AI-Driven Component Prioritization for Yingxian Pagoda Conservation in HBIM

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Abstract

Based on the difficulties in addressing the current state of the structural instability of the Yingxian Wooden Pagoda, a hypothesis is established in this research to combine the Heritage Building Information Modelling(HBIM) technology with the text comprehension ability of Artificial Intelligence(AI) for an effective conservation strategy. The key method is to train an AI study model with Natural Language Processing (NLP) that could be plugged into the BIM software and be able to understand the current damage report of this pagoda from the aspect of structural risk. The problematic architectural components would be classified and categorized in labels with highlighted visual effects in the software. This research could integrate the existing AI diagnosis technique with BIM software to enhance efficiency and flexibility in architectural conservation. It enhances structural analysis precision with automated assessments applied to support a data-driven conservation framework.

1. Introduction

1.1 Background

Yingxian Wooden Pagoda, located in Shanxi Province, China, is distinguished as the highest and most aged wooden structure (Chen et al., 2014). Thus far, it has suffered from a noticeable tilting issue in its structure that leads to a threat of instability. Although the application of Heritage Building Information Modelling (HBIM) technology in recent years has essentially assisted in the documentation of this pagoda by establishing a clear classification and record for the problematic architectural components, the predicament of dealing with such a complex structure with a huge workload in processing has not been solved yet. It indicates that the current HBIM platform for the Yingxian Wooden Pagoda should improve its property to boost a more efficient conservation strategy in structural reinforcement. Consequently, a requirement for improving the heritage documentation environment is raised by developing a technique in the HBIM stage for deterioration level identification and evaluation.

1.2 Hypothesis Statement

As has been mentioned, the biggest challenge in addressing the structural issues of this pagoda lies in the complexity of both the structure itself and the accumulated heritage data. Therefore, if the essential deterioration could be sorted and highlighted as part of the building information efficiently, conservation practitioners may review the condition of the pagoda in a more accessible method. This research hypothesized that an Artificial Intelligence(AI) model could be trained to prioritize unstable components and plugged into the BIM software to propose a rational conservation strategy for the Yingxian Wooden Pagoda.

1.3 Previous Research Review

To verify this hypothesis, preliminary research needs to demonstrate that the current HBIM platform of the Yingxian Wooden Pagoda is relatively mature and the recorded descriptions of relevant deterioration are comprehensive and accurate. In addition, the potential contributions of AI to the HBIM platform also need to be evaluated.

Previous conservation activities for this pagoda have indicated a proficient application of HBIM-related technologies. Early in 2016, the Chinese Academy of Cultural Heritage obtained 3D point cloud data of this Pagoda through laser scanning and built its information platform and numbering system for architectural components documentation. It also analyzed the load bearing condition of the Dougong (斗拱) brackets that indicates a specific utilization of the scanned point cloud data in the HBIM platform (Hou et al., 2016). After this systematic HBIM process, Chen (2017), with his research team, illustrates the method of building an architectural component family for the Yingxian Wooden Pagoda in Revit through 'Secondary Development' in programming, which further enhanced the compatibility of the 3D model with BIM platforms. This demonstrates the inherent flexibility of BIM software in assisting with 3D reconstructive modeling of architectural heritage. Recently, in 2023, the deformation analysis precision of the pagoda has been improved with the introduction of LiDAR scanning and unmanned aerial vehicle (UAV) photogrammetry that it enables a more intuitive and accurate offset angle measurement of the tilting columns (Guo et al., 2023).

Meanwhile, the Chinese Academy of Cultural Heritage also meticulously documented the current deterioration condition of each storey in *A Study on the Conservation of the Yingxian Wooden Pagoda* (Hou Weidong et al., 2016). This section of the book provides a sufficiently comprehensive heritage database that can be referenced in support of this hypothesis. It includes the significant damage description and brief evaluation in phrases on architectural components with the same category.

