



Analysis of Pregnancy Pulse Discrimination Based on Wrist Pulse by 1D CNN

Nan Li¹, Yi Jiao¹, Xiaobo Mao¹, Yuping Zhao², Guoliang Yao¹,
and Luqi Huang^{1,2}(✉)

¹ College of Electrical Engineering, Zhengzhou University, Zhengzhou 450001, China

² China Academy of Chinese Medical Sciences, Beijing 100700, China

Abstract. Wrist pulse contains important information of human health, so the diagnosis and analysis based on pulse signal is of great significance. In this study, a one-dimensional convolutional neural network (1D CNN) model is proposed to distinguish from pregnancy pulse normal pulse. The performance of the proposed 1D CNN was validated with a collected data set consists of 160 subjects. The 1D CNN proposed with clique blocks style architecture and transition blocks is employed. Furthermore, the three clique blocks go through the pooling layer, and extend the one-dimensional data into vectors through the full connection layer, respectively. By using stacked blocks and transition blocks, the proposed CNN leading a promising classification performance. The F -score, accuracy, precision and recall were used to evaluate the effectiveness of this method in pregnancy pulse detection. The experimental results showed that the proposed 1DCNN has a very high averaged accuracy of 97.08%, which indicated that the method can better used for pulse classification.

Keywords: Traditional Chinese medicine · 1D CNN · Pregnancy pulse · F -score

1 Introduction

Traditional Chinese medicine (TCM) is a complete medical system that has widely application in disease diagnosis, treatment and prevention for over 30 centuries [1]. As one of the most important complementary and alternative medicines, TCM has been accepted and used increasingly in the world. In Oriental as well as Western medicine, pulse is considered as a fundamental signal of life, carrying essential information about a persons physical condition and health status [2]. In TCM texts, various pulse qualities have been described [3–5]. The Chinese medical doctors usually use the three fingers of index, middle and ring fingers simultaneously or individually to determine various characteristic features of the pulse [6, 7]. It is generally believed that every pulse can reflect people's different physical conditions, which is widely used in aid of diagnosing cardiovascular disease etc. [8–12].

An important application of pulse diagnosis is the discrimination of pregnancy. A series of physiological changes will take place in women's body, which can be manifested in pulse condition after pregnancy. The pulse condition of pregnancy can objectively reflect a series of changes of the mother's body during pregnancy, which is helpful to judge and understand the health status of the mother. Since the pulse examination has no stimulation, no damage and no radiation, which is better than gynecological examination and is easy to be accepted by pregnant women. Therefore, the in-depth study of pregnancy pulse has clinical application value. A well trained doctor can take the radial pulse to evaluate whether a woman has conceived, to determine the weeks of gestation, and to predict the outcome of pregnancy. Descriptions of the pregnant women's pulse are abundant, as the Huangdi Internal Classic described, but opinions differ on this article [13]. For example, some physicians explain that the slippery pulse is taken on Cun at the first stage of pregnancy, but some describe that the slippery pulse is detected on the cubit during pregnancy. Most doctors believe that Chi pulse is unique compared with inch pulse to pregnant women, and pulse will change with the progress of pregnancy. In addition, there are differences among pulse conditions for pregnant women of different ages. Nevertheless, pulse assessment is a skill that requires long-term experience and is subject to subjective influence. Consequently, an objective and automatic computer assist tool for pregnancy pulse signals analysis is strongly required.

In recent years, more and more attention has been paid to the diagnostic model of combining TCM with artificial intelligence (AI). AI technology can simulate the process of clinical diagnosis thinking and reasoning judgment, automatically analyze and calculate clinical data, and provide an effective way for disease prevention, management, diagnosis and treatment. As the core of AI, deep learning provides an effective way to solve the complex autonomous learning and data analysis problems, such as self coding neural network [14], support vector machine (SVM) [15] and convolutional neural network (CNN) [16], etc. A typical CNN structure is consist of input layer, convolution layer, pooling layer, fully connected layer and softmax layer etc. Owing to the strong feature representation power of deep learning technologies, deep convolutional neural network, as one of the typical deep learning architecture, has achieved tremendous success recently in variety of practical fields. However, CNN is often used to process two-dimensional signals, and the pulse collected is a one-dimensional model. Thus, the 1D pulse signal is usually mapped to a 2D space (for example, a 1D speech signal can be converted into 2D feature maps [17], static feature maps [18], or frequency-time feature [19]) when processing a 1D signal with CNN, which brings inconvenience to signal processing.

