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# Advancing Bridge Construction Monitoring: AI-Based Building Information Modeling for Intelligent Structural Damage Recognition

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**ABSTRACT**

Building Information Modeling (BIM) has emerged as a transformative technology in the construction industry, revolutionizing various aspects of the field. The integration of Artificial Intelligence (AI) techniques with BIM holds significant promise and is gaining momentum in interdisciplinary applications. In China, the construction industry has witnessed notable advancements through the convergence of BIM, AI, and cloud data. However, the current state of intelligent construction technology in China reveals certain limitations that hinder its comprehensive development. This study addresses these challenges by focusing on the design of intelligent recognition algorithms for monitoring structural damage during bridge construction. Previous research has primarily employed classical neural network algorithms, but these approaches have exhibited certain limitations. This paper proposes innovative improvement measures to overcome these limitations and demonstrates their effectiveness through practical arithmetic examples. Furthermore, to enhance the intelligence level of the BIM system, this study integrates the improved neural network recognition algorithm into the BIM framework. The integration enables the BIM system to recognize and assess bridge structure damage efficiently and accurately. The outcomes of this research provide valuable insights into advancing the field of intelligent construction technology, particularly in the context of bridge construction monitoring.

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## Introduction

The “Fourteenth Five-Year Plan” proposes a new direction for the integration of new infrastructure and digital development, and under the traction of this direction, China’s construction industry will further transform and upgrade to the goal of “intelligent building.” Therefore, at the current stage of construction intelligent construction management, it is necessary to combine the new development goals, absorb some new thinking, introduce some new technologies, use

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some new methods, scientifically and rationally develop some effective construction intelligent construction management strategies, solve the current problems in construction management, and lay a solid foundation for the transformation and upgrading in the new period (Jiang and Chen 2021). Specific analysis is as follows.

There is now a relative scarcity of system functions and a relative lag in the idea of system planning in intelligent building construction management. Intelligent construction management is used more in building construction, but its overall usefulness is uncertain (Li et al. 2021). The lack of a system planning concept is one of the reasons, particularly in the process of intelligent construction management of structures. On the one hand, each unit involved in the construction project has a different construction management concept, and the indicators between management practice and management assessment are not uniform, making digital management easily formal; on the other hand, poor integration of construction management technology in independent professional management has resulted in the phenomenon of low utility of digital management (Wan et al. 2022). Thus, in general, the current stage of the construction management concept needs to be updated to the level of systematic management.

The data management center of the terminal equipment at the construction site must be coupled with the data management center of the intelligent construction management of the building. Among these, inadequate data collection will occur owing to insufficient setup of the number of terminal equipment (Yafeng and Hsiang 2021). The communication connection system's degree of association is poor, and certain data are input manually, which might lead to data entry errors and blunders. The data center's data management lacks comparison analysis of each specific management data, which may result in faulty data computation outcomes. According to current experience, the failure to properly perform the duties and roles of construction management technology is the primary cause for its limited deployment (Kensek 2014). There is a lack of synergistic application from the notion of integrating systematic application and supportive application, particularly in the application process of multiple technologies.

BIM is the creation of 3D models based on engineering project information data, the simulation of actual building information using digital information, and the realization of building information exchange and transmission by combining building data and information models (Jiang, Wang, and Wu 2018). With the advancement of research and promotion, BIM has become extensively employed in collaborative design, collision detection, construction simulation, 3D rendering, and operation and maintenance management. Yet, because traditional human data processing methods are inefficient and inaccurate, the potential of engineering data cannot be fully exploited. As a result, the acceptable and effective use of BIM data is a key problem in its growth. With the growth of new technologies such as artificial intelligence, crossborder resource integration to achieve integrated development will be the construction industry's new development path. Integration of BIM technology with artificial intelligence may considerably increase data processing ability and efficiency, allowing BIM data to be widely utilized (Stadel et al. 2011). The use of BIM and related information technology can expand data sources, fully explore the hidden value in data, integrate the construction industry's industry chain resources, build an information model based on industry characteristics, and gradually realize information integration, sharing, and collaboration of the entire industry chain, causing engineering construction to gradually move toward wisdom.

Conventional construction procedures have two-dimensional drawings, the information of each building component is simply conveyed in the form of lines on the drawings, and converting two-dimensional drawings into three-dimensional building entities takes the technicians' creativity. When the drawings are developed, they must be collision checked to identify flaws and omissions. The typical method of working is to compare them manually, which is not only inefficient but also time-consuming and difficult (Rivera et al. 2019). At the same time, numerous elements such as the environment and human people in the building process frequently interfere with engineering projects, making it impossible to manage the construction progress and cost, and the quality and efficiency of construction cannot be guaranteed. Furthermore, the traditional operation and maintenance management mode's main problem is that the status information of each part of the project operation process cannot be controlled in time, especially when the pipeline, fire protection, and other systems fail, accurate positioning and timely processing cannot be carried out, and economic losses and even casualties can easily occur. As a result, traditional construction technology has been unable to satisfy the demands of engineering projects in terms of quality, time, and cost, impeding the construction industry's green, efficient, and sustainable development (Zhao et al. 2022). The use of BIM technology throughout the life cycle of engineering projects, including collision detection, virtual construction, information transfer, 3D rendering, and other functions, can improve construction efficiency, shorten construction time, save money, and lay the groundwork for collaborative design, construction, operation, and maintenance.

The inability to fully use the value of engineering data is a key issue in the deployment of BIM technology. The connection between the independent and dependent variables in practical engineering is frequently nonlinear. Traditional AI techniques like inference, genetic algorithms, forbidden search algorithms, and shallow neural network techniques have mature theoretical bases as well as application scenarios that can analyze and process data and solve problems like multi-objective optimization, search, rule checking, and prediction (Hong, Yongpeng, and Ying 2019). As a result, classical artificial intelligence technology combined with BIM has been applied in a variety of engineering applications. Traditional AI approaches, on the other hand, typically demand constraints on the independent variables in the application, and the value of data with huge oscillations and deep hidden linkages cannot be efficiently mined. There are also issues with picture identification and processing. The ongoing advancement of deep neural network technology may provide a viable answer to the aforementioned issues. Scholars are now combining BIM technology with deep neural network technology to tackle engineering prediction and picture recognition difficulties (Lei et al. 2020).

