Prediction of Negative Conversion Days of Childhood Nephrotic Syndrome Based on the Improved Backpropagation Neural Network with Momentum

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Received: June 19, 2015 **Accepted: November 09, 2015**

Published: December 22, 2015

Abstract: *Childhood nephrotic syndrome is a chronic disease harmful to growth of children. Scientific and accurate prediction of negative conversion days for children with nephrotic syndrome offers potential benefits for treatment of patients and helps achieve better cure effect. In this study, the improved backpropagation neural network with momentum is used for prediction. Momentum speeds up convergence and maintains the generalization performance of the neural network, and therefore overcomes weaknesses of the standard backpropagation algorithm. The three-tier network structure is constructed. Eight indicators including age, lgG, lgA and lgM, etc. are selected for network inputs. The scientific computing software of MATLAB and its neural network tools are used to create model and predict. The training sample of twenty-eight cases is used to train the neural network. The test sample of six typical cases belonging to six different age groups respectively is used to test the predictive model. The low mean absolute error of predictive results is achieved at 0.83. The experimental results of the small-size sample show that the proposed approach is to some degree applicable for the prediction of negative conversion days of childhood nephrotic syndrome.*

Keywords: *Childhood nephrotic syndrome, Negative conversion days, Backpropagation neural network, Momentum factor.*

Introduction

Childhood nephrotic syndrome, also referred to as childhood kidney disease, is one of the common diseases of children's urinary system. The statistics from Chinese Pediatric Society show that the case number of childhood nephrotic syndrome is in second place of all diseases for hospitalized children in China [19]. The nephrotic syndrome which has a great harmful effect on growth and development of children is difficult to treat and cure. It has attracted many attentions in research literatures [1, 3, 10]. From the author's experience, in the diagnosis of childhood nephrotic syndrome parents are always anxious about their sick children and eager to know how long it takes to rehabilitate them. Consequently, it is necessary to predict negative conversion days for children with nephrotic syndrome scientifically and accurately, so as to provide patients with better treatment through the cooperation of their informed parents and physicians.

Prediction of negative conversion days for children with nephrotic syndrome according to medical data is a complex multifactor and nonlinear problem. Multiple medical indicators including albumin and blood fat, etc. are involved for analysis. Traditional statistical methods such as linear regression analysis and multiple discriminant analysis have weaknesses such as lack of theoretical rule for weight setting and computational complexity, etc. and therefore sometimes cannot satisfy requirements of practical applications.

Neural networks proposed on the basis of modern neuroscience to simulate human brain are adaptive information processing systems which consist of a large number of interconnected processing units [14]. They are capable of learning and adaptive to inputs because weights of connections can be tuned based on experience. Neural networks and related intelligent information processing technologies currently have been widely applied in medical areas [1, 2, 6, 13]. Iqbal et al. [6] proposed a neural network model for treatment prediction in HBV patients. Naumovic et al. [13] applied neural networks to estimating predictive factors and therapeutic efficacy in idiopathic membranous nephropathy. Bai et al. [1] established the diagnostic model of steroid-resistant nephrotic syndrome by using the backpropagation neural network. In this paper, we propose using the improved backpropagation neural network with momentum to predict negative conversion days of childhood nephrotic syndrome and verify the effectiveness of the proposed approach by experiment.

Improved backpropagation neural network with momentum

Multilayer feedforward neural network

Featured with self-learning, self-organization and adaptability, neural networks are capable of obtaining weights and structure by learning and training. Since McCulloch and Pitts [12] created a computational model for neural networks based on threshold logic in 1943, scholars have made great efforts to develop various neural networks, such as multilayer feedforward neural network [11, 17], self-organizing map [8], recursive neural network [4, 16], support vector machine [18, 22] and deep learning [9, 21], etc.

Among these neural networks the multilayer feedforward neural network can imitate any nonlinear continuous function arbitrarily accurately in theory, and thus it is suitable for modeling and control of nonlinear systems and has been widely used in various areas. The multilayer neural network is composed of three parts of the input layer, the hidden layer and the output layer. The neurons of the input layer receive the input information, namely the input vector. The output layer gives the outcome. The hidden layer between the input layer and the output layer involves several levels composed of numerous neurons and links.

