İSTANBUL UNIVERSITY
CERRAHPAŞA

ORIGINAL ARTICLE
Electrica 2022; 22(3): 351-357

Computer Communication Network Fault Detection Based on Improved Neural Network Algorithm

Dong Sun[1], Pooja Chopra[2]*, Jyoti Bhola[3], Rahul Neware[4]

[1]School of Computer Science and Technology, Henan Polytechnic University, Xinxiang
[2]GNA University, Village Hargobindgarh, Phagwara, Punjab, India
[3]Electronics & Communication Engineering Department, National Institute of Technology, Hamirpur, India
[4]Department of Computing, Mathematics and Physics Høgskulen på Vestlandet Bergen Norway

Cite this article as: D. Sun, P. Chopra, J. Bhola and R. Neware, "Computer communication network fault detection based on improved neural network algorithm," *Electrica*, 22(3), 351-357, 2022.

ABSTRACT

To detect computer communication network failures, a computer communication network fault detection based on an improved neural network algorithm is proposed. A network fault diagnosis example is used to verify the effectiveness of the method. There are many network failure phenomena. Here, the author selected 13 network fault information parameters for a comprehensive diagnosis of network failures. The author designed a three-layer backpropagation (BP) neural network. There are 13 nodes in the input layer, corresponding to the above 13 network fault parameter information. The output layer has three nodes, which output the fault code sequence. The training of the network uses the trainlm() function. The performance function uses the mean square error performance function mse() and set e = 0.001; the network learning rate is set to a = 0.05. The author selects 100 failure data as the training set for network training and selects 10 sets of samples as the test set. The experimental data shows that after the network has been trained 25 times, the output error reaches the set precision e. After training the BP network using this algorithm 140 times, the output error reaches the set precision e. This method effectively improves the effectiveness and accuracy of S network fault diagnosis.
Index Terms—Network failure, improved neural network algorithm, BP neural network algorithm, fault detection

*School of Computer Applications Lovely Professional University, Jalandhar, Punjab, India

Corresponding author:
Dong Sun

E-mail: sundong7@126.com

Received: December 22, 2021

Accepted: March 28, 2022

Publication Date: September 26, 2022

DOI: 10.54614/electrica.2022.21168

I. INTRODUCTION

The types of services that data communication networks provide to people are constantly increasing and updating. It is playing an increasingly important position in the entire human society, economy, social activities, and daily life [1]. The data communication network has the characteristics of complex structure, large scale, high distribution, and heterogeneity. Because it is more and more difficult to maintain a system with such a large amount of operation, it is particularly urgent to remove the faults of the system efficiently. The location and cause of the abnormality in the data communication network require a good analysis method to help data communication network operation and maintenance personnel to troubleshoot and solve the problem of failure [2]. The data communication network is undergoing an intelligent transformation, from a single interconnected data communication medium to a comprehensive service platform for humans to process distributed information. Thus to ensure that the extremely important data communication network runs safely and effectively for a long time, we must strengthen its management to make the operation and maintenance management more scientific and accurate [3]. Among them, the fault diagnosis of the data communication network is a very important link in the whole system. The data communication system is shown in Fig. 1 [4]. The future development direction of diagnostic technology is also progressing along with the progress of science and technology step by step in the direction of synthesis, intelligence, and automation. When the network fails, it is necessary for the network management personnel to accurately locate the fault position, classification, and internal and external factors within as little time as possible to repair the damaged fault place in time. Due to the simple backpropagation (BP) neural network model, its wide application, strong nonlinear approximation, large-scale parallel operation, fault tolerance, and generalization ability, it is very practical to deal with the decision network classification problem, that is, to analyze which type of network form belongs to. Based on the existing research, this paper proposes a fault detection method of computer communication network based on improved neural network algorithm. First, the author introduces

