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Bridge Detection Structure Analysis Software Based on Neural Network Technology

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Abstract: Bridges are the transportation infrastructure of cities, and their safety and health status are related to people's travel safety and the operational efficiency of cities. However, over time, traditional bridge detection methods have shown significant limitations, including low efficiency and insufficient accuracy. This article proposed a bridge detection structure analysis software based on neural network technology. The software adopted Convolutional Neural Network (CNN) as the core algorithm, utilizing its high accuracy and comprehensiveness in image recognition to automatically extract multi-level features in bridge images and effectively identify damage details such as cracks and corrosion. The software design considered modularity and scalability, including key aspects such as data acquisition and preprocessing, neural network model selection and training, user interface design, and performance optimization. The experimental results showed that the developed software performed well in bridge defect detection tasks, with a detection accuracy of up to 99% and a detection time of no more than 785 milliseconds, demonstrating the ability to respond quickly. The CNN model had the lowest missed detection rate, only 0.16%, while the detection coverage reached 99.75%, significantly better than Recurrent Neural Network (RNN) and Generative Adversarial Network (GAN) models. The application cases of the software in actual bridge detection further verified its efficiency and accuracy.

1. Introduction

Due to factors such as natural environment erosion, traffic loads, and material aging, the health condition of bridge structures is gradually deteriorating, and regular and accurate testing of bridges has become particularly important. Traditional bridge detection methods often rely on manual inspection, which is not only time-consuming and labor-intensive, but also has problems with blind spots and subjectivity in detection.

This article proposes and implements a CNN-based bridge detection software that can automatically identify surface damage of bridges, such as cracks and corrosion. The CNN model has been optimized by adjusting the network structure and parameters, significantly improving the accuracy and coverage of detection. Secondly, comprehensive performance testing is conducted on the software, including accuracy analysis, detection speed, and efficiency evaluation, to ensure its effectiveness in practical applications. The application of software in actual bridge detection is explored, and its limitations and future improvement directions are discussed.

The first part of the article is the introduction, which introduces the research background, current situation, and the research contribution and significance of this article. The second part is related work, summarizing the research progress and existing technologies in the field of bridge detection. The third part introduces the software development methods, including the principles of neural network technology and software design. The fourth part presents the results and discussion, showcasing the results of software performance testing and conducting in-depth analysis of experimental data. The last part is the conclusion, summarizing the research results and proposing prospects for future work.

2. Related Work

In today's accelerating urbanization process, as an important transportation facility connecting various parts of the city, the safety and health status of bridges are directly related to people's travel safety and the operational efficiency of the city. Taking an old overpass in a certain city as an example, Guo Caixing aimed to understand the current service status of the old bridge and identify existing problems. Through a comprehensive evaluation and accurate analysis of the bridge structure, he compared and analyzed the appearance inspection, static load test, and dynamic test data of the bridge, and analyzed the service status of the bridge structure based on the inspection results [1]. Yang Bingfeng discussed and analyzed the diseases and detection methods of bridge structures, and took a certain expressway as an example to explain the treatment measures for diseases, which has certain guiding significance for the sustainable development of bridge engineering construction in China [2]. Fang Zhouquan collected crack images of bridge concrete structure construction using a binocular stereo vision model, grayed out the collected crack images, enhanced the crack image effect, and performed threshold segmentation to extract crack feature information. Finally, by combining threshold method with projection calculation of crack length, width, area, etc., the detection of construction cracks in bridge concrete structures was completed [3]. Yu Faqiang used numerical simulation and on-site measurement methods to monitor the stress and deformation of the steel structure of a river crossing steel structure bridge on a highway in Gansu Province, in order to accurately evaluate the operational status of the bridge. The overall technical condition evaluation method was used to evaluate the structural condition [4]. Kong Xiaowu discussed the inspection of a bridge on the top of a hydroelectric power station dam as an example. The gate bridge and traffic bridge of the hydroelectric power station have been in operation for many years, but in recent years, there have been defects such as strong driving shock and cracking of bridge beams and slabs. Relevant departments have conducted inspections on its structure and appearance, and comprehensively evaluated the bridge technology to provide data support for bridge maintenance [5].