Standard backpropagation algorithm

The backpropagation algorithm, abbreviated as the BP algorithm, is proposed by McCelland and Rumelhart in 1986 [11] to train the multilayer feedforward neural network. The standard BP algorithm which iteratively trains the neural network is a general gradient descent algorithm. The BP algorithm is summarized as follows [20]:

Step 1: Give the training error threshold ε, and initialize the weight w_{ij} and the threshold vector.

Step 2: Compute the error objective function *E*. If $E \le \varepsilon$, then go to *Step 3*, otherwise for every instance *p* do:

Step 2.1. Compute the network output *o*:
For every output unit, compute $\delta_k = o_k(1-o_k)(t_k - o_k)$;
For every hidden unit, compute $\delta_h = o_h(1-o_h)\sum_k w_{h,k}\delta_k$;

Step 2.2. Update the network link weight w_{ij}, $w_{ij} = w_{ij} + \Delta w_{ij}$, $\Delta w_{ij} = \eta\delta_j x_{ij}$, where x_{ij} is the output from unit *i* to unit *j* and η is learning rate.

Step 3: End.

Improved backpropagation algorithm with momentum

In practice, the standard BP algorithm has two defects of slow convergence and falling into local minimum. Researchers have proposed various improved algorithms which can be divided into two categories of heuristic methods and numerical optimization methods. The conjugate gradient method and the Newton's method, etc. belong to the latter. They greatly improve convergence rate of neural networks, but increase the computing complexity. The momentum algorithm and the adaptive algorithm, which speed up convergence and avoid falling into local minimum [15], belong to the former. In order to accurately predict negative conversion days for children with nephrotic syndrome, the improved BP algorithm with momentum is applied to training the neural network in this study.

The choice of step-size η is critical for the network learning. The large value of η can accelerate network convergence. However, instability is caused if the value of η is too large. Although the small value of η helps avoid oscillation, it slows down the convergence rate. Momentum is one of techniques to resolve this contradiction [7]. The generalized delta rule is described by:

$$\Delta w_{ij}(n) = \alpha\Delta w_{ij}(n-1) + \eta\delta_j(n)x_{ij}(n),\ 0 \le \alpha \le 1 \tag{1}$$

In Eq. (1), the second term is the correction term in the BP algorithm, and the first term is the momentum term which promotes the stability of weight updating and hence speeds up convergence. α is called momentum factor or forgetting factor, and its value is usually in the range of [0, 1]. Eq. (1) can be written as the time series of variable *t* when the sample instances are inputted sequentially, and therefore can be considered as a first-order differential equation of Δw_{ij}. By solving the differential equation it can be obtained:

$$\Delta w_{ij}(n) = \eta\sum_{t=0}^{n}\alpha^{n-1}\delta_j(t)x_{ij}(t) = -\eta\sum_{t=0}^{n}\alpha^{n-1}\frac{\partial E(t)}{\partial w_{ij}(t)} \tag{2}$$

When the current value of $\frac{\partial E(t)}{\partial w_{ij}(t)}$ has the same sign of its previous value, the weighted sum increases, bringing about the larger $\Delta w_{ij}(n)$ and accelerating the adjustment. When the current value of $\frac{\partial E(t)}{\partial w_{ij}(t)}$ has the opposite sign of its previous value, oscillation happens and then the exponential weighted sum decreases $\Delta w_{ij}(n)$, bringing about stability.

By reducing the sensitivity for local details of error surface, the momentum accelerates the training process and maintains the generalization performance. Therefore the improved BP neural network with momentum is applied to the task of prediction.

Creation of predictive model

Design of neural network structure

In order to obtain accurate negative conversion days of childhood nephrotic syndrome by inputting the medical data, it is significantly important to construct appropriate topology of the neural network.

