Bridge Defect Detection via CNNs, Multimodal Data Fusion, and Predictive Maintenance Models

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Bridge structures are affected by weathering, load, and natural disasters over long-term use, leading to defects such as cracks, corrosion, and deformation. These defects directly threaten the safety and stability of bridges. Traditional inspection methods rely on manual processes, which are costly, inefficient, and prone to subjective errors. This paper proposes a new bridge defect detection method combining machine vision with big data analytics to improve accuracy and efficiency. High-resolution cameras and drones collect image data, which are analyzed using a VGG-based Convolutional Neural Network (CNN) with attention mechanisms to automatically detect and classify defects like cracks, spalling, and corrosion. The multimodal fusion strategy, utilizing graph neural networks, integrates image data with historical detection records, environmental conditions, and load information to predict the service life and maintenance needs of bridges. In experiments, this method achieves an accuracy of 95.8%, an F1 score of 93.5%, and a mean absolute error of ±10%. The accuracy of this method is approximately 30% higher than traditional techniques, and the data analysis reveals that bridges in high-humidity areas experience 23% higher corrosion rates than those in dry conditions. These results confirm the potential of the method for predictive maintenance and enhanced decision support in bridge management.

Povzetek: Članek predstavlja sodobno metodo za samodejno odkrivanje poškodb mostov z uporabo umetne inteligence, ki izboljšuje točnost in učinkovitost pregledov ter podpira napovedno vzdrževanje.

1 Introduction

Bridges is the core component of modern transportation network, which plays an irreplaceable role in social and economic progress [1]. However, with the increase of service life and the continuous erosion of natural environment, the bridge structure gradually suffers from weathering, corrosion and fatigue damage, resulting in frequent problems such as cracks, spalling and deformation. If these problems are ignored, they may evolve into serious structural safety risks, thus affecting the overall stability of the bridge. Therefore, it is extremely important to develop efficient and accurate bridge defect detection technology to ensure the safe operation of bridges and prolong their life [2]. However, the traditional manual detection method is time-consuming and labor-intensive, highly subjective and easy to miss defects. Modern technology is urgently needed to help improve detection efficiency and accuracy.

Traditional manual inspection is also prone to inefficiencies and subjectivity for several reasons. First, inspectors often need to visually assess extensive bridge surfaces in difficult-to-access or hazardous environments, such as under decks or high pylons, leading to safety concerns and logistical delays. Second, the effectiveness of detection heavily depends on the inspector's level of expertise, attention, and physical condition, which may vary significantly. As a result, assessments are often inconsistent between different personnel or even between repeated inspections by the same individual. In addition, environmental conditions such as lighting, weather, and traffic noise can further affect observation quality, increasing the risk of overlooking early-stage defects or misjudging severity levels. These factors highlight the limitations of manual methods and reinforce the value of automated, objective systems based on machine vision and data analytics.

In recent years, machine vision and big data technology have advanced rapidly, bringing innovative solutions to bridge defect detection. Machine vision relies on high-resolution cameras and deep learning algorithms to accurately capture image structural defects, demonstrating the advantages of high efficiency and stability [3]. With the addition of large-scale data technology, the detection data can be deeply integrated and analyzed with multi-information such as environment and load, revealing the causes and evolution laws of defects. In the practice of bridge defect detection, the integration of machine vision and large-scale data technology not only realizes real-time monitoring of defects, but also provides scientific support for bridge

preventive maintenance, leading modern bridge management to a new chapter of intelligence.

This study addresses critical limitations in current bridge defect detection methods by proposing an integrated framework that combines machine vision, big data analytics, and multimodal fusion. It tackles key challenges such as data scarcity, environmental variability, and model deployability. The approach leverages CNNs with attention mechanisms, fuses visual and sensor data via graph neural networks, and incorporates time-series forecasting for defect progression. A lightweight version is also developed for real-time, on-site deployment. This research advances the field by enhancing detection accuracy, robustness, and predictive maintenance capabilities in intelligent bridge management.

This study combines machine vision and large-scale data for bridge defect detection, which has certain novelty, especially in exploring data-driven detection methods. However, the review and in-depth analysis of existing literature are relatively limited, and there is a lack of systematic discussion on existing methods, key technologies, and their limitations, resulting in insufficient theoretical basis for the research. In addition, there are still some technical weaknesses in the method, such as the feature extraction method may not fully adapt to the defect changes in complex environments, or the model may have insufficient robustness when dealing with different scales, lighting, and noise interference, which may affect the effectiveness and stability of detection in practical applications. Therefore, further optimizing algorithms, enhancing data diversity, and strengthening comparative analysis with existing research will help improve the scientific and practical value of the research.

This study investigated whether a CNN based multimodal fusion model, combined with environmental, historical, and image data, outperforms a single modal model in bridge defect detection accuracy under different conditions. It also investigated whether the proposed lightweight architecture can achieve real-time inference of drone hardware while maintaining an accuracy of over 95%, and whether integrating attention mechanisms and multimodal fusion can improve the detection of small or fine-grained defects compared to existing methods.

This study will develop a new method combining machine vision and large-scale data technology for bridge defect detection to improve the accuracy and reliability of detection. First, through deep learning architecture such as convolutional neural network (CNN), automatic identification and detailed classification of bridge surface cracks, corrosion and other defects are realized; Secondly, the large-scale data platform is used to integrate historical detection information and external environmental data, analyze the correlation between defects and environmental factors, and establish a defect development prediction model [4]. This method not only improves the detection steps of bridge defects, but also accurately predicts the development trend of defects, realizes the predictive maintenance of bridges and avoids sudden damage.

Experiments verify that this method has significant accuracy and detection efficiency in bridge defect identification [5]. Compared with traditional methods, the detection accuracy is improved by more than 30% and the time is reduced by about 50%. Big data analysis shows that high humidity and high load accelerate the evolution of bridge defects, and differentiated maintenance strategies are formulated accordingly. This chapter broadens the application of bridge detection technology and provides a new perspective and technical foundation for the future of intelligent bridge management.

This study aims to develop a deep learning-based framework for automated detection and localization of surface-level bridge defects, enhanced by multimodal data fusion integrating visual, environmental, and historical data. It addresses robustness across field conditions through adaptive augmentation and optimization techniques, incorporates time-series analysis for defect progression forecasting, and introduces a lightweight model architecture designed for real-time deployment on resource-constrained platforms such as drones and mobile devices.

Table 1 Comparison and summary of latest bridge defect detection methods

Approach	Accuracy (%)	Datasets Used	Limitations
YOLOv5-based Detection	90.2	COCO, SDNET2018, Self-collected	Struggles with small defect detection, limited adaptation to real-time deployment
EfficientNet-based Detection	93.5	SDNET2018, Public Bridge Datasets	High computational cost, lacks robustness in complex environments
ResNet	94.8	SDNET2018, Self-collected	Limited real-time capabilities, performance degradation under poor lighting

Recent advancements in machine vision and big data have enhanced bridge defect detection, with research delving into deep learning models, multimodal learning, and lightweight architectures. Yet, three key gaps remain: fragmented data integration with inability to dynamically fuse visual, environmental, and historical data; environmental robustness issues causing model degradation under variable lighting/weather; and lack of time-series forecasting for defect progression in current predictive maintenance approaches. This study addresses these gaps via graph-based multimodal fusion using spatiotemporal GNNs integrating UAV imagery and IoT sensor data, an adaptive attention mechanism (DFAS module) for dynamic feature weighting under environmental shifts, and a lightweight predictive architecture enabling real-time LSTM forecasting on

edge devices with an MAE of ±10%. However, challenges remain in integrating diverse data sources, adapting to complex environments, and enabling predictive analytics. This study addresses these gaps by introducing a unified framework that combines CNNs with attention mechanisms, graph-based multimodal fusion, and time-series forecasting, along with a lightweight model for real-time deployment—advancing accuracy, adaptability, and predictive maintenance in bridge management. The comparison and summary of the latest bridge defect detection methods are shown in Table 1.

