ISSN: 2414-1895 DOI: 10.6919/ICJE.202507_11(7).0012

Application of Machine Learning in Bridge Inspection Technology

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Abstract

The traditional bridge inspection technology mainly relies on visual inspection, which can meet the needs of bridge inspection to a certain extent, but with the development of science and technology and the increasing demand for bridge construction, the traditional inspection technology is also facing many challenges and limitations. Intelligent bridge inspection technology realizes comprehensive, efficient and accurate inspection and evaluation of bridge structural status by deeply integrating sensor technology, data analysis and artificial intelligence technology. It mainly introduces the existing bridge inspection technology, the application of machine learning in bridge inspection technology, and summarizes the advantages and prospects of combining bridge inspection technology with artificial intelligence.

Keywords

Bridge Inspection; Machine Learning; Deep Learning; Artificial Intelligence.

1. Introduction

In the 21st century, China has achieved remarkable progress in bridge construction capabilities, ascending to unprecedented heights on a global scale in terms of technical specifications, construction intricacy, and innovative capacities. It now stands as the world's premier bridge-constructing nation. Yet, as the inventory of bridges grows and their service life extends, the maintenance and inspection of bridge structures are encountering novel and daunting challenges. Conventional bridge inspection methods, such as visual examination, physical testing, and loading tests, have been somewhat effective in identifying bridge defects and damage. But these techniques are encumbered by low inspection efficiency, inadequate accuracy, and restricted coverage. Especially for large-scale or intricate bridge structures, as well as for detecting flaws in concealed areas, traditional bridge inspection methods are proving inadequate to satisfy the current demands.

With the ongoing development of technologies like the Internet of Things and big data, China's artificial intelligence sector has witnessed rapid expansion, and bridge inspection and maintenance are progressively relying on intelligent, automated, and digitalised technological approaches.

In recent times, machine learning has been extensively employed in the domain of intelligent bridge inspection, thereby enhancing the maintenance and management efficiency of infrastructure such as bridges and roads. This paper primarily focuses on an introduction to bridge inspection technologies. It delves into the application of machine learning within the realm of bridge inspection technologies and summarises the benefits and prospects of integrating bridge inspection technologies with artificial intelligence.

2. Bridge Inspection Techniques

Conventional bridge inspection approaches primarily entail onsite visual assessments, sounding techniques, and instrumentation-based measurements to evaluate bridge conditions. Trained inspectors perform onsite visual assessments to identify overt structural defects like surface dam age,

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cracks, and corrosion on the bridge deck. However, these methods are incapable of ascertaining internal structural damage and are prone to subjective biases that may result in misjudgments.

(1) Ultrasonic Testing: This technique utilises specialised equipment such as ultrasonic detectors and acoustic transducers to measure the propagation velocity, dominant frequency, and vibration waveforms of ultrasonic pulses. By scrutinising the collected data, internal defects or the structural condition of the bridge can be detected[1]. The advantages encompass minimal detection costs, straightforward operation, and the capacity to detect minor defects or cracks. Nevertheless, the presence of water or air within the bridge structure may interfere with ultrasonic testing. This interference can lead to inaccurate reflection wave data, thereby hindering the precise detection of the internal structure.

(2) Fibre Optic Sensing Technology: This technology transforms external physical quantities into detectable light signals using fibre optics, enabling the detection of parameters such as prestress, overall tension, and strain within bridges. External environmental factors have minimal impact on fibre optic sensing technology. This characteristic allows it to function effectively in complex environments and ensures the accuracy of detection data.

(3) Infrared Thermography: This technique leverages the thermal radiation characteristics of objects. An infrared thermographic camera converts infrared radiation signals emanating from an object's surface into visible thermal images. Analysis of these thermal images can reveal the temperature distribution of the target object, thereby detecting quality issues such as thermal damage, cracks, and leaks by examining the temperature distribution on the bridge surface or structure. However, infrared thermography has stringent requirements for environmental conditions, and factors like temperature and humidity can influence the accuracy of detection results[2].

3. Machine Learning-Based Bridge Inspection Technology

3.1 Overview of Machine Learning

Machine learning algorithms are a key component of artificial intelligence, enabling computer systems to perform specific tasks through programming and statistical models. Their core objective is to learn, identify, and analyse data in order to make predictions and decisions. Based on different learning methods, machine learning techniques can be categorised into three main types: supervised learning, unsupervised learning, and reinforcement learning. Supervised learning trains models using example data to predict the output of unknown data. Unsupervised learning does not rely on labelled data and aims to classify or cluster data based on its intrinsic structure. Finally, reinforcement learning interacts with the environment to continuously optimise strategies to achieve a specific goal. These methods each have their own unique characteristics and are widely applied across various fields, providing robust support for solving complex problems[3].

Reinforcement learning emphasises agent-environment interaction. By sensing environmental states and responding to actions, it aims to maximise benefits through guided actions.

Supervised learning uses labelled data to train algorithms for classification or result prediction. Based on data mining, it addresses classification and regression problems. Classification identifies entities and labels conclusions, using algorithms like linear classifiers and SVMs. Regression predicts variable relationships, with algorithms such as linear and logistic regression.

Unsupervised learning, in contrast, lacks a training process. It groups input data based on features, automatically extracting knowledge from unlabelled data. This can reduce labelled data needs or boost model performance in supervised learning. It includes clustering and dimensionality reduction algorithms. Clustering categorises data for validity checks, while dimensionality reduction transforms multiple indicators into comprehensive ones, lowering dataset dimensionality.