Because a three-layered neural network can approximate any function after sufficient learning, the simple three-tier structure is constructed in this study. Nephrotic syndrome is a nonspecific kidney disorder characterized by three signs of disease: large proteinuria, hypoalbuminemia and edema [5]. As a consequence, physicians usually judge whether the child is suffered from nephrotic syndrome and the severity of the child's disease, according to seven medical indicators of lgG, lgA, lgM, lgE, C3, albumin and blood fat. Considering age is an important feature of sick children, eight indicators involving age (X1), lgG (X2), lgA (X3), lgM (X4), lgE (X5), C3 (X6), albumin (X7) and blood fat (X8) are selected to predict negative conversion days. Therefore the input layer contains eight nodes corresponding to the input vector with eight indicators of X1-X8. The number of hidden layer nodes is uncertainty, and the large number of hidden layer nodes results in the significant nonlinearity of the neural network. Some empirical rules can be used to determine the number of hidden layer nodes. Based on the Kolmogorov theorem the number of hidden layer nodes is defined as $2n + 1$, where n is the number of input layer nodes. Therefore here the number of hidden layer nodes is 17. The output layer contains one node which gives Y, the prediction of negative conversion days. The designed neural network structure is shown in Fig. 1.

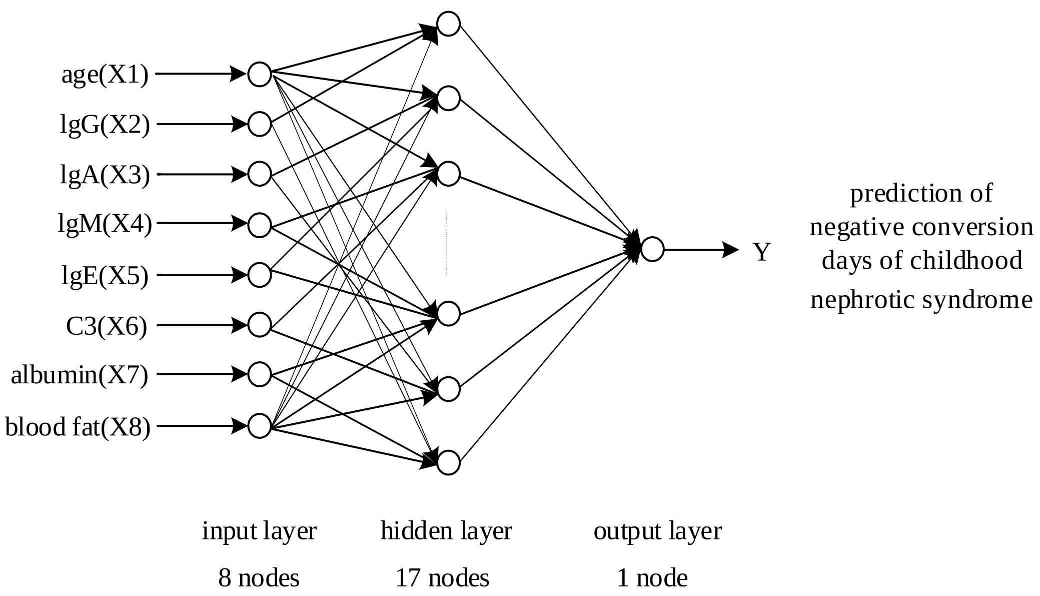

Fig. 1 The designed neural network structure

Data preprocessing and training sample

In order to improve quality of data to accelerate the modeling process and promote the predictive performance of the neural network model, the collected original medical data of patients are preprocessed. The records of patients are checked if there are attributes with missing value. Those records with missing value are removed and only the records with complete attribute values are used for study. The data are normalized to fall into the range of [0, 1] by using minimum-maximum linear transformation as described by:

$$F_j = \frac{x_j - x_{j\min}}{x_{j\max} - x_{j\min}} \tag{3}$$

where F_j is the normalization of x_j, $x_{j\min}$ is the preset smallest value of the j^{th} index, and $x_{j\max}$ is the preset largest value of the j^{th} index.

The sample of 28 cases tabulated in Table 1 is taken as the training dataset. The training sample, together with the test sample given later, is provided by Department of Pediatrics at Changzhou No. 2 People's Hospital in China. All cases are partitioned into six age groups of [0, 2), [2, 3), [3, 4), [4, 5), [5, 7) and [7, 12].

