

# Classification of cardiac abnormality based on BCG signal using 1-D convolutional neural network

Li Zeng<sup>a</sup>, Ruyue Wang<sup>a</sup>, Shanshan Yang<sup>a</sup>, Xiangyu Zeng<sup>b</sup>, Zhenjun Guo<sup>\*a</sup>

<sup>a</sup>School of Computer Science and Engineering, Guilin University of Aerospace Technology, Guilin 541004, Guangxi, China; <sup>b</sup>School of Information Engineering, Inner Mongolia University of Science & Technology, Baotou 014017, Inner Mongolia, China

## ABSTRACT

This paper presents a ballistocardiogram (BCG) classification method based on 1-D convolution neural networks (CNNs), which provides an auxiliary basis for clinical diagnosis, especially in the monitoring of cardiac function in the elderly. Four categories of BCG signals are used as input of 1-D CNN. By moving the convolution kernel on the time axis, the temporal variability of BCG signals can be better satisfied while retaining the frequency band correlation. Then they were sent to the multi-layer sensor, after that the features processed by softmax classifier were classified. We obtained an accuracy of 93.39%, of which the H class is 95.36%, the C class is 86.19%, the D class is 95.31%, and the Y class is 96.57%. Compared with the existing research results, the proposed method achieves a superior classification performance. This method is simple, fast and highly generic, which can serve as a reliable adjunct tool for the daily diagnosis of heart disease in the elderly.

**Keywords:** 1-D CNN, BCG classification, clinical diagnosis

## 1. INTRODUCTION

Cardiovascular disease (CVD) is a widespread condition that poses a severe threat to human health and has overtaken other causes of death in the world. Cardiac monitoring in daily life so as to detect the pathological features in a timely manner is the key to prevent such diseases. Clinically, electrocardiogram (ECG), phonocardiogram (PCG) and magnetocardiography (MCG) have been used, but they need professional equipment, which are difficult to be used for routine monitoring<sup>1,2</sup>. The ballistocardiogram (BCG) signal is derived from a series of mechanical impacts generated by the blood flow in the cardiac pumping process, which contains a great many cardiac physiological information<sup>3,4</sup>. BCG is a non-invasive, non-contact method of monitoring cardiovascular function<sup>5,6</sup>. Compared with ECG, it has higher comfort and convenience, so it is more suitable for monitoring in daily life at home<sup>7</sup>.

BCG has steadily drawn academics' interest as sensors and digital signal processing have advanced. Various signal processing methods have also been applied to the processing of BCG signals for heartbeat location and feature extraction<sup>8</sup>. According to studies, BCG can be used to identify changes in heart rate, heart rate variability, cardiac contractility, and cardiac output.

However, in practical applications, BCG signals are complex and changeable. In this paper, we propose a one-dimensional convolutional neural network model, which is applied to the classification and recognition of BCG signals. The rest of this paper is organized as follows. In Section 2, we mainly explain the data source of the experiment and briefly introduce the pretreatment process. In Section 3 briefly mentioned the contents of CNN, and the details information of the proposed 1D-CNN are given in Section 4, including convolution layer and pooling layer. The performance of the convolutional neural network algorithm is verified in Section 5 by comparing the experimental results with the back propagation (BP) neural networks and support vector machine (SVM) classification after manually extracting the features. Finally, conclusion and future work are presented in Section 6.

## 2. DATA COLLECTION AND PROCESSING

In this paper, a composite acquisition system of BCG signals based on polyvinylidene fluoride (PVDF) piezoelectric film is developed<sup>9</sup>. The system is modified from the acquisition system of cardiovascular physiological signals developed by

\* 1921560212@qq.com

the Institute of Medical Physics, Tsinghua University. It is mainly composed of sensor module, signal processing circuit and signal transmission and storage. The piezoelectric film is embedded in the cushion, and the cushion is placed flat on the chair or fixed to the backrest. The signal conditioning circuit is composed of charge sensitive amplifier, filter circuit, power frequency notch circuit and post-stage voltage amplifier circuit. When collecting data, the tester sits on the chair and breathed calmly. The change of human mechanics is converted into a charge signal by piezoelectric thin film sensor, which is transformed into electric signal by preamplifier circuit. The signal processed by the hardware circuit is transmitted to the upper PC via the acquisition card for real-time display and storage. The acquisition system is shown in Figure 1.