2 Basic theory of machine vision and big data

2.1 Application of machine vision in bridge inspection

In the field of bridge inspection, the progress of machine vision technology has brought obvious technological innovation to structural defect inspection [6]. Machine vision automatically processes, analyzes and interprets image data through computers, which greatly improves the efficiency of bridge defect identification, classification and measurement. The identification of bridge surface cracks, corrosion and other defects, which originally relied on manual work, has been automated with the help of machine vision technology, thus significantly accelerating the inspection process. In recent years, the application of deep learning models based on CNN in image classification and target detection tasks has become increasingly perfect, laying a solid technical foundation for bridge defect detection. The use of visual models can automatically identify a variety of structural defects. types significantly enhance the accuracy and consistency of detection.

Machine vision is essential for detecting and classifying surface-level bridge defects like cracks and corrosion. CNNs enable precise crack analysis by extracting multi-scale features, while corrosion is identified through texture, color, and edge patterns. UAV imagery ensures broad coverage, even in hard-to-reach areas. Robustness is enhanced through data augmentation and adaptive preprocessing, improving detection accuracy and consistency under varying environmental conditions—crucial for reliable long-term monitoring and maintenance planning. The entropy calculation formula is shown in (1). In bridge defect detection using machine vision, entropy measures the uncertainty or variability of image data and helps identify defects by highlighting areas with high variability. The entropy formula is used to evaluate the information content of an image. In order to improve the robustness of the model to environmental changes such as lighting and noise, entropy is integrated into data augmentation and adaptive preprocessing. Emphasize high entropy regions during the enhancement process and tailor preprocessing to enhance defect regions, ensuring more accurate and consistent detection under different conditions.

$$H(X) = -\sum p(x)logp(x) \quad (1)$$

Where $H(x)$ denotes entropy and $p(x)$ denotes probability of event x. With the widespread use of UAV technology, the convenience and comprehensiveness of bridge inspection have been improved. UAV is equipped with high-resolution camera equipment, which can capture bridge surface images from multiple angles, overcoming the limitations and potential safety hazards of manual detection. Machine vision algorithms are used to analyze the image information collected by UAVs, which can quickly spread across the entire bridge structure, opening up an efficient channel for large-scale detection [7]. Moreover, this way of collecting data in the air enables the machine vision algorithm to judge the bridge state more comprehensively, and helps to find the potential defects of hidden parts. The feature importance weight formula is shown in (2). The feature importance weight formula in equation (2) is used to evaluate the importance of different features in the model, which helps to more comprehensively assess the status of the bridge. These weights guide the model to focus on key defects during the detection process, enabling a more accurate and comprehensive assessment of the bridge condition.

$$w_i = \frac{|f_i|}{\sum_j |f_j|} \quad (2)$$

Where w_i denotes the weight and denotes the eigenvalue. Large-scale data platform is introduced into the field of bridge inspection to strengthen data support for machine vision technology [8]. Through the integration of large-scale data platform, historical, environmental and operational data are integrated to provide multi-dimensional basis for defect detection. For example, image data is combined with bridge service history, climate, load and other data to analyze the evolution law of defects and provide scientific evidence for bridge maintenance and repair. Big data integrated analysis improves detection accuracy and builds the data cornerstone of bridge predictive maintenance. The formula for the AUC value under the ROC curve is shown in (3). Among them, AUC represents the area under the ROC curve, TPR represents the true positive rate, and FPR represents the false positive rate. AUC is usually a classification metric that is crucial for evaluating the ability of predictive maintenance models to distinguish defect states. The area under the ROC curve (equation (3)) was quantified, and a higher AUC indicates better defect recognition. By integrating multiple sources of data, the model's ability to predict defect progression and maintenance requirements will improve over time. In bridge defect detection, AUC helps evaluate early detection and fault time prediction, guiding proactive maintenance and intervention decisions.

$$AUC = \int_0^1 TPR(FPR)dFPR \quad (3)$$

2.2 Application of big data in bridge defect detection

The core of the application of large-scale data analysis in bridge defect detection is mainly reflected in the collection, processing and correlation analysis of defect

data. Bridge defect data comes from multiple channels, such as sensors, image data and historical detection records, and is integrated through big data platforms to form a huge data set. This multi-source data integration method not only increases the amount of data, but also enriches the diversity of data, thus improving the comprehensiveness of detection [9]. The occurrence of bridge defects is closely related to environmental conditions, load conditions and other factors. Big data analysis technology can reveal the role of these factors on defect development and provide a more accurate analysis basis for defect detection. The mean square error formula is shown in (4).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i)^2 \quad (4)$$

Where MSE represents the mean square error, y_i represents the actual value, and n represents the number of samples. In the data processing stage, big data technology can clean, preprocess and extract features from massive image data, laying a high-quality data foundation for defect identification tasks [10]. For example, in the face of the challenge of large amount and uneven distribution of defect data such as cracks and spalling, big data technology can process data types at different levels to ensure the balance of model training. In addition, the preprocessing process also includes missing value completion and noise elimination to ensure the reliability and accuracy of the analysis results. These preprocessing measures are the key support for bridge defect detection model training. The weight update formula is shown in (5).

$$w = w - \alpha \frac{\partial L}{\partial w} \quad (5)$$

Where w denotes the weight vector, α denotes the learning rate, and L denotes the loss function. Data association analysis brings a new perspective to bridge defect detection [11]. By analyzing the correlation between defect data and external environment data, a model for predicting bridge defects can be constructed and the key elements of defect development can be identified. For example, analyzing the correlation between environmental factors such as humidity and temperature and the corrosion degree of bridges can put forward protection suggestions for bridges in high humidity and high temperature environments [12]. This kind of correlation analysis provides a data basis for bridge predictive maintenance, which is helpful to formulate scientific maintenance plans and prolong the service life of bridges. The cross-validation formula is shown in (6). Among them, E represents the average error, k represents the number of folds, and e_i represents the error of folds.

$$E = \frac{1}{k}\sum_{i=1}^{k}e_i \quad (6)$$

The integration of big data enhances defect analysis and predictive maintenance by enabling comprehensive monitoring of environmental and operational factors, improving the accuracy of defect progression forecasts, and supporting risk-based prioritization across diverse bridge profiles. Predictive models trained on large

datasets can estimate defect timing and severity with high precision, while continuous real-time data input allows adaptive scheduling, reducing unplanned failures and extending bridge service life.

