

Prediction of Acute Hypotensive Episode in ICU Using Chebyshev Neural Network

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Abstract—An Acute Hypotensive Episode (AHE) is a serious threat to the lives of Intensive Care Unit (ICU) patients. The proposed method of accurately predicting an AHE will allow doctors to make a timely and effective intervention; therefore, it has a high clinical value. In recent years, the Chebyshev neural network model has been favorably applied in other fields. In this study, we built a Chebyshev neural network based on pattern recognition to predict AHE in ICU patients. We preprocessed the arterial blood pressure (ABP) data of the ICU patients, and then, extracted time-domain signal features from the data to construct the feature vector. We trained the neural network using a classified predictive model to predict AHEs. We used the classic BP neural network and its improved versions for comparison. Our experimental results show that our Chebyshev neural network model performs better than other solutions in predicting AHEs; therefore, it can provide a reference for clinical applications.

Index Terms—AHE prediction, Chebyshev neural network, modeling

I. INTRODUCTION

In physiology and medicine, hypotension refers to the condition when the blood pressure is lower than normal, generally, when the systolic blood pressure (SBP) is lower than 90mmHg and the diastolic blood pressure (DBP) is lower than 60mmHg. Hypotension can be either chronic or acute. An Acute Hypotensive Episode (AHE) is defined in <Textbook of Medical Physiology> as any period of 30 minutes or more during which at least 90% of the mean arterial pressure (MAP) measurements are at or below 60 mmHg [1]. The medical industry currently does not have uniform and clear standards for the diagnosis of hypotension.

AHE usually occurs in cases of hemodialysis, spinal

anesthesia, Caesarean section, as well as postoperative cardiovascular intervention [2-4]. It occurs frequently in Intensive Care Units (ICU) [5]. AHE can be caused by many factors, including sepsis, myocardial infarction, arrhythmia, pulmonary embolism, pathological bleeding, dehydration, low blood volume, insufficient cardiac output, or vasodilatory shock. It also depends on the basic clinical status and medical history of the patient. Without an effective early intervention, AHE may cause fainting or shock, resulting in irreversible organ damage in patients or even death [4].

Studies show that AHE, which happens in the ICU after spinal anesthesia administration, Caesarean section, and postoperative cardiovascular intervention, may reduce the effectiveness of the treatment, and even result in the patient's death. Therefore, if we can accurately predict AHEs, doctors would have time to intervene in order to ensure the treatment's effectiveness and greatly reduce patient mortality.

Currently, research on AHE prediction is still at an early stage. Previous studies were based on clinical research, which focused on the selection of a predicted index. With the application of digital signal processing (DSP) technology in the medical field since the 1960s, the research focus gradually moved to information processing algorithms and modeling. At present, three main prediction methods are practiced: the multi-parameter prediction model, the classification prediction model based on pattern recognition, and a prediction model that combines the two. Of these three, the classification prediction model based on pattern recognition received widespread attention in the field of fundamental research. Its main idea is to use pattern recognition to build a mathematical model, based on patient data, so that the model can predict whether a patient would have AHE. The commonly used methods in this model include artificial neural networks (ANN), support vector machines (SVM), and decision trees. As a result of improvement on both theoretical and hardware

levels, a lot of effort was made for introducing ANNs into practical applications. ANNs have a wide range of applications in the field of pattern recognition, artificial intelligence, signal processing, intrusion detection, and portfolio optimization, because of their high degree of parallelism, ability to process non-linear information, and adaptive learning ability, which are similar to the characteristics of the human brain [6-11].

The classic back-propagation (BP) neural network is one of the most important and widely used neural networks. Its main feature is that signals propagate forward and errors propagate backward. However, in a large number of practical applications, the classic BP neural network exhibited a slow convergence rate and the shortcomings of the local minimum objective function value, thus affecting the quality of the solution [12]. Many derivatives and improved algorithms have been proposed and they fall into two main categories [13]:

- Improved algorithms based on the steepest descent algorithm
- Improved algorithms based on the numerical optimization algorithm

These improvements have a common goal, which is to improve network performance with better network training iteration algorithms.

