A machine learning method correlating pulse pressure wave data with pregnancy

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Abstract

Pulse feeling, representing the tactile arterial palpation of the heartbeat, has been widely used in traditional Chinese medicine (TCM) to diagnose various diseases. The quantitative relationship between the pulse wave and health conditions however has not been investigated in modern medicine. In this paper, we explored the correlation between pulse pressure wave (PPW), rather than the pulse key features in TCM, and pregnancy by using deep learning technology. This computational approach shows that the accuracy of pregnancy detection by the PPW is 84% with an area under the curve (AUC) of 91%. Our study is a proof of concept of pulse diagnosis and will also motivate further sophisticated investigations on pulse waves.

KEYWORDS

conventional neural network, deep learning, pregnancy, pulse diagnosis, pulse pressure wave

1 | INTRODUCTION

Pulse feeling, obtained by putting the doctor’s fingers on a patient’s wrist pulse (see Figure 1), has been widely used in traditional Chinese medicine (TCM) for thousands of years.¹,² It has long been claimed that the pulse feeling can be used to detect various health conditions such as kidney failure,³ liver fibrosis,⁴ cardiovascular disease,⁵ and pregnancy.⁶ Every TCM doctor is required to master pulse feeling, which is a very basic technique, but it is hard to teach and learn. The teaching and learning process often takes years, or even a lifetime since the pulse feeling varies for different health conditions and patients. The exact mechanism used in the pulse feeling is highly complex, and there have been many types of descriptions and theories in Chinese medical literature, but many of such theories are often more subjective than objective. One such theory is to characterize a pulse feeling through three key features:⁷ length, depth, and pattern. The length is related to the strength and balance of the blood and energy flow, the depth reflects certain types of pathological condition, and the pattern refers to different phases or features of a pulse feeling (it is usually believed that there are 28 different pulse patterns,⁸ such as the so-called choppy and slippery pulses).

Naturally, it is a subject of research and practical interest if the pulse-feeling technique can be studied and understood through a scientific manner. One can imagine this is an extremely challenging task due to the “subjective” aspect of the pulse-feeling process. There are many different approaches in these studies. One such approach is to analyze the aforementioned three key features of pulse feeling²⁷⁻⁹ via various computational methods, eg, artificial neural network (ANN) developed in recent years. By using certain physical parameters of arterial pressure waveform acquired from six locations (left and right cun, guan, and chi) as inputs, an ANN with one hidden layer of width 45 has been employed⁷ for a regression study of features of pulse feeling. The number of data used in the study was $n = 229$, and the value of $R^2$, a standard parameter measuring model performance, for their ANN model was $0.6 – 0.86$. Another similar ANN with a hidden layer of width 25 has also been developed⁸ to classify normotension versus hypertension. This study was based on certain pulse assessment, namely, the intensity of features of pulse feeling measured by TCM experts, on a dataset with 139
normotension and 121 hypertension. Although the accuracy was 80%, the conclusion in this study was more subjective than objective because features of pulse feeling highly rely on the doctor’s experience. Thus, the conclusions reached by this approach may vary among different doctors and may even vary when given by the same doctor who examines the same patient but at a different time or in a different environment.

Another approach is to use an appropriate medical device to collect pulse signals and then quantitatively interpret these signals for the health diagnosis. One such device that has been used by researchers is the pulse pressure sensor as shown in Figure 1 (right). By placing this type of sensor on a patient’s wrist pulse, pulse pressure waves (PPWs), as shown in Figure 2 (left), can be collected. A PPW reflects pressure changes in the wrist blood vessel and is believed to contain certain information that a TCM doctor uses in pulse-feeling diagnosis. Then a quantitative study can be carried out by analyzing these PPWs. For example, by using PPW as the input, a 12-pulse-pattern classification (such as stringy and slippery) was conducted with a nine-layer 1D convolutional neural network (CNN) (with around 2280 variables). On 200 training and 261 test samples, they obtained a 93.49% accuracy. Moreover, a nine-layer 1D CNN was used to further study the correlation between PPW and arteriosclerosis; 60% of the data were used as training data, and 40% was used as test data from a dataset with 47 participants (35 arteriosclerosis and 12 nonarteriosclerosis) and obtained a 96.33% accuracy rate on classifying the arteriosclerosis versus nonarteriosclerosis. The relationship between important features of the arterial pulse wave (peak, length, etc) and pregnancy has also been studied through using a four-hidden layer probabilistic neural network (the nodes for each layer are 22, 44, 2, and 1). By using 110 samples of training data (45 pregnant and 65 nonpregnant), the neural network reached 100% accuracy on a test dataset with 20 samples (four pregnant and 16 nonpregnant). It is interesting to note that all these studies were based on small datasets (around 200 samples), although the number of variables was relatively large (around 2000). Moreover, the training/test datasets were imbalanced (ie, pregnant/nonpregnant ratio is 2/3 in the training data but is 1/4 in the test data), and there was a lack of cross-validation, which is important for a generalizable computational model.