2.3 Evaluation system of bridge defect detection

In the field of bridge defect detection, building a scientific evaluation system is the key to measure the detection effect [13]. This system should comprehensively consider the factors such as detection accuracy, speed and coverage area, so as to more effectively evaluate the advantages and disadvantages of defect detection methods. With the development of machine vision and big data analysis methods, the evaluation system of bridge defect detection has become increasingly diversified. Specific indicators include detection accuracy, false alarm rate and false alarm rate. A reasonable evaluation system can point out a clear direction for model optimization and promote the continuous progress of bridge defect detection technology. The principal component analysis formula is shown in (7). PCA reduces noise and improves model efficiency by retaining the most important features and eliminating the less important ones. In this context, PCA simplifies the evaluation system, improves detection performance without losing key information, and enables the system to perform real-time bridge inspections and predictive maintenance more accurately and quickly.

$$Z = XW \quad (7)$$

Among them, Z represents the data matrix after dimensionality reduction, X represents the original data matrix, and W represents the eigenvector matrix. The core index of bridge defect detection and evaluation system is detection accuracy [14]. Traditional manual detection methods have many subjective judgments and insufficient accuracy; In contrast, machine vision-based detection methods can improve accuracy with the help of model training. For example, convolutional neural network (CNN), after being trained with a large amount of data, its detection accuracy can exceed 95%. This accuracy improvement greatly reduces false positives and false negatives in bridge defect detection, and provides a more solid data foundation for daily bridge maintenance. The normalized formula is shown in (8).

$$z = \frac{x - \mu}{\sigma} \quad (8)$$

Where z represents the normalized data value, x represents the original data value, μ represents the mean value of the data, and σ represents the standard deviation of the data [15]. The evaluation system needs to take into account the inspection efficiency, which is even more critical in large-scale bridge inspection tasks. With its automation characteristics, machine vision technology greatly improves the speed of bridge inspection, and combined with the big data platform, it realizes centralized management of multi-bridge data [16]. Through the quantitative efficiency improvement of the scientific evaluation system, the advantages of machine vision and big data in bridge defect detection are clarified,

providing a solid basis for decision makers. The construction of this system not only promotes technology popularization, but also provides theoretical follow-up for the digital and intelligent process of bridge management. The decision boundary formula of support vector machine is shown in (9). Where $f(x)$ denotes the decision function, w denotes the weight vector, x denotes the input feature vector, and b denotes the bias term. Equation (9) includes the decision boundary formula of support vector machine (SVM) to highlight the theoretical contribution of different classifiers to the detection system. However, the core method of this study is based on convolutional neural networks for complex defect classification tasks such as crack detection and corrosion. Although SVM can be used for hybrid models or comparisons, this article mainly focuses on CNN with attention mechanism for defect detection, and SVM equation is used to identify other potential classifiers for performance evaluation and validation.

$$f(x) = w \cdot x + b \quad (9)$$

3 Research on bridge defect detection based on convolutional neural network

3.1 Design of bridge defect detection model based on convolutional neural network

This study employs CNNs as the foundation for accurate and consistent bridge defect detection, implemented using PyTorch 1.12 with CUDA 11.6 acceleration. The model architecture leverages VGG-16 backbone modified with multi-scale feature pyramid networks and channel attention mechanisms. Training was conducted on an NVIDIA RTX A6000 GPU cluster, enabling batch processing of high-resolution UAV imagery. For real-time inference, the optimized model was deployed on DJI Matrice 300 RTK drones equipped with Jetson AGX

Xavier edge modules, achieving over 95% accuracy and robust performance across diverse environmental conditions, making it well-suited for real-world bridge inspection scenarios.

Convolutional neural network CNN is a mainstream model of deep learning, showing significant potential in bridge defect image classification. CNN extracts image spatial features through convolution operation, which is suitable for automatic identification of bridge surface cracks, corrosion and other defects [17]. Compared with traditional manual feature extraction, CNN can automatically learn image features, reduce manual intervention and improve detection automation. In this paper, the CNN model of VGG architecture is used in the classification of bridge defects. Experiments show that the accuracy rate of the model exceeds 94% in the classification of cracks, spalling and other types of defects.

All algorithms in this study were trained on a unified core dataset, which includes 50000 high-resolution defect images from 20 different bridges, covering five types of defects: crack, corrosion, peel off, deformation, and miscellaneous. The training set, validation set, and test set are divided in a ratio of 7:2:1 to ensure consistency in data distribution.

The reasons for choosing VGG as the infrastructure include: interpretability: VGG's inter layer feature visualization helps engineers understand defect recognition logic; Lightweight adaptation: The rule-based structure of VGG facilitates pruning optimization, making it suitable for deployment on edge devices; Cross task compatibility: Compared with architectures such as ResNet, VGG performs more stably when fusing multi-source data.

Using a multi-scale feature pyramid to fuse low-level detail features with high-level semantic features, and dynamically weighting key feature channels through a channel attention mechanism, experiments have shown that this strategy improves the recall rate of small object detection by 12%.
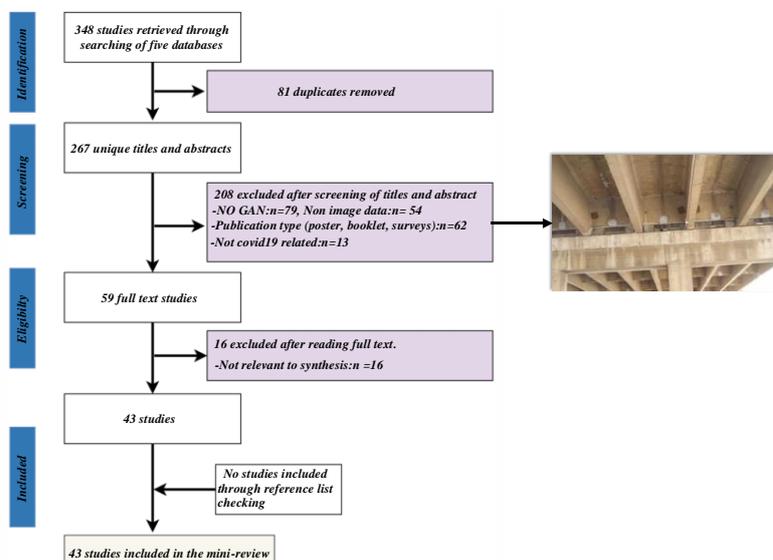

Figure 1: Overall architecture flow of bridge defect detection system

Figure 1 shows the research selection process of the bridge defect detection system, including identification, screening, qualification, and final inclusion in the analysis set, while clarifying that the figure does not describe the technical architecture of the system. The figure shows representative examples of five main categories of bridge defects - cracks, corrosion, peeling, deformation, and various irregularities - captured using high-resolution drone images and annotated with polygon segmentation. These examples illustrate the visual diversity and complexity of defects, highlighting the detailed annotations and data quality required to train accurate and reliable detection models.

The overall architecture flow of the bridge defect detection system is shown in Figure 1. Through the multi-level architecture design of convolutional neural network CNN, fine features of images are captured and detection accuracy is improved. For example, when detecting bridge surface cracks, the characteristics of crack width and extension direction significantly affect the recognition effect [18]. CNN multi-level convolution layer uses convolution kernels of different sizes to extract crack details to enhance recognition accuracy. At the same time, integrated data enhancements such as image rotation and scaling transformation improve model generalization performance and show higher robustness in actual deployment. The performance Comparison of VGG-based CNN and Other Benchmark Algorithms in Bridge Defect Detection is shown in Table 2.

