RCA U-Net with Dynamic Loss Weighting for Automated Crack Segmentation in Structural Health Monitoring

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***Abstract*—Crack detection in concrete structures is critical for Structural Health Monitoring (SHM), yet traditional manual inspection is time-consuming and error-prone. Deep learning approaches, particularly U-Net, have shown promise but struggle with fine crack patterns, class imbalance, and varying environmental conditions. This paper presents a RCA U-NET (Residual-CBAM-ASPP-U-Net) with dynamic loss weighting that addresses these challenges through three key innovations: (1) integration of residual blocks with SE attention and CBAM modules for enhanced feature discrimination, (2) ASPP bottleneck with multiple dilation rates for multi-scale feature extraction, and (3) adaptive loss mechanism balancing binary cross-entropy and Dice loss to handle severe class imbalance. Rigorous 5-fold cross-validation on the DeepCrack dataset yields 71.47% IoU, 81.91% F1-score, and 99.37% ROC-AUC, outperforming CrackSeU, CrackSeg, and Trans-UNet baselines. Ablation experiments demonstrate that attention mechanisms provide the most significant contribution, while dynamic loss weighting improves stability and reduces false predictions. The narrow confidence intervals across folds validate robust generalization, establishing the proposed framework as an effective solution for automated SHM applications in concrete infrastructure.**

***Index Terms*—Crack segmentation, Structural Health Monitoring, U-Net,Deep Learning, Concrete Infrastructure.**

I. Introduction

Image segmentation is a very important process in computer vision and structural health monitoring systems in extracting meaningful information from images by partitioning them into different regions. This technique is particularly important in structural health monitoring applications in obtaining accurate features for subsequent analysis and decision-making [1], [2]. The complexity of crack images necessitates the development of advanced segmentation techniques that can effectively handle noise, variability and occlusion in real-world scenarios. [3], [4].

In the context of structural health monitoring, crack detection is of paramount importance. Cracks in structures such as bridges, buildings, and dams can lead to catastrophic failures if not detected and addressed in a timely manner. Traditional methods of crack detection often rely on manual inspection, which can be time-consuming, subjective, and prone to human error. Consequently, there is a growing interest in automated techniques that leverage image processing and machine learning to enhance the accuracy and efficiency of crack detection [5], [6].

The U-Net architecture has emerged as a leading framework for semantic segmentation, particularly in medical imaging [1]. Its encoder-decoder structure allows for the capture of contextual information while preserving spatial details, making it highly effective for tasks requiring precise boundary delineation. The architecture consists of a contracting path that captures context and a symmetric expanding path that enables precise localization. This unique design facilitates the learning of both low-level and high-level features, which is crucial for accurately segmenting complex structures such as cracks [7].

Despite its success, U-Net alone may struggle with complex patterns and high variability in certain applications, such as crack detection in materials [1], [2]. The presence of noise, varying lighting conditions, and the intricate nature of crack patterns can significantly hinder the performance of traditional U-Net models. Moreover, the model's reliance on pixel-wise classification can lead to challenges in distinguishing between cracks and similar textures or noise in the background [11].

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We address *small-crack segmentation* in concrete imagery, where hairline fissures exhibit weak contrast and occupy only a minute fraction of pixels relative to background texture. We cast the task as pixel-wise binary segmentation using paired RGB images and binary masks. Images are intensity-normalized, masks are resampled with an edge-preserving policy and binarized with a fixed threshold. To guarantee one-to-one correspondence under heterogeneous naming conventions, we normalize filenames by stripping common mask suffixes prior to matching, ensuring robust image–mask pairing without discarding valid hairline structures.

Our network is a residual U-Net augmented with channel–spatial attention and multi-scale context (Residual-CBAM–ASPP U-Net). Encoder–decoder stages employ residual blocks with squeeze-and-excitation to adaptively reweight channels toward discriminative, line-like responses [8], a CBAM module further integrates channel and spatial attention to focus on faint, elongated patterns typical of hairline cracks [9]. At the bottleneck, an atrous spatial pyramid pooling head aggregates context across multiple receptive-field scales while preserving localization, helping to disambiguate thin cracks from background texture [10].

