Research on the application of BP neural network in the construction of TCM dialectical model

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Abstract

The purpose of this paper is to research on the application of BP neural network in the construction of TCM dialectical model. This paper aims to use intelligent techniques to conduct a comprehensive study about syndrome from the two perspectives of Chinese medicine and western medicine. In order to design a standardization and objective framework for TCM syndrome differentiation process, this paper introduces the theory of hybrid intelligent system to establish a hybrid intelligent based syndrome differentiation for CHB. As currently much more research methods applied to TCM syndrome classification, but still have not a universally applicable method. On the other hand, due to the complexity and multi-mode of syndromes, the process of syndrome differentiation cannot be accurately simulated by one technology. Thereby, it is possible to use theories and methods of the complexity of scientific research to study syndrome. The experiment result shows the proposed method can improve the overall performance for the system.

Keywords: Application, BP Neural Network, TCM Dialectical Model.

1. INTRODUCTION

In a long course of struggling against diseases, traditional Chinese medicine (TCM) has been evolved into a unique and integrated theoretical system, and has been remarkably contributing to the health of people in China and all over the world. TCM has been clinically observed to have dramatic performance in treating many chronic and systematic diseases such as the treatment of chronic hepatitis B (CHB) (Alexander et al., 2014; Sun et al., 2011; Zhang et al., 2013). So TCM is getting more and more popularity, and attracted the attention of many researchers. However, it also has been badly hindered from being popularized and further developed due to the empirical, unquantifiable and obscure features of its diagnostics (Ouyang et al., 2011).

Syndrome differentiation in TCM is an important part in the theory of TCM. It is also an important basis for making up a prescription and treatment in clinical. The core of TCM syndrome differentiation is the study of syndrome classification and diagnostic criteria. However, the current process of TCM syndrome differentiation is lack of a strict designed and unified framework, and a standardized and quantitative diagnostic criterion. Therefore, it is the issue to study in this article how to standardize, objectify and be computable with computability the syndrome differentiation of traditional Chinese medicine science, which is full of empirical and obscurity.

On the basis of understanding and analyzing the current syndrome differentiation research state and relating intelligent algorithms, multi-view based hybrid feature selection. Feature selection is an important technique of data pre-processing, which is aimed to recognize so as to eliminate the features, in all features, which are redundant or irrelevant to the issue studied. The dataset of TCM has objective and subjective features; the number is huge (Angel et al., 2009; Ritchlin, 2005; Petersen et al., 1998). At the same time, collecting data is never an easy job in CHB applications because of time consuming and costly work. So feature selection is the key step in the TCM syndrome differentiation. There are so many feature selection methods currently. But they cannot obtain a comprehensive result of the key features of syndromes by itself respectively. So in this paper, we propose a Multi-View based Hybrid Feature Selection (MVHFS) method (Wang,2008). The proposed method firstly partitions features of data into different disjoint views according to the nature of features, such as TCM symptoms, TCM signs, and western indicators. And then, the proposed method applies hybrid feature selection algorithm, which combines many filters based feature selection methods, such as Relief, LVF, mRMR and FCBF, to pick up the key features of each syndrome on each feature view. The obtained key features of each syndrome by proposed method are different each other, which reflects the difference between the syndromes, and to lay the
foundation for subsequent models of syndrome differentiation. Calculate feature weights combined with distribution information. Feature weight is a subjective evaluation and objectively reflection of comprehensive measure about the degree of importance of feature. In the field of TCM, the importance and role of the different features to syndrome diagnosis are different. The more important the role of a feature is, the greater its weight should be. The researchers often calculate the feature weights according to the occurrence frequency of the features in TCM. They do not consider the distribution information of the features between classes. In this paper, we propose a modified TF-IDF method to compute the feature weights. We consider the distribution information of the features between classes. Thereby, it can intuitively distinguish the role of different features to syndromes. It also quantified shows that the role of the same feature to different syndromes is different. This method is consistent with the theory of TCM, and also lays the foundation for subsequent models of syndrome differentiation (Bargallo and Roberts, 1995; Dubois et al., 2009; Zhu et al., 2008).

