A Classification Method for ECG Signals Based on Convolutional Neural Network

Yuan Yang[1], Jin Guo[1*], Fengze Lyu[1], Shuxiang Guo[1,2]

1. The Key Laboratory of Convergence Biomedical Engineering System and Healthcare Technology, The Ministry of Industry and Information Technology, Beijing Institute of Technology, Beijing 100081, China

2. The Department of Electronic and Electrical Engineering, Southern University of Science and Technology, Shenzhen, Guangdong 518055, China

Email: { 3120221428 & guojin }@bit.edu.cn; *Corresponding author

Abstract – **Cardiovascular disease is a chronic disease with high incidence, high disability and high mortality, which poses a great threat to the life and health of people all over the world. At present, the incidence and mortality of cardiovascular disease are increasing year by year worldwide, so the prevention and treatment of cardiovascular disease has become a top priority. In recent years, with the development of computer technology in the field of auxiliary diagnosis and treatment, the research on automatic classification of Electrocardiogram (ECG) signals has ushered in new opportunities. In this study, ECG signals are taken as the research object, to analyze the auxiliary diagnosis needs of users such as patients and pathologists. This study mainly uses ECG data from MIT-BIH database, combined with relevant preprocessing knowledge and deep learning classification model, to achieve ECG reading, denoising, segmentation, classification and so on. It can effectively improve the efficiency of diagnosis. It has certain reference value for assisting users to diagnose arrhythmia.**

Index Terms – *ECG Signals, Auxiliary Diagnostic Platform, Convolutional Neural Network.*

I. INTRODUCTION

Cardiovascular disease is a chronic disease characterized by high morbidity, high disability and high mortality. The incidence and mortality of cardiovascular diseases are increasing all over the world. According to the World Health Organization, in 2019, cardiovascular diseases caused about 17.9 million deaths, accounting for 31% of all deaths worldwide. Of these, 85% die from heart disease or stroke [1].

Clinically, Electrocardiogram (ECG), as an important signal diagnostic tool, is usually used for the detection of arrhythmias. In general, arrhythmias usually precede the onset of cardiovascular disease. If detected early, appropriate measures can be taken to reduce unintended injuries and deaths in the early stages of disease. In recent years, a variety of wearable physiological monitors have appeared on the market, which can realize the early detection of arrhythmia. However, they are limited by factors such as time and place to varying degrees. Patients need to go to designated medical institutions for playback detection regularly to understand the development of the disease. Although the research on automatic classification of ECG signals has been more in-depth, and the related methods have good results. However, there is still a lack of comprehensive automatic classification software with high integration, easy to use and intuitive presentation for patients or medical workers.

The main task of this paper is to complete the classification of ECG signals, so we focus on the relevant steps of ECG classification. The denoising method and classification method of ECG signal are particularly important. In the selection of denoising methods, such as [2], [3], [4], [5], etc., the signal to noise ratio of signals is improved by filtering or reconstruction. Since ECG signals are one-dimensional data, feature extraction and classification of signals are mostly carried out through convolutional neural network, such as [6], [7], [8], [9] and so on.

According to the survey, the current research on ECG signal software analysis system generally focuses on the denoising of ECG signal, the peak extraction of QRS band and the real-time drawing of ECG waveform. Remote monitoring can be realized through real-time waveform, and the results can be feedback to patients or doctors. However, the research and implementation of real-time classification of ECG signals by software analysis system are few. The main reason is that the diagnostic standard of ECG is not unified, and the recognition accuracy of ECG waveform cannot be guaranteed. Of course, the accuracy of automatic analysis is far from the level of clinicians, and it can only provide auxiliary information as a reference for patients or clinicians. Therefore, the goal of auxiliary diagnosis was established at the beginning of this study, hoping to preliminarily identify ECG abnormalities with the help of the classification model, and show the judgment results to patients or doctors.

The application of deep learning method avoids artificial feature extraction and greatly improves the performance of ECG signal classification.

