Application of BP Neural Network Algorithm in Biomedical Diagnostic Analysis

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Abstract: *The research on the application of a neural network in medical diagnosis includes two aspects: theoretical research on a neural network algorithm and research on its application in medical diagnosis. These two closely related research contents are complementary to each other, the former provides the theoretical basis for the latter and the latter takes the former as the basis and provides practical guidance to the former at the same time. The Back Propagation (BP) has the most extensive application in medical diagnosis, but the BP neural network learning algorithm has the shortcomings of slow convergence and the unit quantity being difficult to determine at the hidden layer in the application of medical diagnosis. This paper has made a detailed analysis of and exploration into these problems and proposed targeted solutions and applied them to specific medical diagnosis cases.*

Keywords: *Back Propagation neural network, Biomedical diagnostic analysis, Targeted solutions.*

Introduction

In the promotion of information technology, computer and artificial intelligence technology have been developed rapidly and improved continuously [17]. As a branch of it, the artificial neural network (neural network, for short) is a highly comprehensive cross-disciplinary field integrating neuroscience, information science and computer science together, which is a system of information processing, abstracting, simplifying and simulating the theory of a biological neural network in structure and function [6, 9]. The neural network has good self-adaption, self-organization as well as learning, association, parallel distribution processing and non-linear transformation and is very suitable for solving practical problems [10]. Therefore, its application range continues to increase, which can be applied to the fields of engineering, science and mathematics as well as to the fields of medicine, business, finance and literature etc. At the same time, it has made outstanding progress and extensive applications in numerous fields [24].

Modern medicine takes advantage of the development of high technology in various kinds of frontier technology enabling the medicine to develop rapidly [27]. It has been thirty years since the neural network has been applied to the medical field, however, it has developed rapidly only in the recent ten years [8, 25]. At present, many scholars worldwide have discussed the application of the neural network in medical work. The neural network is mainly applied to three medical fields, which include pharmacy, clinical diagnosis and preventive medicine [4]. In clinical diagnosis, most doctors arrive at conclusions based on some clinical evidence such as patient symptoms, signs and various inspection results as well as their own clinical experience. However, doctors have different opinions on which information should be emphasized and which should be considered secondarily, due to different personal experiences affecting doctors to put different emphasis on various information in making a diagnosis [11]. The capacity of the human brain is large, but it has an inefficient integrating function for large samples, so the medical diagnosis problem is clinically very complicated. However, a neural network has a very strong advantage in this aspect, which can attain the ability of disease diagnosis through learning a large amount of samples. Therefore, the complicated solution for the problem of making a medical diagnosis and the advantages of the neural network itself provide a fertile area for further development of neural networks [23]. The advantages and features of the neural network make it an effective tool for research on medical diagnosis. The operation will become intelligent, automatic and with a high degree of reliability if a suitable neural network model can be established. Training samples with complete data can be confirmed and knowledge and experience of medical experts can be trained through the network model, which can greatly relieve the burden on medical workers, and the neural network has great development potential in the medical diagnosis field [13, 14].

Fig. 1 presents the framework of the Back Propagation (BP) algorithm process.

