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CIVIL ENGINEERING

A BIM technology-based underwater structure damage identification and management method

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Abstract. With the continuous development of bridge technology, the condition assessment of large bridges has gradually attracted attention. Structural Health Monitoring (SHM) technology provides valuable information about the existing health of the structure, keeping it safe and uninterrupted use under various operating conditions by mitigating risks and hazards on time. At the same time, the problem of bridge underwater structure disease is becoming more obvious, affecting the safe operation of the bridge structure. It is necessary to test the underwater structure of the bridge. This paper develops a health monitoring system for a bridge underwater structure by combining building information modeling (BIM) and an underwater structure damage algorithm. This paper is verified by multiple image recognition networks, and compared with the advantages of different networks, the YOLOV4 network is used as the main body to improve, and a lightweight convolutional neural network (Lite-yolov4) is built. At the same time, the accuracy of disease identification and the performance of each network are tested in various experimental environments, and the reliability of the underwater structure detection link is verified.

Key words: building information modeling; underwater structural disease; damage identification; deep learning.

1. INTRODUCTION

Bridges are an important part of the transportation system. With the continuous advancement of technology, the span of bridge construction is increasing, and the length and width of bridge construction are constantly breaking new records. This also determines that bridges play an increasingly important role in national economic construction, bringing considerable economic and social benefits. Therefore, the owners pay more and more attention to the safe operation of the bridge and the state of the bridge. Under the combined action of the natural environment, external loads, aging structural materials, and other factors, the sufficient bearing capacity of bridges will be irreversibly reduced, thus affecting the safe operation of bridges [1]. In extreme cases, it can lead to serious accidents. The development of society has put forward higher requirements on the bearing capacity of bridges.

In most countries, bridges have entered a stage of reinforcement and maintenance. According to America's Infrastructure Report Card 2021 [2], there are more than 617,000 bridges across the United States. Currently, 42 percent of bridges are at least 50 years old, and 46,154 or 7.5 percent of the national bridges, are considered structurally defective. The most recent estimate of the U.S. backlog of bridge repair needs is $125 billion. In the process of bridge inspection and maintenance, the traditional inspection and evaluation methods have problems such as being time-consuming, a large number of participants, and complex processes, which lead to huge costs. Structural health monitoring (SHM) systems are gradually being applied with more advantageous economic costs and the ability to adapt to development. For example, various types of sensors, such as acceleration sensors, strain gauges, and GPS (Global Positioning System) devices, are installed on bridges such as the Tsing Ma Bridge [3], the Akashi Kaikyo Bridge in Japan [4], and the Hong Kong-Zhuhai-Macao Bridge [5]. For long-term health monitoring services. The SHM system changes the traditional bridge maintenance method from "short-term based" to "full life cycle", in which the sensor network monitors key structures around the clock, marks the damage location in time when damage occurs, and provides preliminary solutions [6–9]. In addition to detecting the occurrence of damage at an early stage, a stable SHM system can monitor certain bridge parameters, evaluate bridge performance under various operating loads, validate or update the codes used during the design phase, and prioritize maintenance and repair classes. However, the bridge mentioned above health monitoring system needs to be strengthened in its intuitive visualization. Combining the highly visualized BIM software with the SHM system can effectively avoid this defect.

With the advent of SHM systems, bridge maintenance costs were reduced by avoiding time-consuming inspection and evaluation processes, and great progress was made in automatically detecting surface damage in bridges. Deng *et al*. [10] proposed a BIM-based bridge health status safety warning and information integration management method. The functional plugins of visual warning and monitoring information management were integrated into Revit software through the Revit API interface to form a front-end visual carrier. One should associate

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the BIM model with the monitoring database to improve the visualization and integration of the monitoring system. Brendan McGuire *et al*. [11] mentioned the need for a software systems approach to assist decision-makers in the operation and maintenance (OM) phase of bridge life cycle phases. BIM can benefit bridge managers as a graphical tool, with its 3D visualization capabilities and parametric models that can detail the volume of the disease. Researchers can more intuitively extract the data they want. Qin *et al*. [12] applied advanced BIM technology to a bridge management system (BMS) to simulate repair and test results, and more efficiently and economically guide the repair work of bridge structures. The whole life cycle performance of bridge structures is improved and the collaborative management of bridge life cycle information is realized. Boddupalli *et al*. [13] regard Building Information Modeling (BIM) as a computing environment and an integrated data display platform for SHM, which can store a large amount of sensor data and structural health information in the database and import it into the BIM environment. The above research combines the advantages of BIM with the SHM system, solves the problem of insufficient visualization of the SHM system, and improves the health monitoring problem of the water part of the bridge on land and the bridge in the water.