In addition, Zhang Q proposed a vision-based method for detecting cracks in concrete bridge decks. Experimental results showed that compared with existing detection methods, the proposed method outperformed existing deep learning methods in terms of accuracy and computational time [6]. Nguyen T Q combined discrete models, fast Fourier transform analysis, and deep learning to study the mechanical performance changes of complex bridge structures [7]. Karimi S provided guidance for more accurate identification of bridge structural damage by critically studying different methods, and provided a good reference for other researchers and future work, thus making a significant contribution to the literature [8]. In order to improve the feasibility of laying ballastless tracks on large-span cable-stayed bridges, Sheng X introduced the surface and structural characteristics of Ganjiang Bridge, as well as the construction method of this bridge type [9]. Miyamoto A proposed two modern bridge management systems to evaluate bridge performance and identify the best strategies for inspection and maintenance, and to evaluate the performance of existing bridges by combining manual methods [10]. With the rapid development of artificial intelligence and machine learning technology, how to apply these advanced technologies to the field of bridge detection and improve the automation and intelligence level of detection has become a topic worthy of in-depth exploration. This article aims to develop a new type of bridge detection software that utilizes the powerful data processing and pattern recognition capabilities of neural networks to achieve efficient and accurate analysis of bridge structural states.

3. Methods

3.1 Neural Network Technology

Neural networks refer to computational models inspired by the human brain, which process information by simulating the connections and interactions of neurons in the human brain [11-12]. This type of network consists of multiple layers of neural nodes, each layer consisting of multiple nodes connected by weights that are continuously adjusted during the network learning process.

Its working principle is based on the forward propagation of data and the backward propagation of errors. In the forward propagation process, input data flows through the network, and nodes in each layer weigh and sum the received signals, which are then converted into new signals through activation functions and passed on to the next layer until the final output layer produces a prediction result. The backpropagation of errors is a process of calculating prediction errors using a loss function and adjusting weights by backpropagating these errors through a network, with the aim of minimizing the difference between the output and actual values.

In the selection of neural network models, multi-layer perceptrons serve as the basic model and are suitable for solving various regression and classification problems [13-14]. Convolutional neural networks are particularly suitable for processing image data, as they can automatically extract image features and perform effective recognition. Recurrent neural networks and long short-term memory networks can process sequential data, capture dynamic features in time series, and are suitable for time series analysis of bridge structures. In addition, generative adversarial network models also have unique application value in data augmentation and feature extraction.

3.2 Design of Bridge Detection Structure Analysis Software

The consideration of modularity and expansibility is very important for the software architecture design of bridge structure inspection to adapt to different inspection requirements and emerging technologies in the future. Data collection and preprocessing are necessary components to ensure the quality and correlation of data received by neural network model [15].

The software architecture design requires the software to provide a user-friendly interface, allow the detection results to be clearly presented, and be equipped with operation modules for data input, model training and result analysis. The back-end must be equipped with an efficient data management system to support large-scale data processing and model training. In addition, it must have a storage and management system for test data and model parameters to meet the quality assurance requirements.