BIM technology, with its powerful information integration and multi-dimensional visualization, can help bridge projects from planning, design, construction to later operation and maintenance (Noeldgen, Zillessen, and Muellers 2014). The major emphasis of this paper is the investigation of intelligent bridge construction monitoring system based on artificial intelligence BIM. At the moment, certain professionals and researchers have utilized BIM technology to bridge engineering with positive outcomes. This paper combines the limitations of the classical neural network algorithm in bridge structural defect identification with artificial intelligence technology, proposes corresponding improvement measures, and shows using arithmetic examples how the improved neural network algorithm can improve the efficiency and accuracy of bridge structural damage identification. Furthermore, this study explores the technology for developing an intelligent structural damage diagnosis system for bridges using BIM and a neural network algorithm.

## Related Works

### *Intelligent Building Construction Process*

The term "intelligent building" refers to a building as a platform that is based on the comprehensive use of various types of intelligent information, integrating architecture, systems, management, and optimization of the combination, with a comprehensive intelligence ability embodied as perception, transmission, memory, reasoning, judgment, and decision-making, forming an integrated body with people, buildings, and the environment in coordination with each other, to provide people with a better environment (Lu et al. 2014). Intelligent building is the product of the level of modern science and technology, which plays a vital role in the development of the construction industry. Currently, information technology provides the impetus for the development of intelligent buildings (Atazadeh et al. 2017). Yet, because to cost, technology, and other constraints, the total development of intelligent buildings is currently at a very modest level. With the advancement of old-neighborhood repair projects, the role of intelligent buildings is becoming more important, and intelligent buildings will become the dominant direction of the construction industry's growth.

With the development of science and technology in China, artificial intelligence technology has been widely used in people's lives, especially in the construction industry has achieved good results (Pezeshki and Ivari 2018). Yet, there is still an issue of low level of construction technology in constructing intelligent construction, which is tremendously unfriendly to increasing the overall quality of the structure. Some construction units use old construction procedures to decrease construction costs; nevertheless, these traditional construction approaches can no longer match the demands of the current construction sector, and various quality problems can develop. Meanwhile, certain construction design schemes are incapable of meeting the construction needs of intelligent buildings and frequently fail to develop an effective integration of intelligent theory and practice (Hu et al. 2018). In addition, the managers neither develop a perfect construction plan nor establish a scientific management system. These problems not only hinder the development of intelligent construction technology in buildings, but also affect the economic and social benefits of construction units.

At the present stage, many construction units in China lack the sense of innovation and rely excessively on foreign technology when applying building intelligent construction technology. However, there are obvious differences in the construction environment at home and abroad, and the standard requirements of construction technology are not the same (Zhao, Gao, and Ni 2022). In this scenario, over-reliance on foreign construction technology makes it impossible to verify the quality of intelligent building construction, stifling China's construction industry's progress. Nevertheless, China's building industry's key rules are not yet flawless. Construction firms sometimes lack legal backing, which causes obstacles in implementing intelligent construction management in structures. With the advent of the information era, individuals have been subjected to enormous pressures such as "information explosion," "chaotic information space," and "data overload," all of which have both good and bad aspects. These forces have both positive and bad aspects to them. It is quite tough to separate meaningful and helpful information from a big volume of data (Wu et al. 2019). Such issues are now affecting the market positioning of intelligent building initiatives. The project investment project in intelligent building construction management must be founded on the premise of market demand. Yet, a vast volume of information may quickly disrupt decision makers' judgment, which is particularly damaging to the development of intelligent buildings. Only developers, designers, builders, and managers completely comprehend artificial intelligence technology in the intelligent building construction process in order to successfully raise the level of intelligent building construction management. In practice, however, the staff's lack of understanding of building intelligent construction management, as well as the developers' failure to actively introduce building intelligent construction management talents, have seriously hampered the smooth implementation of building intelligent construction.

Intelligent building project construction management covers additional layers, particularly construction management and construction acceptance. In recent years, the occurrence of inadequate quality in China's construction projects has been common, necessitating the need for structures to be remodeled and rebuilt, which usually raises the construction cost of construction projects (Isikdag, Zlatanova, and Underwood 2013). The key influencing element is that there is no timely quality and safety monitoring work in intelligent construction, and the essential staff lack a feeling of duty and mission, causing intelligent construction management to fail to move ahead toward the intended objective. At the same time, the application effect of new technologies in intelligent construction management is weak, which would limit construction project management efficiency. Even if China's intelligent advanced technology receives the necessary development conditions, many construction project managers have one-sided cognition of intelligent engineering, and the constructors are unable to correctly recognize the necessity of intelligent engineering management, causing the constructors to fail to implement the construction work on time, further limiting the intelligent building engineering construction process. Construction employees themselves have weak intelligent technology operating ability, are unable to apply current advanced technology correctly, and fail to develop their quality and ability on time, all of which diminish the intelligent construction management safety index (Zhang et al. 2020).

Building construction management, to truly implement intelligent management, but also rely on intelligent programming system, so intelligent security management mode is very necessary, otherwise there will be intelligent security management risks, unable to adjust the construction management of building intelligence in a timely manner.

First of all, we should form a security protection subsystem, protect the building intelligent construction information in all aspects, improve the security protection system according to the security facilities, especially the firewall and information authentication, and set the necessary key for it. For the management of information equipment for wireless networks, improve the structure of the security protection subsystem to avoid the security management of non-trust networks (Li and Cao 2020).

Secondly, the formation of security protection, the construction of intelligent building management system, the relevant personnel to select the security management software with comprehensive performance, regular review of the security index of intelligent engineering, the security protection network system for multiple module division, once the problem is found, the timely dynamic adjustment of the operation of the security protection system, and the information security management data to the general manager.

Finally, it is to carry out network security protection, intelligent building construction management, relying on the advantages of advanced technology, the relevant personnel should develop network operation protocols, reasonable regulation of security protection measures, the implementation of network security supervision from the root, to improve the security protection effect of intelligent construction management.

