1D Convolutional Neural Network Based ECG Classification System for Cardiovascular Disease Detection

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***Abstract*—The study of cardiovascular disease has always been a popular medical topic around the world. This paper presents a deep learning (DL) method based on a convolutional neural network (CNN) algorithm to identify patients' cardiovascular arrhythmia by using a multi-lead ECG signal. In addition to the input and output layers, the proposed CNN model includes six layers, i.e., two convolution layers, two pooling layers, and two fully connected layers within a residual block. The focus of this work is to classify the ECG signals into five classes; namely, Left Bundle Branch Block (LBBB), Right Bundle Branch Block (RBBB), Atrial Premature Contraction (APC), Premature Ventricular Contraction (PVC), and Normal beat(N). We evaluated the proposed method by using the MIT-BIH arrhythmia dataset. According to the results, our proposed method achieved an average accuracy of 97.8% for the classification of 13,200 instances.**

***Index Terms*—Healthcare, cardiovascular disease, electrocardiogram (ECG), convolutional neural network (CNN), deep learning.**

I. INTRODUCTION

Cardiovascular diseases are a global public health problem since they are behind about 30% of global mortality and 10% of global diseases.

The traditional CVD diagnosis paradigm is based on an individual patient's medical history and clinical examinations. These results are interpreted according to a set of quantitative medical parameters to classify the patients based on the taxonomy of medical diseases. Unfortunately, the traditional rule-based diagnosis paradigm becomes inefficient to deal with a large amount of heterogeneous data which requires significant analysis and medical expertise to achieve adequate accuracy. The problem is more pronounced in developing countries where there is a lack of medical experts and clinical equipment.

Electrocardiogram (ECG), as reachable and non-invasive monitoring, is the most frequently used to screen heart activity [4]. By scrupulously analyzing ECG morphology, various types of heartbeats usually can be recognized. However, ECG is not widely useful for non-stationary signals. This last's morphology varies for time, and these variations are shown not only between different cases but also within the same patient [5]. The early diagnosis of arrhythmia mainly relies on experienced doctors to interpret the characteristics of ECG signals. It requires high professional knowledge of doctors. Computer-aided detection and diagnosis in ECG signals for cardiovascular diseases are gaining expanding consideration. However, developing and selecting the highest performing diagnostic model suitable for clinical implications is very difficult. Consequently, many ECG heartbeat recognition and classification algorithms were developed based on different techniques such as wavelet transform [6], hidden Markov models [7], support vector machine [8], and artificial neural networks [9]. The majority of these ECG beat classification methods perform well on training but give poor accuracy due to the importance of precision in the medical field. A deep learning-based ECG classification system using convolutional neural networks (CNNs) is proposed in this study to classify five types of heartbeat. Considering deep learning and especially CNNs have obtained much attention in recent years due to their remarkable performance in the field of image processing, natural signal processing and has great potential to recognize signals.

II. RELATED WORK

The ECG heartbeat classification is divided into four steps: preprocessing, heartbeat segmentation, feature extraction, and classification. The signal preprocessing targets to eliminate various types of noise in the ECG signal including artifacts and baseline drift in the signal. Numerous methods have been reported in the literature for ECG signal denoising [10]. Among these methods are the traditional filtering operations such as the use of low-pass filters, Weiner filters, adaptive filters [11], and filter banks [12]. Furthermore, many researchers have done related work on the classification of ECG signals and

have used many traditional machine learning algorithms for feature extraction. Moreover, some statistical methods such as principal component analysis (PCA) [13], [14], higher-order statistic (HOS) technique [2], and linear discriminant analysis (LDA) were used for feature extraction of ECG signals.
Most studies affirmed that wavelet transform (WT) has a good result for ECG signal feature extraction because it can extract simultaneously frequency and time information [15]. In [16], they used the WT method to classify five types of beats and they achieved 97.29% accuracy.
Recently, most methods used the deep learning model for classification, which combined the two steps features extraction and classification. For arrhythmia heartbeats classification, Acharya et al. [1] applied nine layers of CNN and achieved an accuracy of 94.03% and 93.47% with original and denoising signals respectively. Note that, with the increase of network layers, the learning ability of the CNN model will be upgraded. However, simply stacking the number of network layers cannot improve the accuracy. This problem is called the vanishing/exploding gradients [3]. It has been largely solved by normalized initialization and intermediate normalized methods [17], [18]. Indeed, even with these techniques, the training of deep neural networks still has the same aforementioned issue that the accuracy decreases with the expansion of network depth. Although, in [19], they used a simple CNN model composed of five layers and achieved an accuracy of 97.5%.

