Original Article

A Novel Pulse-Taking Device for Persian Medicine Based on Convolutional Neural Networks

Abstract

Background: In Persian medicine (PM), measuring the wrist pulse is one of the main methods for determining a person's health status and temperament. One problem that can arise is the dependence of the diagnosis on the physician's interpretation of pulse wave features. Perhaps, this is one reason why this method has yet to be combined with modern medical methods. This paper addresses this concern and outlines a system for measuring pulse signals based on PM. **Methods:** A system that uses data from a customized device that logs the pulse wave on the wrist was designed and clinically implemented based on PM. Seven convolutional neural networks (CNNs) have been used for classification. **Results:** The pulse wave features of 34 participants were assessed by a specialist based on PM principles. Pulse taking was done on the wrist in the supine position (named *Malmas* in PM) under the supervision of the physician. Seven CNNs were implemented for each participant's pulse characteristic (pace, rate, vessel elasticity, strength, width, length, and height) assessment, and then, each participant was classified into three classes. **Conclusion:** It appears that the design and construction of a customized device combined with the deep learning algorithm can measure the pulse wave features according to PM and it can increase the reliability and repeatability of the diagnostic results based on PM.

Keywords: *Convolutional neural network, Persian medicine, pulse signal, pulse taking, temperament*

Submitted: 14-Jun-2021 **Revised:** 08-Mar-2022 **Accepted:** 19-Apr-2022 **Published:** 10-Nov-2022

Vahid Reza Nafisi[1], Roshanak Ghods[2], Seyed Vahab Shojaedini[1]

[1]Biomedical Engineering Group, Electrical and Information Technology Department, Iranian Research Organization for Science and Technology, [2]Department of Traditional Medicine, Institute for Studies in Medical History, Persian and Complementary Medicine, School of Persian Medicine, Iran University of Medical Sciences, Tehran, Iran

Address for correspondence:
Prof. Roshanak Ghods, Research Institute for Islamic and Complementary Medicine, Iran University of Medical Sciences, Tehran, Iran.
E-mail: ghods.r@iums.ac.ir

Introduction

In Persian medicine (PM), temperament is a key concept in defining human health and disease. In many diseases, certain changes occur in a person's temperament that may be differentiated according to some principles. Recognizing the patient's temperament and determining any deviation from either moderate or the appropriate temperament helps to diagnose and treat the disease in PM. By categorizing patients based on their temperament followed by considering the specific temperament of medicinal products, greater success in predicting the effectiveness of medicines and reducing the side effects will be possible to achieve.[1]

Temperament assessment is usually based on qualitative criteria. In PM, especially the pulse of the radial artery in the wrist, it is very important and forms one of the effective bases of diagnosis in traditional medicine.[2-4] Identification of the pulse characteristics depends on the level of expertise of the physician, which affects the accuracy and reproducibility of temperament assessment.[5] One of the most important methods to diagnose disease in traditional Eastern medicine schools, especially in Iran, is measuring the pulse characteristics in the wrist artery. However, the diagnostic and therapeutic instructions depend on the physician's interpretation of the wrist pulse characteristics. At present, traditional medicine practitioners in Iran measure and analyze the wrist pulse with their hand and complicated mental algorithm without using a device. Therefore, it is clear that the measurement and diagnosis depend on the interpretation of the physician, and its reproducibility can be impaired. Generating reproducible results is the main concern in the widespread use of complementary medicine such as PM.

Chinese medicine (CM) has been equipped with modern devices and

This is an open access journal, and articles are distributed under the terms of the Creative Commons Attribution-NonCommercial-ShareAlike 4.0 License, which allows others to remix, tweak, and build upon the work non-commercially, as long as appropriate credit is given and the new creations are licensed under the identical terms.

For reprints contact: WKHLRPMedknow_reprints@wolterskluwer.com

How to cite this article: Nafisi VR, Ghods R, Shojaedini SV. A novel pulse-taking device for Persian medicine based on convolutional neural networks. J Med Sign Sens 2022;12:285-93.

Access this article online
Website: www.jmssjournal.net
DOI: 10.4103/jmss.jmss_133_21
Quick Response Code:

equipment for many years. In CM, the importance of using standard devices to make reliable and reproducible diagnostic results independent of the physician's skills has been well accepted. It has been emphasized that such devices can be effective in understanding the theory of traditional CM and its development.[6] Several studies have used the concepts of CM to distinguish patients with various diseases from healthy people using the wrist pulse signals. In both CM and PM, a physician places his/her fingers on the patient's wrist to indent the radial arteries with various indentation patterns and diagnoses his/her diseases from the tactile sense of the pulse detected by the fingers [Figure 1]. Shirai *et al*. developed a mathematical model for pulse wave measurement based on CM.[7] They realized that the indentation maneuver can give a possible index to predict the vascular stiffness. For this purpose, a device that simultaneously records the pulse signals of three wrist points was made in 2012 and tested in the laboratory and research.[8] It has been shown that useful information about the body's function can be gained by examining how this pulse wave energy is distributed anywhere in the artery. Therefore, instead of using one sensor for each point, it is better to consider an array of sensors for each point.[9,10] Furthermore, the wrist or finger pulse signals have been widely used in modern medicine for the early diagnosis of diseases. Therefore, pulse measurement can be considered a good common point for combining traditional medicine and modern medicine.