### BIM Technology Status

The construction industry is facing serious problems such as inefficiency, high risk, and labor shortage. The annual number of deaths in China's construction industry is increasing year by year, with 1,752 deaths due to construction accidents nationwide in the first half of 2018, up 1.4% year on year, and the number of accidental deaths in the construction industry is even higher (Cheng et al. 2017). The proportion of workers over 45 years old in China's construction industry is increasing year by year, and nowadays young people are increasingly unlikely to choose to become a construction worker. Under such a severe development situation, intelligent construction technology will definitely replace the traditional construction method as an efficient and quality-assured construction method. Nowadays, smart construction is divided into four parts: smart design, smart processing, smart logistics, and smart construction. Smart construction integrates these four components to give a collaborative platform for demand and supply. The purpose of smart construction is to make the building process more responsive to demand, more efficient, safer, and greener.

The development of intelligent construction technology in China is not perfect, and many technical means are quoted from foreign core technology, using foreign innovative construction technology to accelerate the development of domestic intelligent construction (Xu et al. 2021). This state of development has led to the lack of theoretical support for domestic intelligent construction technology. Therefore, the development of core key technologies for intelligent construction, as well as the development and application of intelligent construction-related technologies, and the development of new forms of technology are the main goals of China at this stage.

BIM is mainly used in the process of intelligent construction of buildings to inform the building process by means of information data, so as to achieve intelligence (Yu, Peng, and Zeng 2018). In the building construction process, the building information is collected and then a building database is established to meet the requirements of modern construction through intelligent calculation and analysis. BIM technology makes the building construction process more scientific and reasonable, reduces the waste of materials and the use of manpower in the building construction process, and improves the efficacy and capability of building construction. Building intelligence makes up for and improves the shortcomings and deficiencies in the building construction process through technologies such as big data and cloud computing (Kensek 2014). In the process of building construction, the use of BIM technology makes the construction intelligent, thus reducing the difficulty of construction workers to see the design drawings, which can be presented through three-dimensional visualization, so that workers can clearly and intuitively understand the internal structure of the whole building and optimize the whole construction process, which can not only improve the quality of the project but also reduce the construction time of the project.

In recent years, there are many kinds of BIM software in the market, with different functions, and construction units require BIM to be applied to actual projects in the construction process, but in the actual use of BIM technology is mostly used in the design and bidding stage, and there are relatively few BIM application software in the construction stage, mostly using other software to analyze and adjust the application to the construction site (Liu and Jiang 2021). Now most of the BIM software only meet a certain aspect or a few aspects of the application, comprehensive and high BIM software is less, can be from the design stage all the way through to the operation and maintenance stage of the integrated BIM software is lacking. With the development of the application of BIM technology, data exchange difficulties have become a common situation, China does not widely use the international IFC (Industrial Foundation Class Standard) data standards, at this stage, China's research on foreign standards is also very little, combined with the actual construction projects in China, the expansion of data standards to supplement the work is still not in place (Fu and Liu 2020). China's BIM data standardization still needs to be summarized in more detail. Most of the BIM practitioners now only have the ability to use one or two kinds of BIM software, but this does not meet the actual needs of the construction unit to customize the overall BIM application program (Bastos Porsani et al. 2021). The construction industry now lacks professional BIM talents who master the practical background of construction profession.

The proposal and development of a technology often comes from practical needs [29]. In the field of civil and construction engineering, the demand for refined construction, information management, and multi-disciplinary collaboration has given rise to BIM technology (Shiau et al. 2013). Likewise, BIM-based AI methods come from the construction industry's requirements for saving labor, optimizing solutions, achieving accurate predictions, and achieving optimal benefits. Inference techniques and expert systems can replace some of the work of experts and improve the efficiency of decision making and judgment; DM techniques are used to process large amounts of data and discover the knowledge and patterns in them; neural networks have the adaptability and accuracy that traditional statistical methods do not have; EA and other multi-objective optimization algorithms are used to optimize planning and design solutions (Lu and Lee 2017). Based on BIM and AI technologies, application platforms of various architectures have been developed to achieve functions involving various aspects of design, construction, and operation and maintenance, which broaden the application areas of BIM and provide convenience to participants in all phases of the building's whole life cycle. Some of the research results have been verified by practical engineering and have achieved more satisfactory results.

## Algorithm Design

### Neural Network-Based Bridge Structure Damage Identification

The nonlinear processors in the model are called neurons, which are equivalent to the nerve cells of a human neural network. Both of them work in a similar way and can effectively simulate highly nonlinear input and output index relationships. Therefore, by training the neural network model several times, it can complete a more accurate identification of the bridge structure damage location, degree and even type, and the basic structure diagram of the model is shown in Figure 1.

The traditional BP neural network algorithm requires constant forward and backward error propagation during the training process, but the algorithm is not selective for the sample set and will select operations one by one to satisfy the mapping relationships. The newly calculated mapping relationship matrix is different from the previous one, and the network will fall back again for calculation and adjustment. If the number of sample sets is too large and the number of neurons is on the high side, it will inevitably lead to a reduction in the learning convergence speed. The essence of the BP neural network

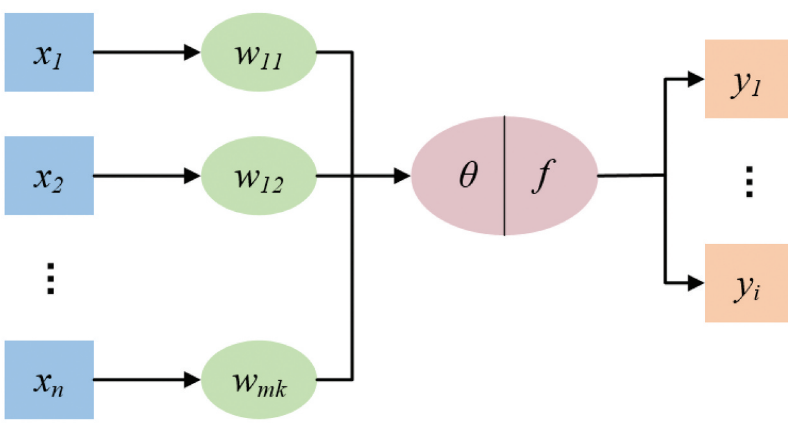


Figure 1. Structure diagram of artificial neuron.

algorithm is an algorithm that uses the sum of squared errors as the objective function and the gradient method to find the value. If the objective function is not a positive definite function, it is likely to produce a local minimum and generate wrong results.

