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DEVELOPMENT OF AN AUTOMATED SURFACE CRACK DETECTION AND BIM-INTEGRATED MANAGEMENT SYSTEM FOR CONCRETE BRIDGES

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Abstract. Bridge inspection work typically requires inspectors to capture hundreds to thousands of images, consuming substantial time for review. This research developed an "Automated Crack Image Cloud Detection System" and the "Auto Predictor" application, enabling automatic crack identification and deterioration image recognition through uploads. This platform integrates with the "Bridge BIM Cloud Management System", connecting crack information with three-dimensional models. Engineers can create BIM models based on structural design drawings, while inspectors can photograph cracks and integrate relevant information. The study utilized deterioration images from long-term bridge inspections in Taiwan, covering various real-world environmental conditions. Through effective deterioration labeling strategies and comparing YOLOv4 and YOLOv7 algorithms with recommended parameters, an optimal model was obtained for system implementation. Research results demonstrate that the "Automated Crack Image Cloud Detection System" successfully identified cracks in bridge inspections and short beam shear test specimens. The deep integration with the "Bridge BIM Cloud Management System" enables automatic component crack identification and generates location charts, providing decision-makers with intuitive visual data. The YOLOv7-based model achieved a mean Average Precision (mAP) of 87.64%, significantly improving bridge inspection efficiency and demonstrating exceptional application potential.

Keywords: bridge inspection, Deep Learning, Artificial Intelligence, crack detection, automation, BIM, management.

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1. Introduction

According to current statistics from the Ministry of Transportation and Communications, there are nearly 27,000 bridges in Taiwan (Su et al., 2018). Among these, more than 22,000 bridges are managed and maintained by local governments, while the rest are managed by various agencies, including the Directorate General of Highways and the National Expressway Engineering Bureau. As the ages of these bridges increase, the workforce demands for maintenance will increase. The current maintenance agencies primarily rely on the "Highway Bridge Inspection and Reinforcement Standards" issued by the Ministry of Transportation and Communications, training materials, and related data (Song et al., 2014) to conduct safety inspections for highway bridges. Bridge inspections can be divided into three categories: routine inspections, special inspections, and detailed inspections. In general, each bridge must be inspected at least once every two years, requiring substantial personnel from both the government and private engineering consulting companies. Bridge inspections are based on visual inspections, and the assessment is often subjective, leading to inconsistencies in evaluation standards.

To enhance the efficiency and accuracy of bridge inspections, this study aims to develop an "Automated Crack Image Cloud Detection System" to improve existing bridge inspection methods and reduce the likelihood of oversight. This cloud platform will integrate a "Bridge BIM Cloud Management System", allowing engineers to create BIM bridge models based on structural design drawings and incorporate inspection data into these models. This integration facilitates the continuous application of bridge inspections in the future, providing more comprehensive management and maintenance.

Regarding the dataset used for training the models, this study utilized degradation images captured during long-term bridge inspection work in Taiwan and combined

YOLOv4 and YOLOv7 for model training to achieve crack recognition. In comparison to other studies, such as that of Li et al. (2023), which employed Faster R-CNN for bridge crack detection, although they achieved commendable results, their computational efficiency was lower, and their capacity to process large-scale datasets was limited. Furthermore, Kruachottikul et al. (2021) explored deep learning-based image processing techniques, which improved accuracy but still lacked adaptability to varying environmental conditions. The contribution of this study lies in training the model specifically for the Taiwanese environment, enabling YOLOv4 and YOLOv7 to achieve a mean Average Precision (mAP) of 87.64% in crack detection, significantly enhancing both detection accuracy and efficiency. This achievement not only provides a more reliable technical foundation for bridge inspections but also serves as a reference for future related research on model selection and training methodologies. Moreover, Davila Delgado et al. (2017) studied the integration of BIM and Application Programming Interfaces (APIs), proposing an API-based bridge monitoring system capable of real-time data collection and analysis, along with providing visual reports. However, this system primarily focuses on data collection and management, lacking sufficient integration with automated image recognition. In contrast, this study not only integrates BIM and APIs but also incorporates automated crack detection technology within the system, establishing a comprehensive monitoring and maintenance framework. This contribution enhances the efficiency and accuracy of bridge maintenance and provides a viable implementation template for future research. Future continuation plans will include ongoing research on degradation scoring mechanisms to further refine the automation of the bridge inspection system.

2. Background and research methodology

In the United States, bridge inspections are predominantly performed based on the PONTIS system developed by the Federal Highway Administration and the BRIDGIT system (Thompson et al., 1998). In Europe, various countries have different bridge management systems. These include the DANBRO system currently used in Denmark (Lauridsen & Lassen, 1999), BridgeMan used in the United Kingdom (Bevc et al., 1999), Edouard employed in France, and the National Road Administration Management System applied in Finland (Kivimäki & Heikkilä, 2010). In Asia, the SHBMS system is utilized in South Korea, J-BMS is employed in Japan (Miyamoto & Motoshita, 2015), and the CBMS3000 system is used in China. In Taiwan, the government initiated the development of the Taiwan Area Bridge Management Information System in November 1999. The system, abbreviated as TBMS, was completed by the end of 2000 and developed further in 2013.

In recent years, with the widespread application of Building Information Modeling (BIM) management systems, an increasing number of bridge management systems have begun to integrate BIM technology to enhance inspection efficiency and maintenance accuracy. Research indicates that BIM technology not only effectively integrates deterioration images captured during bridge inspections with relevant data but also facilitates data querying and application for future engineering management units. Furthermore, a study by Byun et al. (2021) proposed a BIM-based bridge maintenance system that considers maintenance data architecture and information systems, demonstrating the potential application value of BIM in bridge maintenance. The application of BIM in the design and maintenance processes of bridges provides more intuitive visualization tools to assist engineers in decision-making (Azhar et al., 2012), and through data analysis and simulation, it enhances the overall performance of bridges (Kassem & Succar, 2015). Additionally, research combining BIM with traditional inspection methods has shown that this integrated approach can significantly improve inspection accuracy and efficiency while reducing labor and time costs. Moreover, it has been noted that BIM technology can enhance the efficiency of bridge inspections and improve the accuracy of maintenance management through data integration (Li & Zhang, 2022). Furthermore, BIM effectively integrates various inspection technologies, including drone and sensor data, further enhancing the comprehensiveness and precision of inspections (Maqsood & Memon, 2021).

In addition, image recognition can be achieved through deep learning techniques (Lu et al., 2018; Chan, 2019). One critical deep learning model is the convolutional neural network (CNN). In 1998, Yann LeCun applied CNNs to classify handwritten digits, leading to the development of the LeNet5 model (LeCun et al., 1998). This laid the foundation for subsequent advancements in CNNs. In 2020 and 2022, YOLOv4 (Bochkovskiy et al., 2020) and YOLOv7 (Wang et al., 2023) were introduced respectively, which can simultaneously detect multiple objects and their positions, thereby achieving real-time detection with high accuracy. Compared to YOLOv4, YOLOv7 has demonstrated improvements in both speed and accuracy, particularly excelling in the detection of small objects. YOLOv7 employs an enhanced algorithmic architecture that incorporates deeper network layers and more effective feature extraction techniques, allowing it to capture details more effectively when processing complex scenes. Additionally, YOLOv7 introduces multi-scale feature fusion technology, which is particularly crucial for the detection of small objects, as it enables simultaneous detection at different resolutions, significantly improving the recognition rate of small objects. In the selection of deep learning techniques, this study adopts the YOLO series models primarily due to their advantages in real-time detection and computational efficiency. Compared to the widely used Transformer-based architectures in object detection, such as DEtection TRansformer (DETR) (Carion et al., 2020) and Swin Transformer (Liu et al., 2021), the YOLO series demonstrates higher computational efficiency and practicality when processing large-scale bridge inspection images. While Transformer architectures offer advantages in global feature extraction (Khan et al., 2022), their higher computational cost and model complexity may limit their performance in real-time applications (Tay et al., 2022). Furthermore, compared to the recently proposed CNN-Transformer hybrid architectures, the YOLO series models maintain excellent detection accuracy and speed under limited computational resources. The improved architecture of YOLOv7, particularly its capabilities in multi-scale feature fusion and small object detection, provides higher accuracy and stability for bridge crack detection. The choice of YOLOv7 in this study is not only based on its superior performance but also its deployment convenience and low computational cost, which are critical for establishing practical bridge inspection systems (Dosovitskiy et al., 2021). In civil engineering, some researchers have employed deep learning techniques such as DeepLabv3+ and Mask R-CNN, applying the outcomes of these models in structural health monitoring in the field of structural engineering (Hsu et al., 2021; Hsieh, 2018). This study selects the YOLO series algorithms primarily due to their superior performance in real-time detection, along with their commendable accuracy and speed, making them particularly suitable for civil engineering applications that require rapid response.

With the advancement of deep learning technology, an increasing number of researchers are using this technology to detect and classify cracks on roads and buildings (Opara et al., 2021; Zhang et al., 2022; Tong et al., 2018; Rezaie et al., 2020). Zhang et al. (2021) utilized one-dimensional convolutional neural networks (1D-CNNs) and recurrent neural networks (RNNs) such as long short-term memory (LSTM) networks in the frequency domain to train image recognition models using images of cracks in concrete bridges. They achieved high accuracy due to the limited number of convolutional layers in the model, resulting in shorter training times. However, one drawback of their model is that it recognizes fewer and simpler features than other models, making it more suitable for detecting defects in metal materials. Japanese scholars used YOLOv3, trained with 900 images of cracks, to detect bridge deterioration (Dang et al., 2021). Crack recognition models using YOLOv4 were also applied to study aerated concrete samples (Beskopylny et al., 2023). Researchers have employed various image processing techniques, such as capturing images under different acquisition conditions, rotation angles, object deformations, and lighting conditions. This approach expanded the dataset of deteriorated images, ultimately resulting in an accuracy rate of AP@50 = 85%.