In this work, we begin by adopting the coherent latter approach [19], by adding two convolutional layers. To avoid the problem of vanishing/exploding gradients, we added a residual block that contains these two convolutional layers hidden to classify five types of a heartbeat. As a result, we outperformed in terms of accuracy.

III. Methodology

A. Method Overview

To classify the input ECG signal into 5 classes, the recordings are first filtered by moving average filter and Daubechies 4 wavelet transform with 8 levels. Each record is segmented into 200 samples based on the MIT-BIH annotations. Then, a reduction of dimension to 180 samples is applied before training. Finally, the processed heartbeat segments are used directly as input data of the CNN model to achieve the feature extraction and classification of ECG signals. An overview of the proposed approach is given in Figure 1.

B. Data Acquisition and Selection

In this work, we extracted data from the MIT-BIH database [20] which is hosted at PhysioNet (http://www.physionet.org) [21]. This database includes 48 two-channel dynamic ECG records. Each record is up to 30 minutes with a sampling frequency of 360HZ. The MT-BIH provides an annotation of each beat to know to which class it belongs. The number of beats per class in the Mit-Bih database is shown in Figure I. 44 ECG records of the lead II (MLII) were selected from the database to train and verify the feasibility of our method. As indicated by the AAMI standard(102, 104, 107, 217), the 4 beats were excluded as a result of their helpless signal quality for post preparation. We divided our data into two sets, training set (50%) and test set (50%). Each set includes 13200 non-duplicate instances. Table II resumes the number of data selected per class for each dataset.

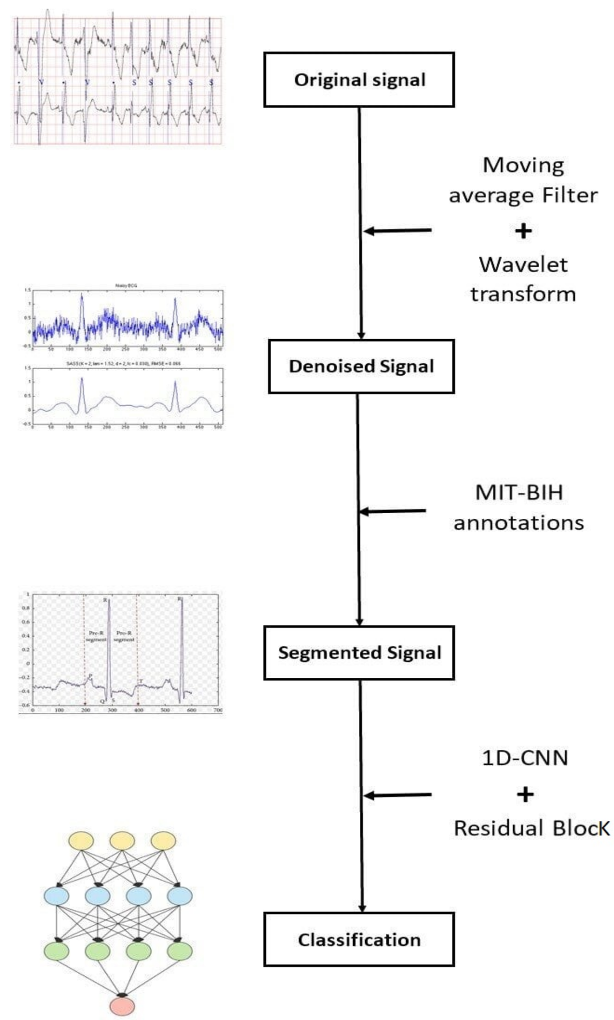

Fig. 1. Diagram of model structure

TABLE I
A SUMMARY TABLE WITH THE BREAKDOWN OF THE 5 CLASSES OF BEAT SUBTYPES IN MIT-BIH.

Heartbeat Types	Annotation	Total
Normal Rhythm NOR	N	74607
Left Bundle Branch Block LBBB	L	8069
Right Bundle Branch Block RBBB	R	7250
Premature Ventricular Contraction PVC	V	7127
Atrial Premature Contraction APC	A	2514

Fig. 2. Waveforms of five types of heartbeats in MLII lead.

TABLE II
THE NUMBER OF ECG BEATS PER CLASS USED.