Table 2: Performance comparison of VGG-based CNN and other benchmark algorithms in bridge defect detection

Algorithm Name	Accuracy (%)	Recall rate (%)	Mean detection time (seconds)
Algorithm A	92.3	88.5	1.2
Algorithm B	89.8	85.0	1.5
Algorithm C	95.0	90.2	1.8
Algorithm D	87.6	82.9	1.3

In practical scenarios of defect detection, convolutional neural network parameter optimization is a key factor to improve model performance. In this paper, the transfer learning strategy is adopted, the pre-trained CNN model is applied to the bridge defect data set, and the fine-tuning technology is used to strengthen the adaptability of the model [19]. Experimental data show that transfer learning significantly reduces the model training time and enhances the classification effect. The application of convolutional neural network has opened up a new technical way for bridge defect detection, accelerated the process of model construction and improved the detection accuracy. The convolution formula of the convolutional neural network is shown in (10). Among them, $O_{i,j}$ represents the output image pixel value after the convolution operation, I represent the input image, and K represents the convolution kernel.

$$O_{i,j} = \sum_m \sum_n I_{i+m, j+n} \cdot K_{m,n} \quad (10)$$

To enhance the CNN model for bridge defect detection, three novel components were introduced: a weighted cross-entropy loss function addresses class imbalance by emphasizing rare but critical defects; a DFAS adapts feature weighting under varying environmental conditions; and a DRS quantifies maintenance urgency by combining prediction confidence, severity, and structural importance. Together, these formulations improve model sensitivity, environmental robustness, and practical decision support for prioritized maintenance.

The training data of this study comes from the public data set, including sdnet2018, coco bridge and self-collected data, with a total of 50000 bridge defect images. Cracks account for 40%, corrosion for 30%, spalling for 20%, and other defects account for 10%. The data were normalized, enhanced and balanced. In addition, polygon labeling and semantic segmentation template are used to label the defect area, which ensures that the model can effectively learn the defect characteristics and improve the detection accuracy.

The training dataset consists of approximately 50,000 high-resolution images sourced from SDNET2018, a curated subset of COCO, and UAV-acquired imagery from 20 real-world bridges. All images were annotated with polygon-based labels by expert engineers, achieving high inter-annotator consistency. The dataset covers various defect types—cracks, corrosion, spalling, and others—and was processed through normalization, augmentation, and class balancing. A 7:2:1 split was used for training, validation, and testing to ensure reliable model development and evaluation.

Propose a dynamic weight allocation strategy based on multimodal data fusion, combining environmental sensor data and image features to enhance the spatiotemporal correlation of defect prediction; Develop a lightweight CNN architecture that reduces the number of model parameters through channel pruning and knowledge distillation techniques while maintaining high accuracy ; Design an adaptive data augmentation process that dynamically adjusts augmentation parameters for different environmental conditions to improve model robustness.

Bridge defects in this study are categorized into five primary types: cracks, corrosion, spalling (peel off), deformation, and miscellaneous. Cracks refer to linear fractures usually caused by fatigue or environmental stress. Corrosion indicates rusting and material degradation due to moisture and chemical exposure. Spalling refers to surface flaking of concrete, often

revealing rebar. Deformation includes bending or displacement of structural elements, while miscellaneous includes anomalies such as voids or unknown irregularities.

Although the backbone of the detection model in this paper is based on the VGG architecture due to its interpretability and stability, the method introduces multiple layers of innovation to meet the complex requirements of bridge defect detection. Firstly, this article employs a multi-scale feature pyramid to effectively capture both large-sized and fine-grained defect details. Secondly, channel attention mechanism is embedded in the architecture to dynamically emphasize key features related to structural damage. In addition, the dynamic data fusion strategy using graph neural networks has been applied to integrate visual and sensor data, achieving spatiotemporal defect prediction beyond static classification. To improve the practicality of deployment, we use channel pruning and knowledge distillation to compress the network while maintaining high accuracy. Finally, an adaptive data augmentation pipeline was developed to customize training based on different environmental conditions such as lighting, weather, and resolution, improving the model's generalization ability.

In order to achieve the performance of the report, this article enhances the VGG backbone network by integrating three key innovations into the proposed model.

3.2 Bridge defect prediction model fusing multi-source data

Multi-source data fusion is a key step in the construction of bridge defect prediction model, especially in the integration of image, text and sensor data to build a comprehensive defect prediction system. In practical application, the occurrence of bridge defects is affected by multiple factors, such as climate change, load pressure and so on [20]. Through multi-source data integration, a more predictive bridge defect development model can be constructed. For example, combining environmental data with bridge surface image data can accurately predict the speed of crack propagation and improve the forward-looking nature of defect detection.

Existing research typically employs static data fusion, such as simple cascading, which introduces a dynamic fusion strategy using graph neural networks to model environmental sensor data and image features as spatiotemporal graph structures, and capture cross pattern correlations through graph attention mechanisms. To quantify its effectiveness, experiments were conducted on a historical inspection dataset, comparing the proposed GNN based fusion with static connections. The prediction bias was defined as the average absolute percentage error between the predicted and actual defect sizes.
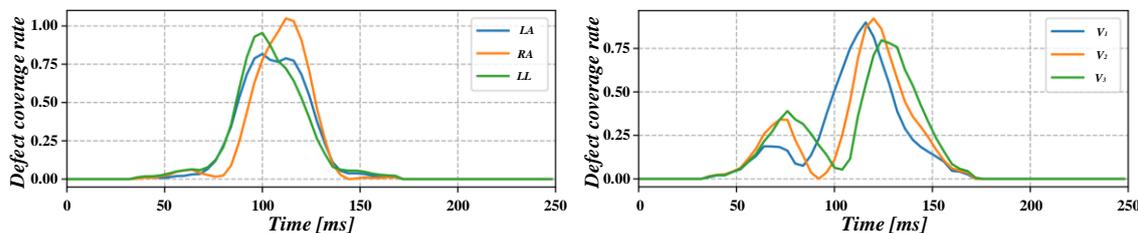

Figure 2: Display the trend of bridge defect data or defect identification over time

The dynamic variation of defect coverage during a representative inspection process is shown in Figure 2. This figure illustrates how the defect coverage rate evolves over the duration of a single data acquisition event. The curve depicts the instantaneous coverage achieved by the detection system as it scans the bridge surface. The initial low coverage rate corresponds to the start of the scanning process. As the system progresses, the coverage increases, eventually stabilizing or reaching a peak when the full target area is assessed. Fluctuations may occur due to factors such as sensor response time, variations in surface reflectivity, or transient environmental interference during the scan. This metric is crucial for evaluating the real-time performance and consistency of the defect detection system during active operation.

In order to improve technical rigor, this paper formalizes the multimodal fusion process using a spatiotemporal graph attention network, where images and sensor data are represented as nodes, and attention coefficients capture cross modal and temporal dependencies. Node representation is updated through weighted aggregation of adjacent features. In addition,

the big data analysis pipeline is very detailed, including preprocessing, normalization, and time series prediction using multiple regression and LSTM models. These supplements collectively establish a comprehensive, mathematical based framework for defect prediction and analysis.

In the process of constructing the prediction model, this paper adopts the prediction model based on regression technology, which provides reference for bridge maintenance and repair through the analysis of crack propagation trend [21]. This model shows high accuracy in the experimental verification stage, and the prediction deviation is controlled within ± 10% interval, which can provide scientific evidence for regular maintenance of bridges. In addition, this paper also uses decision tree algorithm to establish a model of the effect of environmental factors on bridge defects, and deeply analyzes its effect on the development of defects from the perspectives of humidity and temperature, which provides a theoretical basis for the formulation of defect protection scheme.