In recent years, the Chebyshev neural network model has been favorably applied in the field of pattern recognition and image restoration. It can reduce the amount of computation, increase convergence rate, and avoid falling into the local minimum, as in the BP network training process[14]. The Chebyshev neural network solves these problems by improving the neural network structure definition and by replacing the activation function of the hidden layer with a group of Chebyshev orthogonal polynomials. We built a Chebyshev neural network model and used the data of the ICU patients to predict whether the patient would have an AHE. Compared with the results of improved BP

networks, the simulation results showed that the Chebyshev neural network had a better prediction performance.

II. THE PROPOSED METHOD

A. Data

The PhysioNet/Computers in Cardiology Challenge is an annual series of open challenges hosted by PhysioNet and Computers in Cardiology. In 2009, the theme of the challenge was to predict AHE. The data are from the Multi-parameter Intelligent Monitoring for Intensive Care (MIMIC) II database [15], which is provided by the official website of this challenge. Time-series signals of the data used for experimental samples included all the physiological parameters of the patients in the ICU for more than 10h of continuous monitoring. These physiological indicators include the arterial blood pressure (ABP), heart rate (HR), pulse, and oxygen saturation (SpO₂). The sample data was divided into a training set consisting of 60 groups and a test set consisting of 50 groups. The training set was further divided into Group H (patients that had AHE) and Group C (patients with no AHE). Each group had 30 patients. The test set was further divided into Group A with 10 patients (5 from Group H and 5 from Group C) and Group B with 40 patients (14 from group Hand 26 from group C).

For each patient, the time sequence of signals included a forecasting deadline T_0 . The goal is to use the available data to predict before T_0 if the patient will have an AHE that begins within the forecast window (the hour following T_0). We selected the mean blood pressure (MBP) signal and the diastolic blood pressure (DBP) as our research data. Fig. 1 and Fig. 2 show the time sequence of the same patient's MBP and DBP, respectively.

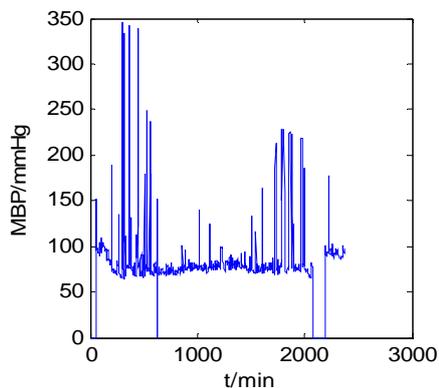


Figure 1. MBP of patient a40439n

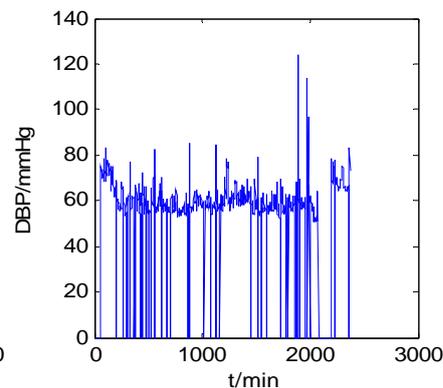


Figure 2. DBP of patient a40439n

B. Neural Network Model

As mentioned, two types of algorithms improved the classic BP neural network algorithm; we generically call them "improved traditional algorithms." To compare the

performance of these algorithms against our algorithm, we built four different BP neural networks to predict AHE on ICU patients and to analyze the results:

- a network based on the classic algorithm,

- a network based on the variable learning rate algorithm,
- a network based on the Levenberg–Marquardt algorithm (LMA), and
- the Chebyshev neural network.

The classic BP algorithm is based on the gradient descent method, which calculates the gradient of the objective function to constantly revise the network weights and thresholds. Its learning rate is a smaller constant; therefore, it converges slowly and easily falls into a local minimum point.

The variable learning rate algorithm, which is based on the steepest descent method, increases the iteration step for the correction weights as much as possible to improve the learning rate, thereby making the convergence faster. The LMA, which is based on numerical optimization, searches for a direction that is close to the optimal value to avoid falling into local minimum points and to improve the convergence rate.