Beyond architecture, we introduce a dynamic composite loss that balances optimization stability and overlap sensitivity for thin boundaries. The objective interpolates between binary cross-entropy and a smooth Dice surrogate via an online-updated mixing weight: improvements on the monitored loss reduce the emphasis on cross-entropy to privilege Dice near boundaries, whereas plateaus increase it to restore stability under class imbalance. The training and evaluation protocol follows standard practice: cross-validation with best-checkpoint selection, a disjoint holdout test, optional data-driven threshold selection to set the operating point, and reporting of pixel-level segmentation metrics with uncertainty estimates. All artifacts (histories, checkpoints, summaries, and qualitative visualizations) are serialized to support rigorous reproducibility.

In this work, our contributions are as follows:

- **Architecture tailored to hairline cracks:** A residual U-Net enhanced with squeeze-and-excitation for channel reweighting [8], CBAM for joint channel–spatial attention [9], and an ASPP bottleneck for multi-scale context [**?**], explicitly targeting sub-pixel morphology and weak contrast.
- **Dynamic composite loss:** An online weighting between binary cross-entropy and a smooth Dice surrogate that adapts to optimization dynamics, curbing over-suppression of faint true positives while maintaining stability under severe class imbalance.
- **Robust pairing and preprocessing:** A normalized, case-insensitive stem-matching procedure that strips common mask suffixes to enforce image–mask bijection, combined with edge-safe resampling and consistent normalization to preserve thin boundaries.

Section 1 introduces the problem context, motivation, and a summary of our contributions. Section 2 reviews related work on crack segmentation, attention mechanisms, and multi-scale context for thin structures. Section 3 details the proposed Residual CBAM–ASPP U-Net and the dynamic composite loss. Section 4 describes experimental setup and dataset. Section 5 provides quantitative and qualitative results, including cross-validation and holdout analysis. Section 6 concludes the paper.

II. Related Work

There are currently many traditional methods in crack segmentation such as thresholding and edge detection as well as advanced deep learning approaches [3], [2], [7]. Thresholding techniques have been widely used to segment cracks based on pixel intensity, but they often fail to deal with noise and varying lighting conditions [11], [12]. On the other hand, deep learning methods have shown superior performance in various segmentation tasks due to their ability to learn hierarchical features from data [1], [2].

One of the frequently used architectures in crack segmmentation is the U-Net Architecture which has been successfully applied to various crack detections [1], [4]. Skip connections facilitate the preservation of spatial information to accurately delineate cracks. However, the U-Net model still faces challenges when dealing with complex crack patterns, thus requiring the incorporation of additional techniques to improve its performance [1], [2]. The U-Net architecture is also capable of classifying each pixel based on its inclusion in the crack dimension [13].

One important approach in crack detection is the pixel-based refinement method for crack detection on road surfaces. This study emphasizes the importance of quantitative and qualitative evaluation of the segmentation results. The evaluation is necessary to perform a robust classification of crack types based on the segmentation output [14]. In the field of pavement crack detection deep learning fusion models are better when combining the strengths of various convolutional neural network (CNN) architectures, including the U-Net model and Single Shot MultiBox Detector (SSD) [15]. The method aims to achieve accurate crack classification with the calculation of geometric parameters and overcome the challenges posed by different crack appearances and environmental conditions.By utilizing its high-resolution features, the two-stream boundary-aware crack segmentation network effectively addresses the challenges posed by the varying appearance of cracks and complicated backgrounds in concrete images. [16]A vision transform-based approach for automatic crack detection can handle high-resolution images and complicated backgrounds. [17]

Moreover, the integration of attention mechanisms has become a focal point in recent research. For example, the use of attention mechanisms to improve segmentation performance while significantly reducing model parameters [18]. In addition, there are generalized attention-based models that are able to improve segmentation performance across different scenarios by abstracting away the sub-problems underlying crack detection [19]. The approach of using attention mechanisms

has highlighted the growing need for adaptive and context-aware segmentation strategies.