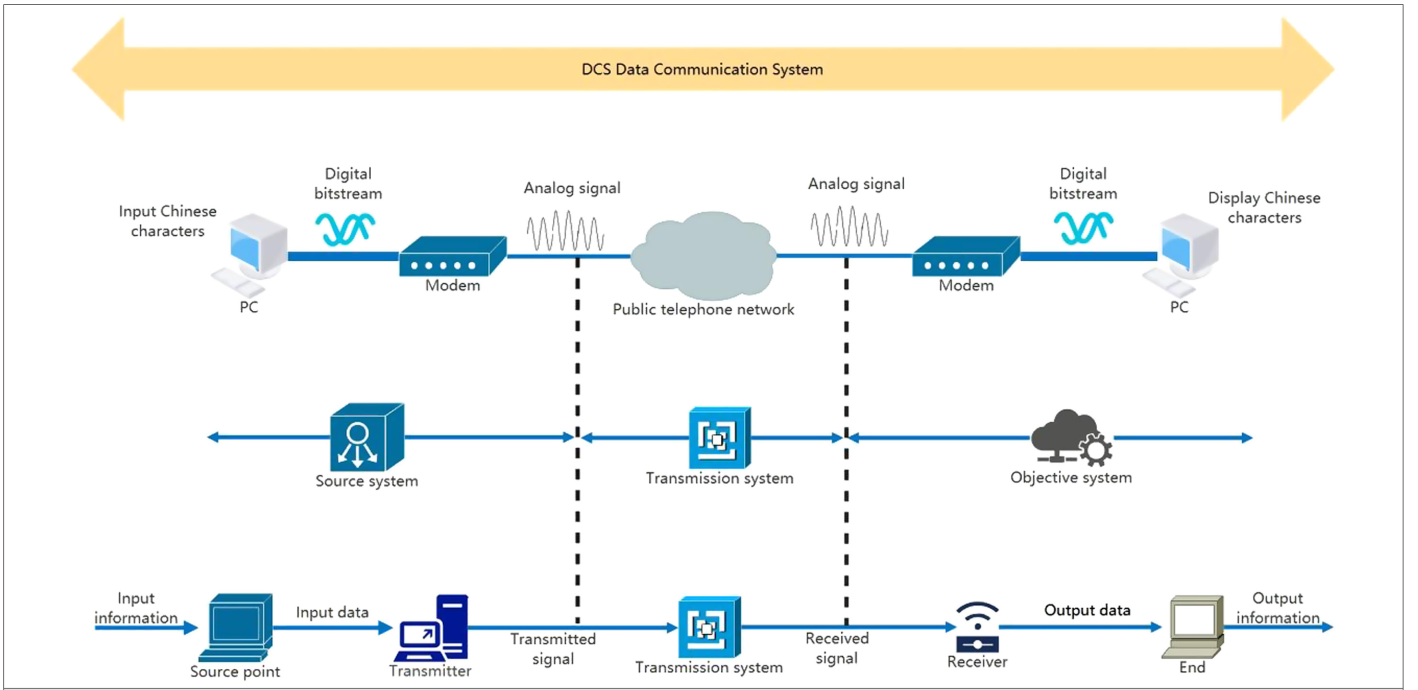

Fig. 1. Data communication system process.

the BP neural network algorithm and the improved BP neural network algorithm. The author verifies the effectiveness of the method through a network fault diagnosis example. There are many network failure phenomena. Here, the author selected 13 network fault information parameters for a comprehensive diagnosis of network failures. The author designed a three-layer BP neural network. There are 13 nodes in the input layer, corresponding to the above 13 network fault parameter information; The output layer has three nodes, which output the fault code sequence; The training of the network uses the trainlm() function. The performance function uses the mean square error performance function mse() and sets e = 0.001, and the network learning rate is set to a = 0.05. The author selects 100 failure data as the training set for network training and selects 10 sets of samples as the test set. The comparison of experimental results shows that the improved BP network proposed by the author has fewer iterations and converges faster. This shows that the fault diagnosis method based on the improved BP network can approximate the actual situation with higher accuracy. Thus, this method can meet actual application needs.

