Identification of Crack Location to Aid Preventive Conservation of Timber-framed Buildings

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Understanding the location of surface cracks relating to surrounding architectural and structural elements such as windows and columns is crucial for assessing the condition of buildings and implementing appropriate maintenance and repair strategies. Identifying crack location on exterior building walls is a systematic process of image acquisition, preprocessing, crack detection, and localization. This process is crucial for understanding deterioration mechanisms in aging structures and maintaining structural integrity. It reveals how loads and stresses are distributed, helping focus restoration efforts and preserve authenticity with minimal intervention. Current methods often fail to accurately locate cracks in heritage timber buildings, making it hard to assess their severity. This assessment is especially challenging due to the complex interaction between plaster and timber, and the unique way these structures distribute loads. The lack of advanced diagnostic tools for precise crack mapping and evaluation hampers efforts to effectively address structural vulnerabilities, posing risks to these culturally significant buildings' structural stability and historical authenticity. This study aims to identify crack locations in timber-framed buildings in relation to surrounding structural elements. The process begins with capturing high-resolution images of the building wall under good lighting followed by preprocessing these to enhance crack visibility through noise reduction, contrast, and edge enhancement. Cracks and architectural elements, such as windows and doors, are then identified using bounding boxes, and the distances between them are measured to analyze spatial relationships. The results are evaluated based on Loss Values and Average Precision metrics. Based on these results, the study supports improved structural diagnostics through image-based automation. This contributes to the fields of architecture, heritage conservation, structural assessment, and restoration planning by enabling more targeted and data-informed interventions. In doing so, it provides a foundation for advancing structural health monitoring and improving decision-making in heritage preservation practices.

Keywords: *Crack Detection, Timber-Framed Buildings, Preventive Conservation, Image Processing.*

INTRODUCTION

The precise localization of surface cracks on architectural and structural elements, such as windows, columns, and load-bearing walls, is crucial for assessing the condition of buildings and implementing targeted maintenance and restoration strategies. Although crack detection has been extensively studied, most existing research focuses on detecting cracks in homogenous materials, such as concrete and masonry, with limited attention to heterogeneous and multi-material structures like heritage timber-framed buildings. These historic structures pose unique challenges due to the complex interactions between plaster and timber, differential material aging, and distinct load redistribution mechanisms. As a result, conventional crack detection methods often fail to provide accurate spatial localization of cracks, making it difficult to assess their severity and structural implications in these settings.

A critical gap in the literature lies in the lack of advanced diagnostic tools that can integrate crack localization with an understanding of the surrounding architectural and structural context. Existing studies primarily focus on crack segmentation and classification, yet they do not explicitly address the spatial relationship between cracks and key structural components. This omission limits the ability to determine whether a crack indicates significant structural deterioration or merely a superficial defect. Additionally, heritage conservation efforts require precise mapping techniques beyond crack presence to analyze crack propagation patterns in relation to architectural elements, which remain an underexplored area.

This study proposes a novel methodology for crack localization in heritage timber-framed buildings by integrating automated image-based detection with structural analysis to address these limitations. This approach not only identifies cracks but also situates them within their architectural context, offering insights into deterioration mechanisms and potential structural risks. By refining crack mapping techniques for complex, multi-material structures, this research advances existing methodologies and provides a more comprehensive diagnostic tool for heritage conservation and structural assessment. The findings contribute to developing targeted restoration strategies, ultimately improving the resilience and longevity of historically significant timber-framed buildings.

BACKGROUND

Identifying stress-induced crack locations in timber-framed buildings necessitates understanding the intricate interactions between the internal structural elements and external environmental factors. Stress can result from factors such as thermal expansion, moisture variations, and the general aging of materials, all of which demand regular inspection and timely intervention to prevent significant deterioration (Golding et al, 2022; Chaiyasarn, 2018).

Some recent effective tools for crack detection in historic buildings are machine learning and image processing technologies. For instance, deep learning models, particularly convolutional neural networks (CNNs), have accurately identified cracks on building surfaces. These systems can process vast datasets compiled from historical structures, significantly reducing the reliance on manual visual inspections that are often subjective and time-consuming (Hacıefendioğlu et al, 2023; Chen et al, 2023). The use of specialized datasets like Historical-crack18-19, which contains annotated images specifically for such detection tasks, enhances the training of automated systems, allowing for the detection of cracks under varying environmental conditions (Elhariri et al, 2022).