To address the above problem, this paper introduces the additional momentum term, the core idea of which is to accelerate the search speed if the current gradient descent is in the same direction as the previous gradient present descent during the gradient descent search, and to decelerate the search if the opposite is true. Specifically, it is based on the back-propagation method, adding the newly introduced additional quantity to the original entitled change quantity, and finally generating new weights. The formula for the weights with additional momentum can be written as:

$$\Delta w(k+1) = (1-m_c)\eta \;\; f(w(k)) + m_c(w(k) - w(k-1)) \tag{1}$$

This equation prevents the case where the amount of change in the weights at the last adjustment is zero, prompting the network to disengage from the local minima of the error surface. However, the convergence rate of the model training speed is reduced when applying this method.

In addition, this paper introduces the leverberg-Marquardt (LM) acceleration algorithm, which is similar to the Newtonian optimization algorithm and can accelerate the convergence speed due to the advantage of second-order convergence speed and no need to calculate the Hesse matrix. The error sum of squares can be set as:

$$E = \frac{1}{2}\sum\nolimits_u (\varepsilon^u)^2 = \frac{1}{2} \parallel \varepsilon \|^2 \tag{2}$$

where $u$ denotes the $u$th sample data, $\varepsilon$ denotes a vector with $\varepsilon^n$ as an element, and $\varepsilon^n$ is the error between the actual output and the desired output.

Let the connection weights be at $w^k$ and move to the next weight $w^{k+1}$, and if the move $w^{k+1} - w^k$ is small, then $\varepsilon$ can be expanded through the Yaylor series as:

$$\varepsilon\left(w^{k+1}\right) = \varepsilon\left(w^k\right) + J\left(w^{k+1} - w^k\right) \tag{3}$$

where the elements of $J$ are:

$$(J)_{ui} = \partial\varepsilon^u / \partial w_i \tag{4}$$

So, the error Equation (3) can be rewritten as:

$$E = \frac{1}{2} \parallel \varepsilon\left(w^k\right) + J\left(w^{k+1} - w^k\right) \|^2 \tag{5}$$

Inverse problems such as structural damage identification can be essentially summarized as pattern recognition and pattern matching problems. As mentioned in the previous section, neural networks have a strong ability to solve problems such as pattern classification, and can establish reasonable input-output nonlinear mapping relationships based on multiple learning, which are applicable to bridge structure damage recognition under different working conditions.

Before using neural network for damage recognition, it is necessary to obtain sufficient amount of damage sample data to complete the learning and training process of neural network. The quantity and quality of samples determine the learning effect and efficiency of neural network learning to a certain extent, but the exact quantity of sample data needs to be determined according to the specific actual situation. The steps to obtain the sample database are shown in Figure 2.

To ensure optimal network performance, it is crucial to carefully select a suitable network topology for both training and testing. This entails determining the appropriate configuration for various components, including the number of neurons in the input layer, hidden layers, and output layer. Each of these parameters should be chosen based on the specific format and size of the sample data.

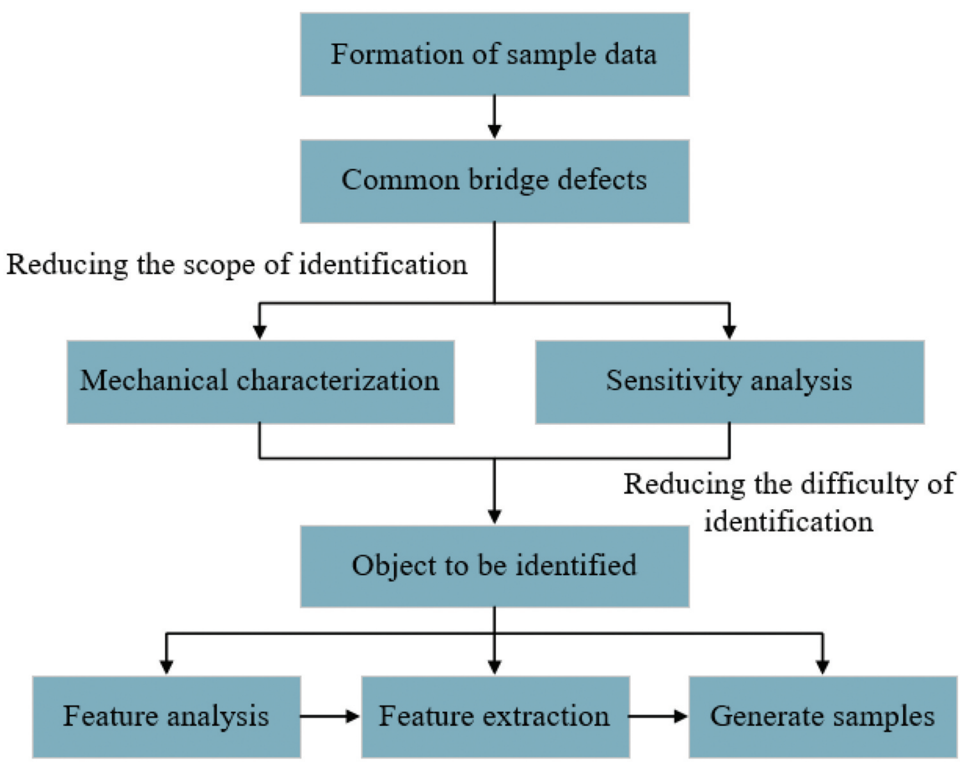


**Figure 2.** General steps for forming sample data.

The selection of a suitable algorithm is essential to prevent issues such as non-convergence of results and becoming trapped in local minima during the training process. The algorithm choice plays a vital role in the efficiency and effectiveness of training the neural network. By selecting an appropriate algorithm, the training process can be optimized, leading to improved performance and accuracy.

Once the training is complete, it is important to evaluate the network's ability to interpolate and extrapolate by inputting patterns that have not appeared in the training samples. This step enables assessment of the network's generalization capability, determining how well it can recognize and process unseen data.