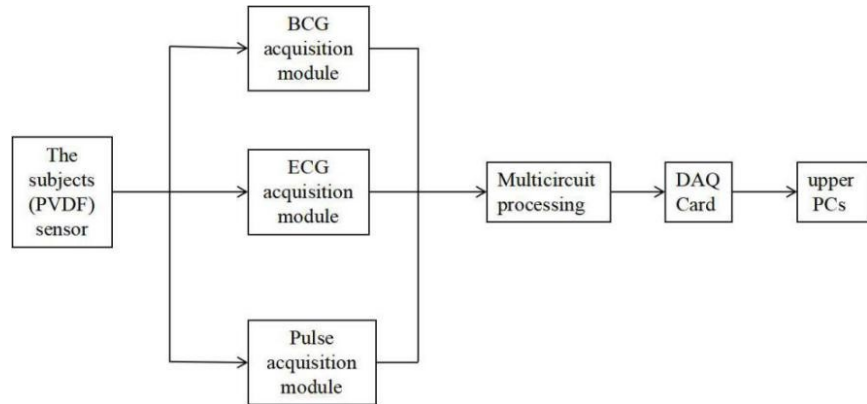


Figure 1. Hardware overall design block diagram.

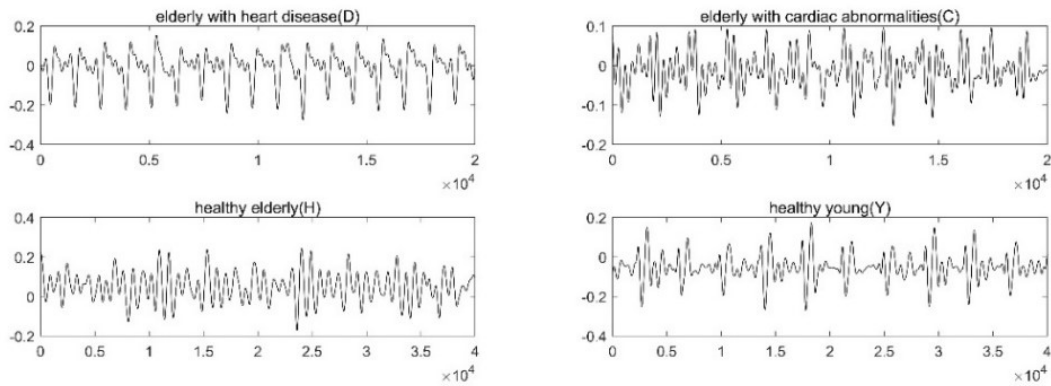


Figure 2. An illustration of BCG segments.

The data set used in this paper contains four types of BCG signals: healthy young (Y), healthy elderly (H), elderly with cardiac abnormalities (C), and elderly with heart disease (D). Due to the low frequency and weak characteristics of BCG signal, it is inevitable to mix in the respiratory signal and other noise interference, which increases the difficulty of detection. Therefore, it is necessary to design a digital filter for processing and obtain the signals required in the experiment. Firstly, the trend items such as breathing are eliminated by high-pass filter, then the low-pass filter with cut-off frequency of 30 Hz is used to eliminate the high-frequency electromagnetic noise generated in the circuit. Finally, a 50Hz notch filter is designed to eliminate power frequency interference. The pre-processed signal is shown in Figure 2.

After filtering, the waveform features of BCG signal are clearly visible, with good periodicity and repeatability, indicating that the filtering effect is good. Comparing the four types of waveforms, it can be seen that the waveforms of class H is basically consistent with the standard waveform, and the waveforms of class D change obviously, but show certain periodicity regularity. The waveforms of class C and H are not obvious, and the waveforms of class C are similar to those of class Y.

### 3. CONVOLUTIONAL NEURAL NETWORK (CNN)

Fukushima originally developed the convolutional neural network (CNN) in 1980<sup>10</sup>, while LeCun et al. later enhanced it<sup>11</sup>. It is a feed-forward neural network that draws inspiration from the biological natural vision's cognitive process. Convolutional layer and pooling layer are typically alternated, resembling the simple and complicated cells in the human visual cortex<sup>12</sup>. Figure 3 illustrates its fundamental structure.