Turning to the aspect of the application of AI in heritage conservation, it primarily demonstrates an ability to identify architectural objects in the BIM database. According to Yu et al.(2019), a trained AI model could classify various buildings in a city scale through visual learning on amount of building images. Zooming into a specific architecture, an AI model could also identify and classify the architectural components in images (Croce et al., 2023). However, a noticeable research gap remains in the capacity of AI models to interpret and classify heritage-related textual records and to effectively integrate them with the existing 3D model. This limitation poses a major challenge in verifying this hypothesis. For long-standing architectural heritage, especially traditional Chinese architecture, textual records contain dense and valuable information, making them highly important for conservation efforts. Therefore, it is necessary to leverage AI's ability to process continuous natural language interpret and classify large volumes of textual records.

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2. Methodology

2.1 General Research Method

To demonstrate the viability of this hypothesis, the research method of this study is technically oriented and based on the experiment of applying the trained AI study model to the simulated 3D model of the Yingxian Wooden Pagoda. This aims to simulate the workflow in a practical application, in order to test the rationality of each proposed step and evaluate the accuracy of the results generated by the AI model, thereby identifying perspectives for refinement. Based on a considerable number of architectural components and the complex structure of this pagoda, the representative storey with the most significant deterioration condition would be selected as the analysis target.

2.2 Proposed Workflow

Firstly, a BIM environment of the pagoda would be built with families of architectural components classified for further editing of the properties in the next steps. Due to the intensive workload involved in manual modeling, utilizing an existing 3D model of the Yingxian Wooden Pagoda proves to be a more efficient approach. Wang (2024) and his research team established the digital model in 3dm format with a script for Dougong in parametric design will be referred. Such well-developed plug-ins could be employed to support efficient and rapid 3D modeling. Although Wang (2024) claims that the 3D model does not reflect the actual condition of the Yingxian Wooden Pagoda but only represents its ideal condition, its relatively detailed modeling can still be utilized in this study.

Turning to AI training and development, Natural Language Processing (NLP) will be utilized as a technique to process the current textual damage description of the pagoda. As the research is still in the stage of hypothesis validation, this study prioritizes the use of a published pre-trained language model to evaluate its effectiveness in text classification. The text is proposed to be added to a long block of code in a programming language after the model is installed. In the initial expectation, the model is assumed to be capable of analyzing the text to identify and classify different levels of deterioration based on the specific descriptions provided in each paragraph.

As the necessary textual information is processed and divided into different categories, it would be reflected in the BIM model through a secondary development by editing the parameters. The output could be added to the properties of the target architectural components in #C language through the Revit API. The set of code would be connected to modify the BIM model by add-in manager function in Revit. To enhance visual distinction, a color scheme can also be applied at this stage to indicate different levels of deterioration and enabling a clearer distinguish of different damaged components.

A verification process would be applied in the research to validate the AI-generated results and obtain utilizable feedback reflected on the accuracy of its learning outcome. In this research, the result could be compared with the data provided by the conservation report because it was precisely measured on-site. However, in practice, conservation programs, the identified problematic components could be verified by comparing them with the ground truth of the Yingxian Wooden Pagoda. Technically, the precise LiDAR-derived point cloud data for this pagoda established by Guo(2020) and the research team could be referred to as a comprehensive dataset for its current structural issues. By analyzing the successfully identified rate of the components and the accurate rate of the final outcome, the AI-model could be modified and enhanced for better performance in the future application.

