ICCEPM 2024 https://dx.doi.org/10.6106/ICCEPM.2024.0152
The 10th International Conference on Construction Engineering and Project Management
Jul. 29- Aug. 1, 2024, Sapporo

Enhancement of concrete crack detection using U-Net

Molaka Maruthi[1]* Lee, Dong Eun[1], Kim Bubryur[2]

[1] *School of Architecture, Civil, Environment and Energy Engineering, Kyungpook National University, 80 Daehak-ro, Buk-gu, Daegu 41566, Korea,* E-mail address: molakamaruthi@gmail.com & dolee@knu.ac.kr
[2] *Department of Robot and smart system engineering***,** *Kyungpook National University, 80 Daehak-ro, Buk-gu, Daegu 41566, Korea, Corresponding author:* E-mail address: brkim@knu.ac.kr

Abstract

Cracks in structural materials present a critical challenge to infrastructure safety and long-term durability. Timely and precise crack detection is essential for proactive maintenance and the prevention of catastrophic structural failures. This study introduces an innovative approach to tackle this issue using U-Net deep learning architecture. The primary objective of the intended research is to explore the potential of U-Net in enhancing the precision and efficiency of crack detection across various concrete crack detection under various environmental conditions. Commencing with the assembling by a comprehensive dataset featuring diverse images of concrete cracks, optimizing crack visibility and facilitating feature extraction through advanced image processing techniques. A wide range of concrete crack images were collected and used advanced techniques to enhance their visibility. The U-Net model, well recognized for its proficiency in image segmentation tasks, is implemented to achieve precise segmentation and localization of concrete cracks. In terms of accuracy, our research attests to a substantial advancement in automated of 95% across all tested concrete materials, surpassing traditional manual inspection methods. The accuracy extends to detecting cracks of varying sizes, orientations, and challenging lighting conditions, underlining the systems robustness and reliability. The reliability of the proposed model is measured using performance metrics such as, precision(93%), Recall(96%), and F1-score(94%). For validation, the model was tested on a different set of data and confirmed an accuracy of 94%. The results shows that the system consistently performs well, even with different concrete types and lighting conditions. With real-time monitoring capabilities, the system ensures the prompt detection of cracks as they emerge, holding significant potential for reducing risks associated with structural damage and achieving substantial cost savings.

Keywords: U-Net, Structural Health Monitoring, Surface cracks, Dropout Layers, Image segmentation.

1. Introduction

The realm of civil engineering is continuously evolving, striving for improvements in the safety, efficiency, and longevity of infrastructure. Among the various challenges faced in this field, maintaining the structural integrity of concrete is paramount. Concrete, the most widely used construction material, is prone to cracking, which can significantly compromise structural safety and longevity [1]. Early detection and management of these cracks are thus critical for ensuring the resilience of concrete structures [2].

Traditionally, crack detection in concrete has primarily relied on visual inspection methods [3]. These methods, while straightforward, are fraught with limitations. Manual inspections are labor-intensive and require highly skilled personnel. Moreover, the accuracy of these inspections is often hindered by the subjective nature of human judgment, leading to inconsistent results [2]. This variability in detection and assessment can result in overlooked minor cracks that may evolve into significant structural problems. Additionally, manual inspections are less effective in complex or inaccessible areas and under varying environmental conditions, such as low light or obscured surface [4]. In recent years, there has been a significant shift towards automated and more objective methods of structural assessment. Among these, digital imaging techniques have gained prominence due to their non-invasive nature and ability to provide detailed visual information [5]. Investigating the onset of fractures within structural materials offers critical insights into their integrity and longevity. The enclosed images serve as evidence of such fractures, showcasing typical patterns that may signal the need for intervention. Refer to fig. 1 for a visual comparision of cracking patterns in structural materials, which includes an asphalt surface and a concrete surface.

