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Object Detection Method for Automated Classification of Distress in Rabat's Built Heritage

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Abstract. Rabat, the capital city of Morocco, proudly boasts a rich and complex architecture-al legacy that beautifully blends historical influences ranging from Islamic to con-temporary designs. Conserving this unique heritage holds paramount importance in safeguarding the city's distinctiveness and cultural significance. Conventional approaches to cataloging and categorization have been time-consuming and susceptible to human errors. Hence, this study aims to overcome these obstacles by creating a sophisticated object detection model to streamline the classification process. In this study, we propose an innovative deep learning-driven approach to detect and classify various degradations of built heritage. The dataset used in this study comprises numerous captured images that display diverse types of degradation, including cracks, collapse, rising damp, spalling, delamination, and lichens. Manual annotation was conducted to label the various damages present in the dataset. These labeled images were then used to train and validate the model. Multiple performance metrics were employed to assess and evaluate the model's performance, including precision and recall. Based on the results, the developed model has demonstrated excellent performance in both detecting and classifying different types of damage. This model's effective use aids local authorities in urban planning, heritage preservation, education, and tourism promotion, yielding broad implications.

Introduction

Rabat, the majestic urban center and political hub of Morocco, confidently harbors a plethora of age-old monuments. These notable locations serve as lasting testimonials to the civilizations that played a pivotal role in influencing the course of North African history, especially during the Roman and Islamic epochs. Within this collection of historical treasures are numerous locations with origins tracing back to the 8th century, including the distinguished Chellah.

The charm of Chellah captivates a growing multitude of visitors coming from varied backgrounds and age brackets, establishing it as a top-tier tourist hotspot. Yet, this extraordinary location bears the force of nature's relentless influence, undergoing both physical and chemical deterioration. The primary reasons behind the physico-chemical decline of historical structures in Chellah can be pinpointed as follows: environmental elements like rainfall, surface water runoff, and moist air, abundant in salts from the Atlantic Ocean, penetrate the materials either through infiltration or capillary ascent.

To safeguard this historical landmark from decay, it is crucial to conduct regular evaluations of these structures to ensure their protection and conservation. Promptly recognizing and categorizing any damage will streamline timely interventions and upkeep initiatives. The prevailing methods for identifying surface damage in historical heritage sites largely rely on on-site visual inspection techniques, complemented by dedicated equipment [1]–[5]. Nevertheless, due to the rapid progress of deep learning methodologies, the previously mentioned challenges can be tackled. Several Convolutional Neural Networks (CNNs) have emerged, demonstrating outstanding precision in classification and recognition. As an example, Makantasis et al. utilized a three-layer CNN to examine cracks in tunnels [6]. Cha et al. have proposed a method for visual evaluation based on the Faster Region-based Convolutional Neural Network, with the goal of achieving nearly instantaneous concurrent identification of various types of impairments. The detection technology, formerly constrained to contemporary civil engineering, poses challenges in terms of compatibility. In this research, we employed the YOLO (You Only Look Once) method for identifying and categorizing diverse damages found in Chellah.

Dataset and Method

The dataset employed in this study includes images manually taken at Chellah using a Canon 700D camera. A total of 120 images is at your disposal, each showcasing unique dimensions influenced by the diverse scales of the captured scenes. These images specifically concentrate on various forms of impairments observed at Chellah, encompassing delamination, cracks, lichens, rising damp, spalling and partial collapse. Fig. 1 presents some samples of this dataset.

In this research, YOLOv5 is employed as the chosen model to achieve the task of object detection. Table 1 presents the structure of YOLOv5, revealing its complex design and composition. The algorithm framework is primarily divided into three essential components: The foundational network, the bottleneck layer network (Neck), and the detection layer (Head).

The foundational network includes a regular convolution module (Conv), a C3 module, and a spatial pyramid pooling module-fast (SPPF). The neck module incorporates a blend of crucial elements, encompassing a standard convolution module (Conv), a C3 module, concatenation, and an up-sampling process. The detection layer (Head) consists of three layers of detection.