Arrhythmia Types	Training set	Testing set
NOR	3000	3000
LBBB	3000	3000
RBBB	3000	3000
PVC	3000	3000
APC	1200	1200

C. Data Processing

In general, due to the weakness of the ECG signal and the influence of acquisition equipment, many interference noises would be easily mixed during the acquisition process. However, these noises are very unfavorable for the analysis of ECG signals. Therefore, effective preprocessing of ECG signals is a key issue before the classification of ECG. Common ECG signal interference noises include power frequency interference, baseline drift, and electromyographic interference. To denoise ECG signal moving average filter and Daubechies 4 wavelet transform are applied together. In practical cases, noise signals usually appear as high-frequency signals in signal processing, but useful signals appear as either low-frequency or more smooth signals. When the wavelet transform decomposes the signals, the ones with noise get the high-frequency wavelet coefficients. Then, the threshold processing high-frequency wavelet coefficients to eliminate electromyographic noise and power line interference. Finally, signals are reconstructed using the inverse wavelet transform. While moving the average filter eliminates the baseline drift noise. Figure 3 shows the effect of denoising.

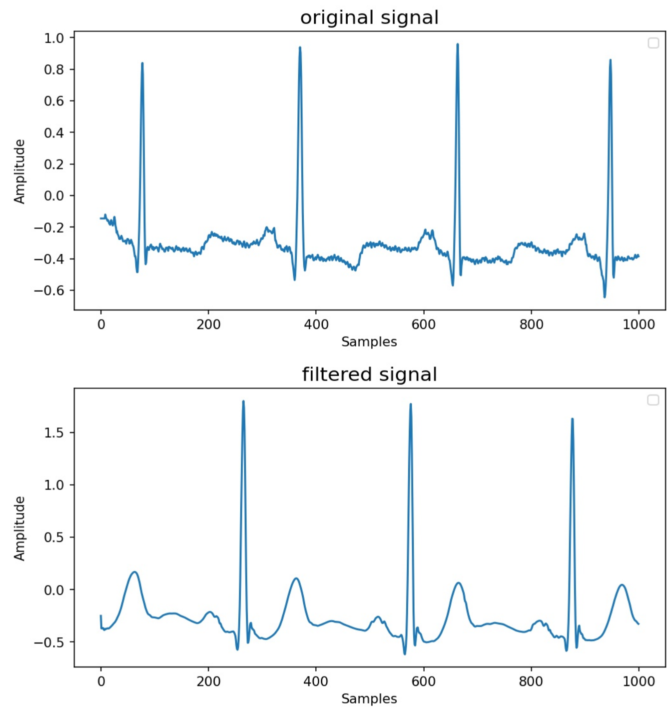

Fig. 3. The diagram of the denoising effect

D. Heartbeat Segmentation

The three essential components of a heart cycle are QRS complex, T wave, and P wave which are named fiducial focuses. The information about the R-peak locations (annotations) given in the database was used for heartbeat segmentation. A single heartbeat consists of 100 samples before R-peak and 100 samples after R-peak. This segment size contains the maximum information of a single heartbeat as shown in Figure 4. Then we applied a down-sampling function to 180 samples before used as an input to the CNN model.

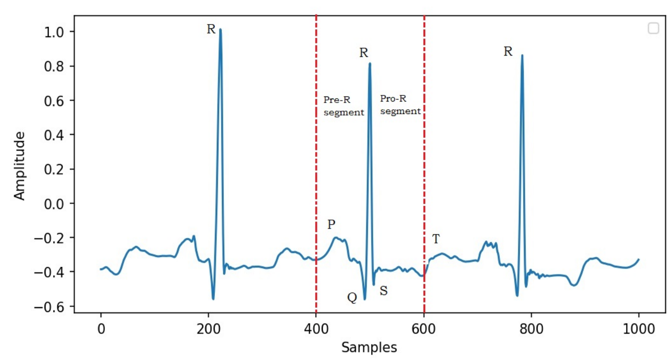

Fig. 4. the diagram of heartbeat segmentation

E. CNN architecture

Traditional machine learning methods use different hand-engineered features to obtain representations of input data. In