One of the initial steps in the software design process is to collect data, which requires collecting various types of data from the bridge structure, including vibration response, stress and strain, displacement and temperature input data. These data are collected through sensor networks, video surveillance and historical maintenance records, as shown in Table 1:

Table 1: Bridge structure data

Collection No.	Vibration Response (m/s²)	Stress (MPa)	Horizontal Displacement (mm)	Vertical Displacement (mm)	Ambient Temperature (℃)	Structural Temperature (℃)
1	0.5	150	10	2	25	30
2	0.6	155	11	2.1	26	31
3	0.55	160	12	2.2	27	32
4	0.7	145	13	2.3	28	33
5	0.75	140	14	2.4	29	34
6	0.65	135	15	2.5	30	35
7	0.60	130	16	2.6	31	36

Table 1 records the key data collected during the monitoring process of bridge structures. By monitoring these indicators in real-time, abnormal behavior of the structure can be detected in a timely manner, and corresponding maintenance measures can be taken to avoid potential safety risks. Meanwhile, long-term data accumulation can also provide scientific basis for the design, construction, and maintenance of bridges, helping engineers better understand the performance of bridges under various environmental conditions.

In this article, CNN is selected as the core model due to its excellent performance in image recognition and classification tasks. CNN can automatically extract multi-level features from bridge images, accurately capture damage details such as cracks and corrosion, and process complex image patterns. The powerful generalization ability enables the model to provide reliable detection results even when facing bridges under different environmental conditions.

3.3 Software Implementation Technology

In this study, Python is chosen as the programming language. Python supports TensorFlow and PyTorch learning frameworks, which provide comprehensive tools for building, training, and deploying neural networks. These frameworks support automatic differentiation, model construction, training loops, and various optimization algorithms.

During the development process, Visual Studio Code is used as the main integrated development environment, which supports Python development and has code highlighting, intelligent prompts, code refactoring, and debugging functions. At the same time, Git as a version control system is supported through plugin extensions.

Because Qt provides rich component and layout management, it can build a beautiful and powerful user interface. Therefore, in terms of user interface design, the Qt framework is used to create cross platform desktop applications. In terms of data visualization, the Matplotlib library is used to generate charts and graphs, displaying the structural health data of bridges and the analysis results of neural networks.

Software performance optimization identifies bottlenecks through code analysis and performance testing, improves data processing efficiency through the use of multithreading and asynchronous programming techniques, and ensures that the software can still maintain fast response when processing large-scale datasets. In terms of security, the software implements data encryption storage and secure data transmission mechanisms to protect user data from unauthorized access.

4. Results and Discussion

4.1 Software Performance Testing

In order to highlight the effectiveness of the constructed bridge detection structure analysis software in practical applications, this article applies it to 25 different bridge structure detection tasks to measure the accuracy and efficiency of the software in detecting bridge defects. Among them, the detection accuracy is shown in Figure 1:

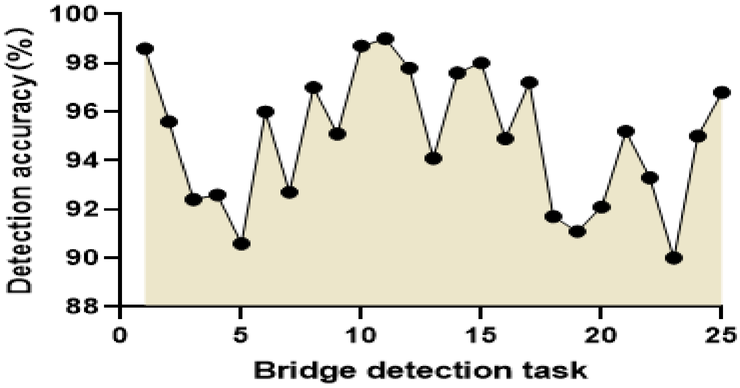

Figure 1: Detection accuracy

According to the experimental data in Figure 1, the software achieves a high level of defect detection accuracy in different bridge detection tasks, with the highest reaching 99%. This result indicates that the software has excellent defect recognition ability and can achieve high-precision automated detection in various detection scenarios. This high accuracy implementation is attributed to the advanced neural network algorithms adopted by the software, which have been trained with a large amount of annotated data and can accurately distinguish between normal and abnormal areas in bridge structures. In addition, the software considers various bridge structures and material characteristics during design, enabling it to adapt to different detection environments and conditions.