Ongoing research also emphasizes the need for robust models that can perform well under various conditions and backgrounds. For example, the development of a fast road crack detection method with adaptability of semantic segmentation techniques in different cracks [20]. This adaptability is further echoed in the work that proposes a feature pyramid network for crack segmentation by improving the model's ability to detect cracks across different scales and complexities. [21]

III. Methods

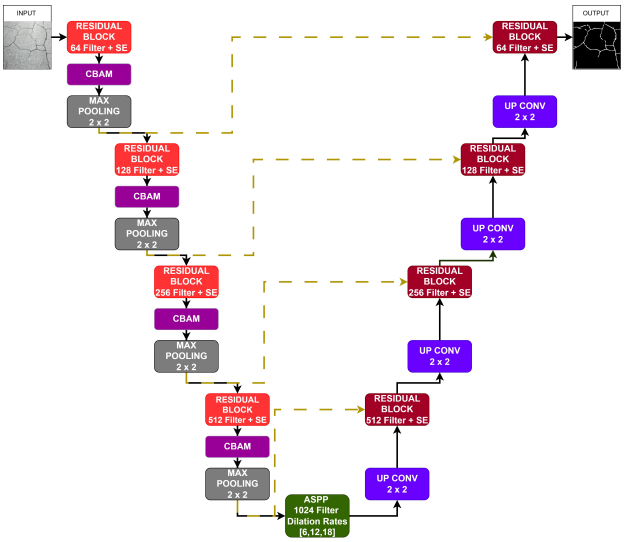

Fig. 1. Overview of the proposed Residual-CBAM-ASPP U-Net architecture for concrete crack segmentation.

A. Proposed Architecture

The proposed crack segmentation model employs a Residual-CBAM-ASPP U-Net architecture that integrates residual learning, attention mechanisms, and multi-scale feature extraction, as illustrated in Fig. 1. The encoder pathway consists of four hierarchical blocks with progressively increasing channel dimensions (64, 128, 256, and 512 filters), where each block comprises two residual blocks with integrated Squeeze-and-Excitation (SE) attention, followed by a Convolutional Block Attention Module (CBAM) and max-pooling for downsampling. Each residual block contains two 3×3 convolutional layers with batch normalization and ReLU activation, accompanied by a skip connection that adds the input directly to the output, facilitating gradient flow during backpropagation. The SE blocks within each residual block enhance channel-wise feature recalibration through global average pooling and fully connected layers. CBAM further refines the feature maps by sequentially applying channel and spatial attention mechanisms, enabling the network to focus on crack-relevant regions while suppressing background noise.

The bottleneck employs an Atrous Spatial Pyramid Pooling (ASPP) module with 1024 filters and dilation rates of [6, 12, 18] to capture multi-scale contextual information without losing spatial resolution. The decoder pathway mirrors the encoder through four upsampling blocks that progressively reconstruct spatial details. Each decoder block consists of a transposed convolution for upsampling, concatenation with corresponding encoder features via skip connections to preserve fine-grained details, and a residual block for feature refinement. The final layer applies a 1×1 convolution with sigmoid activation to generate binary segmentation masks at the original input resolution (256×256×1). This architecture effectively combines local feature extraction through residual blocks, adaptive feature weighting via attention mechanisms, and multi-scale context aggregation through ASPP to achieve robust crack detection performance.

B. Dynamic Loss Function

To effectively handle the severe class imbalance and sub-pixel continuity of fine cracks, a *dynamic composite loss function* is proposed to adaptively balance pixel-wise accuracy and spatial overlap. The formulation is defined as

$$\mathcal{L}(\alpha) = \alpha\,\mathrm{BCE}(y,\hat{y}) + (1-\alpha)\log\big(\cosh(1-\mathrm{Dice}(y,\hat{y}))\big), \tag{1}$$

where y denotes the ground-truth crack mask and $\hat{y}$ the predicted probability map. The BCE term represents binary cross-entropy loss, emphasizing pixel-level classification, while the Dice term measures the overlap between prediction and ground truth, computed as

$$\mathrm{Dice}(y,\hat{y}) = \frac{2\sum(y\hat{y})+\varepsilon}{\sum y + \sum \hat{y} + \varepsilon}, \quad \varepsilon = 10^{-5}. \tag{2}$$

The adaptive weighting factor $\alpha \in [0.10, 0.90]$ dynamically shifts between the two loss components: decreasing α enhances the influence of Dice to improve boundary localization on thin cracks, whereas increasing α emphasizes BCE to maintain optimization stability under class imbalance. This formulation ensures robust convergence and better preservation of weak crack regions that are often overlooked by fixed or single-loss approaches.

IV. Implementation

A. Experimental Setup

This experimental research was conducted using a computer with Ryzen 5 5600X processor specifications, 32 GB DDR4 3200 MHz RAM, B560M motherboard, RTX 3050 8GB Vga and 512 GB SSD.