Additionally, robotic systems are increasingly recognized for their effectiveness in the automated inspection of timber structures. These robots, equipped with advanced sensory technologies, help detect cracks and map them in complex environments. Their application can be seen in various historic and fragile constructions, where traditional inspection methods pose risks and limitations (Wu et al, 2023; Zhang et al, 2022). Integrating robotic platforms into the monitoring systems of cultural heritage sites represents a significant shift towards enhanced preventive conservation strategies, thereby addressing challenges such as accessibility and safety (Yu et al, 2022).

Moreover, the literature highlights how environmental factors, nearby structural elements, and material variations influence the initiation and progression of cracks. For instance, changes in humidity and temperature can lead to differential expansion and contraction of timber elements, exacerbating crack formation (Saadatmorad et al, 2023). Thus, crack location identification systems should not only focus on the visual detection of cracks but also incorporate predictive modeling that factors in these operational environmental parameters to yield more comprehensive assessments of structural health (Ravichand et al, 2022).

In summary, the integration of advanced imaging, machine learning, and robotic systems offers a powerful approach to identifying and assessing stress-induced cracks in timber-framed buildings. To improve the effectiveness of these technologies in preventive conservation, it is essential to understand how cracks are influenced by the contextual factors that are key to ensuring the longevity of historic structures.

METHODOLOGY

The methodology depends on four main steps (Figure 1): 1) data input and preprocessing, 2) feature extraction and detection, 3) post-processing, and 4) analysis. This study draws on a curated dataset of high-resolution images of heritage timber-framed buildings to evaluate the proposed model. The dataset captures various crack formations and their spatial proximity to architectural elements such as windows, timber beams, and plastered surfaces. Images in the dataset are captured under controlled lighting to ensure clarity and minimize shadows that could obscure crack visibility. The collected images are manually annotated with bounding boxes and polygonal segmentation to accurately label cracks and structural elements. This annotation process, as exemplified in Figure 2, is carried out using the Roboflow platform, ensuring consistent labeling throughout the dataset. Data augmentation techniques, including flipping, contrast adjustments, and Gaussian noise addition, are applied to enhance model robustness and generalization. Such augmentations help improve the model's ability to detect cracks in diverse lighting conditions and from various angles.

To optimize the performance of crack detection, the dataset is divided into training (70%), validation (20%), and testing (10%) subsets.

A deep-learning object detection model is then trained to identify cracks and their surrounding architectural elements. The model architecture is based on YOLOv12, selected for its effective balance between detection accuracy and inference speed, and is fine-tuned on the annotated dataset to detect cracks, windows, timber beams, and plaster regions. Training is carried out using the Ultralytics framework with the following hyperparameters:

- Total number of images in the dataset: 1989 images
- Image size: 640 × 640 pixels
- Dataset split ratios: training (70%), validation (20%), and testing (10%)
- Batch size: 16
- Learning rate: 0.001
- Number of epochs: 220

The model's performance is evaluated using Loss Values and Average Precision. The trained model is then tested on unseen images to assess its effectiveness in detecting cracks and their spatial relationships with structural elements.

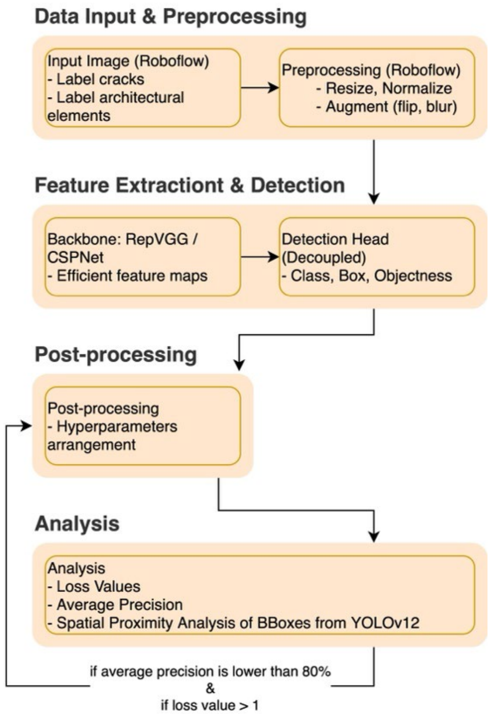

Figure 1: Workflow.