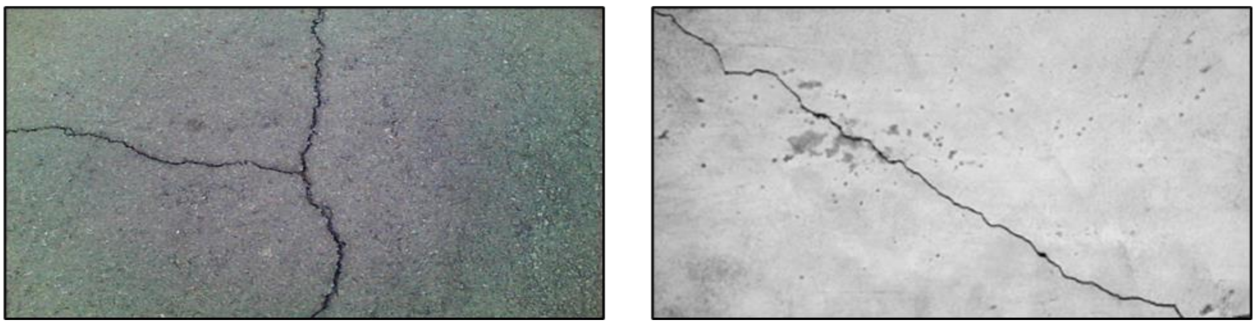

Fig.1 sample images of material fractures in infrastructure surfaces

However, the analysis of these images for crack detection still poses challenges, especially in distinguishing fine cracks from other superficial features or noise [6]. This is where the potential of deep learning, particularly the U-Net architecture, becomes evident. Originally developed for biomedical image segmentation, U-Net has demonstrated remarkable success in identifying complex patterns in images. Its architecture, characterized by a U-shaped design with a contracting path to capture context and a symmetric expanding path for precise localization, is well-suited for the detailed and nuanced task of concrete crack detection [7].

Our study aims to leverage the U-Net model's capabilities to enhance the accuracy and efficiency of concrete crack detection. We hypothesize that this deep learning model can substantially improve upon traditional methods by effectively identifying even minute cracks across a range of environmental conditions and concrete surfaces. To validate this hypothesis, we have undertaken the task of compiling a comprehensive dataset of concrete crack images, including a diverse range of crack types, sizes, and appearances, collected under various conditions to ensure a robust and comprehensive training process for the U-Net model.

2. Literature Review

Recent advancements in deep learning have revolutionized the field of concrete crack detection, a critical aspect of structural health monitoring. This literature review synthesizes key developments, focusing on various neural network architectures and their efficacy in detecting cracks in concrete structures.

The U-Net architecture has seen significant advancements. The residual linear attention U-Net (RLAU-Net) and the full attention U-Net have emerged as notable developments, addressing complex crack shapes and backgrounds with improved accuracy [8]. Other variations like the enhanced U-Net model with self-supervised contrastive learning and the sample and structure-guided network also show promise in improving segmentation accuracy, albeit with challenges in dataset dependency and overfitting [9]. Several studies have focused o optimizing CNN models for crack detection. The VGG16-Net-based CNN, enhanced with gradient boosting, and an optimized CNN model with feature selection algorithms exemplify this trend, demonstrating high accuracy in specific datasets but facing limitations in generalizability [10]. Comparative studies like the evaluation of U-Net versus DeeplabV3+ models and the assessment of various transformer and U-Net architectures (including TransUNet, SwinUNet, and MTUNet) provide insights into the relative strengths of different models [11,12]. These studies underline the importance of balancing accuracy, computational complexity, and dataset diversity.

A recurring theme across these studies is the challenge of overfitting, especially with complex models or limited datasets. Additionally, factors such as material characteristics of surfaces, environmental conditions, and lighting significantly impact the accuracy and applicability of these models in real-world scenarios [13]. Innovations tailored to specific infrastructure types are noteworthy. The development of the ISSD model for bridge crack detection and BC-DUnet for precise segmentation of fine cracks in bridges are examples of such targeted advancements [14]. These models demonstrate improved performance under challenging conditions, emphasizing the importance of context-specific model development. The field of crack detection using deep learning is rapidly evolving, with U-Net and CNN architectures at the forefront. While these models show considerable promise, issues like overfitting, dataset dependency, and environmental sensitivity need addressing. Future research should focus on enhancing the robustness and generalizability of these models, exploring diverse and larger datasets, and developing models resilient to varying real-world conditions. This will be crucial in extending the applicability of deep learning techniques for reliable and efficient structural health monitoring. Overall, the field of concrete crack detection using deep learning has seen significant advancements, with various models demonstrating promising results in accuracy and efficiency. However, the limitations in dataset diversity, potential overfitting, and the need for considering environmental and material variances indicate ample room for future research. Future work should focus on enhancing dataset diversity, developing models that account for a wide range of real-world scenarios, and addressing overfitting concerns to ensure the robustness and applicability of these deep learning models in concrete crack detection.