In order to meet the characteristics of one-dimensional signal, 1D CNN has become one of the hot spots in the current research. Compared with the 2D CNN, the 1D CNN has the following advantages. Firstly, the 1D temporal signal is directly collected from data acquisition system, so it is more natural to use the 1D input. Secondly, the 2D CNN requires additional 1D-to-2D conversion process (e.g. time-frequency representation method) that may lose some useful information related to faults due to irreversible conversion. Finally, the 2D input signal

usually has a higher dimension than the 1D input, which makes the CNN calculation more complex and time-consuming [20, 21]. Nowadays, 1D CNN is widely used in image and engineering problems and has achieved good results. Xu et al. study on efficiently real-time behavior recognition algorithm using acceleration sensor. They propose a human behavior recognition method based on improved One-Dimensional Convolutional Neural Networks (1D CNNs) and the method can reach the average accuracy of 98.7% in the recognition of 11 human activities [22]. Wang et al. proposed a novel attention mechanism and multi-attention 1D CNN to diagnose wheelset bearing faults. The 1D CNN used can adaptively recalibrate features of each layer and can enhance the feature learning of fault impulses [23]. Fu et al. study the features in the pulse waves of women during pregnancy. They choose continuous cycles waves with different period length and then do the LSQ regression by 12 harmonics fitting to build mathematical model, then do classification and identification of pregnant women [24]. Chowdhury et al. proposed 1D triplet convolutional neural network to combine the two features (Mel frequency cepstral coefficients and linear predictive coding) in a novel manner, thereby enhancing the performance of speaker recognition in challenging scenarios [25]. Hussain et al. present a new dynamic self-organized network immune algorithm that classifies term and records, over sampling and cross validation techniques are evaluated [26]. These literature show that 1D CNN could be used for TCM clinical diagnosis study with intelligent thought.

In this work, a novel 1D CNN structure is proposed in this paper for effective pregnancy pulse classification. Firstly, each layer of the 1DCNN network adopts the block stack structure, including the block and the transition block. Moreover, a bidirectional connection structure is constructed by using the updated layer to update the previous layer alternately, which the system can obtain effective features. Secondly, the three clique blocks go through the pooling layer, and extend the one-dimensional data into vectors through the full connection layer, respectively. Finally, by combining the feature map blocks of different groups, the fusion of multi-scale features is realized. On this basis, the pulse of pregnant women was identified and the expected effect was achieved. The experiment verifies the feasibility and effectiveness of the proposed method.

The rest of paper is organized as follows. In Sect. 2, some related work will be present. In Sect. 3, the 1D CNN system was proposed and introduced. In Sect. 4 the experimental result and discussion were given. Finally, the conclusions and perspectives of future work are presented in the last section.

2 Related Work

In this part, pulse data acquisition, sample expansion, and train and test data were performed.

2.1 Data Acquisition

A total of 80 health volunteers from Zhengzhou University and 80 pregnant women from the Fifth Affiliated Hospital of Zhengzhou University have been

recruited in this study, with a mean age of 24.2 ± 5.5 . All volunteers agreed with the exposed terms by signing a written informed consent. In addition, each participant has a questionnaire to ensure the accuracy of the experiment. Data were collected by ZM-300 Intelligent Pulse Meter of Traditional Chinese Medicine, which the sampling frequency 200 Hz. The volunteers were asked to sit still or rest for at least 5 min before the acquisition. During the collecting process, participants were required to sit or stay supine, relax, not talk and breathe normally. Then, the TCM pulse bracelet was placed over the Chi position in the left hand to capture the pulse signals under six pressures for 10 s, respectively. Subjects were excluded from analysis if they lacked complete data for control or outcome variables or had significant disease. Each person collects six groups of data under six different pulse pressures, each group of data consists of 2000 data points. The waveform under the optimal pressure was selected as the experimental object. So the pulse dataset contains a total of 160 pulse signals that are unevenly distributed into normal people and pregnant women. As shown in Fig. 1 and Fig. 2, pulse wave cycle data were obtained in all subjects.