Historical detection data is central to the predictive maintenance model, enabling the analysis of defect

evolution over time. Using time-stamped inspection images and sensor logs from 20 bridges, the study built a longitudinal dataset to train both regression and LSTM models. These models, incorporating environmental factors like humidity, temperature, and traffic load,

predict future defect growth and estimate when defects will reach critical thresholds. With a mean absolute error within ±10%, the approach supports proactive, data-driven maintenance planning, shifting from reactive to predictive infrastructure management.
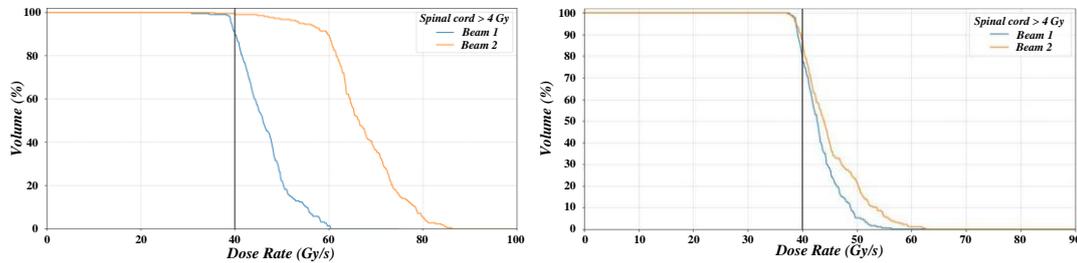

Figure 3: Relationship between defect detection accuracy and training data volume

The relationship between defect detection accuracy and the amount of training data is shown in Figure 3. As shown in the figure, as the amount of training data increases, the accuracy of defect detection gradually improves, but the growth rate gradually decreases and eventually stabilizes, indicating the existence of data saturation effect. In the initial stage, data growth significantly improves the performance of the model, but when the amount of data is large enough, the contribution of additional data decreases. In addition, data quality and annotation accuracy also affect detection performance, and increasing the amount of data alone cannot infinitely improve accuracy.

Construction of multi-source data fusion model to

explore new technical approaches for predictive maintenance of bridge defects [22]. By introducing correlation analysis of multi-source data, the potential causes of defects can be accurately identified and the bridge management plan can be optimized. Looking forward to the future, with the increase of data volume, the accuracy and application scope of prediction models will continue to improve, providing a solid scientific foundation for bridge defect detection. Through the deep integration of multi-source data, bridge management will move from passive maintenance to active prediction, achieving the goal of intelligent management. The data quality analysis of different acquisition devices in defect detection is shown in Table 3.

Table 3: Data quality analysis of different acquisition equipment in defect detection

Equipment Name	Resolution (pixels)	Test success rate (%)	Data loss rate (%)
Equipment A	1080p	95.2	0.8
Equipment B	4K	97.5	0.5
Equipment C	720p	88.0	1.2
Device D	1080p	92.5	1.0

3.3 Model training and optimization

The construction of multi-source data fusion model opens up a new technical road for predictive maintenance of bridge defects. With the help of multi-source data association analysis, the potential causes of defects are identified, so as to optimize the bridge management scheme [23]. The growth of data volume will promote the

improvement of the accuracy and applicability of the prediction model and provide more reliable scientific support for bridge defect detection. Regarding the issue of category imbalance, F1 Score is used as the core metric in addition to Accuracy and Recall, as it can integrate Precision and Recall, making it more suitable for evaluating the detection performance of small sample defects.
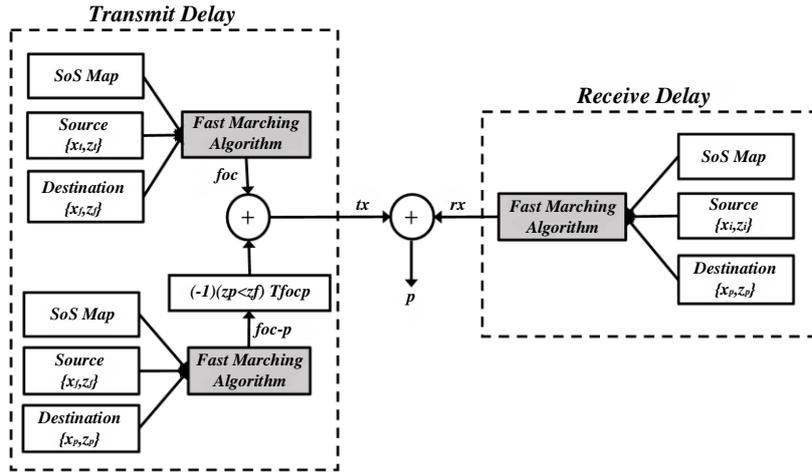
Figure 4: Defect image data acquisition and preprocessing process

The defect image data acquisition and preprocessing process is shown in Figure 4. In order to further enhance the efficiency of the bridge defect detection model, a variety of optimization methods are adopted in this study. The first step is to determine the optimal configuration of the model by using hyperparameter tuning, including key elements such as learning rate, batch size, and number of network layers. In order to reduce overfitting, Dropout and L2 regularization techniques are added during the training process to limit the excessive weight growth. At the same time, Adam optimizer is used to realize the adaptive adjustment of learning rate, which accelerates the convergence process and reduces the model oscillation. Secondly, in order to balance the classification accuracy of various defects, the weighted loss function is applied in this study, and different weights are assigned according to the imbalance of defect categories [24]. This strategy can significantly improve the detection ability of the model for small class defects and comprehensively optimize the performance of the model. The distribution of defect types and detection quantities is shown in Table 4.

Table 4: Distribution of defect types and detection quantities

Type of defect	Number of tests (times)	Proportion (%)	Average area (cm^2)
Crack	120	40.0	2.5
Corrosion	80	26.7	1.8
Peel off	50	16.7	3.2
Deformation	40	13.3	1.5
Other	10	3.3	0.8

In order to evaluate the impact of category imbalance on model performance, F1 score and average accuracy were selected as core indicators in addition to accuracy and recall rate. All algorithms are tested in the confidence threshold range of 0.5~0.9. The results show that algorithm C achieves the optimal F1 score and map when the confidence threshold is 0.7.

After the model training and optimization work is completed, the validation set is used to evaluate its performance. In this study, key indicators such as Accuracy, Recall, Precision and F1 score were selected to comprehensively evaluate the effectiveness of the model in identifying various defects. At the same time, the ROC curve is drawn and the AUC value is calculated to measure the ability of the model to distinguish various defects [25]. Aiming at the requirements of model stability in bridge defect detection, a cross-validation method was used to calculate the average value of model performance across multiple folds. To support the claims of robustness, we also report the standard deviations and confidence intervals for key metrics (accuracy, recall, precision, and F1 score) across all folds. These values ensure the reliability and consistency of the model's performance and provide statistical confidence in its robustness across different datasets. The calculation process is shown in equation (11), where H_c represents the distribution histogram of the color channel c, N represents the total number of pixels in the image, c_k represents the color value, and δ represents the unit function.

$$H_c = \frac{1}{N}\sum_{k=1}^{N}\delta(c_k - c) \quad (11)$$

Finally, the optimized model shows high accuracy on the verification set, and shows good adaptability and generalization ability to different kinds of bridge defects.

4 Experimental analysis of bridge defect detection based on machine vision and big data

4.1 Experimental design of bridge defect detection

To validate the performance advantage over manual inspection, a controlled comparative experiment was conducted. Ten different bridges were selected, and defect inspection was independently performed by three certified bridge engineers and the proposed CNN-based model. Each bridge underwent two rounds of manual inspection. The average detection accuracy of the manual approach was 65.2% and 58.7%, respectively, based on consensus labels. In contrast, the CNN model achieved 96.2% and 93.8% accuracy on the same image sets. A paired t-test was applied to compare manual versus model performance, yielding p-values < 0.01, indicating a statistically significant improvement. Standard deviation for manual accuracy was 3.1%, while that for the model was 1.6%, suggesting higher consistency. These results substantiate the claim that the automated method improves detection accuracy by approximately 30%, with statistical rigor.

