LSTM) for further refinement of the model. Since the ECG data are time-series signals having long term dependencies and thus LSTM may be a good choice against CNN.

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