Hybrid intelligent syndrome differentiation model is based on feature selection. The essence of TCM syndrome differentiation is syndrome classification. There are many classifying methods currently. However, we cannot use single classifier or single model to improve the classification accuracy of syndrome differentiation due to the complicated relationships between syndromes and features of TCM and western medicine. In additions, it is important to obtain the class probability estimation about each patient in the field of TCM diagnosis. Accordingly, the doctors can accurately make up the prescription and treatment programs for each patient. In this paper, we introduce the theory of hybrid intelligent system, weighted fuse Bayes Net, WPET and WCBA methods, and construct a hybrid intelligent syndrome differentiation model based on feature selection. From the experimental results, we can see that this method can obtain optimal performance on UCI datasets and CHB dataset. It is shown that the validity of the method. We use the proposed method to predict the class probability of new 180 cases, and obtain consistent results with clinical. Further, the proposed method shows the potential applications in clinical practice. We integrate some of the proposed algorithms to develop a hybrid intelligent based syndrome differentiation system, which is applied to CHB dataset. By this system, we can obtain the optimal feature subsets and predict the syndrome and class probability of an input case. In the future, this system can fuse new technology for further improvement (Pereira and Carrasco, 2006).

2. MATERIALS AND METHODS

2.1 Overview

Traditional Chinese medicine (TCM), one of the most important complementary and alternative medicines, is invaluable for its rich practical knowledge and a unique integrated theoretical system established since ancient times. TCM has been clinically observed to have dramatic performance in treating many chronic and systematic diseases such as the treatment of liver cirrhosis. During the diagnosis, syndrome differentiation is the most key step. Syndrome differentiation is the method of recognizing and diagnosing diseases or body imbalances by analyzing patient information based on TCM theories and the doctor’s experiences. Syndrome enables the doctor to determine the stage that the disease developed and the location of the disease. However, the lack of objective diagnosis standards hinders TCM wide acceptance. One cannot apply this prescriptive methodology in a professional standard until or unless one has mastered the syndrome differentiation process. The purpose of this paper is in an attempt to achieve effective and objective standard of syndrome prediction. In order to obtain the objective rule of syndrome differentiation, this paper applies the data mining technique into TCM syndrome prediction. The inherently nonlinear, ambiguous and complex characteristic of TCM data increases the difficulty of data mining for TCM. The research on syndrome differentiation can’t be the simple cause and effect between the symptoms and the syndrome (Ji et al., 2004)].

The traditional Chinese medicine is one quintessence of Chinese culture, and it is also a piece of gem in traditional culture. In traditional Chinese medicine, there are the Yin and Yang theory, the differentiation of symptoms and signs, the four examines of watching, auscultation and olfaction, asking and feeling pulse, the pulse 28 phenomena, the meridian theories, and so on. They are the diagnosis experience and developing in clinical in medical tests by several generations of medicine, and the traditional Chinese medicine has its own distinctive theory system and practical research value. Professor L.A. Zadeh established the theory of fuzzy mathematics which has obtained the widespread application in the digitization research of the Chinese medicine. Because the basic question in Chinese medicine has dynamically fuzziness, the classic fuzzy theory only can solve the static problem in traditional Chinese medicine.
To set up analysis model according to the demand analysis, at the same time, establishing the analysis model is also a further analysis of demand, analysis model mainly includes use case diagram and interaction diagram (Craiu and Lee, 2005), the use case diagram is a static modeling mechanism of RUP, while the interaction diagram is a dynamic modeling mechanism of RUP (Wang, 2001).

1) Use case diagram

Use case is the method of capturing demand; use case diagram defines the framework and boundary of system, makes models for the behavior of future system, preliminary determines the system structure of the future. Use case diagram illustrates information completely in vernacular way, to help developers have a clearer understanding of the system behavior. In this paper, only take the use case diagram of user management modules for instance, as shown in Figure 1.

Interactive diagram describes how the cases realize the interaction among objects; it is used for establishing the system dynamic behavior model. After analyzing and mapping use case diagram, it is necessary to analyze the main use case interactive behavior. We can understand the behavior of the cases much more clearly, further adjust the case view, and determine solutions of problems. There are two kinds of interactive diagrams: sequence diagram and collaboration diagram. Sequence diagram is used to demonstrate the relationships between objects, and also emphasizes the chronological order of the messages between objects, and at the same time shows the interaction between objects; Collaboration diagram is used to describe the consumption of the identified transactions, and to describe the structural relationship of the massages connection between each objects. Sequence diagram emphasizes the chronological order of the messages, but it does not explicitly express the relationships between objects; Collaboration diagram emphasizes the organizational relationships of the objects involved in the interaction, the chronological order can be obtained from the sequence number. Sequence diagram and Collaboration diagram are semantically equivalent, they can be totally converted each other.