Training of neural network

In this study the scientific computing software of MATLAB 2014a and its neural network toolbox are used to create and test the neural network model. The function of *traingdm* which implements the momentum gradient descent learning is used to train the neural network. The tangent Sigmoid function of *tansig* is used as transfer function between the input layer and the hidden layer, and the linear function of *purelin* is used as transfer function between the hidden layer and the output layer. Learning rate *lr* is set to 0.01, the maximum number of training steps *epochs* is set to 10000, and *show* is set to 100. Using mean squared error abbreviated as MSE as the error measurement, *goal* is set to 0.1. The momentum factor *mc* is not set and its default value is 0.9. Critical source code is as follows:

```
net = newff(minmax(P'),[17,1],{'tansig','purelin'},'traingdm');
net = init(net);
net.trainparam.epochs = 10000;
net.trainparam.lr = 0.01;
net.trainparam.show = 100;
net.trainparam.goal = 0.1;
```

Table 1. Training sample

No.	Age	lgG	lgA	lgM	lgE	C3	Albumin	Blood fat	Group	Negative conversion days
1	1.83	4.020	1.080	1.650	148.000	1.620	18.40	10.41	1	7.00
2	1.58	2.560	1.650	1.040	124.000	1.810	22.60	6.57	1	25.00
3	1.92	2.040	0.537	1.420	52.300	1.440	21.50	8.12	1	9.00
4	1.83	1.420	1.450	2.390	24.400	1.220	21.80	7.83	1	8.00
5	1.67	2.260	1.370	1.340	353.000	1.340	20.30	10.50	1	9.00
6	1.50	4.840	0.512	0.740	230.000	1.310	29.50	7.80	1	7.00
7	2.50	1.370	0.500	2.500	1000.000	1.510	11.30	11.64	2	8.00
8	2.75	3.020	0.953	1.850	175.000	1.470	18.20	9.85	2	13.00
9	2.08	5.710	0.913	1.950	139.000	1.470	21.40	8.90	2	4.00
10	2.08	5.740	1.490	1.890	107.000	1.540	25.40	10.70	2	7.00
11	2.17	4.140	0.627	1.100	71.200	1.100	28.40	6.71	2	7.00
12	2.58	2.730	0.254	2.220	1000.000	1.130	21.90	11.80	2	10.00
13	2.08	4.040	0.727	2.190	210.000	1.040	16.10	12.10	2	7.00
14	2.75	2.490	0.778	1.230	1000.000	1.830	15.30	10.40	2	7.00
15	3.17	2.570	0.440	1.060	20.000	1.190	27.20	9.60	3	7.00
16	3.25	3.500	0.799	1.260	148.000	1.530	23.30	9.80	3	5.00
17	3.50	1.960	0.892	0.925	174.000	1.320	18.20	16.90	3	13.00
18	3.17	4.970	0.535	2.390	20.000	1.160	14.50	15.31	3	7.00
19	4.00	4.370	1.460	2.090	632.000	0.949	18.90	9.67	4	3.00
20	4.67	4.260	0.524	1.830	112.000	1.280	19.80	10.86	4	10.00
21	5.67	5.220	0.835	1.070	282.000	1.110	25.80	7.10	5	4.00
22	5.00	1.960	1.500	1.270	1000.000	1.040	20.40	14.20	5	6.00
23	5.17	4.480	2.660	2.590	139.000	1.290	18.00	8.50	5	14.00
24	9.00	2.040	1.270	1.690	141.000	1.090	18.30	10.41	6	9.00
25	8.00	2.500	1.830	1.220	77.300	1.770	17.30	14.80	6	9.00
26	9.00	2.340	1.890	2.390	133.000	1.320	23.50	10.88	6	10.00
27	11.00	4.580	0.810	1.270	546.000	1.480	14.00	10.18	6	9.00
28	10.00	1.110	1.540	2.300	61.400	1.170	4.60	9.75	6	13.00

Fig. 2 shows the error curve of the improved BP neural network with momentum trained by the function of *traingdm*. When the training epoch reaches 3024, MSE of the network meets the error threshold of 0.1 and the training stops. Fig. 3 shows the gradient descent curve and the verification result. The predictive results for the training sample are tabulated in Table 2. Fig. 4 shows the correlation coefficient of the actual values and the predictive values of negative conversion days of the training sample. The correlation coefficient is 0.99721 which indicates that the predictive values are closely correlated with the actual values.