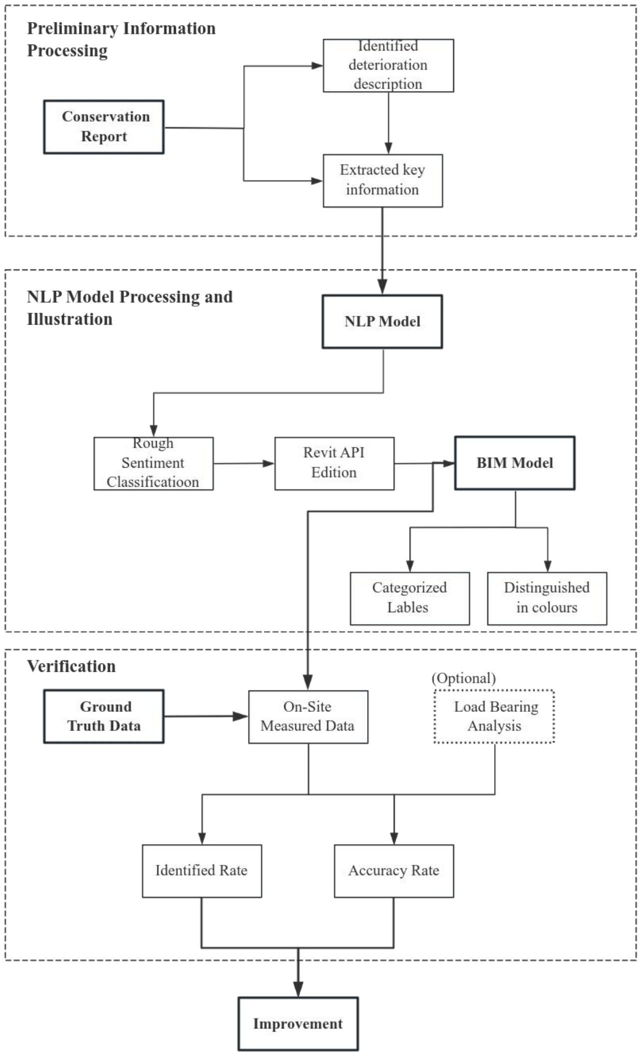

Figure 1. Proposed Workflow Chart

3. Results

3.1 Establishment of the BIM Platform

As Hou Weidong et al (2016) described, the column tilting issue in the intermediate platform of the second floor is significant in general, with a comprehensive record and classification of the deterioration extent in the report. In addition, the point cloud data of this pagoda collected by Guo Ming et. al (2020) also suggested the worse condition of this level, therefore, the columns in the intermediate platform of the second floor are selected as the study object. As has been shown in Figure 2 below, this level was generated in Revit through the Rhino in Revit plugin through a parametric design script in Grasshopper.

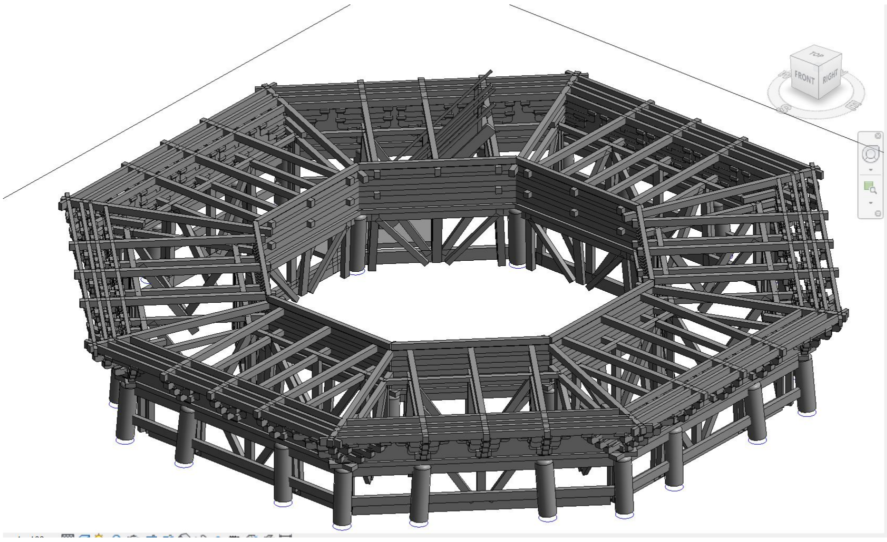

Figure 2. Intermediate Platform Layer of the 2nd Floor in BIM

To precisely match the description in natural language mentioned in the report with the architectural components in Revit, the target columns were properly categorized during the generation process in Grasshopper by selecting the element category in a filter. This ensured that each component was embedded with metadata aligning with the documentation structure, laying the groundwork for later data-driven operations. This step is intended to facilitate accurately filtering the overall category of the target components during later secondary development using the Revit API.