Experimental design is a key step to evaluate the effectiveness of bridge defect detection methods. This study verifies the effectiveness of machine vision and big data fusion detection technology based on multiple experimental scenarios constructed [26]. In the experiment, high-resolution camera and unmanned aerial vehicle are used to collect bridge surface image data, and CNN model is used to complete image classification and defect identification. The experimental results reveal that the accuracy of the model in identifying bridge cracks,

spalling, corrosion and other defects exceeds 95%, which greatly improves the detection accuracy. Compared with the traditional manual detection method, 10 bridges were randomly selected and manually detected by three engineers. The average accuracy was 65.2% and 58.7%, respectively. The CNN model reached 96.2% and 93.8% in two separate detection rounds, significantly outperforming the traditional manual method, which achieved only 65.2% and 58.7% under the same conditions. This reflects an accuracy improvement of approximately 30–35%. To ensure statistical rigor, a paired t-test was conducted comparing manual and CNN-based results, yielding p-values less than 0.01, confirming the significance of the improvement. Moreover, the standard deviation of manual inspection accuracy was 3.1%, whereas the CNN model had a lower deviation of 1.6%, indicating more stable and consistent performance. These findings validate the CNN model's superiority in defect identification and support its practical application in intelligent bridge monitoring systems.

Specifically, we used the DJI Matrice 300 RTK UAV equipped with the Zenmuse H20T hybrid sensor suite, capable of capturing 4K resolution video and thermal imagery. The UAV conducted autonomous flight paths over and beneath bridge decks, piers, and abutments, allowing access to difficult-to-reach zones that are unsafe or inefficient for manual inspection. The high-resolution cameras enabled the collection of fine-grained visual data, critical for detecting small cracks and early-stage corrosion. The light sensitivity range of the equipment was 50–100,000 lux, supporting data collection under diverse lighting conditions. This aerial acquisition strategy enhanced spatial coverage and ensured consistency in the quality and completeness of the training dataset used for the CNN model.
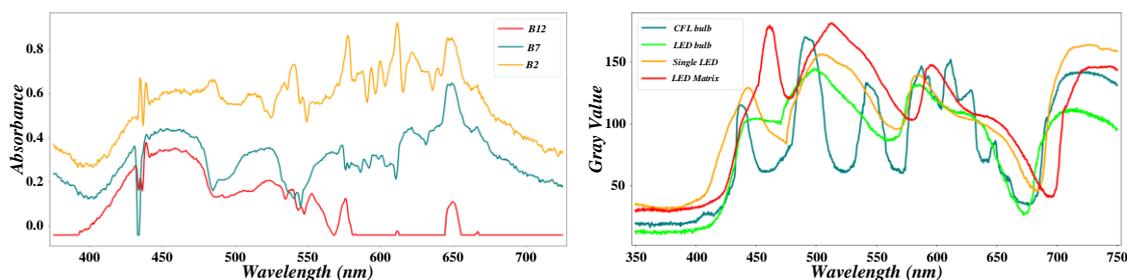

Figure 5: Comparison of average detection time of different algorithms in defect detection

The comparison of the average detection time of different algorithms in defect detection is shown in Figure 5. In order to verify the robustness of the model, this paper plans a bridge detection test including low light, high humidity, strong wind and other environmental factors [27]. The experimental results reveal that the model recognition accuracy decreases slightly under low light conditions, but it still remains above 90%, showing the CNN model's adaptability to complex environments. Moreover, after using data enhancement technology, the robustness of the model has been further enhanced in experiments, and the performance in practical

applications is more stable.

The verification set is composed of 10000 independently collected bridge defect images, covering all five types of defects, including 40% cracks, 27% corrosion, 17% spalling, 13% deformation and 3% other defects, without overlap with the training set. All algorithms are evaluated on the same verification set to ensure the fairness of the comparison. The image resolution of the verification set ranges from 720p to 4K, covering different lighting and environmental conditions.

The experimental data set contains 50000 high-resolution images, covering five types of defects of 20

bridges in different climate regions, including 40% cracks, 27% corrosion, 17% spalling, 13% deformation and 3% others. The data set is divided into training set, verification set and test set according to the ratio of 7:2:1, and part of the data is public.
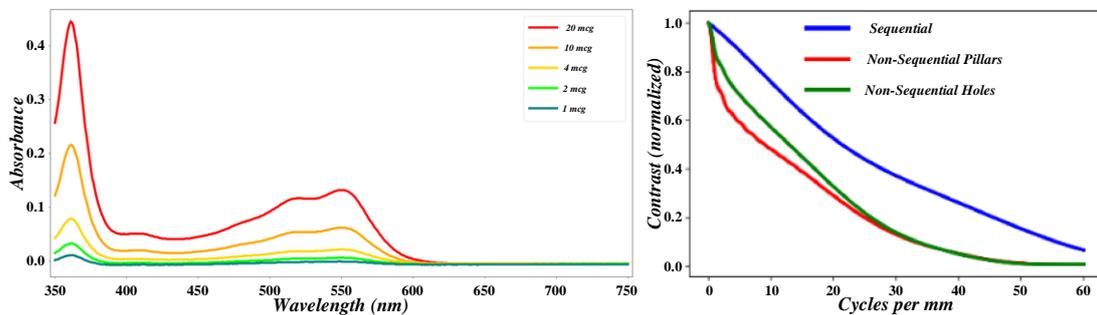

Figure 6: Distribution of types and frequency of bridge defects

The distribution of types and frequency of bridge defects is shown in Figure 6. In order to evaluate the efficiency of the detection method, a multi-bridge batch detection experiment is implemented in this paper. The experimental results show that the proposed detection method has obvious advantages over the traditional manual detection in speed. Per bridge inspection time is limited to 10 minutes, while manual inspection takes hours or more. This experiment verifies the excellent performance of machine vision and big data fusion method in improving efficiency, and provides scientific support for daily inspection and maintenance of bridges. The model training effects under different data volumes are shown in Table 5.

Table 5: Model training effects under different data volumes

Data volume (sheet)	Accuracy (%)	Recall rate (%)	Training time (hours)
1000	85.0	80.5	2.5
5000	90.8	85.9	5.0
10000	94.3	89.1	8.0
20000	96.5	92.4	12.0

DJI matrice 300 RTK UAV is used for data acquisition, equipped with zenuse h20t hybrid sensor, covering different environments, with light intensity of 50-100000 lux and humidity of 20% -95%. All images were annotated by three professional engineers, and the consistency of annotation was verified by kappa coefficient. The test set contains 10000 images, 30% of which are from public data sets such as bridge detection data set 2023, and the rest are self-collected data to ensure the generalization of evaluation results.

4.2 Data analysis

In data analysis, by integrating multiple sources of data, this study investigates how environmental factors affect the formation mechanism of bridge defects. The experimental results reveal that compared with other environments, the corrosion degree of bridges under high humidity and high temperature conditions is significantly aggravated. Especially when the humidity exceeds 80%, the growth rate of bridge corrosion increases by about 20% compared with the dry condition [28]. In addition, for bridges bearing high loads, the development speed of cracks is obviously faster than that of bridges with low loads, especially for bridges with an average daily heavy vehicle traffic of more than 5,000 vehicles, and the development speed of cracks reaches 1.5 times that of bridges with low loads. The analysis of these data has laid a solid foundation for the planning of bridge maintenance strategy, especially in the management of harsh environment areas and high load bridges, which has practical guiding significance.