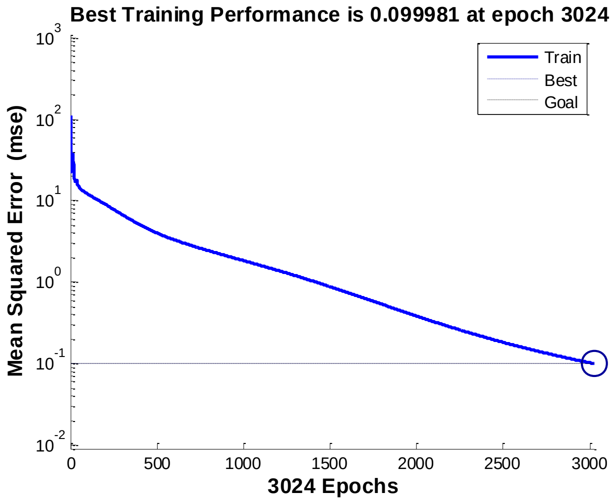

Fig. 2 Error curve of network training

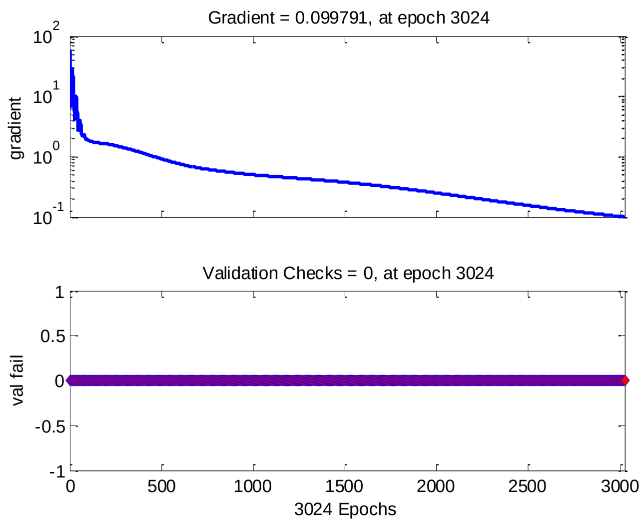

Fig. 3 Gradient curve and validation check curve

Table 2. Predictive results of the training sample

No. 1-10	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
	7.6734	24.8176	9.2744	8.0755	8.9597	6.7670	8.0685	11.9620	3.9488	6.6675
No. 11-20	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
	7.2999	9.8820	7.3160	6.9691	6.6375	5.7730	12.9512	6.9108	3.0878	9.9728
No. 21-28	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**		
	3.8548	6.0250	13.9791	9.0331	9.0150	10.0617	9.0052	12.9708		

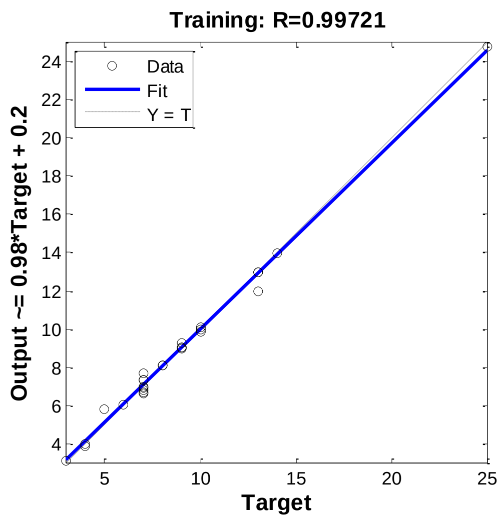

Fig. 4 Correlation coefficient of actual negative conversion days and predictive values of the training sample

At present, the neural network model for predicting negative conversion days of childhood nephrotic syndrome has been created.

Test results and discussion

In this section, the created neural network model is tested with 6 typical cases belonging to six different age groups as shown in Table 3.