II. LITERATURE REVIEW

In response to this research question, Wijaya and others put forward at the seminar on simulation intelligence of machines that artificial intelligence (AI) is a high-tech discipline that studies machine intelligence and intelligent machines. It simulates, extends, and expands human intelligence and realizes the technical basis of certain mental labor automation. It is an important scientific approach to explore the mysteries of the human brain and a broad field of computer applications. Artificial neural network is a relatively prominent and fast-developing algorithm model among them [5]. Li and others invented the BP algorithm [6]. Zhang and others discovered the algorithm again [7]. Guo et al. proved that this algorithm can generate complex input pattern representations for hidden units [8]. Teh et al. proved that BP algorithms can explain within the scope of neuroscience, the function and role of some nerves in the human cerebral cortex. After that, the atmosphere of studying neural networks reached a climax and in-depth applications of neural networks have also appeared in many fields [9]. Xu and others innovated a brand new diagnostic system algorithm model which aimed at the complicated non-linear mapping relationship in the relationship between symptoms and faults. This model uses the fuzzy neural network to obtain the diagnosis matrix from the statistics of previous diagnosis examples, uses fuzzy transformation for reasoning, synthesizes the reasoning conclusions of the rules through the dynamic weight synthesis method, comes to the final diagnosis, solves the problem of non-orthogonal rules, and makes the diagnosis result statistically significant, and it solves the difficulty of obtaining rules in common methods and the problems that it is not easy to modify in use [10]. Fathian and other researchers used genetic algorithm to improve the BP neural network algorithm and reduce some of the inevitable shortcomings when using the BP algorithm alone. A diagnostic algorithm model combining genetic algorithm and BP neural network is presented as shown in Fig. 2 [11]. Li. and others conducted in-depth research on the feasibility, basic principles, diagnosis process analysis, and parameter optimization process of neural network for fault diagnosis and got a more ideal diagnosis result [12]. Agarwals et al. proposed a neural network method suitable for remote diagnosis and a remote network fault diagnosis model based on this method, realized the intelligent diagnosis, and finally through the experiment, verified the feasibility of this model [13]. Zhou et al. proposed the implementation process of the interface module of the fault diagnosis platform based on self-organizing neural network. They used Delphi to realize the input of classified samples and the graphical user interface function of the platform and for a relatively simple cluster analysis of the samples [14].

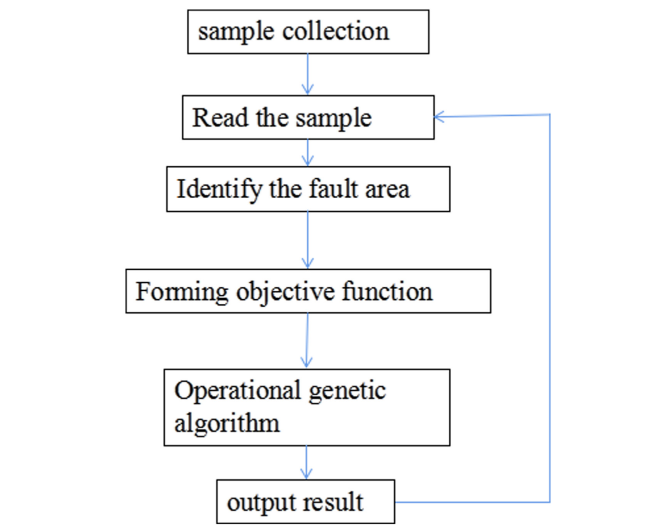

Fig. 2. Technical scheme of system fault diagnosis method based on genetic algorithm.

On the basis of current research, the author detected computer communication network failures. A computer communication network fault detection based on an improved neural network algorithm is proposed. First, the author introduces the BP neural network algorithm and the improved BP neural network algorithm. The author verifies the effectiveness of the method through a network fault diagnosis example. There are many network failure phenomena. The author selected 13 network fault information parameters for a comprehensive diagnosis of network failures. The author designed a three-layer BP neural network. There are 13 nodes in the input layer, corresponding to the above 13 network fault parameter information. The output layer has three nodes, which output the fault code sequence. The training of the network uses the trainlm() function. The performance function uses the mean square error performance function mse() and sets e = 0.001, and the network learning rate is set to a = 0.05. The author selects 100 failure data as the training set for network training and 10 sets of samples as the test set. The comparison of experimental results shows that the improved BP network proposed by the author has fewer iterations and converges faster. This shows that the fault diagnosis method based on the improved BP network can approximate the actual situation with higher accuracy, this method can meet actual application needs. Example shows that the method effectively improves the effectiveness and accuracy of network fault diagnosis, better than previous studies, and provides a feasible idea for network fault diagnosis.

III. METHODS

A. BP Neural Network Algorithm

One of the most widely used and mature neural network models at the moment is the BP neural network. This model belongs to the instructor, multi-layer forward structure network of unidirectional transmission. The composition of this model usually contains three or more layers, which can be divided into input layer, intermediate layer (hidden layer), and output layer [15].

