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Automated Damage Detection on Concrete Structures Using Computer Vision and Drone Imagery †

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Abstract: Manual Inspection of concrete structures, such as tall buildings, bridges, and huge infrastructures can be time-consuming, and costly, and damage assessment is a crucial task that requires close-range inspection of all surfaces. The proposed system uses computer vision model to identify various types of damages on these structures. The computer vision model and was trained on a large dataset of drone footage, which was annotated manually to ensure accuracy. The model was then tested on new data, and the results showed that it could accurately detect and identify structural damage on concrete structures with 94% accuracy. The system is much faster and more efficient than manual inspection, reducing the time and cost required for damage assessment. The proposed system has the potential to revolutionize the way we perform damage assessment on concrete structures. It can help to preserve and protect these valuable assets by enabling early detection of damage and facilitating timely repairs.

Keywords: drone-based automated system; computer vision; structural damage detection; deep learning algorithms; Internet of Things (IoT); close-range footage analysis

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1. Introduction

Manual inspection of concrete structures, such as tall buildings, bridges, and huge infrastructures, is a time-consuming and risky process for human employees. Drones with sensor camera nodes have showed potential in gathering close-range footage, but the problem is rapidly analyzing enormous volumes of data to detect and diagnose structural deterioration. This study deals with these challenges by presenting an Internet of Things (IoT), computer vision and deep learning-based automated solution. The primary issue addressed in this research is the requirement for a more efficient and reliable way of identifying structural damage on Concrete Structures.

The traditional manual inspection technique is time-consuming and expensive, making timely repairs and maintenance impossible. As a result, an automated solution is necessary to speed up the damage assessment process while reducing dangers to human personnel. The proposed system focuses on detecting various types of damage, such as cracks, Alkali-Silica Reaction (ASR), concrete degradation, and others, on Concrete Structures using drone-captured video footage [1,2]. The system's scope includes developing a Convolutional Neural Network (CNN) architecture tailored to this specific task and implementing a seamless process for automatically obtaining video data from drones.

The primary objective of this work is to create and implement an automated damage detection system capable of identifying structural damage on Concrete Structures in an efficient and accurate manner. The technology intends to expedite the inspection process by utilizing IoT, computer vision and deep learning techniques, enabling proactive maintenance and preservation activities. The novelty of the proposed system is a custom-designed CNN architecture that is optimized for detecting damage on Concrete Structures and a system architecture based on IoT to automatically capture data, perform analysis and reporting. The performance of the proposed automated damage detection system was evaluated using a diverse dataset of drone-captured video footage containing various types of damage on Concrete Structures. The CNN architecture demonstrated impressive results, achieving an accuracy of 94% in correctly identifying different types of structural damage.

The approach involves capturing close-range footage of the infrastructure with drones and processing the footage using a computer vision model to identify and classify damage. The proposed method can provide an efficient and cost-effective way to detect damage to cultural heritage sites and help preserve these important historical structures for future generations. The working of the system is shown in Figure 1.

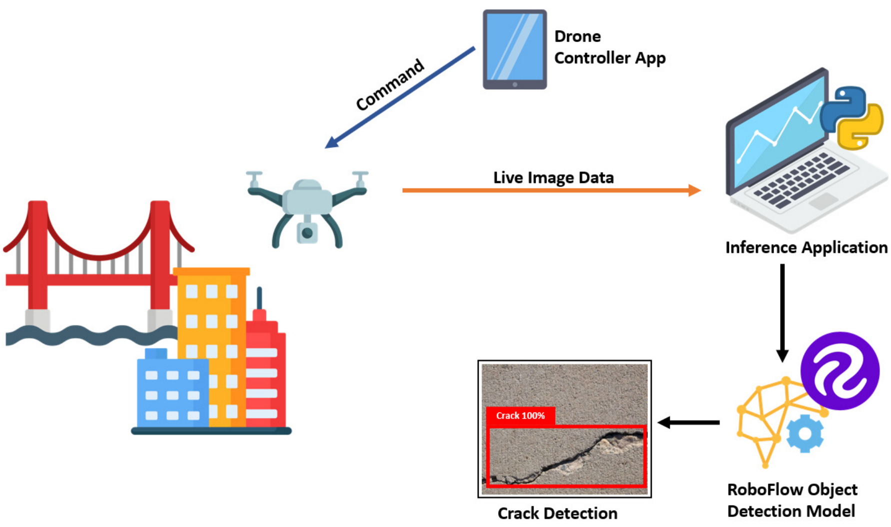

Figure 1. System Architecture.