The development of the bridge health monitoring system (SHM) is relatively complete, but there are still some deficiencies. In the underwater structure of bridges, the methods of bridge health monitoring still lack the external detection of bridge underwater structures.

Due to initial defects and external loads, there will be different types and degrees of damage in the use of materials, and cracks are the most common material damage. Concrete is one of the most commonly used materials in construction engineering. The intelligent identification of concrete cracks is not only conducive to the health monitoring of the damage degree of existing structures but also provides a reference for the intelligent identification of cracks in other materials. Under the background of the API development of computer technology, the method of crack detection begins to develop in the direction of computer vision images. Due to the powerful capabilities of artificial intelligence, many deep learning algorithms are applied to the intelligent identification of material defects and the optimal design of material parameters. Chen and Jahanshahi proposed a deep learning framework based on a convolutional neural network (CNN) and a naive Bayesian data fusion scheme called NB-CNN [14] for analyzing a single video frame for crack detection, applying a new data fusion scheme is proposed to integrate the information extracted from each video frame, enhance the overall performance and robustness of the system, and improve the detection efficiency. Cha *et al*. proposed [15] a method to detect concrete cracks using a deep architecture of a convolutional neural network (CNN) without computing defect features. Atha and Jahanshahi [16] introduced different methods for the corrosion assessment of metal surfaces based on convolutional neural networks. The effects of different colour spaces, sliding window sizes, and convolutional neural network architectures are discussed. The proposed smaller architectures Corrosion7 and Corrosion5 can achieve a similar signal-to-noise ratio to ZF Net, slightly less stable but faster than VGG-16 and VGG-15. Saeed Moradi and Zayed [17] employ a hidden Markov model (HMM) for a proportional data modelling algorithm to automatically detect sewer defects from the data obtained from CCTV inspection videos, performing real-time anomaly detection and localization. The training model size of FCN proposed by Li *et al*. [18] is smaller, the FCN-based method can provide good damage detection results, and the number of parameters has a significant advantage compared to SegNet. Liang [19] proposed a post-disaster bridge detection method based on three-level images. Based on Bayesian optimization, three corresponding deep-learning models are sequentially developed and trained with VGG-16. When the corresponding labeled training data is available, the proposed method is suitable for identifying damage to other structural components of bridges. Cao Vu Dung *et al*. [20] developed a method that uses the concept of transfer learning as an alternative to training the original neural network to reliably detect cracks. A shallow convolutional neural network built from scratch, a VGG-16 network architecture trained on the generic ImageNet dataset, and the top layers of VGG-16 fine-tuning are studied. Combined with data augmentation, the best crack detection performance is achieved in the gusset plate joints of steel bridges. To improve the detection accuracy of blurred cracks, Wenbo Jiang *et al*. [21] proposed the HDCB-Net – a deep learning-based network with the hybrid dilated convolutional block (HDCB) for pixel-level crack detection. The research of the above-mentioned personnel conforms to the development of the times and uses deep learning algorithms and image recognition to improve the efficiency of damage detection. Bridge crack detection methods are gradually increasing, such as drone detection of bridge cracks [22, 23]. However, most researchers more frequently applied image detection to damage identification in the above-water structural parts of bridges, and less often in the underwater parts due to the complex underwater environment. In this paper, we consider a variety of complex environments and attempt to apply the improved YOLOv4 network to underwater structure detection. At the same time, there are fewer methods for monitoring underwater structures on bridges and some stand-alone inspection methods are not compatible with the SHM system. Combining an underwater structure inspection with a BIM system can fill this gap.

Building information modelling (BIM) technology has been widely used since it was first introduced in 1974 [24]. BIM is an open platform with information integration and engineering features [25]. It can provide a visual and developable digital expression environment for health monitoring, and effectively improve monitoring information visualization and information sharing. In this paper, combining the advantages of BIM technology and underwater structure damage algorithm, a BIM-based bridge underwater structure monitoring system is established. This article divides into the following parts. First, the damage identification method and the proposed system framework are introduced in Section 2. A specific case study is then discussed in Section 3. Finally, research gaps and further research are discussed and conclusions are drawn.

2. BRIDGE UNDERWATER STRUCTURE MONITORING

2.1. Bridge underwater structure monitoring module system design

The underwater structure of bridges is a part of bridges, and the importance of underwater structure detection is gradually increasing. Compared with bridge deck inspection, underwater structure inspection is more difficult to operate and requires professional underwater operators. Based on BIM technology, combined with the underwater structure detection method, the monitoring function of the underwater structure is realized. The architecture of the underwater structure monitoring module is shown in Fig. 1.

