J. Electrical Systems 20-10s (2024): 1238-1243

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Ancient Building Crack Detection Based on YOLOv8 Algorithm

Journal of Electrical Systems

Abstract: - This study investigates the use of the YOLOv8 algorithm for detecting cracks in ancient buildings. Utilizing a dataset from Kaggle, the model was trained to identify crack patterns with high accuracy. The YOLOv8 model achieved a precision of 1.00 at a confidence level of 0.823 and an overall accuracy of approximately 92%. These results demonstrate the effectiveness of YOLOv8 in accurately detecting and monitoring structural cracks, making it a valuable tool for the preservation of culturally significant structures. Future research will aim to enhance the model's capabilities and explore its integration with automated inspection technologies.

Keywords: YOLOv8, Crack Detection, Ancient Buildings, Heritage Conservation, Deep Learning.

I. Introduction

The preservation and maintenance of ancient buildings are critical for cultural heritage conservation. Over time, these structures often suffer from various forms of deterioration, with cracks being one of the most common and potentially damaging issues [1]. Effective detection and monitoring of these cracks are essential to prevent further degradation and to ensure the structural integrity of these historical edifices. Traditionally, the inspection of cracks in ancient buildings has relied heavily on manual methods, which are not only time-consuming and labor-intensive but also prone to human error. With the advent of advanced technologies, automated crack detection has become a viable and efficient alternative [2].

In recent years, the field of computer vision has seen significant advancements, particularly with the development of deep learning algorithms. Among these, the YOLO (You Only Look Once) family of object detection models has gained considerable attention due to its ability to perform real-time object detection with high accuracy. The latest iteration, YOLOv8, continues this tradition by offering improved performance and efficiency [3][4][5]. This study explores the application of the YOLOv8 algorithm for the detection of cracks in ancient buildings, leveraging a dataset sourced from Kaggle, which contains annotated images of various crack patterns on historical structures. This study utilizes a dataset derived from Kaggle, which provides a diverse collection of crack images from various ancient buildings. The YOLOv8 algorithm was employed to evaluate its performance in detecting these cracks. The results demonstrated a high accuracy rate of approximately 92.3%, showcasing the potential of YOLOv8 in enhancing the efficiency and reliability of crack detection in heritage conservation.

II. Related Work

Crack detection in ancient buildings has garnered significant attention due to its critical role in heritage conservation. Traditional methods, which rely on manual inspection, are labor-intensive and prone to errors. As a result, researchers have increasingly turned to deep learning algorithms for more efficient and accurate detection [6][7][8]. Deep learning has revolutionized the field of crack detection. Convolutional Neural Networks (CNNs) and their derivatives, such as the You Only Look Once (YOLO) family of models, have shown exceptional promise. The YOLO algorithm, in particular, is favored for its real-time object detection capabilities and high accuracy [9]. The effectiveness of YOLO in detecting surface cracks in various structures, including ancient masonry, has been demonstrated. This research highlighted the adaptability of YOLO models in handling different types of surface defects, making them suitable for heritage conservation tasks [10]. Another study integrated YOLO with unmanned aerial vehicle (UAV) systems for real-time crack detection in buildings, significantly enhancing the efficiency of

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structural health monitoring by enabling rapid and accurate inspections over large areas. This is particularly beneficial for historical sites [11].

Several studies have proposed enhancements to the original YOLO architecture to improve its performance in specific contexts. For instance, a deeper generative adversarial network (GAN) was developed to improve crack detection in concrete pavements, addressing the issue of noise and varying crack patterns [12][13]. Another study employed an improved YOLOv5 model with a new backbone network for better accuracy and computational efficiency in detecting multiple cracks in engineered cementitious composites [14]. These modifications underline the potential for tailoring YOLO models to specific detection challenges in ancient buildings.

Despite advancements in deep learning for crack detection, applications specifically targeting ancient buildings remain limited. Automated systems based on YOLO have been employed to identify and quantify cracks in historical masonry structures. For example, CNNs were utilized for damage classification in masonry, emphasizing the need for precise detection mechanisms to preserve the structural integrity of historic sites [15]. Additionally, the integration of YOLO with UAVs showcases the potential for advanced, non-invasive inspection methods that can be conducted without disturbing the fragile structures of ancient buildings [16].