After detecting cracks and architectural elements, a spatial analysis is conducted to determine the proximity of cracks to surrounding elements. The shortest distance between cracks and structural components is calculated using an edge-to-edge distance approach. This method considers the minimum horizontal or vertical distance between two bounding boxes. Given a bounding box representation $[x_1, y_1, x_2, y_2]$, where (x_1, y_1) is the top-left corner and is the bottom-right corner, the distance between two bounding boxes was computed as follows:

- Computing horizontal and vertical distances:

Horizontal distance: $d_x = \max(0, x_1^{(b)} - x_2^{(a)}, x_1^{(a)} - x_2^{(b)})$ (1)

Vertical distance: $d_y = \max(0, y_1^{(b)} - y_2^{(a)}, y_1^{(a)} - y_2^{(b)})$ (2)

- Determining the shortest distance:

If bounding boxes overlap, d = 0. (3)

Otherwise, $d = \sqrt{d_x^{\,2} + d_y^{\,2}}$. (4)

This method ensures that cracks are correctly classified based on their spatial relationships with windows, beams, and plaster. A predefined threshold distance (e.g., 50 pixels) was used to categorize cracks as either "near" or "distant" from structural elements.

To validate the results, detected cracks and their measured proximity to architectural elements are visualized using OpenCV. Bounding boxes are drawn around detected objects, with connecting lines indicating proximity where cracks are classified as "near" an element. This visual output supports a qualitative assessment of the accuracy in the spatial analysis. Additionally, the model's predictions are compared against ground-truth annotations, and statistical

Figure 2: Sample images from the training dataset.

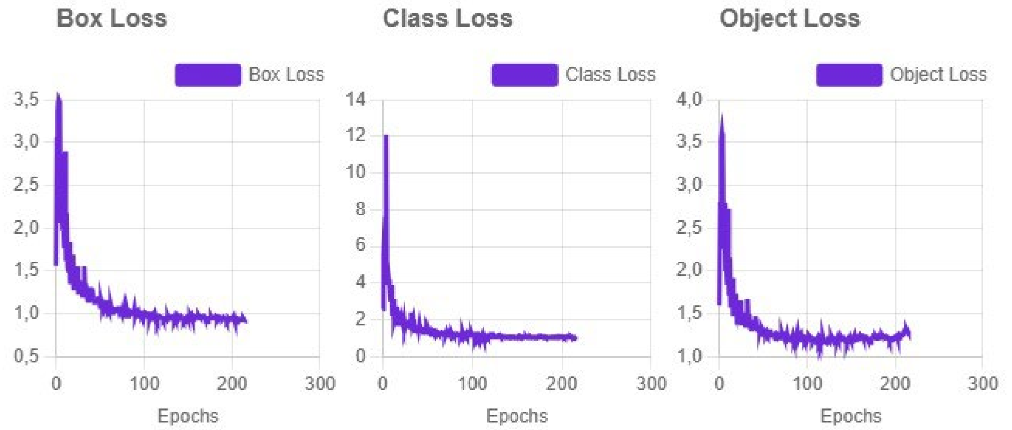

Figure 3: Loss values.

evaluation is conducted to assess the overall effectiveness of the approach.

RESULTS

The model's training results show stable convergence, as reflecting in the loss curves. Box loss, class loss, and object loss all decrease sharply within the initial epochs and stabilize at relatively low values (Figure 3). This trend demonstrates that the model successfully learns to detect crack patterns and distinguish contextual architectural elements. The rapid decrease in class loss suggests an efficient classification of cracks and structural elements, while the stabilization of object loss highlights the model's improved ability to detect relevant features with minimal false positives.

The training procedure is assessed by the loss values for bounding box regression (Box Loss), object classification (Class Loss), and objectness confidence (Object Loss), monitored across 220 epochs. The Box Loss starts at essentially 3.4 and exhibited a sharp decrease throughout the initial 50 epochs, later stabilizing between 0.6 and 0.8. This pattern demonstrates that the model rapidly acquired the ability to identify crack locations and then enhanced these predictions with commendable spatial precision. The Class Loss, initially 13, has a significant reduction during the early training phases and stabilizes 1.0 to 1.5. This reduction indicates the model's enhanced capacity to precisely categorize crack characteristics and background factors, sustaining consistent performance. Correspondingly, the Object Loss, which commences near 3.9, decreases consistently and stabilizes within the range of 1.2 to 1.5, indicating the model consistently enhanced its confidence in identifying pertinent objects within the input frames. The persistent decline and stabilization in all loss categories signify successful learning and convergence. No overfitting or divergence is detected, affirming the model's dependability in performing this specialized crack detection task.