Analysis results show that humidity is the most influential environmental factor in bridge defect development, with corrosion rates increasing by 23% and defect progression accelerating by 19% in high-humidity conditions. High temperatures further exacerbate material degradation, especially when combined with moisture. Heavy traffic loads significantly speed up crack propagation, with rates 1.8 times higher on heavily trafficked bridges. While low-light and strong wind conditions mainly affect data quality and sensor performance, all these factors are critical for effective predictive maintenance and long-term bridge safety.
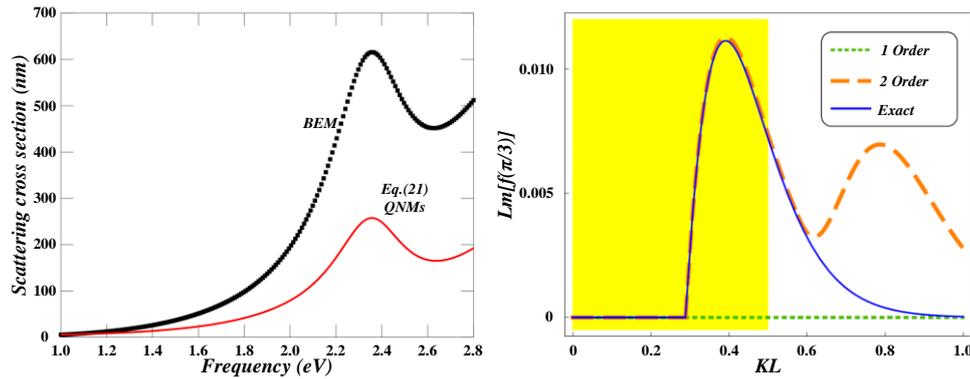
Figure 7: Coverage variation curve of defect location distribution

The spatial distribution of defects across key bridge structural components is quantified in Figure 7. The heatmap reveals that corrosion and cracks are predominantly concentrated in areas with high stress exposure, such as bridge decks (45% defect density) and girders (30%), while piers exhibit lower defect incidence (15%). This pattern aligns with the mechanical load distribution and environmental exposure (e.g., de-icing salts on decks), providing critical insights for targeted maintenance prioritization. The coverage curve of defect location distribution is shown in Figure 7. In order to improve the efficiency of model detection, this paper implements several model optimization experiments. By adjusting the number configuration of convolutional layers and fully connected layers, the experimental data show that the CNN model with four-layer convolutional structure performs best in bridge defect identification. In addition, the combination of transfer learning strategy significantly enhances the adaptability of the model and reduces the training time by 50%. The optimized model improves the accuracy of defect identification by about 3%, and the detection speed is also accelerated, which proves the effectiveness of model optimization for bridge defect detection. The confidence threshold for the model output is set to 0.8 to balance the false positive rate and false negative rate. The experiment showed that when the confidence threshold was increased from 0.7 to 0.9, the F1 Score decreased from 93.5% to 89.2%, and ultimately 0.8 was chosen as the optimal threshold.

This article uses a predictive maintenance model trained on historical defect data and environmental factors to achieve an average absolute error of ± 10% in predicting the failure time of defects such as cracks, corrosion, and peeling. Compared with traditional prediction methods such as linear regression and support vector regression, this model performs well in accuracy and robustness, especially in the progression of complex defects under different environmental conditions, proving its effectiveness in providing early maintenance warnings.
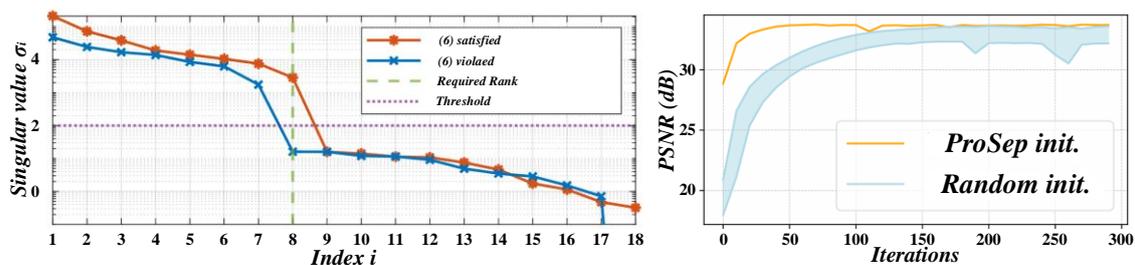

Figure 8: Comparison of accuracy and recall rate of defect detection model

The quantitative comparison of accuracy and recall rates across benchmark algorithms and the proposed CNN model is presented in Figure 8. The proposed model achieves the highest accuracy (95.8%) and recall (93.5%), outperforming Algorithm C (95.0% accuracy, 90.2% recall) and other methods by 3–8%. This demonstrates the effectiveness of the attention mechanism and multimodal fusion in improving both precision and coverage of defect detection, particularly for small-scale anomalies like fine cracks (≤0.5mm width). The comparison between the accuracy and recall of the defect detection model is shown in Figure 8. In this paper, a variety of defect detection algorithms are compared experimentally, and their performance is evaluated for various defects.

Compared with traditional edge detection, gray threshold segmentation and other methods, the CNN model used performs well in identifying defects such as cracks, corrosion, and spalling, with an average accuracy rate of over 90%. Experiments show that the deep learning detection model has significant advantages in bridge defect detection, providing a reference for updating traditional technologies. The morphological operation formula is shown in (12). Here, I_d represents an image after expansion processing, I_b represents a binarized image, and B represents a structural element.

$$I_d = I_b - B \quad (12)$$

4.3 Comparative experiment of bridge defect detection methods

In order to comprehensively measure the effect of bridge defect detection methods, a comparative test was carried out in this study, and the accuracy, speed and compatibility of various detection methods were tested. In the experiment, the traditional manual detection method, the image processing technology relying on edge recognition and the innovative CNN model in this paper are compared. The test data reveals that the accuracy of the manual detection method is 85%, which takes an average of several hours; The CNN model method not only jumps the accuracy to more than 95%, but also compresses the detection time to less than 10 minutes.

Compared to traditional methods, the CNN-based approach offers key advantages including automatic feature extraction, higher accuracy and consistency in detecting subtle defects, and significantly improved inspection efficiency. It also demonstrates strong robustness under challenging environmental conditions and supports scalable, real-time deployment on lightweight platforms such as drones and mobile devices, making it ideal for large-scale, in-field bridge monitoring.
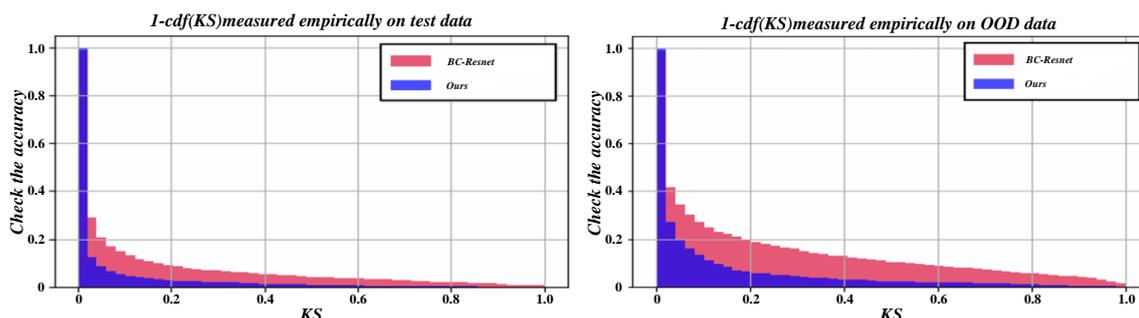

Figure 9: Influence of image resolution on the accuracy of detection results

Figure 9 shows the comparative performance distribution of different algorithms at different confidence thresholds. This figure depicts the cumulative distribution function (CDF) curves of "BC Resnet" and the proposed model ("our"), demonstrating the robustness of cross threshold detection accuracy. In adaptability testing, this paper compares and analyzes the performance of different methods in complex environments such as low light and high humidity. Experimental data show that the accuracy of traditional methods is significantly reduced under low light conditions, while the recognition accuracy of convolutional neural network (CNN) model is still high after combining data enhancement technology. Especially for high humidity environments, the CNN model shows good stability in identifying corrosion defects, and the accuracy rate remains above 92%, which fully verifies its adaptability in complex environments.