In view of the above problems, this study, based on the relevant knowledge of ECG signal classification, carries out denoising, R-peak detection and segmentation through the input of ECG data. Finally, the convolutional neural network model is constructed to complete the classification and prediction task. The purpose of this study is to accurately detect the potential of arrhythmia for users, and to respond to the situation of sudden heart disease in a timely and effective manner. It can assist patients to conduct self-examination and assist medical staff to diagnose, which has reference significance for ensuring physical health and life safety.

II. RESEARCH CONTENTS

The ECG signal is a signal measured on the surface of the human body, which is a comprehensive embodiment of the

electrical activity of various cardiac cells. The generation of ECG signals is related to the depolarization and repolarization of cardiomyocytes.

On a technical level, ECG signals are also one of the first biological signals to be studied in humans and successfully applied in clinical practice. Compared with other bioelectrical signals, it is easier to detect and more regular. To complete the classification task of ECG signals in this study, it is necessary to complete four aspects of work: ECG signal acquisition, preprocessing, waveform display, algorithm classification.

A. Introduction to ECG signal
1) Mechanism of ECG signal generation

A series of highly coordinated electrical stimulation pulses generated by the heart, stimulates muscle cells in the atria and ventricles. It makes the atria and ventricles in turn excited, and rhythmically diastole and contract, so as to achieve the "blood pump" role and maintain the body's blood circulation. Depolarization and repolarization of cardiac muscle cells can cause potential differences at different points on the surface of the body. This potential difference signal detected from the human body surface is the ECG signal. Different signals can be obtained by placing the probe electrode in different positions, which have different meanings in clinical practice. Electrocardiogram can record the depolarization and repolarization process of cardiomyocytes from a macroscopic view, and can reflect the physiological state of various parts of the heart better, so it has a very important role in clinical.

2) Feature analysis of ECG signals

The waveform for a complete cardiac cycle is shown in Fig. 1 below. Normal ECG waveform include P wave, QRS wave and T wave, etc. [10] In addition to heart rate indicators, the detection of P, QRS and T waves in the ECG can also be used to understand the activity and health of the heart.
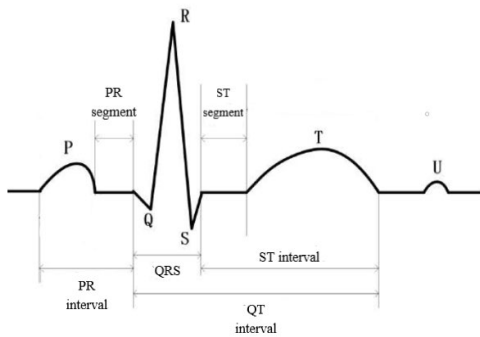

Fig. 1 ECG waveforms in a single ECG cycle

P wave, QRS complex and T wave are the most important characteristic waves in ECG waveform. They and PR interval, QT interval and ST segment formed on their basis contain the most important characteristic information of ECG.

B. MIT-BIH Arrhythmia Database

The data in this study were derived from MIT-BIH database, an arrhythmia research database provided by the Massachusetts Institute of Technology. There are 48 sets of arrhythmia data in MIT-BIH arrhythmia database, and each set of data consists of 3 files.

```
119 2 360 650000
119.dat 212 200 11 1024 825 2943 0 MLII
119.dat 212 200 11 1024 930 -26388 0 V1
# 51 F 1129 654 x2
# Pronestyl
# The PVCs are uniform.
```

Fig. 2 Header file 119.hea data plot

119.hea is a header file, as shown in Fig. 2, which records the data format of this set of ECG signals.

119.dat is the storage file of ECG data. The two-channel data of the MIT-BIH database is stored as two binary numbers every three bytes.

119.atr is the annotated document. It records the expert's diagnosis of the corresponding ECG signal.

C. Studied ECG abnormalities

Among 48 groups of heartbeat records in the database, there are 16 different types of heartbeats. Among them, there are more data on normal beats, Premature ventricular contractions, left bundle branch block and right bundle branch block. And there is a large gap between the number of other types of beats and these four types.