In the field of networking technology, HTTP serves as the foundation for contemporary internet applications (World Wide Web Consortium, 2022; Berners-Lee et al., 1996; Fielding et al., 1999; Krishnamurthy et al., 1999). Communication interfaces employing this protocol are utilized in a wide range of applications, including mobile apps and embedded devices. These interfaces consist of two endpoints: the client and the server. The client is typically the user, who inputs a specific IP address to access the server. The status code is used to rapidly determine the success or failure of message transmission between the two endpoints, aiding in the quick resolution of any issues. Clients use HTTP methods such as GET to query server resources and POST to add resources. By combining HTTP methods with web application design principles (Jailia et al., 2016), the cloud platforms have been established.

In this study, the HTTP communication protocol is planned to be utilized alongside programming languages such as Laravel, PHP, Python, and C (Laravel, 2022; Python Software Foundation, 2023) to develop an "Automated Crack Image Cloud Detection System". This system includes the construction of a server, the design of a web API, the development of a deterioration detection module, a data analysis module, and an auto predictor application, as well as a "Bridge BIM Cloud Management System". This infrastructure enables the automated uploading of deteriorated images, crack image recognition, result downloading, and report generation on the developed cloud platform, thereby achieving automated crack detection while integrating BIM bridge models for deterioration records.

To train the crack image detection model, deteriorated bridge inspection images acquired in Taiwan are used in the training, validation, and testing datasets. These images not only depict the specific deterioration characteristics of bridges in Taiwan but also reflect the unique crack patterns found in Taiwanese bridges. The image content includes the essential elements needed by bridge inspection personnel. This approach distinguishes this study from previous studies on crack image detection in bridge deterioration, which used less original training images and relied on image processing techniques, such as image cropping, to augment the dataset. Such methods may not adequately represent the deteriorated characteristics resulting from long-term environmental impacts and usage habits specific to the bridges in this region.

3. Collection of deterioration images and training of the crack image recognition model

3.1. Deterioration images

Taiwan currently employs the Bridge Management System (TBMS2) for managing its bridge infrastructure. This system utilizes a standardized bridge evaluation form to document inspection findings and store corresponding images of deterioration. To facilitate component identification, TBMS2 assigns unique codes to elements such as girders, abutments, and piers. Inspectors systematically assess the condition of each component, recording details such as location, quantity, damage type, and potential causes. Furthermore, the system allows for recommendations on repair methods and associated costs. This comprehensive data enables engineers to effectively manage inspection and maintenance tasks, ultimately enhancing both efficiency and safety in bridge maintenance operations, as shown in Table 1 in real case scenarios.

Table 1. Bridge regular inspection form (Su et al., 2018)

<table>
<tr><th>Inspection Items</th><th>Location</th><th>Number</th><th>D</th><th>E</th><th>R</th><th>U</th><th colspan="2">Damage Location</th><th>Deterioration Type</th><th>Cause of Damage</th></tr>
<tr><td>Pier/Cap beam</td><td>P004</td><td>P4</td><td>3</td><td>1</td><td>2</td><td>2</td><td colspan="2">P4 Backside of Cap Beam</td><td>Concrete Structural Crack</td><td>Visible cracks in concrete with infiltration</td></tr>
<tr><th colspan="7">Recommended Repair Method</th><th>Quantity</th><th>Unit</th><th>Unit Repair Price (NTD)</th><th>Remarks</th></tr>
<tr><td colspan="7">0.3mm Concrete Crack Repair</td><td>2</td><td>meters</td><td>700</td><td>P4 Visible concrete cracks with infiltration on the backside of cap beam, 2M*1 site.</td></tr>
<tr><td>Inspection Photos
Date of Capture
2020/03/11</td><td colspan="10">
</td></tr>
</table>

To facilitate the identification of individual bridge components, the TBMS2 system employs a unique coding system using a combination of letters and numbers. Each code starts with a specific letter that designates the component type, followed by a sequential number assigned according to the component's position along the bridge, typically from the abutment at the starting point to the ending abutment. For instance, spans are denoted by the letter "S" and numbered sequentially from the starting abutment, such as S1, S2, and S3, representing the first, second, and third spans, respectively. Similarly, girders are represented by "G", abutments by "A", and piers by "P", all numbered sequentially. Therefore, within the TBMS2 system, "S1G2" refers to the second girder on the first span, and "P1-1" indicates the first sub-component of the first pier. This systematic coding scheme enables users to effortlessly identify and distinguish different structural elements within a bridge, as illustrated in Figure 1.

During the inspection, each component's condition is investigated according to the procedure. Bridge deterioration manifests in various forms, primarily categorized as structural damage and surface deterioration. Structural damage significantly compromises the load-carrying capacity and safety of bridges. Examples include *structural cracks* that penetrate bridge decks, beams, and columns, as well as *corrosion* of reinforcement, leading to *spalling* of concrete and reduced structural durability. Surface deterioration primarily impacts the aesthetics and service life of bridges. This category encompasses issues such as *infiltration*, which causes deterioration of internal bridge materials due to moisture; *efflorescence*, which affects the bridge's appearance; and *trusty stains* on metal components. These deterioration phenomena often interact and accelerate bridge degradation. Therefore, timely inspection and maintenance are crucial to ensuring the safety and proper functioning of bridges, as shown in Figure 2. The "Highway Bridge Inspection and Retrofitting Code" provides assessment tables for various bridge components (Su et al., 2018). In the assessment tables for each component, there are items related to concrete structural crack evaluation, including degree (D), relevancy (R), and urgency (U) scores. During the evaluation process, in addition to considering the width of cracks, it is essential to assess whether water infiltration has occurred. When water infiltrates concrete cracks, steel reinforcement corrosion can occur, reducing the effective cross-sectional area and affecting the concrete design strength. This emphasizes the significance of crack detection in bridge inspections. Therefore, the deteriorated images collected for this study primarily include cracks and are mainly acquired from bridge inspections in Taiwan, with a final dataset of 4,307 images.

3.2. YOLO deep learning model algorithm

The YOLO algorithm was introduced in 2015 and can recognize dynamic postures of pedestrians and vehicles. In addition, 2D image classification and 3D recognition technologies have been extensively developed (Lin et al., 2019; Chang et al., 2017). In this study, the YOLOv4 and YOLOv7 algorithm (Redmon et al., 2016; Bochkovskiy et al., 2020; WongKinYiu, 2023) were employed for training the crack image recognition model for deteriorated images. Initial training was conducted on the Colab platform (Google, 2021), followed by further training on a workstation. The model's training results were evaluated based on the intersection over union (IOU) and mean average precision (mAP) metrics. The definition of the IOU metric is illustrated in Figure 3, where "predict bounding box" represents the boundaries of the predicted object, and "ground truth" represents the boundaries of the actual object.

