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Retraction

Retracted: Computer Communication Network Fault Detection Based on Improved Neural Network Algorithm

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] Y. Na, "Computer Communication Network Fault Detection Based on Improved Neural Network Algorithm," *Mobile Information Systems*, vol. 2022, Article ID 3897180, 7 pages, 2022.

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Research Article

Computer Communication Network Fault Detection Based on Improved Neural Network Algorithm

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In order to meet the new requirements of fault diagnosis response and intelligent degree in the current computer network, a fault detection of computer communication network based on an improved neural network algorithm is proposed. First, from the perspective of deep learning, based on the KDD99 data set, the network fault diagnosis method based on the convolutional neural network model is studied, and the data conversion operation of grayscale matrixed raw data is proposed. And experiments are carried out, the convolutional neural network structure is designed according to the scale of data features, a series of optimization studies including discarding learning, gradient optimization algorithm, and data enhancement based on this is carried out, and the establishment of the entire fault diagnosis model is completed. The experimental results show that, in the diagnostic model designed in this paper, the Tanh activation function is used in the first fully connected layer to achieve the best convergence speed. During the training process, it can start to converge after about 24 iterations, and the accuracy rate of the model training process can reach 98.1%, verifying the correctness and superiority of the algorithm and model.

1. Introduction

There are several problems faced by network fault diagnosis at this stage: (1) with the profound evolution of the digital society and the promotion of social events, the current computer network is in an unprecedentedly huge network scale and user scale and the failure of a large-scale network. With the intricate relationship between the composition of the local area network, the cause of the failure and the phenomenon of the failure are also relatively vague. Under this premise, once the network fails and remains unresolved for a long time, it will bring problems to the current stage of digital social production and life and even social government affairs. The service produces heavy losses and greatly damages the vital interests of each user; (2) The network equipment has high complexity, such as desktop computers, notebook computers, tablet computers, mobile phones, smart wearables, and Internet of Things mobile terminals [1]. With the continuous introduction of Internet devices, the functions are diversified. In particular, in the process of the gradual development of the Internet of Things, various types of local area network edge networking devices will further appear which will increase the load of network fault diagnosis [2]. (3) The development of private networks, especially some government and enterprise private Lans, is of great significance to their social mission.For example, the government's online government server network, a technology company's data center network, part of which uses a variety of fusion of network interaction transmission technology and network storage [3, 4]. A network fault detection model based on neural network is shown in Figure 1.

It can be seen that the network fault diagnosis is of great significance to the development of the digital process and the stable operation and fault management of the network. Traditional network fault management relies too much on network experts and network operation and maintenance engineers to do it manually. At this stage, it can no longer meet the requirements of network fault management. At this stage, there is an urgent need for intelligent network fault diagnosis technology [5], which liberates the human work of network experts and network engineers, realizes the