In this study, the four more heartbeat patterns are used as training samples to ensure that the model training data set is large enough. The following is a brief overview of the abnormal heartbeat studied.

1. Premature ventricular contractions (PVCs) are abnormal ventricular beats caused by premature impulse of ectopic pacemaker points below the branch of the bundle.

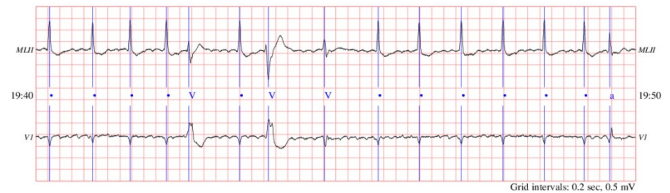The marked "V" is the ventricular premature beat.

Fig. 3 Electrocardiogram of PVCs

2. Bundle branch block refers to the delay or obstruction of cardiac electrical signal transmission below the bifurcation of His bundle.

The labeled "L" is the left bundle branch block beat (LBBB).

Fig. 4 Electrocardiogram of LBBB

The labeled "R" is the right bundle branch block beat(RBBB).

Fig. 5 Electrocardiogram of RBBB

D. ECG signal pretreatment

ECG signal is an important life signal, which is characterized by strong randomness, low intensity, and poor anti-interference ability. Because of these characteristics, the signal acquisition process is often affected by the human body's internal and external environment, resulting in large noise. In order to ensure the accuracy of ECG signal classification and improve the recognition rate, denoising is essential before classification.

1) Types of ECG noise

The main noises in ECG signal include power frequency interference, baseline drift and electromyographic interference.

Power frequency interference: Power frequency interference is a low-amplitude interference caused by the power supply system. The frequency band overlaps the frequency band of the measured signal, covering the subtle transition curve in the normal ECG. It is manifested as sine waves and their superposition on the ECG.

Baseline drift: Baseline drift is a common low-frequency noise in ECG signals, and the frequency is generally lower than 2Hz. The baseline of ECG signals generally deviates from the normal baseline position, which is mainly manifested as amplitude modulation of ECG signals.

Electromyography interference: For various reasons, the impedance interference between the skin and the electrode is called electromyography interference. The frequency of electromyography interference may exist in the range of 5Hz to 300Hz, which is manifested as a rapidly changing irregular waveform [11].

2) Selection of denoising methods

Wavelet transform method has the characteristics of multi-resolution analysis and good time-frequency domain properties. Singular value decomposition method has good stability and invariance, which can effectively reflect the various properties of the signal by decomposing the singular value. Therefore, the wavelet transform method and the singular value decomposition method are selected for denoising the ECG signal.

E. Convolutional Neural Network

The essence of deep learning is to fit various parameters with algorithms. It extracts some features or rules from massive data so as to recognize and predict new data or unknown situations. Convolutional Neural Networks (CNN) are an important deep learning neural network. The convolutional neural network contains multiple hidden layers and estimates the posterior probability to achieve the classification prediction of the data.

Convolutional neural networks are mostly composed of convolutional layers, activation layers, pooling layers, normalization processing, and fully connected layers. The convolutional layer is used to extract the local features of the input data. The activation layer is used to increase the nonlinear operation between multi-layer networks. The pooling layer is added to complete the feature down-sampling between the convolutional layers. The normalization method was used to optimize the variance and mean of the data to make the distribution of the neural network data more realistic. The fully connected layer completes feature classification in the form of linear classifiers and realizes end-to-end analysis.

Deep learning does not need to manually extract the features of data, but combines feature extraction with classification. And it uses deep neural network technology to achieve a unified model of feature extraction and classifier training, so as to effectively improve the recognition rate. Practice has proved that deep learning does have better effects when dealing with massive data. Therefore, this study uses convolutional neural network to analyze and process ECG signals [12].