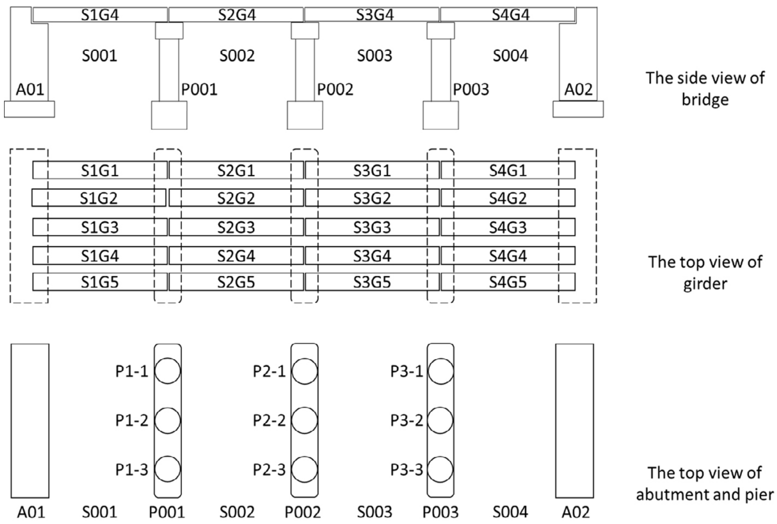


Figure 1. Diagram of component coding method

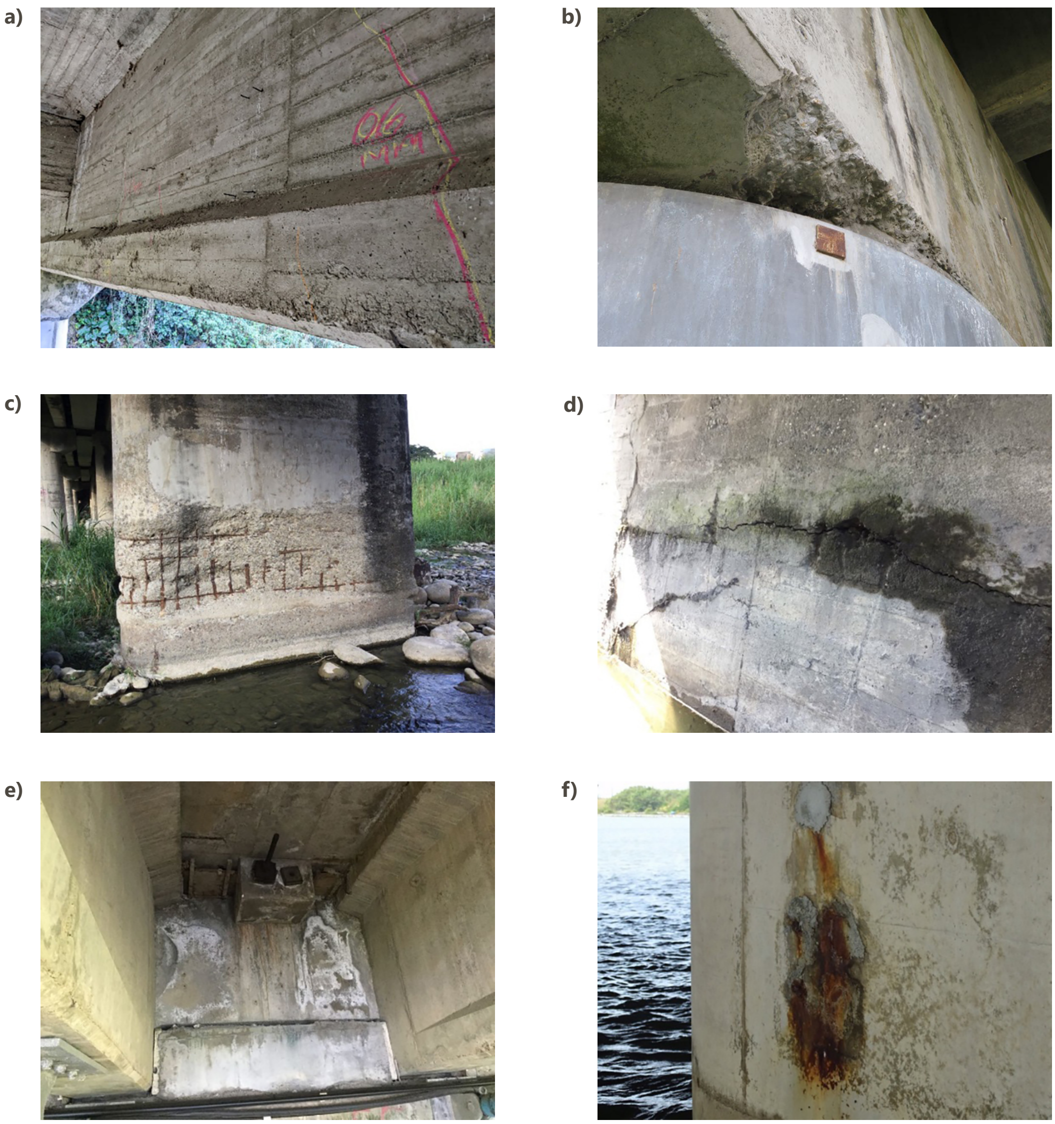


Figure 2. Typical deterioration patterns, with: a – structural crack; b – spalling; c – corrosion; d – infiltration; e – efflorescence; and f – rusty stain

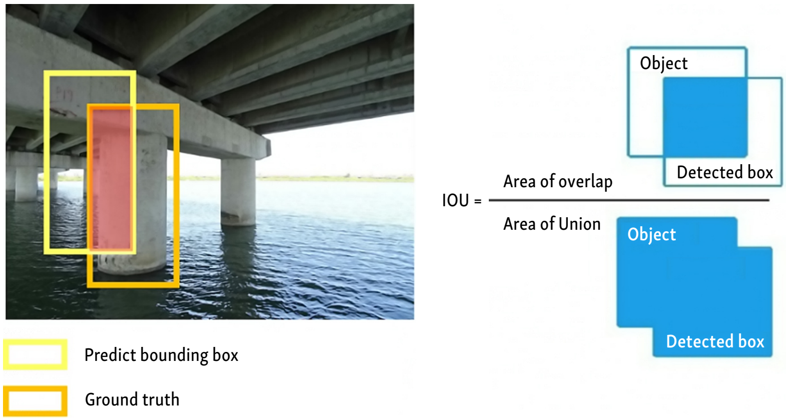


Figure 3. Definition of IOU (intersection over union)

The mAP is calculated as the average of the sums of the average precision (AP) values for each category. The AP is defined as the area under the precision-recall (PR) curve. The X-axis of this curve represents the recall, while the Y-axis represents the precision (Pedregosa et al., 2011). The calculation formula is presented in Eqn (1), where $P(k)$ represents the precision at a given recall point, and $rel(k)$ denotes the true positive (TP) value (1 or 0) (Zhu, 2004). The definitions of the precision and recall are provided in Eqns (2) and (3), respectively:

$$AveP = \frac{\sum_{k=1}^{n} \left(P(k) \times rel(k)\right)}{\text{number of relevant documents}}; \quad (1)$$

$$\text{precision} = \frac{TP}{TP + FP}; \quad (2)$$

$$\text{recall} = \frac{TP}{TP + FN}. \quad (3)$$

3.3. Training workflow for the crack image recognition model

The training of deep learning neural networks consists of five main phases, as shown in Figure 4. First, the model makes predictions based on the training data, which are then evaluated by the loss function. Subsequently, the optimizer updates the model's weights and biases. This process repeats iteratively until the model converges. The dataset is divided into training and validation sets in a 4:1 ratio, with annotation performed using open-source software (Tzutalin, 2021). The validation set helps accelerate model convergence during training. The loss function comprises three core components: 1. Object localization loss (IOU loss): Evaluates the overlap between predicted and actual annotation boxes; 2. Confidence loss: Measures the model's confidence in its predictions; 3. Classification loss: Assesses the accuracy of category predictions. The calculation of the loss function is detailed in Eqns (4) to (8) (Guo et al., 2021). Additionally, pretrained weights and parameter settings are specified in Table 2. These parameter configurations not only expedite model convergence but also ensure optimal training results.

$$L_{ciou} = 1 - IoU + \frac{\rho^2\left(b, b^{gt}\right)}{c^2} + \frac{\beta\upsilon^2}{\left(1 - Iou\right) + \upsilon}; \quad (4)$$

$$\upsilon = \frac{4}{\pi^2}\left(\tan^{-1}\frac{w^{gt}}{h^{gt}} - \tan^{-1}\frac{w}{h}\right)^2; \quad (5)$$

$$L_{confidence} = \sum_{i=0}^{S\times S}\sum_{j=0}^{M} -1_{ij}^{obj}\left[\hat{C}_i \log C_i + \left(1-\hat{C}_i\right)\log\left(1-C_i\right)\right] - \lambda_{noobj}\sum_{i=0}^{S\times S}\sum_{j=0}^{M} 1_{ij}^{noobj}\left[\hat{C}_i \log C_i + \left(1-\hat{C}_i\right)\log\left(1-C_i\right)\right]; \quad (6)$$

$$L_{class} = \sum_{i=0}^{S*S} 1_{ij}^{obj} \sum_{t\in classes}\left[\left(\hat{P}_i(t)\right)^{\gamma} P_i(t)\log\hat{P}_i(t) + \left(1-\hat{P}_i(t)\right)^{\gamma}\left(1-P_i(t)\right)\log\left(1-\hat{P}_i(t)\right)\right]; \quad (7)$$

$$Loss = L_{ciou} + L_{confidence} + L_{class}. \quad (8)$$

Table 2. Training parameters in YOLOv4 & YOLOv7

Pre-trained weight	Weight size	Number of anchors	Width & height	Batch size	IoU threshold
yolov4-tiny.conv.29	19 MB	6	416x416	64	0.213
yolov4.conv.137	162 MB	9	416x416	64	0.213
yolov7.pt	72 MB	Anchor-free	416x416 640x640	32	0.20
Yolov7x.pt	136 MB		416x416 640x640	32	0.20

Note: Regarding pre-trained weights, both YOLOv4 and YOLOv7 offer various options, each accompanied by a corresponding configuration file. The parameters for Batch size and IoU threshold are set to default values.

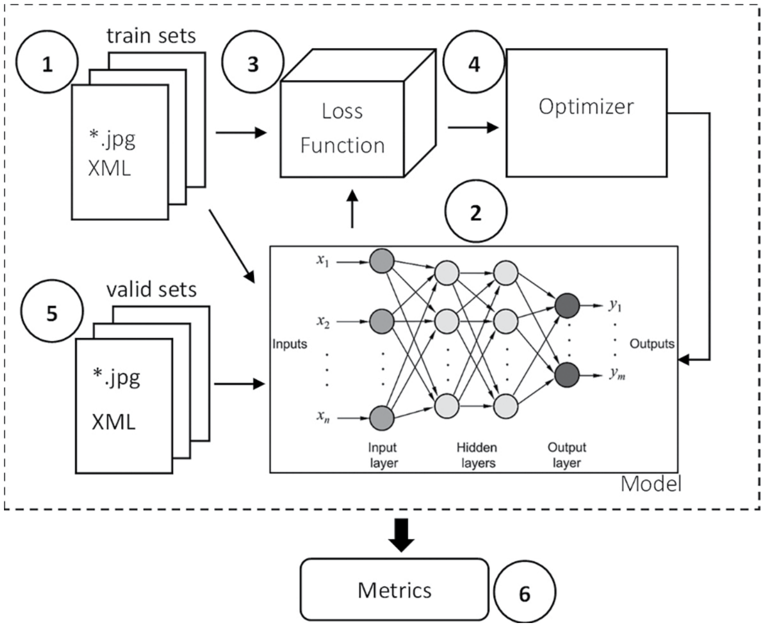


Figure 4. Neural network training process

4. Establishment of the server platform and Web API

4.1. Construction of the server network system architecture

The network server in this study adopts a standard Client-Server architecture, utilizing a router to manage external connections and internal network distribution. The system operates on port 8080 for service communication and employs a fixed IP for external services. Internal network communication is conducted through port 80 for HTTP protocol, ensuring system stability and security. The overall network architecture, as shown in Figure 5, effectively distributes fixed IP addresses to internal network devices through the router.

4.2. Web API design

The Web API developed in this study is based on the HTTP communication protocol, implementing three core functional interfaces: data upload, data download, and deterioration detection module integration. Through integration with the auto predictor application, users can easily invoke these functions to achieve automated crack image recognition processes, as shown in Figure 6. The API design emphasizes reliable data transmission and processing efficiency while providing an intuitive user interface.

