STUDY ON THE APPLICATION OF DEEP LEARNING TECHNOLOGY AND BIM MODEL IN THE QUALITY MANAGEMENT OF BRIDGE DESIGN AND CONSTRUCTION STAGE

Weiqi Zhu

Department of Economics and Management, Jiangyin Institute of Technology, Jiangyin, Jiangsu, 214405, China

zhu20218882021@163.com

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ABSTRACT

The development of the transportation industry can effectively accelerate the speed of economic development, in which bridges occupy an important position in transportation. The safety of the bridge design and construction process is a key part of bridge construction, and relying on human resources to investigate safety hazards greatly affects efficiency. In this paper, we combine deep learning technology and BIM model to explore the synergistic effect of both on the quality management of bridge construction phase and analyze the measured data. The results show that the application of BIM model can improve the efficiency by 35% compared with the traditional 2D CAD drawings, and the accuracy of data analysis can be improved by 12.51% and 14.26% for DNN and DBN models based on deep learning, respectively. The addition of the GSO algorithm leads to a further 19.19% improvement in the training accuracy of the coupled model. Finally, the optimization model was used to analyze the load factors and force majeure factors that affect the safety of the bridge, and to find the structural factors that affect the safety of the bridge design, which provides guidance to ensure the quality of the bridge during the construction process.

KEYWORDS

BIM model; CATIA modeling; deep learning; bridge construction; quality and safety

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1. INTRODUCTION

With the continuous development of China's economy, transportation modes are showing a trend of diversification. The establishment of a well-connected transportation network is of great importance for the development of national transportation, the promotion of inter-regional economic exchanges and the flow of talents [1,2]. Among them, bridge construction is the core link in the transportation network, which can effectively solve the problem of inconvenient traffic on both sides of the river basin. The safety of bridges is a key consideration in the design and construction process of bridges, which can cause very serious traffic accidents if the quality is not up to par [3-5]. Safety problems not only cause national economic losses, but also have a destructive effect on the ecological environment to some extent [6-8]. The safety issues of bridges should have a preliminary prediction during the construction phase and also throughout the construction phase of the project, where data from all aspects of bridge construction should be collected, processed and analyzed. Bridge quality and safety monitoring mainly include two aspects of data acquisition as well as safety index evaluation [9,10]. BIM technology is a technology that integrates the data in the construction process through a building information model. By integrating a large amount of data and information, it can read the key information and realize data interoperability. It enables information transfer and resource sharing in the pre-project preparation, process implementation and quality control stages at the end of the project. It plays an important role in quality inspection, safety management, budgeting, and progress monitoring of the construction process [11-14]. BIM technology can effectively improve efficiency, increase calculation accuracy, shorten construction cycle time and scientifically maintain equipment. Neural network deep learning is a modern tool for data interpretation and result prediction, which can quickly read information and extract data feature values, and input calculation results after training with embedded algorithms. This learning approach is currently combined with various fields, and the use of a deep learning approach can help us to quickly make predictions about the results and greatly improve efficiency [15-19]. If the deep learning approach is applied to the quality inspection in the bridge construction process, not only the rate of problem solving can be improved but also the accuracy of calculation results will be enhanced. Currently, some scholars have conducted studies on the use of BIM technology and deep learning methods in bridge construction and obtained desirable results [20-24].