During the recognition phase, the trained neural network model receives the measured data as input. Through basic parameter adjustments and data analysis, the neural network model processes the information and completes the recognition of the location and extent of structural damage. This final step utilizes the knowledge and patterns learned during the training process, allowing the neural network to provide accurate assessments of the damage location and degree based on the input data.

Overall, the selection of a suitable network topology, algorithm, and evaluation of the network's performance on unseen data are all critical aspects of successfully utilizing a neural network model for structural damage recognition. These considerations contribute to ensuring the reliability and accuracy of the recognition process, ultimately aiding in making informed decisions regarding the condition and maintenance of structures.

## *BIM-Based Bridge Monitoring System*

The system mainly consists of four parts: (1) Model operation module. It can view all kinds of basic information such as member identity information, type information, management information and member safety information of the main body of the project. In addition, in order to complete the bridge structure damage identification work, this module can automatically extract and convert the relevant information of the BIM model into the file format recognizable by the finite element software. (2) Information operation module. The content includes data input, viewing and visualization of relevant data for the later operation and maintenance of the bridge. (3) Neural network module. The module functions include both input of initial data of neural network and structural damage identification using neural network. The former requires inputting the dynamic feature values under each working condition into the system based on the analysis results obtained from the finite element analysis software, and the system automatically trains the neural network model based on the input data. The system automatically trains the neural network model based on the input data. The latter will input the real-time monitoring data or finite element simulation data as parameters to the trained neural network model and then perform calculations. (4) Structural damage recognition result output module. This module provides the list output of damage recognition results and the visualization of model damage situation.

The system framework consists of three layers: data layer, data processing layer and user layer. The basic information data of the model, the bridge monitoring data and the calculation results from the finite element analysis software for different damage states together constitute the data layer. The main functions of the data processing layer are: processing the relevant data operation instructions generated by the user through the interface, such as uploading, downloading, modifying and generating curves and graphs; extracting the correlation information to complete the automatic conversion of the model; using the database to learn the neural network model from the initial analysis data input by the user, and linking the database to extract the measured data or test data of the model at the later stage of calculation, and The user layer, which mainly realizes the information of the bridge. The user layer mainly realizes the query, entry and change of bridge information, and visualizes the calculation results of the data processing layer through the BIM model. The intelligent and visualized structural damage identification is accomplished through the three-layer architecture.

The user converts the existing BIM model into a finite element analysis model through the system and simulates the analysis in the finite element software. After the finite element analysis is completed, the user enters various parameters including the number of identification units, the number of working conditions, and the type of damage degree when simulating the damage through the finite element analysis software MidasCivil according to the prompt, and the system automatically generates the sample library data form according to this training requirement. After filling out the form, the user confirms or adjusts the number of input neurons, the number of implied layers, the number of output layers and other parameters of the training neural network model according to the actual situation. In order to solve some defects of the neural network, this system introduces the above algorithm modification measures to accelerate the whole training process. At the end of the training, the system will display the results of this training, and the user can save the results of this training as needed. In the testing phase of the data, after selecting the corresponding training model data and linking the real test data, the system will then output the results of structural damage recognition. The specific workflow is shown in Figure 3.

In order to meet the needs of storage, management, analysis and visualization of project information, a relevant database needs to be established and embedded into the BIM software. This paper adopts SQL Server as the database management system and uses the rich classes and methods of

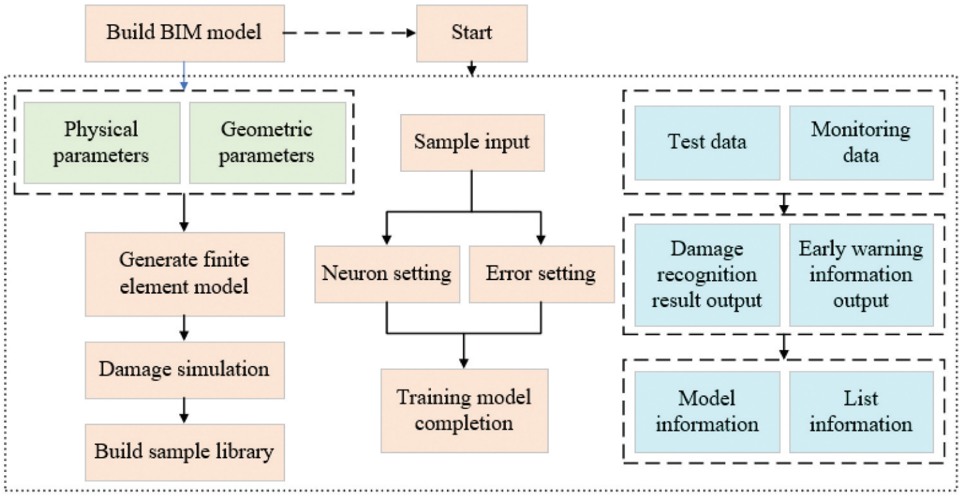


**Figure 3.** System workflow.

RevitAPI to realize the data import of bridge structure damage identification based on BIM.VS2015 can access the data in the database with the help of ADO.NET structure system, and the database contains system user, access object, data provider, server and database. The database is not always in the state of occupied links, which can improve the efficiency of system resources utilization.

The data input of the neural network module is determined by the number of samples under different conditions of the finite element simulation, and first the user needs to set the relevant parameters to generate the correct data table. The number of modal orders is based on the number of measured data or on the number of FEM analyses. The higher the value, the larger the number of samples and the higher the effectiveness of the model for training and identification. The damage degree category limits the damage degree of the structure to a limited range to prevent singularity or distortion of the analysis results. Controlling the number of recognition units within a reasonable number and selecting locations where the structure is more sensitive or important can improve the efficiency of model training or recognition to achieve a reasonable balance between damage recognition accuracy and computational speed.

## Experiments

### *Experiment Preparation*

The hardware environment for this chapter is Windows 10 64-bit operating system, CPU is Intel Core i7-6700k, memory is 16 G, and GPU is NVIDIA GeForce GTX 1070 8 G. The software environment is Keras 2.1.0 deep learning framework, Tensorflow 1.4.0 is used as the backend, and programming Python 3.5 language was used, and the development environment was Visual Studio 2017.

