Automatic Bridge Maintenance Strategy Generation Framework based on Multimodal Neural Networks

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Introduction

Bridge maintenance is crucial for ensuring the safety, longevity, and functionality of infrastructure. Traditionally, this involves inspection, evaluation, planning, and execution, relying heavily on specialist expertise (Hurt and Schrock 2016). However, as bridges age, the demand for maintenance has grown exponentially, making traditional methods insufficient (Kim et al. 2022). Many studies have attempted to automate the key steps for bridge maintenance to improve efficiency. For instance, for bridge inspection, Unmanned Aerial Vehicles (UAV) based automatic inspection methods have replaced the traditional manual inspections by virtue of their advantages in costs, reduced risk, and higher inspection quality (Seo et al. 2018). Furthermore, with the explosion of deep learning, many computer vision-based bridge damage identification and evaluation methods have been proposed in recent years. For instance, Dung et al. (Dung et al. 2019) developed a robust crack classifier for detecting cracks at gusset joints in steel bridges using a deep-CNN. Similarly, Li et al. (Li et al. 2023) combined a faster R-CNN for bridge crack detection using UAVs. Despite these advancements in damage detection and evaluation, the generation of maintenance strategies (also known as maintenance planning) remains a highly knowledge-intensive task that requires considerable expertise and practical experience. This complexity makes maintenance planning a challenging process that relies on the efforts of human specialists, leaving a gap in the automation of maintenance strategy generation.

To address this problem, the paper proposed an automatic maintenance strategy generation framework that provides recommended maintenance strategies based on bridge damage images. In this framework, a multimodal neural network is utilised to explore the interconnectedness between damage images and maintenance strategies. Through a multimodal network, the damage evaluation and maintenance strategy generation are integrated as one step, bypassing the need for damage identification and diagnosis. Therefore, outperforms existing methods in efficiency. In addition, the proposed method also eliminates the significant effort of experts in maintenance planning and fills the gap in automated maintenance strategy generation. The advent of an automatic bridge maintenance strategy generation approach will substantially enhance the efficiency and cost-effectiveness of bridge maintenance and bring rapid and fully automated bridge maintenance one step further to reality.

Methods

The proposed multimodal network consists of two functional modules: an image-processing module and a text-generation module. The image-processing module uses a CNN-based network called EfficientNetB0 to capture features from damage images, fine-tuned with ImageNet pre-trained weights to reduce training costs. Due to the advantages of handling contextual information in complex and long texts, the Transformer architecture was adopted for strategy generation, which employs an encoder and decoder structure (Cornia et al. 2022). The encoder focuses on the generation of new representations of the image features, while the decoder concentrates on the extraction of the textual feature of the maintenance strategy and the feature association between damage images and maintenance strategies. To further enhance the performance of the strategy generation module, the multi-head attention mechanism is applied to the training process. Figure 1 illustrates the overall structure of the proposed multimodal network.

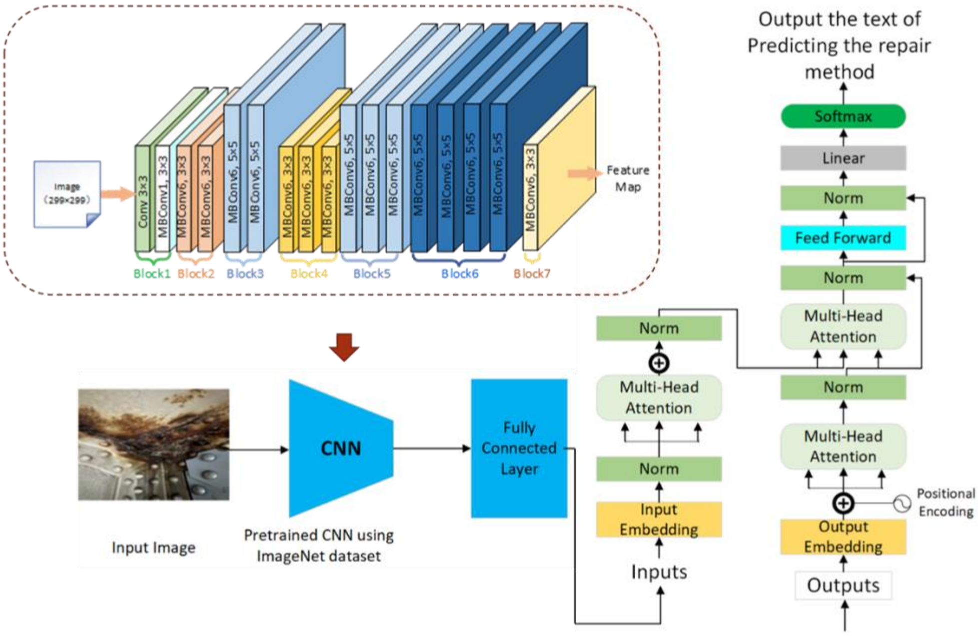

Figure 1 - Overall structure of the proposed multimodal network

Results and discussions

To validate the proposed framework, a domain dataset was developed with the help of our industrial partner, which contains 507 damage images and their corresponding repair recommendations extracted from actual bridge inspection reports. The framework's performance was evaluated by comparing its generated solutions to the expert-provided ground truth in the reports (Table 1).

Table 1: Some representative solutions generated by the framework and the comparison between the ground truth provided by experts.

Damage Image				
Predicted solution	Painting as per approved for construction design adequate	Cover with welded plate applying a 6mm Carbon Fiber Wrap	Cover with a small, welded plate, applying a 6mm Carbon Fiber Wrap corroded section non-structural defect	Cut out corroded section non-structural defect

Ground truth	Painting as per approved for construction design adequate	Weld a new plate over the hole with a 6mm Carbon Fiber Wrap to stop further water ingress.	Cover with a small, welded plate by applying a 6mm Carbon Fiber Wrap.	Cut out the corroded section.

Overall, the framework yielded 69% of fully identical restoration recommendations. When considering partially correct results (differently expressed but consistent in meaning), the accuracy rate reached 82%. The errors in the results are organised as follows. (1) The output text is correct, but the repair description is incomplete. For example, the description of the repair location is missing from the output text. (2) The output suggests one of the repair methods (e.g., the ground truth says, "unable to insert new bolt, fill the hole," while the output suggests "cover with welded plate applying a 6 mm cold-formed weld"). (3) The repair methods differ (deviations in repair position, material, and size). For example, the output text suggests using rivets and reinforcing plates for reinforcement, whereas experts recommend a more reinforced steel area and rejoining.

While the framework shows promising performance, there is room for improvement. Future work will explore enhancing performance by expanding the dataset and experimenting with different backbone models.

Conclusions

This research developed an innovative automatic bridge maintenance strategy generation framework. By leveraging a multimodal model, it integrates bridge damage assessment and maintenance planning, significantly improving efficiency and laying the groundwork for fully automated bridge maintenance. Practical validation shows the framework achieves over 80% accuracy, demonstrating strong usability potential. In addition, the proposed method exhibits a high level of generalisation. Maintenance decision-making for various building structures can be easily implemented by switching different datasets.

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