III. DATA PROCESSING METHOD AND RESULT

This study needs to complete the task of ECG signal classification, including ECG signal acquisition, preprocessing and algorithm classification.

A. ECG signal acquisition

In order to process and monitor batch data, this study uses MATLAB for data reading. The data reading process is as follows.

1)First, read the data structure of the header file: The number of signal channels (2), the data sampling frequency (360), the number of integers per mV (200) and the integer value corresponding to the zero of the ECG signal (1024) are obtained.

2)Second, read-in data: the 3 bytes read each time are set as a row of data in the data matrix to ensure that each row has only a group of 2 data. All rows now have the same data structure.

3)Thirdly, Binary to decimal: Third, binary to decimal: Each unit of data read into the data is stored in the workspace in decimal form, so this study carries out the bit operation. Move the lower 4 bits of the second byte to the left by 8 bits and add them to the data in the first column to get the voltage reference value for channel 1. Move the high 4 bits to the left 8 bits and add the third column of data to get the voltage reference value of channel 2, and then process the overflow data.

4)Finally, Calculate the voltage value: The reference value corresponding to the zero voltage of the signal is obtained from the header file is 1024. Divide the difference of the voltage of each data cell with respect to the reference value of 1024 by 200 per mV transform. The result is the standard voltage value of the ECG signal.

Because the total amount of data is too large, only one set of data is used to show the program effect. The data number 103 is read into the figure as shown in Fig. 6 below.
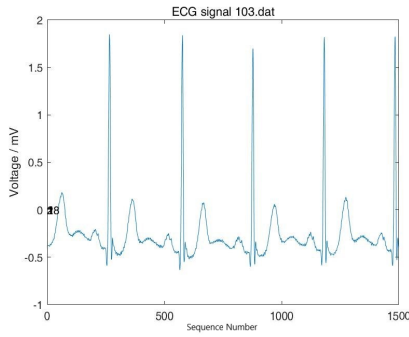
Fig. 6 Data reading effect

B. ECG signal preprocessing

1) Singular value decomposition

In general, 99 percent of the total singular value is contained in the first 1 to 10 percent of the singular value. Therefore, matrix A can be fitted with its singular values at and before the appropriate positions, and its corresponding column and row eigenvectors.

Therefore, the singular value decomposition method is adopted to reduce the dimension of data and filter the signal to remove unnecessary redundant components during signal denoising in this study.

The operating environment of singular value decomposition is MATLAB. The data matrix is generated by the translation of the sliding window, and the window width is slightly less than the number of eigenvalues. Svd() function is called for feature decomposition, and the result is saved in U, S and V matrices. A new matrix is generated by processing the diagonal elements of matrix S. This study uses the new matrix, U and V to reconstruct the denoised signal.

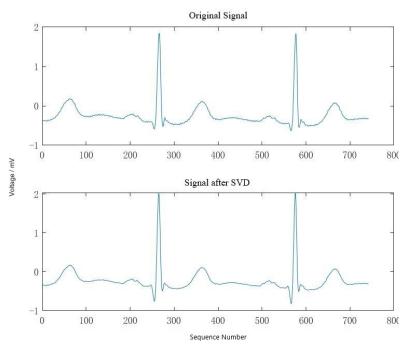The comparison of the read signals before and after SVD denoising is shown in Fig. 7 as follows.

Fig. 7 Effect of SVD

The upper part of the figure is the signal just read in, and the lower part is the signal after SVD denoising. It can be seen that the denoised signal has a reduction in micro serrations. That is singular value decomposition method has a strong ability to remove power frequency interference and myoelectric interference.

2) Wavelet transform

Wavelet transform has the feature of multi-resolution, which can be regarded as a method to reconstruct signal after coarse section and detail decomposition by bandpass filter banks. The high-pass filtering part contains the detail information of the signal and has a higher resolution in the frequency domain. In the low-pass filtering part, the time domain resolution is higher, so it can be further segmented. It is because of this good adaptive characteristic that this method is especially suitable for weak signal and strong noise signal analysis.