Therefore, the lack of a reliable device that can measure and analyze pulse wave in accordance with the principles of PM is strongly felt. This issue can be an obstacle to the development of PM. As a result, the use of tools that are less influenced by external factors appears necessary for PM. Then, the aim of the present research is to achieve a user-independent and reproducible method for measuring and assessing wrist pulse characteristics.

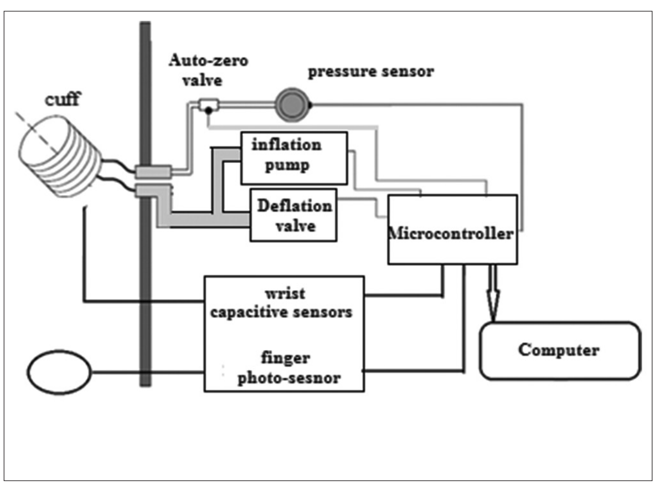


Figure 1: PM expert pulse-taking method (only two fingers were shown). PM - Persian medicine

Methods

Datasets

This preliminary study was conducted at the Behesht Healthcare Center of Iran University of Medical Sciences in the winter of 2020 with 34 volunteers with different temperaments. The volunteers met the inclusion criterion which was no history of disease. All the medical ethics issues were considered. After obtaining written consent from the volunteers, a PM specialist assessed their wrist pulse according to the PM interpretation methods. In PM, the following indicators of wrist pulse are observed in order to diagnose conditions and diseases:[4]

- Pulse propagation characteristics
    - Length = Wave propagation in length of artery
    - Width = Wave propagation in lateral side of artery
    - Height = Proportional to depth of artery.
- Pulse pace (proportional to time of vascular filling)
- Pulse rate
- Pulse strength
- Vessel elasticity.

According to these characteristics, a PM physician defined different pulse types that can be used to identify a person's temperament [Table 1].

After medical examination, the wrist pulse of each participant was recorded at 7 points on the wrist using the customized pulse-taking device made by this research group.

Pulse-taking device

The pulse-taking device that attaches to a person's wrist possesses two general parts:

- Measurement hardware, which is equivalent to the sense of touch and pressure applied to a patient's wrist by a PM specialist. The hardware components of the device include:
    - An inflation pump for creating different pressures on the pulse position [this inflating cuff and the pump imitates how taken the pulse by a PM expert, Figure 1]
    - Pulse sensors at several points in the pulse-taking position
    - Finger photoplethysmography sensor.
- Pulse signal recording/processing/analysis software for the interpretation and diagnosis of diseases and temperaments.

The main structure of this device is shown in Figure 2. Three types of sensors have been used to record the pulse signal according to PM principles:

- Seven capacitive sensors that measure the characteristics of stroke volume in different parts of the wrist
- An optical sensor that measures the intensity of blood pulse in the patient's finger
- A pressure sensor that measures and controls the pressure applied to the cuff on the patient's wrist.

Table 1: participants labeling according to various characteristics of the wrist pulse

Subject	Pace	Rate	Vessel elasticity	Strength	Width	Length	Height
2	1	1	1	1	2	1	1
3	2	2	3	2	2	2	2
4	3	2	2	2	3	2	2
6	2	2	3	0	2	2	2
7	1	1	1	0	2	2	2
8	2	1	0	2	2	2	2
9	3	2	3	3	1	3	3
10	2	2	3	2	2	2	2
11	1	1	3	2	2	2	2
12	2	1	3	3	2	3	3
13	2	2	3	3	2	2	3
14	2	2	3	3	2	2	3
15	1	1	3	2	2	2	2
16	1	2	1	2	2	1	2
17	1	1	1	2	2	1	2
18	1	1	3	2	2	2	2
19	2	2	3	3	2	2	3
20	1	1	1	1	1	2	1
21	2	2	3	1	2	2	3
22	1	1	3	1	3	3	3
23	2	1	0	3	3	3	3
24	1	1	3	3	1	3	3
25	2	2	1	2	2	3	2
26	2	1	2	0	2	2	3
27	2	1	0	2	2	2	2
28	2	2	3	2	1	3	3
29	2	2	3	2	2	2	3
30	2	1	3	2	2	2	3
31	1	1	3	3	3	3	3
32	1	1	1	1	2	1	2
33	1	1	3	0	3	1	2
34	1	1	1	2	3	2	3

The meaning of the numbers of 0, 1, 2 and 3:
"0": Not evaluated.
"1": the mentioned parameter has been interpreted to 'Low' level, according to PM.
"2": the mentioned parameter has been interpreted to 'Normal' level, according to PM.
"3": the mentioned parameter has been interpreted to 'High' level, according to PM

The reproducibility and reliability of a measuring device is an important issue. Hence, the customized pulse meter has been compared with a calibrated pulse oximeter reference device. It has shown that its performance is valid.[11] Some technical specification of the device is written in Table 2.