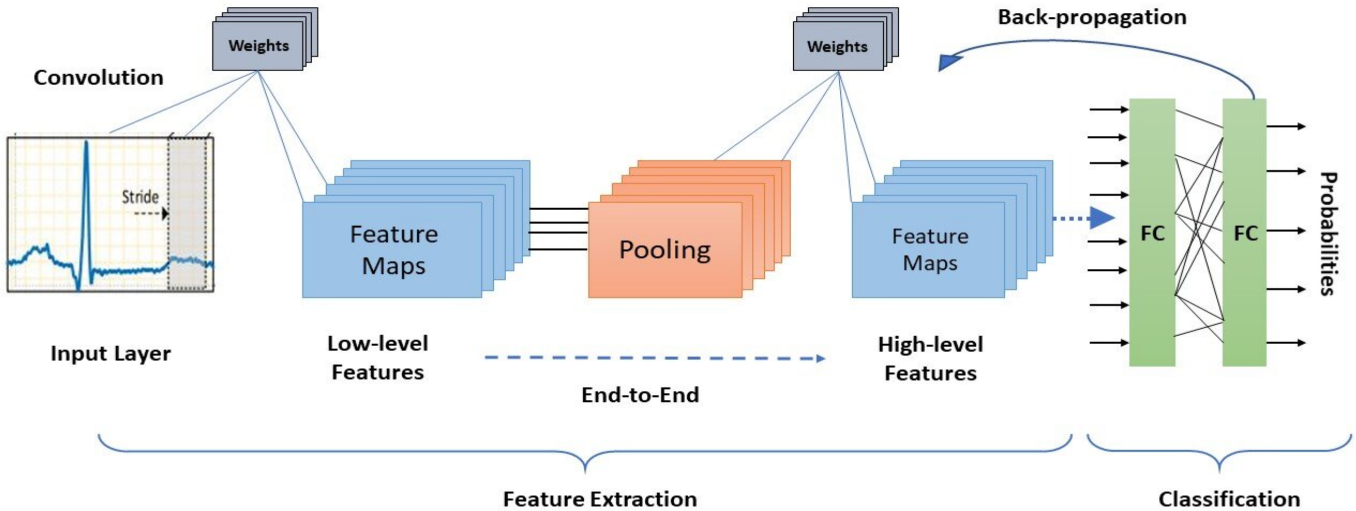

Fig. 5. CNN architecture

the case of deep learning, there is an automatic learning process from the low-level representations obtained from multiple layers to the higher abstract representations [22] as shown in Figure 5.

CNN is one of the most commonly used types of artificial neural networks. Conceptually, a CNN resembles a multilayer perceptron (MLP). An MLP becomes a deep MLP when more than one hidden layer is added to the network. In MLP each perceptron is connected with every other perceptron which makes the problem that the number of total parameters can grow very high. This is inefficient because there is redundancy in such high dimensions. Another disadvantage is that it disregards spatial information. It takes flattened vectors as inputs. The CNN model resolved these problems by taking into account local connectivity. Also, all layers are partially connected rather than fully connected.

In CNN architecture, there are 3 basic layers– convolution layer, pooling layer, and fully-connected layer. As well, it is composed of two parts: the first one is a feature extractor, which automatically learns the features from raw input data, while the second part is a fully connected multi-layer perceptron (MLP). The feature extractor includes the first two-layer: the convolution layer and the pooling layer. The first layer uses filters and performs convolution operations as it is scanning the input with respect to its dimensions. Its hyper-parameters include the filter size and stride. The resulting output, called feature map or activation map, is added by a bias and then put through the activation function to produce a feature map for the next layer. Let $x_i^0 = [X_1, X_2 ....X_n]$ as the beat samples data input vector, where n is the number of samples per beat. The output of the convolution layer is:

$$c_i^{l,j} = \sigma(b_j + \Sigma_{m=1}^{M} w_m^j x_{i+m-1}^{0j}), \quad (1)$$

where l is the layer index, σ is the activation function, b is the bias term for the j^{th} feature map, M is the kernel/filter size, w_m^j is the weight for the j^{th} feature map and m^{th} filter index. The layer just after the convolution layer is the pooling layer. It is a down-sampling operation. It serves to reduce the size of the activation map that results in the generation of medium-level features. The pooling of a feature map in a layer is given by

$$P_i^{l,j} = \underset{r \in R}{max}(c_{i \times T+r}^{l,j}), \quad (2)$$

where R is the size of the pooling window and T is the pooling stride. The last layer is the fully connected layer (FC). It operates on a flattened input where each input is connected to all neurons. In each neural, an activation function was applied which is a mathematical equation that determines the output of a neural network. The function is attached to each neuron in the network and determines whether it should be activated or not, based on whether each neuron's input is relevant for the model's prediction. In this study, ReLu [23] is used as an activation function. Considering It has become the default activation function for many types of neural networks. there is no complicated math. Therefore The model can take less time to train or run. Mathematically, it is defined as: $y = max(0, x)$. Visually, it looks like Figure 6: For beat classification, a simple softmax classifier is used and is placed at the last of CNN architecture. It is a mathematical function that converts a vector of numbers into a vector