This research uses binary images and masks. In the process of simplifying and ensuring the uniformity of the image and mask, they were resized to 256×256 pixels. In addition, the image is normalized by dividing by 255, and the mask is converted to binary with the aim to limit the pixel value to 0 or 1.This research uses Adam's optimizer and is performed over multiple epochs, with the model performance evaluated on the test set [12].

B. Dataset

The datasets used in this study are images of road surface structures, walls, and concrete. The datasets in this study are illustrated in Fig. 2. The DeepCrack dataset comprises 537 RGB images designed for the identification of structural cracks. These survey images capture a broad range of real-world environments, including highways, buildings, and various concrete surfaces. Each image, with a resolution of 544 × 384 pixels, has been manually annotated to indicate both the location and geometry of visible cracks, providing reliable ground-truth labels for supervised learning approaches. The dataset is systematically divided into three subsets: 376 images for training, 107 for validation, and 54 for testing, enabling consistent evaluation and model generalization.

C. Evaluation Metrics

The performance of the crack segmentation model is evaluated using standard pixel-level metrics: Intersection over Union (IoU), Precision, Recall, F1-score, Accuracy, and ROC–AUC. These metrics jointly measure the model's capability to localize and detect cracks under severe class imbalance.

The IoU quantifies spatial overlap between predicted and ground-truth crack regions:

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}. \tag{3}$$

Precision measures the proportion of correctly predicted crack pixels, where TP and FP denote true positives and false positives:

$$\text{Precision} = \frac{TP}{TP + FP}. \tag{4}$$

Recall measures the fraction of actual crack pixels successfully identified, where FN denotes false negatives:

$$\text{Recall} = \frac{TP}{TP + FN}. \tag{5}$$

The F1-score provides a harmonic mean between Precision and Recall:

$$\text{F1} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}. \tag{6}$$

Accuracy represents the overall classification correctness, where TN denotes true negatives:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}. \tag{7}$$

The ROC–AUC integrates the True Positive Rate and False Positive Rate across varying thresholds, providing a threshold-independent assessment of model discrimination capability.

V. Results and Discussion

A. Ablation Experiment Performance

Table I presents the ablation study results, revealing the incremental contribution of each architectural component. The baseline U-Net established a foundation with 80.99% F1-score and 70.49% IoU. Interestingly, adding residual blocks alone (U-Net Residual) decreased performance to 78.71% F1-score, with a notably high FNR of 22.36%, suggesting that residual connections without attention mechanisms may introduce feature redundancy. However, incorporating SE attention (U-Net Residual SE) dramatically improved performance to 83.80% F1-score and reduced FNR to 15.59%, demonstrating that channel attention effectively guides the network to focus on crack-relevant features.

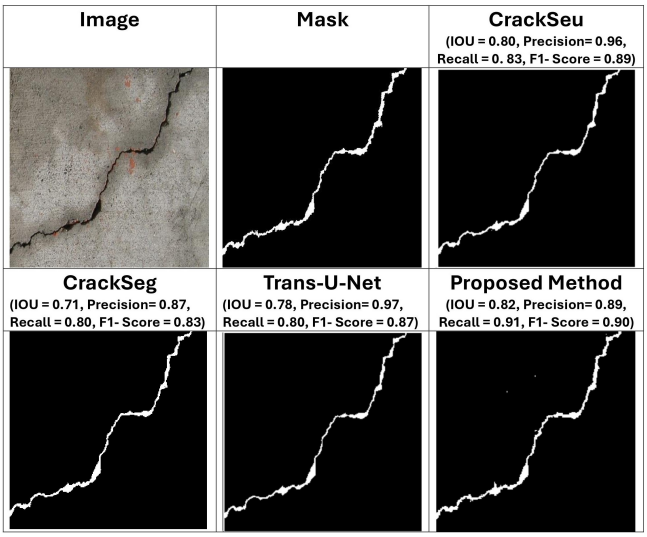

Fig. 2. Comparative analysis of crack segmentation methods on concrete surface. White pixels represent detected crack regions.

The comparison between SE and CBAM attention reveals that SE (83.80% F1) slightly outperforms CBAM (82.14% F1), indicating that channel attention is more critical than spatial attention for crack segmentation. Adding ASPP provides multi-scale context but shows marginal metric decrease (81.16% F1) due to increased model complexity. The proposed full model with dynamic loss weighting achieves the best F1-score of 83.76% with superior stability (lowest std: 12.96%) and the best trade-off between FNR (13.90%) and FPR (0.44%). The dynamic loss mechanism adaptively emphasizes boundary pixels during training, resulting in more consistent segmentation across diverse crack patterns and challenging scenarios.