![Figure 1. System use case diagram](image)

2.2 Neural Network Model and Algorithm

Neural network model originates in neurobiology. From Figure 2, we can see that the calculation process is similar to the reaction in the process of biological neurons.
In neural networks, many different neurons axon terminals can enter a single neuron dendrite and the formation of synapses. All of the different sources of synaptic release of neurotransmitter can change the membrane potential of neurons to produce the same effect. It can be seen that the dendrite of neurons in the input information from different sources can be integrated. Based on this ability, people create an artificial neuron model simulating the reaction of neurons, as shown in Figure 3. Figure symbol description is shown in Table 2.

When students begin to work, they are capable of their work. Compared with developed countries, there are serious problems in Chinese university education. Theoretical knowledge is not enough. The students lack of actual operating capacity. Trinity teaching mode is applied to the teaching reform in higher cases and samples. It can improve the teaching quality of university education in China. Comparative tests were carried out between traditional education model and the new model of education. Integrated teaching model has many advantages in terms of higher training nursing students, training of personnel in line with the objectives and requirements and the education law. Figure 4 shows the two kinds of image of excitation function. In this paper, the model uses the second excitation function.

In which,
\[ u_i = \sum_j w_{ij} x_j - \theta_i \]  

Therefore,

\[ y_i = f \left( u_i \right) = f \left( \sum_j w_{ij} x_j - \theta_i \right) \]

is a complete mathematical model expression for the individual neurons.

BP neural network is a multi-layer to the former network, using the calculation minimum mean square error. When the back-propagation algorithm is applied to the feed forward multi-layer network, using Sigmoid as an excitation function, the following steps is obtaining to net weights.

For \( w_{ij} \) assigning, we assign a relatively small number of non-zero random for each layer, \( w_{j(n+1)} = -\theta_i \). This model is run by Matlab. The assignment process is a random process.

Input sample values \( x = (x_1, x_2, \cdots, x_n, 1) \), corresponding to the desired output \( y = (y_1, y_2, \cdots, y_n, 1) \).

Calculate the output in each layer. The output of \( i \) neuron is \( x_{ik} \), for the first layer.

\[ y_{ik}^1 = f \left( u_{ik}^1 \right) \]

In which,

\[ u_{ik}^1 = \sum_j w_{ij} x_j^{k-1} - \theta_i^k \]

In which, \( x_{i(n+1)}^{k-1} = 1, w_{i(n+1)} = -\theta_i \).

Solve calculation error \( d_{ik}^k \) in each layer. The output layer is \( k = m \).

\[ d_{ik}^m = x_i^m (1 - x_i^m) (x_i^m - y_i^m) \]

For other layers,

\[ d_{ik}^k = x_i^k (1 - x_i^k) \left( \sum_j w_{ij} x_j^{k-1} - \theta_i^k \right) \]

Correct \( w_{ij} \) and \( \theta_i \).

\[ w_{ij}(t+1) = w_{ij}(t) - \eta d_{ik}^k x_j^{k-1} \]

When the weights of various layers are obtained, we can determine compliance with the requirements in accordance with established criteria. If not, we return to the third step. On the contrary, the calculation is ended.

The algorithm can be expressed as following equation (8):
\[ \gamma_i(\vec{k}, \omega) = \frac{1}{\rho_0 \omega^2} \left( \frac{e_{15}^0}{\eta_{11}^0} \right)^2 \frac{\beta_i^2}{k^2 - \beta_{\perp}^2} m_i \]
\[ g_{ik}(\vec{k}, \omega) = -\frac{1}{\eta_{11}^0} \left( \frac{e_{15}^0}{\eta_{11}^0} \right)^2 \frac{\beta_i^2}{k^2 - \beta_{\perp}^2}, \quad (8) \]

In which,
\[ \alpha^2 = -\frac{\rho_0 \omega^2}{c_{11}^0} \]
\[ \alpha^2 = -\frac{\rho_0 \omega^2}{c_{66}^0}, \beta_{\perp}^2 = \frac{\rho_0 \omega^2}{c_{44}^1} \]
\[ c_{44}^1 = c_{44}^0 + \frac{(e_{15}^0)^2}{\eta_{11}^0} \]