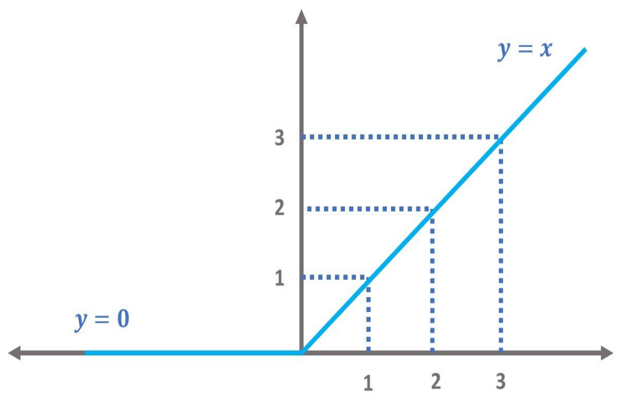

Fig. 6. Rectified linear activation function(ReLu)

of probabilities, where the probabilities of each value are proportional to the relative scale of each value in the vector [24]. When the predicted output is obtained by the forward propagation, the prediction error is calculated using the loss function. Then Backpropagation is performed in which the predicted error propagates back on each parameter of each layer and weights are adjusted by computing the gradient of the convolutional weights as shown in Figure 5. Forward and backward propagation is repeated until specific numbers of epochs are reached.

The depth of the deep learning network is an important factor that affects the final classification and recognition results. The usual idea is to make the design of the neural network as deep as possible. However, at a certain point increasing the depth will degrade the performance of the deep learning network. This problem is known as vanishing/exploding gradients, which makes network training more difficult. This challenge was solved by adding a residual block. It is a stack of layers set in such a way that the output of a layer is taken and added to another layer deeper in the block. It is an improved deep learning algorithm for CNN, which avoids these problems by using "shortcut connections" that skip multiple network layers [25].

The proposed model is an improvement of the model proposed in [19] by adding two convolutional layers. To avoid the aforementioned issue, we added the two layers in a residual block. Our proposed model architecture starts with an Input layer which is a segment of ECG signals with 180 sampling points. It contains 2 convolutional layers (the size of kernels, the strides, and the number of filters are 3, 2, and 18 respectively), 2 pooling layers (the pooling size and the strides are 2 and 2 respectively), 2 fully connected layers, and a softmax layer. After each convolutional layer rectified Linear function(ReLu) was applied. As shown in Figure 7, there is a residual block that contains 2 convolutional layers (18 convolution kernels with a length of 7 and stride 2).

