AUTOMATIC CRACK DETECTION IN BUILT HERITAGE MASONRY USING YOLOV5

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1. CONSERVATION OF BUILT HERITAGE

The conservation of built heritage is a fundamental challenge in maintaining cultural and historical structures. Pathologies such as cracks in masonry can significantly affect structural integrity, leading to long-term damage if not identified and addressed in time (Philipparie, 2019). Traditional visual inspection methods, which rely on expert evaluation, are time-intensive and subject to human interpretation, potentially leading to inconsistencies in diagnosis (Watt & Swallow, 1995). The use of existing digital documentation techniques based on photogrammetry and lasergrammetry already enhances the accuracy and repeatability of visual surveys (Hallot et al., 2022). Moreover, the integration of artificial intelligence and deep learning presents an opportunity to automate and further improve the accuracy of pathology detection in heritage buildings, enhancing expert analysis (Mishra & Lourenço, 2024).

2. DEEP LEARNING FOR PATHOLOGY DETECTION

Deep learning has emerged as a powerful tool for image analysis in built heritage pathology detection. Among various deep learning models, YOLOv5 (You Only Look Once) stands out for its real-time object detection capabilities and effectiveness in training, making it well suited for analyzing cracks in heritage masonry (Guo et al., 2024).

Studies like Pratibha et al. (2023) and Karimi et al. (2024) assess that YOLOv5 can efficiently classify and localize cracks with high precision, reducing the need for exhaustive manual inspections. Yet, the emphasis of those studies lies on the performance of the DL model, and rarely on the actual accessibility of the technology for the experts who could benefit from it. In this study, we examine the variability of detection depending on the influence of image acquisition in real-world conditions. Specifically, we analyze the variation of the Ground Sampling Distance (GSD) parameter within an image. This resolution parameter serves as a crucial operator to guide photogrammetry-trained users in the automatic detection process. This article explores the benefits and limitations of deploying a model like YOLOv5 in a practical situation to assess its relevance for cultural heritage conservation.

3. DEPLOYMENT METHODOLOGY OF YOLOV5

YOLOv5 was trained on the dataset of masonry images from the work of Karimi et al. (2024), featuring different types of cracks under varying lighting conditions and material textures (Figure 1). The model achieved a mAP50 of 96.8% and a mAP50-95 of 68.3% after training. Two main steps were evaluated during the study. First, we evaluated the robustness of YOLOv5 under practical conditions and assessed the accessibility of the technology for its potential users. To do so, we conducted a real-world case study on various buildings, manually verifying detected cracks against AI predictions.

Secondly, YOLOv5's robustness was tested by varying the image resolution, the distance to the defect, the lighting conditions, both natural and artificial, as well as the incidence angle. The impact on predictions of image rotations and irrelevant objects was also explored. Figures 2 and 3 illustrate some of these tests.

Finally, a detailed explanation of the necessary steps to effectively utilize the technology was provided, along with an in-depth analysis of both local and cloud-based execution environments employed to run the model. This guide includes the basic understanding of a programming language and its execution, YOLOv5 model training and its various training parameters, and the extraction of predictions with the trained model.

4. PREDICTIONS RESULTS AND DISCUSSION

Preliminary results indicate that YOLOv5 achieves high accuracy in detecting previously unseen cracks, which could significantly enhance the speed and consistency of inspections compared to manual assessments. However, some limitations remain, including false positives caused by variations in image resolution and noise.

Despite training on a rather small sample of images from Portugal, YOLOv5 demonstrated strong generalizations in detecting cracks on varied brick types in Belgium. Performance remained robust under challenging conditions, including high incidence angles, low lighting, and non-ideal framing. However, the model struggled with certain crack typologies; particularly horizontal and stepped cracks, due to insufficient representation during training. Image rotation experiments confirmed that these limitations originated from insufficient training rather than model deficiencies.

5. CONCLUSION

The integration of Deep Learning models like YOLOv5 into built heritage conservation already represents a significant advancement in automated crack detection, assisting manual inspections while improving diagnostic accuracy. Nonetheless, automatic pathology detection still requires refinements to address environmental and architectural variations.

Despite promising results, deploying Deep Learning models in local environments remains complex, requiring significant computational resources, particularly during training. On the other hand, the use of cloud-based execution environments enhances accessibility by eliminating local computational constraints. Cloud-based execution platforms like Google Colab eliminate hardware constraints and compatibility issues, making automatic pathology detection more user-friendly.

A standardized protocol has already been developed, allowing any interested individual, regardless of programming expertise, to experiment with crack detection in an open and cloud-based environment. This initial step in the democratization of the process will not only attract a broader audience to the use of such technologies but also contribute to improving the system's robustness over time. Pretrained weight sharing could also allow for quicker and easier model deployment, reducing risks of errors related to overfitting or incorrect dataset handling during training.

While automation in built heritage pathology detection proves relevant and accessible, operator training remains essential to ensure correct model usage and interpretation. Creating guidelines such as those presented in this paper can enhance the accessibility of Deep Learning models for visual inspection experts. Future developments should also focus on collaborative tools with simplified interfaces to enhance usability and facilitate knowledge-sharing among researchers and experts, as well as further integrating AI with existing 3D documentation techniques.

6. REFERENCES

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7. FIGURES

Figure 1. Example of masonry cracks used to train YOLOv5.

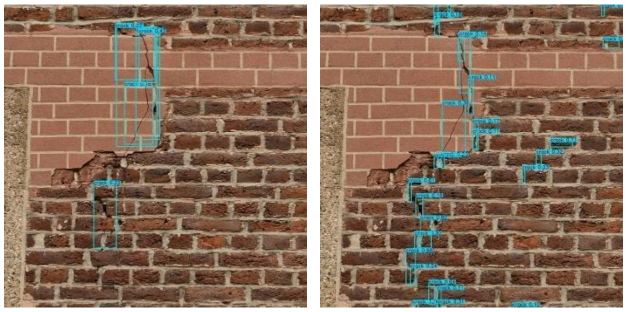

Figure 2. Impact of image resolution on predictions for the same crack

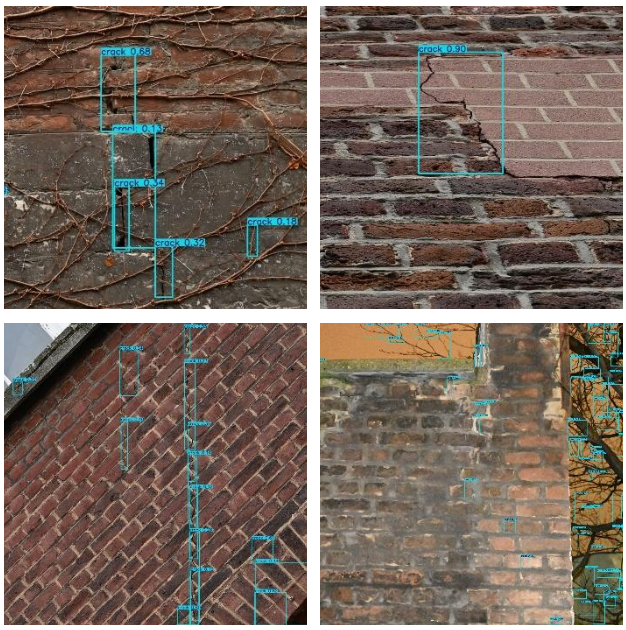

Figure 3. Various predictions of YOLOv5