The new module mainly includes three contents: bridge information model, underwater structure detection, and damage data management; the bridge information model is built with Revit software and contains certain basic bridge information. In the underwater structure detection module, the basic information on the bridge can be inquired, the bridge Revit model can be browsed, and the bridge model and the bridge damage database can be regarded as a whole to carry out the overall system design. According to the above design requirements, a plug-in for underwater structure detection based on Revit software and C# programming language was developed. The integrated application of Revit and underwater structural damage monitoring realizes the display of inspection information and inspection results in the BIM model. The method of realizing the system main functional modules is as follows.

2.1.1. Bridge underwater structure information model

Bridge foundation structure is an important part of bridges. A 3D bridge infrastructure model is established in Revit. After the bridge disease (cracks, concrete falling off, etc.) detection information is imported into the system, the selected bridge infrastructure model can be monitored and analyzed. Bridge maintenance is performed by querying detection information. The visual part of detection information includes information management and information processing. To realize the function of this module, we developed a visualization plug-in using Revit API in the Visual Studio development environment. The bridge damage module allows users to view bridge damage detection data. Through the bridge disease analysis, the evaluation of the structural state is realized. Through the two data nodes of bridge name and detection time, the creation of bridge disease inspection items and bridge disease management is realized.

2.1.2. Structural damage database

SQL SERVER 2012 is used as the software support for the bridge structural damage database. The communication between detection data and the REVIT API interface is realized in the C# programming language. The overall architecture adopts a hierarchical approach to clarify the relationship between data. The top layer adds disease inspection: including the bridge name, the bridge disease detection time, and the bridge model file. The next level of the bridge contains the detection of the bridge structure, that is, the photos of the bridge structure damage, the location of the bridge damage, and the concrete damage of the bridge structure. After the system identifies the bridge damage, the structural damage photos will be saved, downloaded, and uploaded to the bridge damage module.

2.2. Underwater structure detection module

The underwater structure detection module consists of two parts: underwater structure camera structure data acquisition and bridge crack damage identification algorithm. The underwater structure camera scans and extracts the apparent feature data of the bridge structure and uses the improved damage identification algorithm (Lite-yolov4) to identify and verify the collected data. During the identification process, the algorithm identified the crack damage to the bridge underwater structure and marked the damaged data. The marked damage data will be saved to the database.

2.2.1. Underwater image acquisition system

To obtain underwater structure information, this paper adopts the method of an underwater robot equipped with a binocular camera. The onboard camera is an ordinary binocular camera, sealed with a self-designed sealing structure. The underwater structure image acquisition system is shown in Fig. 2.

2.2.2. Bridge underwater structural damage recognition algorithm

The mainstream target detection algorithms are broadly classified into one-stage (e.g. R-CNN [26]) and two-stage (e.g. Yolo series). The YOLO series, which is part of the regression target detection network [27], offers higher detection accuracy and faster real-time detection.

The core idea of the YOLO series is to solve the target detection as a regression problem and use an end-to-end network to

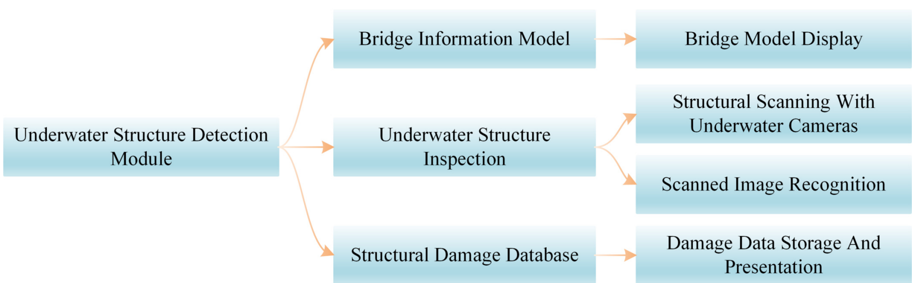


Fig. 1. Structural design of underwater structure detection module

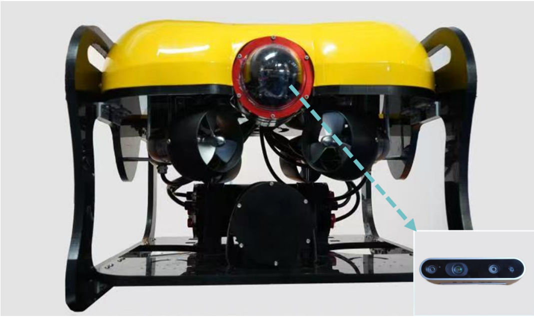


Fig. 2. Underwater image acquisition system: binocular camera and underwater vehicle

input the target image into the model, which outputs the target type and marks the object position in the image [28].