Table 3. Test sample

No.	Age	lgG	lgA	lgM	lgE	C3	Albumin	Blood fat	Group	Negative conversion days
1	1.92	4.850	1.090	1.380	554.000	0.947	37.50	5.70	1	7.00
2	2.08	1.200	0.965	1.980	26.100	1.290	16.80	11.20	2	12.00
3	3.25	2.470	0.933	2.600	32.300	1.370	34.90	7.90	3	7.00
4	4.25	2.480	1.180	1.850	279.000	1.030	15.90	11.51	4	6.00
5	6.00	3.230	1.160	1.010	20.000	1.540	24.20	13.70	5	9.00
6	8.00	4.310	1.060	1.330	1000.000	1.100	21.30	8.10	6	5.00

After normalizing the test dataset, the well-trained neural network is used to predict the negative conversion days. Predictive results of the test sample are shown in Table 4. The predictive values of negative conversion days are rounded up and then the absolute error is calculated. From the results shown in Table 4, there are 2 cases with error of 2 days, 1 case with error of 1 day and 3 cases with exactly accurate prediction. The low mean absolute error of predictive results is achieved at 0.83.

The test results show that the improved BP neural network with momentum has good performance in predicting the negative conversion days for cases in Table 3. With the established neural network model the predictive results can be obtained easily by inputting the normalized medical index data. The success of the proposed approach for the small-size sample is owed to three main reasons. Firstly, as an implicit mathematical processing approach, neural networks are different from commonly used statistical methods. In the neural network approach, the results are obtained conveniently and quickly by inputting preprocessed data to the well-trained network. Secondly, weights are obtained through adaptive learning without manual intervention, and therefore the subjectiveness in the modeling process is eliminated and result distortions are avoided to some degree. Lastly, in the training process of the improved BP neural network the momentum factor reduces the network oscillation tendency, and hence the generalization performance of the neural network is promoted and predictive results become more objective and reliable.

Table 4. Predictive results of the test sample

No.	Actual negative conversion days	Predictive negative conversion days	Predictive values after rounded up	Absolute error
1	7.00	6.6218	7	0
2	12.00	10.3116	10	2
3	7.00	6.4193	6	1
4	6.00	8.3249	8	2
5	9.00	9.1568	9	0
6	5.00	4.7496	5	0

However, there are two weaknesses of the study. Firstly, the created model is relatively hard to explain because neural networks are more concerned about the actual number of variables rather about their nature. Secondly, we find that the quantity and quality of data in the sample greatly affect learning ability of neural networks. The problems are expected to be solved with developments of neural network methods and relative mathematical tools in the future.

Conclusion

It’s necessary to explore approach for prediction of negative conversion days for children with nephrotic syndrome, so as to help physicians with medical decision-making and provide patients with better treatment and care. In this study, the three-layered feedforward neural network trained by the improved BP algorithm with momentum is applied to the task of prediction. The experimental results show that the proposed approach is effective for the small-size sample. Despite some weaknesses, this study can provide a valuable reference to application of neural networks in the medical area of childhood nephrotic syndrome.

Acknowledgements

The work is supported by Applied Basic Research Program of Jiangsu University of Technology (No. KYY14005), Pre-research Program of Jiangsu University of Technology (No. KYY13049), Open Project of Key Laboratory of Cloud Computing and Intelligent Information Processing of Changzhou City (No. CM20123004-KF05, KF06) and Guangxi Higher Education Key Laboratory of Science Computing and Intelligent Information Processing (No. GXSCIIP201408).

References

1. Bai Y., W. Liu, Q. Guo, Y. Zou (2013). Screening for Urinary Biomarkers of Steroid-resistant Nephrotic Syndrome in Children, Experimental and Therapeutic Medicine, 5(3), 860-864.