2. Related Work

The comprehensive analysis [3] explores into the critical issue of damage detection in civil engineering, emphasizing the transformational potential of Computer Vision and Deep Learning algorithms. The research [4] presents a Deep Convolutional Neural Network-based Damage Locating (DCNN-DL) approach for steel frame inspection that outperforms existing techniques with 99.3% accuracy. The approach uses the DenseNet architecture to properly identify and detect damaged regions, providing a fast real-time solution for visual damage evaluation in civil structures. The research in [5] investigates the use of computer vision algorithms in conjunction with remote cameras and unmanned aerial vehicles (UAVs) for non-contact civil infrastructure evaluation. The study in [6] presents a unique structural identification framework for bridge health monitoring that makes use of computer vision-based measures. It employs a novel damage indicator, a displacement unit influence surface, and successfully identifies and localizes simulated damage on a large-scale bridge model, demonstrating its use in structural health evaluation. The thorough study in [7] addresses gaps in the current literature on computer vision-based crack diagnosis for civil infrastructure by providing a complete evaluation of qualitative and quantitative methodology, including deep learning-based approaches.

Despite extensive research into image-based damage identification and quantification, this technology is still in its early phases, with limitations and gaps for further investigation. Despite efforts to improve the reliability of image-based approaches, it is realized that attaining total automation in damage assessment and categorization remains a substantial task.

3. System Design

The proposed system involves the use of a drone to capture image data, which is then fed to an object detection model to identify different types of structural damage in cultural heritage sites. In this section, we provide a detailed methodology for building and deploying the system, which involves collecting images of cracks in buildings, labeling and training the model using, and deploying the model using a Python script.

3.1. Dataset Collection

The first step in building the system is to collect images of cracks in buildings. These images are taken using a drone, which captures high-resolution images of the building's surface. The images are then annotated with labels indicating the type of damage using the Roboflow platform. The labeling process involves drawing bounding boxes around the damaged area and assigning them a label indicating the type of damage, such as cracks, ASR, or concrete degradation.

Different images of cracks were collected. The images are sized to 800 × 800 pixels which is a standard transformation applied before training. The dataset is then split up the images into a train, test, and validate split:

- 2527 images used for training.
- 2149 images used for validation.
- 279 images used for testing.

With the use of the Roboflow platform's rectangular "bounding box" tool, each picture in the dataset is labelled for object detection. The labelling for the various photos is shown in the following figure:

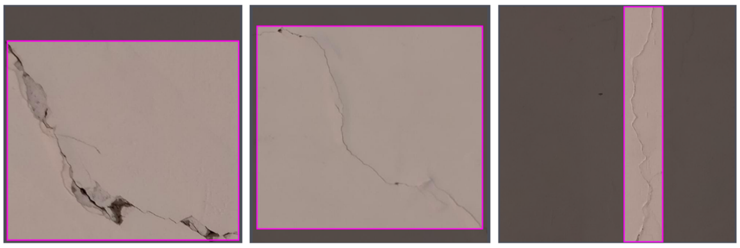

Figure 2. Annotated images in the dataset. Bounding box for cracks detection.

3.2. Model Training

The annotated data is then used to train the object detection model. The model is trained using a deep learning algorithm, YOLO.

The trained model is deployed using a Python script, which receives a live camera stream and runs the object detection model to detect the cracks. The Python script uses the Model API to query the hosted version of the model and return the results. The API provides a simple interface for sending images or video to the model and receiving the output in a standardized format.