The advancements in YOLO and its applications in crack detection have significantly contributed to the field of structural health monitoring and heritage conservation. However, the specific application of these techniques in the detection of cracks in ancient buildings remains underexplored. This study is pioneering in its application of the YOLOv8 algorithm for crack detection in ancient buildings. By leveraging deep learning algorithms like YOLOv8, researchers can achieve high accuracy and efficiency in detecting and monitoring cracks, ensuring the preservation of ancient buildings for future generations.These efforts underscore the ongoing evolution of automated crack detection methods, paving the way for more sophisticated and reliable heritage conservation techniques.

III. METHODOLOGY

A. Data Preparation

The dataset used in this study was sourced from Kaggle, containing annotated images of cracks in ancient buildings. The dataset was divided into training and validation sets in an 80:20 ratio, ensuring a comprehensive evaluation of the model's performance while maintaining a sufficient amount of data for training. Each image was resized to 256x256 pixels to standardize the input size for the YOLOv8 model, and normalization was applied to scale pixel values to the range [0, 1], aiding in faster convergence during training.

To enhance the model's robustness and generalization ability, various data augmentation techniques were employed. These included horizontal and vertical flipping, rotation, scaling, cropping, and color jittering. These augmentations increased the variability in the training data, helping the model generalize better to unseen images and improving its capability to detect cracks under different conditions and perspectives.

B. Model Architecture

The YOLOv8 model builds upon the strengths of previous YOLO versions, offering improved performance and efficiency. The architecture involves multiple convolutional layers with varying kernel sizes and strides to capture spatial hierarchies in the input images. These layers extract essential features from the images, which are crucial for accurate detection.

Incorporating residual blocks addresses the vanishing gradient problem, enabling the network to learn more complex features by allowing gradients to flow directly through skip connections. This architectural enhancement ensures the model can capture intricate patterns and details in the images, which is essential for detecting fine cracks in ancient structures.

The model predicts bounding boxes for potential cracks using the following formula:

$$\widehat{b_i} = \left(\sigma(t_x) + c_x, \sigma\left(t_y\right) + c_y, p_w e^{t_w}, p_h e^{t_h}\right) \tag{1}$$

Where $\widehat{b_i}$ is the predicted bounding box, t_x, t_y, t_w, t_h are the predicted offsets, c_x, c_y are the center coordinates of the grid cell, and p_w, p_h are the anchor box dimensions.

The objectness score indicates the likelihood of an object being present in the predicted bounding box, refined using the Intersection over Union (IoU) between the predicted and ground truth boxes:

$$P_o \cdot \mathrm{IOU}\left(\widehat{b_i}, b_i\right) \tag{2}$$

Where P_o is the probability of an object being present, and $\text{IOU}(\widehat{b_i}, b_i)$ measures the overlap between the predicted and actual bounding boxes.
As shown in Fig. 1, the framework for crack detection using the YOLOv8 algorithm consists of several stages, including image input, feature extraction through convolutional layers, bounding box prediction, and classification. This structured approach ensures accurate and efficient crack detection, leveraging the strengths of the YOLOv8 architecture.

