Journal of Engineering Mechanics and Machinery (2024)
Clausius Scientific Press, Canada

DOI: 10.23977/jemm.2024.090204
ISSN 2371-9133 Vol. 9 Num. 2

Technical Problems and Solutions for Highway Bridge Detection

Wangming Wu[1,a], Gongxing Yan[2,b,*], Wenjie Yang[3,4,c], Xiaoping Zou[3,d], Yuhu Sun[1,e]

[1]Aneng Third Bureau Chengdu Engineering Quality Testing Co., Ltd, Chengdu, 611130, China
[2]School of Materials Science and Engineering, Wuhan Institute of Technology, Wuhan, 430205, China
[3]Sichuan Jinghengxin Construction Engineering Testing Co., Ltd, Luzhou, 646000, China
[4]School of Intelligent Construction, Luzhou Vocational and Technical College, Luzhou, 646000, China
[a]149852848@qq.com, [b]yaaangx@126.com, [c]158284644@qq.com, [d]18982406335@qq.com, [e]306787639@qq.com
[*]Corresponding author

Keywords: Bridge Detection Technology; Crack Identification; Deep Learning Models; Data Augmentation; Structural Health Monitoring

Abstract: In recent years, the number of newly built bridges has been increasing, bringing great convenience to people's transportation. However, due to the sharp increase in traffic volume and load capacity, some existing bridges have gradually exposed a series of quality problems, threatening the safety of bridge operation. Therefore, it is necessary to scientifically increase the detection and evaluation of bridge quality diseases, take effective maintenance and reinforcement measures based on the specific disease situation of the bridge, comprehensively improve the bearing performance of the bridge, and ensure its service life. This article combines specific engineering practices to systematically analyze bridge detection and reinforcement technology, which can improve the level of bridge maintenance and reinforcement technology and promote the comprehensive development of bridge engineering. Firstly, the importance of highway bridge detection and the shortcomings of traditional inspection methods were introduced, and the research progress in this field worldwide was summarized. Next, the experimental methods were elaborated in detail, including data acquisition, data augmentation, model training, and image processing steps, and the experimental results were analyzed and discussed. The results indicate that the YOLOv4 (You Only Look Once Version 4) model performs the best on various indicators. Its accuracy reaches 0.96, recall rate is 0.94, F1 score is 0.95, providing scientific basis and technical support for the safe operation and maintenance of bridges.

1. Introduction

Highway bridges are the most important part of urban road construction in China, undertaking huge traffic and freight tasks. However, during service, bridges may develop various diseases such as cracks, corrosion, and deformation. If not detected and rectified in a timely manner, it can bring great harm to road safety and economic development. Therefore, the periodic inspection and evaluation of highway bridges are of great significance. The traditional bridge structure inspection method mainly relies on manual inspection and visual inspection, which has shortcomings such as low efficiency, strong subjectivity, and inability to comprehensively evaluate. With the continuous development of science and technology, many new testing methods suitable for highway bridges have emerged. Based on this, this article aims to analyze and apply highway bridge detection technology, and explore its feasibility and effectiveness in practical engineering. By studying and comparing various bridge detection technologies, scientific basis and technical support can be provided for the safe operation and maintenance of highway bridges.

This article first introduces the importance of highway bridge detection and the shortcomings of traditional detection methods. Then, it summarizes the relevant research progress in the field of bridge detection technology worldwide. Then, it elaborates in detail on experimental methods, including data acquisition, data enhancement, model training, and image processing steps. Subsequently, the experimental results were analyzed and discussed to evaluate the performance of each detection method. Finally, the advantages and limitations of different detection techniques were summarized, providing suggestions and directions for future bridge detection and maintenance work.