Pan [25] et al. investigated a clustering-based log mining method for building information modeling (BIM), while combining a novel clustering algorithm with an efficient fuzzy Kohonen clustering network (EFKCN) to classify information with different characteristics. The data were analyzed using regression prediction method and the results showed that the model can be better for model building. D Forgues et al [26] used the BIM model to reduce the cost of project completion and shorten the project cycle by classifying the data through linear regression. The results showed that the use of the BIM model can effectively discover the causes affecting the quality of bridge construction and improve efficiency. R Edirisinghe [27] developed a safety life cycle BIM prediction model with high maturity and analyzed the factors affecting the model by data from real cases. As a result, five main factors affecting the BIM model were found, and the model was improved to propose a life cycle BIM maturity model (LCBMM) supported by actual data. Liang et al [28] proposed a novel deep learning model based on a three-stage image training strategy to analyze the bridge design structure, and in order to train and analyze the data effectively focused on the model's robustness of the model was focused on in order to train and analyze the data effectively. The results show that the robustness of the model is very good and the accuracy of the prediction is more than 90%. T Abbas [29] et al. used a neural network (ANN) model to predict and analyze the aerodynamic phenomena around the bridge design process. In the paper, the neural network and the structural model were combined and trained on bridge data with different interfaces and different geometric features. The results show that artificial neural networks can predict the bridge construction process more accurately, and this method can provide ideas for the design of bridges with larger spans. Qz A [30] proposed a vision-based method for the detection of cracks in concrete bridge decks, which is a one-dimensional convolutional neural network (1D-CNN) and long short-term memory (LSTM) method in the image frequency domain. The method is trained using a large number of cracked or uncracked bridge deck images with high efficiency and accuracy. The results show that the developed model can reach 99.25% accuracy with respect to the test data. Moreover, the 1D-CNN-LSTM model can effectively reduce the computation time compared with other neural network deep learning approaches. Ma [31] et al. proposed a data-driven method for strain data detection and differentiation of vehicles for detecting vehicle operation in large-span bridges. A neural network deep learning approach is used to track and identify vehicles to ensure traffic safety on bridge pavements. The results show that this detection method is relatively robust and accurate and is able to predict traffic conditions well despite the presence of noise. Dinh K [32] et al. proposed a coupled algorithm combining traditional image processing techniques and deep convolutional neural networks for the localization and detection of steel reinforcement during the construction of bridge construction. The images are first processed by offset and normalization methods for locating the pixels containing potential rebar peaks. The results obtained in the first step were then classified by a convolutional neural network (CNN) and a total of 26 bridge data were analyzed. The results showed that the average accuracy of the model's calculation results exceeded 97.75%, and the overall accuracy of the whole bridge test was about 99.60%. Kim [33] et al. proposed a vision sensor-based UAV bridge inspection method to troubleshoot the deterioration of bridges over a long period of time to ensure the quality and safety issues of bridges. The test first used a UAV to fly around and obtain a point cloud-based background model. A regional convolutional neural network (R-CNN) model was then used to detect the crack structure on the bridge surface and calculate the thickness and length of the cracks. A new network is generated from the pre-trained network and used to collect 384 crack images with 256 × 256 pixel resolution. The results show that the model is highly accurate in the identification and detection of bridge quality. Yang [34] et al. proposed a deep learning model to evaluate the stability and safety of bridge structures, and the model maps a

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network of large data into a very small volume of eigenspheres. Where the data in the spheres are normal values and the abnormal data are outside the eigenspheres. The results show that this model learning approach is effective and the computed practical results are superior compared to other advanced methods. In summary, the application of BIM technology and deep learning neural networks for monitoring the management of safety issues in bridge construction has ideal results in terms of both data resources and access integration and project outcome prediction. However, the two technologies are separate in the research work so far, and the combined use is relatively rare.

Therefore, this paper explores the synergistic effect of coupled models in the application of bridge construction stage quality management based on the BIM model, combined with a deep learning approach. Firstly, the bridge structure is parametrically modeled by CATIA software, and the potential problems in the bridge construction process are identified through the BIM model. Then the information is input into the neural network through the input layer, while comparing the deep learning approach with the traditional calculation method, and evaluating the accuracy of the deep learning approach according to the calculation results. Further, the GSO algorithm is used to optimize the deep learning method, and the validity of the computational results of the optimized algorithm is analyzed. Finally, the structural factors affecting safety and stability, including load factors and force majeure factors, are analyzed by this optimization algorithm. It provides an idea for the bridge construction process monitoring and the bridge quality and safety prediction.