The numbering system established in the report was also referred to in this stage to locate the mentioned columns. It enabled that the physical components in the model were aligned with the analytical framework established in the report. 2 shared parameters were created under this category, which were 'Component Code', matching the columns numbering system, and the 'Deterioration Level', indicating the condition of the columns in a standardized evaluation parameter for structural diagnostics. They are included in the properties of the columns as annotation labels with textual information written that enabling cross-platform interoperability .

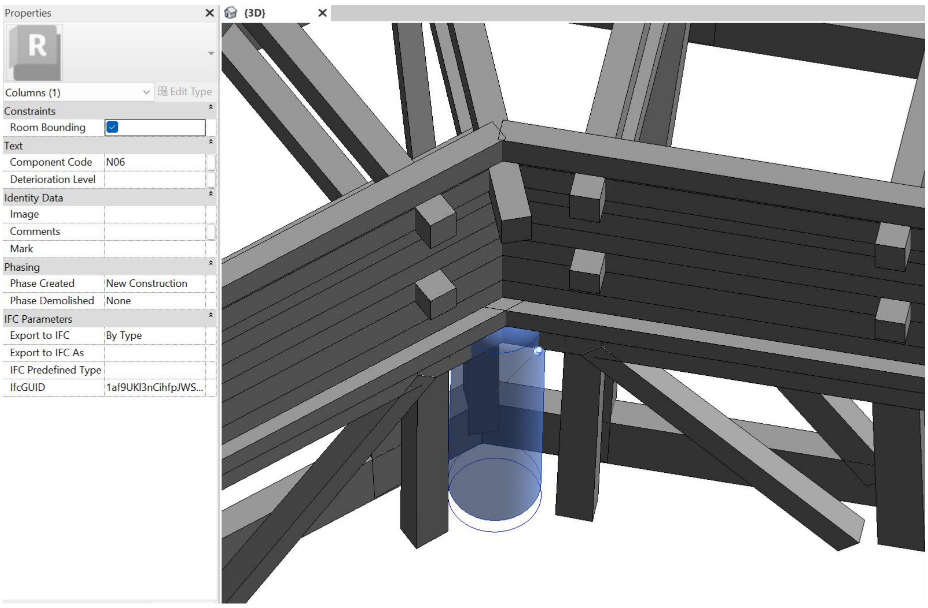

Figure 3. Categorized Columns

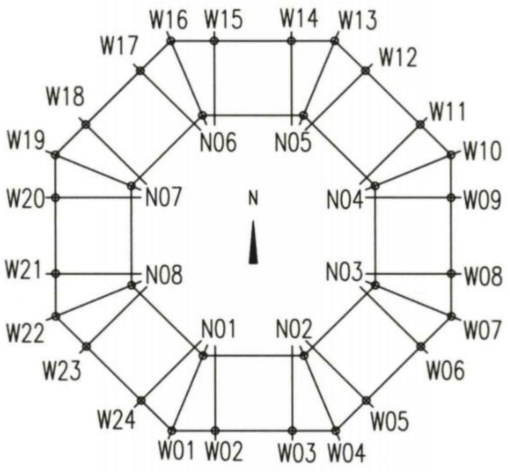

Figure 4. Columns Numbering System

3.2 The Training of the NLP model for text classification and Verification

In the deterioration condition section of the report, the columns W18, W19, and W20 were considered to be the most significantly damaged (Hou Weidong et al., 2016), which were elaborated in an independent paragraph. The descriptive natural language for each column was classified as a target sentence to be dealt with by the NLP model.

As the original language of the report was written in Chinese, a Chinese-based model was selected for precise understanding of the text. It was published in the hugging face transformers library named ‘yiyanghkust’. After having the target sentences input into the model, it is processed by analyzing the meaning it conveys. The output sentiment was divided into ‘Positive’, ‘Neutral’, and ‘Negative’, so comparing the sentiment labels on the 3 columns could indicate the most severe deterioration. According to Table 1 and Table 2 below, the column W19 is labelled ‘Negative’, which suggests its worst condition among the 3 columns. Comparing the W18 and W20, W18 reaches a higher ratio in positive, which could be considered to be the lowest deterioration level.