The Chebyshev neural network also improves on the classic BP network with changes to the network structure and the excitation function, which are based on polynomial interpolation and the function approximation theory [16–17].

Fig. 3 is a model of a Chebyshev neural network. It consists of the input layer, the hidden layer, and the output layer. The input layer and the output layer use a linear activation function with a weight value of 1 and a threshold value of 0. The hidden layer neurons use a set of successively higher order Chebyshev orthogonal polynomial basis functions (COPBF) $\varphi_i(x)$ as the activation function, which are defined as follows:

$$\begin{cases} \varphi_0(x) = 1 \\ \varphi_1(x) = x \\ \varphi_{i+1}(x) = 2x\varphi_i(x) - \varphi_{i-1}(x), i = 1, 2, \dots \end{cases}$$

The network training uses the classic BP network error back-propagation algorithm. In theory, this neural network can be used for any nonlinear function approximation.

III. RESEARCH METHOD

The clinical data provided in the MIMIC II database included noise data, pseudo-differential data, and deletions; therefore, it cannot be directly used for feature extraction. We selected the MAP and DBP data in the 10 h before T0 as our research data and performed data preprocessing. First, we cut off signals that were above 140mmHg and lower than 35mmHg, because an adult with an arterial pressure above 140mmHg is considered in the hypertensive range, whereas an adult with an arterial pressure below 35mmHg would be in a coma or deceased. We then complemented the missing data using linear interpolation.

Because the arterial blood pressure signal is a low-frequency signal [6], its main feature would be contained in its low-frequency segment, and the high-frequency portion may be regarded as interference noise. Therefore, the second step of the data preprocessing is to run the selected signal through a low-pass filter. Then we obtained the MAP and DBP signals. Fig. 4 shows the MAP time series of the same patient before and after the data preprocessing.