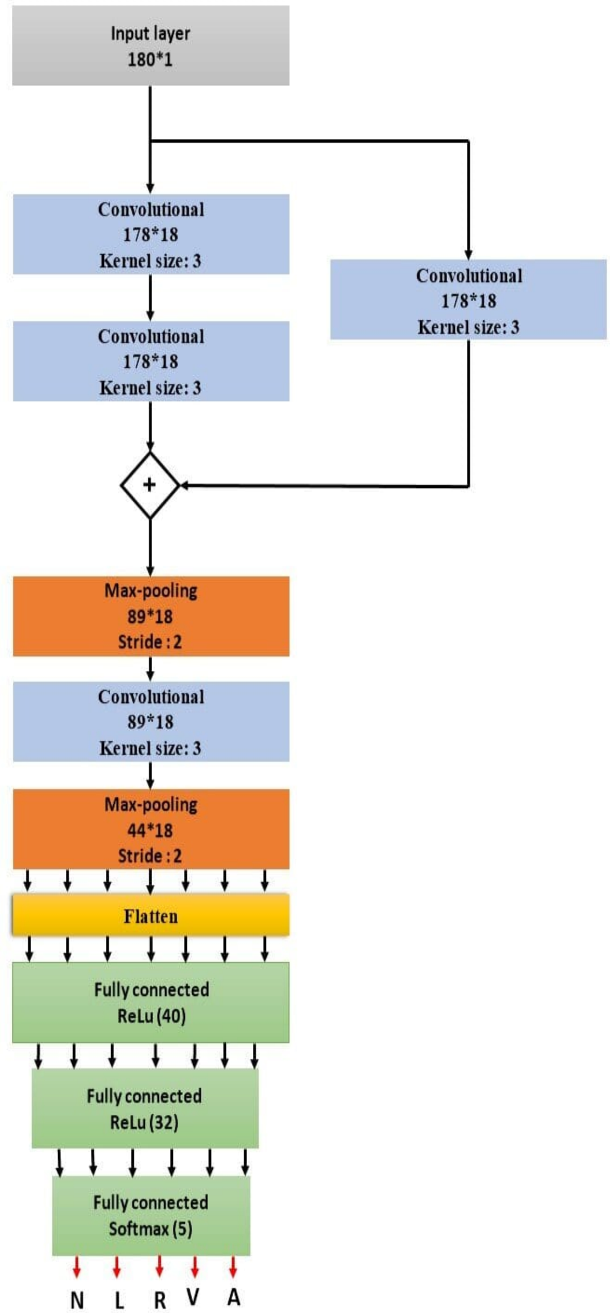

Fig. 7. Proposed CNN model

IV. Experimental Results

We have trained our model on a workstation with Intel(R) Core(TM) i5 6200U CPU @2.30GHz processor and 8GB RAM. Our experimental data came from the international standard ECG database MIT-BIH. It has a precise and comprehensive expert annotation and generally utilized in ECG research. This data was divided into two sets for training and testing, each contains 13200 instances. The number of epochs for training was 300. In each epoch, the batch size used for the dataset was 32, and it was extended over all input data. Also, the learning rate used is 0.001. we use signal rescaling to the range [-1,1] of data before training which gives better accuracy than without normalization. The accuracy and loss curves for training and validation are shown in figures 8 and 9. To evaluate our model we used the following metrics: accuracy, specificity, and sensitivity as depicted by the equations (3), (4), and (5) where TP is the true positive, TN is the true negative, FP is the false positive and FN is the false negative. The proposed CNN model achieved 97.8% of accuracy, 97.0% of sensitivity, and 97.32% of specificity after experimental verification.

$$accuracy = \frac{TP + TN}{TN + FP + TP + FN} \times 100 \tag{3}$$

$$specificity = \frac{TN}{TN + FP} \times 100 \tag{4}$$

$$sensitivity = \frac{TP}{TP + FN} \times 100 \tag{5}$$

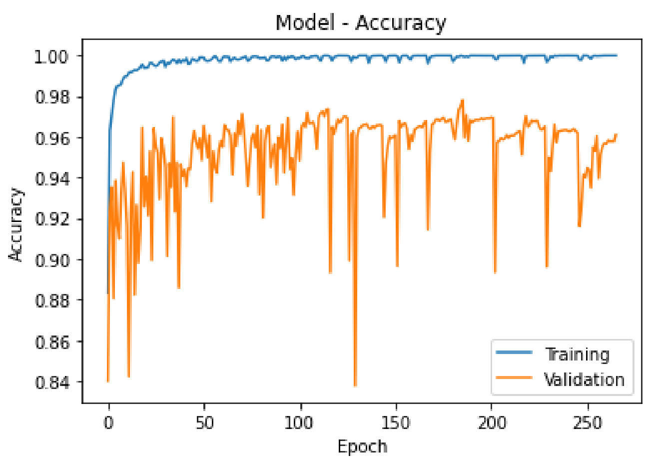

Fig. 8. Accuracy of the trained model

The confusion matrix of ECG beat classification for test data is given in Figure 10.
The comparison of the current work with other existing algorithms is given in Table III. We can show that the proposed method improves the accuracy of ECG classification compared to the other proposed methods by using moving average filter and wavelet transform for preprocessing step and 1D-CNN with residual block for classification. The five heartbeat types in this study are ”N.L.R.A.V”. Each type represents a single arrhythmia signal. However, the AAMI standard rules classified ECG signals into five types: normal beats (N), supraventricular ectopic beats (S), ventricular ectopic beats (V), fusion beats (F), and unclassifiable beats (Q).