Classification method

The proposed method consists of a convolutional neural network (CNN) architecture for classification with three one-dimensional convolution layers and fully connected layer, as shown in Figure 3. The term "input array" in

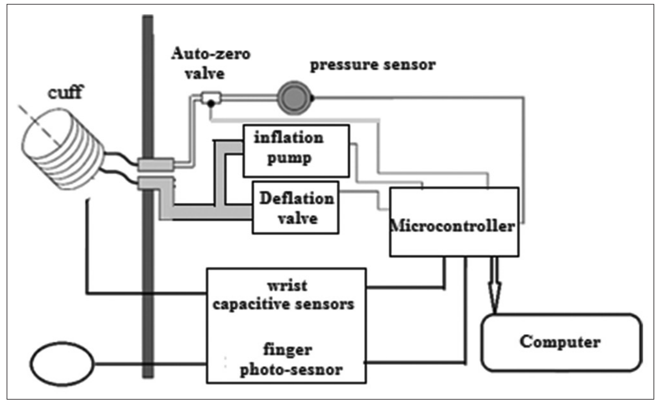


Figure 2: System diagram for pulse-taking device

Figure 3 refers to all raw signals obtained from seven capacitive sensors, the photoplethysmography sensor and the pressure sensor. Therefore, dimension of "input array" is 9 × (temporal length of signals). The ReLU activation function was used after each layer, and to control the overfitting problem, L2-regularization with a rate of 1e-6 on the weights was applied for all the layers. The optimization was done with a learning rate of 0.001, and we used four different batch sizes of 20, 32, 64, and 128 for each run to evaluate the influence of the batch size on the accuracy. For each run, the number of epochs was applied equally to 100. The proposed method has been tested in Google Collaborator with NVIDIA Tesla T4 GPU allocation and has been implemented using Python 3 Keras framework with TensorFlow library.

There are various kinds of cross validation methods which have been widely used to improve validity and accuracy in classification issues when these are no enough experimental samples. One of the most reliable ones is nested cross-validation.[12] Hence, we used it [Figure 4]. The selected signal's samples were randomly partitioned into k subsets which one subset is considered as the test data and the remaining k-1 subsets are used as training data. The cross-validation process is repeated k times, with each of the k subsets used exactly once as the test data. These combinations of feature selection and classification were repeated for 50 iterations. After that, the statistical measures (accuracy, sensitivity, and specificity) were averaged and its standard deviations were calculated. The number of iteration (50 iterations) is not a critical item. It was just selected to overcome some randomness in the statistical parameter.

According to subsection A, the PM specialist assessed participant's pulse characteristics (pace, rate, vessel elasticity, strength, width, length, and height) and classified each participant into three classes. Hence, the structure in Figure 3 was repeated for seven different pulse characteristics. Furthermore, 50% of data were allocated for training and 20% for validation in training phase of CNN. The rest of data (30%) were used for test.

Results

As mentioned before, 34 volunteers participated in the study. Two participants (number 1 and 5) were excluded from the study because of inconsistent data and low-quality capacitive sensors. The PM specialist assessed their wrist pulses and identified seven characteristics for each participant: length/width/height/strength/pace/rate/vessel elasticity. After that, each participant was labeled to a class (no. 1, 2, or 3) based on each pulse characteristic. Therefore, according to each pulse characteristic, a participant belonged to three different classes. This information is shown in Table 1. In this table, “0” means that the participant has not been assessed for the corresponding characteristic.

Table 2: Technical specification of the device

Acquisition time (minute)	1-1.5 (for each person)
Sample rate (samples/s)	200
Pressure (mmHg)	0-180
Pre-processing	Low pass filter: 20 Hz

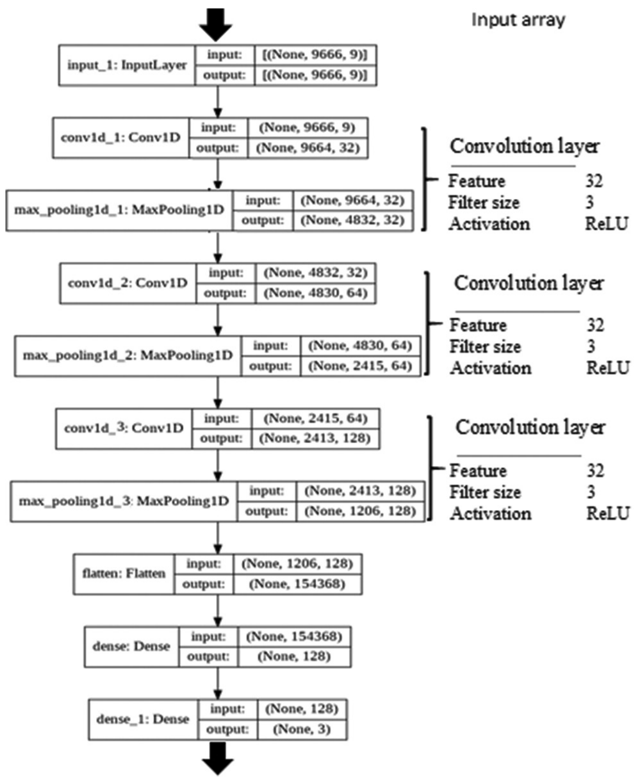


Figure 3: The configuration of CNN. CNN - Convolutional neural network

When pressure is applied on the wrist [Figure 5], the wrist pulse signal reaction is related to the characteristics of the cardiovascular system (such as vessel elasticity) and strength of the pulse wave. Figure 6 shows the changes in the received signals in the capacitive and optical sensors at different pressures.