Fig. 1. ZM-300 intelligent pulse meter.

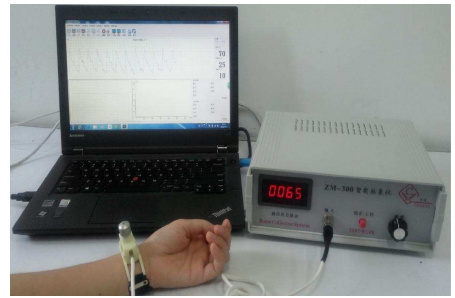


Fig. 2. Pulse acquisition.

2.2 Sample Expansion

In order to make better use of the structure of 1D CNN, the data collected is amplified. Since the acquisition frequency 200 Hz and acquisition time of each group data is 10 s, we use 2 s as a segmentation cycle to expand the data and take them as the research object. Therefore, 160 pulse signals were segmented and amplified. Finally, 800 effective waveforms sets were obtained after expanding the data.

2.3 Train and Test Data

1DCNNs require numerous samples to train for improved generalization. However, the data set used in our experiment is relatively small. In order to obtain as much effective information as possible from the limited data, the 10-fold cross

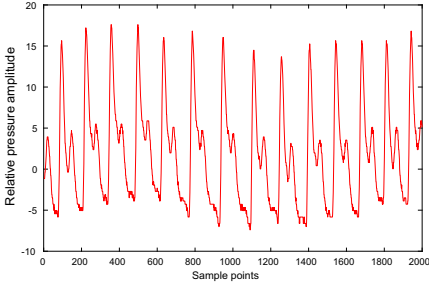


Fig. 3. Original pulse wave.

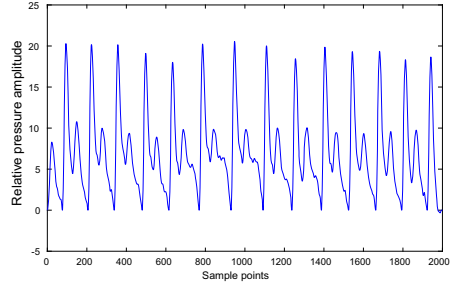


Fig. 4. Filtered pulse wave.

validation was used to process the data and obtained the training set and test sets. The training set contained 560 samples, and the test set contained 240 samples (Figs. 3 and 4).

3 1D CNN Design for the Proposed System

The 1D CNN is analogous to a regular neural network but it has generally raw data as input instead of handcrafted features. Such input data is processed to learn the appropriate representation of the input by several trainable convolution layers. The proposed models consist of batch normalization, residual learning, and down-sampling in the initial layers of the CNN. The structure of the 1D CNNs was simplified as a basic structure of convolution layer, a pooling layer, and a full network layer. The convolution layer had feature maps, and the transfer function was sigmoid. The pooling layer used max-pooling, and the stride was 3. The softmax classifier was used in full network layer to output the posterior probability of each class.

3.1 1D CNN Topology

As described in Fig. 5, the proposed 1D CNN takes pulse set as inputs and outputs predicted results of the corresponding classifier. The proposed model is mainly constituted by three clique blocks and two transition blocks. Each transition block connects the subsequent blocks and gradually reduces the mapping features. The feature map of each block is not only input into the next block, but also the original data was compressed in channel dimension. The features connected and compressed by different blocks are sent into pooling to obtain the multi-scale representation. Finally, the compression features of different scales are combined together and the full connect layer is implemented by softmax to achieve the classification results.