The *j*th neuron of the *k*th layer in the BP neural network has the following input and output connection formula (1):

$$y_j^{(k)} = f_j^k\left(\sum_{i=1}^{N_{k-1}} W_{ij}^{(k-1)} y_i^{(k-1)} - \theta_j^{(k)}\right) \tag{1}$$

Formula $\left(k = 1,2,...,M; j = 1,2,...,N_k\right)$

Among them, $W_{ij}^{(k-1)}$ is the connection weight from the *i*th node to the node in the (*k*−1)th layer; $\theta_j^{(k)}$ is the function of the (*k*) node; $_{Nk}$ is the number of nodes in the *k*th layer; *M* is the total number of layers. $f_j^{(k)}$ is taken as the sigmoid function $f(x) = 1/\left(1+e^{-x}\right)$.

The learning method of BP neural network uses the error BP algorithm and the weight adjustment is as follows:

$$W_{ij}^{(k-1)}(t+1) = W_{ij}^{(k-1)}(t) + \eta\sum_{h=1}^{l}\delta_{hj}^{(k)} y_{hj}^{(k-1)} \tag{2}$$

Among them, *l* is the total number of samples, $0 < \eta < 1$ is the learning step size, and $\delta_{hj}^{(k)}$ is the error transmission term. For the output layer, the error calculation formula is:

$$\delta_{hj}^{(k)} = \left(\hat{y}_{hj}^{(M)} - y_{hj}^{(M)}\right) f_j\left(y_{hj}^{(M)}\right) \tag{3}$$

For other layers, the error calculation formula is:

$$\delta_{hj}^{(k)} = f_j\left(y_{hj}^{(k)}\right)\sum_{i=1}^{N_{k+1}}\delta_{hj}^{(k+1)} W_{ij}^{(k)}(t) \tag{4}$$

The calculation formula of the error ε1 output by the neural network is:

$$\varepsilon_1 = \sum_{h=1}^{l}\sum_{j=1}^{N_M}\left(\hat{y}_{hj}^{(M)} - y_{hj}^{(M)}\right) \tag{5}$$

If ε1 > ε (ε is the preselected setting error), then continue to the next round of learning process; the purpose is to change the size of the weight, otherwise the network learning will be stopped. The network composed of the weights of $_{Wij}$ after learning can achieve the desired output within the error range set by ε. Backpropagation network has the characteristics of high nonlinear approximation ability, can calculate the conclusion of the sequence of numbers, has no lack of generalization ability, and the stored abnormal pattern is recorded in the connection weight. In the process of diagnosis, the BP network can not only distinguish the fault but also the abnormal degree value. It is just that there are unavoidable shortcomings based on the BP network algorithm and the training process is not guaranteed to be very stable, even locally highlight the minimum value. In addition, because the discrimination performance of BP network depends on the existing information in the information database, a large number of sample information is needed for network training. Otherwise, once a new fault signal appears, it is likely that the best corresponding sample cannot be found, resulting in unsatisfactory diagnosis effect [16].

B. Improved BP Neural Network Algorithm

In the actual application process, the traditional BP learning algorithm has problems such as poor anti-interference ability, slow learning rate, and the objective function easily falling into a local minimum [17]. For these questions, researchers have proposed improved learning algorithms such as batch learning method, additional momentum method, adaptive parameter adjustment method, and Levenberg–Marquardt (L–M) method. Compared with other improved algorithms, the L–M algorithm converges very quickly when the network weight is small for several months. Compared with the traditional BP and its improved algorithm, the number of iterations is less, the convergence speed is fast, and the accuracy is high. L – m algorithm makes each iteration no longer follow a single negative gradient direction, but allows the error to search along the deterioration direction. At the same time, through the adaptive adjustment and optimization of the network weight between the steepest gradient descent method and Gauss Newton method, the network can converge effectively, which greatly improves the convergence speed and ability of the network [18].

In the network fault diagnosis algorithm based on BP neural network, in order to prevent the learning algorithm of the BP network from trapping the local minimum and its divergence and at the same time to speed up the calculation speed of the system risk assessment and in order to improve the accuracy of the evaluation, the author chooses the improved L–M algorithm to modify the network weights. In addition, the performance of BP neural network also depends on the generalization ability of the network [19]. The test of generalization ability generally adopts an initial termination method and randomly divides the available samples into two parts: one part is used as the training set and the other part is used as the test set. The training set is used to calculate the gradient of the network performance response number and the updated network weight and the test set is used to test the training results of the neural network. If the error of the network to the training set samples is small, the error of the test set samples would be very large, indicating that the network has been trained too much and does not have good generalization ability [20].