2. Related Works

Experts have long conducted specialized research on the technology of highway bridge detection. Bertola N J proposed a bridge condition risk assessment method based on visual inspection data, which combines the impact of component degradation and failure on the overall structure. A case study was conducted on 60 bridges, and it was found that this method is more accurate and avoids unnecessary repairs [1]. Congress S S C conducted a 360 ° inspection of three bridges in Alaska using drones, generated 3D models, and evaluated the impact of thermal load using infrared images. The results show that this method can save more than 90% of storage requirements and promote the application of unmanned aerial vehicle bridge detection [2]. Bianchi E L proposed a simple method to register bridge detection videos or images from different stages and directly measure damage changes. Experimental tests on rigid, deformable, and hybrid image registration methods have shown that rigid transformation is superior to advanced deformable methods [3]. Plotnikov M reviewed the current bridge detection standards and procedures of various state transportation departments, evaluates the experience of drone integration, and explores related issues and challenges. He emphasized the importance of appropriate drone platforms, sensors, processing software, and pilot training [4]. Li Y introduces a virtual reality-based unmanned aerial vehicle bridge detection training system, which includes four modules: simulation detection, operation interface, real-time feedback, and personalized evaluation. Concept validation studies have shown that the system can effectively identify training needs, enhance the drone operation skills and confidence of inspectors [5].

Futai M M believed that combining modern communication technology with 5G and the Internet of Things can improve maintenance efficiency and asset reliability. The new predictive maintenance method utilizes a large amount of data to improve diagnostic accuracy [6]. Aliyari M proposed a comprehensive method of hazard identification, expert judgment, and risk assessment for preliminary hazard analysis of unmanned aerial vehicle assisted bridge detection, with the Grimes Bridge in Norway as a demonstration [7]. Talebi S has developed a framework for digital visual inspection of masonry railway bridges using various non-destructive testing technologies such as ground laser scanning, infrared thermal imaging, 360 degree imaging, and drones. Research has found that the new method relies less on subjective interpretation than traditional detection, increases quantitative analysis, and the detection process is safer [8]. Azari H introduced unmanned aerial vehicles and sensors for auxiliary detection, the data requirements of bridge owners, and how to manage the large amount of data collected by unmanned aerial vehicle systems, aiming to enhance industry awareness and knowledge base among stakeholders [9]. Mohamed M systematically reviewed 172 articles from 16 advanced academic journals between 2000 and 2021. The results showed that bridges and hot mix asphalt accounted for the largest proportion in the research, and construction progress monitoring received the most attention [10]. Chen A summarized China's experience in damage detection and performance evaluation of reinforced concrete bridges [11].

Bah A S introduced a degradation management framework for concrete structures under northern climate conditions. The model prediction results can be used to estimate corrosion risk and structural component status, to supplement visual observations. The application of this method in Montreal bridges has shown good consistency in the predicted results [12]. Munawar H S proposed a deep Convolutional Neural Network (CNN) framework for automatic detection of cracks in concrete structures. Validation shows that the framework exhibits superior performance on datasets, with F-score, Recall, and Precision reaching 0.870, 0.861, and 0.881, respectively [13]. Mugnai F explored two bridges on the Arno River in Lastra a Signa, Italy. He established a terrain reference network using global navigation satellite systems and laser scanning technology, and obtained three-dimensional point clouds of submerged bridge sections and riverbed through water depth measurements [14]. Zhang C has developed a multi-task deep learning model. The model utilizes the close relationship between bridge components and defects to improve task performance and generalization ability through feature decomposition, cross sharing, and multi-objective loss functions. Quantitative and qualitative evaluations have shown that compared to single task models, this multi-task model exhibits significant advantages in bridge component analysis and corrosion segmentation [15]. Although bridge detection technology has made significant progress in various aspects, it still needs to overcome a series of bottlenecks and challenges in data management, technology integration, model accuracy, personnel training, security, real-time performance, automation, and widespread application to achieve more efficient and reliable bridge detection and maintenance.

3. Methods

3.1 Working Principle of Highway Bridge Detection System under Big Data

The design, construction, and service life of highway bridges have a huge impact on road construction. It is necessary to ensure that the bearing capacity, stiffness, and power meet the requirements, while also requiring strong seismic and wind resistance. In data control, its subsystems are required to control data collection, transmission, processing, etc. Then, the data is calibrated and tested accordingly, and its status is evaluated. In data management and evaluation of data subsystems, there are mainly functions such as monitoring data management, structural status warning, reliability evaluation, fatigue evaluation, and comprehensive evaluation of structural status.