3.2 Network Model of 1D CNN

The 1D CNN model has a multi-layer structure, which is mainly divided into the following five parts: input layer, convolution layer (Conv), pooling layer (Pool),

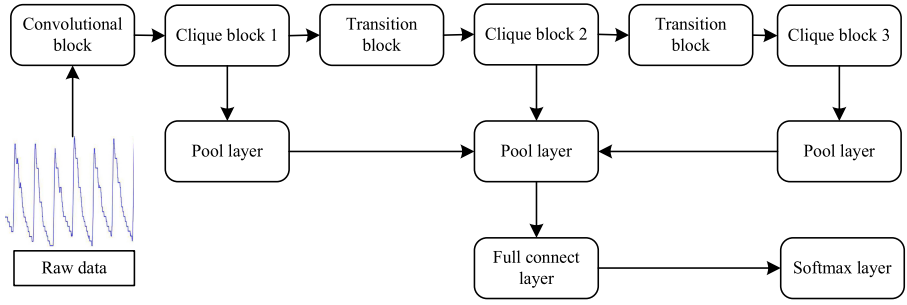


Fig. 5. Flow chart

fully connected layer (FC), and softmax layer. The 1D CNN model structure constructed in this paper is shown in Fig. 6.

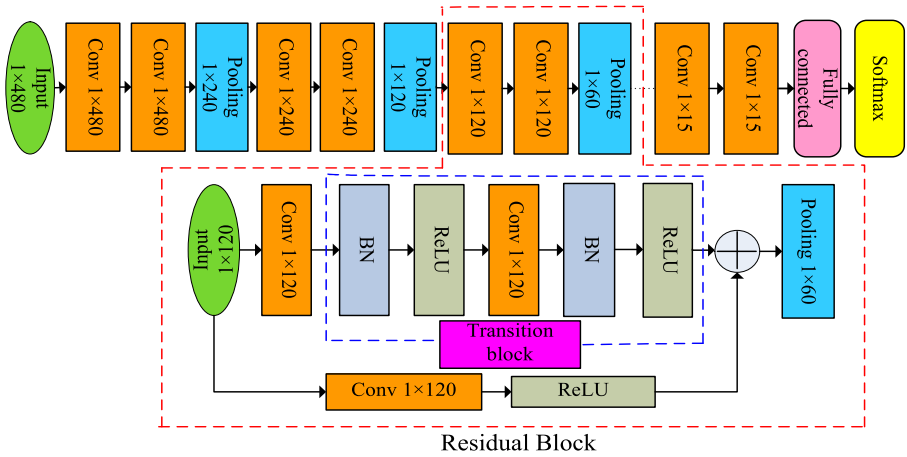


Fig. 6. Network structure of the proposed 1D CNNs

Input Layer: The input layer of 1D CNN can handle one-dimensional data. In this paper, the original data is processed and input in 1×480 form. The hidden layer is composed of convolutional layers, pooling layers, and fully connected layers.

Convolutional Layer: The convolutional layer extracts feature from input data. The pool layer receives the eigenvalues from the convolutional layer and carries out feature selection and information filtering. With the increase of the number of convolution layers, low-level features can be merged into high-level features, and the objects can be classified according to the features. For a typical one-dimensional convolution mechanism, information flows to the next layer through convolution operation and then processed by activation function.

Pooling Layers: The pool layer is called down sampling. It is mainly used to reduce the dimension of features, compress the number of data and parameters, reduce over fitting, and improve the fault tolerance of the model. Mean-pooling and max-pooling are two common pooling functions. Max-pooling divides the input feature mapping into several subregions, while preserving the maximum value of each sub region, reducing the phenomenon that the convolutional layer parameter error causes the estimated mean shift, and makes the image texture information better expressed.

Fully Connected Layers: The fully connected layer is equivalent to the hidden layer in the feed forward neural network, which expands the multidimensional data into vectors and transfers them to the next layer by using the excitation function. The fully connected layer is obtained by adding the weight coefficient to the nodes of the previous layer for many times and adding bias.