2. DESIGN OF THE MODEL

2.1. PARAMETRIC MODELING OF THE BRIDGE STRUCTURE

At present, BIM models are more widely used in all stages of engineering design, construction and maintenance, among which the application in the transportation industry is the most. Various urban transportation fields in China have made application requirements for the application of BIM technology, and strict standards have been set for the accuracy of the results. The standardized regulations are important to ensure the construction quality and safety of the project, and all aspects of bridge design should be carried out in strict accordance with the standards. the key aspect of BIM application lies in the construction of the initial model, and the efficiency and quality of the modeling directly affect the project. CATIA software is a good modeling tool, which is a software developed by Dassault Systèmes, France, mainly used for the construction of mechanical structure models. the most important feature of CATIA is that it can model according to parametric spatial points, spatial curves and surface features, and has a good effect on the parametric modeling of large bridges (arch bridges, T-bridges, etc.).

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CATIA is an integrated software with CAD/CAE and CAM, which can provide a set of mature technical solutions from product design and final product landing. CATIA has the functions of 3D parametric design, dimensional constraints, parametric modification, etc. The specific connotations of parametric include the following.

1. Custom parameters: Users can input specific parameters according to their actual needs during the modeling process, and there are various types of parameters to meet different types of customers.

2. All-round dimensional constraints: This is the advantage of CATIA. Dimensional constraints refer to the specific constraints on the dimensions of each drawing that are mandatory for users in the modeling process. If the markup is missed, the modeling process cannot proceed. Also, the user has to give a global dimension so that the accuracy can be effectively controlled during the modeling process.

3. Dimensional parameter modification: In the process of parametric modeling, there must be constraints on the overall dimensions. But the detail part may exist with the subject management, the size can not be completely determined. CATIA can give the drive size modification function to this part, to achieve size modification and change.

4. Structural logic: In the design process respect the top-to-bottom concept, specifically expressed as a loop. In the setting or modification link soft solutions are made to record, the user can check or modify again.

5. Standardized design: For the frequently used structure, the software provides a parametric template. That is, the software can save this part of the design in the inventory, and the same is defined in accordance with the standard size. Users can transfer in and out from the library in the process of use, to facilitate the work of users.

2.2. DEEP LEARNING MODEL

In recent years, deep learning (DL) and artificial intelligence have been very closely integrated and have penetrated into many industrial fields. DL has unique advantages in extracting feature values from big data and processing data, and therefore has a wide range of applications in computer systems, speech idiosyncratic recognition and language expression. The input is generally located at the lower level. The input transmits the data further to a higher layer. The layers of transmission finally reach the output layer, which is the highest layer. It is important to note that the data is mined step by step during the transfer process, and finally, the data is obtained with some distribution pattern. The bridge structure is composed of many different small parts, and each part is related. Therefore, many details need to be considered when evaluating construction safety and quality, and the amount of data is relatively large. To address this problem this paper uses the DL model for analysis, and adds the deep

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neural network (DNN) model and the deep belief network (DBN) model to the DL model, aiming to further improve the accuracy of the model prediction results. Which can be transformed into an output matrix when extracting the feature values, as shown in Equation 1.

$$R = \begin{pmatrix} r_1 & r_2 & \cdots & r_{1,n} \\ r_{1,1} & r_{2,2} & \cdots & r_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n,1} & r_{n,2} & \cdots & r_{k,n} \end{pmatrix} \tag{1}$$

Where k denotes the fault information and r_{nk} denotes the fault parameters. By constructing a mixture model about the features, the distribution expression of the features of the faults can be obtained as follows.

$$R_i = \frac{\sum_{i=1} R + r_{n,k}}{m_i} \tag{2}$$

Where m_i denotes the frequency of the fault wave and the subscript i expresses the number of faults. According to the deep learning method, the dynamic components of the faults can be obtained by the distribution probabilities of the visible and implicit layers corresponding to the initial detection and model reconstruction of the bridge as shown in the following equation.