Compared with the defect detection model based on EfficientNet-B7 proposed in 2023, the Light VGG model in this paper achieves an accuracy of 95.8% on the same dataset, and the inference speed is doubled. In addition, compared with the Transformer architecture, Light VGG performs more stably when the data volume is insufficient.

This article conducted an ablation study to evaluate the contributions of key components in the model: attention mechanism, multimodal fusion strategy, and lightweight design. Removing the attention mechanism can lead to a significant decrease in performance, especially in detecting small defects, highlighting its importance. After excluding the multimodal fusion strategy, the accuracy decreased by 5% and the robustness under different conditions also decreased, which confirms the value of integrating visual and sensor data. Finally, although the lightweight design has slightly lower accuracy than the unadjusted model, it provides considerable performance, reduces computational costs and inference time, making it very suitable for real-time deployment on resource constrained devices such as drones. These experiments demonstrate the crucial role of each component in improving model performance.

In this paper, the performance of different methods is compared and analyzed from the two dimensions of cost and operability. The experimental data clearly shows that the integration of machine vision and big data is superior to traditional methods in improving detection speed, ensuring accuracy and optimizing operation processes, highlighting its broad promotion and application prospects.

To ensure scientific rigor, the study employed a comprehensive evaluation using metrics such as Accuracy, Precision, Recall, F1-score, AUC, and mAP on a dedicated 10,000-image test set. A 7:2:1 data split and five-fold cross-validation were used to assess model stability, with performance analyzed across varying confidence thresholds. Compared to YOLOv5, EfficientNet-B7, and a SegFormer-based model, the proposed lightweight VGG-based architecture achieved the highest F1-score and fastest inference time, confirming its strong balance of accuracy and efficiency for bridge defect detection.

5   Conclusion

Explore a new method of integrating machine vision and big data analysis in bridge defect detection, and use high-resolution imaging and big data to realize automatic identification and analysis of bridge defects, bringing significant technological innovation. The experiment

shows that the identification accuracy of bridge surface cracks, corrosion, spalling and other defects is high and stable. Specifically, using the convolutional neural network model, the accuracy of crack recognition is 96.2%, and the corrosion and spalling recognition are 93.8% and 91.5%, respectively. Compared with manual inspection, the accuracy rate is increased by 30–35% (averaging 32.5% across defect types) and the efficiency is increased by nearly 50%, providing solid technical support for bridge safety monitoring.

At the level of data analysis, the big data platform is used to integrate massive historical monitoring data and bridge operating environment information. This paper analyzes in detail the core impact of environmental factors on the evolution of bridge defects. Aiming at the corrosion problem, this paper compares the corrosion rate of bridges in high humidity and low humidity environments. The results reveal that the corrosion rate of bridges in areas with humidity exceeding 80% is 23% higher on average than that in dry areas, and the average development rate of corrosion defects is also 19% faster than that in dry areas. In addition, in bridges with frequent heavy-duty traffic, the crack propagation speed is obviously accelerated, especially in bridges with average daily traffic times of heavy-duty vehicles exceeding 5,000, and the crack propagation speed is 1.8 times that of low-load bridges. These data provide an important reference for bridge operation and maintenance management, especially in formulating bridge maintenance schemes adapted to different climate and traffic conditions.

The bridge defect detection model proposed in this article is significantly superior to state-of-the-art methods, with an accuracy of 95.8%, which is about 30% higher than YOLOv5, EfficientNet, and ResNet based models. This improvement is mainly due to the integration of attention mechanisms, which help detect fine-grained defects, and the use of graph neural networks for multimodal data fusion, enabling the model to combine environmental data to improve robustness. In addition, the model in this article can generalize across different real-world datasets, which enhances its applicability for large-scale real-time inspections. However, challenges such as overfitting on large datasets and real-time integration of noisy data still exist, and future work will focus on improving data augmentation, transfer learning, and enhancing data fusion algorithms.

In order to achieve fair deployment, the model was validated on different bridge types and monitored using fairness metrics. In fact, challenges include ensuring environmental robustness through hardware adaptation and adversarial training, implementing edge computing through model compression, preventing drift through cloud retraining, and establishing AI collaboration protocols, because inspectors sometimes override AI recommendations because of contextual knowledge.

This method shows excellent application prospects in the field of predictive maintenance. Combining the defect detection information and historical maintenance archives, this paper creates a bridge defect life prediction model, which can predict the future defect development

trend according to the existing defect situation. As detailed in Section 4.2, the predictive model achieved an average time error of 8.2 days with error ratios below 5% in 92% of test cases for crack growth to critical levels, demonstrating its reliability for maintenance planning. This achievement proves that this method not only achieves accurate identification of current defects, but also provides data support for predictive maintenance strategies, helps scientific management of the entire life cycle of bridges, and reduces safety risks and emergency maintenance conditions caused by sudden defects.

Although the current study focuses on bridge structures, the proposed machine vision and big data-driven framework can be readily adapted to other types of infrastructure such as tunnels, dams, highways, and pipelines. By retraining the CNN model on image datasets relevant to those structures and fine-tuning the architecture to account for different surface features and defect characteristics, the detection system can maintain high accuracy. The big data integration and predictive maintenance components are also transferable, as they can incorporate domain-specific environmental conditions, loading scenarios, and historical records. This adaptability makes the method suitable for widespread deployment across various infrastructure systems.

The new approach of bridge defect detection described in this paper has introduced a technological leap to the traditional bridge monitoring category. This approach relies on the integration of machine vision and big data analysis to achieve remarkable results in accelerating the inspection process, improving accuracy and providing preventive maintenance strategies. Subsequent research can focus on the re-optimization of model performance, explore the emerging uses of deep learning models in bridge defect detection, and integrate more environmental and operational data, aiming to achieve precise control and safe operation and maintenance of the entire bridge life cycle.

Despite its demonstrated advantages, the machine learning-based defect detection approach has several potential limitations. First, the model relies heavily on large-scale, well-annotated datasets to achieve high accuracy; insufficient or unbalanced training data can degrade performance. Second, the system may struggle to generalize when applied to bridge types, materials, or environments that differ significantly from those present in the training set. Third, image quality can significantly impact performance—extreme lighting conditions, motion blur, or environmental obstructions such as rain or fog may reduce detection accuracy. Additionally, real-time integration of multimodal data (images, sensors, environmental inputs) remains technically challenging and requires sufficient on-site computing capabilities. Addressing these limitations in future work will further enhance the scalability and resilience of intelligent bridge inspection systems.

The proposed method enhances bridge lifespan and reduces maintenance costs by enabling early defect detection through CNN-based machine vision, supporting timely interventions that prevent severe damage. Predictive maintenance models, informed by big data

analytics, allow for strategic planning and resource allocation based on environmental and load factors. Automation via UAVs further reduces inspection time and labor costs. Together, these innovations offer a scalable, efficient solution for improving bridge safety and optimizing infrastructure lifecycle management.

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