The implementation environment of wavelet transform method is MATLAB. Wavedec() function is called to decompose the read signal with db9 for 8-layer decomposition, and the decomposition results are saved. The wrcoef() function is then called to specify Layer 8 detail for reconstruction to reconstruct the new ECG signal.

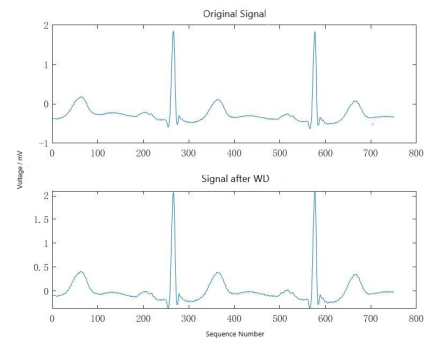The signal comparison before and after denoising by wavelet decomposition is shown in Fig. 8.

Fig. 8 Effect of WD

In the figure, the upper part is the signal just read in, and the lower part is the signal after wavelet decomposition and denoising. As can be seen from the figure, the main change of the signal after wavelet decomposition is that the baseline is lifted up by about 0.3mV. This indicates that unlike the SVD method, the wavelet decomposition method has a stronger ability to remove baseline drift.

3) Realization of peak detection and signal segmentation

By observing the denoised ECG data, we can see that the ECG signal voltage ranges from -0.4mV to 2mV, and most of the values are negative. It is roughly predicted that only one part of each cardiac cycle is slightly higher than 0mV (T-wave) and one part is much higher than 0mV (QRS wave). Add 1 to all the signal voltage values and raise them to the fifth power. The original negative segment result approaches 0, and the QRS band result is much higher than the T-band result.

The average of the five power results plus one is the detection threshold of the R peak. Since the number of signal sampling values of R peak is very small compared with the sampling frequency of 360 signal per second, the detection threshold of R peak is very close to 1. The abscissa of points greater than this threshold was recorded. In each cardiac cycle, there are points where the voltage is greater than this threshold, and the point corresponding to the maximum of the ordinate is the R peak. The peak extraction results are shown in Fig. 9.
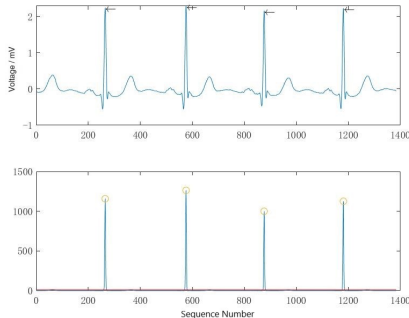
Fig. 9 Peak extraction effect

On the basis of peak detection, signal segmentation is easy to achieve. It only needs to record a certain length of ECG signals from the peak point R to the left and right. Combined with the input of the model and the waveform characteristics of ECG signals, a total of 250 data can be recorded by heart rate, forward and backward to represent an ECG cycle.

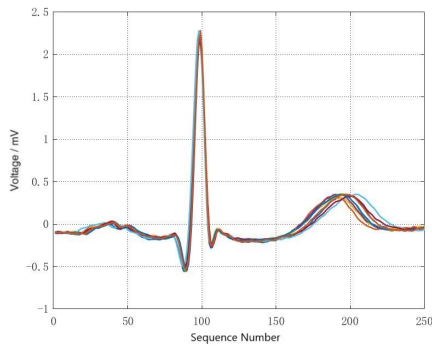The signal segmentation results are shown in Fig. 10.

Fig. 10 Signal segmentation effect

IV. CLASSIFICATION METHODS AND RESULTS

A. *Classification and prediction methods*

In this study, normal beats, premature ventricular beats, left bundle branch block beats, and right bundle branch block beats with a large amount of data in the MIT-BIH arrhythmia database were used as training samples. Based on the above four sets of data, the model training dataset was made, and the corresponding four classifications of ECG signals were realized.

In order to make the data set of the model, this study divides and de-noises the 48 groups of ultra-long signals according to the time points of ECG signal changes in the annotation file. The following available ECG beat modes are obtained.