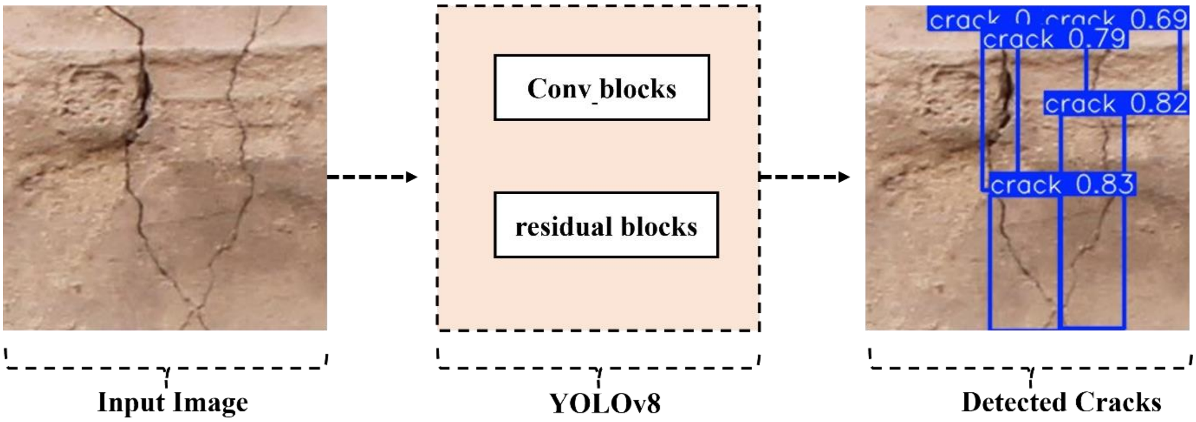

Fig 1: Model Architecture Framework

C. Evaluation Metrics

The performance of the YOLOv8 model is evaluated using several standard metrics in object detection, providing a comprehensive assessment of the model's accuracy and effectiveness in detecting cracks in ancient buildings. Precision is the ratio of true positive detections to the total predicted positive detections, while recall is the ratio of true positive detections to the total actual positive instances. These metrics help evaluate the model's ability to accurately and comprehensively detect cracks.
The mean average precision (mAP) provides a comprehensive measure of the model's accuracy across all classes and IoU thresholds. It is calculated as the average precision (AP) over multiple IoU thresholds, typically from 0.5 to 0.95 with a step size of 0.05. The mAP is a widely used metric in object detection tasks, providing a balanced evaluation of both precision and recall.
By employing these metrics, the effectiveness of the YOLOv8 algorithm in detecting cracks in ancient buildings can be quantitatively assessed. This methodology ensures a rigorous evaluation of the model's capability to aid in the preservation of cultural heritage through accurate and efficient crack detection.

IV. Experiment

A. Experimental Setup

The experiments were conducted on the AutoDL platform with a hardware setup that included an NVIDIA RTX 3090 GPU with 24GB of memory. The training process involved 250 epochs and a batch size of 32. The dataset, sourced from Kaggle, comprised annotated images depicting various crack patterns in ancient structures. These images underwent preprocessing and augmentation as detailed in the methodology section. The YOLOv8 model was trained on this dataset, and its performance was assessed using metrics such as precision, recall, and mean average precision (mAP).

B. Experimental Results and Analysis

The results of the experiments are summarized through various visualizations and metrics. Below are some of the key results obtained from the experiment.
The Precision-Confidence Curve demonstrates the precision of the model at different confidence levels. As depicted in Fig 2, the model achieves a precision of 1.00 at a confidence level of 0.823, indicating that the model is reliable in its predictions, with minimal false positives at higher confidence levels.