B. Visual Comparison Results

The visual comparison of crack segmentation results is presented in Fig. 2, which illustrates the performance of four different methods: CrackSeu, CrackSeg, Trans-U-Net, and the proposed method. Visually, all methods successfully detect the main diagonal crack pattern in the concrete surface. However, notable differences are observed in the thickness and continuity of the segmented cracks. The proposed method produces segmentation results that most closely match the ground truth mask, with finer crack details and more consistent representation compared to other methods. CrackSeu tends to produce thinner segmentation with some discontinuities, while CrackSeg shows slightly fragmented results in certain regions.

Quantitatively, the proposed method achieves the best overall performance with an F1-Score of 0.90, IOU of 0.82,

TABLE I
RESULT OF ABLATIONS EXPERIMENT.

Model	IoU (%)	Precision (%)	Recall (%)	F1 (%)	FNR (%)	FPR (%)
Full Model (Dynamic Loss)	73.84 ± 16.24	83.10 ± 16.35	86.10 ± 10.50	**83.76 ± 12.96**	13.90 ± 10.50	0.44 ± 0.47
U-Net Residual SE	73.73 ± 15.77	85.02 ± 14.80	84.41 ± 11.27	83.80 ± 11.96	15.59 ± 11.27	0.43 ± 0.53
U-Net Residual CBAM	71.66 ± 17.31	82.78 ± 17.58	84.03 ± 11.16	82.14 ± 13.56	15.97 ± 11.16	0.52 ± 0.75
U-Net Residual CBAM ASPP	70.95 ± 19.34	79.83 ± 19.90	85.32 ± 14.85	81.16 ± 16.54	14.68 ± 14.85	0.64 ± 1.02
Baseline U-Net	70.49 ± 19.06	83.52 ± 17.13	82.08 ± 15.96	80.99 ± 15.35	17.92 ± 15.96	0.51 ± 0.77
U-Net Residual	67.44 ± 19.28	85.25 ± 16.27	77.64 ± 18.31	78.71 ± 16.16	22.36 ± 18.31	0.44 ± 0.91

TABLE II
TOP 5 HYPERPARAMETER CONFIGURATIONS FROM 15 GRID SEARCH COMBINATIONS BASED ON TEST SET PERFORMANCE (ALL VALUES IN %)

Rank	Trial	Val Dice	Test IoU	Test Precision	Test Recall	Test F1	LR	Batch Size	Optimizer
1	9	85.59	73.14±17.8	82.01±18.4	86.67±10.2	83.01±14.4	5e-04	4	adam
2	3	84.82	73.08±17.4	81.92±18.6	86.83±8.5	83.05±14.0	1e-03	4	adam
3	11	84.87	72.21±17.6	80.75±17.9	87.12±10.5	82.45±14.1	5e-04	4	adam
4	7	83.93	71.85±16.4	81.19±17.3	85.88±9.5	82.40±12.8	5e-03	2	rmsprop
5	1	83.66	71.48±17.3	78.91±18.2	88.55±10.0	82.00±13.7	5e-03	2	rmsprop

TABLE III
PERFORMANCE COMPARISON OF DIFFERENT METHODS USING 5-FOLD CROSS-VALIDATION

Method		IOU	Precision	Recall	F1-Score	ROC-AUC
Crack-Seu	Mean	70.03	85.67	79.18	80.92	99.58
	STD	2.51	3.18	4.48	1.98	0.06
	CI	66.55 - 73.51	81.26 - 90.08	72.96 - 85.40	78.17 - 83.67	99.50 - 99.66
CrackSeg	Mean	64.11	78.60	78.43	75.92	99.05
	STD	8.77	12.80	5.17	7.37	0.63
	CI	51.94 - 76.28	60.84 - 96.37	71.25 - 85.60	65.68 - 86.15	98.17 - 99.92
Trans-Unet	Mean	66.43	81.95	79.03	78.08	99.43
	STD	4.24	8.47	9.04	3.11	0.12
	CI	60.54 - 72.32	70.19 - 93.70	66.48 - 91.58	73.75 - 82.40	99.25 - 99.60
Proposed Method	Mean	71.47	81.79	83.96	81.91	99.37
	STD	2.84	2.40	2.46	2.40	0.19
	CI	67.52 - 75.41	78.46 - 85.13	80.55 - 87.38	78.58 - 85.25	99.11 - 99.63

Note: All results are obtained using 5-fold cross-validation. Mean values, standard deviations (STD), and 95% confidence intervals (CI) are reported across all folds.