C. Fault Diagnosis Algorithm Based on Improved BP Network

Based on the improved BP neural network fault diagnosis algorithm, the algorithm steps are described as follows:

The first stage: training and test sample set design

(1) Design a sample set based on network fault information parameters;
(2) Divide the sample set into two parts. Among them, N samples constitute the training sample set and M samples constitute the test sample set.

The second stage: construct and train BP neural network.

(3) According to the collected data, design a three-layer BP neural network, the input layer contains n nodes, the hidden layer contains l nodes, and the output layer contains m nodes. Among them, if the number of hidden layer nodes is based on empirical formula, the trial and error method is used to determine the nodes.
(4) Encode the failure mode, output an m-dimensional vector, and in the case of meeting the number of failures, make the dimension m of the output vector as small as possible.
(5) Set the network's transmission speed, training function, performance number, convergence error learning rate, and the initial value and national value of the neuron connection weight. The training number is the train() function, which uses the L–M learning algorithm.
(6) Use the training set samples to train the BP network until a stable network weight and predetermined error accuracy are obtained.
(7) Use the test set samples to test the training results of the trained BP network and see if the predetermined error requirements are met.

The third stage: fault diagnosis of unknown samples

(8) Input the unknown samples into the trained BP network and get the network fault diagnosis result.

IV. RESULTS AND ANALYSIS

The author verified the effectiveness of the method through a network fault diagnosis example. There are many network failure phenomena. The author selected 13 network failure information parameters for comprehensive diagnosis of network failures and designed a three-layer BP neural network [21]. There are 13 nodes in the input layer, corresponding to the above 13 network fault parameter information. The output layer has three nodes, which output the fault code sequence. According to the empirical formula, the number of hidden layer nodes is set to 6. The logarithmic sigmoid function is used to transfer the number between the input layer to the hidden layer and the hidden layer to the output layer [22]. The training of the network uses the trainlm() function [23]. The performance function uses the mean square error performance function mse() and set e=0.001; the network learning rate is set to a = 0.05 [24]. The author selects 100 fault data as the training set for network training, and at the same time, 10 sets of samples are selected as the test set. Some training samples are shown in Table I.

Tables II and III show the network status information represented by L-M. The error output and training times of BP network are increased to the training sample set, as shown in Fig. 3. The abscissa represents the number of training of the network and the ordinate represents the error accuracy of the BP network [25]. As can be seen from Fig. 4, after the network has been trained for 25 times, the output error reaches the set precision e. The training output of the BP network using the adaptive gradient descent method is shown in Fig. 4.

TABLE I. PART OF THE TRAINING SAMPLES

Serial number	A	B	C	D	E	F	G	H	I	J	K	L	M	Fault
1	1	2	2	0	0	0	0	0	0	0	0	0	0	Connection blocking
2	2	2	2	0	0	0	0	0	0	0	0	0	0	Port closed
3	1	1	1	0	0	0	0	0	0	0	0	0	0	Broadcast storm
4	1	1	1	0	0	0	0.5	0.5	0.5	0.95	0.95	0.02	0.02	Buffer overflow
5	1	1	1	0.05	0	0	0	0	0	0.2	0.2	0.02	0.02	Line interference

TABLE II. A-F VARIABLE DESCRIPTION

Symbol	Illustrate	Ranges
A	Port management status	1-up 2-down
B	Link protocol status	l-up 2-down
C	The current status of the port.	1-up 2-down
D	Cyclical Redundancy Check error rate	0–1
E	Conflict rate	0–1
F	Backward conflict rate	0–1

TABLE III. G-M VARIABLE DESCRIPTION

Symbol	Illustrate	Ranges
G	Enter the packet loss rate	0–1
H	Output packet loss rate	0–1
I	Total packet loss rate	0–1
J	Input queue length/maximum length	0–1
K	Output queue length/maximum length	0–1
L	Average input flow/port speed	0–1
M	Average output stream address/port speed	0–1