To conduct a comprehensive analysis, five different damage conditions were chosen as representative samples in this study, which serve as the control sections. These samples are located at specific positions within the structure, namely, side span 1/4 L, side span 1/2, top of the pier, mid-span 1/4 L, and mid-span 1/2. To simplify reference, these locations are designated as A, B, C, D, and E, respectively.

The primary focus of identification lies in the overall cross-sectional stiffness damage type of the structural unit. To achieve this, a systematic approach was adopted. Specifically, damage conditions were selected at 10% intervals within the damage level range of 10% to 50%. This allowed for a thorough exploration of the various degrees of damage. The distribution of samples for different damage cases is illustrated in Figure 4, serving as a guide for arranging the data.

To establish a comprehensive damage sample library, finite element analysis was employed to obtain frequency information for all damage conditions. The first ten orders of frequency were extracted as significant parameters for characterization. By capturing these frequencies, a detailed representation of the structural response under different damage scenarios was achieved.

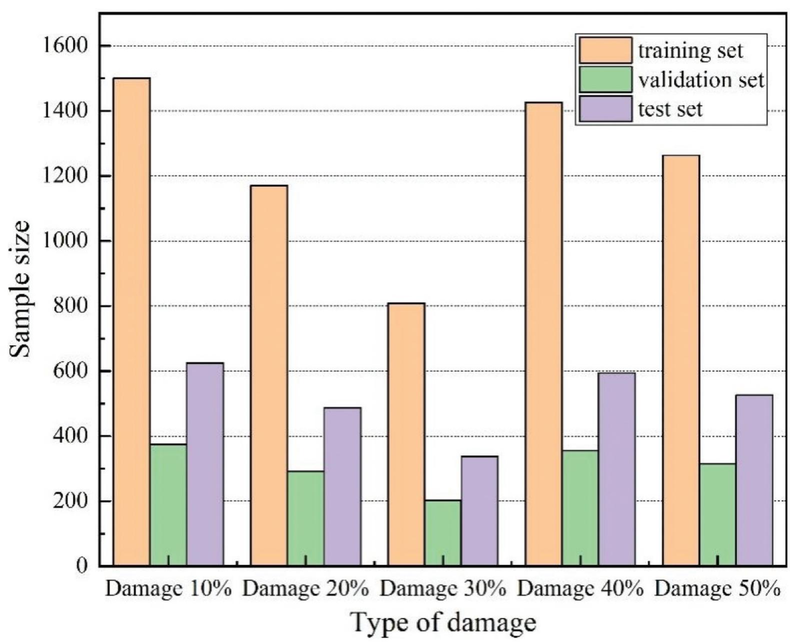


Figure 4. Distribution of bridge structure damage dataset.

**Table 1.** First 10th order self-oscillation frequency of the structure under partial damage conditions (Hz).

| Order | Damage10% | Damage20% | Damage30% | Damage40% | Damage50% |
|---|---|---|---|---|---|
| 1 | 0.676731 | 0.676613 | 0.676510 | 0.676373 | 0.676191 |
| 2 | 1.125434 | 1.125052 | 1.124719 | 1.124277 | 1.123700 |
| 3 | 1.992544 | 1.991280 | 1.990160 | 1.988639 | 1.986598 |
| 4 | 2.569577 | 2.568049 | 2.566703 | 2.564887 | 2.562472 |
| 5 | 3.458108 | 3.456375 | 3.454848 | 3.452789 | 3.450050 |
| 6 | 4.319442 | 4.319267 | 4.319110 | 4.318895 | 4.318604 |
| 7 | 4.457569 | 4.455445 | 4.453540 | 4.450917 | 4.447329 |
| 8 | 5.376948 | 5.370691 | 5.365119 | 5.357507 | 5.347218 |
| 9 | 5.700947 | 5.698506 | 5.696413 | 5.693668 | 5.690153 |
| 10 | 5.018453 | 5.984823 | 5.954613 | 5.913835 | 5.860353 |

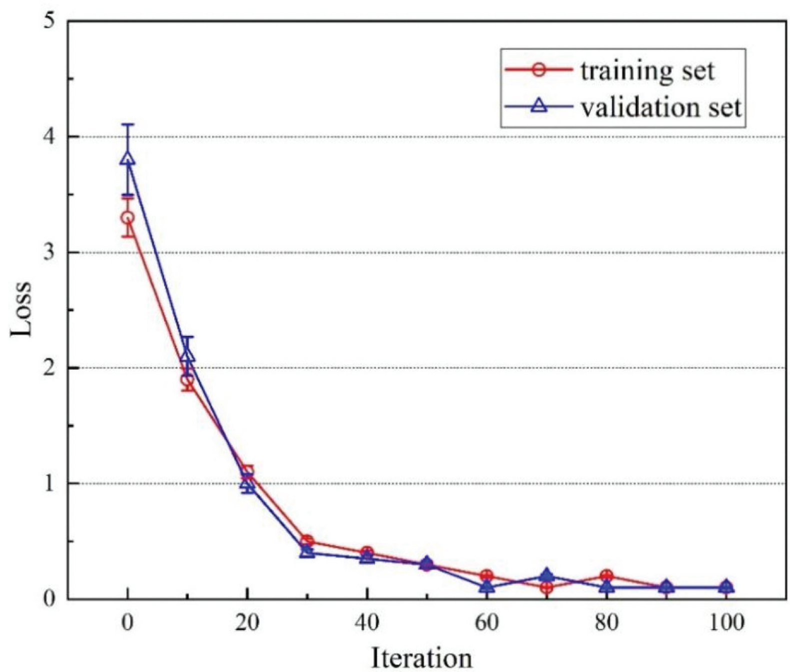


**Figure 5.** Loss variation of neural network training process.

Table 1 provides a concise summary of the self-oscillation frequencies exhibited by the structure under specific damage conditions. This table serves as a valuable reference, presenting essential data that showcases the structural behavior in response to different degrees of damage. By examining the frequency variations, researchers can gain insights into the unique characteristics and patterns associated with each damage condition.