Softmax: Softmax is the classifier of this architecture, it makes the prediction using the inputted features. Softmax is a generalization of logistic regression to the problem of multi-class classification. The class label y takes on more than two values. Softmax function can be defined to be

$$w_{ij}z_i = \sum_{j=1}^N h_j w_{ij} \quad (1)$$

$$\text{softmax}(z)_i = p_i = \frac{e^{z_i}}{\sum_{j=1}^N e^{z_j}} \quad (2)$$

where e^{z_i} is the input of softmax, h_i is the activation and w_{ij} is the weight value.

Output Layer: The output layer of 1DCNNs uses the softmax function or the logistic function to output the classification results.

4 Experimental Result and Discussion

In our experiments, the number of iterations is set to 100, and the batch size varies according to the size of the input feature. The models with the best validation accuracy were saved. All experiments were conducted on a desktop computer equipped with Intel Core i7-9700 CPU (72 core, 16.0 GHz) having 16 GB RAM and Nvidia GeForce GTX 1050 GPU. The operating system was Ubuntu version 16.04.

Experiments based on 1D CNNs for pregnancy pulse recognition have effectively improved the recognition accuracy. The curve of accuracy rate and loss rate of the 1D CNN proposed were shown in the Fig. 7 and Fig. 8, respectively. It can be seen from the Fig. 7 that the average accuracy of the identification of pregnancy pulse is 97.08%. ROC curve was shown in Fig. 9. In addition, the F - score was used to indicate the tests accuracy in the statistical analysis of binary classification, The F - score is the harmonic mean of the precision and

recall, where an $F - score$ reaches its optimal value at 1 and worst at 0. The $F - score$, precision and recall to quantify the performance of the method in this study, shown in Table 1.

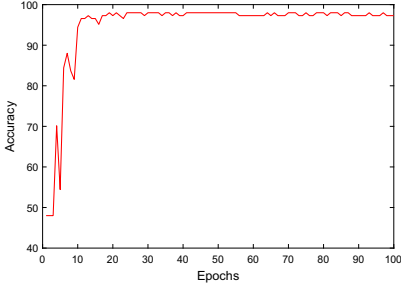


Fig. 7. Test accuracy rate of 1DCNN.

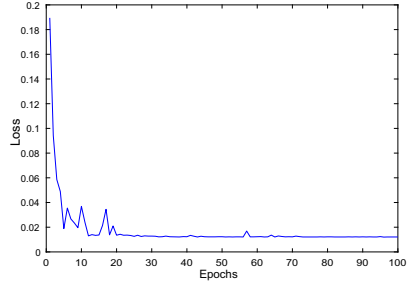


Fig. 8. Test loss rate of 1DCNN.

- (1) Accuracy: The ratio of the number of correctly classified samples to the total number of samples.
- (2) Precision: The ratio of the number of activities of a certain type to that of all activities of that type. It is an index for predicting results.
- (3) Recall: A certain type of activity is correctly predicted as the ratio of the number of such activities to the original total number of such activities. It is an indicator for the original sample instance.

The $F - score$, accuracy, precision and recall can be calculated using the following equation.

$$F - score = 2 \times \frac{\frac{TP}{TP+FP} \times \frac{TP}{TP+FN}}{\frac{TP}{TP+FP} + \frac{TP}{TP+FN}} \quad (3)$$

$$Accuracy = \frac{TP}{TP + TN + FP + FN} \quad (4)$$

$$Precision = \frac{TP}{TP + FP} \quad (5)$$

$$Recall = \frac{TP}{TP + FN} \quad (6)$$

where, TP is the number of activities correctly predicted to be positive, TN is the number of activities correctly predicted to be negative, FP is the number of activities incorrectly predicted to be positive, and FN is the number of activities

Table 1. Displacement spans for different acquisition position.