5. Development of the server platform and deterioration detection website functions

5.1. Frontend design of the deterioration detection website

In the frontend, HTML (hypertext markup language) is used to create and edit web content, marked with tags to present the website's designed content, as shown in Figure 7. The HTML-based web structure is built using various tags to create browsing pages for the deterioration detection website. In the backend, the PHP scripting language and Laravel are used to create the development framework. Laravel follows the model-view-controller (MVC) architecture, with the model representing logic and database design, the view for the web page display created using HTML, and the controller responding to requests and han-

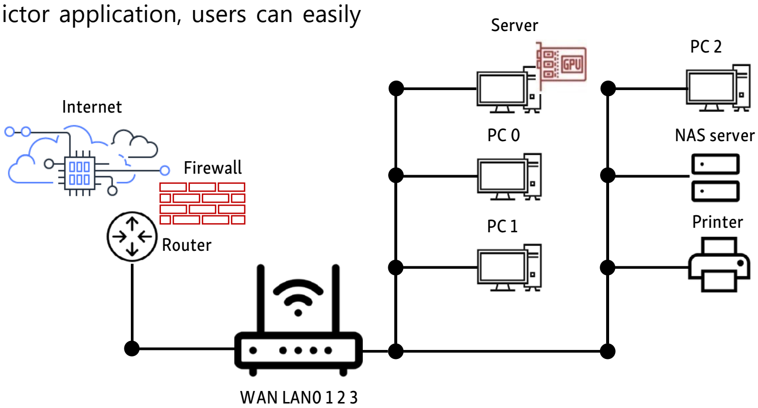


Figure 5. Network system configuration architecture

dling requested content. The controller can retrieve data from the model and display it on the browsing web page. In this study, HTML, PHP, and Laravel are utilized to develop and manage the system, following the framework's specifications, and create the deterioration detection website.

5.2. Website functions and results display

The website designed in this study includes functions such as select file, upload, reselect, and crack detection. Users can access the deterioration detection website via a web browser, click the "select file" button to choose either single or multiple deteriorated images, and click the "upload" button to upload the deteriorated images to the AI server platform. If the wrong images are selected, users can click the "reselect" button to clear the selected deteriorated images. Once the deteriorated images are uploaded, users can click the "crack detection" button to initiate crack image detection. The results are stored in the "predicted_images" folder on the server platform, as shown in Figure 8.

In the internal design of the website, the deep learning crack image detection model is integrated with the "crack detection" button; this button allows the program to initiate the crack image detection model. Additionally, the data import and export interfaces need to be designed appropriately. The data import interface ensures that the data to be recognized are correct and that the parameters are appropriate. The data export interface receives and stores the detection results, enabling subsequent data processing. Bridge inspection personnel can use the deterioration detection website using a web browser, without the need for additional applications to perform crack image detection tasks. However, the process still requires manual operation, and complete automation is a future development goal. In this study, several crack image detection methods were developed to provide more operational choices.

6. Cloud platform development

In this study, the core architecture revolves around the "Automated Crack Image Cloud Detection System", which seamlessly integrates a deterioration detection module, a data analysis module, and an auto-predictor application.

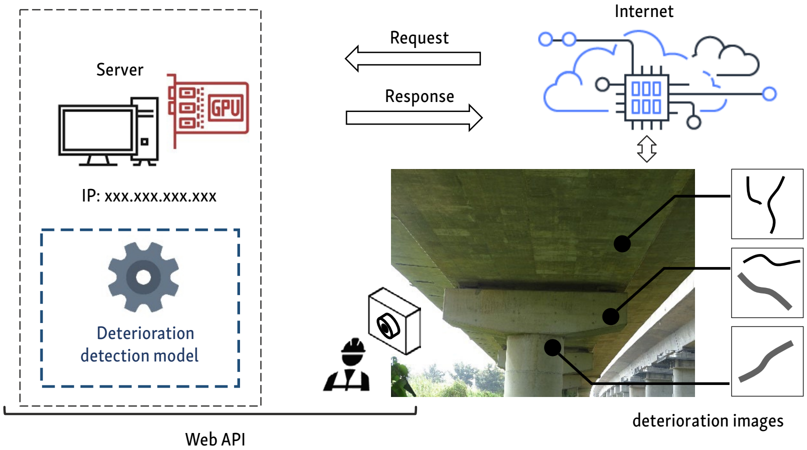


Figure 6. Web API function description

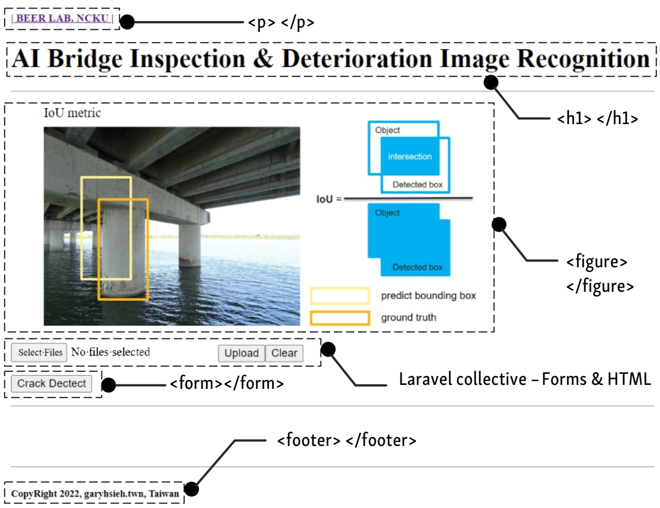


Figure 7. Frontend design of the deterioration detection website

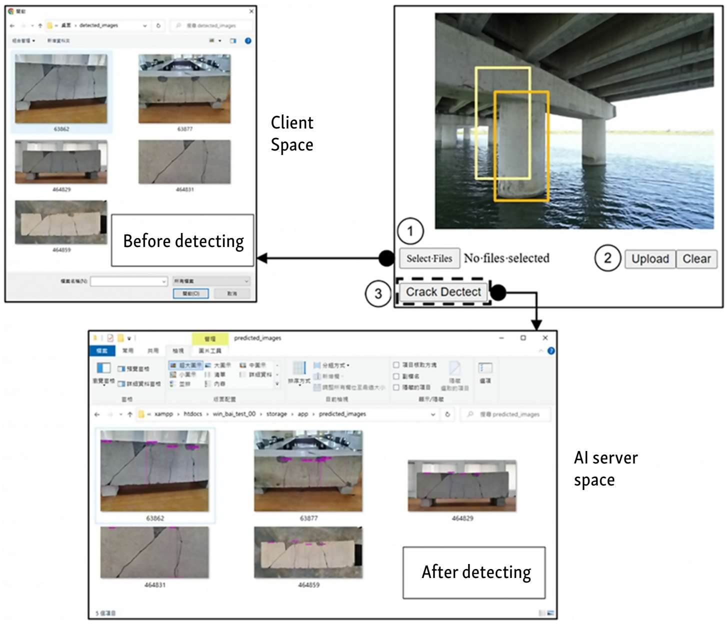


Figure 8. Operation and results display of the deterioration detection website

Collectively, these components form a holistic system that facilitates automated functionality, enabling users to effortlessly upload selected deterioration images, download detection outcomes, and conduct in-depth analyses of crack detection results. Ultimately, users receive both the image detection results and a comprehensive outcome report. The deterioration detection module is integrated with the web API and systematically performs operational procedures. This allows direct communication and control over the crack image recognition model. When a user uploads deteriorated images to the server, the deterioration detection module is automatically initiated to perform deterioration detection tasks. After the detection task is completed, the detection network is automatically shut down, as the module's tasks have been accomplished. To modify the crack image recognition model, only the corresponding module needs to be adjusted, obviating the need for a complete redesign. In addition to the aforementioned, this research has also developed a "Bridge BIM Cloud Management System", which is synergistically integrated with the Automated Crack Image Cloud Detection Platform. Bridge inspection personnel can initially create a comprehensive BIM model, as illustrated in Figure 9, and subsequently upload it to the cloud management system. The primary structure of the bridge's BIM model is delineated into three key components: (1) Structural Elements, (2) Span Systems, and (3) Pier Systems, as elaborated in Figure 10.

6.1. Image encoding and decoding – Base64 format

To prevent data bit loss during the transmission of deterioration images and ensure that the server does not encounter unrecognizable bits, each deterioration image is encoded and subsequently decoded upon receipt. The

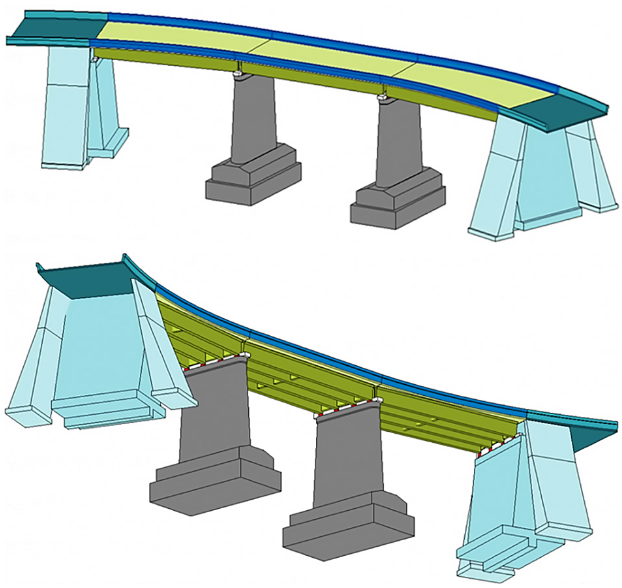


Figure 9. Bridge BIM model diagram

encoder and decoder designed in this study utilize the Base64 encoding system, which converts data into ASCII characters (ASCII Table, 2022), as illustrated in Figure 11. Furthermore, each encoded image is stored with the JSON data format. The upload and download of the deterioration images involve JSON format files.