The YOLOv4 backbone feature extraction network is improved based on the YOLOv3 backbone (darknet-53) and proposes a CSPdarknet-53 feature extraction network. CSPnet divides darknet residual blocks into two parts, one of which continues to stack residual blocks as the backbone, and the other is directly connected after simple processing. This improved method reduces the amount of network computation and avoids the problem of gradient disappearance.

The YOLOv4 uses SPP and PANet structures as feature fusion networks. The SPP structure maximizes the pooling of feature maps, converts them into feature maps of different scales, and then enters them into the PANet network to stitch them together with the original feature map. This part upsamples and downsamples the three feature layers extracted through the backbone feature extraction network to obtain three optimized features with more generalization.

The prediction network outputs three feature graphs, respectively, to detect a large, medium, and tiny target. Each point in the feature graph has three prediction boxes, and the offset, width, and height of the prediction box are set, as well as the type and position of the final output target.

In summary, based on YOLOv4, this paper studies a lightweight convolutional neural network Lite-YOLOv4, which can be used in mobile devices. The following specific improvements are made based on the original YOLOv4:

1. Mobilenetv3 replaces CSPDarkent as the backbone feature extraction network and modifies the feature layer scale of Mobilenetv3 to connect it with the subsequent network. The extracted preliminary feature layer is input to the enhanced feature extraction network for feature fusion.
2. A large number of 3×3 ordinary convolutions are used in the PANet network. This paper replaces ordinary convolutions with 3×3 depth wise separable convolutions to reduce the amount of computation.
3. The prior box is improved. The original three feature output layers are changed into one output layer.

The structure of the improved YOLO-v4 network model, namely the lightweight network model Lite-YOLO-V4, is shown in Fig. 3.

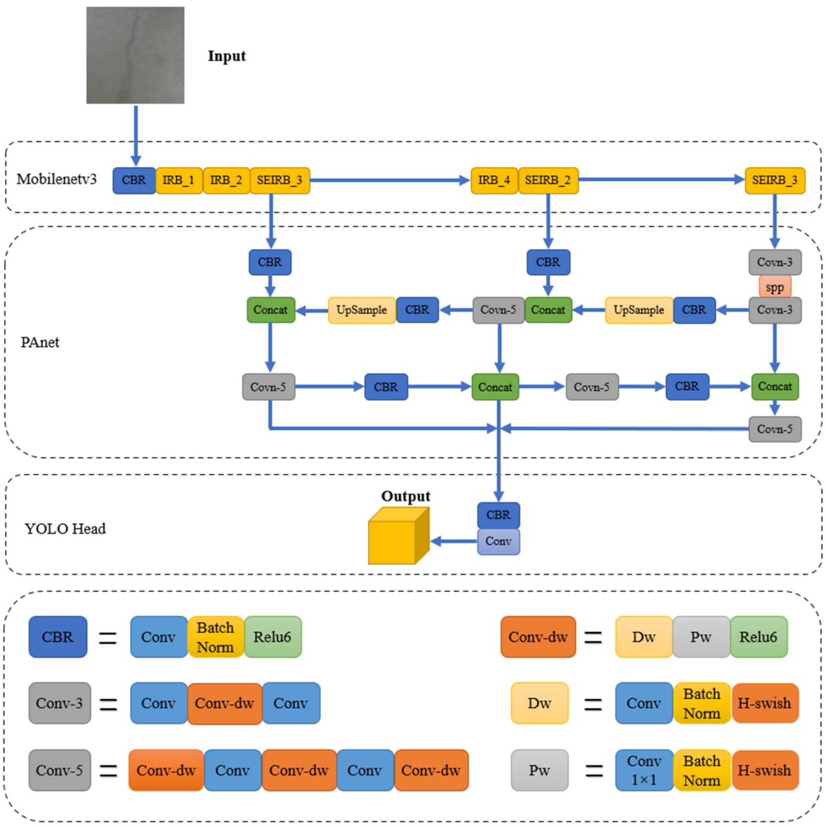


Fig. 3. Structure of the Lite-YOLO-v4 crack detection algorithm

3. BRIDGE UNDERWATER STRUCTURE MONITORING MODULE IMPLEMENTATION

3.1. Experimental environment

Bridge underwater crack detection model experiments use the TensorFlow framework to build the network. The processor running deep learning is the NVIDIA Quadro K1200 model GPU with a video memory of 4 GB and using the deep learning platform TensorFlow-GPU = 1.13.2, Keras = 2.1.5. The data set in this experiment mainly comes from materials provided by a bridge underwater inspection company and collected from the Internet. After processing, a total of 8,780 pictures were collected. The different underwater crack environments are mainly divided into the clear water environment, muddy water environment, and deepwater environment. Among them, the deepwater environment has an overall greenish image due to the absorption of light by water. The underwater crack pictures are marked by Labeling software, and the prepared data set is divided into a training set and a test machine according to the ratio of 8:2. Figure 4 shows some photos of the three types of environments.