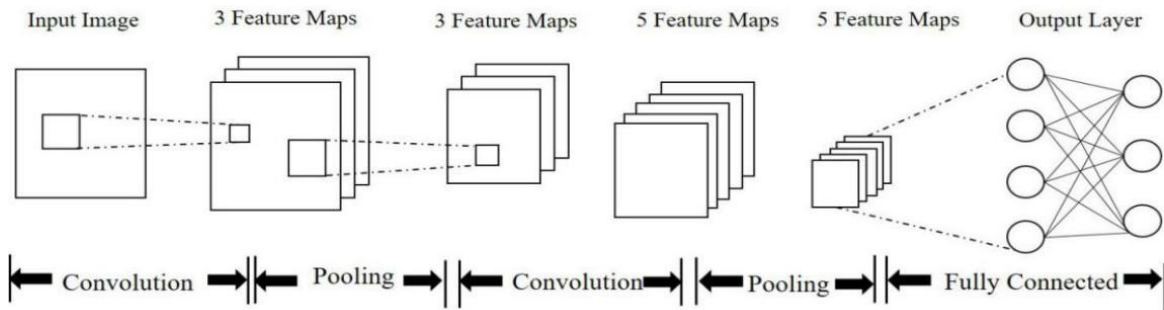


Figure 3. The architecture of the CNN.

CNN is widely used in various application fields, it is also used as an automated diagnostic tool in the medical field to help clinicians<sup>13,14</sup>. It is worth mentioning that the greatest feature of CNN is sparse connectivity (local receptive field) and weight sharing. CNN extracts spatial local association information from natural images by enhancing local connections between nodes of adjacent layers in neural networks. The input of the  $m$ -layer nodes is only a part of the  $m-1$  layer nodes, which have spatial adjacent receptive field of vision. As shown in Figure 4a. The parameters of a filter are the same when it convolves with a feature map from the preceding layer, resulting in the same convolutional result, the parameters (weights and biases) are shared. This is illustrated in Figure 4b. Sparse connections and weight sharing can lower the number of training parameters, simplify computations, and increase learning effectiveness, and thus improve the learning efficiency. So this makes CNN have better generalization ability in recognizing scenes.

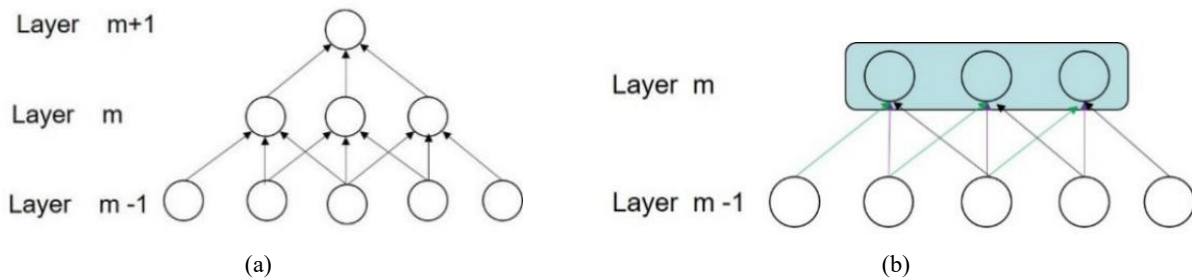


Figure 4. The characteristics of CNN. (a): Local receptive field; (b): Weight sharing.

### 4. 1-D CNN

The data to be processed in this paper are discrete time series. While maintaining the local observation, weight sharing, and high-level aggregation properties of convolutional neural networks, Figure 5 illustrates the construction of a CNN appropriate for the 1-D properties of BCG signals using one-dimensional convolution as the convolution layer while maintaining the local observation.

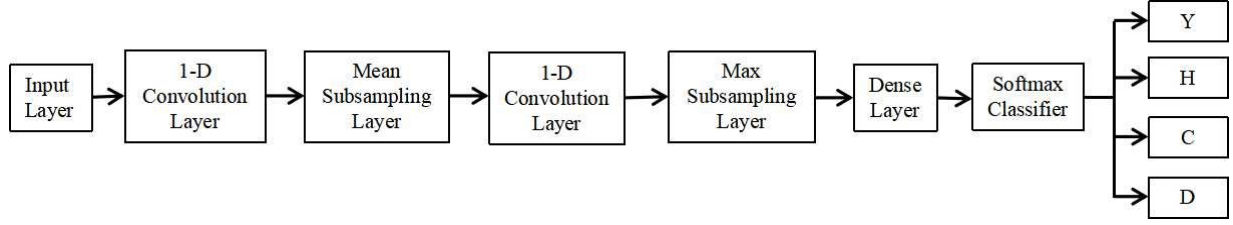


Figure 5. 1-D CNN implementation.