$$T = \frac{R_i(n+1) + R}{m_i} \tag{3}$$

Where n denotes the fusion transfer parameter containing the fault features, and based on the above-extracted eigenvalues, combined with the spectral analysis, the density component of the monitoring fault phase coupling is obtained as shown in the following equation.

$$R_x = \frac{v_x}{T + R_i} \times \sum_{i=1} R \tag{4}$$

Where v_x represents the peak of the bridge fault state. The joint analysis method is applied to it, and the expression of energy distribution can be obtained as follows:

$$M = \frac{N_x}{R_i + R_x} + \sum_{i=1} R \tag{5}$$

Where N_x denotes the dimensionless parameter for equipment failure in the bridge monitoring process, and analysis of the data yields the output of automatic fault tolerance for bridge equipment failure monitoring as:

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$$G = 2T + \frac{N_g + N_x}{m_i} \tag{6}$$

From the above analysis, it can be seen that when a bridge fails, the extraction of fault feature values can help engineers quickly determine the cause of the failure and find the location of the failure. The bridge fault tolerance model constructed can improve the fault tolerance of the device.

DNN is an artificial neural network composed of the input layer, implicit layer and output layer, DNN is mainly through the learning behavior to solve the mapping relationship between the input layer and output layer. DNNs can achieve more satisfactory results for both feature value extraction and computational result prediction.

DBN is a generative model with multiple hidden layers because it is composed of multiple restricted Boltzmann machines (RBMs) cumulatively, which is a model with random probability distribution consisting of a set of visible units as well as hidden units. DBN is able to retain data features and on this basis, the computational process can be simplified by reducing the dimensionality as much as possible. Therefore, the effective learning method of DBN can be thought of as reducing the complex model to a combination of many simple models, and learning the input parameters by passing them in layers. The DBN is more accommodating and can input different kinds of data. And the data transfer is iterative, i.e., the previous data calculation result will be used as the next input data, so DBN has an efficient learning method as well as scientific classification performance.

3. ENGINEERING APPLICATION RESEARCH

Deep learning technology and BIM models have a role in the quality management of bridge design and construction phases that should not be underestimated. Among them, BIM technology and the CATIA software module available in recent years have a guiding role in the design of the bridge in the early stage and the subsequent construction problem ranking, which can reduce the manual input. Deep learning technology, on the other hand, can be used to troubleshoot bridge quality problems that occur during the construction phase and to monitor the bridge quality monitoring system, which can provide statistical analysis efficiency by excluding invalid data. This section will detail the specific application of the BIM model and deep learning approach in bridge construction.

3.1. SPECIFIC APPLICATION OF THE BIM MODEL IN THE DESIGN AND CONSTRUCTION OF BRIDGE ENGINEERING

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For the bridge project, the bridge design and construction and bridge engineering feasibility links, through the application of BIM technology, can more effectively accelerate the progress of the bridge project design. the advantages of BIM technology applied to bridge design are mainly the following two points, one is that through the use of the technology, you can check out in advance whether there are defects and deficiencies in the project, timely improvement and processing, for the later bridge engineering project The first is that by using this technology, the defects and shortcomings of the project can be identified in advance, and timely improvements can be made to bring more convenience to the later bridge projects. The second is that the application of BIM technology helps designers and constructors to have a deeper understanding of the project, and can accurately analyze and judge the different cost situations involved in the project to facilitate further reduction of bridge project costs. the main contents of the four main steps of BIM technology application are:

1. In the design and construction of bridge projects, the first step of BIM technology application requires that the designer should continuously improve the model according to the requirements of different periods and the actual needs of the project so as to ensure the accuracy of the model. The construction process mainly has the following three steps: the first is to establish the relevant parameter library, the second is to build a scientific and accurate model, and the third is to reasonably set the corresponding reinforcement module. Among them, the establishment of the relevant parameter library and the next step of building the model can use Dassault's CATIA software to achieve parametric modeling. CATIA 3D model can pass management object data, index data, etc. to the construction stage, which can make the modeling process more convenient with higher accuracy.