TABLE I
HEART BEAT INITIAL DATA SET

Name	Value
Nb	74932*250 double
Vb	7034*250 double
Lb	8068*250 double
Rb	7254*250 double

Nb represents normal beats, Vb represents ventricular premature beats, Lb and Rb represent corresponding left and right bundle branch block beats. 5000 beats in each of the four categories were selected as the data set of the model, 3/4 of which were selected as the training set, the rest as the test set. 1250 beats in each of the unselected beats were selected as the verification set, and the trained model was used for prediction. The confusion matrix, calculation accuracy and F1 score were drawn to evaluate the classification effect of the model intuitively.

The convolutional neural network for ECG signal classification established in this study consists of four convolutional layers, four pooling layers and fully connected layers. The network structure of the neural network is shown in Fig. 11.

Fig. 11 Network structure diagram of classification model

The first, third, fifth and seventh layers are the convolutional layers, and the dimensions of the convolutional nuclei are 128, 80, 56 and 80, respectively. In the convolution process of each layer, zero complement operation is not performed. Each convolutional layer is followed by a pooling layer, , with the number of cores for the first three pooling layers set to 2 and the number of cores for the fourth pooling layer set to 3. The step size of both the convolution layer and the pooling layer is set to 1. Table II shows the detailed parameters of the network structure.

TABLE II
DETAILED PARAMETERS OF NETWORK STRUCTURE

Layer serial number	Type	Output size	Kernel size	Step size
1	Convolutional layer	4*110	4*32	1
2	Pooling layer	4*109	2	1
3	Convolutional layer	8*51	8*10	1
4	Pooling layer	8*50	2	1
5	Convolutional layer	8*23	8*7	1
6	Pooling layer	8*22	2	1
7	Convolutional layer	16*7	16*5	1
8	Pooling layer	16*6	3	1
9	Pooling layer	4	—	—

The activation function in this study selects ReLU function to nonlinearly express the results of the input layer or the upper layer. The optimizer learning rate is set to 0.001. The number of training sessions was 30. The cross-entropy loss function is used to evaluate the fitting performance of the network in real time, and determine the relationship between the actual output and the expected output. The smaller the real value of the loss function, the better the robustness of the model.

After the model is trained, the model is saved, and the trained model is called in the prediction process to input the correct data. The final model feature values are mapped to the

output label. And the input label is associated with the class name to complete the display of the prediction results.

B. Classification and prediction results

According to the above, the training times of the model are 30 times, and the following table Ⅲ describes the update of the loss function of the model with the training times. It can be clearly seen that the loss of the model training set is lower than 0.01 after 5 times of training, and the model has the possibility of convergence.

TABLE III
LOSS-TRAINING TIMES TABLE (PART)

	0	1	2	3	4	5	6
Train loss	0.43	0.07	0.03	0.02	0.02	0.01	0.01
Text loss	0.15	0.06	0.03	0.03	0.02	0.02	0.02

The loss of the model for 30 times of training is plotted in turn as shown in Fig. 12. The curve shows that the loss of the model is greatly reduced, and the loss of the model is almost stable at a small value after the fifth training, so the model can be judged to converge successfully.
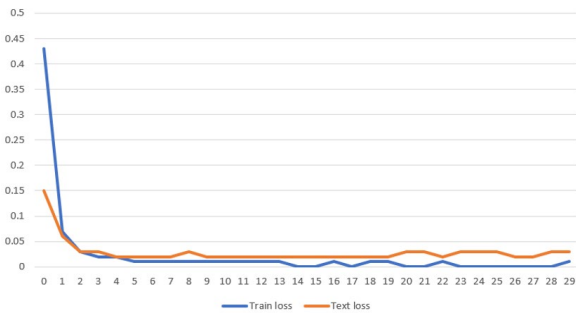