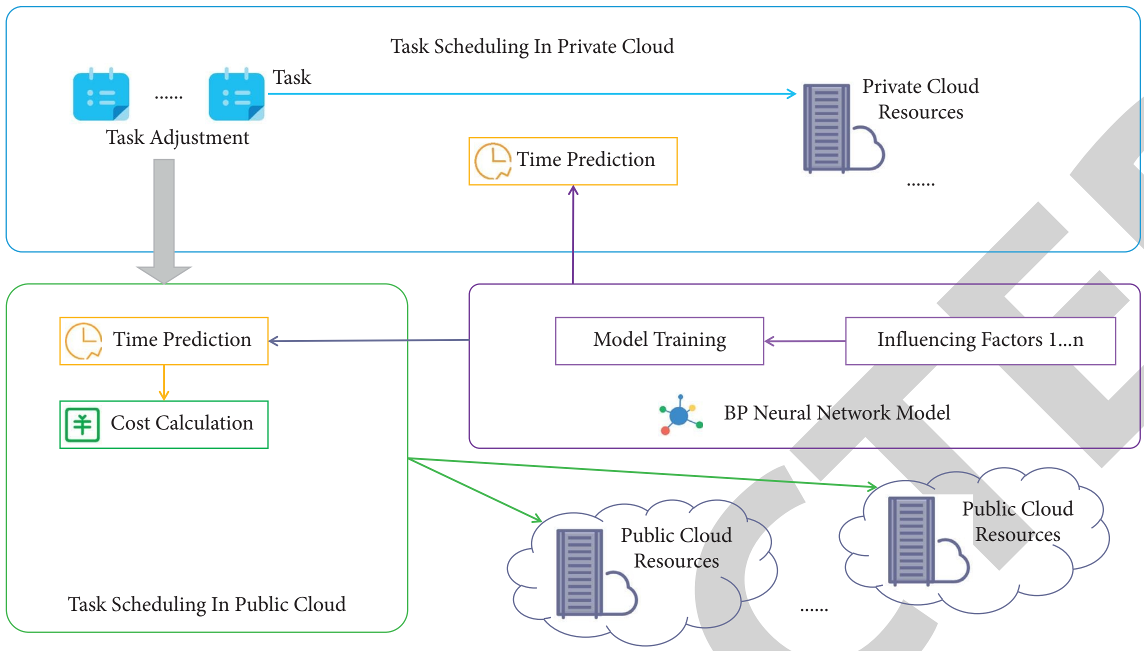

Figure 1: A network fault detection model based on neural network.

development of the automatic process of network fault diagnosis, and then guarantees the construction of the information society at this stage and the leap of the information age.

2. Literature Review

With the expansion of network scale and network composition, fault diagnosis technology under LAN has become one of the important network problems to be solved urgently in academia. Chen et al. pointed out that due to the relatively late start of computer network technology, China has been at a relatively backward level since the end of the last century. The system has begun to explore the network fault diagnosis topics of major scientific research institutes and has begun to develop from expert systems to diversified, cross-integrated, and achieved certain results [6]. However, according to the report of Samarthrao et al. on the whole, the research and exploration of network fault diagnosis system, from 0 to 1, will gradually develop and will continue to move towards the goal of further improvement [7]. Fang et al. pointed out that the development stage of fault diagnosis technology is divided into three stages as a whole as shown in Figure 2, and the corresponding stage descriptions are shown in Table 1 [8].

With the continuous development of subject research in academia, fault diagnosis technology also presents a large number of overlapping characteristics. Various intelligent diagnosis methods and theories collide, penetrate, and combine with each other, and the characterization of the fault is more comprehensive and complete, but also towards a more intelligent direction. At present, many scientific research teams and technology companies in the world have developed corresponding fault diagnosis systems and solution platforms for network fault diagnosis, and some

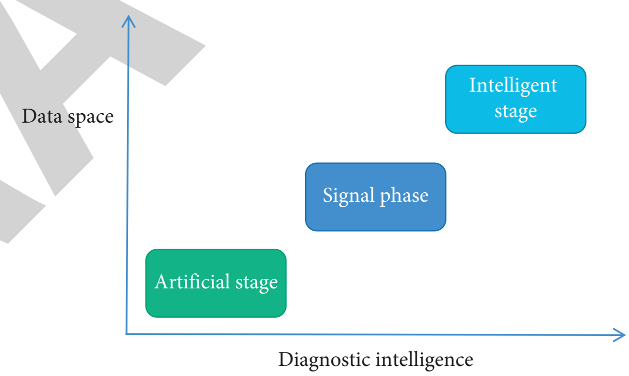

Figure 2: Development stage of fault diagnosis technology.

products have already entered the market, playing an important role in network fault management in the market. Rxa et al. believed that the theoretical basis of network fault diagnosis comes from information theory, graph theory, artificial intelligence, and other computer science fields, so their diagnostic principles and methods are also derived from them. For example, some are based on rule-based reasoning, some are based on expert systems, some are based on neural networks, and so on [9].

