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Post-seismic structural damage segmentation using YOLOv8-seg model

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ABSTRACT

A customized YOLOv8-seg architecture is hired in this study to automatically detect and segment post-earthquake damage, such as cracks, spalling, reinforcement exposure, crushing, buckling, and structural failure, that appears on bridge piers tested using slow and fast cyclic tests, shaking table tests, and real-time hybrid simulations. Using a hybrid loss function, the YOLOv8-seg model processes 32×32 and 256×256 pixel image patches, extracted from 124 large RGB images, for cracks and other seismic damage categories, respectively. Training is conducted on the image patches and their corresponding labeled annotations, distinguishing between seismic damage and background (non-damage) pixels. The model is trained with a batch size of 16, utilizing the Adamax optimizer, an exponential learning rate scheduler, and weight decay techniques to improve training stability and performance. The results demonstrate that the generated mask patches closely resemble the actual damage patterns.

1. INTRODUCTION

Following an earthquake, the rapid and reliable assessment of structural damage is vital for public safety, rehabilitation planning, and resource allocation. While initial inspections primarily aim to ensure immediate safety, they often provide only superficial evaluations due to time and logistical constraints. As a result, detailed damage assessments are essential to guide effective retrofitting and reconstruction of reinforced concrete (RC) structures such as buildings and bridges. Engineers require accurate, efficient, and standardized methods to assess structural integrity and prioritize interventions (Maeda et al. 2017).

Traditional structural health monitoring relies on contact-based sensors, such as

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LVDTs, and accelerometers, which offer valuable real-time data. However, these systems are typically complex to install, measure localized behavior only, and require ongoing maintenance. In contrast, non-contact methods, particularly computer vision-based systems, offer broader coverage, lower maintenance, and simplified deployment, making them highly suitable for comprehensive damage monitoring (Hamidia et al. 2024).

Post-earthquake evaluations have traditionally depended on visual inspections by certified engineers. Although effective, this approach is time-intensive and subject to human variability. In large-scale seismic events, limited expert availability can delay assessments and hinder emergency responses. Recent advances in computer vision and deep learning have shown promise in automating damage detection from images and video, enabling rapid, objective, and scalable assessments (Narazaki et al. 2021; Miao et al. 2021). However, challenges persist, most notably, the need for large, annotated datasets and robust models capable of generalizing to real-world conditions and handling small-scale features like fine cracks or distinguishing between multiple, co-existing damage types in complex field imagery (Zhang et al. 2024; Xia et al. 2025; Zou et al. 2022; Dong et al. 2024).

To address these gaps, this study employs a customized YOLOv8-seg architecture to detect and segment various forms of post-earthquake damage, such as cracks, spalling, reinforcement exposure, crushing, buckling, and structural failure, on bridge piers subjected to slow and fast cyclic loading, shaking table tests, and real-time hybrid simulations (see Fig.1). Unlike traditional models, YOLOv8-seg combines object detection and segmentation in a unified framework, offering high-speed inference and the ability to detect fine-grained damage patterns across varying scales. By leveraging its potential, this research aims to improve the accuracy, efficiency, and practical deployability of automated post-earthquake damage assessment tools for RC bridge piers.

(a) Fast and slow cyclic tests (b) Shaking table test (c) RTHS

Fig. 1. Bridge pier experiments under different loading protocols.