Figure 2 shows the detection time:

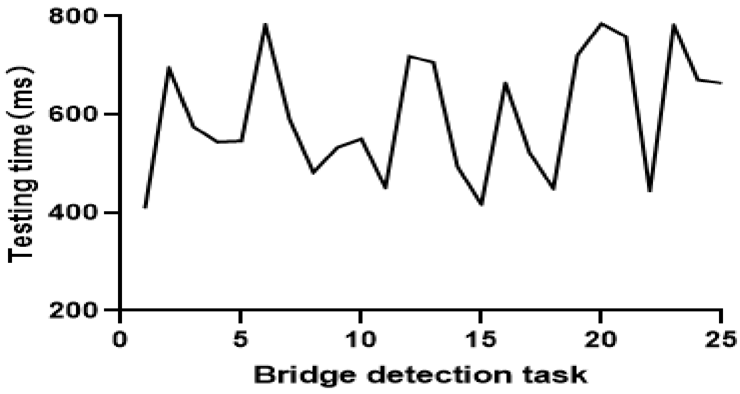

Figure 2: Detection time

As shown in Figure 2, the detection time of bridge defects by the software does not exceed

785ms, which is at a relatively low level. This advantage of rapid detection, combined with the 99% high accuracy mentioned earlier, makes the software a powerful tool suitable for automated bridge detection and monitoring systems. The low latency detection process not only improves the user experience, but also allows for the evaluation of more bridge structures in a limited time, significantly improving the efficiency of detection work.

4.2 Optimization Effects of Neural Network Models

Through a detailed performance comparison analysis of CNN, RNN, and GAN, this article focuses on two key indicators: missed detection rate and detection coverage. The missed detection rate measures the proportion of damage that the model fails to recognize, while the detection coverage reflects the type and range of damage that the model can recognize. The comparison results are shown in Figures 3 and 4, respectively:

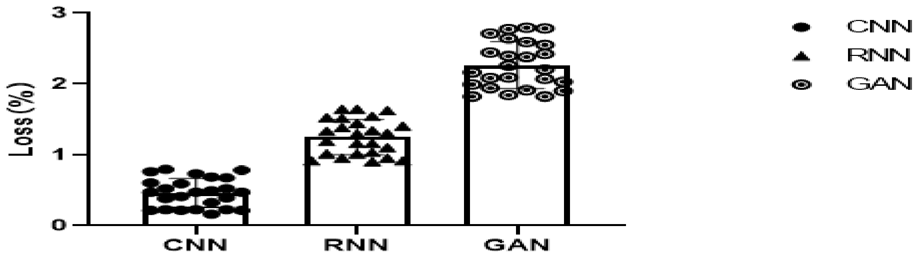

Figure 3: Misdetection rate

According to the comparison results of the missed detection rates of the three models, it can be concluded that the detection software under CNN has the lowest missed detection rate, with the lowest being only 0.16%, followed by RNN, with the lowest being 0.9%, and the highest being GAN, with the lowest missed detection rate reaching 1.82%. This indicates that CNN has extremely high accuracy and reliability in identifying bridge damage. Its deep network structure and powerful feature extraction ability enable it to effectively capture subtle damage features in image recognition tasks, significantly reducing the possibility of missed detections.