3.2 Crack Identification

Support Vector Machine (SVM) is a commonly used crack recognition classifier that can identify cracks and non crack areas based on the feature vectors obtained during the feature extraction stage [16-17]. The key parameters of SVM include kernel function type (linear kernel, polynomial kernel, radial basis function kernel), regularization parameter C, and kernel function parameters (polynomial kernel degree or RBF (radial basis function) kernel γ value). SVM using RBF kernel needs to adjust γ and C values to obtain optimal performance. The expression for the RBF kernel is:

$$K(x_i, x_j) = exp(-\gamma \times \| x_i - x_j \|^2 \tag{1}$$

In the formula, $K(x_i, x_j)$ is the RBF kernel function used to calculate the similarity between samples x_i and x_j; γ is a free parameter of the RBF kernel, which determines the smoothness of the decision boundary; $\| x_i - x_j \|^2$ is the square of the Euclidean distance between two sample points [18].

RF (Random Forest) is composed of multiple decision trees, each of which uses a randomly selected subset of features during the training process. Its key parameters include the number of trees, the depth of trees, and the method of feature selection. Increasing the number of trees can improve the stability and accuracy of the model. DNNs can capture complex feature relationships using multi-layer nonlinear transformations. Its key parameters include the number of network layers, the number of neurons in each layer, the type of activation function (ReLU, Sigmoid), learning rate, and regularization strategy (Dropout, L2 regularization). Object detection models such as YOLOv3 or YOLOv4 can use convolutional neural networks to extract features and anchor box mechanisms for bounding box prediction. Its key parameters include the size of the input image, the size and aspect ratio of the anchor box, the confidence or value, and the non-maximum suppression (NMS) or value.

(1) Grayscale image

A grayscale value can be obtained by averaging the brightness of the three components R, C, and B in the image. Algorithm as shown in formula (2)

$$Gray(i,j) = (R(i,j) + G(i,j) + B(i,j))/3 \tag{2}$$

(2) Image brightness value adjustment

Map the brightness in grayscale image $Gray(i,j)$ to the new value in L, as shown in formula (3)

$$S = \begin{cases} low_{out} & r \le low_{in} \\ cr^{y} & low_{in} \le r \le high_{in} \\ high_{out} & r > high_{in} \end{cases} \tag{3}$$

In the formula, r represents the grayscale of image $Gray(i, j)$, and S represents the grayscale of image L. This article takes $[low_{in}, high_{in}]$ and $[low_{out}, high_{out}]$ as $[0,1]$ and $[1,0]$ for linear mapping, respectively.

(3) Threshold extraction can be used for image segmentation and image inversion to highlight diseases. It divides the image into foreground and background parts based on its grayscale characteristics. When choosing the optimal threshold, the difference between the two parts should be the greatest.

(4) Using the connected domain to remove interference information, and finally displaying the crack area.

4. Results and Discussion

4.1 Dataset Collection

The experiment takes a highway bridge in Guangdong as the research object, and high-definition cameras are used to observe it. The camera lens is adjusted to be close to the crack surface of the bridge deck, and the area with good lighting and obvious crack characteristics is selected at 30 cm for collection.

Table 1: Dataset Collection Table

Numbering	Picture No.	Location	Lighting Conditions	Shooting Distance (cm)	Remarks
1	IMG_001	Guangdong Highway Bridge Section A	Good	30	No
2	IMG_002	Guangdong Highway Bridge Section A	Good	30	No
3	IMG_003	Guangdong Highway Bridge Section B	Good	30	No
4	IMG_004	Guangdong Highway Bridge Section B	Good	30	No
5	IMG_005	Guangdong Highway Bridge Section C	Good	30	No

In this experiment, high-definition cameras were used to collect initial datasets in a highway bridge area in Guangdong. During the collection process, this article ensures that the camera lens is parallel to the surface of the bridge crack, with a shooting height of about 30 centimeters, and selects areas with good lighting and obvious crack characteristics for shooting. Through this method, a total of 500 high-resolution crack images were collected in this article. These images provide a high-quality data foundation for subsequent deep learning model training, as depicted in Table 1.