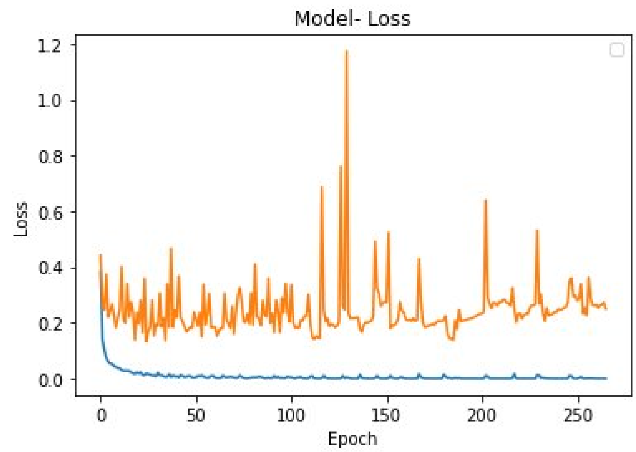

Fig. 9. Loss of trained model

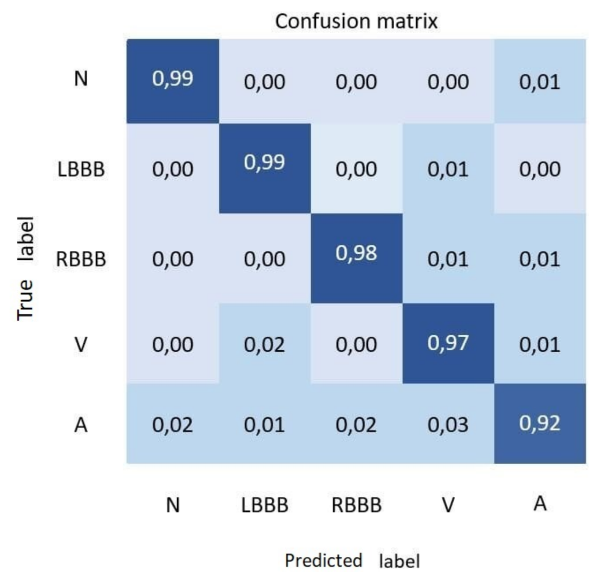

Fig. 10. Confusion matrix

V. Conclusion

The proposed model is sound to be introduced into clinical as an adjunct tool to help the cardiologists to recognize patients' cardiovascular arrhythmia. In clinical use, this model will reduce the patient waiting time and the cost of ECG signal processing in hospitals. We should emphasize that a model with high accuracy in diagnosing cardiovascular disease will reduce medical errors. In this work, we used moving average filter and wavelet transform 4 in 8 levels for denoising signal. In addition to input and output layers, our CNN model includes 6 layers with a residual block to classifier five types of heartbeat. In the experimental results, we used the standard Mitbih database (lead II) to test the trained model which achieved an accuracy of 97.8%. In future work, we aim to improve accuracy by using residual architecture like ResNet or DenseNet.

TABLE III
COMPARISON WITH OTHER METHODS

Article	Class	Preprocessing	Feature Extraction	Classification	Accuracy
Acharya et al. [1]	N,S,V,F,Q	Wavelet transform	CNN	Softmax	94.03%
Zubair et al. [29]	N,S,V,F,Q	Band pass filter	CNN	Softmax	92.7%
Thomas et al. [26]	N,L,R,V,P	Band pass filter	DWT DTCWT	ANN	91.23% 94.64%
Isin and Ozdalili [27]	N,R,P	moving average filter Band-stop filter	transferred deep learning(AlexNet)	Softmax	92%
Li et al. [28]	N,S,V,F,Q	low-pass finite impulse response (FIR) filter	WPE + RR	RF(Random Forests)	94.61%
R.J.Martis et al. [14]	N,L,R,V,A	Wavelet transform	Pan Tompkins + PCA	NN+LS-SVM	93%
Li et al [19]	N,L,R,V,A	Wavelet Combination	1D-CNN	Softmax	97.5%
Proposed method	**N,L,R,V,A**	**Moving average filter Wavelet transform**	**1D-CNN + Residual Block**	**Softmax**	**97.8%**

REFERENCES

[1] U Rajendra Acharya, Shu Lih Oh, Yuki Hagiwara, Jen HongTan, Muhammad Adam, Arkadiusz Gertych, and RuSan Tan. A deep convolutional neural network model to clas-sify heartbeats.Computers in biology and medicine, 89:389–396, 2017.

[2] Rashid Ghorbani Afkhami, Ghanbar Azarnia, and Moham-mad Ali Tinati. Cardiac arrhythmia classification using sta-tistical and mixture modeling features of ecg signals.PatternRecognition Letters, 70:45–51, 2016.

[3] Yoshua Bengio, Patrice Simard, and Paolo Frasconi. Learn-ing long-term dependencies with gradient descent is difficult.IEEE transactions on neural networks, 5(2):157–166, 1994

[4] Fan Liu, Xingshe Zhou, Zhu Wang, Tianben Wang, and Hongbo Ni. A light-weight data preprocessing and integrative scheduling framework for health monitoring. In 2016 IEEE-EMBS International Conference on Biomedical and Health Informatics (BHI), pages 192–195. IEEE, 2016.

[5] Fei-yan Zhou, Lin-peng Jin, and Jun Dong. Premature ventricular contraction detection combining deep neural networks and rules inference. Artificial intelligence in medicine, 79:42–51, 2017.

[6] Rudi Hoekema, Gerard JH Uijen, and Adriaan Van Oost- ´ erom. Geometrical aspects of the interindividual variability of multilead ecg recordings. IEEE Transactions on Biomedical Engineering, 48(5):551–559, 2001.

[7] Douglas A Coast, Richard M Stern, Gerald G Cano, and Stanley A Briller. An approach to cardiac arrhythmia analysis using hidden markov models. IEEE Transactions on biomedical Engineering, 37(9):826–836, 1990

[8] Stanislaw Osowski, Linh Tran Hoai, and Tomasz Markiewicz. Support vector machine-based expert system for reliable heartbeat recognition. IEEE transactions on biomedical engineering, 51(4):582–589, 2004.