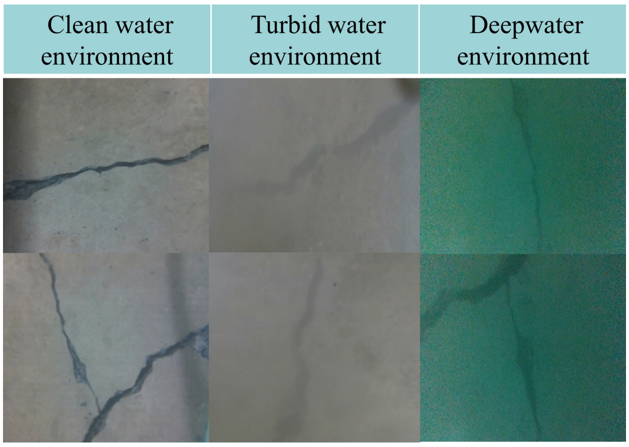


Fig. 4. Partial underwater crack image

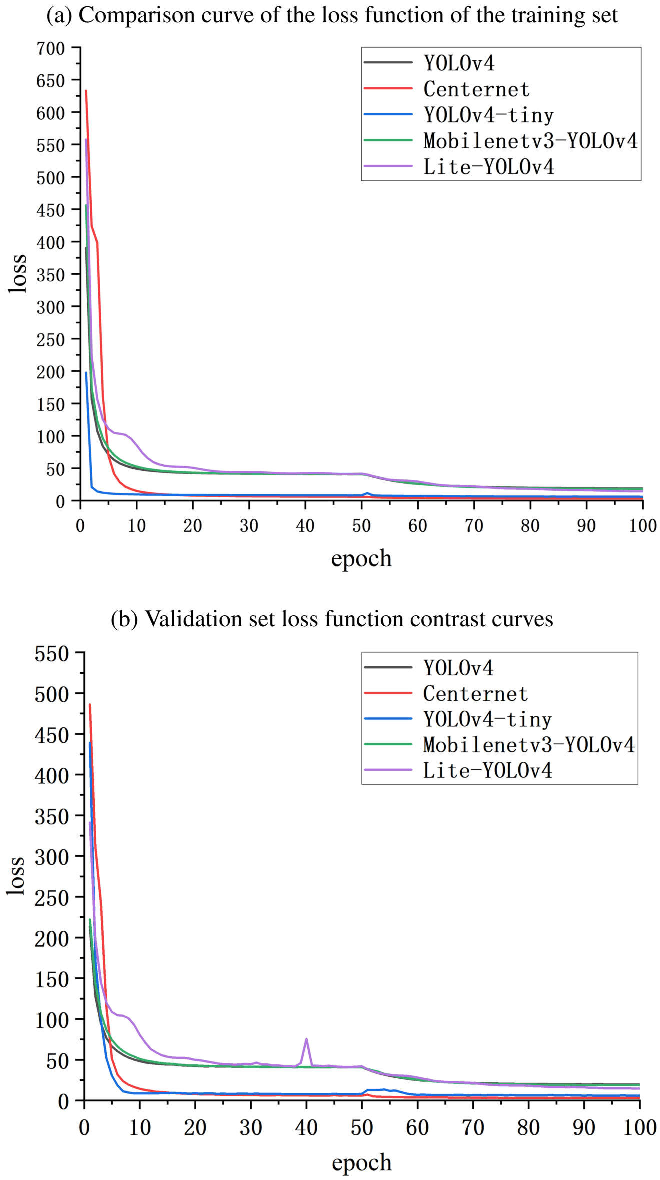


Fig. 5. Model loss function plot

3.2. Experiment results and analysis

In this section, to verify the improvement of detection accuracy and speed of the model studied in this paper, the model is compared with CenterNet, YOLO-v4, YOLO-v4-tiny, and Mobilenetv3-YOLO-v4 algorithms. All models were trained with the same training parameters and data sets. Figure 5 shows the loss function curves of the five models. It can be seen that the training set and validation set loss functions of the five networks can converge at 15 epochs. This indicates that the training parameters of the dataset and model set established in this paper are appropriate. There is no over-fitting phenomenon in the training effect of the five models, and each model training results are reliable. The network can be used for the comparison experiment of the actual detection effect later.