After the data collection, whole data (whole signals captured from capacitive and photo and pressure sensors) are inserted into the classification algorithm for each labeled column of Table 1 separately. At first, a multilayer perceptron (MLP) neural network (3 layers: 1024 neurons in the first layer, 128 neurons in the second layer, and 3 neurons in output layer) as the classifier was used. Its performance is shown in Table 3 for three labels of Table 1.

The statistical measures of the algorithm on the “test” data which are shown in Table 3 are calculated by Eq. 1 to 3.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$\text{Sensitivity} = \frac{TP}{TP + FN} \tag{2}$$

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{3}$$

Where TP, TN, FP, and FN are true positive, true negative, false positive, and false negative, respectively.

It is worth mentioning that decision-making process for the classification of the wrist pulse characteristics is very complicated in PM. Therefore, it is expected

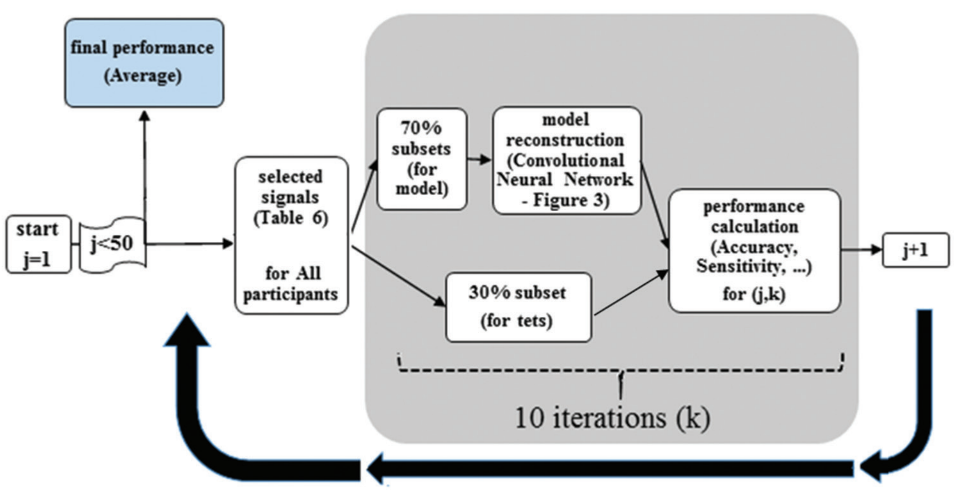


Figure 4: Performance calculation flowchart

that simple classifier such as MLP would have low performance and we need to complex classifier such as CNN which reveals high quality of results in comparison to MLP [Table 4].

As mentioned before, the results in Table 4 were based on the use of all recorded signals from 9 sensors. The question is, for each of the pulse wave propagation characteristics, the combination of all the signals is the best, or it is possible that the use of one or more specific sensors will give a better answer?

For this purpose, the classification of participants for each label [Table 1] was examined using different combinations of sensors [Table 5]. Our guide in choosing such combinations has been based on our interpretation of the physics of wave propagation in the vessels and surrounding tissues and the thinking method of the PM expert.

The result of the accuracy of classifying the participants based on their different pulse characteristics using different combinations of sensor analysis is listed in Table 6. In this table, in each row, the first number indicates the value of accuracy and the second number indicates the coefficient of variation, which is calculated by Eq. 4.

$$CV(\mathrm{X}) = \frac{\text{standard deviation(x)}}{\text{average(x)}} \quad (4)$$

The bold numbers in Table 6 represent the highest value of accuracy and the lowest coefficient of variation in each row.

As shown in Table 6, the use of all signals does not always give the optimal result, and some simpler combinations of signals can provide results with higher accuracy and smaller coefficients of variation. In terms of classification accuracy, there are several optimal combinations for some indicators (vessel elasticity and length). To select the most optimal combination, the sensitivity and specificity of the classifier for these cases can be also examined. It will be more discussed in the Discussion section.

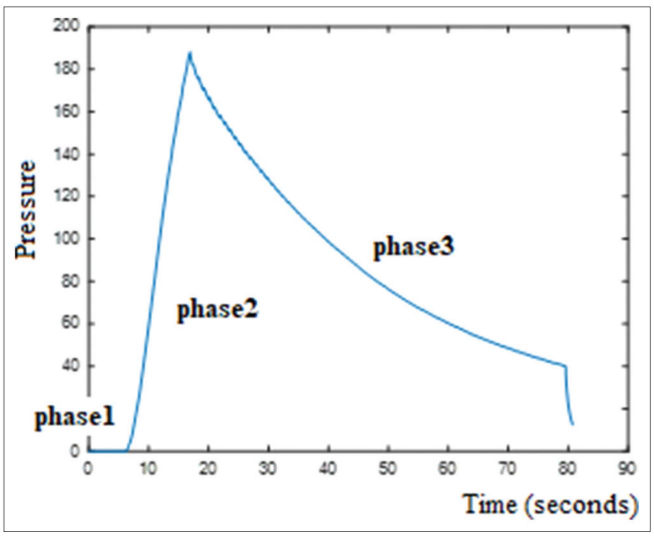


Figure 5: Pressure phases

Discussion

In this study, some measurements required and mentioned by PM were assessed:

- Pulse signals at seven points on the wrist
- Blood volume variation in the finger (finger photoplethysmography).