2. Damage state definition

Seismic damage evaluation guidelines classify structural damage into five distinct levels based on visual indicators and their correlation with the lateral force-displacement response (see Fig. 2), which is used to assess structural performance (Maeda et al. 2017). Damage State I is characterized by fine cracks less than 0.2 mm in width, occurring without reinforcement yielding and maintaining essentially linear elastic behavior. Damage State II, involving cracks between 0.2 mm and 1.0 mm, marks the onset of yielding. Damage State III includes wider cracks (1.0–2.0 mm) and minor cover concrete loss, with structural behavior transitioning into the nonlinear hardening phase. More severe deterioration is observed in Damage State IV, defined by cracks exceeding 2.0 mm, significant loss of cover concrete, and exposed reinforcement. While lateral load capacity may be reduced, gravity load support is typically maintained. The most critical, Damage State V, involves severe structural degradation such as reinforcement buckling, concrete crushing, vertical deformation, and a substantial loss of lateral load-carrying capacity (Maeda et al. 2017). These defined damage states are essential for determining appropriate repair and retrofitting strategies. In this study, visible seismic damage is classified into five categories aligned with these damage states: Class 1 (Cracks), Class 2 (Spalling), Class 3 (Reinforcement Exposure), Class 4 (Concrete Crushing), and Class 5 (Buckling/Failure). Undamaged areas are assigned to Class 0, serving as the background. These categories serve as the basis for supervised learning in the segmentation model.

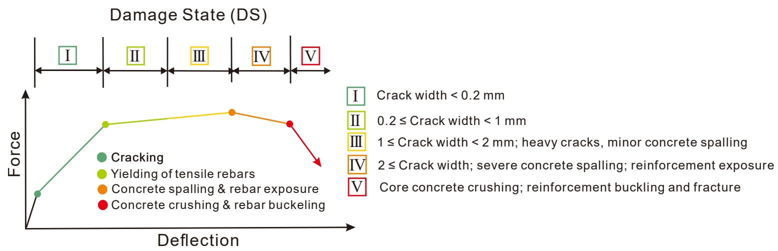


Fig. 2. Bridging Visual Seismic Evidence and Structural Damage State in RC Components.

3. Image Preprocessing and Class Imbalance Handling

Preprocessing plays a foundational role in preparing image data for semantic segmentation using deep learning. It not only improves training efficiency and model stability but also ensures more reliable and generalizable predictions. In this study, several preprocessing techniques are adopted to optimize the performance of the segmentation network. Pixel values are first normalized to a [0,1] range to ensure consistency across inputs. Data augmentation methods, such as rotation, flipping, and blurring, are employed to increase variability and prevent overfitting. To maintain alignment between input patches and their corresponding ground truth masks, geometric corrections are applied. Furthermore, to handle large image sizes and avoid out-of-memory issues, a patch-based approach is adopted. The YOLOv8-seg model is first developed for a multi-category seismic damage segmentation, which segments classes 0, 2, 3, 4, and 5 using 256×256-pixel patches, and then for crack segmentation, which detects classes 0 and 1 using finer 32×32-pixel patches. Both models are trained with a batch size of 16. For the multi-category model, a total of 1723 image patches are used, with 20% (344 patches) reserved as unseen test data. The remaining 1379 patches are split into 70% training (965 patches) and 30% validation (414 patches).