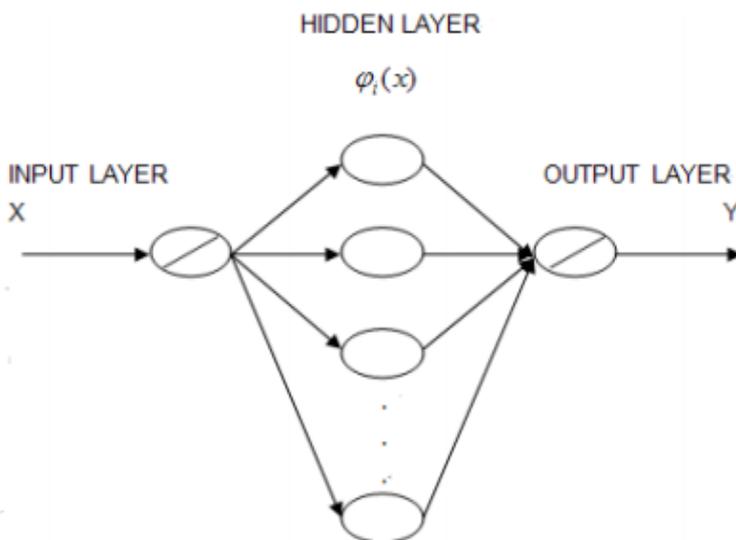


Figure 3. Chebyshev neural network model

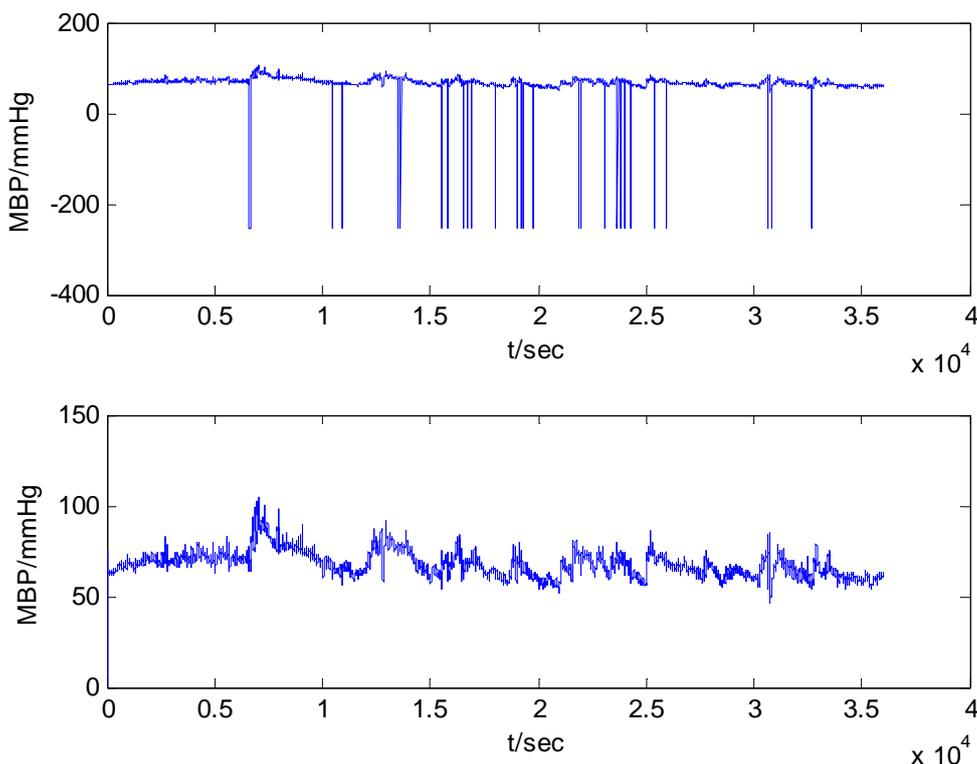


Figure 4.MBP Time series of patient 101bnm before and after the data preprocessing

We extracted four feature parameters from all the preprocessed signals. Index I, II, and III are the 5-min time sequence averages of MBP, DBP, and ABP, respectively, before T₀. Index IV is the predicted MBP at

the midpoint of the forecast window, which is derived via the linear regression of the 1-hMBP before T₀. Tab. 1 shows the feature parameters of some patients of Group H and Group C.

TABLE I.
FEATURE PARAMETERS OF GROUP H & GROUP C (PARTIALLY)

Number(Group)	Index I	Index II	Index III	Index IV
a40439(H)	68.72	50.28	124.20	56.56
a40493(H)	67.82	45.64	110.84	69.92
a40764(H)	75.40	57.20	104.40	61.75
a40834(H)	62.94	51.06	92.48	54.61
a40282(C)	78.14	60.46	120.90	62.49
a40473(C)	102.90	77.06	151.18	96.58
a40551(C)	94.12	71.26	129.52	61.97
a40802(C)	84.86	65.82	99.14	68.97

The specific modeling process is as follows:

1. Construction of the input feature vector: From a training set comprised of 30 patients from Group H and 30 patients from Group C, extract the 4 feature parameters and store them into a 4 × 60 feature vector. Normalize the data in the feature vector to cancel the magnitude differences between the input and output data in each dimension [18]. We obtain the input feature vector P (4 × 60);

2. Construction of the target vector: The target vector is comprised of 30 rows of 1 and 30 rows of 0, where 1 indicates that the AHE will occur within an hour after T₀, and 0 indicates that the AHE will not occur within an hour after T₀; then, we obtain the target vector T (1 × 60);

3. Training of four neural networks: Use the feature vector P as input, and the target vector T as the expected output. Train the neural networks. The parameters of each neural network are shown in Tab. 2. Select the hidden layer nodes that reflect

the minimum classification error in the experiment. Fig. 5 shows the relationship between the hidden layer nodes and the classification error. Stop the training when the training error reaches a specified number.

4. Network Tests: Use the same method to process the test set. The feature vector for Group A is $A(4 \times 10)$, and the feature vector for Group B is $B(4 \times 40)$. Obtain the output vector, which comprises

rows of 1's or 0's, from the network. The 1's indicate the patients who will have AHE within the forecast window, and the 0's indicate the patients who will not have AHE.