According to the report of Jiang et al., the research on network fault diagnosis technology in China is mainly concentrated in the research topics of higher research institutes, but some technology companies have also developed corresponding systems to improve their own product or business. At the same time, for different research fields, their networks range from the organizational network of wireless sensors to the local area communication network in multiple scenarios. There are academic achievements, some of which are still related to the further evolution of expert systems, and some are based on cutting-edge technologies

Table 1: Troubleshooting development stage description.

	Stage description	Data requirements
Artificial phase	Experience guide	Artificial phenomenon
Signal stage	Signal processing and modeling	Key information
Smart stage	Computer technology support	Knowledge base and training at scale

[10]. The investigation of Jiang et al. pointed out that if the network fault is not solved in time, especially for some large computer rooms or data centers of government and enterprises, it is easy to evolve into a small fault and affect a large range of nodes. It will eventually lead to a wide range of failures, so it is an urgent need to diagnose and solve the failure in time [11]. Lv et al. of the University of California, Los Angeles, proposed the construction of a new network expert system, which uses the learning and reasoning of artificial neural network to obtain network knowledge from the original data training, avoiding the cumbersome process from the network expert side avoiding the tedious process of acquiring knowledge from network experts [12]. The big data attribute selection method in distributed network fault diagnosis database was proposed by Chang et al. through the support vector machine; the distributed network fault diagnosis database is deeply mined, the fault attribute weight is calculated, and the network fault is completed. The attribute classification of the diagnostic database improves the efficiency of network fault diagnosis [13]. The integrated convolutional neural network ISECNN for fault diagnosis based on diversity regularization proposed by Singh et al. uses diversity regularization to generate multiple local minima during the training process and put them into the iterative training process. The improvement improves the generalization ability of the local minimum group, and the generalization ability of the entire fault diagnosis model is improved accordingly. Tests show that the generalization ability of the ISECNN model is improved without reducing the prediction accuracy [14]. Trg et al. proposed a novel deep belief network model that integrates principal component analysis and long short-term memory network for fault diagnosis. It can diagnose faults in an early frame and identify early unclassified new fault types and evaluate the severity of faults when they occur through models. The model has good feasibility after four fault types and a blind simulation test [15].

3. Research Method

3.1. Network Failure Scenario Analysis. The KDD99 dataset comes from nine weeks of underlying network data collected on a virtual network simulating the U.S. Air Force LAN. According to specific intrusion faults, it is divided into training data with identification and test data without identification [16]. Among them, the test data and training data have different probability distributions and contain certain types of non-attacks, which makes the division of intrusion faults more realistic and hierarchical. Each record in the KDD99 dataset consists of 41 features and a marker representing the type, representing a network connection. Data in the dataset are marked as normal and attack. Among them, the attack types are divided into four categories, a total of 39 types, of which 22 types of attacks appear in the training set and test set and the remaining 17 types of attacks only appear in the test set [17]. The identification types of the experimental data of the KDD99 fault set are shown in Table 2.

After analysis, combined with the research on the local area network faults and current fault diagnosis technology [18], it can be found that the local area network environment is relatively complex; if the traditional qualitative fault diagnosis method is used, it is often difficult to effectively model the problem and extract the expert knowledge of network fault. The rapid changes in scale and hierarchy, and the emergence of various business scenarios and military scenarios, the requirements for network management and fault diagnosis will only increase. Therefore, the traditional qualitative method for network fault diagnosis will not be suitable for the development needs of the new era. With the support and drive of a large amount of local area network data, more intelligent fault diagnosis technology is worthy of being proposed and used. Here, this chapter proposes a fault diagnosis method based on convolutional neural network. Through the data collection of local area network information, the feature data set is constructed according to feature engineering, and the model is provided for fault diagnosis. Driven by the historical data set of the local area network, the model itself is trained and optimized offline first and can be launched after a certain level of fault detection rate is reached, so as to realize rapid diagnosis of network faults in the local area network.