Moreover, with an average precision of 82.1%, the model demonstrates robust performance in identifying and localizing cracks relative to surrounding architectural elements. This level of precision suggests that the model can effectively distinguish cracks near architectural elements such as windows. However, there may still be room for improvement in challenging cases where cracks blend with textured backgrounds or when lighting variations affect detection accuracy.

Some misclassifications were observed, particularly in cases where cracks were faint or partially occluded by overlapping materials. Additionally, minor fluctuations in loss values following stabilization suggest room for further fine-tuning, such as expanding the dataset or applying more diverse augmentation techniques to enhance model generalization.

The methodology integrates deep learning and spatial analysis to automate crack detection and localization in heritage timber-framed buildings. The findings support structural health monitoring by enabling data-driven decision-making in preservation efforts, reducing the need for manual inspection, and improving early intervention strategies for damage mitigation.

CONCLUSION

This study advances the field of heritage conservation and structural assessment for identifying crack locations in relation to architectural elements in timber-framed buildings. The methodology integrates deep learning-based object detection with spatial analysis techniques to assess crack localization concerning structural components in heritage buildings systematically. The proposed approach enhances structural health monitoring by enabling automated detection and quantification of crack proximity to critical elements, aiding in targeted maintenance and restoration planning.
The findings demonstrate that automated crack mapping, when combined with an understanding of surrounding structural components, enhances the accuracy of deterioration assessment and supports data-driven maintenance and restoration planning.

The proposed methodology contributes to structural health monitoring and preservation practices by providing an efficient, scalable, and non-invasive tool for diagnosing crack-related vulnerabilities. This approach not only aids in the early detection of structural risks but also improves conservation decision-making by enabling targeted interventions that minimize unnecessary repairs and maintain historical authenticity. The following points highlight the contribution of this study:

- Introduces a method for identifying crack positions relative to architectural elements (e.g., windows, columns) in ageing heritage structures
- Combines image-based automation with structural analysis to provide crack mapping, essential for assessing structural integrity.
- Supports minimally invasive restoration through data-informed decision-making.
- Enables automated detection of crack proximity to key features, allowing early identification of structural risks.
- Establishes a basis for further studies in heritage preservation, including multi-sensor integration and spatial modeling.
- Aims to enhance the resilience and longevity of timber-framed heritage buildings through advanced digital diagnostics.

The YOLOv12 architecture employed in this work is not inherently innovative; nonetheless, it significance resides in its tailored adaption and implementation in a previously underexamined area: crack detection in timber framed heritage structures. Current deep learning research predominantly concentrates on concrete and masonry structures, resulting in a noticeable gap in examining timber building structures exhibiting distinct surface textures, joint configurations, and deterioration characteristics. This study enhances object detection models for digital heritage documentation and structural health monitoring by fine-tuning the model on a curated dataset of timber framed façades and incorporating spatial proximity analysis to essential structural elements such as beams, columns, and openings within a context that is both technically demanding and culturally important. This methodology offers novel insights into the preventive conservation of heritage buildings and illustrates the adaptability of deep learning technologies in particular architectural settings.

This study provides a foundation for improved crack diagnostics in timber-framed buildings.

Expanding the dataset and incorporating multi-sensor data could enhance the robustness of crack localization across diverse architectural contexts. While the proposed methodology demonstrates promising results, several limitations should be considered. This study primarily focuses on detecting cracks and their proximity to architectural elements visible from the exterior, such as windows and doors. Other structural components, such as internal beams, hidden joints, and decorative elements, were not analyzed due to visibility constraints. Including a broader range of structural elements could enhance the model's applicability in more comprehensive structural assessments.

Additionally, the reliance on edge-to-edge distance measurement for proximity analysis may introduce inaccuracies in cases where cracks have irregular or non-linear shapes. Future work could explore more advanced spatial modeling techniques, such as semantic segmentation, to improve localization precision. Furthermore, while data augmentation improved model generalization, real-world variations in lighting, weather conditions, and material textures may still impact detection accuracy. Expanding the dataset to include diverse environmental conditions could further refine the model's robustness.

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