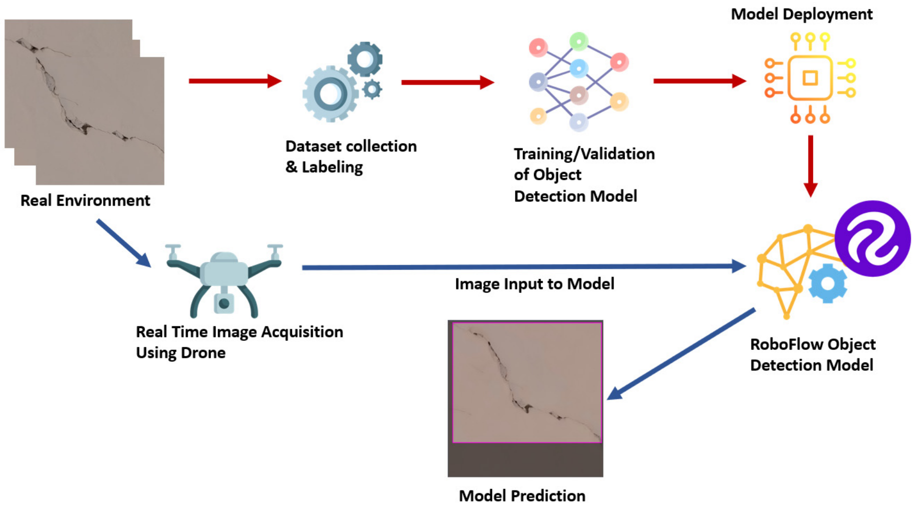

Figure 3. Methodology of the system.

The selection of hardware components plays a crucial role in this research as they enable the deployment and testing of the computer vision model. Specifically, a drone and a camera module are utilized to facilitate the implementation of the model. The figure below illustrates the setup of the drone used in this research. The setup of the drone, as depicted in the figure, showcases the integration of the camera module and other necessary components to ensure seamless data capture and transmission.

Figure 4. Drone with WiFi Camera Module.

The system incorporates several essential hardware components for its operation. It utilizes a Quadcopter Drone Kit, WiFi Camera Module, a Roboflow account, and a Python development environment.

4. Results & Discussion

In this section, the results of experiments using different object detection models for detecting structural damage in cultural heritage sites has been discussed. The three different models, YOLOv8, YOLOv7, and YOLOv5, are used to evaluate the performance of the system on a test dataset of annotated images for the field of cultural heritage monitoring and protection.

Performance of the YOLOv8, YOLOv7, and YOLOv5 models has been evaluated on the test dataset of annotated images. The models were trained using the dataset from Roboflow platform. As transfer learning is used in this research, the following tables shows the pre-trained YOLO models used and training settings.

Table 1. YOLO pre-trained models.

Model	Weights	Layers	Parameters	Gradients	GFLOPs
YOLOv8	yolov8m.pt	295	25,856,899	25,856,883	79.1
YOLOv7	Yolov7.pt	407	37,194,710	37,194,710	105.1
YOLOv5	Yolov5m.pt	291	20,871,318	20,871,318	48.2

Table 2. Training Settings.

Model	Image Size	Learning Rate	Batch Size	Epochs
YOLOv8	800	0.01	16	200
YOLOv7	640	0.01	16	200
YOLOv5	800	0.01	16	200

The evaluation metrics used were precision, recall, and F1 score. The equation from 1 to 4 are used to evaluate the performance of machine learning models and measure its accuracy, precision, recall, F1 score, and latency:

$$\text{Accuracy} = (\text{TP} + \text{TN})/(\text{TP} + \text{TN} + \text{FP} + \text{FN}) \tag{1}$$

$$\text{Precision} = \text{TP}/(\text{TP} + \text{FP}) \tag{2}$$

$$\text{Recall} = \text{TP}/(\text{TP} + \text{TN}) \tag{3}$$

$$\text{F1Score} = (2 \times \text{Precision} \times \text{Recall})/(\text{Precision} + \text{Recall}) \tag{4}$$

The following Table 3 shows the results of the evaluation for each model.

Table 3. Performance matrix of different YOLO models.

Model	Precision	Recall	F1 Score
YOLOv8	0.91	0.85	0.89
YOLOv7	0.85	0.81	0.86
YOLOv5	0.71	0.75	0.82

As shown in Table 1, the YOLOv8 model achieved the highest performance in terms of precision, recall, and F1 score. The model achieved a precision of 0.93, recall of 0.85, and F1 score of 0.89. The YOLOv7 model also performed well with a precision of 0.92, recall of 0.81, and F1 score of 0.86. The YOLOv5 model achieved a precision of 0.90, recall of 0.75, and F1 score of 0.82.