The learning rate for the neural network training is taken as 0.0001 and the momentum coefficient is fully set to 0.99. Stochastic gradient descent is used as the optimizer. Figure 5 shows the loss curves on the training and validation sets, and it can be seen that the model converges after approximately 60 iterations.

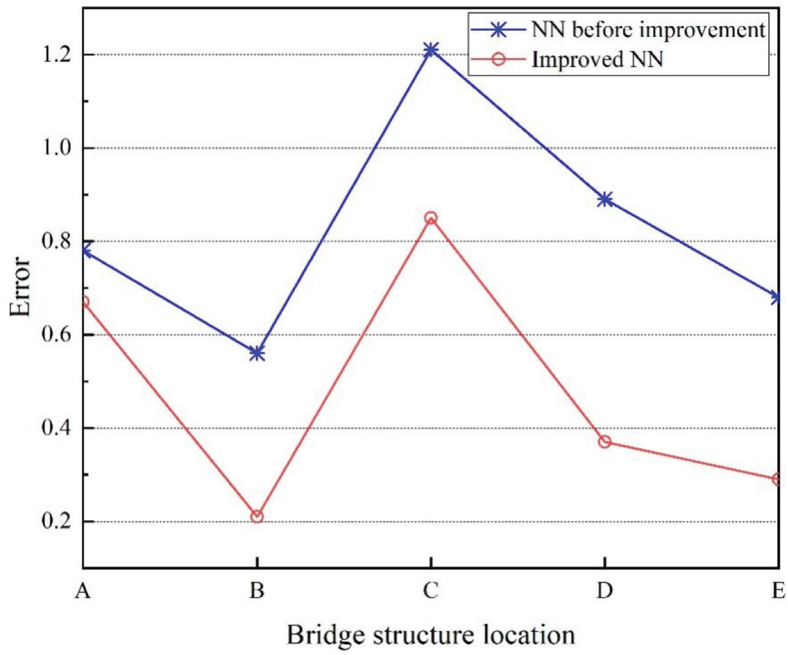


**Figure 6.** Prediction performance of neural network before and after improvement.

### *Bridge Structure Damage Identification Effect*

To verify the effectiveness of damage identification at different locations (A, B, C, D, E), Figure 6 shows the comparison of the prediction error before and after the improvement of the neural network algorithm on the test set. Regardless of the location of the bridge structure, the prediction error of the improved neural network shows a significant improvement compared to that before the improvement.

The damage at different locations can be characterized by an array of 5 neurons, i.e. A (10000), B (01000), C (00100), D (00010), E (00001). The degree of damage is characterized by a value between 0 and 1.

After the completion of training the neural network models using a set of sample data consisting of 10 datasets (A–10%, B–10%, C–10%, D–10%, E –10%, A–80%, B–80%, C–80%, D–80%, E–80%), these datasets were inputted into both the classical neural network algorithm and the improved neural network algorithm. The computational results obtained from these experiments are presented in Tables 2, Figures 7, and 8.

Table 2 provides a comprehensive overview of the recognition accuracy achieved by the two neural network models. It includes the average error rates for the recognition of 10% and 80% damage levels in the bridge structures. The classical neural network algorithm yielded an average error rate of 0.77% for recognizing a 10% damage level, while for an 80% damage level, the average error rate increased to 1.66%. On

**Table 2.** Comparison of identification results of neural networks for 10% damage.

| Method | Location | Actual Output | | | | | Average error |
|---|---|---|---|---|---|---|---|
| Traditional NN | A | 0.107 | 0.005 | 0.013 | 0.001 | 0.016 | 0.77% |
| | B | 0.009 | 0.092 | 0.011 | 0.017 | 0.004 | |
| | C | 0.00 | 0.005 | 0.091 | 0.019 | 0.006 | |
| | D | 0.009 | 0.015 | 0.005 | 0.106 | 0.012 | |
| | E | 0.015 | 0.001 | 0.004 | 0.012 | 0.108 | |
| Improved NN | A | 0.091 | 0.005 | 0.012 | 0.012 | 0.001 | 0.56% |
| | B | 0.001 | 0.107 | 0.013 | 0.011 | 0.006 | |
| | C | 0.000 | 0.005 | 0.101 | 0.007 | 0.012 | |
| | D | 0.014 | 0.001 | 0.014 | 0.105 | 0.011 | |
| | E | 0.013 | 0.002 | 0.014 | 0.007 | 0.104 | |

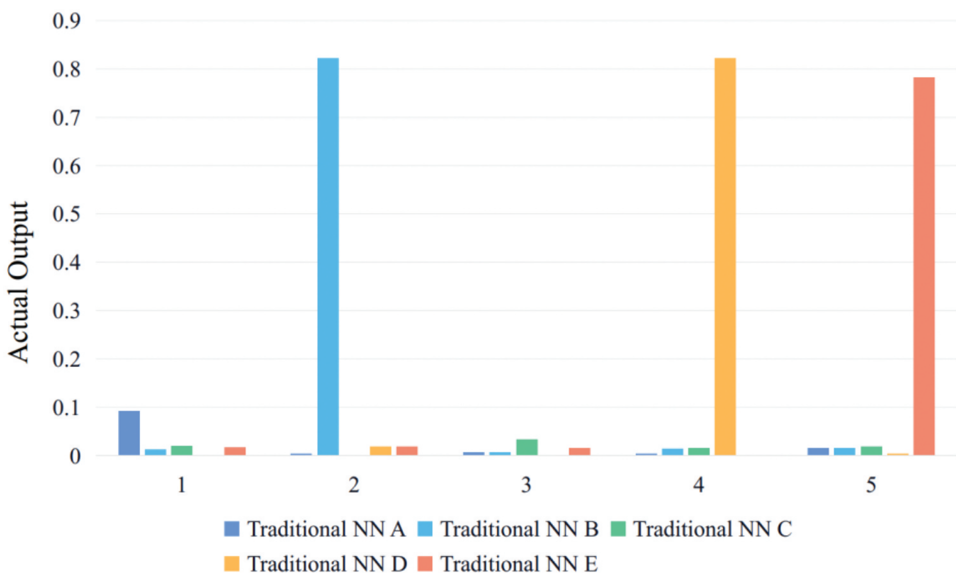


**Figure 7.** Comparison of the identification results of traditional NN for 50% impairment.

the other hand, the improved neural network algorithm demonstrated superior performance, with an average error rate of 0.56% for recognizing 10% damage and 1.21% for recognizing 80% damage. These results clearly illustrate the enhanced accuracy achieved by utilizing the improved neural network algorithm for the recognition of damages in bridge structures.