Rewrite again Eq. (1) as
\[ \hat{f}^a_n(x) = \frac{1}{\Gamma(1 + \alpha)} \int_{-\infty}^{\infty} \frac{f(t)}{(t - x)^a} (dt)^a \]
\[ = \frac{1}{\Gamma(1 + \alpha)} \int_{-\infty}^{\infty} f(t) g(x - t)(dt)^a = f(x) * g(x), \quad (12) \]
\[ \partial_j (C_{ijkl} \partial_i u_j + e_{ijkl} \partial_i \phi) - \rho \dddot{u}_i = 0 \]
\[ \partial_j (e_{ijkl} \partial_i u_j - \eta_{ijkl} \partial_k \phi) = 0 \quad (13) \]

The linear equation can be expressed into the following simplified forms:
\[ L(\nabla, \omega) f(x, \omega) = 0, \quad L(\nabla, \omega) = T(\nabla) + \omega^2 \rho J \]
\[ (15) \]

So we get the PR value as the following:
\[ PR(u) = \sum PR(V) \]
\[ \frac{L(V)}{L(V)} \]
\[ (16) \]
\[ L(\nabla, \omega) f(x, \omega) = 0 \]
\[ (17) \]
From the information security requirements, in the TOP-N algorithm, the construction of digital libraries is shown as the equation (18)-(19):

\[ d_j = \sqrt{\sum_{j=1}^{m} W_j (\alpha_j - \alpha_j)} \]  
(18)

\[ d_i(x_i) = \sum_{j=0}^{n} (x_{ij} - M_y)^2 \]  
(19)

So, we have:

\[ P(C|X) = \frac{P(X|C_i)P(C_i)}{P(X)} \]  
(20)

3. RESULTS AND DISCUSSION

To input the 684 cases and medication records of TCM distinguished veteran doctors into the electronic medical records management system and build a table of symptoms using its statistical function. Then using BP neural network to input the symptoms table into Matlab software and take 669 medical records as training data randomly. The last 15 medical records are taken as test data. It is shown in Table 3.

According to BP neural network model, using Matlab software, we draw the distribution of values, as shown in Figure 5.

![Eigenvalue distribution](image)

In Figure 5, "o" is on behalf of the good conducted integration for the TCM, "*" is on behalf of the worse conducted integration of TCM. As can be seen from the figure, there is a clear line between the two cases and samples.

From effectiveness and patient acceptance, we evaluate integration TCM for five cases and samples (ABCDE). Be judged the same way as the data acquisition of five cases and samples is as same as the data collection of the eigenvalues. The objects are judged, showing in Table 4.

According to the above eigenvalues, combining with the data in Table 4, using BP neural network model, it can be calculated by the Matlab software in Figure 6.

![Evaluation Results Figure](image)
It can be seen from Figure 6 that AD are better integration cases and samples and BCE are worse integration cases and samples.

### Table 1 Expert Survey Results

<table>
<thead>
<tr>
<th>Experts Region</th>
<th>Effectiveness</th>
<th>Patient acceptance</th>
<th>Content</th>
<th>Methods</th>
<th>Technical Requirements</th>
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<td>Central South</td>
<td>78</td>
<td>70</td>
<td>80</td>
<td>70</td>
<td>75</td>
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<tr>
<td>Central South</td>
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<td>70</td>
<td>85</td>
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<td>75</td>
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<tr>
<td>Northwest</td>
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<td>75</td>
<td>72</td>
<td>75</td>
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<tr>
<td>Northwest</td>
<td>75</td>
<td>70</td>
<td>75</td>
<td>80</td>
<td>70</td>
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<tr>
<td>Southwest</td>
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<tr>
<td>Southwest</td>
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<td>70</td>
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<tr>
<td>North China</td>
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<td>88</td>
<td>70</td>
<td>70</td>
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<tr>
<td>North China</td>
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<td>88</td>
<td>85</td>
<td>80</td>
<td>80</td>
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<tr>
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<td>80</td>
<td>75</td>
<td>75</td>
</tr>
<tr>
<td>Northeast</td>
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<td>80</td>
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</tr>
<tr>
<td>East China</td>
<td>78</td>
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<td>75</td>
<td>80</td>
</tr>
<tr>
<td>East China</td>
<td>80</td>
<td>75</td>
<td>90</td>
<td>70</td>
<td>75</td>
</tr>
</tbody>
</table>