Criteria	F-score	Accuracy	Precision	Recall
Values	0.9709	0.9708	0.9669	0.9750

incorrectly predicted to be negative. The accuracy, the recall, and the precision range from zero to one. A larger value means a better discrimination performance. The experimental results of 10-fold cross-validation are summarized in Table 1.

When compared with other well-established methods on average accuracy, the designed 1DCNN network also performs satisfactorily. Table 2 showed the classification accuracy of different algorithms for pregnancy pulse, which indicated that the proposed 1DCNN is feasible.

Table 2. Displacement spans for different acquisition position.

Research work	Accuracy
Fu [24]	0.86
Hussain [26]	0.90
The proposed 1DCNN	0.97

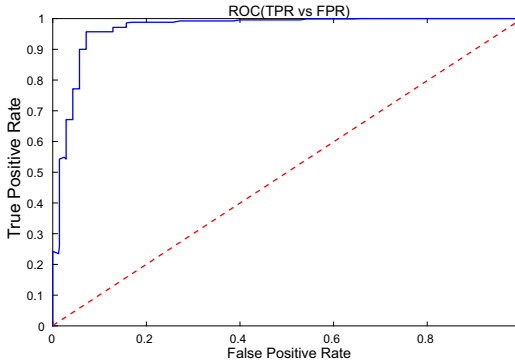


Fig. 9. ROC curve of the proposed 1DCNN

5 Conclusion and Recommendations for the Future

Traditional Chinese medicine believes that human wrist pulse wave contains a lot of important information, which can reflect pathologic changes of the human body condition. In this paper, a 1D CNN model is proposed to distinguish normal pulse from pregnancy pulse. The three clique blocks go through the pooling layer, respectively and extend the one-dimensional data into vectors through the full connection layer. The experimental results show that the accuracy rate of this method is about 97.08% in classifying the pregnancy pulse. In summary, the 1D CNN proposed in this study can effectively improve the classification accuracy of pregnancy pulse.

In the future, the noises factors will be taken into consider to build a model with more robustness for the practical clinical conditions. We will extract more pulse features and use feature dimension reduction to eliminate feature interference caused by feature increase. In addition, the extracted pulse characteristics were used to identify pregnancy pulse from normal pulse, and further verify the new pulse diagnosis method.

Acknowledgments. The work is supported by the key project at central government level (Grant No. 2060302).

References

1. Wu, H.K., Ko, Y.S., Lin, Y.S., et al.: The correlation between pulse diagnosis and constitution identification in traditional Chinese medicine. *Complement. Ther. Med.* **30**, 107–112 (2017)
2. Velik, R.: An objective review of the technological developments for radial pulse diagnosis in traditional Chinese medicine. *Eur. J. Integr. Med.* **7**(4), 321–331 (2015)
3. Xiao, J.H., Lei, Z., Jia, T.X., et al.: Pulse wave cycle features analysis of different blood pressure grades in the elderly. *Evid. Complement. Alternat. Med.* 1–12 (2018). ID 1976041
4. Bilton, K., Zaslowski, C.: Reliability of manual pulse diagnosis methods in traditional East Asian medicine: a systematic narrative literature review. *J. Alternat. Complement. Med.* **22**(8), 599–609 (2016)
5. Hajar, R.: The pulse in ancient medicine part 1. *Heart Views Offic. J. Gulf Heart Assoc.* **19**(1), 36 (2018)
6. Qiao, L.J., Qi, Z., Tu, L.P., et al.: The association of radial artery pulse wave variables with the pulse wave velocity and echocardiographic parameters in hypertension. *Evid. Complement. Alternat. Med.* 1–12 (2018). ID 5291759
7. Huang, Y., Chang, Y., Cheng, S., et al.: Applying pulse spectrum analysis to facilitate the diagnosis of coronary artery disease. *Evid. Complement. Alternat. Med.* 1–10 (2019). ID 2709486
8. De, M.N., Cordovil, I., De, S.F.A.: Traditional Chinese medicine wrist pulse-taking is associated with pulse waveform analysis and hemodynamics in hypertension. *J. Integr. Med.* **14**(2), 100–113 (2016)
9. Zhang, Z., Zhang, Y., Yao, L., Song, H., Kos, A.: A sensor-based wrist pulse signal processing and lung cancer recognition. *J. Biomed. Inf.* **79**, 107–116 (2018)