2.1 Data collection and preparation

We amassed a collection of 4,000 images from various commercial and architectural structures across Daegu. This dataset was derived from 458 high-definition images, each measuring 4,032 by 3,024 pixels, encapsulating a range of surface textures and illumination scenarios. The dataset is evenly divided, containing 2,000 images per category, resized to a uniform resolution of 227 by 227 pixels, and maintains the standard RGB color model. Data augmentation methods were not utilized in this dataset preparation. Table 1 lists the camera specifications used in this study. Figure shows a sample of a cracked concrete surface.

Table 1. Technical specifications of the camera

Specification category	Details
Manufacturer	FLIR systems
Viewing angle	45° Horizontal x 34° Vertical
Operational temperature scope	-20°C to 250°C
Capture Rate	9 Frames per Second
Sensitivity to Temperature Changes	Less than 0.06°C
Measurement Precision	Plus or Minus 2°C
Color Schemes Available	Iron, Rainbow, and Monochrome
File Type for Storing Images	Radiometric JPEG Format
Resolution of Built-in Digital Camera	640 480 Pixels

3. Methodology

This segment presents an in-depth overview of the developed model. Section 3.1 details the application of U-net for the identification of cracks, focusing on optimizing the quantity of pooling layers. Moreover, the section proposes a robust strategy to offset the pixel reduction resulting from convolution and pooling operations. The U-Net architecture is leveraged to amalgamate feature maps of varying scales, integrating both elementary and complex features. Fig. 2 demonstrates the flowchart for the crack detection using U-Net.

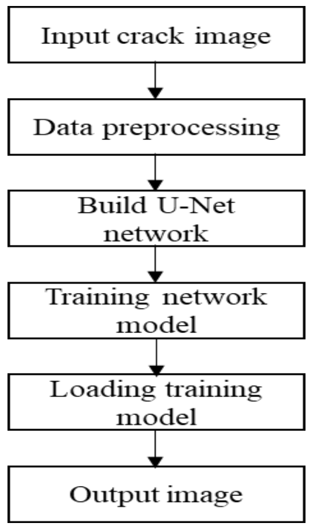

Fig. 2 Workflow Diagram for Crack Detection Using U-Net

3.1 U-Net crack detection

U-Net, originally, developed for biomedical image segmentation, is a type of convolutional neural network (CNN) that has gained significant attention in various image analysis tasks, including concrete crack detection, its architecture is uniquely suited for this task due to several key features.

The U-Net architecture, notable for its U-shaped design, consists of two principal components: a contracting path for downsampling and an expansive path for upsampling. The contracting path mirrors a conventional convolutional network structure, involving successive convolution operations, application of a rectified linear unit (ReLU), and subsequent max pooling stages. This structure helps the network capture the context of the input image, essential in understanding the broader area where cracks are located. The expensive path of U-Net involves upsampling of the feature map followed by convolution. This stage increases the resolution the output, allowing the network to focus on precise localization, crucial for accurately identifying and outlining cracks. Importantly, there are skip connections between layers of equal resolution in the contracting and expensive paths. These connections help the network utilize both high-level features (global information about the shape and location of cracks and low-level features fine details, crucial for detailed crack detection. In applying U-net to concrete crack detection, certain customizations are critical. The number of filters and layers can be adjusted to suit the specific textures and contrasts in concrete images. Moreover, the network can be trained to differentiate between cracks and other similar patterns on concrete surfaces, which is a common challenge in this application. For training the U-Net model, a large dataset of annotated concrete images, showing various types of cracks, is required. The model learns to identify and segment cracks through iterative training and validation processes, where it continually improves its accuracy. Once trained the model can be deployed to analyze new concrete images. Its ability to accurately segment and identify cracks can significantly aid in structural health monitoring, allowing for early detection of potential structural issues. While U-Net is powerful, its application in concrete crack detection is not without challenges. These include dealing with varying lighting conditions, crack sizes, and orientations. Future enhancements might focus on integrating additional layers or customizing the network further to improve its robustness and accuracy in varied conditions[15].