### Table 2 Mathematical Models Symbol Description

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
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<tbody>
<tr>
<td>(x_1, x_2, \ldots, x_n)</td>
<td>Enter part of neurons (send information on the first level)</td>
</tr>
<tr>
<td>(\theta_i)</td>
<td>Threshold of neurons</td>
</tr>
<tr>
<td>(y_i)</td>
<td>Output neuron</td>
</tr>
<tr>
<td>(f[u_i])</td>
<td>Excitation function</td>
</tr>
</tbody>
</table>

### Table 3 The Evaluation Results in Characteristics Colleges

<table>
<thead>
<tr>
<th>Effectiveness</th>
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</tr>
</thead>
<tbody>
<tr>
<td>Good</td>
<td></td>
</tr>
<tr>
<td>81.52</td>
<td>79.64</td>
</tr>
<tr>
<td>83.21</td>
<td>76.68</td>
</tr>
<tr>
<td>79.65</td>
<td>78.53</td>
</tr>
<tr>
<td>78.96</td>
<td>79.87</td>
</tr>
<tr>
<td>80.96</td>
<td>80.12</td>
</tr>
<tr>
<td>Worse</td>
<td></td>
</tr>
<tr>
<td>69.89</td>
<td>72.56</td>
</tr>
<tr>
<td>70.58</td>
<td>69.98</td>
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<tr>
<td>71.56</td>
<td>70.25</td>
</tr>
<tr>
<td>72.83</td>
<td>71.52</td>
</tr>
<tr>
<td>75.02</td>
<td>73.21</td>
</tr>
</tbody>
</table>

### Table 4 The judged object data

<table>
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<th>Sample Type</th>
<th>Effectiveness</th>
<th>Patient acceptance</th>
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</thead>
<tbody>
<tr>
<td>A</td>
<td>80.23</td>
<td>76.23</td>
</tr>
<tr>
<td>B</td>
<td>71.23</td>
<td>72.69</td>
</tr>
<tr>
<td>C</td>
<td>74.89</td>
<td>71.35</td>
</tr>
<tr>
<td>D</td>
<td>83.69</td>
<td>80.25</td>
</tr>
<tr>
<td>E</td>
<td>70.36</td>
<td>69.23</td>
</tr>
</tbody>
</table>

4. CONCLUSION
In this paper, the author researched on the application of BP neural network in the construction of TCM dialectical model. To construct a Traditional Chinese Medicine (TCM) differentiation model by taking qi deficiency syndrome differentiation model as an example. To input the 684 cases and medication records of TCM distinguished veteran doctors into the electronic medical records management system and build a table of symptoms using its statistical function. Then using BP neutral network to input the symptoms table into Matlab software and take 669 medical records as training data randomly. The last 15 medical records are taken as test data. This paper aims to use intelligent techniques to conduct a comprehensive study about syndrome from the two perspectives of Chinese medicine and western medicine. In order to design a standardization and objective framework for TCM syndrome differentiation process, this paper introduces the theory of hybrid intelligent system to establish a hybrid intelligent based syndrome differentiation for CHB. There are many classifying methods currently. However, we cannot use single classifier or single model to improve the classification accuracy of syndrome differentiation due to the complicated relationships between syndromes and features of TCM and western medicine. In additions, it is important to obtain the class probability estimation about each patient in the field of TCM diagnosis. Accordingly, the doctors can accurately make up the prescription and treatment programs for each patient. In this paper, we introduce the theory of hybrid intelligent system, weighted fuse Bayes Net, WPET and WCBA methods, and construct a hybrid intelligent syndrome differentiation model based on feature selection. As currently much more research methods applied to TCM syndrome classification, but still have not a universally applicable method. On the other hand, due to the complexity and multi-mode of syndromes, the process of syndrome differentiation cannot be accurately simulated by one technology. Thereby, it is possible to use theories and methods of the complexity of scientific research to study syndrome. The experiment result shows the proposed method can improve the overall performance for the system. The absolute error in test data and model data shows that there are 3 cases that are greater than 0.6 and the other 12 cases were less than 0.3. The accuracy is 83.3%, specificity is 77.8%, and predication consistency is 80%. This research has developed a TCM syndrome differentiation model with high accuracy based on BP neural network, and explored a new way to summarize experience of TCM distinguished veteran doctors. Therefore, it is worthy of popularizing.

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REFERENCES