4. Proposed YOLOv8-seg model for multi-category pixel-level segmentation

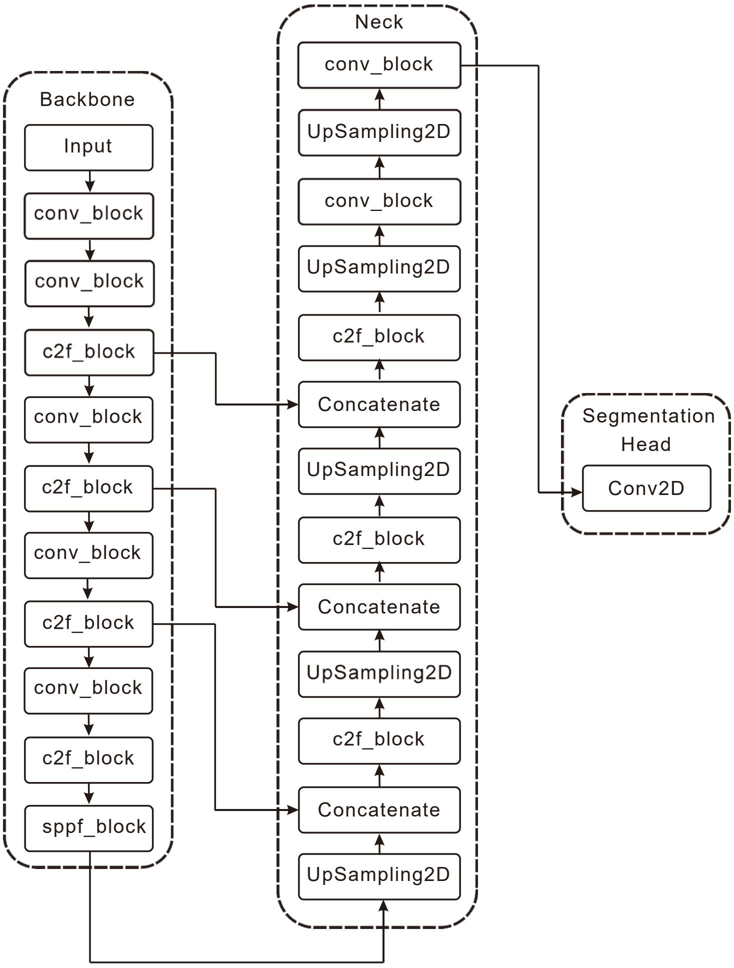
YOLOv8-seg (Zhang et al. 2024; Xia et al. 2025; Zou et al. 2022; Dong et al. 2024) is an advanced variant of the YOLO (You Only Look Once) object detection model (Redmon et al. 2016), optimized for semantic segmentation, assigning a class label to each pixel in an image. Unlike standard object detection, which provides bounding boxes, segmentation requires spatially detailed outputs, making architectural tweaks necessary.

The proposed architecture in Fig. 3 is a customized YOLOv8-seg model designed for efficient and accurate semantic segmentation of seismic damage on bridge pier surfaces. It is composed of a backbone, neck, and segmentation head. The backbone extracts hierarchical features using alternating conv_block and c2f_block modules and ends with a sppf_block to capture multiscale spatial context. The neck aggregates these features through multiple UpSampling2D, c2f_block, and Concatenate operations, forming a feature pyramid that enhances spatial resolution and contextual understanding. Finally, the segmentation head, consisting of a single Conv2D layer, produces dense pixel-wise class predictions. Supporting modules such as the conv_block, c2f_block, and sppf_block are designed for lightweight computation and rich feature extraction, enabling the model to balance accuracy and speed effectively for real-time segmentation tasks.

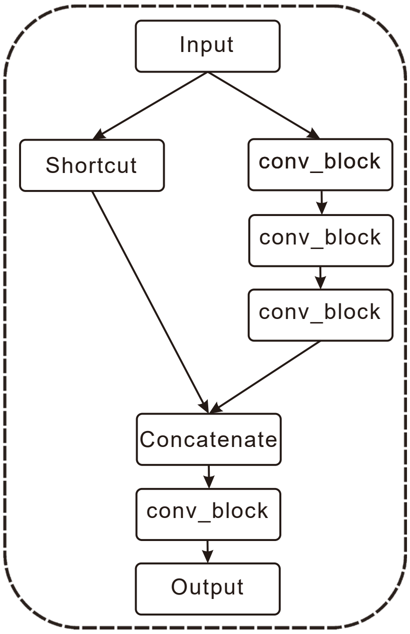
The proposed YOLOv8-seg architecture integrates carefully tuned hyperparameters across its modular design to optimize semantic segmentation performance. The conv_block modules use increasing filter sizes (64–512) and a mix of 3×3 and 1×1 kernels, combined with Batch Normalization and ReLU activation function for stable feature extraction and downsampling. The c2f_block leverages partial fusion with n=3 or 6 repetitions, depending on depth, enhancing gradient flow and efficiency. The sppf_block uses three successive 5×5 MaxPooling layers with a stride of 1 to capture multiscale spatial context before fusion through concatenation and a 1×1 convolution. In the neck, UpSampling2D operations restore spatial resolution while skip connections and c2f_blocks refine feature maps. Finally, a 1×1 Conv2D layer with softmax activation serves as the segmentation head, producing per-pixel class predictions for accurate and real-time semantic segmentation.