6.2. Design of the deterioration detection module

The deterioration detection module is a crucial component of the automated crack image cloud detection system. This module is designed to systematically organize and recognize specified deterioration images. In addition, data preprocessing and postprocessing tasks are performed.

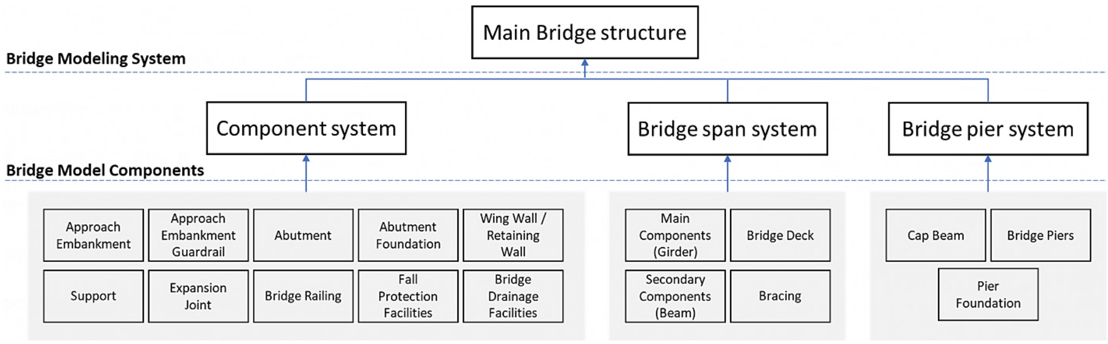


Figure 10. Bridge BIM model architecture diagram

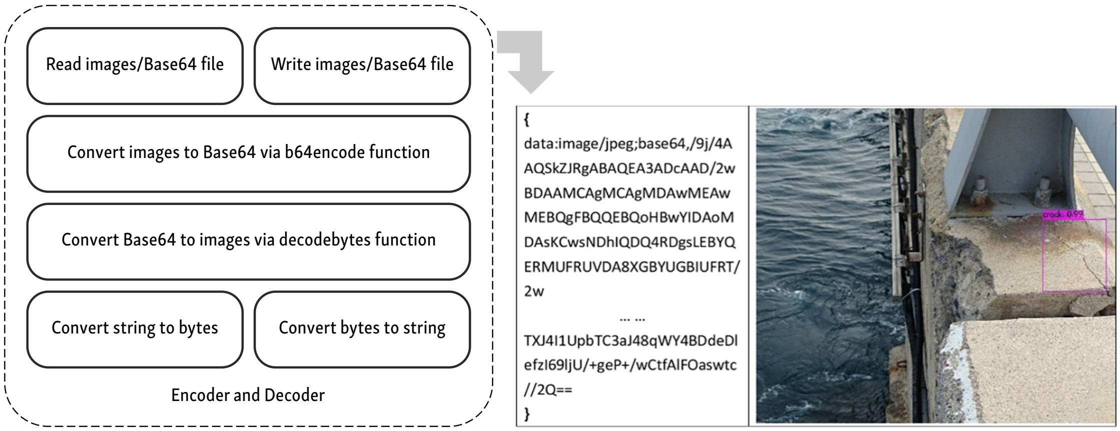


Figure 11. Base64-based encoder and decoder

The method deterioration detection consists of the following main steps, as shown in Figure 12. The deterioration detection module horizontally interfaces with the HTTP protocol and the automated prediction application, as shown in Figure 13. Encoded deterioration images are uploaded to the AI server via the HTTP protocol. The deterioration detection module initiates the crack image recognition model, performs deterioration detection, and generates detection result reports. The detection results are encoded into Base64 format. The web API's download task is initiated upon the completion of the aforementioned processes. The automated prediction application subsequently emits a signal, notifying the AI server that the data can be downloaded. In summary, the respective components of the proposed architecture have the following functions:

- HTTP Request/Response:

  The client and server communicate through standardized Route GET and POST interfaces, as shown in Figure 13. The communication process includes requests from the client and responses from the server, with responses containing either execution results or failure reasons.

- Deterioration Detection Module:

  The deterioration detection module processes data pre-processing and post-processing on the AI Server platform through the Deal with folder function, as shown in Figure 13. This module can batch process multiple deterioration images, sequentially registering and inputting them into the crack image recognition model. Recognition results are stored in designated folders and managed through the Read/Write data function, which records results and reads data uploaded from the local end.

- Automated Prediction Application:

  The Auto predictor application uploads deterioration images to the AI Server platform after base64 encoding, as shown in Figure 14. After the deterioration detection module initiates, it performs image decoding and recognition, then stores the encoded results in a newly created local folder through the Download function. The program terminates after the data analysis module generates the report.

6.3. Design of the data analysis module

After the deteriorated images have been analyzed by the crack image recognition model, they contain degradation information that has not been processed. To handle this large volume of image data, a data analysis module was designed. This module extracts, organizes, and analyzes the detection results to generate a final report. Bridge inspection personnel can review this report to understand the detection outcomes. The report includes details such as the image name, degradation name, degradation category, component code, component name, bridge name, and degradation information, as illustrated in Figure 15. The recorded content is derived from the detection results shown in Figure 16, and the details are as follows: the type of degradation is labeled as "concrete structural crack", the