10. Vallee, A., Petruescu, L., Kretz, S., et al.: Added value of aortic pulse wave velocity index in a predictive diagnosis decision tree of coronary heart disease. *Am. J. Hypertens.* **32**(4), 375–383 (2019)
11. Alemi, H., Khaloo, P., Mansournia, M.A., et al.: Pulse pressure and diabetes treatments. *Medicine* **97**(6), e9791 (2018)
12. Wang, N., Yu, Y., Huang, D., et al.: Pulse diagnosis signals analysis of fatty liver disease and cirrhosis patients by using machine learning. *Sci. World J.* **2015**, 1–9 (2015)
13. Fan, X.D., Wang, R., Chen, W.Y.: Pregnancy outcome of iron-deficiency anemia in third trimester. *J. Int. Obstet. Gynecol.* **41**(3), 274–276 (2014)
14. Cai, J., Dai, X., Hong, L., et al.: An air quality prediction model based on a noise reduction self-coding deep network. *Math. Prob. Eng.* **2020**(3), 1–12 (2020)
15. Wang, H., Tan, B., Fang, X., et al.: Precise classification of forest types uses hyperion image based on C5.0 decision tree algorithm. *J. Zhejiang AF Univ.* **35**(4), 724–734 (2018)
16. Hu, Q., Wang, P., Shen, C., et al.: Pushing the limits of deep CNNs For pedestrian detection. *IEEE Trans. Circ. Syst. Video Technol.* **28**(6), 1358–1368 (2017)
17. Zhao, J., Mao, X., Chen, L., et al.: Speech emotion recognition using deep 1D–2D CNN LSTM networks. *Bio. Signal Proc. Control* **47**, 312–323 (2019)
18. Alaa, T., Gaber, Hassanien, T., Ella A.: One-dimensional vs. two-dimensional based features: plant identification approach. *J. Appl. Logic* **24**, 15–31 (2016)
19. Barrack, D., Goulding, J., Hopcraft, K., et al.: AMP: a new time-frequency feature extraction method for intermittent time-series data. *Comput. Sci.* **65**, 1–11 (2015)
20. Li, F., Liu, M., Zhao, Y., et al.: Feature extraction and classification of heart sound using 1D convolutional neural networks. *J. Adv. Sig. Proc.* **2019**(1), 59–70 (2019)
21. Xiao, B., Xu, Y., Bi, X., et al.: Heart sounds classification using a novel 1-D convolutional neural network with extremely low parameter consumption. *Neurocomputing* **392**, 153–159 (2019)
22. Xu, Z., Zhao, J., Yu, Y., Zeng, H.J.: Improved 1D-CNNs for behavior recognition using wearable sensor network. *Comput. Commun.* **151**(1), 1153–1156 (2020)
23. Wang, H., Liu, Z., Peng, D., Qin, Y.: Understanding and learning discriminant features based on multiattention 1Dcnn For wheelset bearing fault diagnosis. *IEEE Trans. Indust. Infor.* **16**(9), 5735–5745 (2020)
24. Wang, N., Yu, Y., Huang, D., et al.: Research of features in the pulse waves of women during pregnancy. In: *Bio Informatics Bio Medicine*, pp. 730–732 (2010)
25. Chowdhury, A., Ross, A.: Fusing MFCC and LPC features using 1D triplet CNN for speaker recognition in severely degraded audio signals. *IEEE Trans. Inf. Forensics Secur.* **15**, 1616–1629 (2020)
26. Hussain, A.J., Fergus, P., Al-Askar, D., Al-Jumeily, D.: Dynamic neural network architecture inspired by the immune algorithm to predict preterm deliveries in pregnant women. *Neurocomputing* **151**, 963–974 (2015)