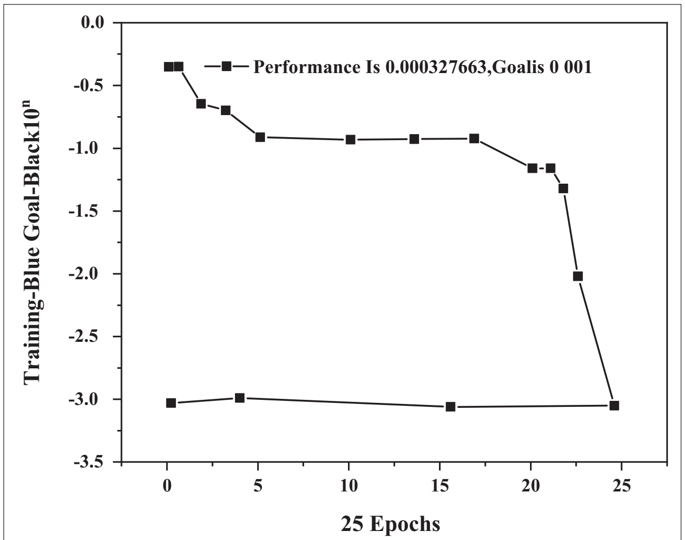

Fig. 3. Output error and training times of the training sample set.

As can be seen from Fig. 4, after training the BP network using this algorithm for 140 times, the output error reaches the set precision e [26]. The comparison shows that the improved BP network proposed by the author has fewer iterations and faster convergence [27].

The output results of network fault diagnosis based on Improved BP network are shown in Table IV. It lists the output of five test set samples.

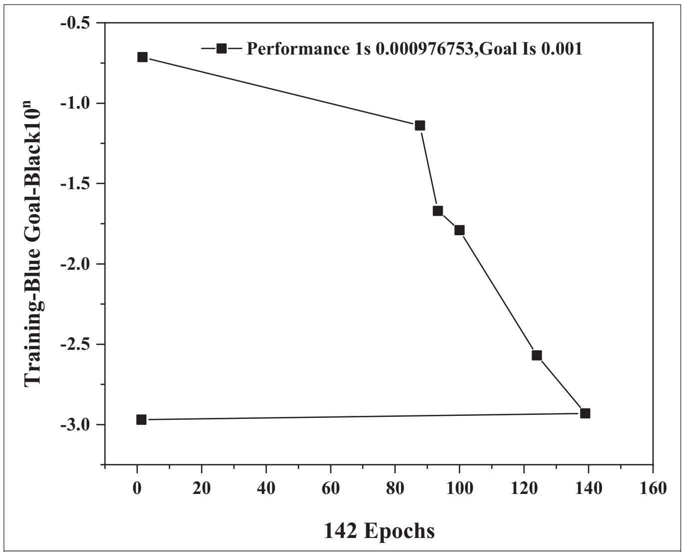

Fig. 4. Output error and training times of traditional BP network. BP, backpropagation.

TABLE IV. OUTPUT RESULTS OF TEST SET SAMPLES

	1	2	3	4	5
y_1	0.0021	0.0281	0.0049	0.0039	0.9981
y_2	0.0032	0.0089	0.9971	0.9979	0.0031
y_3	0.9985	0.0019	0.0003	0.9436	0.0025

It can be seen from Table IV that the output results of fault diagnosis based on the improved BP network have very good consistency with the output results of the test sample set [28, 29].

V. CONCLUSION

The author proposes a computer communication network fault detection based on an improved neural network algorithm, introduces a fault diagnosis algorithm based on an improved BP network, and carries out a network fault diagnosis example to verify the effectiveness of the method. The experimental results improve the error output and training times of the BP network on the training sample set. The abscissa represents the training times of the network and the ordinate represents the error accuracy of the BP network. After the network is trained 25 times, the output error reaches the set precision e. After training the BP network using this algorithm 140 times, the output error reaches the set precision e. The comparison shows that the improved BP network proposed by the author has fewer iterations and faster convergence. This shows that the fault diagnosis method based on the improved BP network can approximate the actual situation with higher accuracy, and this method can meet actual application needs. In order to make the recognition faster and more accurate, it is necessary to further optimize the structure and function of neural network. In order to improve the efficiency and practicability of the algorithm, the Lich knows how to skillfully and effectively construct neural networks and train data samples.

Peer-review: Externally peer-reviewed.

Author Contributions: Concept – D.S.; Design – D.S.; Supervision – J.B.; Funding – D.S.; Materials – P.C.; Data Collection and/or Processing – P.C.; Analysis and/or Interpretation – R.N.; Literature Review – D.S.; Writing – D.S.; Critical Review – J.B.

Declaration of Interests: The authors declare that they have no competing interest.

Funding: Henan Provincial College Teaching Master Workshop Program (Higher Education Office of The Educational Department of Henan Province [2019] No. 618).