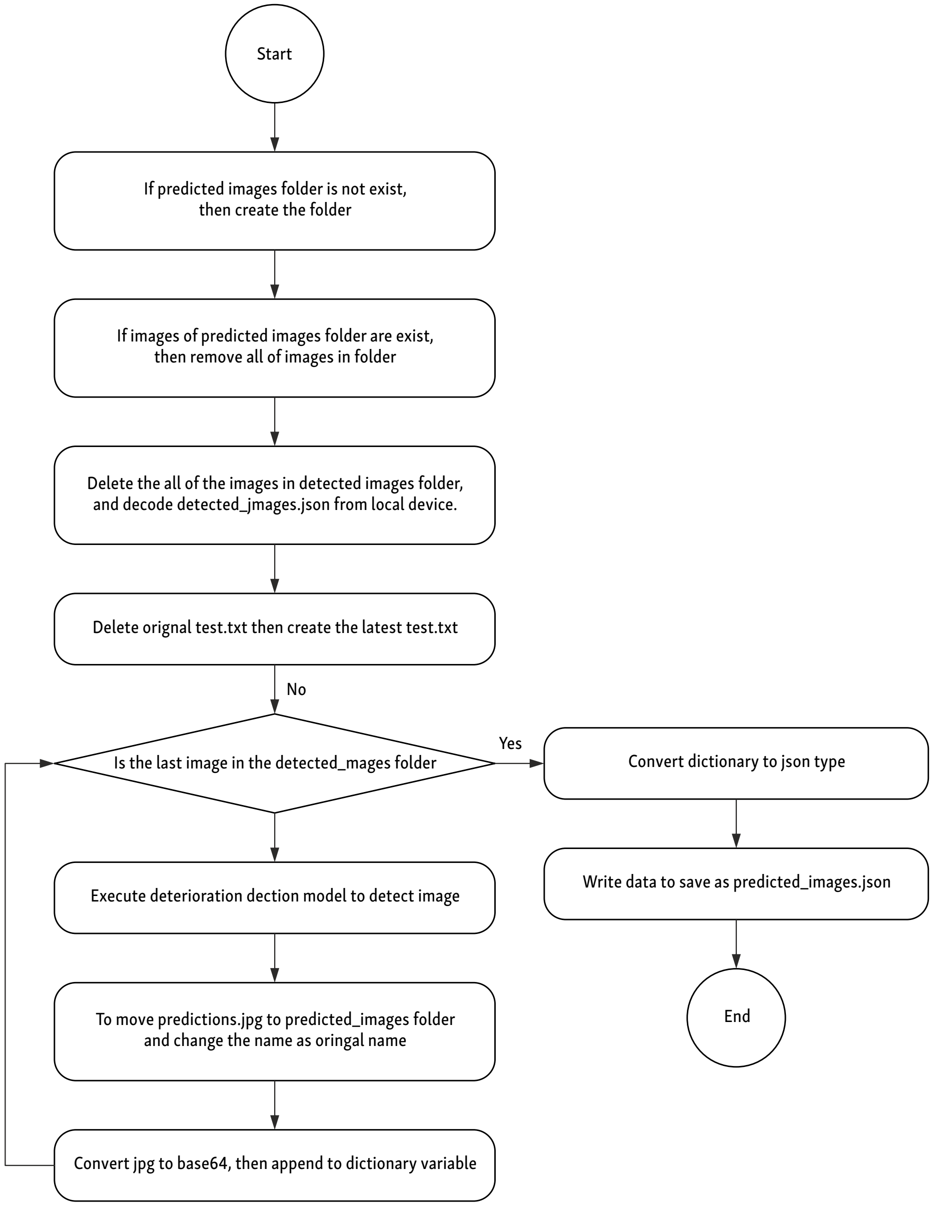


Figure 12. Flowchart of deterioration detection module

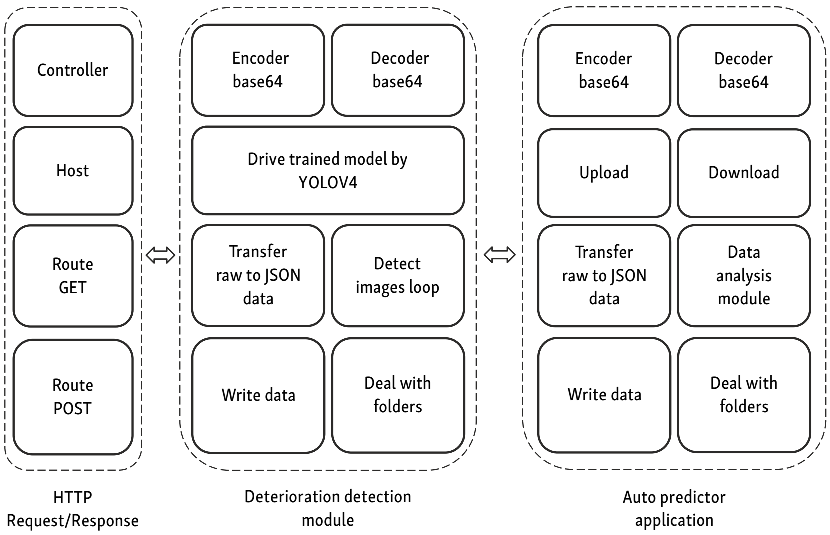


Figure 13. System architecture of the deterioration detection module

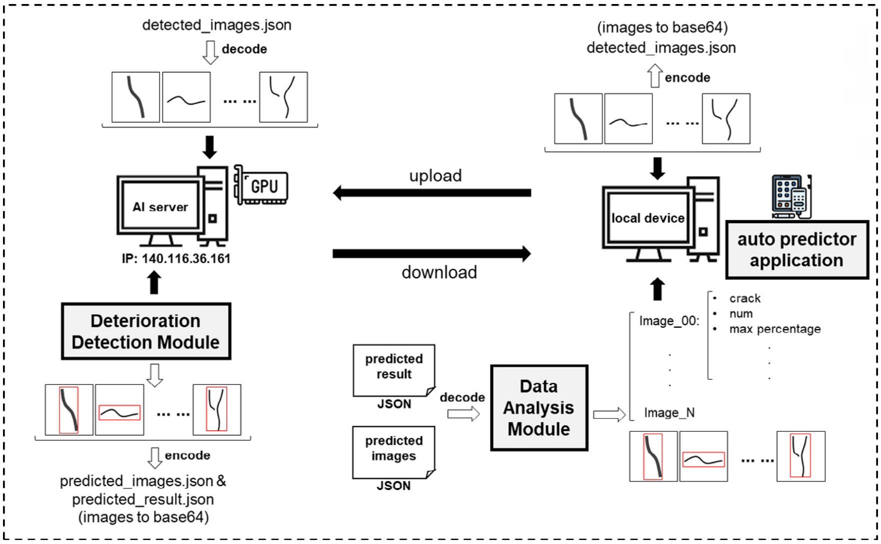


Figure 14. Components of automatic program design

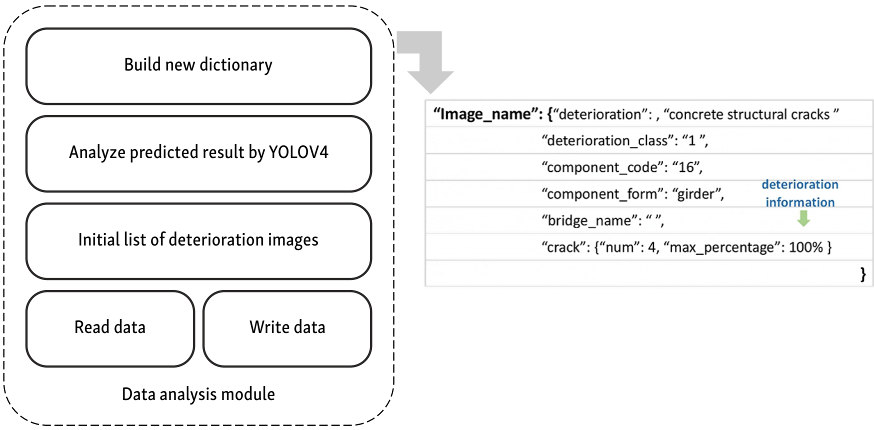
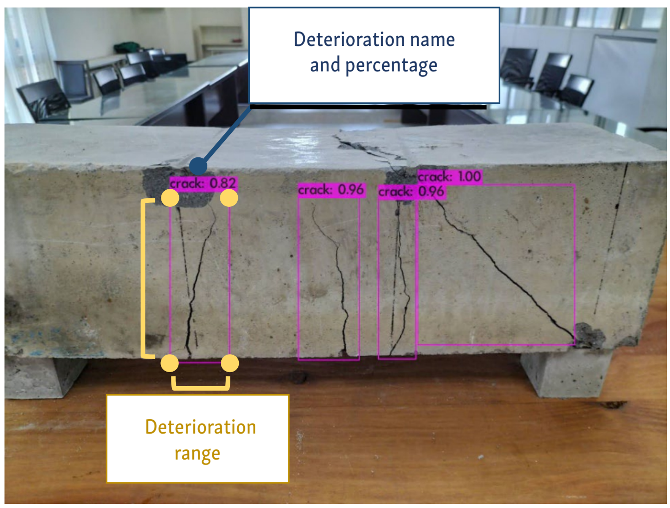


Figure 15. Data analysis module architecture



Note: for this particular deteriorated image, there are four detected cracks, and the highest accuracy percentage for deterioration prediction is 1.0. The coordinates of the deterioration regions are also recorded in the report.

Figure 16. Information of recognized deterioration image

degradation category is “class 1”, the component code is “16”, the component name is “girder”, the bridge name is [bridge name], and the degradation information specifies that there are a total of 4 cracks, with the highest crack probability reaching 100%.

7. Validation of the cloud platform

This study validates the developed cloud platform through two main aspects: (1) evaluation of the crack image recognition model’s performance metrics, and (2) verification of the automated crack detection system in practical applications. During system operation, users only need to execute the auto predictor application locally, which automatically connects to the Server for deterioration image detection. The entire process is highly automated, from image upload to recognition processing and result download, requiring no manual intervention, as shown in Figure 17.

7.1. Evaluation metrics for the crack image recognition model

Using 4307 training images with 416×416 pixel dimensions and YOLOv7 pretrained weights, the model achieved a mean Average Precision (mAP) of 87.64%. By expanding the training dataset, not only was model accuracy improved, but the training process also became more stable, as shown in Figure 18a. The study compared various pretrained weights and image parameters (416×416, 640×640), with comprehensive results showing YOLOv7’s superior performance over YOLOv4, as detailed in Figure 18b and Table 3. Notably, using yolov7.pt achieved optimal results with the shortest training time while maintaining excellent accuracy, as illustrated in Figure 19.

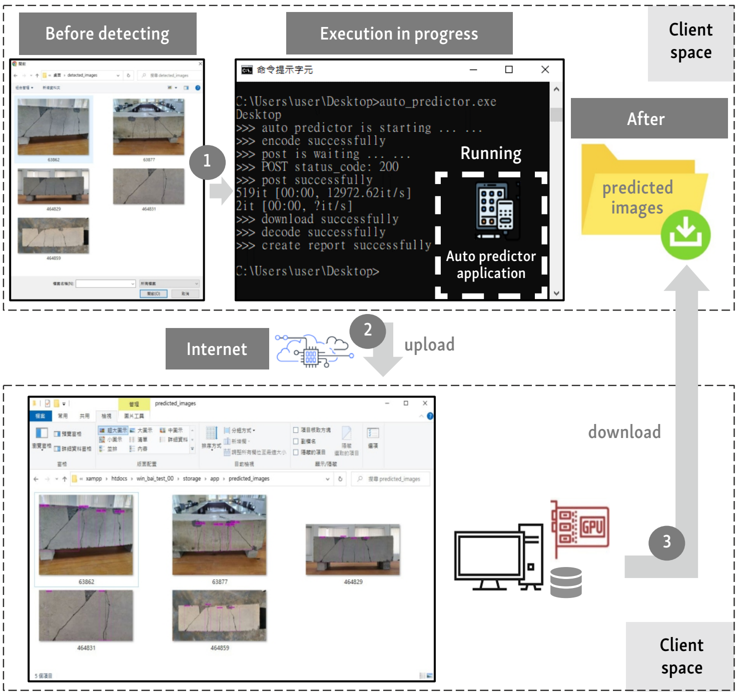


Figure 17. Execution process of the automatic crack image recognition system

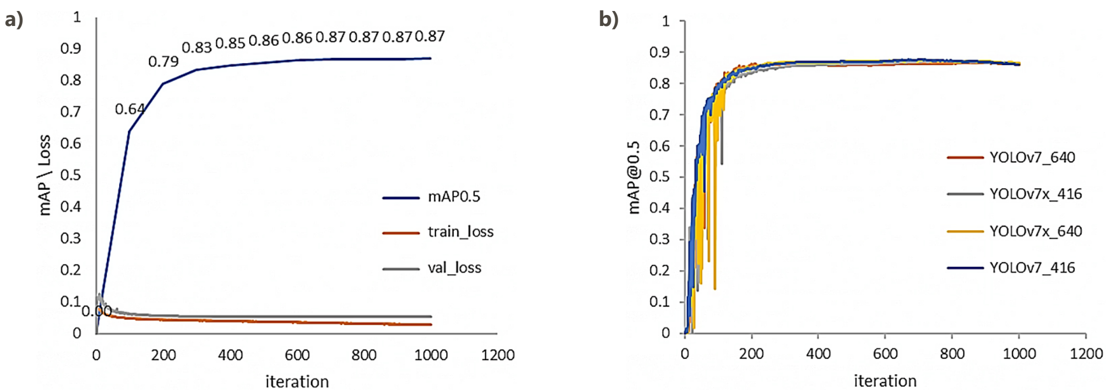


Figure 18. a – mAP – YOLOv7 (for 416); b – mAP – YOLOv7 & YOLOv7x (for 416, 640)