2. Cai J., T.-X. Wu, K. Zhou, W. Li (2015). Recognition of Osteoporosis Based on Texture Analysis and a Support Vector Machine, International Journal Bioautomation, 19(1), 107-118.
3. Çelik Ü. S., A. Noyan, A. K. Bayazıt, M. Büyükçelik, H. Dursun, A. Anarat, G. Attila, S. Matyar (2006). ACE Gene Polymorphism in Turkish Children with Nephrotic Syndrome, Renal Failure, 28(5), 401-403.
4. Elman J. L. (1990). Finding Structure in Time, Cognitive Science, 14(2), 179-211.
5. https://en.wikipedia.org/wiki/Nephrotic_syndrome (Last Access November 23, 2015).
6. Iqbal S., K. Masood, O. Jafer (2011). An ANN Model for Treatment Prediction in HBV Patients, Bioinformation, 6(6), 237-239.
7. Istook E., T. Martinez (2002). Improved Backpropagation Learning in Neural Networks with Windowed Momentum, International Journal of Neural Systems, 12(3-4), 303-318.
8. Kohonen T. (1982). Self-organized Formation of Topologically Correct Feature Maps, Biological Cybernetics, 43(1), 59-69.
9. Liang M., Z. Li, T. Chen, J. Zeng (2014). Integrative Data Analysis of Multi-platform Cancer Data with a Multimodal Deep Learning Approach, IEEE/ACM Transactions on Computational Biology and Bioinformatics, 12(4), 928-937.
10. Lilova M. I., I. G. Velkovski, I. B. Topalov (2000). Thromboembolic Complications in Children with Nephrotic Syndrome in Bulgaria (1974-1996), Pediatric Nephrology, 15(1-2), 74-78.
11. McClelland J. L., D. E. Rumelhart (1986). Parallel Distributed Processing, MIT Press.
12. McCulloch W. S., W. Pitts (1943). A Logical Calculus of Ideas Immanent in Nervous Activity, Bulletin of Mathematical Biophysics, 5(4), 115-133.
13. Naumovic R., D. Furuncic, D. Jovanovic, M. Stosovic, G. Basta-Jovanovic, V. Lezaic (2010). Application of Artificial Neural Networks in Estimating Predictive Factors and Therapeutic Efficacy in Idiopathic Membranous Nephropathy, Biomedicine & Pharmacotherapy, 64(9), 633-638.
14. Negnevitsky M. (2004). Artificial Intelligence – A Guide to Intelligent Systems, Addison-Wesley Educational Publishers Inc.
15. Phansalkar V. V., P. S. Sastry (1994). Analysis of the Back-propagation Algorithm with Momentum, IEEE Transactions on Neural Networks, 5(3), 505-506.
16. Puskorius G. V., L. A. Feldkamp, L. I. Davis (1996). Dynamical Neural Network Methods Applied to On-vehicle Idle Speed Control, Proceedings of IEEE, 84(10), 1407-1420.
17. Rosenblatt F. (1962). Principles of Neurodynamics; Perceptrons and the Theory of Brain Mechanisms, Washington, Spartan Books.
18. Shao Y.-H., C.-H. Zhang, X.-B. Wang, N.-Y. Deng (2011). Improvements on Twin Support Vector Machines, IEEE Transactions on Neural Networks, 22(6), 962-968.
19. Sun J., B. Sun (2014). Observation and Nursing of Nephrotic Syndrome, Guide of China Medicine, 22, 345-346, (in Chinese).
20. Wen J., J. L. Zhao, S. W. Luo, Z. Han (2000). The Improvements of BP Neural Network Learning Algorithm, 5th International Conference on Signal Processing Proceedings, 3, 1647-1649.
21. Yuan Y., L. Mou, X. Lu (2015). Scene Recognition by Manifold Regularized Deep Learning Architecture, IEEE Transactions on Neural Networks and Learning Systems, 26(10), 2222-2233.
22. Zhou W.-G., Y.-F. Cui, Y. Li (2015). A Modified Method Combined with a Support Vector Machine and Bayesian Algorithms in Biological Information, International Journal Bioautomation, 19(2), 135-146.

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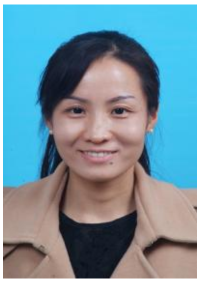

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Xiangjun Chen was born in Shaoyang, China in September 1977. He got his M.Sc. degree in Computer Science and Technology from Center South University in 2006. He is currently a lecturer at School of Computer Engineering of Jiangsu University of Technology in China. His research interests include pattern recognition and its applications.