[9] Yu Hen Hu, Willis J Tompkins, Jose L Urrusti, and Valtino X Afonso. Applications of artificial neural networks for ecg signal detection and classification. Journal of electrocardiology, 26:66–73, 1993.

[10] Gayadhar Pradhan Pratik Singh, S. Shahnawazuddin. An efficient ecg denoising technique based on non-local means estimation and modified empirical mode decomposition. Circuits Syst Signal Process, 2018.

[11] M.A. Slonim T.-Y.M. Slonim and E.A. Ovsyscher. The use of simple fir filters for filtering of ecg signals and a new method for post-filter signal reconstruction. Proceedings of Computers in Cardiology Conference, 1993.

[12] T.Q. Nguyen Shen Luo V.X. Afonso, W.J. Tompkins. Ecg beat detection using filter banks. IEEE Transactions on Biomedical Engineering, 1999.

[13] Shanshan Chen, Wei Hua, Zhi Li, Jian Li, and Xingjiao Gao. Heartbeat classification using projected and dynamic features of ecg signal. Biomedical Signal Processing and Control, 31:165–173, 2017.

[14] Roshan Joy Martis, U Rajendra Acharya, KM Mandana, Ajoy Kumar Ray, and Chandan Chakraborty. Cardiac decision making using higher order spectra. Biomedical Signal Processing and Control, 8(2):193–203, 2013.

[15] Chia-Hung Lin, Yi-Chun Du, and Tainsong Chen. Adaptive wavelet network for multiple cardiac arrhythmias recognition. Expert Systems with Applications, 34(4):2601–2611, 2008.

[16] OZAL YILDIRIM. Ecg beat detection and classification sys- ¨ tem using wavelet transform and online sequential elm. Journal of Mechanics in Medicine and Biology, 19(01):1940008, 2019.

[17] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Delving deep into rectifiers: Surpassing human-level performance on imagenet classification. In Proceedings of the IEEE International Conference on Computer Vision (ICCV), December 2015.

[18] Andrew M Saxe, James L McClelland, and Surya Ganguli. Exact solutions to the nonlinear dynamics of learning in deep linear neural networks. arXiv preprint arXiv:1312.6120, 2013.

[19] Dan Li, Jianxin Zhang, Qiang Zhang, and Xiaopeng Wei. Classification of ecg signals based on 1d convolution neural network. In 2017 IEEE 19th International Conference on eHealth Networking, Applications and Services (Healthcom), pages 1–6. IEEE, 2017.

[20] George B Moody and Roger G Mark. The impact of the mitbih arrhythmia database. IEEE Engineering in Medicine and Biology Magazine, 20(3):45–50, 2001.

[21] Ary L Goldberger, Luis AN Amaral, Leon Glass, Jeffrey M Hausdorff, Plamen Ch Ivanov, Roger G Mark, Joseph E Mietus, George B Moody, Chung-Kang Peng, and H Eugene Stanley. Physiobank, physiotoolkit, and physionet: components of a new research resource for complex physiologic signals. circulation, 101(23):e215–e220, 2000.

[22] Yann LeCun, Yoshua Bengio, and Geoffrey Hinton. Deep learning. nature, 521(7553):436–444, 2015.

[23] Prajit Ramachandran, Barret Zoph, and Quoc V Le. Searching for activation functions. arXiv preprint arXiv:1710.05941, 2017.

[24] Jiuxiang Gu, Zhenhua Wang, Jason Kuen, Lianyang Ma, Amir Shahroudy, Bing Shuai, Ting Liu, Xingxing Wang, Gang Wang, Jianfei Cai, et al. Recent advances in convolutional neural networks. Pattern Recognition, 77:354–377, 2018.

[25] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), June 2016.

[26] Manu Thomas, Manab Kr Das, and Samit Ari. Automatic ecg arrhythmia classification using dual tree complex wavelet based features. AEU-International Journal of Electronics and Communications, 69(4):715–721, 2015.
[27] Ali Isin and Selen Ozdalili. Cardiac arrhythmia detection using deep learning. Procedia computer science, 120:268– 275, 2017
[28] Taiyong Li and Min Zhou. Ecg classification using wavelet packet entropy and random forests. Entropy, 18(8):285, 2016.
[29] Muhammad Zubair, Jinsul Kim, and Changwoo Yoon. An automated ecg beat classification system using convolutional neural networks. In 2016 6th international conference on IT convergence and security (ICITCS), pages 1–5. IEEE, 2016.