After the modeling process, the parameters of each neural network have attained the optimum value by training. Furthermore, we need to analyze the prediction of each network.

TABLE II.
PARAMETERS OF NETWORKS

Type of Networks	Number of input layer neurons	Transfer function of input layer	Number of hidden layer neurons	Transfer function of hidden layer	Number of output layer neurons	Transfer function of output layer	Training function	Minimum mean square error
Classic BP Neural Network	4	Purelin	13	Tansig	1	Purelin	traingd	10^{-8}
Variable Learning Rate BP Neural Network	4	Purelin	13	Tansig	1	Purelin	traingda	10^{-8}
LMA BP Neural Network	4	Purelin	13	Tansig	1	Purlin	trainlm	10^{-8}
Chebyshev Neural Network	4	Purelin	13	COPBF	1	Purelin	traind	10^{-8}

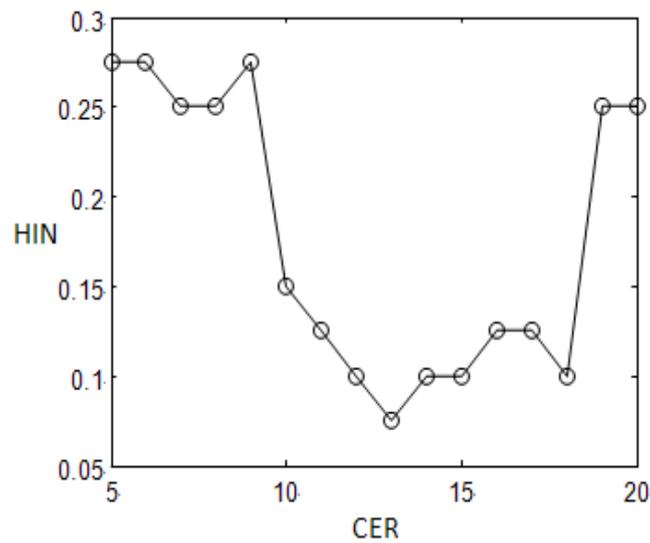


Figure 5. Relationship between the hidden layer nodes(HIN)and the classification error rate(CER)

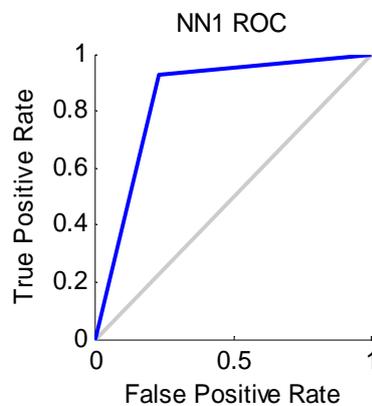
IV. RESULTS AND DISCUSSION

A total of 60 test samples were divided into Group A and Group B; the prediction results of four neural networks for Group A all have reach 100%, the prediction results of four neural networks for Group B are shown in Tab.III, respectively. The evaluation indexes of

the prediction results include accuracy, sensitivity, and specificity. For Group B, we also used the receiver operating characteristic curve (ROC Curve) as an evaluation index, as shown as Fig. 6. NN1, NN2, NN3, and NN4 correspond to the four neural networks.

Table III.
Results for Group B

Type of networks	Accuracy	Sensitivity	Specificity
Classic BP Neural Network	82.5%	92.86%	76.92%
Variable Learning Rate BP Neural Network	90%	85.71%	92.31%
LMA BP Neural Network	90%	100%	84.62%
Chebyshev Neural Network	92.5%	100%	88.46%