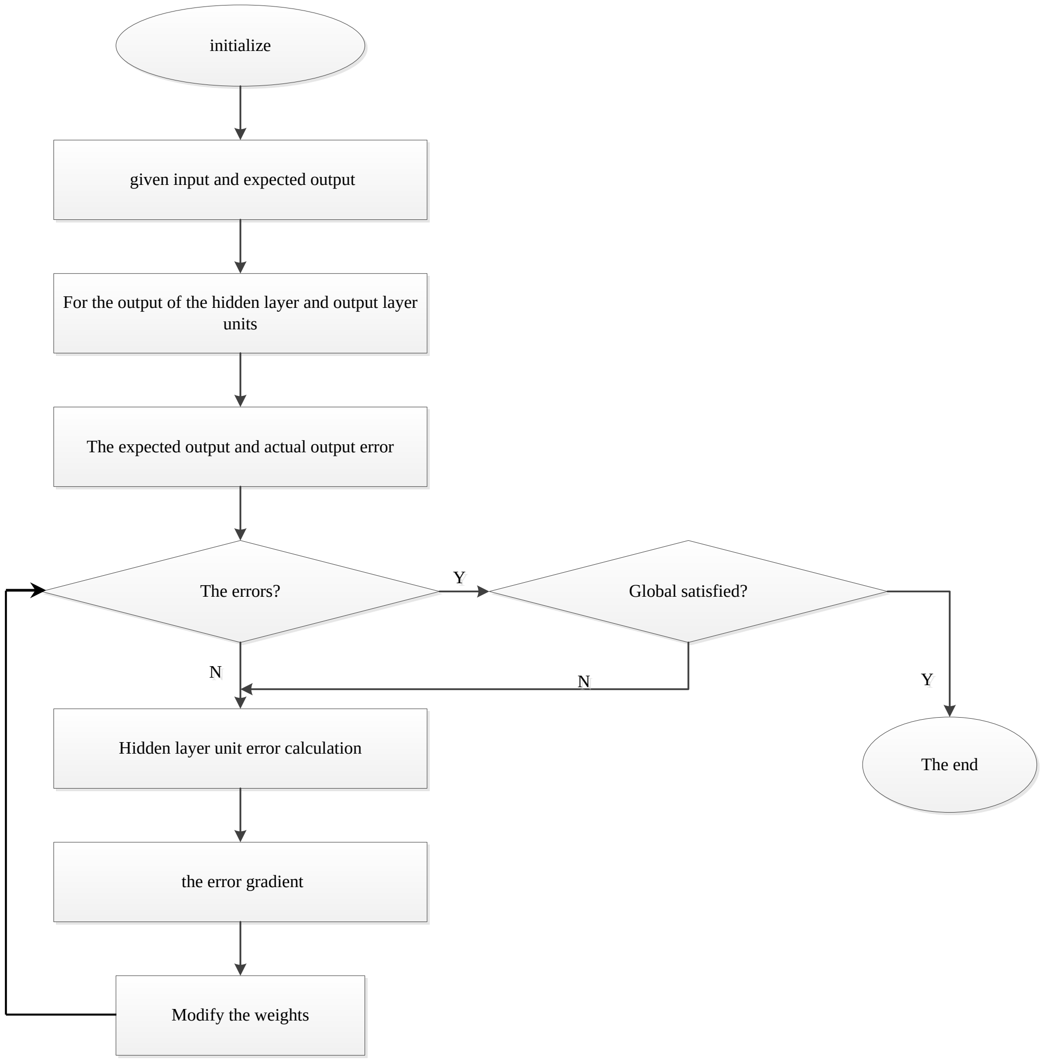

Fig. 1 BP algorithm process framework

Materials and methods

There are many neural network models, and they have the following basic characteristics in common:

(1) Distributed storage information

The manner of information storage by neural network is different from the manner of a traditional computer [2]. The information is not stored in one place but distributed throughout different places. One part of the network does not store a certain kind of information, and its information is distributed and stored in various parts. A neural network expresses special information through connections of a large number of neurons as well as the distribution for each connection weight [5, 12] Therefore, this kind of distributed storage method can recover original information even if the local network is damaged, which means that it is very robust and fault-tolerant.

(2) Self-adaption

Self-adaption of the neural network refers to the ability of the whole neural network to self-regulate, which includes four aspects of learning, self-organization, generalization and training [7]. Learning is the behavior change produced by the interaction with the environment, which results in the establishment of a new model reacting to external stimulation. Generally, when the connection weights among neurons are adjusted, this is considered as learning [3]. The connection strength among neurons in neural network is expressed with weight [18]. This weight can be offered in advance and can also make self-adaptive modifications change according to the surrounding environment, which is called the learning process of the neuron. The learning process of the neural network simulates the way of thinking of people and is a totally different method of non-logical language from traditional symbolic logic [15].

Self-organization refers to when various neurons make improvements at the same time according to certain rules [1]. The iterative correction process of a neural network is similar to the process of accumulating experiences [21, 22]. Generalization ability is also referred to as promotion ability, referring to the ability of a network to react to input never seen before. Generalization itself can further learn and self-regulate. Training is the neural network's method of learning. The concepts of "learning" and "training" are usually used interchangeably.

(3) Parallelism

Each neuron of a neural network can make independent calculations and processing of the received information, and then transfer the output results to other neurons to make simultaneous (parallel) processing [19, 26]. The method of information processing of a traditional computer is serial processing, where calculation and storage are totally two independent actions, and this then may cause a bottleneck in the channel between memory and arithmetic unit of the computer, which greatly restricts its operational capacity [20].