The propagation of the pulse wave in the radial artery is affected by the characteristics of the vessel. Tissue elasticity plays a major role in the proper functioning of the cardiovascular system. The vessels that carry blood from and to the heart are not rigid tubes but rather have flexible walls that stretch in response to the blood pressure inside and external pressure (cuff) outside them. A simple diagram of how the volume in a compliant vessel is related to the net pressure (=blood pressure minus cuff pressure) is shown in Figure 7. Increasing the net pressure will linearly increase the vessel's volume – up to a point where the limit of elasticity is reached. In the linear region, the proportionality constant between net pressure (P) and volume (V) is called the vessel

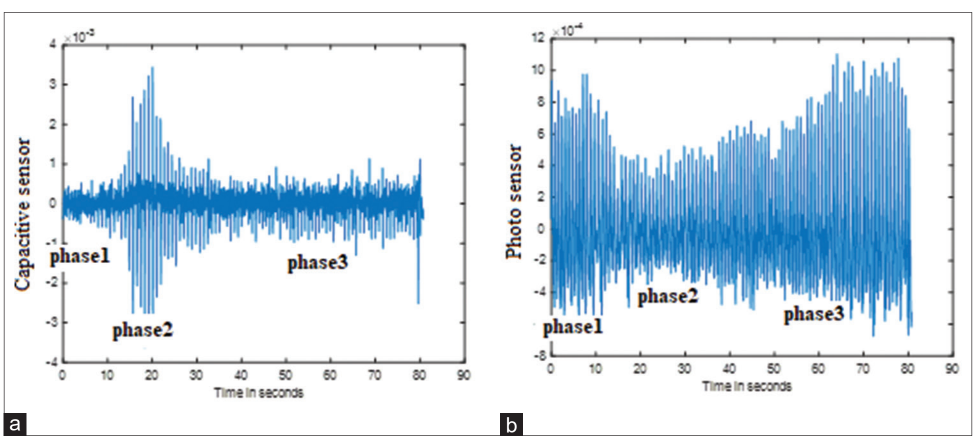


Figure 6: Sensors variation during pressure changes. (a) Capacitive sensors (b) photo sensor

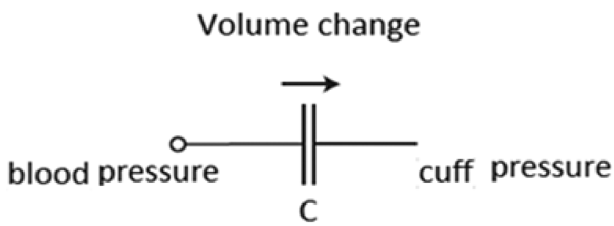


Figure 7: Vessel wall is interpreted as a compliance

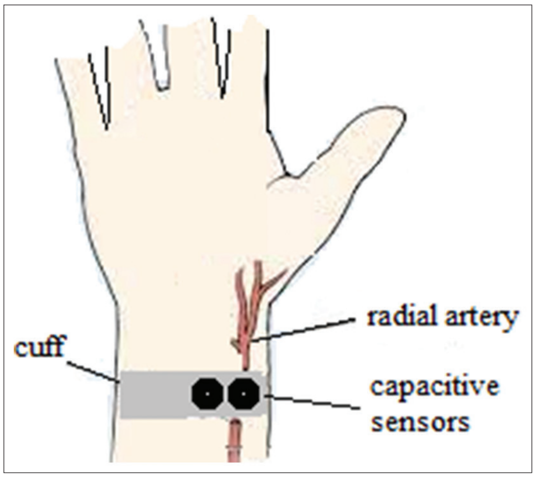


Figure 9: Capacitive sensors aligned in width of the artery

Table 3: Performance of the classification algorithm based on multilayer perceptron for three labels (three columns of Table 1)

	Accuracy (%)	Sensitivity (%)	Specificity (%)
Pace			
Maximum	52.9	22.2	100
Mean	47.3	1.56	99.8
Minimum	47.1	0.0	96.0
Vessel elasticity			
Maximum	67.6	100	100
Mean	53.5	36.0	97.6
Minimum	35.3	0	56.3
Height			
Maximum	56.3	50.0	100
Mean	52.0	23.0	100
Minimum	46.9	0.0	100

compliance (C). The larger the vessel's compliance, the larger the volume for a given pressure. Mathematically, the relationship can be stated as (Hooke's law):

$$V = V_{\varphi} + C. P \quad (5)$$

Vφ is residual volume.

On the other hand, the propagation of this wave along the artery affects each of the sensors used in the device.