3.2. Faulty Convolutional Neural Network Implementation Detection. Convolutional neural network, as one of the commonly used deep learning network models, belongs to the feedforward neural network [19, 20]. The general hierarchical structure of a convolutional neural network is in series, and the whole consists of one or more convolutional layers and a fully connected layer at the back end. The original input is convolved through the convolution kernel of the convolution layer to obtain multichannel feature slices, which are then aggregated by the pooling layer, and the neurons in the entire network model are activated through an appropriate activation function to make them work [21, 22], and finally, the confidence vector of fault label is output after the full connection layer. In the convolutional neural network selected in this paper, the ReLU6 convolutional layer is an important layer. In the entire convolution process, the convolution operation is performed with a two-dimensional convolution kernel (also known as a discrete two-dimensional filter) as the core, and the original input matrix is subjected to a convolution process to

Table 2: KDD99 Identification type of experimental data of failure set.

Identity type	Logo meaning	Specific subcategory identification
Normal	The network is normal	Normal
DOS	DOS attack failure	Back, land, neptune, pod, smurf, and teardrop
Probing	Surveillance probe	Ipsweep, nmap, portsweep, and satan
R2L	Remote illegal access fault	ftp_write, guess_passwd, imap, multihop, phf, and spy

produce a feature map. The whole process is often convolved by multiple two-dimensional convolution kernels. Therefore, the entire convolution process will generate a multi-channel feature map to complete the convolution feature of the original input matrix. The convolution feature extraction of the original input matrix is completed. A convolution process is the convolution kernel, which traverses all the positions on the two-dimensional matrix in turn. The sliding process needs to use the design step size as the sliding step size, and at each position, the convolution kernel and the pixels on the position are inner products. Inner product operation is performed on the convolution kernel and pixels at each position [23].

In a convolutional neural network, the convolution operation is a discrete convolution in mathematics. The definition of discrete convolution is as follows:

$$(f * g) = \sum_{m=-\infty}^{\infty} f[m]g[n-m] = \sum_{m=-\infty}^{\infty} f[n-m]g[m]. \tag{1}$$

Among them, f[n] and g[n] are two discrete functions for convolution operation, and the length of g[n] is M. Correspondingly, in the convolutional neural network, the discrete convolution formula is as follows:

$$(f * g_k) = \sum_{i=0}^{H} \sum_{J=0}^{W} f_{i,j} \cdot (g_k)_{i,j}. \tag{2}$$

Among them, f is the convolution kernel, H and W are the number of rows and columns of the convolution kernel, g_k is the overlapping area where the two-dimensional matrix of the input convolution layer slides into the convolution kernel during the convolution process, and f_i and j are the volumes and the value of the element of the convolution kernel at position (i, j). For each convolution operation, the calculation process is as follows: the original input is 4×4 two-dimensional matrix data, and the size of the convolution kernel is 2×2. The size of the convolution window is the size of the convolution kernel, and its initial position is the upper left corner of the two-dimensional matrix; after calculating the inner product between each sliding convolution window and the convolution kernel, the element at the corresponding position of the convolution result is obtained, and the convolution window is immediately sliding backwards, the rule for sliding backwards is move the corresponding step size coordinates according to the step size, from left to right in turn, when the right edge of the convolution window coincides with the right side of the original input, the convolution of this row ends; from top to bottom, move the step column and continue until the convolution window slides to the lower right corner to complete a convolution calculation; the bias parameter is often added after the convolution [24]. At the same time, the original input specification does not always guarantee the smooth sliding of the sliding convolution window, so the original input matrix will also take edge zero-padding operation according to the situation.

For this ReLU6 detection model, the specific training and testing steps are as follows. Step 1: perform data preprocessing on the original data set, including feature digitization, feature dimension reduction based on principal component analysis, and feature data reconstruction into grayscale features one-hot encoding implementation of matrix and network fault types. Step 2: for the detection model, reasonably divide the training set and the test set. Step 3: establish a convolutional neural network fault detection model and initialize the trainable parameters such as neurons in each layer and bias vector. Step 4: train the convolutional neural network, and the data in the training set is calculated based on the feedforward. Propagate until the fault type identification is output, and based on the backpropagation of the cross-entropy loss function, the trainable parameters such as neurons in each layer and the bias vector are updated; here is the loop iteration until the predesigned number of iterations is completed. Step 5: for training for a good network, save the model and use some of the samples divided in the training set for performance verification. Step 6: after passing the performance test in Step 5, test the performance of the network under the test set data for performance verification.