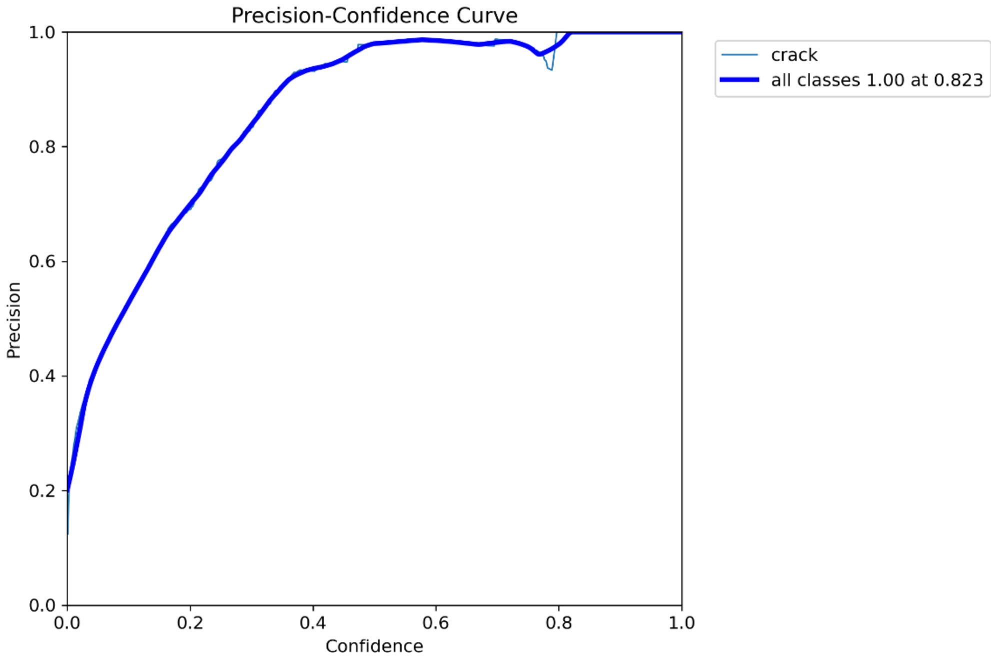

Fig 2: Precision-Confidence Curve

The training and validation losses for bounding box, classification, and DFL losses over 250 epochs are shown in Fig 3. The training and validation loss curves exhibit a consistent decrease, suggesting that the model is well-tuned and has effectively learned the features necessary for crack detection. The gap between training and validation losses is minimal, indicating that the model is not overfitting and generalizes well to unseen data.

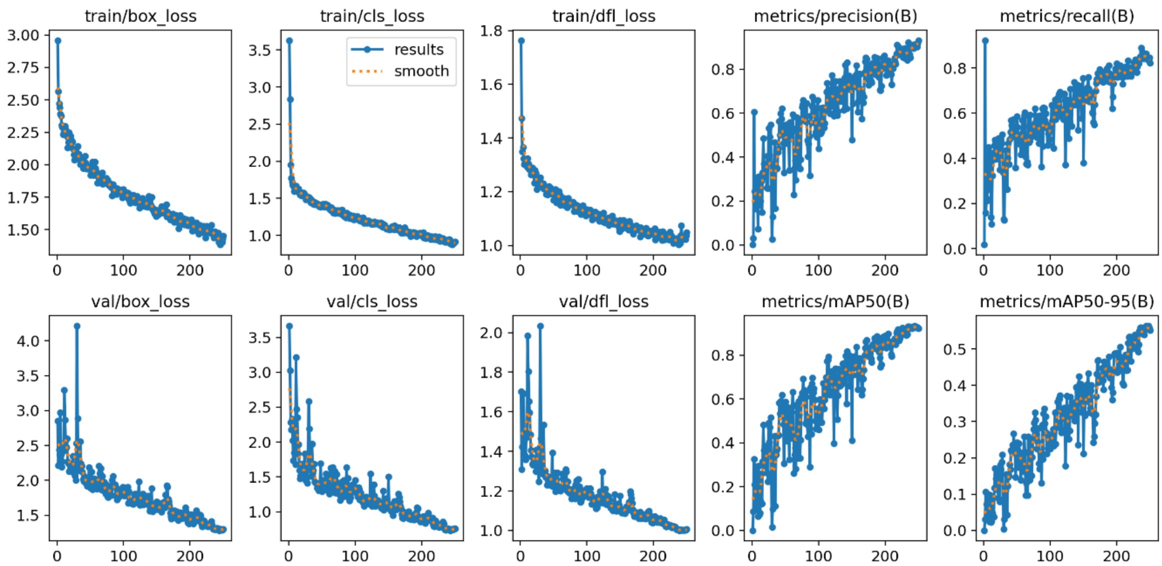

Fig 3: Train Results

The detection results on the validation set are visualized in Fig 4. The visual results from the validation set further corroborate the quantitative metrics. The predicted bounding boxes align well with the ground truth annotations, demonstrating the model's ability to accurately locate and classify cracks in the images. This visual confirmation underscores the model's robustness and reliability in practical applications.