The following table that compares the mAP scores for each class across the YOLO8, YOLO7, and YOLO5 models:

Table 4. Class wise accuracy of different YOLO models.

Class	YOLO8 mAP Score	YOLO7 mAP Score	YOLO5 mAP Score
Plastic shrinkage cracks	0.89	0.8	0.66
Crazing & Crusting Cracks	0.93	0.85	0.73
Settling cracks	0.9	0.84	0.7
Expansion cracks	0.91	0.83	0.72
Heaving cracks	0.78	0.85	0.65
Overloading cracks	0.92	0.83	0.68
Corrosion of Reinforcement	0.93	0.86	0.71

As shown in the table, the YOLO8 model has the highest mAP score for all classes except for “Heaving cracks”, where the YOLO7 model performs slightly better. The

YOLO7 model also shows good performance for "Crazing & Crusting Cracks", "Settling cracks", and "Corrosion of Reinforcement". The YOLO5 model generally shows lower mAP scores for all classes compared to the other two models, but still performs relatively well for "Crazing & Crusting Cracks" and "Corrosion of Reinforcement". The following table compares the inferencing time for all three model.

Table 5. Comparison accuracy and speed of YOLO models.

Model	mAP Score	Inference Time (ms)
YOLO8	0.91	25
YOLO7	0.85	32
YOLO5	0.71	18

As shown in the table, the YOLO8 model has the highest mAP score and a relatively fast inference time, making it the best overall option for detecting structural damages. The YOLO7 model has a moderate mAP score but a slightly slower inference time compared to the YOLO8 model. The YOLO5 model has the fastest inference time but the lowest mAP score, making it a suitable option for applications where speed is a priority over accuracy.

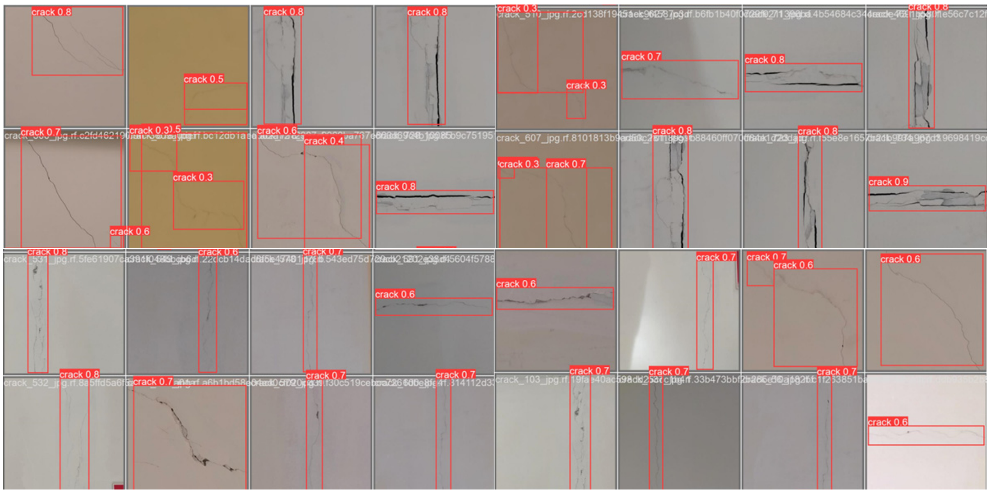

Figure 5. Inferencing result showing detection of cracks on wall.

5. Conclusions

This research demonstrates the effectiveness of using drone-captured imagery and computer vision techniques for the inspection of structural damage in heritage buildings. By employing object detection models such as YOLO8, YOLO7, and YOLO5, various types of damage, including plastic shrinkage cracks, crazing & crusting cracks, settling cracks, expansion cracks, heaving cracks, overloading cracks, and corrosion of reinforcement has been successfully identified. The evaluation of the models has shown promising results, with high mAP scores across different classes.

This research has highlighted the potential of leveraging computer vision and drone technology in damage assessment, providing a safer, cost-effective, and efficient alternative to traditional manual inspections. By automating the detection process, we reduce the need for manual evaluation, which can be time-consuming and prone to human error. The integration of these technologies allows for comprehensive and detailed inspections, facilitating early detection and timely intervention to mitigate further damage to concrete structures.

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