To more accurately evaluate the training results of the above five network models, this paper adds common indicators for the evaluation of convolutional neural networks. The specific evaluation index data of the five networks in this paper are shown in Table 1.

As shown in Table 1, when conducting underwater crack detection, the model size of the improved Lite-YOLOv4 network is 20% of the original, and the average detection accuracy is 7.13% lower than that of the YOLOv4 network. However, the detection speed is 178% higher than that of the YOLOv4 network. At the same time, the training speed is greatly improved compared with the YOLOv4 network. It can meet the requirements of real-time detection of mobile equipment with low computational power. Compared with the CenterNet network, the model size is only 40% of CenterNet. The detection frame rate increases by 66.7%, and the training speed is also greatly improved. Compared with the YOLOv4-tiny network, the average detection accuracy is increased by 10.21%. The detection speed is increased by 78%, the training time is 25% of the original, and the difference between the other data indicators is very small. The comprehensive comparison shows that the comprehensive performance of the network in this paper is

Table 1
Values of the five model indicators under the crack dataset

Model	Recall	Precision	mAP	FPS	Model Size/MB	Training Time/epoch
YOLOv4	53.61%	95.62%	84.2%	9	244	15 min
CenterNet	48.53%	94.31%	77.1%	15	125	8 min
YOLOv4-tiny	40.03%	87.64%	66.86%	27	22.5	1.5 min
Mobilenet v3-YOLOv4	41.03%	91.2%	75.13%	14	152	9 min
Lite-YOLOv4	47.98%	93.97%	77.07%	25	44.3	2 min

effectively improved, which is more conducive to small mobile devices.

The above table proves that the network in this paper has a noticeable improvement compared with other networks, but there is no actual detection effect for comparison. To make the experiment more complete, the detection results of the five models are compared from different detection environments, angles, and crack shapes.

3.2.1. Model detection results under three detection environments

By comparing the crack detection experiments under different working conditions, it can be proved that this network can improve the overall performance of the network compared with other networks while improving the detection speed and can ensure accurate crack detection under complex working conditions. This network can be applied to the actual detection of underwater cracks in bridges. As shown in Fig. 6, there are significant differences between the five networks for crack detection in the three underwater environments and the detection of tiny cracks. YOLOv4 and CenterNet are comparable for detecting tiny cracks, but there are some missed detections; YOLOv4-tiny has multiple overlapping detection frames, Mobilenetv3-YOLOv4 has the worst detection effect and the most severe missed detection phenomenon, and Lite-YOLOv4 has the best detection effect. In the deep water environment, the first four networks all have some leakage; CenterNet has the most severe overlap of detection frames, and the detection frames heavily obscure the cracks; Lite-YOLOv4 has the best detection results. In turbid water, CenterNet could not detect cracks; YOLOv4-tiny and Mobilenetv3-YOLOv4 networks had some missed detection; YOLOv4 and Lite-YOLOv4 networks were comparable. In the clear water environment, YOLOv4 and Lite-YOLOv4 network detection were the best, and YOLOv4-tiny and Mobilenetv3-YOLO-v4 had some misdetection cases.

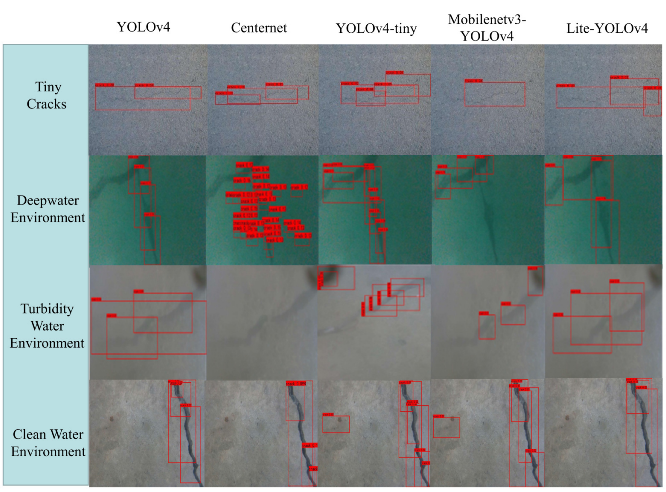


Fig. 6. Comparison of model detection effects in a clean water environment

3.3. System function verification

In this paper, the developed bridge underwater structure disease management module, underwater structure model visualization, and Lite-YoloV4 identification of bridge underwater structure cracks are applied to bridge underwater structure detection. The applicability of the bridge structure detection module in the detection process is verified, and the usability of lite-YOLOv4 on equipment and the universality of underwater structure detection is verified by experiments. Based on the main pier foundation of Changshan Bridge, this paper carries out systematic verification, which is divided into the following processes:

Step 1:

Establish the BIM model of the main pier foundation of Changshan Bridge and realize the visualization function. In bridge detection, there are certain differences in the primary data of the tested bridge, so it is necessary to establish the BIM model of the bridge independently by referring to the data of each bridge. Because of the differences between the bridge frames, the basic member family library of each bridge frame is established. In the process of building the overall model of the bridge, each part of the bridge is named and numbered according to the naming rule to facilitate the subsequent process to retrieve the corresponding data.