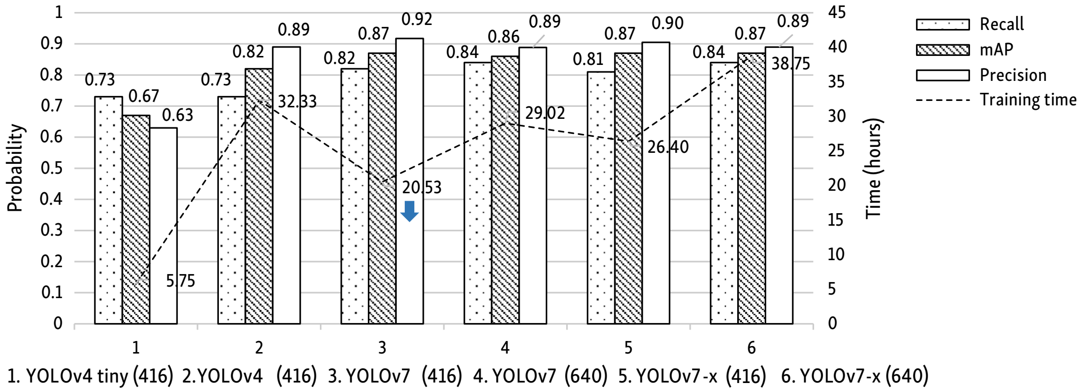


Figure 19. Comparison of recall, mAP, precision and training time

Table 3. Training result in YOLOv4 & YOLOv7

Model	Pre-trained weights	Network Size	Precision	Recall	mAP@0.5	F1	Training time (h/m)
YOLOv4 tiny	conv.29	416×416	0.63	0.73	0.67	0.676	05/45
YOLOv4	conv.137	416×416	0.89	0.73	0.82	0.802	32/20
YOLOv7	yolov7.pt	416×416	0.9171	0.82	0.87	0.828	20/32
YOLOv7	yolov7.pt	640×640	0.8886	0.84	0.86	0.835	29/01
YOLOv7-X	yolov7x.pt	416×416	0.9049	0.81	0.87	0.84	26/24
YOLOv7-X	yolov7x.pt	640×640	0.8898	0.84	0.87	0.845	38/45

7.2. Using the automated crack cloud detection system to evaluate deteriorated images

System validation was conducted using two types of test images: bridge inspection photographs and deterioration images from short beam shear experiments. The results, shown in Figure 20 and Figure 21, demonstrate that even with complex background conditions, the system accurately identifies and frames major cracks in structural components. These results confirm that the system not only achieves its automated detection objectives but also provides bridge inspection personnel with a quick and accurate crack identification tool.

7.3. Automated integration with bridge BIM cloud management system

During the inspection process, bridge inspection personnel photograph and annotate the discovered cracks, as illustrated in Figure 22, thereby systematically investigating the locations of crack occurrences on the bridge. Regarding the captured deterioration images, the system automatically transmits them to the Server, and upon completion of the detection results, the outcomes are automatically fed back into the BIM model, as depicted in Figure 23. The relationship between the Server and the BIM Cloud Management System is further elucidated in Figure 24.

8. Conclusions and recommendations

This study develops a cloud-based platform, which is divided into five main components: (1) AI Server platform and Web API design, (2) deterioration detection website development, (3) automated program design (including deterioration detection module, data analysis module, and auto predictor application program), (4) training of crack image recognition model, and (5) bridge BIM cloud management system. Through the integration of these modules, the deterioration recorded in the bridge BIM model can be automatically uploaded to the cloud platform, where crack image recognition is performed, and the results are then downloaded and visualized on the bridge BIM model, achieving automated crack recognition. The training and validation datasets used in this study were original images of deterioration taken by bridge inspectors, without any image enhancement or cropping. Similarly, the test dataset images used for deterioration detection were also not processed. Additionally, this study developed a deterioration detection website, where users can log in by entering the website address, select the deterioration image to be recognized, and immediately perform crack image recognition. In summary, the conclusions and recommendations of this study are as follows:

- This study successfully improved the traditional manual identification of deterioration images by developing an automated crack detection system using both YOLOv4 and YOLOv7 algorithms for model training. The YOLOv7 model achieved a mean Average Precision (mAP) of 87.64%, with crack prediction probability exceeding 80%, significantly enhancing the objectivity and consistency of bridge inspections. The integration of this system with the Bridge BIM cloud management system has markedly improved inspection efficiency and reduced the likelihood of crack omissions.