Component Code	Ratio of Positive	Ratio of Neutral	Ratio of Negative
W18	0.3589727580547333	0.29779431223869324	0.3432328999042511
W19	0.3454486131668091	0.2899303734302521	0.36462101340293884
W20	0.3413166105747223	0.31796231865882874	0.34072116017341614

Table 1. Scores of the Labels

Component Code	Label
W18	Positive
W19	Negative
W20	Positive

Table 2. Sentiment Results

Turning to the verification process, the output processed by the NLP model is generally accurate, as column W19 exhibits the most severe tilt according to the table of columns. However, the model fails to accurately assess columns W18 and W20, given that W18 has an inclination angle of 4.27°, which exceeds W20’s angle of 2.93°(Hou Weidong et al., 2016).

3.3 The Edition of the Parameters in Revit

To reflect the processed output from the NLP model, the shared parameter ‘Deterioration Level’ could be edited. This parameter is defined using four numerical levels (1 to 4), where a higher value denotes a greater degree of deterioration. For instance, column W19, as illustrated in Figure 4, is classified as Deterioration Level 4. Accordingly, an override colour scheme was added to the BIM model as well to visually indicate the deterioration level, as shown in Figure 5. Red, orange, yellow, and gray represent level 4, 3, 2, and 1, respectively.