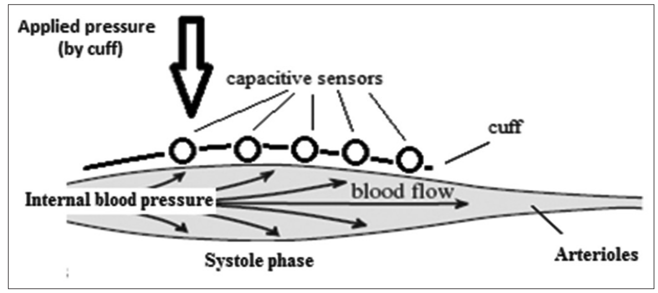


Figure 8: Capacitive sensors aligned in length of the artery

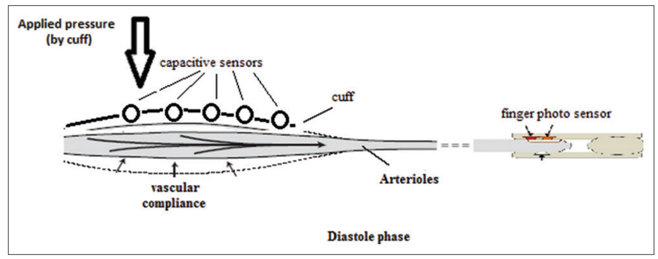


Figure 10: During diastole, artery wall elasticity accelerates the blood flow to the fingers

Therefore, the pulse wave on the sensors varies according to the characteristics of the vessel. For example, it can be said that when the capacitive sensors receive the pulse signal at higher pressures, it indicates the higher the strength of the cardiovascular system in the patient, and this is one of the diagnostic indicators in PM.

The vessel compliance has at least two important consequences:[13]

1. The pulsating blood pressure is damped by the compliance of the arteries and arterioles walls in conjunction with their resistance. Figure 8 shows that the damping effect of vascular system can be evaluated by capacitive sensors aligned in length of radial artery.

Furthermore, there are two capacitive sensors aligned in width of radial artery which could evaluate vascular elasticity and expansion in lateral axis [Figure 9].

2. The energy of blood pulses discharged by the heart ventricles during systole phase is temporarily stored as potential energy in the stretched walls of the vessels. During diastole phase, this potential energy is converted to additional blood velocity, helping push the blood down the arteries to the fingers that can be evaluated by finger photo sensor [Figure 10].

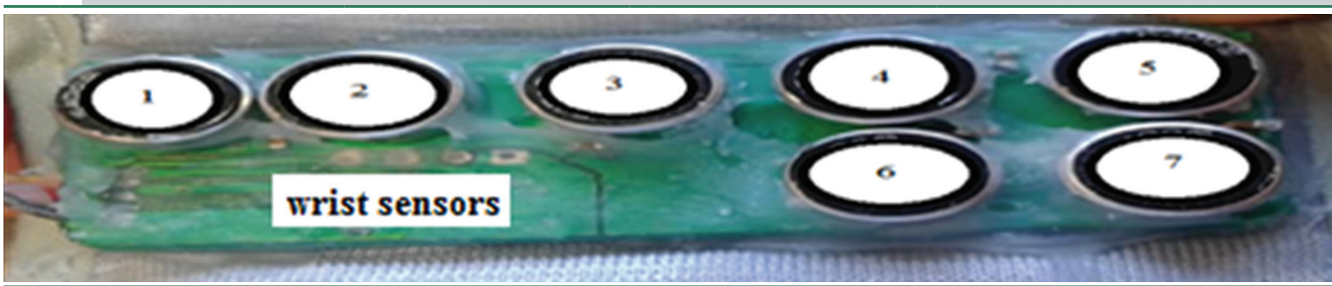
Thus, it can be expected to obtain appropriate information about the patient's cardiovascular system and his health status by sensors data fusion in different pressure phases on the wrist. For this reason, all 9 signals recorded during the test (7 capacitive sensors on the wrist, a finger photoplethysmography sensor, and cuff pressure sensor) were used for each participant in order to classify the pulse profile. The performance of the classifier confirms it.

Table 4: Performance of the CNN classification algorithm for each label (columns of Table 1)

	Number of classes		Accuracy (%)	Sensitivity (%)	Specificity (%)
Pace	3	Maximum	100	100	100
		Mean	91.8	83.6	99.1
		Minimum	56.7	7.14	93.8
Rate	2	Maximum	100	100	100
		Mean	94.4	100	86.2
		Minimum	59.3	100	59.4
Vessel elasticity	3	Maximum	100	100	100
		Mean	97.4	93.8	99.8
		Minimum	82.8	50.0	95.2
Strength	3	Maximum	100	100	100
		Mean	98.6	99.0	100
		Minimum	96.4	80.0	100
Width	3	Maximum	100	100	100
		Mean	94.1	86.3	100
		Minimum	68.8	25.0	100
Length	3	Maximum	100	100	100
		Mean	100	100	100
		Minimum	100	100	100
Height	3	Maximum	100	100	100
		Mean	94.7	92.5	100
		Minimum	71.9	50	100

Table 5: Various sensor combination analyses

	Wrist sensor 1	Wrist sensor 2	Wrist sensor 3	Wrist sensor 4	Wrist sensor 5	Wrist sensor 6	Wrist sensor 7	Finger sensor	Pressure sensor
C1			✓					✓	
C2					✓			✓	
C3				✓				✓	
C4							✓	✓	
C5						✓		✓	
C6	✓							✓	
C7		✓						✓	
C8				✓	✓	✓	✓	✓	
C9	✓	✓	✓	✓	✓			✓	
C10	✓	✓	✓	✓	✓	✓	✓	✓	
C11	✓	✓	✓	✓	✓	✓	✓	✓	✓



Recently, the using deep learning networks to determine the characteristics of biomedical signals have increased significantly. It attempts to classify patterns using multiple nonlinear processing layers.[14] CNN is a powerful data-driven method to handle the massive data which provides a good alternative approach to extract the features of raw data automatically compared to the traditional methods.[15] CNNs have recently become a technique for complicated and multidimensional signal processing applications such as structural health monitoring.[16-19]