#### 4.1 Convolution layer

Referring to convolution, we have typically been exposed to the convolution of 1-D signals, that is,

$$y[n] = x[n] * h[n] = \sum_k x[k]h[n - k] \quad (1)$$

where  $x[n]$  is the input signal and  $h[n]$  is the unit response in signal processing. As a result, the output signal  $y[n]$  is the superposition of the input signal  $x[n]$  delayed response. Weighted superposition/integration is the essence of 1-D convolution as well.

The filter  $w_t$  ( $t = 1, \dots, m$ ) sequentially performs a local convolution operation on the input features of the preceding layer given a sequence of input signals  $x_t$  ( $t = 1, \dots, n$ ). In general, the filter's length  $m$  is substantially shorter than the signal sequence's length  $n$ . The convolution's result is:

$$y_t = \sum_{k=1}^m w_k \times x_{t-k+1} \quad (2)$$

In a convolutional layer, each neuron in the  $l$ th layer connected to only one neuron in the local window of the  $l-1$  th layer, forming a locally connected network.

Then the input of the  $i$ th neuron in the  $l$ th layer is defined as:

$$a_i^l = f(\sum_{j=1}^m w_j^l * a_{i-j+m}^{l-1} + b^l) = f(w^l * a_{(i+m-1):i}^{l-1} + b^l) \quad (3)$$

where,  $w^l \in R^m$  is the  $m$ -dimensional filter,  $a_{(i+m-1):i}^l = [a_{(i+m-1)}^l, \dots, a_i^l]^T$ ,  $b^i$ , ( $i = 1, 2, \dots, n$ ) is the bias parameter,  $w^l$  is the same for all neurons in this convolutional layer.

#### 4.2 Pooling layer

Convolution layers is convolution of the adjacent regions of the image to acquire neighborhood features. The pooling layer uses the pooling technology to integrate the feature points in the tiny neighborhood to obtain new features<sup>15</sup>. Specifically, a value is obtained from a region as a feature in a certain way, and then utilized to take part in subsequent training, which is the pooling process. For the feature map  $X^l$  that is derived from convolution layer are divided into multiple regions  $R^k$  ( $k = 1, \dots, K$ ).

$$pool_{max}(R_k) = \max_{i \in R^k} a_i \quad (4)$$

$$pool_{avg}(R_k) = \frac{1}{|R_k|} \sum_{i \in R^k} a_i \quad (5)$$

The commonly used pooling method is to take the maximum or average value of all neurons in the region. The Max-pooling is a nonlinear downsampling method, and has two characteristics: (1) It reduces the computational complexity of the upper layer; (2) It provides transformation invariance and has good robustness to shift changes.

#### 4.3 Experimental setup

The experimental data set for this study is smooth and high-quality wave. Due to the small amount of data gathered from older patients with heart disease, the sample record was expanded using several segments of heart-beat interception method, and eventually four matrices with minor differences were created and used as the input of a convolution neural network.

We're going to design a 1-D CNN in this case with two convolution layers, two pooling layers, and one full connection layer. There are numerous restrictions due to the relatively straightforward construction of this 1-D CNN. To do

nonlinear feature mapping, a convolution layer needs an activation function  $f(x)$ . The term “activation function” refers to how to through functions to preserve and map the characteristics of activated. This is the key to solving nonlinear problems in neural networks.

ReLU with a faster convergence rate and Softmax for multiclassification are chosen as the activation functions in this work. The following are the formulas:

$$f(x) = \max(0, x) \tag{6}$$

$$y(x_i) = \frac{\exp(x_i)}{\sum_{i=1}^m (\exp(x_i))} \tag{7}$$

4.3.1 Determination of Super-Parameters in 1-D CNN. The learning rate, batch block size, and iteration epoch number must all be specified when utilizing the stochastic gradient descent (SGD) method for training. The values of these parameters are determined based on the results of the step-by-step experiment.