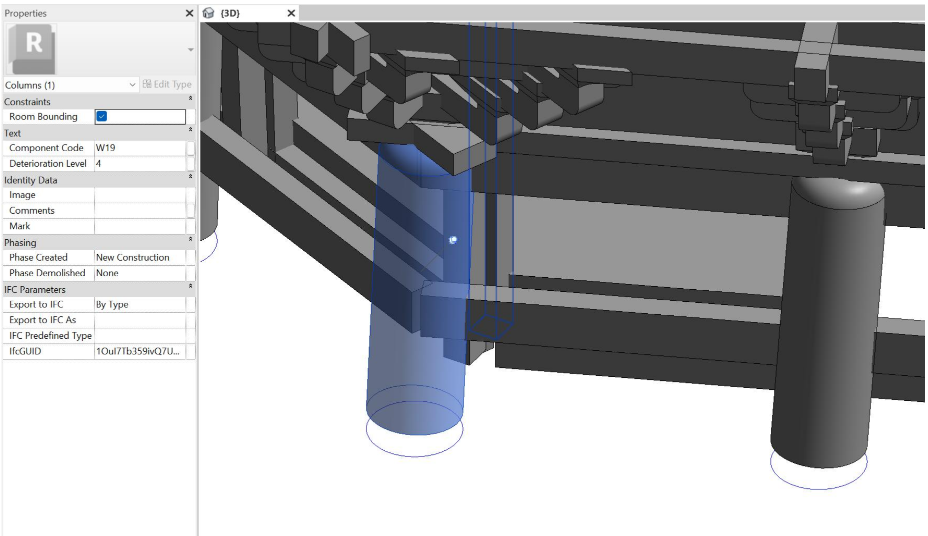

Figure 5. The Filled Shared Parameter in Properties

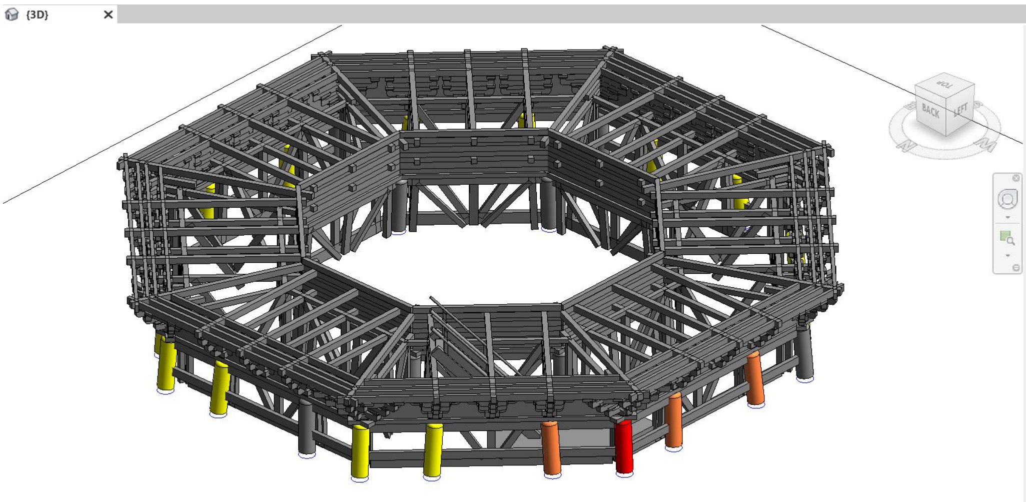

Figure 6. The Highlighted Columns in Colour

4. Discussion

Based on the analysis of the external columns at this level, an initial evaluation indicates that the proposed hypothesis is feasible with a few perspectives of limitations.

The performance of the AI model could be evaluated from both its capability for textual information processing and its practical applications. In terms of textual interpretation, the classified results were reflected through a tendency of either positive or negative, which aligns with the key logic of most NLP-based classifiers that are primarily designed for sentiment analysis. This inherent bias limits the ability of the model to accurately process rational and descriptive language, which may explain the inconsistencies observed in the results. Nevertheless, in real-world applications, the model could demonstrate significant potential in processing oral information collected during field research. Its ability to detect implicit attitudes or concerns within descriptive language may support assessments of the perceived severity of deterioration in specific structures. However, when dealing with a large amount of measured data, such as damage areas or inclination angles, traditional classification methods based on predefined standards and direct input of textual information are likely to be more efficient and reliable than AI-based classification.

The application of Revit API for secondary development is technically feasible, but it is less convenient compared to editing parameters directly within the software interface. Its advantage appears in enabling massive operations to make it more suitable for handling a large number of components simultaneously. Furthermore, API-based development could enhance the interactivity between the information embedded in the model and its users, offering greater flexibility in customizing data display and user engagement.

5. Conclusion

5.1 Research Summary

In conclusion, this research initially proposes the hypothesis that AI could effectively identify, classify, and prioritize deteriorated architectural components by interpreting related textual descriptions of the heritage. The processed outcome is expected to be intuitively visualized within the BIM platform, enhancing the efficiency of conserving architectural heritage with complex structures and historical layers. The most severely damaged columns in the intermediate platform on the second floor of the Yingxian Wooden Pagoda were selected as a case study. The research employed a pre-trained NLP model to conduct textual analysis of the relevant part in the conservation report, resulting in a severity-based ranking of the three most deteriorated columns. By comparing the ranking with the actual column inclination sheet, the AI model was found to possess the capability to process heritage textual information, although its accuracy in handling specific details remains limited. Regarding compatibility with BIM software, although it is possible to edit the properties of selected architectural components via the Revit API, improvements in data programming efficiency are still necessary.

5.2 Suggestions for Future Research

While this study provides preliminary insights into the availability of utilizing an AI model to assist in architectural heritage condition evaluation to improve conservation efficiency, future research could further explore how the proposed workflow could be implemented in real-world heritage conservation projects. Initially, improving the accuracy of the NLP model in classifying and analyzing Chinese-language texts is necessary, which can be achieved through a massive input of literature in the target language. Second, future work should focus on enhancing the ability to batch-edit textual parameters and override colors of architectural components during secondary development within the Revit API, to facilitate rapid differentiation of ranked deterioration levels within the 3D model. Finally, from the perspective of pagoda heritage conservation, the preservation workload of the Yingxian Wooden Pagoda is considerable. Even if the technology proposed in this hypothesis is implemented, sustained effort from scholars and practitioners will still be required to support the ongoing conservation program.

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