Step 2:

Import the established bridge pier foundation model into the system. REVIT API provides convenience for the secondary development of functions with Revit software. Use the API interface to establish a system to realize the visualization of the bridge model, open the model from the file project, display the bridge model, and perform some series of operations on the bridge model. The visualization of the model is shown in Fig. 7.

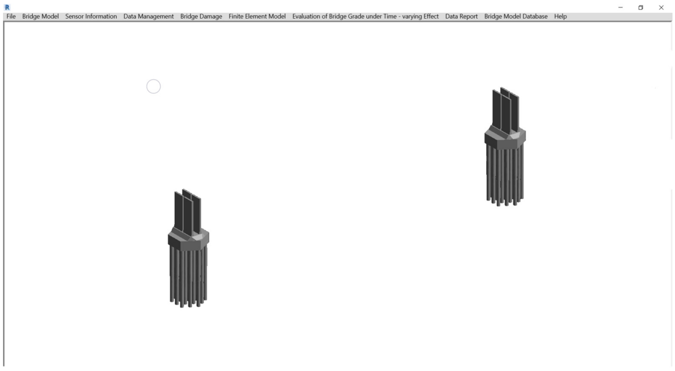


Fig. 7. Visualization of the bridge foundation model

Step 3:

Establish a bridge foundation inspection model database. The inspection item information is established according to the inspected bridge name, bridge inspection time, and bridge model information. The successful establishment of the project is shown in Fig. 8.

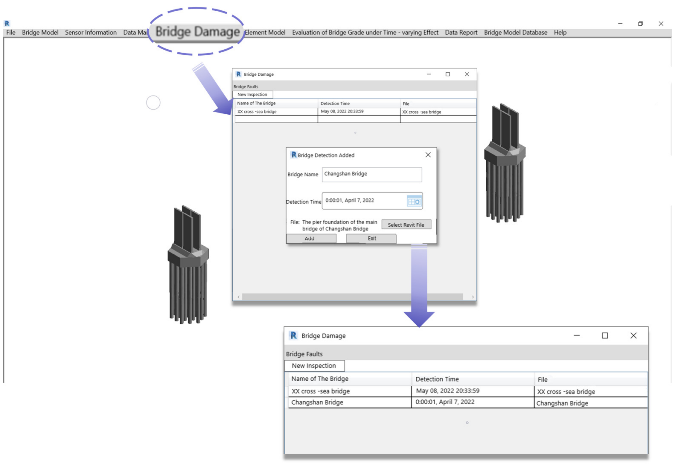


Fig. 8. Establish a bridge foundation disease inspection database

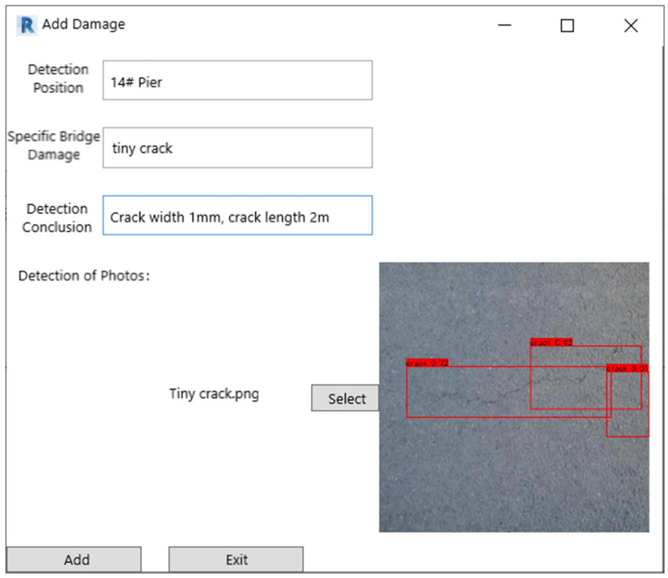
Step 4:

Structural damage identification. The experimental results in Section 3.2 fully show the advantages of Lite-Yolov4 in bridge underwater crack identification. The Lite-Yolov4 network can adapt to the complex underwater environment, accurately detect the damage to the bridge underwater structure, and save the detection results.