Fig. 4 presents the semantic segmentation results for seismic damage on unseen bridge piers, evaluated using per-class Intersection over Union (IoU). The analysis is based on randomly extracted RGB image patches, their corresponding ground truth labels, and predicted mask outputs. As observed in Fig. 4(a)-(c), the model achieves IoU scores of 0.9846 for Class 0, 0.9541 for Class 2, and 0.6771 for Class 3, while Classes 4 and 5 are absent in this sample. The overall mean IoU (mIoU) for this instance is 0.8719. For Figs. 4(d)-(f), the model results in a mIoU of 0.9727, with high per-class IoU scores: 0.9816 for Class 0, 0.9700 for Class 2, 0.9654 for Class 4, and 0.9739 for Class 5.

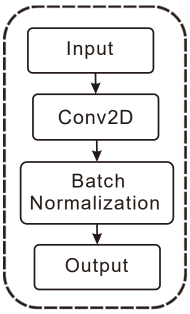
Crack segmentation results are presented in Fig. 5. As illustrated, the proposed model can identify crack pixels with a high level of accuracy, achieving mIoU scores of 0.9021 and 0.9247 for the image patches in Figs. 5(a) and 5(d), respectively. Moreover, the model effectively distinguishes crack regions from non-crack areas such as gridlines and background occlusions, demonstrating strong discriminative capability.



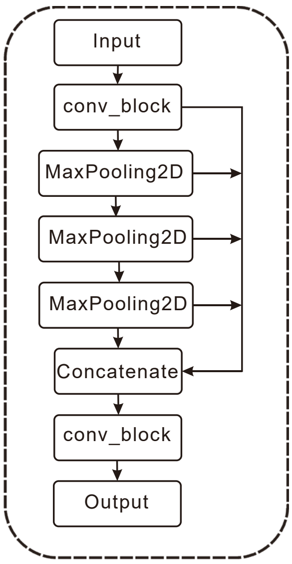
(a) Customized YOLOv8-seg model



(b) c2f_block

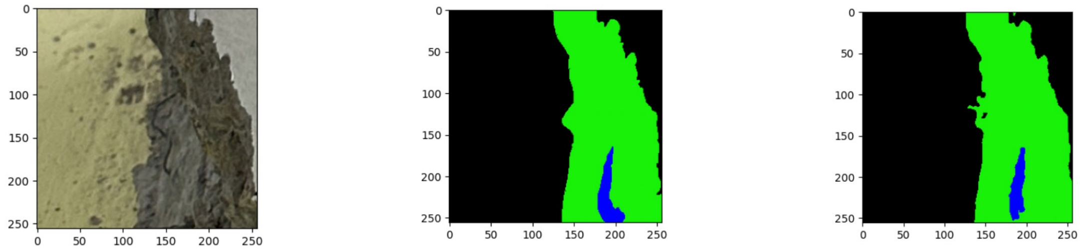


(c) conv_block



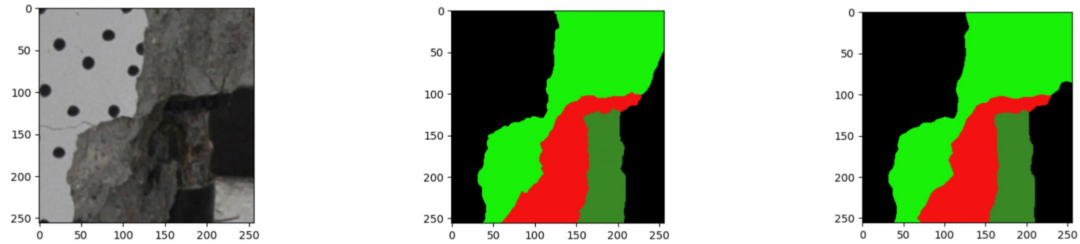
(d) sppf_block

Fig. 3. Proposed YOLOv8-seg model architecture.