Table 2: Data Enhancement Table

Numbering	Original Image Number	Enhancement Method	New Image Number	Remarks
1	IMG_001	rotating	IMG_001_R1	Rotate 15 Degrees
2	IMG_001	Flip	IMG_001_F1	Flip Horizontally
3	IMG_001	Zoom	IMG_001_S1	Zoom 1.2 Times
4	IMG_002	Rotate	IMG_002_R1	Rotate 15 Degrees
5	IMG_002	Flip	IMG_002_F1	Horizontal Flip

In order to expand the dataset, this article applied data augmentation methods such as rotation, flipping, and scaling to expand the initial dataset to 40000 crack images. Data augmentation not only improves the model's generalization ability, but also enhances its ability to identify cracks from different angles, sizes, and directions. Through this process, this article ensures the diversity and richness of training data, laying a solid foundation for subsequent model training, as shown in Table 2.

Table 3: Model Training Parameters Table

Model Type	Kernel Function Type/Number Of Trees	Parameter C	Parameter γ / Depth Of Tree	Activation Function	Learning Rate	Remarks
SVM	RBF	1	0.1	-	-	Optimal Parameter
RF	100	-	10	-	-	-
DNN	-	-	-	ReLU	0.001	-
YOLOv3	-	-	-	-	-	Input Image Size 416 x 416

During the model training phase, this article selected models such as SVM, RF, Deep Neural Networks (DNN), and YOLOv3/YOLOv4 for crack recognition. The key parameters of each model have been optimized to ensure optimal performance in crack identification tasks. The SVM model uses RBF kernel function, while the RF model uses 100 trees. The activation function of DNN model is ReLU, and the input image size of YOLOv3 and YOLOv4 models is set to 416 × 416, as shown in Table 3.

Table 4: Image processing steps table

Numbering	Picture Number	Grayscale	Brightness Adjustment	Threshold Extraction	Connected Field Removal	Remarks
1	IMG_001	√	√	√	√	-
2	IMG_002	√	√	√	√	-
3	IMG_003	√	√	√	√	-
4	IMG_004	√	√	√	√	-
5	IMG_005	√	√	√	√	-

In the image processing stage, this article processed the collected crack images by grayscale, brightness value adjustment, threshold extraction, and connected domain removal of interference information. These processing steps significantly improve the prominence of the crack area, enabling the model to more accurately capture key information when identifying cracks. Through grayscale processing, this article converts the three component brightness of the image into a single grayscale value, simplifying the subsequent processing steps. The adjustment of brightness value further enhances the contrast of the image, making the distinction between cracks and background more obvious. The combination of threshold extraction and connected domain removal of interference information effectively reduces noise and interference information, and improves the accuracy of crack recognition, as shown in Table 4.