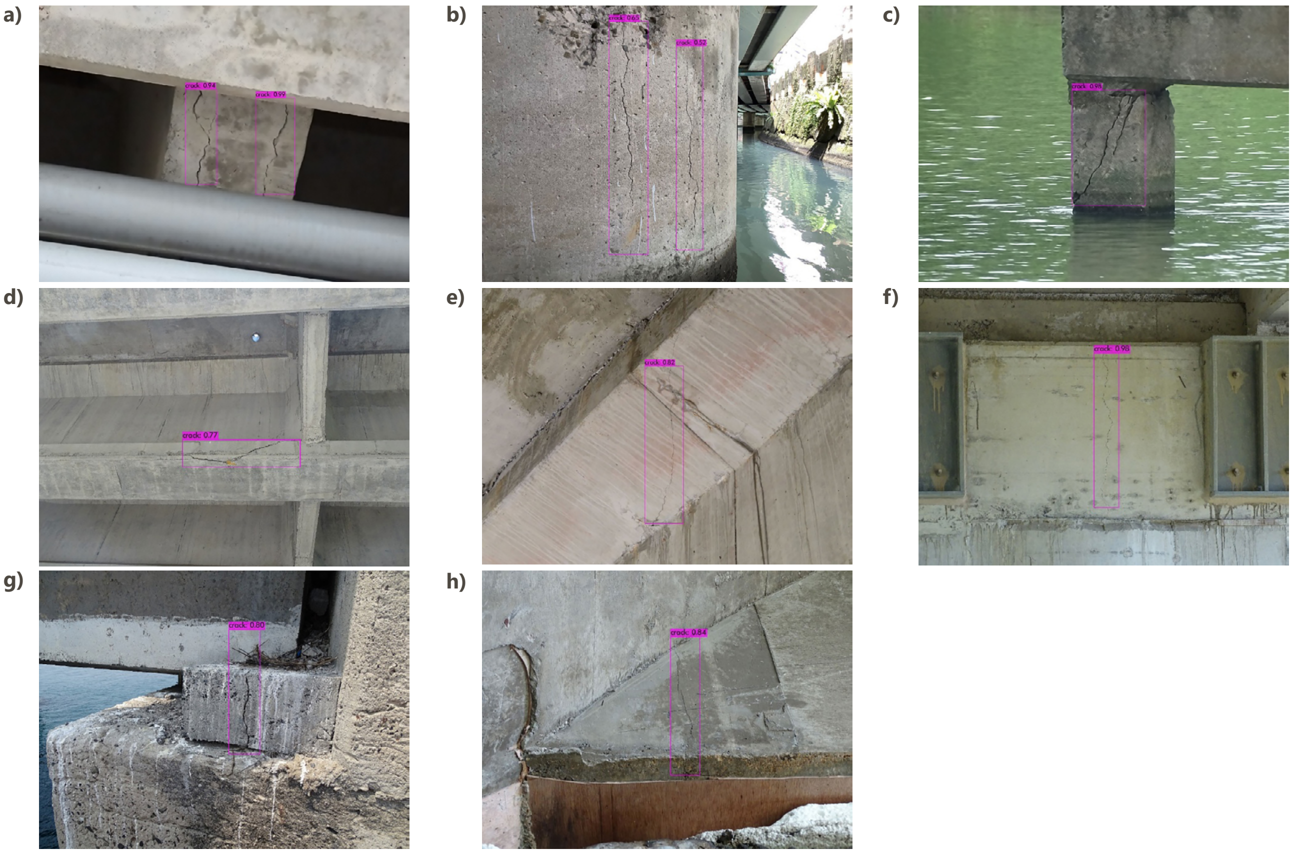


Figure 20. Validation for bridge inspections

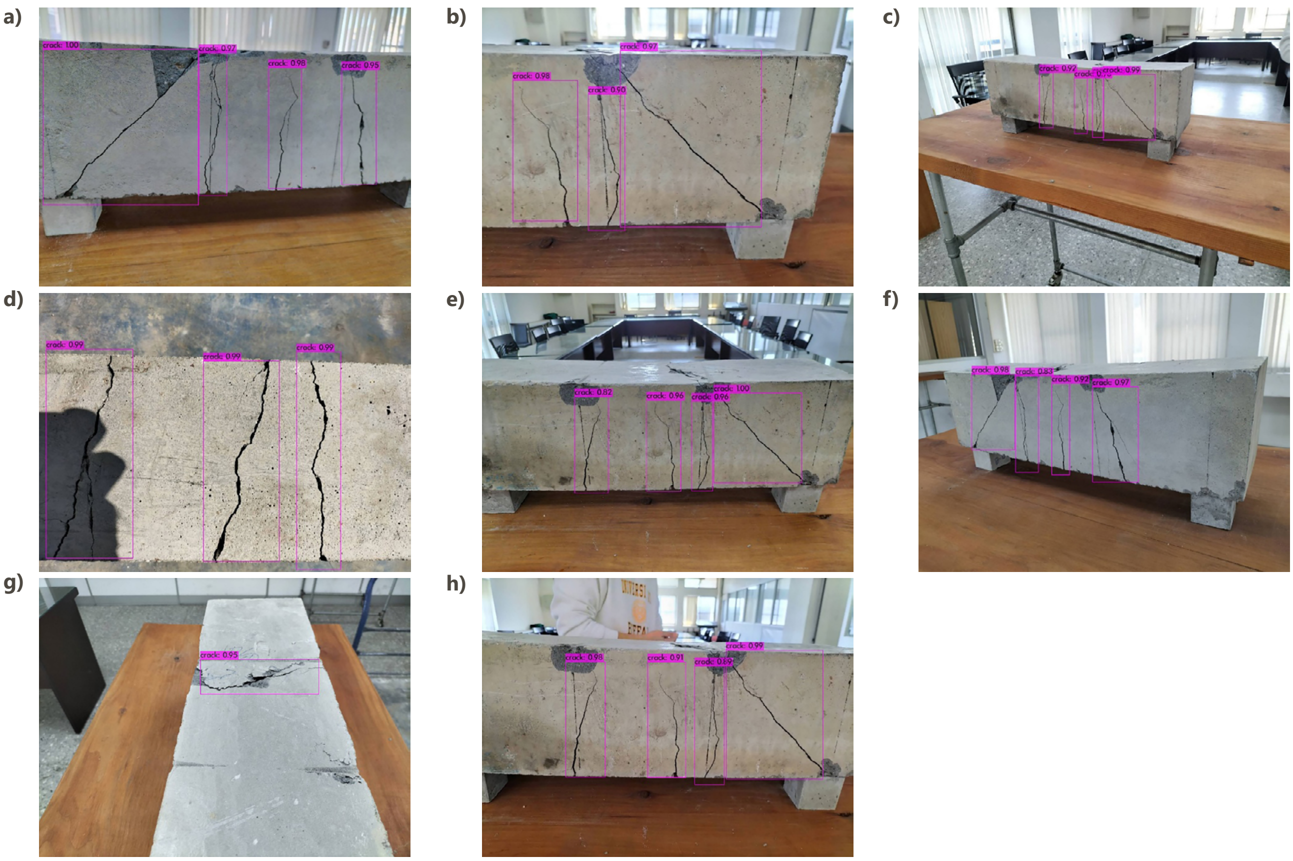


Figure 21. Validation for short beam specimens

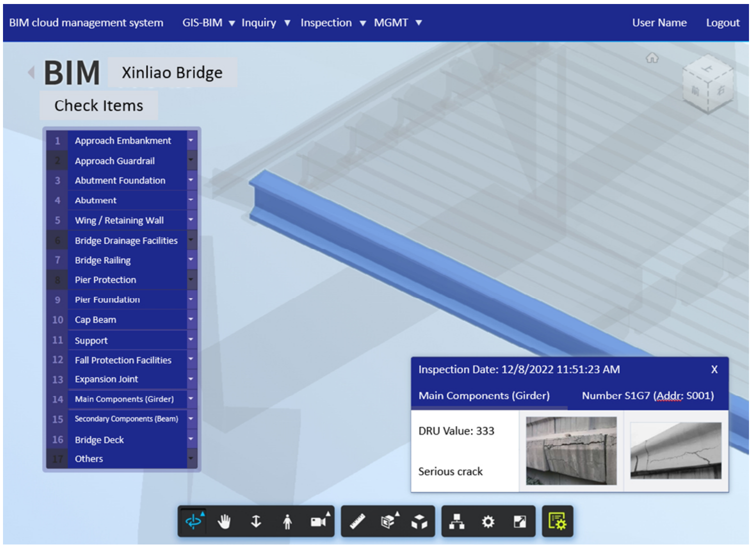


Figure 22. Deterioration records on the bridge BIM model

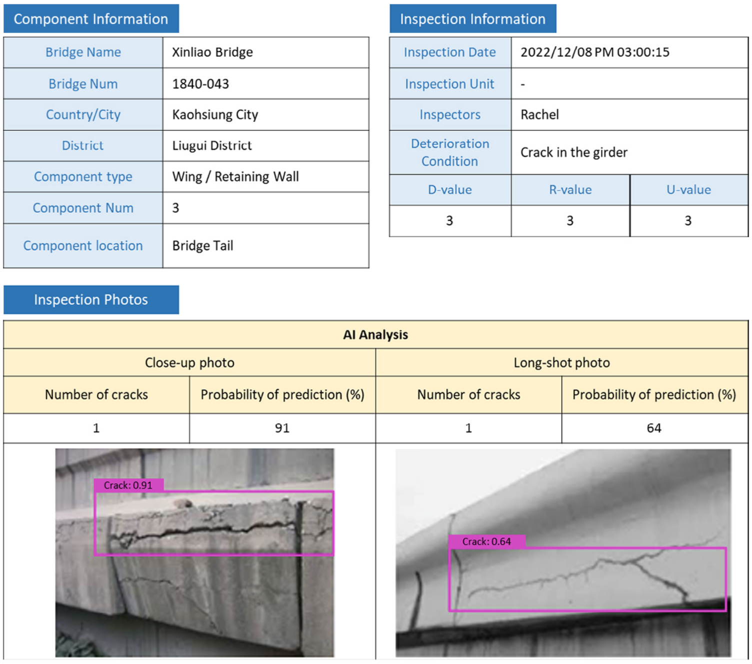


Figure 23. Displaying analysis results on the BIM model

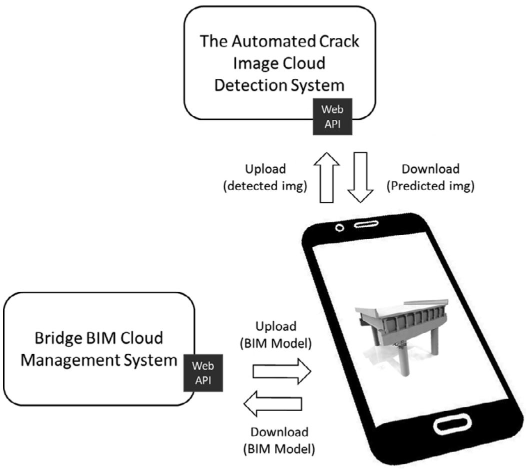


Figure 24. Automated crack image cloud detection system and bridge BIM cloud management system

- This study pioneered the use of 4,307 deterioration images from long-term bridge inspections in Taiwan for model training. These images encompass Taiwan's unique environmental conditions and crack characteristics, providing a locally optimized deep learning solution for Taiwan's bridge inspection sector with high regional applicability.
- The deterioration detection website enables bridge inspection personnel to perform crack image recognition through a web browser without specialized equipment or complex operations, significantly lowering technical barriers. The system offers multiple detection methods, allowing inspectors to choose the most suitable approach for different scenarios, enhancing inspection flexibility and efficiency, as illustrated in Figure 8.
- This research successfully achieved deep integration between the "Automated Crack Image Cloud Detection System" and the "Bridge BIM Cloud Management System", enabling direct linkage between crack information and three-dimensional models. This innovation allows engineering personnel to intuitively view crack locations and information on visualized bridge models, substantially improving the intuitiveness and efficiency of bridge maintenance management while providing decision-makers with comprehensive visual data support.
- Engineering personnel can create BIM bridge models based on structural design drawings and store them in the cloud. During deterioration inspection, inspectors can photograph cracks, and the system automatically integrates model and crack information with descriptions, achieving full digital management from inspection to maintenance, providing a complete digital solution for bridge lifecycle management.
- The deterioration detection module of the "Automated Crack Image Cloud Detection System" implements a fully automated process from image upload, sorting, and recognition to result encoding, thoroughly addressing the time-consuming and error-prone issues of traditional manual inspection. The data analysis module automatically summarizes, organizes, and analyzes recognition results, generating comprehensive reports including crack location, type, and severity, enabling bridge inspection personnel to quickly grasp structural health conditions. This automation not only improves work efficiency and ensures consistency and reliability of inspection results but also provides timely and accurate data support for maintenance decisions, significantly enhancing the scientific nature of bridge management.
- The auto predictor application demonstrates stable operation across various operating systems, including Windows 10, Windows 11, and Windows Server 2019, ensuring system applicability in diverse work environments and providing highly practical tool support for bridge inspection work.
- The system achieved excellent recognition results in both real bridge inspection environments and laboratory short beam shear test deterioration images, demonstrating its applicability and reliability across different scenarios. These comprehensive validation results, as shown in Figure 20 and Figure 21, prove the system's effectiveness in supporting practical bridge inspection requirements and providing reliable technical assurance for bridge safety monitoring.
- In this study, the automated crack recognition model's test results may exhibit misjudgment, where the model incorrectly labels non-crack regions as cracks, affecting accuracy and reliability. The primary reason is the diversity issue of the training data, which, despite utilizing deterioration images from Taiwan, fails to encompass all environmental variations, such as different lighting conditions and background noise, resulting in poor model performance in new environments. Furthermore, although YOLOv4 and YOLOv7 models are employed, these models may still misclassify background textures or shadows as cracks in complex backgrounds. Therefore, future research can consider utilizing updated versions of the YOLO model to enhance detection accuracy and adopt a robust annotation method for deterioration.
- Although the system demonstrates strong technical performance, its practical effectiveness requires further validation due to the current limitation of lacking direct feedback from engineering users. To enhance the system's practicality, future research will implement a comprehensive user evaluation plan, inviting bridge inspection engineers to test the system. Through questionnaires and interviews, we will collect user feedback on various aspects, including system operation, crack detection, workflow integration, and BIM visualization interface, to optimize system functionality and ensure alignment with practical requirements.
- Future research directions will focus on optimizing the latest YOLOv9 algorithm to improve the accuracy of crack recognition. Additionally, we plan to develop an API interface with existing bridge management systems (such as TBMS2) to facilitate data exchange and achieve information interoperability. Furthermore, we will develop an automated evaluation mechanism for DRU (Degree, Relevancy, Urgency) values, which will automatically generate scores based on crack characteristics, reducing the subjective nature of manual evaluations.

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Disclosure statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in the paper.

Data availability statement

Data has been shared in this text.

Author contributions

Wein Zhu: Methodology, Data analysis, results discussion, Writing – Original draft; Jianing Li: Data collection, Data analysis, Methodology; Writing – Original draft; Linghan Wang:Data collection, Data analysis, Methodology; Xiaodong Li: Supervision; results discussion, Writing – Reviewing and Editing.

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