Step 5:

Damage to the underwater structure of the bridge is added. The damage addition of bridge structure includes four parts: detection location, specific damage, detection conclusion, and photos of bridge underwater structure damage detection in the fourth step. Fill in the form according to the test results and store the actual images of the test site in the system. The system arranges information according to the filling order, facilitating the subsequent test results review. Clicking on the bridge inspection photo will enlarge it, which helps review the inspection results. Damage addition is shown in Fig. 9.

(a) Tiny crack damage import



(b) Underwater crack damage query

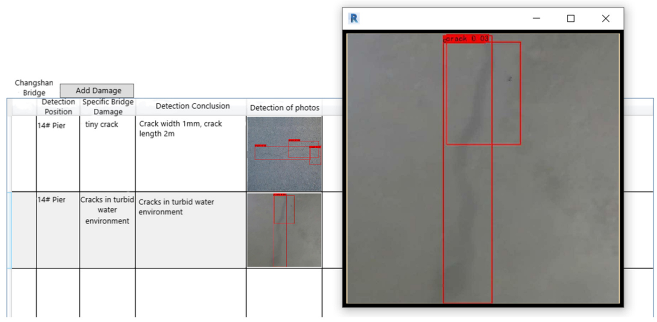


Fig. 9. Damage data import and damage data query

4. DISCUSSION AND CONCLUSION

The bridge structure monitoring system is becoming increasingly perfect, the number of various sensors installed in each part of the bridge structure is increasing, the bridge monitoring information obtained is more complete, and the structural status of the bridge can be more accurately judged based on the monitoring information. With the continuous advancement of bridge technology, the bridge structure has become increasingly complex. Still, due to the complexity of the underwater environment, the bridge structure monitoring system has certain deficiencies in monitoring the underwater structure of wading bridges. This paper mainly studies how to combine BIM technology with underwater bridge structural damage identification to further improve the ability and detection effect of underwater structure detection.

Based on the Revit software, this paper uses the Revit secondary development tool Revit API and uses C# as the programming language of the system to design the SQL Server database according to the detection content. Using a special underwater detection camera, the system integrates the underwater structure damage identification algorithm to identify the bridge structure damage and realizes the bridge underwater structure health monitoring module. Using the Revit API development tool, the bridge model can be visualized in the system, and the bridge BIM model can be imported into the system. At the same time, the bridge underwater structure damage data management module is implemented to effectively manage the bridge underwater structure monitoring data.

Due to the complexity of the underwater environment, it is difficult to detect the underwater structure of bridges. Bridge underwater structure detection is the core link of this system. To verify the reliability of the core links, a variety of underwater environments (clear water environment, deep water environment, turbid water environment) and three kinds of cracks (single crack, network crack, and microcrack) are designed to test the reliability of the network. The damage identification algorithm needs to use many computing resources, but the Lite-YOLOv4 algorithm proposed in this paper can significantly reduce the amount of computation. The lightweight neural network based on YOLOv4 used in this paper removes the classification layer and output layer from Mobilenetv3, replaces the CSPDarkent53 network structure, and serves as the backbone feature extraction network of YOLOv4. In the residual network, a lightweight attention mechanism is introduced, and the PANet structure. A large number of ordinary convolutions are replaced by depthwise separable convolutions. Multi-feature fusion is performed on the prior box. The amount of parameters and computation of the improved network model is greatly reduced, and the model size is only 1/5 of the original, which improves the detection efficiency while ensuring detection accuracy. By comparing with the commonly used damage identification algorithms YOLOv4, CenterNet, YOLOv4-tiny, and Mobilenetv3-YOLOv4, it is found that although the Lite-YOLOv4 algorithm in this paper reduces the amount of calculation, the algorithm identification accuracy can be comparable to the YOLOv4 complete network. In the network identification speed, the improvement is noticeable, and it can be better applied to complex underwater environment detection. It can also ensure accurate crack detection under tough working conditions and deploy embedded equipment to detect bridge underwater cracks.

To develop and verify the function of this system, a BIM model of the bridge is established based on the actual data of a particular bridge. The BIM model of the bridge is used to verify the system visualization function. The components of the bridge are numbered reasonably, which lays the foundation for the establishment of the bridge damaged database. At the same time, the secondary development system, under the support of the underwater camera and the damage identification algorithm Lite-yolov4, adds the damage identification results to the bridge damage database to complete the entire process of bridge damage identification and management. The comprehensive results show that the system runs well and the damage identification algorithm has certain stability and reliability.

In addition, the Revit API provides many additional interfaces for the design and development of the system. Other functions can also be developed on an existing basis to further improve the system functions.

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