4.2 Experimental Results

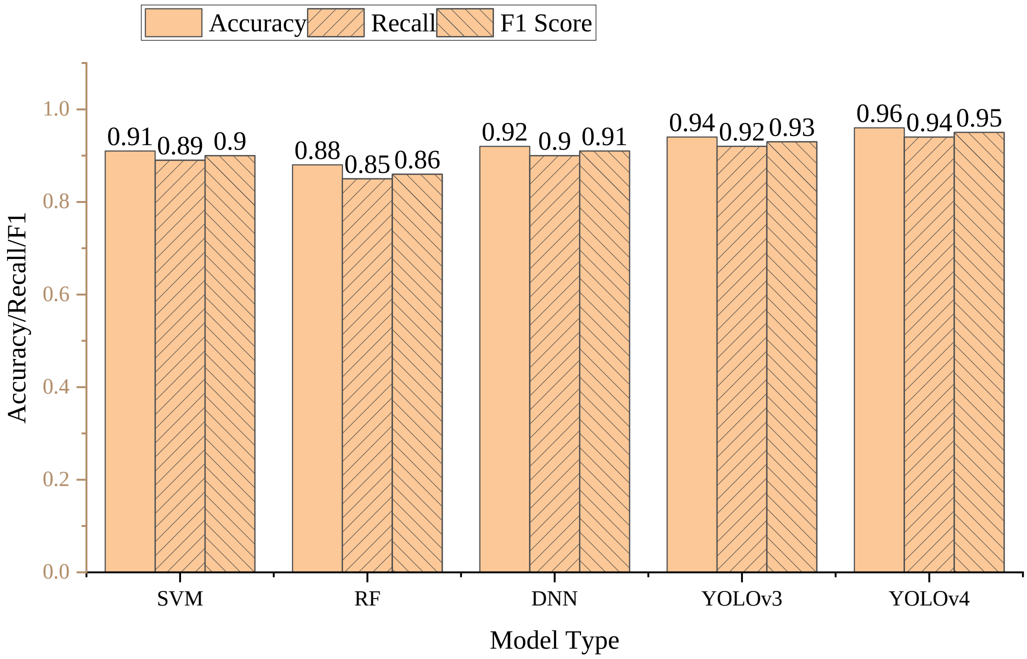

Figure 1: Performance comparison of the model

From Figure 1, it can be seen that the YOLOv4 model has achieved the highest levels of accuracy, recall, and F1 score, with values of 0.96, 0.94, and 0.95, respectively. YOLOv3 followed closely, with an accuracy of 0.94, a recall of 0.92, and an F1 score of 0.93. This indicates that the YOLO series models perform well in crack recognition tasks, especially YOLOv4, which has improved in performance. DNNs exhibit stable performance in accuracy, recall, and F1 score, with values of 0.92, 0.9, and 0.91, respectively.

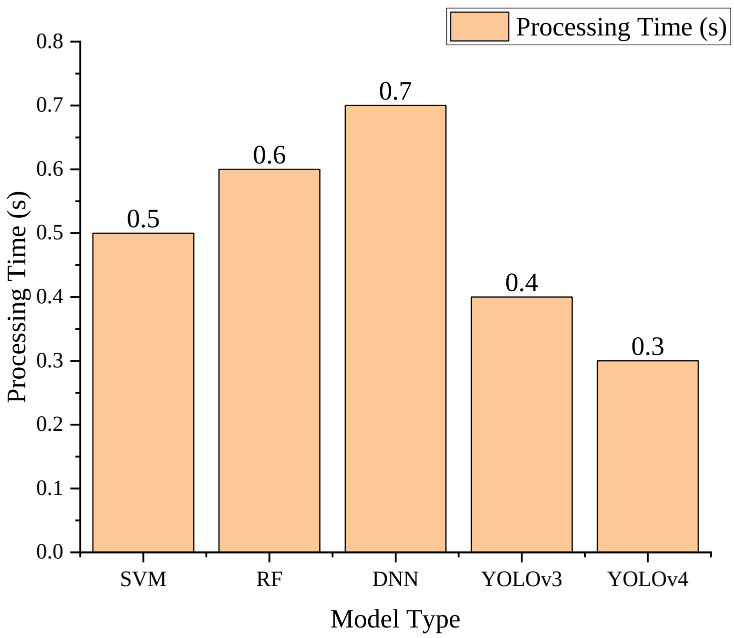

Figure 2: Processing time of the model (s)

From the experimental data in Figure 2, it can be seen that the YOLO series models (YOLOv3 and YOLOv4) have significant advantages in processing time, especially YOLOv4, whose efficient processing ability makes it the best choice for crack recognition tasks. This is mainly due to the optimized architecture and efficient feature extraction ability of YOLOv4, which enables it to complete a large amount of image data processing in a short period of time. SVM and RF model perform moderately in processing time, with 0.5 seconds and 0.6 seconds, respectively. Although these two traditional machine learning methods have good performance in certain tasks, their efficiency in processing large-scale image data is not as good as the YOLO series models.

5. Conclusions

As an important component of transportation infrastructure, highway bridges carry a large amount of traffic flow and cargo transportation tasks. However, due to long-term use and the influence of natural environment, bridge structures may have various defects and damages, such as cracks, rust, deformation, etc. If these problems are not detected and repaired in a timely manner, they can have a serious impact on traffic safety and economic development. Therefore, regular inspection and evaluation of highway bridges is particularly important. The traditional bridge detection method mainly relies on manual inspection and visual observation, which has disadvantages such as low efficiency, strong subjectivity, and inability to comprehensively evaluate. With the progress and development of technology, various advanced highway bridge detection technologies have emerged. Based on this, this article aims to analyze and apply highway bridge detection technology, and explore its feasibility and effectiveness in practical engineering. By studying and comparing various bridge detection technologies, scientific basis and technical support can be provided for the safe operation and maintenance of highway bridges. Through this experiment, this article verifies the feasibility and effectiveness of various advanced bridge detection technologies in crack identification, providing scientific basis and technical support for the safe operation and maintenance of highway bridges. In the future, this article can further optimize the model parameters, combine more practical engineering data, and improve the model's generalization ability and real-time detection performance. Meanwhile, this article can explore other advanced image processing and analysis technologies, such as 3D imaging and multi-sensor fusion, to further improve the accuracy and efficiency of bridge detection.