Table 6: Accuracy and Coefficient of variation for various combination scenarios

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
Pace	0.88	0.86	0.93	0.92	0.91	**0.98**	0.94	0.92	0.97	0.93	0.92
	0.17	0.19	0.10	0.13	0.13	**0.06**	0.11	0.17	0.08	0.10	0.17
Rate	0.91	0.89	**0.98**	0.94	0.84	0.95	0.97	0.89	0.89	0.93	0.94
	0.16	0.22	**0.04**	0.10	0.25	0.07	0.06	0.20	0.19	0.18	0.15
Vessel elasticity	0.93	0.97	0.94	0.95	0.95	**0.98**	0.97	**0.98**	**0.98**	0.95	0.97
	0.12	0.07	0.10	0.07	0.08	**0.06**	0.06	**0.06**	**0.06**	0.09	0.06
Strength	0.95	0.95	0.95	0.96	0.95	0.95	0.94	0.92	0.95	0.95	**0.99**
	0.05	0.06	0.07	0.05	0.09	0.07	0.09	0.10	0.05	0.06	**0.02**
Width	0.93	**0.96**	0.94	0.93	0.94	0.95	0.95	0.91	0.91	0.93	0.94
	0.09	**0.08**	0.08	0.09	0.09	0.07	0.06	0.10	0.09	0.09	0.10
Length	0.99	**1.0**	0.98	0.99	1.0	1.0	0.96	1.0	**1.0**	**1.0**	**1.0**
	0.05	**0.0**	0.08	0.02	0.001	0.01	0.10	0.02	**0.0**	**0.0**	**0.0**
Height	0.96	0.96	0.91	0.92	0.95	**0.97**	0.94	0.95	0.92	0.90	0.95
	0.06	0.04	0.10	0.09	0.05	**0.03**	0.09	0.06	0.08	0.11	0.09

Table 7: comparison between some Chinese pulse measurement systems and present study

Ref.	Wang *et al.*[21]	Kan-beng *et al.*[22]	Kabigting *et al.*[23]	Jin *et al.*[24]	Present study
Year of report	2012	2015	2017	2019	2020-2021
Wearable wristband	No	No	Yes	Yes	Yes
Multi-sensors	Wrist array sensor	3 wrist sensors	3 wrist sensors	3 wrist sensors	7 wrist sensors, 1 finger sensor, 1 pressure sensor
Combined and detachable	No	No	No	Yes	Both
Adjustable position	Yes	Yes	No	Yes	No
Pressurization method	Motor + shaft	Motor + shaft	Manually	Pump + air bag	Pump + air bag
Sampling frequency (Hz)	>50	1000	11	1000	200
Pulse-taking pressure acquiring	Yes	Yes	No	Yes	Yes
High-level analysis and classification	No	No	No	No	Yes

These signals need to convert into the feature space, but the selection of the best features is critical to improve the ability of classifiers. However, CNNs can directly be applied to the raw signals without any preprocessing such as de-noising and feature extraction.[20] Therefore, CNN is a good solution for our situation, and Tables 4 and 5 show its superiority to the conventional neural networks.

Due to the lack of similar studies specific to PM and due to the similarities between Persian and Chinese traditional medicine, here we mainly review the researches carried out in the field of pulse signals in CM. Chinese experts believe the radial pulse changes that are felt in different parts of the wrist are related to the diseases of a specific organ. They identified three points on the main artery of the wrist that could be measured by three fingers. Table 7 shows the comparisons of some recent pulse measurement systems (based on CM) and the present method.

Finally, for better explanation of results in Table 6, it is worth mentioning that the neural networks used for diagnostic applications (such as those discussed in this article) try to construct a model which is based on training data. This model tries to recognize test data. Thus, these types of networks act as a kind of interpolator. A very important factor in the compatibility of the model resulting from this interpolation is the degree of consistency and homogeneity of the data used in the construction of the model and in the testing process. It is a well-known principle in either traditional or deep neural networks that the more focused the training and test data, the better the performance of the model, both in terms of convergence and test results. Thus, in the scenario where the data of different sensors are used to construct and test the model (i.e., connected to different parts of the body), we are faced with data with higher variance and in fact heterogeneous. In contrast in the other scenario, we are faced with a model that is trained and tested with highly homogeneous and centralized data, thanks to recording signals belonging to each network from the same point of body. According to the above explanations, as a rule, in the latter method, we can see higher homogeneity, more consistent model, and more desirable accuracy. Of course, it should be noted that the increase in accuracy is not specific to this study, and in various studies in various fields, we see the same phenomenon in neural networks. For example, some researchers used similar neural networks to diagnose breast cancer from images.[25] After that images were taken from different angles, training and subsequently the test procedures of separate networks were provided for images taken from each angle. In fact, the effect of improving the homogeneity of data was preferred due to the increase in their number, and this is exactly what we have found in the present study that when the data are partially diverse (i.e., signals from different points of body which have different statistics), the effect of homogeneity is superior to the increasing amount of data.

Conclusion

This study showed that designing and implementing a customized device for recording and analyzing pulse wave according to PM is feasible, and when it is combined with the deep learning algorithm, it can reduce the dependence of the interpretation of the wrist pulse by the physician.

Acknowledgment

The authors wish to thank Ms. Mohadeseh Haydarpanah for her commitment and responsibility in collecting and categorizing the data.