Fig. 1: *sample images of Chellah monument*

Table 1. *architecture of YOLOV5*

Layers	Stride	Arguments
Backbone	Conv	[3, 64, 6, 2, 2]
	Conv	[64, 128,3, 2]
	C3	[128, 128, 3]
	Conv	[128, 256, 3, 2]
	C3	[256, 256, 6]
	Conv	[256, 512, 3, 2]
	C3	[512, 512, 9]
	Conv	[512, 1024, 3, 2]

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	C3	[1024, 1024, 3, 2]
	SPPF	[1024, 1024, 5]
Neck	Conv	[1024, 512, 1, 1]
	Upsample	-
	Concat	[1]
	C3	[1024, 512, 3]
	Conv	[512, 256, 1, 1]
	Upsample	-
	Concat	[1]
	C3	[512, 256, 3]
	Conv	[512, 512, 3, 2]
	Concat	[1]
	C3	[512, 512, 3]
	Conv	[512, 512, 3, 2]
	Concat	[1]
	C3	[1024, 1024, 3]
Head	Detect	-

(1)

Results and discussion

To evaluate the improved efficiency of the YOLOv5 algorithm in detecting damages within the Chellah context, precision-confidence and recall-confidence curves are employed. These curves function as vital instruments for evaluating the model's performance by examining the relationship between precision and confidence, and recall and confidence. In Fig. 2(a), the precision-confidence curve for the proposed model is depicted. This curve holds a vital role in understanding the reliability of the model's predictions. It allows us to evaluate the equilibrium between precision and confidence. As we move along the curve, there is a simultaneous increase in both precision and confidence. This signifies the model's growing confidence in its predictions and its enhanced ability to accurately identify true positive instances of damage. Fig. 2(b) depicts the display of the recall-confidence curve for the proposed model. Examining this curve enables the assessment of the equilibrium between recall and confidence. Advancing along the curve, we notice a simultaneous increase in both recall and confidence. This signifies a fortification of the model's prediction certainty, resulting in the successful detection of a higher number of authentic damage instances. As a result, the recall rate increases, emphasizing the model's improved proficiency in identifying actual damages. Furthermore, the elevation of confidence levels underscores the growing reliability of the model's predictions.

To verify the outcomes produced by the model, Fig. 3 displays the results generated by the model in identifying bounding boxes for each damage type. Based on these findings, one can infer that the model demonstrates an impressive capacity to distinguish among the various deteriorations in Chellah. This affirms its effectiveness in accurately identifying and precisely locating different anomalies across the surveyed surfaces.

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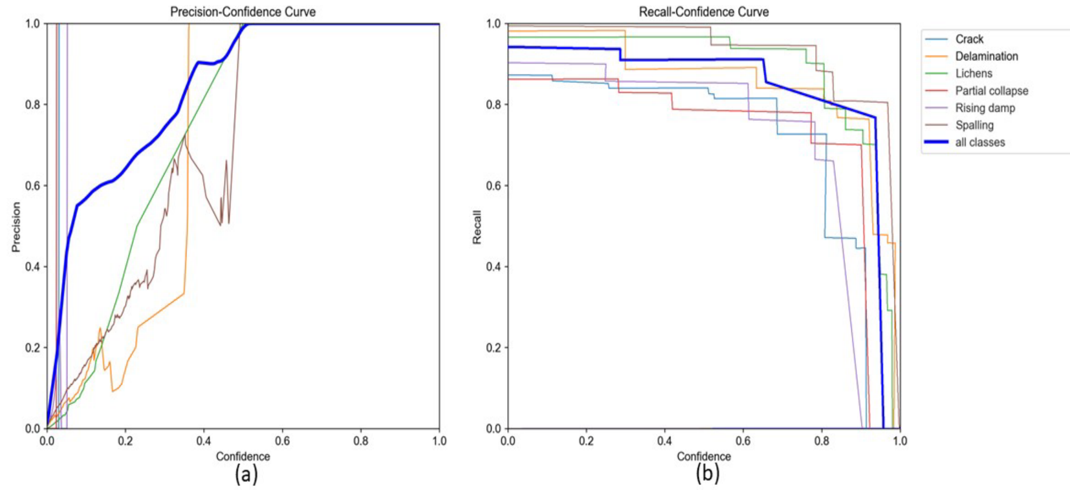

Fig. 2. (a) *Precision-confidence curve of the proposed model for the six damages, (b) Recall-confidence curve of the proposed model for the six damages.*

Fig. 3. *Illustrative instance showcasing predicted bounding boxes utilizing the YOLOv5 model.*

Conclusions

The captivating allure of Chellah draws an increasing number of tourists from diverse backgrounds and age groups, cementing its position as a premier tourist destination. However, this exceptional site carries the impact of nature's unyielding forces, facing both physical and chemical degradation. Assessing damages frequently demands the proficiency of experienced specialists, who dedicate substantial time and effort to the evaluation procedure. To overcome these constraints, this research presents a novel automated damage detection method employing a deep learning network. Utilizing the YOLOv5 object detection technique, our method strives to accurately detect and classify the various types of damage within the Chellah monument. Derived from the obtained results, the model has effectively identified and precisely pinpointed various damages existing in Chellah, overcoming challenges such as imbalanced datasets and a restricted database.

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