Acknowledgement

This work was supported by Sichuan Province Luzhou city of Stars science and technology planning project (2022-GYF-6) and scientific research and innovation team construction project of Luzhou vocational and Technical College (2021YJTD07).

References

[1] Bertola N J, Brühwiler E. Risk-based methodology to assess bridge condition based on visual inspection[J]. Structure and Infrastructure Engineering, 2023, 19(4): 575-588.
[2] Congress S S C, Escamilla III J, Chimauriya H, et al. Eye in the Sky: 360° Inspection of Bridge Infrastructure Using Uncrewed Aerial Vehicles (UAVs)[J]. Transportation Research Record, 2024, 2678(4): 482-504.
[3] Bianchi E L, Sakib N, Woolsey C, et al. bridge detection component registration for damage evolution[J]. Structural Health Monitoring, 2023, 22(1): 472-495.
[4] Plotnikov M, Collura J. Integrating unmanned aircraft systems into state department of transportation highway bridge inspection procedures: challenges, implications, and lessons learned[J]. Transportation research record, 2022, 2676(2): 529-540.
[5] Li Y, Karim M M, Qin R. A virtual-reality-based training and assessment system for bridge inspectors with an assistant drone[J]. IEEE transactions on human-machine systems, 2022, 52(4): 591-601.
[6] Futai M M, Bittencourt T N, Carvalho H, et al. Challenges in the application of digital transformation to inspection

and maintenance of bridges[J]. Structure and Infrastructure Engineering, 2022, 18(10-11): 1581-1600.
[7] Aliyari M, Ashrafi B, Ayele Y Z. Hazards identification and risk assessment for UAV–assisted bridge inspections [J]. Structure and Infrastructure Engineering, 2022, 18(3): 412-428.
[8] Talebi S, Wu S, Al-Adhami M, et al. The development of a digitally enhanced visual inspection framework for masonry bridges in the UK[J]. Construction Innovation, 2022, 22(3): 624-646.
[9] Azari H, O'Shea D, Campbell J. Application of unmanned aerial systems for bridge inspection[J]. Transportation Research Record, 2022, 2676(1): 401-407.
[10] Mohamed M, Tran D Q. Content analysis of e-inspection implementation for highway infrastructure construction projects [J]. Engineering, construction and architectural management, 2023, 30(7): 2621-2644.
[11] Chen A, Fang X, Pan Z, et al. Engineering practices on surface damage inspection and performance evaluation of concrete bridges in China[J]. Structural Concrete, 2022, 23(1): 16-31.
[12] Bah A S, Sanchez T, Zhang Y, et al. Assessing the condition state of a concrete bridge combining visual inspection and nonlinear deterioration model[J]. Structure and Infrastructure Engineering, 2024, 20(2): 149-164.
[13] Munawar H S, Hammad A W A, Waller S T, et al. Modern crack detection for bridge infrastructure maintenance using machine learning[J]. Human-Centric Intelligent Systems, 2022, 2(3): 95-112.
[14] Mugnai F, Bonora V, Tucci G. Integration, harmonization, and processing of geomatic data for bridge health assessment: the Lastra a Signa case study[J]. Applied Geomatics, 2023, 15(3): 533-550.
[15] Zhang C, Karim M M, Qin R. A multitask deep learning model for parsing bridge elements and segmenting defect in bridge inspection images[J]. Transportation Research Record, 2023, 2677(7): 693-704.
[16] Kurani A, Doshi P, Vakharia A, et al. A comprehensive comparative study of artificial neural network (ANN) and support vector machines (SVM) on stock forecasting[J]. Annals of Data Science, 2023, 10(1): 183-208.
[17] Chaabane S B, Hijji M, Harrabi R, et al. Face recognition based on statistical features and SVM classifier[J]. Multimedia Tools and Applications, 2022, 81(6): 8767-8784.
[18] Shuo W, Ming M. Exploring online intelligent teaching method with machine learning and SVM algorithm[J]. Neural Computing and Applications, 2022, 34(4): 2583-2596.