2. After constructing an accurate parametric model of the bridge project in the early stage, to develop a perfect construction strategy, advanced BIM technology needs to be further applied. By means of simulation, the link is clearly presented, and the construction differences are compared, so that the simulated construction process is visualized and dynamic. This step will enable the designer to make a more scientific and accurate judgment on the safety and economy of the bridge structure.

3. Volume statistics, refers to the application of BIM technology application statistics to obtain accurate volume calculation values in the bridge engineering design period. Compared with the traditional method of calculating the points, lines and surfaces of the two-dimensional plane, the calculation task is completed with Excel tables. Using BIM technology, in building an accurate three-dimensional model of the bridge, it is possible to scientifically select the design components and suitable materials, and use the automated measurement function to achieve the purpose of determining the bridge volume. This method, in addition to reducing the calculation time, improves the accuracy of calculation by about 35% on average and saves the energy input

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of design staff. In addition, for the modeling of complex curves under linear engineering, it is also possible to accurately determine the twisted part and accurately measure the length, area and volume of the bridge by using the CATIA software in BIM technology.

4. In the design and construction of bridge projects, after completing the above work, Navisworks and other related software can be further used. For the construction of the BIM model for collision analysis, to complete the preliminary check, proofreading and audit and other different work. At the same time, it helps to find out whether there are defects and deficiencies in the construction drawings, and further correct them. In addition, the use of BIM technology can also achieve the task of comparing procurement lists and determining what needs to be procured.

3.2. SPECIFIC APPLICATION OF DEEP LEARNING TECHNOLOGY IN BRIDGE ENGINEERING QUALITY MONITORING

It is necessary to monitor the health system data in the design and construction of bridges. Compared to most traditional test and analysis methods that rely on statistical theory and require extensive domain knowledge, monitoring systems based on deep learning techniques are more suitable for large-scale data sets. The main work of the deep learning technique monitoring system is to perform health monitoring and data characterization of bridge structures. Its main purpose is to study the different distribution characteristics of the data for subsequent processing of the data. One of the bridge quality monitoring devices for monitoring bridge structure data is an important device for monitoring faults and status, and the reliability of bridge quality monitoring devices is to be ensured in performing bridge quality monitoring. However, the reliability of the bridge quality monitoring device cannot be guaranteed due to the bridge's own structural factors that easily affect the bridge quality monitoring device. In order to guarantee the reliability of monitoring data, this paper proposes an intelligent bridge quality monitoring device fault tolerance system automatically based on deep learning technology, and carries out hardware design and application testing.

Establish the communication module of bridge quality monitoring equipment in the fault-tolerant system of the upper computer, and carry out the interface interaction design of bridge quality monitoring equipment fault judgment through reset control and Internet networking control technology. Set the dual ports as RAM, apply the Internet of Things networking technology to obtain the PCI protocol of the dual ports, and obtain the bus control parameter analysis model for fault-tolerant judgment of bridge quality monitoring equipment according to the PCI protocol control signal. Set the operating main frequency of the system to 180MHz/MIPS, and carry out the joint multi-channel control of bridge quality monitoring equipment fault judgment by PCI protocol. The bridge quality monitoring sensor module with data bus set to LD[16:0] signal is used for VXI transmission of bridge quality monitoring equipment fault tolerance system automatically to build a network monitoring model for bridge quality monitoring equipment fault tolerance judgment. To reduce the error of fault information, the register initialization process is carried out, and finally, the monitoring information of bridge quality monitoring equipment fault automatic fault tolerance system sends data to the main control computer through the bus.

4. RESULTS AND DISCUSSION

4.1. ANALYSIS OF TEST RESULTS

A part of the data from the China Construction Project Database was used as the experimental data set for the experimental testing of the bridge quality monitoring device fault automatic fault tolerance system designed based on deep learning. The output curve of fault feature monitoring of the bridge quality monitoring device is shown in Figure 1.