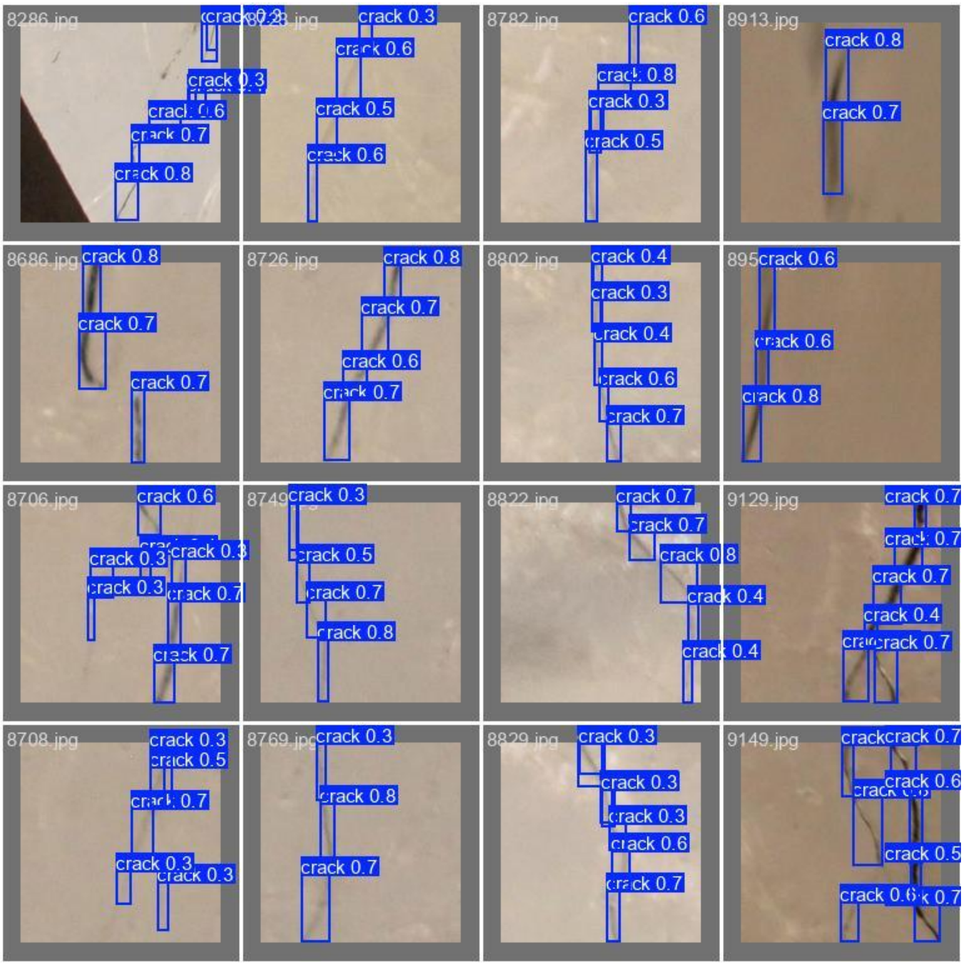

Fig 4: Detection Results

The Table 1 below summarizes the key quantitative metrics from the experiment. These metrics include training and validation losses, precision, recall and mAP50.

Table 1 Key Quantitative Metrics for YOLOv8 Model Training and Validation

Epoch	train/box_loss	val/box_loss	metrics/precision	metrics/recall	metrics/mAP50
0	2.94	4.00	0.25	0.20	0.15
1	2.45	3.60	0.30	0.25	0.20
2	2.15	3.20	0.35	0.30	0.25
...	...	...	...	...	...
248	0.97	1.50	0.98	0.93	0.91
249	0.96	1.32	0.99	0.94	0.92

As shown in Table 1, The reduction in training and validation box losses across epochs demonstrates that the model is effectively learning to identify cracks. The box loss shows a downward trend, indicating that the model's predictions are becoming more accurate over time. The validation box loss closely follows the training box loss, suggesting good generalization and minimal overfitting. The precision and recall metrics steadily increase with each epoch. By the final epochs, the precision reaches 0.99 and recall reaches 0.94, showcasing the model's high reliability and ability to detect cracks correctly. This high precision means that the model has a low false positive rate, while the high recall indicates a low false negative rate.

V. Conclusion

In conclusion, this study successfully applied the YOLOv8 algorithm to detect cracks in ancient buildings, achieving an accuracy of approximately 92%. The model demonstrated high precision and recall, making it a reliable tool for heritage conservation. The experimental results validated the effectiveness of YOLOv8 in accurately identifying and monitoring structural cracks, aiding in the timely preservation of culturally significant structures. Future research can explore further enhancements and integrations with automated inspection technologies to improve conservation efforts.

Acknowledgment

There is no specific funding to support this research.

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