#### 4.4 Experimental results

By comparing the design of the convolution structure and the specification of the hyper-parameters, the results show that the size of the first convolution kernel and the value of the learning rate have a great influence on the recognition rate. Tables 1 and 2 are the results of comparison, and the recognition rates in the tables are all statistical average results. As can be seen from Table 1, convolution kernel is not as small as possible. Especially for sparse data, it may not be able to express its characteristics when using a relatively smaller convolution kernel. If a larger convolution kernel is used, the complexity will be greatly increased. Table 2 shows that the recognition effect is not good if the learning rate is too low, which leads to a slow convergence rate, while the number of iterations in the experiment is less.

Table 1. The influence of convolution kernel size on recognition rat.

<b>Convolution kernel</b>	<b>1</b>	<b>16</b>	<b>31</b>	<b>46</b>	<b>61</b>
Total (%)	75.02	86.04	91.59	88.64	84.33
H (%)	80.61	90.27	92.86	93.52	87.72
C (%)	67.01	76.64	84.09	84.21	79.79
D (%)	83.98	89.53	93.08	91.97	88.26
Y (%)	68.44	87.74	96.30	84.93	81.63

Finally, after many experiments, the convolution network settings and Super-parameters are adjusted and optimized continuously. The final average recognition rate is 93.39%, of which the H class is 95.36%, the C class is 86.19%, the D class is 95.31%, and the Y class is 96.57%. Among them, the accuracy of Class Y is the highest, and the recognition rate of class C is lower than that of other classes, because some of them are misclassified as Class Y, which is consistent with our analysis results in Figure 2.

Table 2. The influence of learning rate on recognition rate.

<b>Learning rate</b>	<b>0.01</b>	<b>0.03</b>	<b>0.06</b>	<b>0.1</b>	<b>0.3</b>
Total (%)	61.43	82.47	88.47	91.67	85.36
H (%)	49.81	91.95	95.37	94.37	94.80
C (%)	71.60	77.82	82.22	84.70	86.21
D (%)	53.90	91.87	95.90	95.78	96.04
Y (%)	56.84	68.24	80.31	91.78	64.29

Compared with the traditional classifier, the specific results are shown in Table 3, the classification results of Back Propagation (BP) Neural Networks and Support vector machine (SVM) are 86.82% and 91.67% respectively. Traditional machine learning frameworks rely heavily on the extraction of artificial features. Extraction of high-quality features might be difficult if the algorithm designer lacks sufficient experience, this is also the limitation of traditional machine learning frameworks. The method suggested in this work has the advantage that features can be automatically collected from vast data without manual design. The experimental results are satisfactory, not only the recognition effect is improved, but also the classification categories are more diverse.

Table 3. Classification results of BP and SVM.

Method	Feature	Accuracy (%)	Method	Feature	Accuracy (%)
BP	Time domain	83.33	SVM	Time domain	86.25
	Frequency domain	80.67		Nonlinear	81.39
	Time and frequency domain	86.82		Time domain, nonlinear	91.67

## 5. CONCLUSION

In this study, in view of the one-dimensional characteristic of BCG signal, we propose an elderly BCG signal classifier for the elderly BCG signal with 1-D CNNs, and its convolution kernel is used as observation window to slide on the time axis of BCG signal. It can be used to extract the local features of the signal and ensure the time variability of the BCG signal, the correlation and integrity of the frequency band. Compared with the traditional pre-feature extraction and re-classification process, for each elderly over a simple CNN, it is not only unnecessary to extract handcrafted manual features, or any kind of pre-processing and post-processing. In addition to the speed and computational efficiency attained, the proposed method only needs 1-D convolutions, which simplifies and lowers the cost of hardware implementation.

The experimental results show that the proposed method can achieve good classification performance and can be used as an auxiliary basis for medical staff to diagnose heart diseases. However, in practical applications, the classification performance should be further improved. For the future research work, BCG signal processing and classification algorithms have to enhance in order to improve the reliability of the medical system. In the next step, the signal is firstly extracted from the higher-order spectrum and then sent to the CNN for identification. It should be mentioned that the signal processing method proposed in this paper can be applied to other signals in addition to BCG data classification. And develop the discipline from a specialized area into an established method that is frequently employed in clinical practice.

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