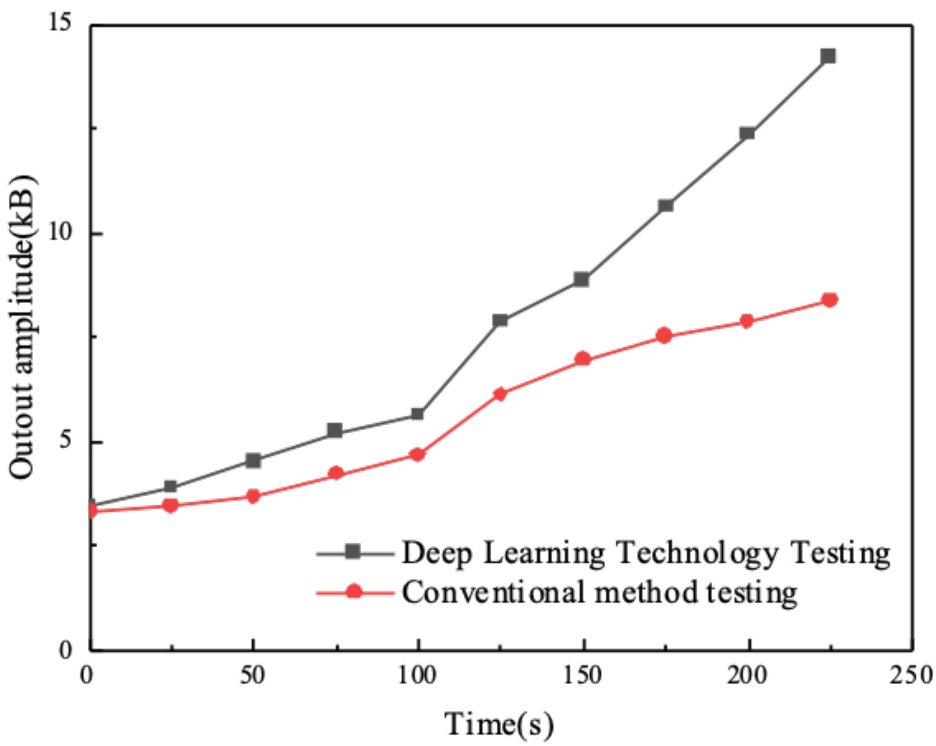

Figure 1. Monitoring output amplitude change curve

As can be seen from Figure 1, the deep learning technique-based test method for bridge quality monitoring equipment fault monitoring has a high level of sample fusion. In addition, compared with the traditional test method without troubleshooting, the highest output value of the deep learning technique test is 28.64% higher in the first 125S and 69.97% higher in the second 250S, which greatly improves the fault

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tolerance level of the bridge quality monitoring equipment and the reliability of the measured data. The fault tolerance level of the bridge quality monitoring equipment is greatly improved and the reliability of the measured data is also greatly enhanced. On this basis, the bridge quality monitoring equipment fault judgment was implemented, and the fault tolerance convergence level evaluation results were obtained as shown in Figure 2.