(4) Association-memory function

During the training process of a neural network, the input terminal offers a model to be memorized and the network can "memorize" all the input information through learning to reasonably regulate the weight in the network [16]. During implementation, if the input information is polluted by noise, or if incomplete and/or inaccurate information is input into the input terminal of the network, the recovered complete and accurate information can be attained at the output terminal.

Results and discussion

(1) Confirmation of data set

The original data set adopted in this paper is the medical records of Parkinson's patients in one hospital from 2002 to 2005. There were a total of 200 cases, in which there were 105 cases of Parkinson's and 95 cases of non-Parkinson's. The group of experts from the Department of Neurosurgery considered all the Parkinson's cases, which meet the diagnosis standards made by the National Conference on Vertebral Body Disease. The medical information included the general situation, risk factors, medical history, family history, symptoms, signs, inspection results and drug treatment.

(2) Index and quantification of Parkinson's diagnosis

In disease diagnosis, much qualitative data has been processed. Combining the use of qualitative data and quantitative data can fully use the information in these data and study the relationship and regularity between disease and symptom more comprehensively. We made a quantified and unified treatment for the qualitative data in the original data, and the data value is between 0 and 1. For example:

$$X_{\text{age}} = \begin{cases} 0, & \text{age} < 40 \\ 0.25, & 40 < \text{age} < 50 \\ 0.5, & 50 < \text{age} < 60 \\ 0.75, & 60 < \text{age} < 70 \\ 1, & 70 < \text{age} \end{cases} \quad (1)$$

$$X_{\text{sex}} = \begin{cases} 0, & male \\ 1, & female \end{cases} \quad (2)$$

Based on this principle, the case data in the medical record database after quantification and unified treatment is taken as the original data matrix of the network model. The input vector is set as X, and then $X = \{X_1, X_2, X_3, \ldots, X_{63}\}$, where input volumes are clinical characteristics of a Parkinson's diagnosis. The network output vector is expressed as Y, $Y = \{Y_i\}$, $Y_i = \{0, 1\}$, where "0" indicates the Parkinson's diagnosis is not established and "1" indicates the Parkinson's diagnosis is established.

(3) Sample grouping

Samples can be divided into two groups based on a 4:1 random sampling method:

- The A group, training sample: 100 cases (male 60, female 40); Parkinson's/ non-Parkinson's: 60/40; aged at 26-68 years, (40 ± 4) years old on average – it is used for training the network.
- The B group: testing sample: 100 cases (male 56, female 44); Parkinson's/ non-Parkinson's: 45/55, aged at 23-70 years, (50 ± 4) years old on average – it is used for testing network performance.

(4) Confirmation of each diagnosis network model structure

For each diagnosis network it is included how many indexes are there and how many input units it has. Based on the method of determining the number of units in the hidden layer by boundary number, the best unit number at the hidden layer of each diagnosis network is confirmed respectively and the network structure of each diagnosis network is verified with experiments, as shown in Table 1.

Table 1. The diagnosis of network structure of the network

Diagnosis of network	Input unit number	Hidden layer unit number	Output unit number
Network training based on the basic situation of diagnosis	5	3	1
Training diagnosis network based on risk factors	5	3	1
Training diagnosis network based on family history	1	2	2
Training diagnosis network based on symptoms and signs	32	16	2
Based on the results of medical examination in the diagnosis of network training	6	3	1
Training diagnosis network based on therapeutic effect	16	5	1

(5) Framework of diagnosis system
The framework of the diagnosis system is shown in Fig. 2.