Other techniques related to PPW are also commonly used in modern medical practices. The most directly related technique is the pulse wave velocity (PWV) that has been used as an index of arterial stiffness and a biomarker of cardiovascular risk and even other diseases. Another relevant technique is based on photoplethysmogram (PPG), which is an optically obtained plethysmogram that can be used to detect blood volume changes in a microvascular bed of
A PPG signal, as shown in Figure 2 (right), is similar to a PPW signal as shown in the left panel of Figure 2. PPG has been widely used in modern clinical practice as a noninvasive diagnostic technique and also for monitoring heart rate, cardiac cycle, respiration, and other bodily processes.

In this paper, we will use deep learning techniques, more specifically CNN, to study PPW. There are several points in our study that significantly differ from the existing studies. First, our study is based on a relatively large clinical dataset that was collected from over 4000 women consisting of over 1800 pregnant and 2200 nonpregnant women. In comparison, existing studies were based on much smaller datasets (for example, six samples, 47 samples, and 130 samples). Second, in this paper, we developed a modern computational approach based on CNN with two different neural network models and data preprocessing methods to analyze the underlying correlation between the PPW and health conditions. Due to the similarity among PPW, PPG, and electrocardiogram (ECG), our approach can be generalized to the diagnosis of human health conditions by other available clinical imaging data (PPG, ECG, etc.). Third, we studied the correlation between the PPW and pregnancy as a proof of concept due to the following reasons: (a) the status of pregnancy is clear and definite, unlike kidney weakness and neurasthenia, which are vague and unclear; (b) the label of pregnancy is very accurate due to standard and effective techniques for pregnancy detection, such as urine tests (with high accuracy) and blood tests; (c) it has been widely claimed in TCM that pregnancy can be accurately detected by pulse feeling; (d) during pregnancy, there are many physiological changes in the reproductive system, circulatory system, urinary system, respiratory system, etc. Therefore, the maternal blood volume increases by 45% above nonpregnant values, which may change pulse wave patterns. By taking the original PPW segments as the only input, our models provided an 85% accuracy of pregnancy prediction. The paper is organized as follows: First, we introduce the data used in our study and two data preprocessing approaches; second, we present our computational approach, which consists of two different neural networks; the detailed results for both approaches and discussion are then presented.

2 THE AVAILABLE DATASET AND PREPROCESSING

The PPW data were collected from over 4000 people (age 28.69 ± 8.60) in Nanjing, China. The collections were taken under the HK-2010/1 single channel pulse sensor, by experienced and trained nurses, from volunteers' left wrists when the pulse repeated in a regular pattern for about 40 seconds. The pulse sensor measured the blood pressure with a time resolution of 1/150 seconds. In Figure 2, we have plotted an image with the x-axis assigned to the measurements while the y-axis is assigned to the pulse wave amplitude. Then our PPW imaging dataset was selected based on similar periods and amplitudes. The number of people with respect to all pregnancy weeks is shown in Figure 3. There are two peaks centering around the 12th and 23rd weeks since two major pregnancy examinations happen around these weeks. The low quality refers to the irregular pattern and large noise introduced by the external environment and the collecting operation. After this filtering process, only 1840 samples (of which 645 are pregnant) are left. In order to obtain reliable and reproducible results, we designed a data preprocessing approach: the restrict the PPW to one period and append zeros to construct the...
measurement interval. In our study, we chose the measurement interval as 256 unit pixels since all the periods are smaller than 256 unit pixels. By denoting our dataset \( D = \{ a_1, \ldots, a_d, \ldots \} \) where \( a_i \in D \) is one datapoint, we describe the data preprocessing approach to preprocess each data \( a_i \in D \) as follows:

1. Divide \( a_i \) into several subintervals by local minimums, which are shown as red lines in the left part of Figure 4.
2. And pick one of the subintervals in the first step and normalize linearly into \([0,1]\) with 256 pixels (append zeros if less than 256 since all the periods are less than 256) shown in the right part of Figure 4.