REFERENCES

1. W. Ding, Y. Sun, L. Ren, H. Ju, and M. Li, "Multiple lesions detection of fundus images based on convolution neural network algorithm with improved sfl," *IEEE Access*, vol. PP, no. 99, pp. 1–1, 2020.
2. F. Liu, W. Huo, Y. Han, S. Yang, and X. Li, "Study on network security based on pca and bp neural network under green communication," *IEEE Access*, vol. PP,no. 99, pp. 53733–53749, 2020. [CrossRef]
3. J. H. Du, "Automatic text classification algorithm based on gauss improved convolutional neural network," *J. Comp. Sci.*, vol.21, no.jul, pp. 195–200, 2017. [CrossRef]
4. H. Wu, J. Xian, J. Wang, S. Khandge, and P. Mohapatra, "Missing data recovery using reconstruction in ocean wireless sensor networks," *Comput. Commun.*, vol.132,no.NOV,pp, 1–9, 2018. [CrossRef]
5. M. A. Wijaya, K. Fukawa, and H. Suzuki, "Neural network based transmit power control and interference cancellation for mimo small cell networks," *IEICE Trans. Commun.*, vol.E99.B, no.5, pp. 1157–1169, 2016. [CrossRef]
6. F. Li, X. G. Gao, and K. F. Wan, "Research on rbm networks training based on improved parallel tempering algorithm," *Acta Autom. Sin.*, vol.43, no.5, pp. 753–764, 2017.
7. P. Zhang, Q. Guo, S. Zhang, and H. H. Wang, "Pattern mining model based on improved neural network and modified genetic algorithm for cloud mobile networks," *Clust. Comput.*, vol.22, no.S4, pp. 9651–9660, 2019. [CrossRef]
8. L. Guo, "Research on anomaly detection in massive multimedia data transmission network based on improved pso algorithm," *IEEE Access*, vol. PP,no. 99, pp. 1–1, 2020.
9. J. S. Teh, A. Samsudin, and A. Akhavan, "Parallel chaotic hash function based on the shuffle-exchange network," *Nonlinear Dyn.*, vol.81, no.3, pp. 1067–1079, 2015. [CrossRef]
10. L. Xu, G. Z. Tan, and X. Zhang, "Probabilistic inference-based service level objective-sensitive virtual network reconfiguration," *Comput. Commun.*, vol.57, no.feb.15, pp. 25–36, 2015. [CrossRef]
11. M. Fathian, and A. R. Jafarian-Moghaddam, "New clustering algorithms for vehicular ad-hoc network in a highway communication environment," *Wirel. Netw.*, vol.21, no.8, pp. 2765–2780, 2015. [CrossRef]
12. Y. Li et al., "Multiple measures-based chaotic time series for traffic flow prediction based on bayesian theory," *Nonlinear Dyn.*, vol.85, no.1, pp. 179–194, 2016. [CrossRef]
13. S. K. Agarwal, S. Shah, and R. Kumar, "Group based swarm evolution algorithm (gsea) driven mental task classifier," *Memetic Comput.*, vol.7, no.1, pp. 19–27, Feb,2015. [CrossRef]
14. X. Azhou, & P. Jiang, "Variation source identification for deep hole boring process of cutting-hard workpiece based on multi-source information fusion using evidence theory", *Memetic Comput.*, vol.28, no.2, pp. 255–270, 2017.
15. F. Shokraneh, S. Geoffroy-Gagnon, M. S. Nezami, and O. Liboiron-Ladouceur, "A single layer neural network implemented by a 4×4 mzi-based optical processor," *IEEE Photonics J.*, vol.11, no.6, pp. 1–12, 2019. [CrossRef]
16. H. Zhang, Y. Chen, Y. Song, Z. Xiong, and Q. Wu, "Automatic kidney lesion detection for ct images using morphological cascade convolutional neural networks," *IEEE Access*, vol. PP,no. 99, pp. 1–1, 2019.
17. M. Liu, J. Ma, L. Lin, M. Ge, Q. Wang, and C. Liu, "Intelligent assembly system for mechanical products and key technology based on internet of things," *J. Intell. Manuf.*, vol. 28, no. 2, pp. 271–299, 2017. [CrossRef]
18. N. H. Ho, H. J. Yang, S. H. Kim, and G. Lee, "Multimodal approach of speech emotion recognition using multi-level multi-head fusion attention based recurrent neural network," *IEEE Access*,vol. PP,no. 99, pp. 1–1, 2020.
19. W. J. Hwang, Y. C. Tung, Y. L. Chen, P. Y. Lai, and C. H. Ho, "A novel user-oriented quality of service algorithm for home networks," *IEEE Syst. J.*, vol. PP, no. 99, 548–559, 2015. [CrossRef]
20. B. Subba, S. Biswas, and S. Karmakar, "A game theory based multi layered intrusion detection framework for vanet," *Future Gener. Comput. Syst.*, vol.82, no. MAY, pp, 12–28, 2018. [CrossRef]
21. A. Adeel, H. Larijani, and A. Ahmadinia, "Random neural network based novel decision making framework for optimized and autonomous power control in lte uplink system," *Phys. Commun.*, vol.19, no. Jun, pp. 106–117, 2016. [CrossRef]
22. E. Crisostomi, C. Gallicchio, A. Micheli, M. Raugi, and M. Tucci, "Prediction of the italian electricity price for smart grid applications," *Neurocomputing*, vol.170, no.C, pp. 286–295, 2015.
23. H. Cheng, and H. Jiang, "VPinning synchronization for directed networks with node balance via adaptive intermittent control," *Nonlinear Dyn.*, vol.80, no.1, pp. 295–307, 2015.
24. A. Avena-Koenigsberger, J. Goni, R. Sole, and O. Sporns, "Network morphospace," *J. R. Soc. Interface*, vol.12, no.103, pp. 20140881–20140881, Feb,2015. [CrossRef]
25. M. H. Jali *et al.*, "Joint torque estimation model of semg signal for arm rehabilitation device using artificial neural network techniques," *Lect. Notes Electr. Eng.*, vol.315, no.7, pp. 671–682, 2015. [CrossRef]
26. M. C. Hu, W. H. Cheng, C. S. Hu, J. L. Wu, and J. W. Li, "Efficient human detection in crowded environment," *Multimedia Syst.*, vol.21, no.2, pp. 177–187, 2015. [CrossRef]
27. D. L. Li, J. H. Wang, J. C. Xu, and X. K. Fang, "VDensely feature fusion based on convolutional neural networks for motor imagery eeg classification," *IEEE Access*, vol. PP,no. 99, pp. 1–1, 2019.
28. W. Xin, Z. Xingwang, and Z. Wenhao, "Design of fault detection observer based on new-type neural networks," Fifth International Conference on Instrumentation and Measurement, Computer, Communication and Control (IMCCC), Vol. 28, 2015, pp. 326–329. [CrossRef]
29. S. Verma, S. Dutta, P. K. Sadhu, M. J. Bharata Reddy, and D. K. Mohanta, "Islanding detection using bi-directional energy meter in a DFIG based active distribution network," International Conference on Computer, Electrical & Communication Engineering (ICCECE), Vol. 29, 2019, pp. 1–4. [CrossRef]