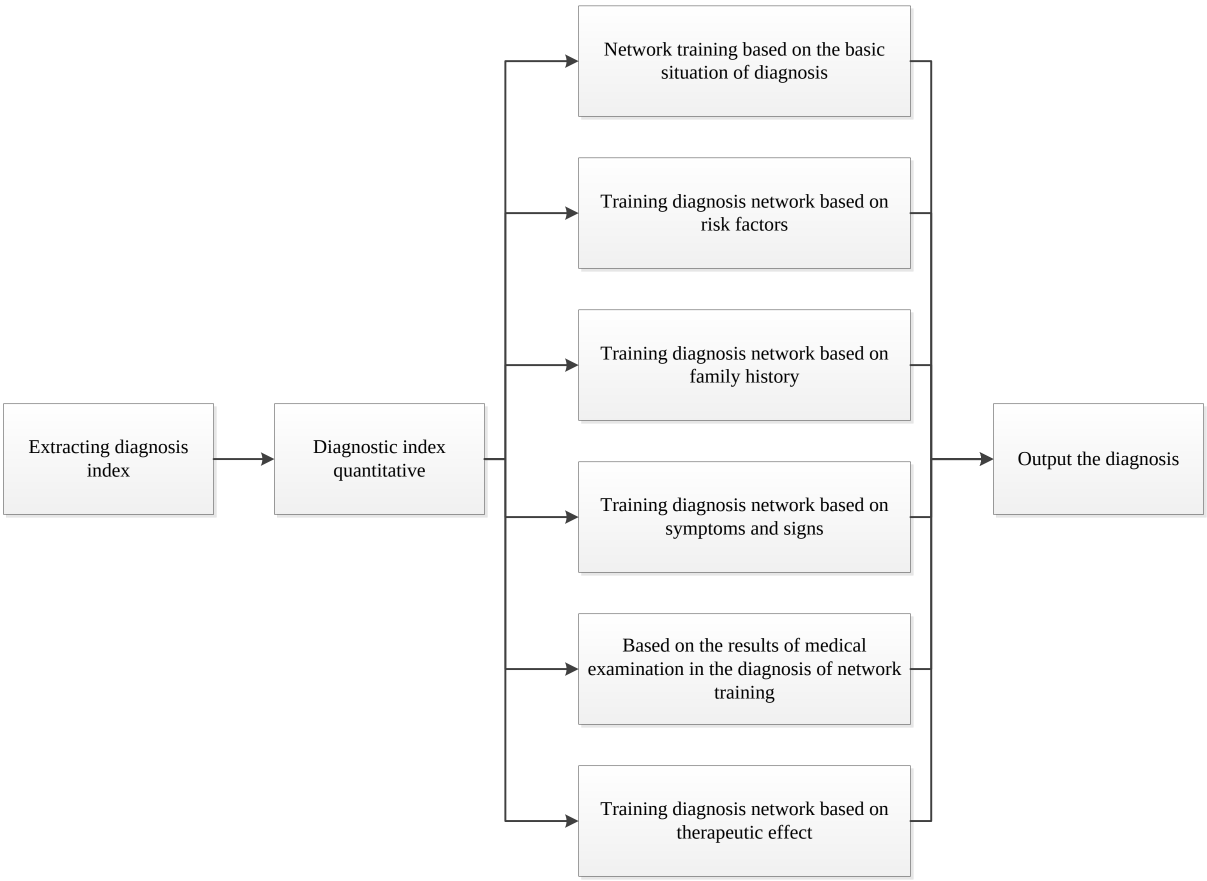

Fig. 2 BP neural network diagnosis system framework of Parkinson’s disease

(6) Diagnosis results
The diagnosis index describing various situations of patients is taken as input data of the forward network and is added to the input terminal. Meanwhile, the connection weight among neurons is adjusted to make the output of the network in line with the actual case. When the patients have Parkinson's disease, the output result of the network also indicates Parkinson's, and vice versa. If the network output of all training sets are basically the same as the actual results (95% or above), then the training process is finished. The neural network has a set up function for mapping the relation between various factors of the patient and can determine if the patient has Parkinson's disease. For a new patient, all that is needed is to input information about that patient's situation into the trained neural network and then confirm if he/she has Parkinson's based on the output results. Accuracy of the diagnostic test sample and accuracy of the training sample based on different pathogenic factors are shown in Table 2.

Table 2. Based on the different factors in the diagnosis of disease

Diagnosis of network	Training sample accuracy, %	Test sample accuracy, %
Network training based on the basic situation of diagnosis	50.2	46.5
Training diagnosis network based on risk factors	74.2	70.5
Training diagnosis network based on family history	65.3	54.6
Training diagnosis network based on symptoms and signs	85.3	98.5
Based on the results of medical examination in the diagnosis of network training	92.4	91.2
Training diagnosis network based on therapeutic effect	65.8	64.8

The above results indicate that different types of factors should be considered separately, and the results of each diagnosis network should be combined to attain the final judgment.

The reliabilities of the results attained from above six diagnosis networks are different, where the diagnosis accuracy based on medical inspection results is the highest. Therefore, its diagnosis results should be the focus in the following comprehensive analysis and we set a relatively maximum weight for it. Secondly, a diagnosis based on the symptoms and risk factors of patients is also highly accurate. Therefore, the weight offered to them are also high but smaller than medical inspection results. The other three kinds of factors only have a reference function in the diagnosis related to Parkinson's, so the set weights are small.