In addition to Table 2, Figures 7 and 8 provide visual representations of the computational results obtained from the experiments. These figures offer a graphical representation of the accuracy rates achieved by the two algorithms for recognizing 10% and 80% damage levels. Figure 7 illustrates the recognition accuracy achieved by the classical neural network algorithm, showcasing the corresponding average error rates for different datasets. Similarly, Figure 8 depicts the recognition accuracy obtained from the improved neural network algorithm for the same datasets. These visual

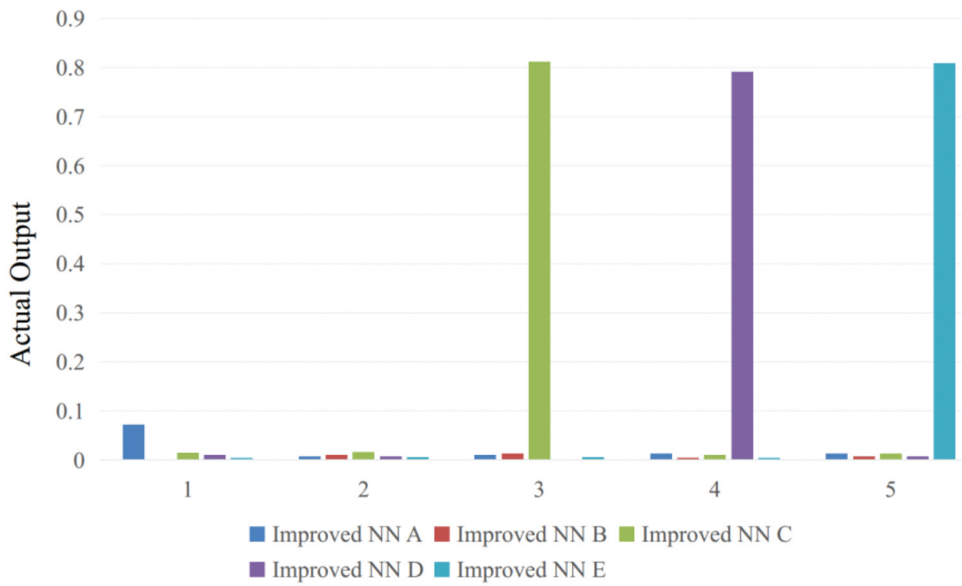


**Figure 8.** Comparison of identification results of improved NN for 50% impairment.

representations further highlight the significant improvement in recognition accuracy offered by the improved neural network algorithm compared to the classical approach.

The results of the recognition experiments highlight the notable differences in average recognition errors between the two models. With an equal amount of training time, the classical neural network algorithm achieves an average recognition error of 0.77% for identifying a 10% damage degree in a specific region, whereas the improved neural network algorithm achieves a significantly lower average recognition error of 0.56% for the same damage degree. Similarly, when it comes to identifying an 80% damage degree in a region, the classical algorithm yields an average recognition error of 1.66%, whereas the improved algorithm achieves a lower average recognition error of 1.21%.

These results clearly demonstrate that both algorithms exhibit improved accuracy in identifying the location and extent of overall damage in bridge sections compared to traditional methods. However, it is important to note that the improved neural network algorithm outperforms the classical algorithm in terms of accuracy for damage identification in continuous rigid bridge structures.

By leveraging the improved algorithm, engineers and researchers can enhance their ability to precisely identify and assess the extent of damage in continuous rigid bridge structures. This advancement is particularly significant, as it contributes to the overall safety and structural integrity of bridge infrastructure. Accurate identification of damage enables proactive maintenance and timely repair, reducing the risk of structural failures and ensuring the longevity and reliability of bridges.

Furthermore, the improved algorithm's effectiveness in enhancing damage identification accuracy paves the way for future advancements in bridge monitoring and inspection techniques. The ability to detect and analyze even subtle damages with greater precision allows for early intervention, leading to improved maintenance strategies and cost-effective resource allocation.

In summary, the recognition results demonstrate that both the classical neural network algorithm and the improved neural network algorithm exhibit improved accuracy in identifying the location and extent of damage in bridge sections. However, the improved algorithm offers a significant advantage in accurately identifying damage in continuous rigid bridge structures. These findings have practical implications for the field of bridge engineering, supporting the development of more efficient and reliable bridge inspection and maintenance practices.

## Conclusions

China has made significant advancements in intelligent construction technology, resulting in the establishment of an initial intelligent construction equipment industry system. The nation's support for intelligent construction has been steadily increasing, positioning it as the frontrunner for future building construction. This marks the beginning of a new revolution in the construction industry, coinciding with the information age, which serves as a platform for the rapid development of the sector.

Intelligent construction technologies amalgamate data from various stakeholders, including design, construction, and management, thereby laying a strong foundation for transforming the construction industry and facilitating the advancement of intelligent construction technology.

In this research paper, a novel perspective on artificial intelligence, Building Information Modeling (BIM), is employed to design an algorithm model capable of identifying damages in bridge structures using neural networks. A significant disparity in recognition accuracy is observed between the classical neural network algorithm and the improved neural network algorithm for damage recognition in bridge structures.

When utilizing the classical neural network algorithm, the average error in recognizing a 10% damage level in a region is found to be 0.77%, while for an 80% damage level, it is 1.66%. However, the improved neural network algorithm showcases superior performance, exhibiting an average error of 0.56% for recognizing 10% damage and 1.21% for recognizing 80% damage in a region. These results underscore the enhanced accuracy achieved by employing the improved neural network algorithm for damage recognition in bridge structures.

To further advance bridge construction monitoring intelligent technology research, our future plans involve incorporating recurrent neural networks and knowledge graphs into our methodologies. These additions hold the potential to bolster the capabilities of bridge construction monitoring, leading to further advancements in intelligent technology.

## Disclosure statement

No potential conflict of interest was reported by the author(s).

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