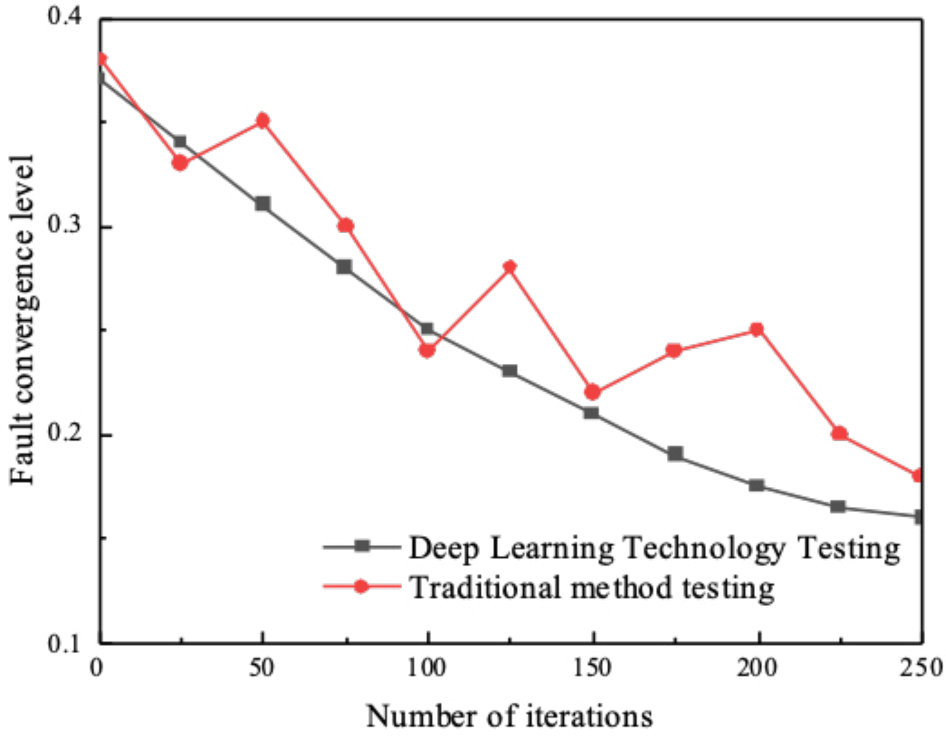

Figure 2. Monitoring convergence level curve

From the convergence curve comparison, it is known that the convergence curve of the method designed in this paper for bridge quality monitoring equipment fault monitoring is smooth and of high quality, with small overall changes and reliable data measured by side feedback. In contrast, with the data obtained from the traditional method test, the data reliability cannot be guaranteed due to the failure of the monitoring equipment and automatic error reporting is not excluded. Although the highest convergence level and the lowest convergence level of the test method based on deep learning technology are smaller than the traditional test method by about 0.01-0.02, the overall level change rate is only 2.1% per 25 iterative steps, the fault reliability is large, the judgment ability is high, and the overall fault tolerance convergence is high.

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4.2. DATA VALIDITY ANALYSIS

After excluding the bridge quality monitoring equipment fault monitoring data, the validity analysis of the measured monitoring data is performed. The prediction results of decision-tree, random-forest, SVM, DNN, DBN and other machine learning classification methods were compared. For the same dataset collected, the DBN model can improve the accuracy by 14.27% compared with the decision tree. The experiments prove that the deep learning model has stronger data analysis capability and is more suitable for validity analysis of bridge quality monitoring data obtained from monitoring.

Although deep learning models such as DNN and DBN have a great improvement for data analysis accuracy, but because there are more parameters in the two models and the initial values of the parameters are set randomly, it is easy to lead to local optimum during the training process of deep learning, which affects the training results of network models and reduces the testing accuracy. For this reason, a firefly swarm optimization algorithm, combined with artificial GSO, is used to further optimize the DBN model. Since GSO has a strong ability to solve local optimization problems, its objective function can be a loss function, and the initial parameters of the model are optimized through GSO to improve the model's applicability and test accuracy. the DBN-GSO model represents a random initialization of parameters to the original DBN-R model, and the results show that the data accuracy obtained from testing through the DBN-GSO optimized model is higher than that of the initial model by The accuracy is improved by 19.19% compared with the initial model, indicating that the GSO optimization algorithm can further optimize the DBN model and improve the training test accuracy.

4.3. STRUCTURAL SAFETY ANALYSIS

Based on the above analysis, it is clear that the optimized DBN algorithm has improved the model prediction accuracy, so this subsection further analyzes the structural parameters affecting bridge safety by the optimized DBN algorithm. The bridge construction process is fixed by the connection between the piers, the bridge body and the bridge deck, and its structural integrity is an important factor affecting the stability of the bridge. This paper focuses on the structural analysis of bridges, including the bearing of bridges under overload conditions of use and force majeure factors. These factors include mainly pedestrian and vehicle loads (lateral and longitudinal), ambient temperature, typhoons and seismic natural disasters, and the input layer data of the influencing factors under certain criteria are imported into DL, as shown in Table 1.

