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Deep learning-based automated damage detection in concrete structures using images from earthquake events

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ABSTRACT

Timely assessment of integrity of structures after seismic events is crucial for public safety and emergency response. This study focuses on assessing the structural damage conditions using deep learning methods to detect exposed steel reinforcement in concrete buildings and bridges after large earthquakes. Steel bars are typically exposed after concrete spalling or large flexural or shear cracks. The amount and distribution of exposed steel reinforcement is an indication of structural damage and degradation. To automatically detect exposed steel bars, new datasets of images collected after the 2023 Turkey Earthquakes were labeled to represent a wide variety of damaged concrete structures. The proposed method builds upon a deep learning framework, enhanced with fine-tuning, data augmentation, and testing on public datasets. An automated classification framework is developed that can be used to identify inside/outside buildings and structural components. Then, a YOLOv11 (You Only Look Once) model is trained to detect cracking and spalling damage and exposed bars. Another YOLO model is fine-tuned to distinguish different categories of structural damage levels. All these trained models are used to create a hybrid framework to automatically and reliably determine the damage levels from input images. This research demonstrates that rapid and automated damage detection following disasters is achievable across diverse damage contexts by utilizing image data collection, annotation, and deep learning approaches.

Keywords: cracks, spalling, exposed rebars, deep learning, earthquake, structural damage detection, damage levels

1. INTRODUCTION

Large earthquakes can inflict significant damage on buildings and bridges, ranging from minor issues to partial or complete collapse. Visual inspection is vital for immediate safety assessments and forms the basis for informed decisions on building interventions, like repair, demolition, or reconstruction. It also plays a key role in accurately determining financial responsibilities among insurers, government agencies, or individual owners.

Deep learning techniques have demonstrated significant promise in recent years for facilitating quick and scalable damage detection. This advancement is built upon foundational work, including the development of extensive public image datasets for structural damage (Gao and Mosalam, 2018; Yeum et al., 2018) and the effective use of deep convolutional neural networks (CNNs) for image-level damage classification (Cha et al., 2018; Fan, 2024). More sophisticated studies have used various YOLO versions and object detection models like Faster R-CNN to localize multiple damage types simultaneously, including exposed rebar, cracks, and spalling (Bai et al., 2021a; Zou et al., 2022; Ghosh Mondal et al., 2020). Despite these developments, significant obstacles remain (Bai, 2022). First, even human inspectors find it difficult to discern damage levels, particularly when there are faint or obscure visual indicators. Second, diverse, well-annotated datasets representing a range of structural configurations, materials, lighting conditions, and damage types are necessary for reliable real-world performance. Third, few studies examine the structural significance of multiple damage types simultaneously, whereas many examine isolated damage, such as cracks or spalling.

This study aims to close these gaps by presenting a strong deep learning framework that automatically recognizes and categorizes earthquake-induced damage levels in reinforced concrete (RC) structures, with a particular emphasis on crucial damage indicators like cracking, spalling, and exposed rebar. The model used in this paper was trained using labeled image data from the 2023 Kahramanmaraş Earthquake in Türkiye and several benchmark datasets, including PEER Hub ImageNet (ϕ-Net created by Gao and Mosalam (2018, 2020)) and publicly available crack-spalling datasets (Bai et al., 2021a, b). The generalization performance of the model was assessed using separate post-earthquake datasets from the 2017 Mexico Earthquake (Purdue University, 2018) and the 2017 Pohang Earthquake in South Korea (Sim et al., 2018). This data fusion allows us to train and test our models on diverse real-world scenarios and to improve the generalization capacity

2. METHODOLOGY

2.1 Data preparation

Four separate image datasets were used to train and evaluate the proposed framework, as summarized in Table 1. These datasets were developed using both publicly available resources (e.g., ϕ-Net) and newly collected images from the 2023 Türkiye Earthquake.

Table 1 Summary of the image datasets used for training and evaluation.

Dataset Type	Image Count	Resolution Range	Purpose	Notes

Inside/Outside Classification	18,193	224×224 – 1080×1440	Classify indoor vs. outdoor	Based on ϕ-Net + Türkiye EQ
Structural Component Recognition	4,939	224×224 – 1080×1240	Identify beams, columns, and walls	Subset of ϕ-Net
Structural Damage Level Detection	8,731	1080×1440	Classify damage level (0–3)	Collected from Türkiye EQ
Damage Type Detection	3,064	Varying	Detect cracks, spalling, rebar	Bounding boxes annotated manually

2.2 Deep learning models for structural damage classification and detection

YOLOv11, one of the latest iterations in the YOLO series by Ultralytics (Jocher and Qiu, 2024), marks a substantial leap forward in real-time object detection. The YOLO model allows for its application across various tasks: object detection, instance segmentation, image classification, pose estimation, and object tracking (Jegham et al., 2024).

2.3 Hybrid deep learning framework for post-earthquake damage detection

The framework is made up of a fusion logic after cascading YOLOv11-based classifiers and detectors. Prior to detecting structural elements and damage types (crack, spalling, and rebar), an image must first be classified as either inside or outside of a building. Lastly, a hybrid decision mechanism assigns one of four damage levels by combining predictions based on models and rules. Rebar validation and environment-aware filters are integrated into the updated RuleFusion v2, which improves accuracy without increasing the model size. Fig. 1 shows the overall workflow.