Precision of 0.89, and Recall of 0.91. The high recall value demonstrates the method's capability to detect more actual crack regions, while maintaining good precision indicates minimal false positives. Although CrackSeu achieves the highest precision (0.96), its lower recall (0.83) results in a lower overall F1-Score of 0.89. Trans-U-Net demonstrates balanced performance with an F1-Score of 0.87, but still falls behind the proposed method. These results validate the effectiveness of the proposed approach for concrete crack segmentation tasks, particularly in achieving superior balance between precision and recall metrics.

C. Hyperparameter Optimization Insights

Table II shows Trial 9 as the optimal configuration with 85.59% validation Dice and 73.14±17.8% Test IoU, using Adam optimizer with learning rate 5e-04 and batch size 4. The top three trials all employ Adam with batch size 4 and learning rates between 5e-04 and 1e-03, consistently achieving Test IoU above 72%. This pattern indicates that Adam with moderate batch sizes provides superior convergence for crack segmentation tasks.

RMSprop appears in the bottom two configurations (Trials 7 and 1) with smaller batch sizes (2) and higher learning rates (5e-03), generally underperforming Adam by approximately 1-2 percentage points in Test IoU. The precision-recall trade-off is evident across configurations, with Trial 1 achieving the highest recall (88.55±10.0%) but lower precision (78.91±18.2%), while Trial 9 demonstrates better balance. Learning rate 5e-04 emerges as the most effective, appearing in two of the top three configurations and consistently delivering robust performance with lower variance.

D. Comparative Performance and Cross-Validation Analysis

Table III presents a comparative analysis of four segmentation architectures evaluated under a 5-fold cross-validation protocol. The proposed method exhibits the most consistent and superior performance across all key metrics, confirming its robustness and generalization ability in crack segmentation tasks. Specifically, it achieves the highest mean IoU of 71.47% and F1-Score of 81.91%, with narrow confidence intervals (CI = 67.52–75.41 for IoU), indicating reduced variability and stable performance across validation folds. This consistency underscores the model's capacity to maintain segmentation accuracy despite variations in the data distribution.

In comparison, the *Crack-SeU* model records relatively high precision (85.67%) but lower recall (79.18%), suggesting that it tends to identify crack pixels accurately while occasionally missing fine or discontinuous crack regions. The *CrackSeg* model exhibits the lowest average IoU (64.11%) and the largest standard deviation (STD = 8.77), reflecting high sensitivity to data heterogeneity and limited robustness. Meanwhile, *Trans-UNet*, which integrates convolutional and transformer-based encoding, shows balanced yet moderate results (IoU = 66.43%, F1 = 78.08%), but its relatively large variation in recall (STD = 9.04) indicates potential overfitting to local textures or feature distributions.

Overall, the proposed approach demonstrates a well-balanced trade-off between precision (81.79%) and recall (83.96%), as reflected in its high F1-Score and ROC-AUC (99.37%). This indicates that the model effectively discriminates between crack and non-crack regions while maintaining structural continuity in segmentation outputs. The quantitative evidence thus substantiates that the proposed deep learning framework achieves both accuracy and reliability, making it a viable candidate for deployment in real-world *Structural Health Monitoring* (SHM) systems focused on automated crack detection.

VI. Conclusion

This study introduces a RCA U-Net architecture with dynamic loss weighting for automated crack segmentation in concrete structures. The proposed model achieves an average IoU of 71.47%, F1-score of 81.91%, and ROC-AUC of 99.37% through 5-fold cross-validation, with narrow confidence intervals indicating robust generalization. The integration of SE attention, CBAM modules, and ASPP bottleneck enables effective multi-scale feature extraction and precise localization of discontinuous crack patterns. Comparative analysis demonstrates consistent superiority over baseline methods with reduced performance variance. These results establish the proposed framework as a reliable solution for automated Structural Health Monitoring applications in concrete infrastructure assessment.

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