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Table 1. Input layer parameter characteristics

No.	Load Type	Load design limit value		
		Base value setting basis	Minimal value	Maximum value
1	Vehicle load /（$kN·m^{-2}$）	Consider the overload situation	0	1.3
2	Crowd Load /（$kN·m^{-2}$）	Number of people in large events	0	2.8
3	Temperature /（°C）	Meteorological statistics temperature maximum value	-15	40
4	Windward load（$m·s^{-1}$）	Category 10 typhoon	0	27.6
5	Upwind load（$m·s^{-1}$）	Category 10 typhoon	0	27.9
6	Transverse vehicle load /.kN	Consider the overload situation	0	45000
7	Longitudinal vehicle load /kN	Consider the overload situation	0	18000
8	Seismic load /g	8 magnitude earthquake	0	0.24

For the input parameters, the DL model is calculated iteratively to obtain the output results as shown in Table 4. The output layer results represent the structural influences on the safety and stability of the bridge, highlighting the most jointed areas. This is because of the large and complex structure of the bridge and the high degree of correlation between the internal structures. Relying solely on the engineer's experience to make judgments about safety issues at design time would slow down the project schedule on the one hand, and there is no guarantee that the experience is accurate and that any safety-threatening issues in the bridge design must be eliminated. The structure obtained from the DL model can help engineers find the key aspects of the construction problem and provide guidance for the bridge design. Table 2 lists the force problems during the use of the bridge. The main sources of force are load and wind, and the parts that are subject to the greatest axial force, bending moment, and shear can be obtained from the input results. The offset is then the stability problem of the bridge in the presence of stresses. The same analysis was carried out for different parts to get the sensitive areas affecting the main girders, piers and towers.

Table 2. Output layer parameters and characteristics

No.	Type		
	Major Categories	**Minor Categories**	**position**
1	Inner Strength	Axial force	Tower main beam
2			Tower Root Section
3		Bending moment	Bridge pier main girders
4			Tower Headquarters (Yokohama direction)
5		Shear force	Bridge pier main girders
6			Tower root (longitudinal bridge direction)
7	Offset degree	Main beam	Middle of main beam
8		Bridge pier	Left side of the bridge pier
9		Bridge Tower	Tower top (cross-bridge direction)

5. CONCLUSION

This paper is based on the definition and role of both deep learning technology and the BIM model, and discusses the significance of both in the quality management of bridge design and construction stage, systematically analyzes the guidance significance of the BIM model in bridge design and construction, describes the application process of deep learning technology and its role in monitoring experimental test in bridge quality monitoring equipment failure, and obtains the following conclusions.

1. The application of the BIM model in bridge engineering design and construction mainly through the construction of models, the development of construction strategies, statistical engineering volume and fault monitoring and material statistics during construction, compared to the traditional two-dimensional CAD drawings BIM model has more aspects of bridge engineering design and construction, improving the efficiency of about 35%.

2. Deep learning techniques applied in bridge quality management monitoring can improve the reliability of measurement data and analysis efficiency. The bridge quality monitoring equipment fault monitoring and troubleshooting system designed in this paper can improve up to 69.97% in 250S iteration time compared with the data obtained from the traditional method testing, while the

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level value of the convergence curve is high, with a change rate of only 2.1% per 25 iterative steps.

3. The validity analysis of the measured data after the bridge quality monitoring equipment fault monitoring and elimination, the DNN model and DBN model in the deep learning technique can improve the accuracy of data analysis by 12.51% and 14.26%, respectively, and the DBN-GSO model combined with the GSO optimization algorithm can also avoid the local optimization results and improve the training accuracy by 19.19% compared with the original model. The optimized model is further analyzed for load-stress analysis and safety issues of force majeure factors for bridge structures. Based on the imported parameters, the specific structural parameters affecting the bridge quality and safety were obtained by iterative learning.

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