The final result y is:

$$y = g_1 y_1 + g_2 y_2 + g_3 y_3 + g_4 y_4 + g_5 y_5 + g_6 y_6 \tag{3}$$

$$g_1 + g_2 + g_3 + g_4 + g_5 + g_6 = 1 \tag{4}$$

When $y > 0.5$, the final diagnosis result is Parkinson's disease and it is normal on the contrary. The data of diagnosis results for all cases with the above methods are shown in Table 3.

Table 3. Neural network analysis of Parkinson's disease diagnosis

Neural network diagnosis	Training sample		Test sample	
	Parkinson's disease patients	No Parkinson's patients	Parkinson's disease patients	No Parkinson's patients
Patients with a diagnosis	60	3	54	3
Diagnosis of the patients	0	36	3	46

Among the training samples, the detection accuracy rate for Parkinson's patients is 100%, the detection accuracy rate for non-Parkinson's patients is 95% and misdiagnosis rate is 5%. Among the testing samples, the detection accuracy rate for Parkinson's patients is 96.3%, the detection accuracy rate for non-Parkinson's patients is 93.3% and misdiagnosis rate is 6.7%. For the non-optimized network, the specific comparison is shown in Table 4.

Table 4. Diagnosis of comparison

Neural network diagnosis	Training sample				Test sample			
	Parkinson's disease patients		No Parkinson's patients		Parkinson's disease patients		No Parkinson's patients	
	Correct detection rate	Mis-diagnosis rate	Correct detection rate	Mis-diagnosis rate	Correct detection rate	Mis-diagnosis rate	Correct detection rate	Mis-diagnosis rate
Patients with a diagnosis	100	0	96	5	96.2	3.9	93.3	6.9
Diagnosis of the patients	96	6	91.2	6.8	91.2	9.8	89.6	13.9

Table 4 shows that compared with the non-optimized network, there are great improvements in the results attained from this program which has improved the detection accuracy rate for diagnosis of both Parkinson's patients and non-Parkinson's patients and decreased the misdiagnosis rate of Parkinson's patients and non-Parkinson's patients.

Conclusion

In recent years, the neural network has been widely applied in the field of medical diagnosis. The neural network has good self-adaption, self-organization as well as learning, association, parallel distribution processing and non-linear transformation, which make the application of the neural network increasingly widespread and more reliable. In a large number of practical applications, many problems of the neural network have been discovered, such as slow convergence speed of the network, being trapped in a local minimum and selection of network structure. This paper has made a series of research experiments and practice to address the above problems and implemented the following work based on the specific cases in medical diagnosis.

First, the application research of neural network theory, medical diagnosis and the use of a neural network in medical diagnosis have been analyzed.

Second, research on the BP neural network which is applied most extensively in medical diagnosis has been implemented, the structure and learning rules of the BP neural network has been analyzed in detail, and a method of confirming the best unit number at the hidden layer has been proposed as well as a method of confirming the unit number at the hidden layer with a boundary limit for the shortages of slow convergence speed of the network and the difficulty in confirming the unit number at the hidden layer and verified the feasibility of this method. Finally, the modular network of neural network diagnosis model has been applied and verified.

Finally, on the basis of analysis and summarization of the modular network, the above optimized BP neural network structure and modular network have been applied to specific cases of medical diagnosis of Parkinson's cases and the diagnosis indexes have been classified into one, two, three, four, five and six. Individual determinations were made for each diagnosis network and then their results were combined together to obtain the final judgment. The results have indicated that this program has improved the detection accuracy rate of diagnosing both Parkinson's and non-Parkinson's patients and decreased the misdiagnosis rate of Parkinson's and non-Parkinson's patients.

This subject has attained some meaningful understandings and conclusions through analyzing the problems in the current application of the neural network in medical diagnosis and combining specific cases. The main results of this study are as follows:

(1) A method of confirming the best unit number at the hidden layer has been proposed, as well as a method of confirming the unit number at the hidden layer with a boundary limit for the shortcomings of difficulty in confirming the unit number at the hidden layer. Furthermore, the structure of the BP neural network has been optimized, and the feasibility and superiority of this method has been verified.

(2) The method of the modular network was firstly applied to the Parkinson's diagnosis model. Then, the modularized Parkinson's diagnosis model was optimized with a method of confirming the unit number at the hidden layer with a boundary limit, and the feasibility was analyzed and verified with cases.

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