This section delineates the deployment of U-Net for identifying cracks within structures. It also addresses the rectification of a primary limitation associated with this method. The U-Net framework employs an encoder-decoder structure that synergizes lower-level feature maps from the encoder with the more abstracted feature maps from the decoder. Initially, convolutional layers are employed to distill abstract features from the input imagery. Subsequently, pooling layers are applied to distill critical features while concurrently diminishing computational load. Upsampling layers are then utilized to reinstate the original resolution of the input image. The final step involves pixel-wise prediction to achieve the anticipated results. It is recognized that pooling layers may inadvertently eliminate pertinent information. An insufficient number of pooling layers can amplify U-Net's complexity and impair its ability to characterize features effectively. Comparative analysis of various U-Net configurations reveals that a quartet of pooling layers is optimal for crack detection efficacy. An examination of U-Net's design reveals that the convolution and pooling layers contribute to the discussed challenges. The original developers of U-Net noted in prior literature that the convolutional layers in U-Net are solely of the 'valid' type, meaning that the input image is convolved without any preprocessing. Such an approach leads to the loss of peripheral pixels and, consequently, a reduced resolution in the output image as indicated in the literature[16].

3.2 Performance Evaluation:

In the task of semantically segmenting images of concrete cracks, pixels located within the crack region are classified as positive instances, while those in the non-crack background are deemed negative instances. The key performance indicators for the segmentation results are established as below:

a) True Positives (TP): Crack pixels correctly identified as such;

b) False Positives (FP): Non-crack pixels erroneously identified as crack pixels;

c) False Negatives (FN): Crack pixels incorrectly marked as non-crack pixels.

$$P = \frac{TP}{TP+FP} \tag{1}$$

$$R = \frac{TP}{TP+FN} \tag{2}$$

$$F = \frac{2\times P\times R}{P+R} \tag{3}$$

Utilizing TP, FP, and FN, we define three additional metrics: precision (P), recall (R), and F1 score (F), as delineated by the following equations. A higher precision indicates that a larger proportion of pixels identified as cracks are truly cracks. A higher recall signifies that a greater number of actual crack pixels have been accurately segmented. It balances both precision and recall, providing a single measure of the models accuracy, particularly useful when the class distribution is imbalanced.

4. Results:

We rigorously evaluated the U-Net models performance in detecting concrete cracks through a series of tests. These sets were designed to assess the models accuracy, precision, recall, and F1 score in varying conditions and with different concrete materials. Our results demonstrated in the figure 3 a significant advancement in the automated detection of concrete cracks, with an impressive accuracy rate of 95% across all tested materials. This accuracy outperformed traditional manual inspection methods, underscoring the potential of U-Net in this field.