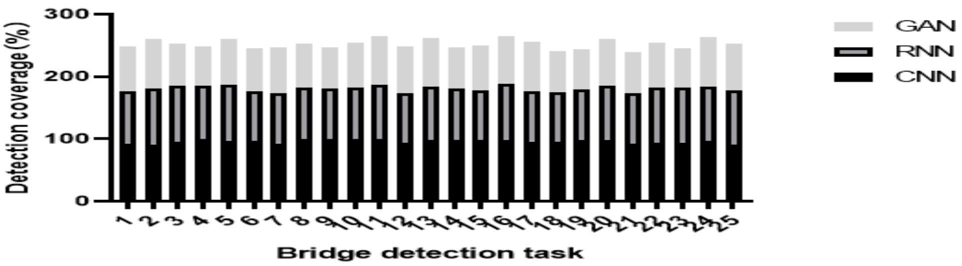

Figure 4: Detection coverage

The detection coverage data in Figure 4 shows that CNN has the highest coverage, reaching 99.75%, while RNN and GAN have the highest coverage of only 89.85% and 79.86%, respectively. This result indicates that CNN has extremely high accuracy and comprehensiveness in identifying bridge structural problems. In contrast, RNN and GAN may not be able to detect all structural issues in certain situations. Furthermore, the specific impact of parameter adjustment on model performance is explored. Through experiments, it is found that increasing network depth can improve the complexity and learning ability of the model, but at the same time, L2 regularization is also needed to control the risk of overfitting.

4.3 Application of Software in Actual Bridge Detection

In the practice of bridge inspection, the software has been applied to various types of bridges, such as bridges with different materials, designs and service lives. These bridges suffer from various damages due to environmental factors and service loads, such as cracks, corrosion and skin peeling on the bridge main body. The software uses a high-resolution camera system to scan the bridge surface, collect image data, and analyze the model to successfully identify the damage, including those small injuries that are difficult to identify with the naked eye.

The analysis of software detection results shows that the detection accuracy is very high. The highest coverage rate can reach 99.75%, and almost all damages can be detected. In the detection of reinforced concrete bridges, the software can not only identify the cracks on the main girder and pier, but also accurately classify the severity of the cracks. The software can also evaluate the development speed and potential impact of damage, and provide data support for bridge maintenance.

Although the software performs well in practical application, there are still some challenges. The change of ambient light and bridge deck condition affects the accuracy of image recognition. In addition, the software has limited ability to detect the internal damage of bridges, so other technologies need to be considered besides more comprehensive structural analysis.

4.4 Discussion

Although this research has made remarkable achievements, there are also related limitations. The limitations mainly focus on data dependence, computing resource consumption, user-friendly interface, multi-technology integration ability, model updating mechanism, cost-benefit analysis, environmental adaptability, regulatory compliance and technology popularization. Aiming at data dependence, the recognition ability of the model for different damage types is improved by data enhancement and transfer learning. The problem of high consumption of computing resources is alleviated by model optimization and cloud computing. In terms of user interface, it is committed to simplifying the operation process and enhancing the visual display, so that users can understand the test results faster.

In response to the issue of software mainly relying on visual data, integrated acoustic and electromagnetic detection technologies are explored to achieve more comprehensive detection of bridges. The establishment of an automated model update process ensures that the software can adapt to changes in bridge structures over time. Cost benefit analysis has helped prove the economic rationality of the software, while the development of image preprocessing technology has improved the stability of the software under different lighting and climate conditions. It is also ensured that the testing results of the software meet industry standards and are consistent with regulations. The improvement of technology popularity is achieved through user training and education, in order to increase the trust of potential users in AI detection technology.

5. Conclusions

This article developed a CNN-based bridge detection structure analysis software, aiming to improve the automation level and accuracy of bridge detection. Through system design, implementation, and comprehensive performance testing of the software, not only have the low efficiency and high cost problems in traditional detection methods been solved, but the accuracy and coverage of damage identification have been significantly improved by introducing deep learning algorithms. The experimental results verified the efficiency of the software in quickly and accurately identifying surface cracks and corrosion damage on bridges. At the same time, the application cases of the software in actual bridge detection further proved its practicality and effectiveness.

Although significant progress has been made in the automation of bridge detection in this article, software requires high quality image data, and changes in environmental lighting and surface conditions may affect the detection results. In addition, the software currently mainly focuses on detecting surface damage of bridges, and the ability to detect damage to the internal structure of bridges needs to be strengthened. In terms of user interface and interaction design, further optimization is needed to enhance the user experience.

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