Financial support and sponsorship

None.

Conflicts of interest

There are no conflicts of interest.

References

1. Naseri M, Rezaeizadeh H, Taheripanah T, Naseri V. Temperament theory in the Iranian traditional medicine and variation in therapeutic responsivenes, based on pharmacogenetics. J Islam Iran Tradit Med 2010;1:42-237.
2. Naseri M. A review of the generalities of traditional Iranian medicine. In: Pulse Studies. Ch. 2. Iran: Shahed University Press; 2003.
3. Nafisi A. Brief History of Medical Sciences Up to the Beginning of the Contemporary Century. Isfahan: Isfahan University Press; 1976. p. 118-25, 233-55.
4. Nazim J, A, zam-khan M. Nayer-Azam: In Recognizing the Pulse and Its Types. Tehran: Traditional Persian Medicine Press; 2016.
5. Mozaffarpur SA, Saghebi R, Khafri S, Mojahedi M. An assessment of the agreement between persian medicine experts on Mizaj identification. Tradit Integr Med 201;2:113-8.
6. Chu X, Sun B, Huang Q, Peng S, Zhou Y, Zhang Y. Quantitative knowledge presentation models of Traditional Chinese Medicine (TCM): A review. Artif Intell Med 2020;103:101810.
7. Shirai A, Nakanishi T, Hayase T. Numerical analysis of one-dimensional mathematical model of blood flow to reproduce fundamental pulse wave measurement for scientific verification of pulse diagnosis. J Biomech Sci Eng 2011;6:330-42.
8. Hu CS, Chung YF, Yeh CC, Luo CH. Temporal and spatial properties of arterial pulsation measurement using pressure sensor array. Evid Based Complement Alternat Med 2012;2012:745127.
9. Lin Wang YY, Sze WK, Bau JG, Wang SH, Jan MY, Hsu TL, Wang WK. The ventricular-arterial coupling system can be analyzed by the eigenwave modes of the whole arterial system. Applied Physics Letters 2008;92:p153901.
10. Chen C, Li Z, Zhang Y, Zhang S, Hou J, Zhang H. A 3D wrist pulse signal acquisition system for width information of pulse wave. Sensors (Basel) 2019;20:11.
11. Yousefipoor F, Nafisi V. A novel method for pulsometry based on traditional Iranian medicine. J Med Signals Sens 2015;5:230-7.
12. Vabalas A, Gowen E, Poliakoff E, Casson AJ. Machine learning algorithm validation with a limited sample size. PLoS One 2019;14:e0224365.
13. Christensen DA. Introduction to biomedical engineering: biomechanics and bioelectricity – Part I. Synth Lect Biomed Eng 2009;1:1-118.
14. Alaskar H. Convolutional neural network application in biomedical signals. J Comput Sci Inf Technol 2018;6:45-59.
15. Wena L, Gaoa L, Lia X, Wangb L, Zhuc J. A jointed signal analysis and convolutional neural network method for fault diagnosis. Procedia CIRP 2018;72:1084-7.
16. Shimazaki S, Kawanaka H, Ishikawa H, Inoue K, Oguri K. Cuffless blood pressure estimation from only the waveform of photoplethysmography using CNN. Annu Int Conf IEEE Eng Med Biol Soc 2019;2019:5042-5.
17. Kasaeyan Naeini E, Azimi I, Rahmani A, Liljeberg P, Dutt N. A real-time PPG quality assessment approach for healthcare internet-of-things. Procedia Comput Sci 2019;151:551-8.
18. Liang Y, Chen Z, Ward R, Elgendi M. Photoplethysmography and deep learning: Enhancing hypertension risk stratification. Biosensors (Basel) 2018;8:101.
19. Perepelkina O, Artemyev M, Churikova M, Grinenko M. HeartTrack: Convolutional Neural Network for Remote Video-Based Heart Rate Monitoring, Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) Workshops; 2020. p. 288-9.
20. Kiranyaz S, Ince U, Abdeljaber O, Gabbouj M. 1-D Convolutional Neural Networks for Signal Processing Applications, IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP 2019). [doi: 10.1109/ICASSP. 2019.8682194].
21. Wang P, Zuo W, Zhang H, Zhang D. Design and Implementation of a Multi-Channel Pulse Signal Acquisition System, In IEEE International Conference on Biomedical Engineering and Informatics, ChongQing, China; 2012. p. 1063-7.
22. Kan-Heng Z, Peng Q, Chun-Ming X, Yi-Qin W. Research on a novel three-channel self-pressurized wrist pulse acquisition system. In: Biomedical Engineering Systems and Technologies. Cham, Germany: Springer; 2015. p. 49-59.
23. Kabigting JE, Chen AD, Chang EJ, Lee W, Roberts RC. Mems Pressure Sensor Array Wearable for Traditional Chinese Medicine Pulse-Taking. In Proceedings of the IEEE 14th International Conference on Wearable and Implantable Body Sensor Networks (BSN), Eindhoven, The Netherlands; 9-12 May 2017.
24. Jin C, Xia C, Zhang S, Wang L, Wang Y, Yan H. A wearable combined wrist pulse measurement system using airbags for pressurization. Sensors (Basel) 2019;19:386.
25. Sánchez-Cauce R, Pérez-Martín J, Luque M. Multi-input convolutional neural network for breast cancer detection using thermal images and clinical data. Comput Methods Programs Biomed 2021;204:106045.