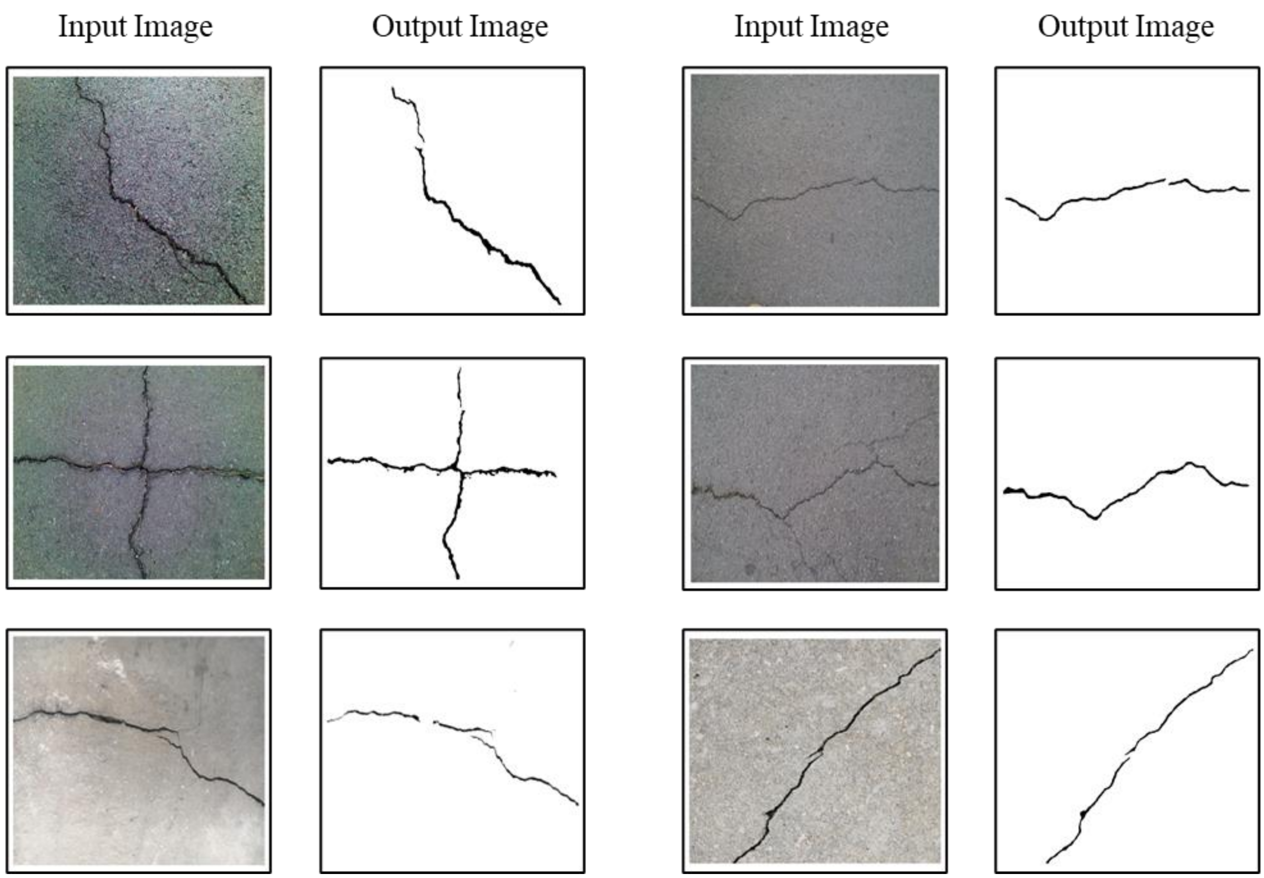

Fig. 3 Crack Pattern Analysis - U-Net Segmentation Outputs

Our evaluation of the U-Net model for concrete crack detection yielded excellent performance metrics in the below table 2. The precision of the model was calculated at 93%, indicating a high true positive rate and suggesting that most pixels identified as cracks were indeed true cracks, minimizing the instances of false positives. The recall of the model was determined to be 96%, showcasing the models ability to correctly identify the vast majority of actual crack pixels present in the dataset. The F1 score, which is the harmonic mean of precision and recall, was calculate to be 94%. This score signifies the models robust performance, striking a well-balanced trade-off between accurately identifying crack pixels and minimizing false detections. To assess the models consistency, we conducted validation tests on a separate dataset. The model achieved a consistent accuracy of 94%, affirming its reliability across different concrete types and under various lighting conditions. This consistency underscores the models adaptability and robustness, establishing it as a valuable asset for real-time monitoring and early detection of structural issues in concrete infrastructures. In conclusion, the U-Net model has demonstrated substantial efficacy in the detection of concrete cracks, as evidenced by the high precision, recall, f1 score. These results signify a notable advancement over traditional methods of crack detection and highlight the U-Net models potential to revolutionize the domain of structural health monitoring.