4. Result Analysis

4.1. Lab Environment. The experimental data of the convolutional neural network detection model are the KDD99 data set and the self-built data set. For different data sets, the model needs to be adjusted accordingly. The training and detection inputs of the model are the CSV regularized table data of the corresponding data set [25]. The experimental running environment of the diagnostic model is supported by the TensorFlow framework, and the whole process is implemented by *Python* programming. The collection and verification of the board prototype was completed on the terminal host computer, the actual sampling of the prototype host computer is completed on the terminal host, and the acquisition function and filtering function of the board card are verified. Qt has a good operation interface and has cross-platform features. The KDD99 dataset is used in the experiment, in which the data type division model is trained using a training set of about 500,000 pieces of data extracted from the complete dataset during the training phase. The training set is completely extracted for the few fault classes in the complete dataset, and the classes with a larger proportion are sampled in a certain proportion. The test set consists of about 300,000 pieces of data that do not appear in the full dataset.

4.2. Network Fault Diagnosis Process Results and Analysis. In the model training and tuning stage, the fully connected layer is tested with different activation functions. The convergence speed and accuracy of the training process are shown in Figure 3, and the corresponding convergence points are also recorded. According to the characteristics of the KDD99 data set, in the diagnosis model of this paper, the first fully connected layer uses the Tanh activation function to achieve the best convergence speed, and it can start to converge in about 10 iterations during the training process. Observing the convergence speed of the training process under different activation functions of the convolutional layer, it can be found that the convolutional layer has the best performance when using the ReLU6 activation function in this paper, and it starts to converge in about 5 iterations, which is better than Tanh's about 10 times. Finally, the specific parameters of the diagnostic model of the convolutional neural network are established. The change curve of the accuracy rate of the entire training process is shown in Figure 4. The entire training process converges after about 12 iterations, and the accuracy rate of the model training process can reach 98.1%.

If the detection rate of 60% is defined as the basic qualified line, the accuracy should be higher than 1.5 as the basic qualified line. Obviously, the overall detection rate of convolutional neural network and SVM seems to be at a high level, but in each classification detection, the SVM detection ability is poor. In particular, the Tanh and ReLU6 categories are directly annihilated and cannot be detected. The other three categories still maintain a high detection rate depending on the absolute proportion of the number of samples. For the detection model in this paper, it can effectively adjust the invariance of this data set. Balance the characteristics to obtain better detection results for each classification. Among them, the Tanh fault type is too scarce due to the lack of training samples. No matter how sampling and data mixed enhancement are used for training and tuning, the detection rate is still not up to the standard. The final conclusion is that the overall detection rate of the detection model based on the convolutional neural network is 96.8%, the accuracy is 30.9, and the detection rate (sensitivity) of each classification is better than that of SVM. Some categories still maintain a high detection rate, but the accuracy of the probing category is lower than that of SVM. Similarly, in the final result, it also corresponds to the characteristics of the dataset as follows:

(1) The scale of normal and DOS data is large, the proportion of data is high, the model has good generalization ability, and the detection accuracy and precision are high.