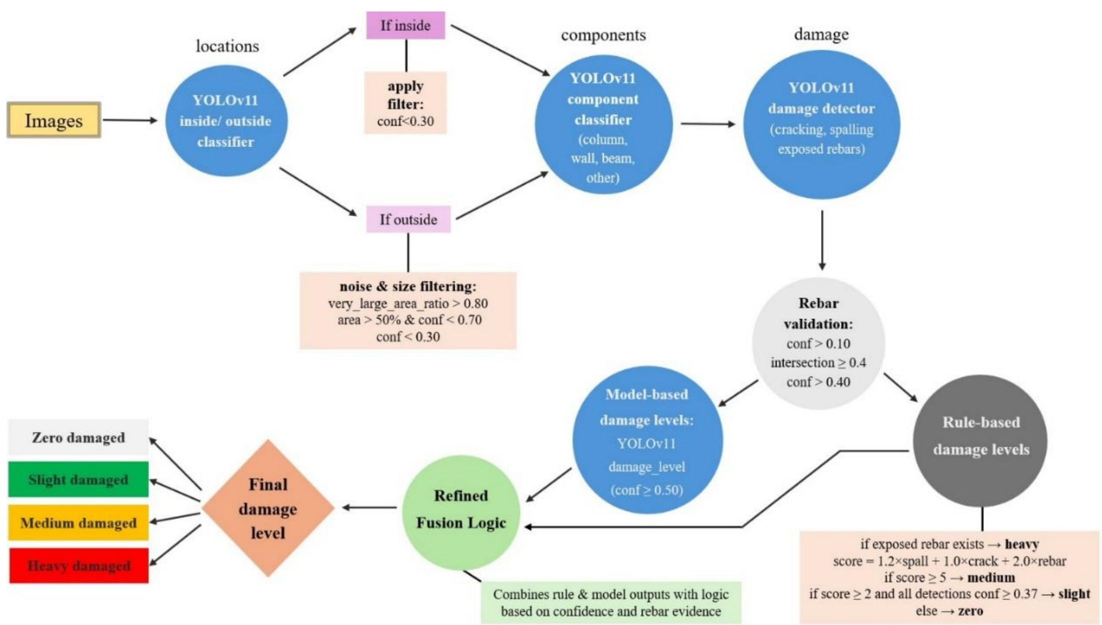

Fig. 1 Workflow of the proposed hybrid framework for post-earthquake building damage assessment

2.4 Rule-based damage levels

Initially, a rule-based classifier was created to improve reliability and interpretability. Damage is immediately classified as "heavy" if exposed rebar is found. If not, a weighted score is determined by counting the number of rebar, spalling, and cracks found as shown in Fig. 1. The damage is then categorized as zero, slight, or medium using thresholds. This reasoning guarantees consistent and comprehensible results, particularly under difficult visual circumstances.

3. RESULTS

The proposed hybrid framework was tested on 2017 Pohang Earthquake image (PEI) dataset (Sim et al., 2018) and 2017 Mexico City Earthquake image (MEI) dataset (Purdue-University, 2018), which include 4,109 and 4,136 high-resolution images collected by experts after these two Richter magnitude 5.2 and 7.1 earthquakes struck these regions. The model's overall performance was strong, but because of image quality, structural variations, lighting, and more complex context, its quantitative performance on the Mexico dataset was somewhat worse. Table 2 presents the accuracy results for different fusion and meta-model configurations. On the more difficult MEI dataset, however, the meta-model based on logistic regression performed poorly (Test No. 4). Consequently, an advanced LightGBM-based (Ke et al., 2017) meta-model was introduced, yet it only achieved an accuracy of 41.96% (±1 accuracy: 79.29%), indicating dataset-specific difficulties. These numerical insights suggest opportunities for further improvement through targeted hyperparameter tuning, feature engineering, or enriched training data in future studies.

Table 2 Accuracy comparison of the baseline hybrid model and the meta-model on different test datasets.

Test	Dataset	Method	Model type	Accuracy (%)	±1 Accuracy
1st	PEI	Final Decision (Baseline)	Rule Fusion v1	61.54	68.32
2nd	PEI	Final Decision	Rule Fusion v2	71.04	91.92
3rd	PEI	Meta-Model Decision	Logistic Regression	73.72	92.80
4th	MEI	Final Decision	Rule Fusion v2+LightGBM	41.96	79.29

** v2 = v1 + environment-aware noise filtering, ambiguity-aware component bias, and refined rebar validation (see Section 2.3)*

The accuracy of the baseline fusion method on the 2017 PEI dataset was enhanced by incorporating a meta-model based on logistic regression, as indicated in Table 2. However, due to the previously mentioned dataset-specific complexities, neither Logistic

Regression nor an advanced LightGBM meta-model significantly improved performance on the more difficult 2017 MEI dataset.

Table 3 Per-class F1 scores on 2017 PEI dataset

Metrics	Zero	Slight	Medium	Heavy
F1 Score	0.844	0.384	0.128	0.641

Table 3 displays the per-class F1 scores of the top-performing configuration (Meta-Model Decision with Logistic Regression), which achieved 73.72% exact and 92.80% ±1 accuracy on the 2017 PEI dataset. The model is more accurate for zero and heavy damage classes, but less accurate for medium and slight damage levels.

4. CONCLUSIONS

This study presents a strong hybrid framework that combines deep learning, rule-based logic, and meta-learning for the precise classification of earthquake-induced structural damage. Key findings and contributions are summarized below:

(1) The suggested framework facilitates quick and accurate post-disaster evaluations by combining object detectors, image classifiers, and a fusion-based decision mechanism.

(2) The method successfully addressed class imbalance and produced results that were easy to understand by achieving high accuracy in identifying zero and heavy damage levels.

(3) The damage detection model demonstrates limitations in accurately identifying finer cracks, despite its success in detecting noticeable damage such as spalling and exposed rebar. This is because such damage looks obscured or subtle and is hard to discern from background textures.

Future research will concentrate on addressing performance limitations on some datasets by examining image-aware fusion techniques. The LightGBM or other machine learning algorithms will be incorporated into the scene-level embedding for the unmanned platforms with cameras.

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