Sun Dong (1980-), male, Han Nationality, Xinxiang, Henan Province, master, associate professor, mainly engaged in artificial intelligence, cloud computing, network security research. Address: Henan Institute of Technology, No.699, Pingyuan Road, Xinxiang City, Henan Province.

Dr. Pooja Chopra completed her doctorate from PTU Jalandhar. She has over 15 years of experience in the field of teaching. Her research interest areas are cloud computing and Artificial intelligence.

Dr. Jyoti Bhola has done her B. Tech. in Electronics and Communication Engineering from Kurukshetra University. She did her M. Tech. in Electronics and Communication Engineering, from Punjab Technical University, Jalandhar. She did her PhD from National Institute of Technology, Hamirpur in Electronics and Communication Engineering. She is currently working as Assistant Professor at Madanpalle Institute of Technology and Science, Andhra Pradesh, India. Her area of interest in research is Wireless Sensors Networks and Adhoc Networks. He has published more than 20 research articles in reputed SCI / SCOPUS journals and conferences.

Rahul Neware received the B.E. degree in Information Technology from the RTM Nagpur University India, in 2015, and the M.Tech. degree in Computer Science and Engineering from G. H. Raisoni College of Engineering Nagpur India, in 2018. He is currently pursuing a Ph.D. degree in Computing from Western Norway University of Applied Sciences, Bergen campus, Norway. His area of interest includes Cybersecurity, Systems of Systems, Cloud and Fog Computing, Advanced Image Processing, Remote Sensing. He is a member of various professional bodies like IEEE, ASR, CSI, IAENG, and Internet Society.