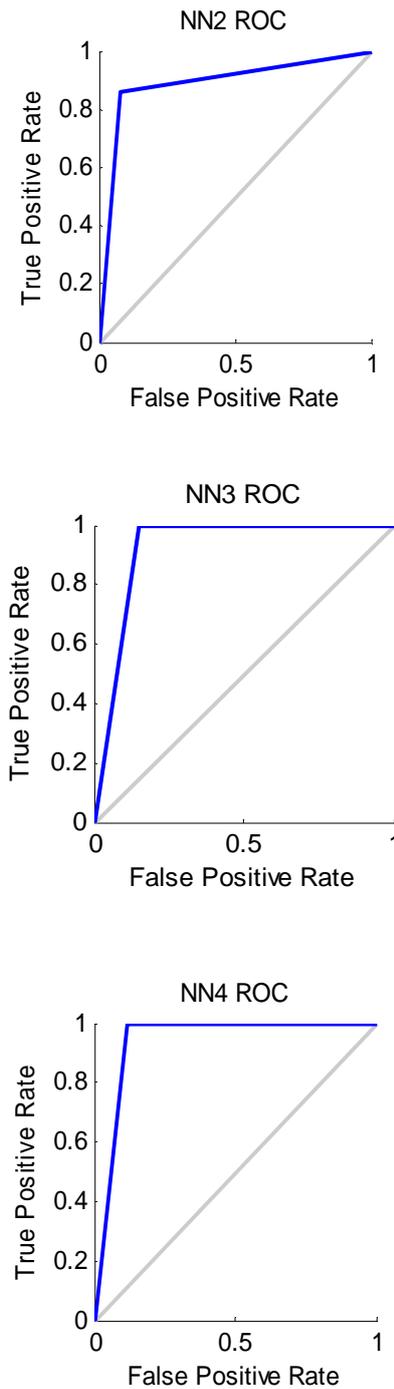


Figure 6. ROC Curve classification of Group B

According to the results in Tab. 3 and 4, the four neural networks obtained a prediction accuracy rate of 100% for the Group A test set. For the Group B test set, the two networks based on the improved algorithms of the BP network have slightly better prediction results than the classic BP network. The Chebyshev neural network exhibited the best forecast performance with 92.5% accuracy. In terms of sensitivity, Both the LMA BP network and the Chebyshev neural network correctly predicted all AHE test samples. In terms of specificity,

the Chebyshev neural network wrongly predicted only 3 AHE test samples, which indicates the second highest specificity. In terms of the ROC curve, the areas under the curves of the improved networks are significantly larger than that of the classic BP network. The area under the ROC curve of the Chebyshev neural network is even larger. In conclusion, the Chebyshev neural network overcomes the existing problems of the improved BP networks, thereby significantly improving its predictive capability.

Many research teams have been committed to AHE prediction, also many methods have been raised. The mainstream methods include SVM, Auto Regression, Logistic Regression, rule-based, Decision Tree, Leave-One-Out Cross Validation(LOOCV), based on risk scoring model etc [19-28]. These methods can be divided into two categories: based on numerical analysis and based on pattern recognition. Our method belongs to the latter one. In the 2009 PhysioNet/Computers in Cardiology Challenge, 19 teams or persons took part in the competition and Teresa Rocha et al. got the best results with the accuracy of 37/40 [5]. It is worth noting that the prediction results of Chebyshev neural network equal to the best results, which reflects the superiority and novelty of our method.

Many things need to be improved. First, the study used a small data sample, making the forecast results prone to randomness and uncertainty. Second, the extracted feature parameters only contain the parameters of the time-domain signal. Therefore, in future research, we hope to expand the training samples, in order to develop a neural network with good generalization ability. At the same time, we plan to use the digital signal processing (DSP) technology to extract the signal features on the transform domain.

V. CONCLUSION

In this study, we built a Chebyshev neural network based on pattern recognition to predict AHE in ICU patients. The Chebyshev neural network is built up by improving the neural network structure definition and by replacing the activation function of the hidden layer with a group of Chebyshev orthogonal polynomials. Compared with the traditional improved BP network model, the Chebyshev neural network reflects better predictive performance and generalization. This study provides a new method to predict the AHEs in ICU, and also overcomes the defects of traditional prediction model. It is in line with the four Ps of the medicine development model—personalized, predictive, preventive, participatory, and can provide a reference for clinical applications [29].

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