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3.2 Machine Learning Algorithms

3.2.1 Support Vector Machines

SVMs algorithms are mainly used for classification and regression analysis. Rooted in statistical learning theory, SVMs were once a dominant machine learning technology before the emergence of deep learning. An SVMs is a binary classification model that aims to identify the optimal separating hyperplane to divide a training dataset, maximizing the geometric margin between different classes.

SVMs offer several distinct advantages in dealing with small sample sizes, non-linear issues, and high-dimensional pattern recognition. They possess strong generalization abilities, exhibit robustness to noisy data, can handle high-dimensional data and non-Linear problems, and have a relatively simple model structure that facilitates implementation. However, they also have limitations, such as long training times for large-scale datasets, sensitivity to parameter and kernel function selection (requiring parameter tuning), and significantly increased computational complexity when data dimensions are extremely high.

In the context of bridge damage detection, SVMs can utilize dynamic response data from bridges (e.g., acceleration and displacement). By comparing data changes before and after potential damage, SVMs can determine whether damage has occurred and can preliminarily identify the location and severity of the damage. Moreover, SVMs are applicable for structural health monitoring of bridges. Through the analysis of long-term monitoring data, they can establish a non-linear relationship model between temperature and deflection. This enables the precise separation of temperature effects and the timely identification of potential safety hazards.

3.2.2 Backpropagation Neural Network

Backpropagation (BP) neural networks are commonly used machine learning tools for training feedforward neural networks[4]. They consist of an input layer, hidden layers, and an output layer, and utilise the gradient descent algorithm for forward signal propagation and backward error propagation. Error calculation is based on the difference between the output layer results and the actual labels to calculate the error or loss.By leveraging the nonlinear combinations of multiple neural layers, BP neural networks can achieve nonlinear mappings of input data, addressing issues that linear models cannot handle. During training, overly complex network structures or excessively long training times may lead to overfitting, causing the model to perform well on training data but poorly on unknown data.

In bridge inspection, designing a reasonable predictive model is crucial for providing early warnings and references for bridge maintenance decisions. When identifying structural damage in bridges, BP neural networks can analyse dynamic response information to determine the location and severity of damage. Compared to traditional methods, they offer faster computation speeds and higher identification accuracy. Additionally, this model can identify moving loads on bridges, including their location, speed, and magnitude.

When combined with genetic algorithms, the BP neural network further enhances the efficiency and accuracy of intelligent detection and prediction of bridge damage. It also plays a significant role in separating the influence of environmental temperature on bridge strain responses, aiding in real-time temperature correction and the setting of dynamic warning thresholds. This provides important technical support for bridge structural health monitoring.

3.2.3 Random Forest

Random Forest is a classifier or regressor made up of numerous decision trees. It uses ensemble learning principles to aggregate the prediction results of multiple decision trees through voting or averaging, thereby obtaining the final prediction outcome. The advantages of Random Forest include interpretability, robustness, and high prediction accuracy.

In terms of data preprocessing for bridge inspection, Random Forest can effectively fill in missing values in the dataset. When compared to traditional statistical methods for imputing missing values, Random Forest demonstrates superior performance, particularly when applied to bridge inspection

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data. The algorithm can analyze multi-source inspection data, such as strain, deflection, and temperature, and provide more accurate prediction results. Moreover, Random Forest can assess the damage state of bridges under seismic loads. By training models that incorporate structural dynamic parameters and bridge configuration parameters, Random Forest can predict the damage state of bridges with an accuracy rate exceeding 90%.

3.2.4 Deep Learning Algorithms

Deep learning, a sub-branch of artificial intelligence, is based on data and algorithms. It adjusts model parameters using training data. As a specialized machine learning method, deep learning employs neural network models and utilizes backpropagation algorithms along with gradient descent optimization techniques to adjust network weights and parameters. Through continuous iteration and optimization, deep learning models can process large-scale datasets. This enhances the accuracy of identifying bridge structural conditions and improves predictive capabilities[5].

In bridge inspection, the application of deep learning models primarily includes the following aspects:

(1) Defect Detection: Convolutional neural networks are widely used to identify defects on bridge surfaces. For example, the YOLOv5 algorithm has been employed for bridge defect detection using drones. By combining image segmentation with the APAP algorithm for image stitching, this system can detect 13 types of bridge surface defects in real time.

(2) Crack Detection: By integrating attention mechanisms and transfer learning, deep learning models can enhance the learning ability of crack feature channels. This helps reduce background noise interference and improve the accuracy of bridge crack detection.

(3) Sensor Optimization: Deep learning models can optimise the layout of bridge inspection sensors, improving the quality of inspection data and the efficiency of the inspection system.

Despite their advantages, deep learning models face several challenges in bridge detection. Firstly, model training requires a large amount of labelled data, and the cost of data acquisition and labelling is high. Secondly, the generalization ability of the model needs further improvement to ensure good performance on new data. Lastly, real-time detection places higher demands on the model's computational power and response time.

4. Conclusion

This paper provides a detailed review of the development history of traditional bridge inspection technologies and delves into the potential of machine learning and deep learning algorithms in bridge inspection applications. Compared to traditional inspection methods, machine learning algorithms demonstrate significant advantages in terms of improving inspection accuracy and real-time performance. With the continuous advancement of artificial intelligence technology, bridge inspection technology is expected to achieve greater breakthroughs in the areas of digitalisation, intelligence, and integration, making it more advanced and precise.

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