3 | COMPUTATIONAL MODELS

We applied two different types of 1D-CNN models from He et al\textsuperscript{28} and He and Xu,\textsuperscript{29} respectively, to analyze the PPW data and to compare the results. Model 1, which is based on the 1D ResNet and uses BasicBlocks,\textsuperscript{28} has more channels, parameters (the number of parameters is 242 642), and a better generalization capability. The detailed structure of model 1 is shown in Table 1. Here, BasicBlocks, which insert identity shortcut connections to the plain convolutional layers,\textsuperscript{28} are commonly used in deep neural networks of the ResNet to reduce the computational cost. Model 2 is based on the 1D MgNet\textsuperscript{29} and uses 18 layers with only eight channels (the number of parameters is 3450). We note that the structures (and the number of weights used herein) between model 1 (which is based on the standard ResNet) and model 2 (which is based on the new MgNet) are quite different, but, as we shall see later, the outcomes of these two different models are similar, which provides a cross-validation of the liability of using the deep learning approach on the PPW data.

![Figure 4](image)

**FIGURE 4** The illustration of one period restriction: locating local minimum for sample data (left); one sample period after preprocessing (right)

| TABLE 1 | The detailed structure of model 1 |
|----------|---------------------------------|
| **Layer Name** | **Input Size** | **Output Size** | **Layer Parameters** |
| Convolution | 256 \( \times \) 1 | 128 \( \times \) 16 | \([7, 16] + [16]\) |
| Pooling | 128 \( \times \) 16 | 64 \( \times \) 16 | 3 for max pooling |
| BasicBlock1 | 64 \( \times \) 16 | 64 \( \times \) 16 | \([3, 16] \times 2\) |
| Block with downsampling1 | 64 \( \times \) 16 | 32 \( \times \) 32 | \([3, 32] \times 3\) |
| BasicBlock2 | 32 \( \times \) 32 | 32 \( \times \) 32 | \([3, 32] \times 2\) |
| Block with downsampling2 | 32 \( \times \) 32 | 16 \( \times \) 64 | \([3, 64] \times 3\) |
| BasicBlock3 | 16 \( \times \) 64 | 16 \( \times \) 64 | \([3, 64] \times 2\) |
| Block with downsampling3 | 16 \( \times \) 64 | 8 \( \times \) 128 | \([3, 128] \times 3\) |
| BasicBlock4 | 8 \( \times \) 128 | 8 \( \times \) 128 | \([3, 128] \times 2\) |
| Pooling | 8 \( \times \) 128 | 256 | 7 for average pooling |
| Fully Connected | 256 | 2 | 256 \( \times \) 2 |
4 | RESULTS

The implementation of these two computational models is based on the PyTorch library.\textsuperscript{30} The optimization problem is based on the cross-entropy loss, which is defined as

\[
L(y, \hat{y}) = -\frac{1}{n} \sum_{i} y_i \ln \hat{y}_i + (1 - y_i) \ln(1 - \hat{y}_i),
\]

(1)

where \( n \) is the total number of data samples, \( y_i \) is the true label for the \( i \)th PPW data, and \( \hat{y}_i \) is the predicted label of the computational models. The Adam method\textsuperscript{31} was employed to solve the optimization problem. The learning process was stopped after running 200 epochs, and then, we chose the model with the best validation accuracy. The loss and accuracy of the first fold for both models are shown in Figure 5. For model 1, the average testing accuracy is 84.73\%, while model 2’s average testing accuracy is 84.68\%.

![Figure 5](image)