Fig. 12 Loss function curve

The data of the validation set is input into the trained model to obtain the predicted label of the model, which is compared with the actual data label of the validation set, and the confusion matrix of the model is updated according to the correctness of the alignment. The final confusion matrix is shown in Fig. 13 below.
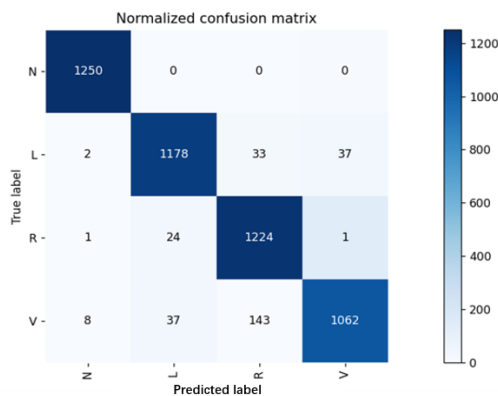

Fig. 13 Confusion matrix

According to the confusion matrix, the classification accuracy and F1 score of each class of the model can be calculated, as shown in Table Ⅳ below.

TABLE IV
MODEL PREDICTION ABILITY EVALUATION

	N	L	R	V	Whole model
Accuracy rate	100%	94.24%	97.92%	84.96%	94.28%
F1 score	0.996	0.947	0.924	0.904	0.942

REFERENCES

[1] Sahar Ramezani Moghadam, Babak Mohammadzadeh Asl, "Automatic diagnosis and Localization of Myocardial Infarction using Morphological Features of ECG Signal," Biomedical Signal Processing and Control, vol. 83, 104671, May 2023.
[2] Manas Rakshit, Susmita Das, "An efficient ECG denoising methodology using empirical mode decomposition and adaptive switching mean filter," Biomedical Signal Processing and Control, vol. 40, pp. 140-148, 2018.
[3] S A. Malik, S. A. Parah and G. M. Bhat, "Electrocardiogram (ECG) de-noising method utilizing Empirical Mode Decomposition (EMD) with SWT and a Mean based filter," 2021 2nd International Conference on Intelligent Engineering and Management (ICIEM), London, United Kingdom, pp. 322-326, 2021.
[4] Nasser Mourad, "ECG denoising based on successive local filtering," Biomedical Signal Processing and Control, vol. 73, 103431, 2022.
[5] Z. Wang et al. "A new modified wavelet-based ECG denoising," Computer assisted surgery, Abingdon, England, vol. 24, pp. 174-183, 2019.
[6] Kiranyaz, Serkan et al. "Real-Time Patient-Specific ECG Classification by 1-D Convolutional Neural Networks," IEEE transactions on biomedical engineering, vol. 63, 664-675, 2016.
[7] Y. Zhao, J. Cheng, P. Zhang and X. Peng, "Ecg classification using deep cnn improved by wavelet transform," Computers, Materials & Continua, vol. 64, no. 3, pp. 1615–1628, 2020.
[8] T. Wang et al. "Automatic ECG Classification Using Continuous Wavelet Transform and Convolutional Neural Network," Entropy, Basel, Switzerland, vol. 23, pp. 119-119, 2021.
[9] J. Lu et al., "Efficient Hardware Architecture of Convolutional Neural Network for ECG Classification in Wearable Healthcare Device," in IEEE Transactions on Circuits and Systems I: Regular Papers, vol. 68, no. 7, pp. 2976-2985, July 2021.
[10] Szczepański, A., Saeed, K., Ferscha, A., "A New Method for ECG Signal Feature Extraction," ICCVG 2010: Lecture Notes in Computer Science, vol. 6375, Springer, Berlin, Heidelberg, pp. 334–341, 2010.
[11] Rahul Kher*, "Signal Processing Techniques for Removing Noise from ECG Signals," Journal of Biomedical Engineering and Research, vol. 23, no. 6, pp. 1-9, 2019.
[12] M.M. Al Rahhal, et al, "Deep learning approach for active classification of electrocardiogram signals," Information Sciences, vol. 345, pp. 340-354, 2016.