(a) RGB image patch (b) RGB label patch (c) Predicted mask patch

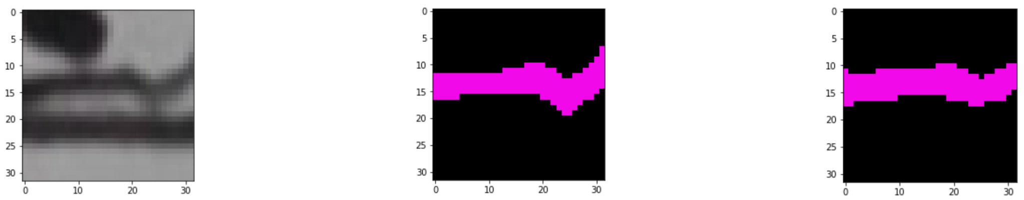
per-class IoU					mIoU
Class 0	Class 2	Class 3	Class 4	Class 5	
0.9846	0.9541	0.6771	-	-	0.8719



(d) RGB image patch (e) RGB label patch (f) Predicted mask patch

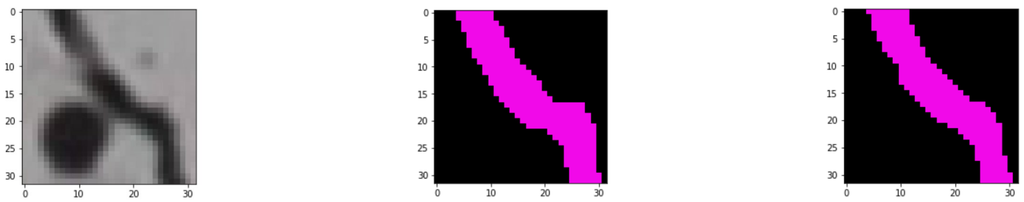
per-class IoU					mIoU
Class 0	Class 2	Class 3	Class 4	Class 5	
0.9816	0.9700	-	0.9654	0.9739	0.9727

Fig. 4. Patched image, corresponding label, and predicted mask including multicategory damage.



(a) RGB image patch (b) RGB label patch (c) Predicted mask patch

per-class IoU		mIoU
Class 0: 0.9640	Class 1: 0.8402	0.9021



(d) RGB image patch (e) RGB label patch (f) Predicted mask patch

per-class IoU		mIoU
Class 0: 0.9600	Class 1: 0.8893	0.9247

Fig. 5. Image patches and the corresponding labels and predicted mask patches including crack category damage.

5. CONCLUSIONS

This study introduces a computer vision-based approach utilizing a customized YOLOv8-seg model for pixel-level, multi-category segmentation of seismic damage in RC bridge piers. A comprehensive and diverse image database is assembled, incorporating data from cyclic loading tests, shaking table experiments, and RTHS, offering a more realistic representation of seismic damage than traditional cyclic tests alone. The annotation process categorizes damage into five classes: crack, spalling, exposure, crushing, buckling, and failure. To address significant data imbalance, the training strategy incorporates data augmentation, class weighting, and a hybrid loss function, applied at both the sample and pixel levels. The multi-category segmentation model (excluding cracks) is trained on 256×256 image patches, while the dedicated model for crack segmentation uses 32×32 patches. This patch-based approach enables efficient processing of high-resolution images while avoiding GPU memory limitations. Unlike prior studies that rely on simplified cyclic test protocols, which may misrepresent true seismic demands, this research emphasizes the use of RTHS-generated imagery for more accurate damage representation. Furthermore, critical structural response indicators, such as residual crack width and lateral force-drift hysteresis, benefit directly from the improved segmentation accuracy. By integrating deep learning with realistic seismic testing data, this work enhances the precision of damage detection and contributes to more reliable post-earthquake assessment and resilience planning for RC bridge infrastructure.

Acknowledgment

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