**TABLE 2** Accuracy and AUC for two models (red color for model 1, while blue color for model 2)

| Test Fold | Training Epochs | Accuracy Training | Validation | Testing | AUC, % |
|-----------|-----------------|-------------------|------------|---------|--------|
| 1         | 28              | 91.58             | 89.61      | 90.22   | 90.76  | 88.04  | 86.96  | 94.20  | 95.12  |
| 2         | 84              | 100.00            | 90.29      | 84.78   | 84.78  | 87.50  | 87.50  | 89.55  | 91.67  |
| 3         | 81              | 100.00            | 89.67      | 85.87   | 84.24  | 86.41  | 82.07  | 88.54  | 89.36  |
| 4         | 5               | 86.48             | 90.08      | 87.50   | 88.59  | 79.35  | 77.17  | 84.39  | 85.69  |
| 5         | 12              | 88.45             | 90.96      | 88.04   | 86.96  | 83.70  | 82.07  | 82.85  | 91.83  |
| 6         | 18              | 88.11             | 89.88      | 91.30   | 89.67  | 83.70  | 84.78  | 91.14  | 89.59  |
| 7         | 55              | 99.46             | 92.53      | 86.41   | 90.22  | 86.96  | 92.93  | 89.04  | 93.90  |
| 8         | 19              | 91.00             | 90.15      | 85.87   | 86.96  | 84.24  | 86.96  | 93.14  | 91.93  |
| 9         | 67              | 100.00            | 86.28      | 89.67   | 85.87  | 80.98  | 82.07  | 81.56  | 92.25  |
| 10        | 31              | 91.85             | 89.33      | 89.67   | 88.59  | 86.41  | 84.24  | 92.18  | 89.10  |
| avg       | 40              | 93.70             | 89.88      | 87.93   | 87.66  | 84.73  | 84.68  | 89.66  | 91.04  |

Abbreviation: AUC, area under the curve.
In order to test the generalizability of these computational models, we used the 10-fold cross-validation to test the classification accuracy of our models. In particular, we divided the dataset \( (n = 1840) \) into 10 folds of equal sizes, namely, 184 data samples in each fold. The test set was chosen from folds 1 to 10, the validation set was chosen from the next fold, and the remaining data was used as the training set. The cross-validation results are shown in Table 2 (the left side of each column is for model 1 while the right side is for model 2). Moreover, the receiver operating characteristic (ROC) curve of the true positive rate (TPR) versus the false positive rate (FPR), an important indicator in statistics, is plotted in Figure 6 to illustrate the first fold. For all the folds, we computed the test area under the curve (AUC) shown in Table 2. The average AUC is 89.66\% (model 1) and 91.04\% (model 2). Finally, we also compared the results of our models with the SVM, the logistic regression method from the Scikit-learn library,\textsuperscript{32} and other CNN models.\textsuperscript{10-12} The accuracy and the AUC for different models are shown in Table 3, which clearly shows that the results of our computational models are more accurate than the others.

### TABLE 3  Comparisons of our models with the SVM and logistic regression

| Model | Description | Test Accuracy, % | AUC, % |
|-------|-------------|------------------|--------|
| 1     | Model 1     | 84.73            | 89.66  |
| 2     | Model 2     | 84.68            | 91.04  |
| 3     | CNN 1\textsuperscript{11} | 80.71            | 87.43  |
| 4     | CNN 2\textsuperscript{10} | 80.76            | 88.19  |
| 5     | ANN\textsuperscript{12} | 81.09            | 88.63  |
| 6     | SVM         | 75.54            | 75.72  |
| 7     | Logistic regression | 78.80            | 78.24  |

Abbreviation: AUC, area under the curve.

### 5 | CONCLUSION AND DISCUSSION

In this paper, we have employed modern machine learning techniques to explore the relationship between pulse and pregnancy, which has been claimed to exist in TCM over a long history. Two computational models, based on the 1D CNN, have been developed and have shown that the best accuracy of pregnancy detection by PPW is 84\% and the best AUC is 91\%. The computational models we developed in this paper provide a rigorous and scientific approach to analyze the PPW data. This approach, based on deep learning, provides a systematic way to “learn” the correlation between the PPW data and pregnancy. Although this “learning” approach, similar to the Alpha-go,\textsuperscript{33} may not be able to understand the underlying biological mechanisms, this approach may be very helpful for the early diagnosis of various diseases such as cardiovascular disease in clinical practice. In order to achieve this long-term goal, we need to deal with the following potential barriers in the current setup: (a) the data noise and (b) the dataset size. Regarding the data noise, due to our straightforward and crude pulse acquisition equipment, the quality of the pulse waves is not satisfactory, so the measurement noise introduced during the collection needs to be quantified more carefully. As far as the dataset size, the current PPW dataset includes about 4000 samples, which are not quite enough to train a high accuracy deep learning model. Our computational models will be further validated once more clinical data becomes available. We will also explore the correlation between the PPW and time series data, such as the PPW versus the size of arterial plaque, in the future.
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