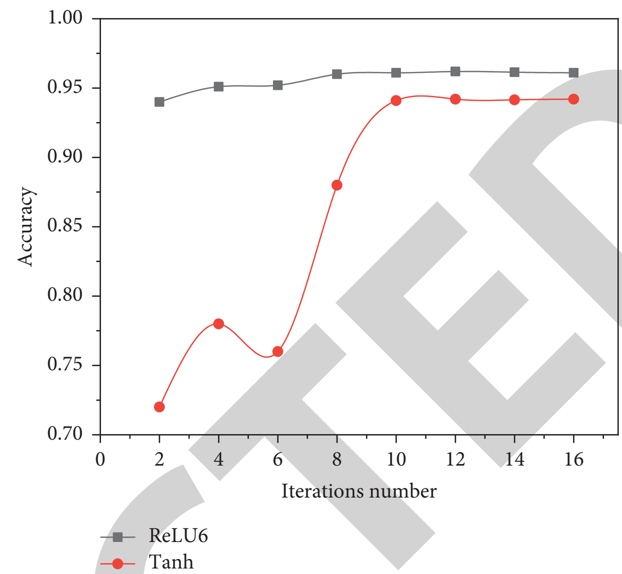

FIGURE 3: Convergence comparison of different activation functions of convolutional layers (KDD99 dataset).

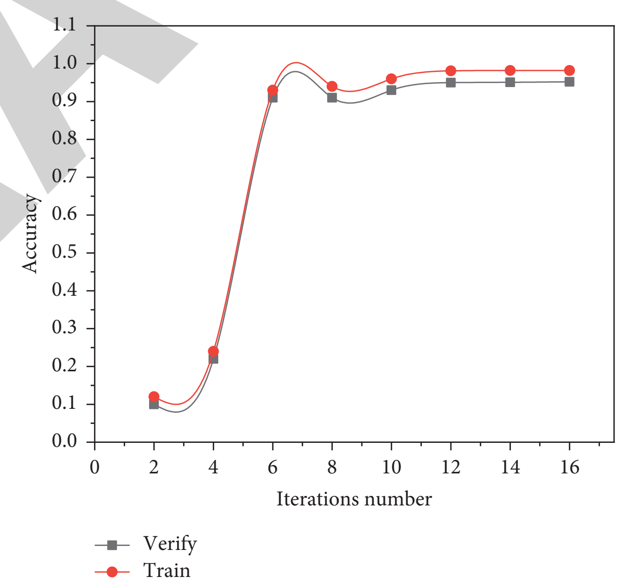

FIGURE 4: Iterative change curve of diagnostic model training accuracy (KDD99 dataset).

(2) Compared with Tanh, ReLU6 has more data, and the unbalanced performance is optimized by data resampling and hybrid enhancement.

(3) There are very few Tanh data, and resampling and hybrid enhancement are difficult to make up for the unbalanced defect, and it is difficult for the model to generalize well, and the detection accuracy and precision are the lowest.

5. Conclusion

Network fault diagnosis has efficient guiding significance for the healthy operation and fault location of the network and equipment in the local area network. Local area network, as the position closest to users in computer networking, often plays an important role in business support in enterprises, campuses, and so on. Therefore, in traditional manual fault diagnosis or expert systems and other diagnostic systems that require manual experience, the regularized fault knowledge and manual participation of the network are cumbersome and inefficient. Intelligent and efficient detection technology is the future research direction and development trend. In view of the above problems, this paper has carried out a series of research work and experiments, established a network fault diagnosis model based on convolutional neural network, and designed a set of algorithm models based on the KDD99 data set. It mainly involves the hierarchical design of the diagnostic model and the selection of feature selection and coding. For the algorithm model, optimization schemes such as discarding learning and gradient descent and data enhancement optimization schemes based on datasets are proposed to enhance the efficiency of training and the effectiveness of model detection.

The technical methods of network fault diagnosis and the research on systematic and complete solutions are still evolving. For the research work of this paper, there are still some areas for improvement. This paper still needs to be improved and improved in the following aspects: The simulation scenario of data acquisition is relatively small and lacks some authenticity compared with the complexity and complexity of real LAN in data scale and data complexity. The scale of the LAN should be expanded and the data collection time should be lengthened. At the same time, in a real local area network, because the manufacturers of each network terminal are inconsistent, the service performance and fault performance of each terminal are often inconsistent, and there is heterogeneity, which puts forward new requirements for the integration of data collection. In the next stage of research, the unification of data ports will be a continuous process..

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares that there are no conflicts of interest.

Acknowledgments

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