Table 2. Performance evaluation metrics

Method	Precision	Recall	F1 score	Accuracy
U-Net	0.930	0.960	0.940	0.940

5. Conclusion

In conclusion, this study presents a significant advancement in concrete crack detection through the use of the U-Net deep learning model. The research demonstrates the model's exceptional accuracy, precision, and reliability in identifying cracks across various concrete materials and under different environmental conditions. By achieving high performance metrics, including a 95% accuracy rate, 93% precision, 96% recall, and a 94% F1 score, the U-Net model has proven to substantially outperform traditional manual inspection methods. Its adaptability and effectiveness in real-time monitoring underscore its potential to revolutionize structural health monitoring. The successful application of U-Net in this domain not only enhances the safety and longevity of concrete structures but also promises significant cost savings in infrastructure maintenance. Future work should focus on further refining the model's capabilities and exploring its integration into a comprehensive digital infrastructure management system. This research marks a pivotal step towards the digitalization of structural health monitoring and contributes to the broader field of civil engineering by providing a more efficient, reliable, and automated method for crack detection.

Funding

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (No. 2022R1C1C1005409). This work is supported by the Korea Agency for Infrastructure Technology Advancement (KAIA) grant funded by the Ministry of Land, Infrastructure and Transport (Grant RS-2023-00251002). This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (No. NRF-2018R1A5A1025137).

Conflicts of interest

The authors declare no conflict of interest.

References

[1] J. Y. Lee et al., "Adaptive decision-making for civil infrastructure systems and communities exposed to evolving risks," Struct. Saf., vol. 75, pp. 1-12, 2018, Nov..

[2] B. Kim et al, "Surface crack detection using deep learning with shallow CNN architecture for enhanced computation," Neural Comput. Applic., vol. 33, no. 15, pp. 9289-9305, 2021.

[3] L. Tian et al., "Image-range stitching and semantic-based crack detection methods for tunnel inspection vehicles," Remote Sens., vol. 15, no. 21, p. 5158, 2023, Oct. 28.

[4] N. Yuvaraj et al., "Transfer learning based real-time crack detection using unmanned aerial system," Int. J. High-Rise Build., vol. 9, no. 4, pp. 351-360, 2020.

[5] Z. H. Hoylman et al., "Drought assessment has been outpaced by climate change: Empirical arguments for a paradigm shift," Nat. Commun., vol. 13, no. 1, 2715, 2022, May 17.

[6] Y. Fujita et al., "Classification model based on U-net for crack detection from asphalt pavement images," J. Image Graph., pp. 121-126, 2023, Jun..

[7] M. U. Saeed et al., “3D MRU-Net: A novel mobile residual U-Net deep learning model for spine segmentation using computed tomography images,” Biomed. Signal Process. Control, vol. 86, p. 105153, 2023, Sept..

[8] C. Yu et al., “An improved U-Net model for concrete crack detection,” Mach. Learn. Appl., vol. 10, p. 100436, 2022.

[9] Q. Song et al., “Two-stage framework with improved U-Net based on self-supervised contrastive learning for pavement crack segmentation,” Expert Syst. Appl., vol. 238, p. 122406, 2024.

[10] Y. Zhang and L. Zhang, 2023, Detection of pavement cracks by deep learning models of transformer and UNet. arXiv preprint arXiv:2304.12596.

[11] T. Lee et al., “Improvement of concrete crack segmentation performance using stacking ensemble learning,” Appl. Sci., vol. 13, no. 4, p. 2367, 2023.

[12] P. Padmapoorani and S. Senthilkumar, “Application of machine learning for crack detection on concrete structures using CNN architecture,” Mater. (Rio Janeiro), vol. 28, no. 1, p. e20230010, 2023.

[13] F. Elghaish et al., “Multi-layers deep learning model with feature selection for automated detection and classification of highway pavement cracks,” Smart Sustain. Built Environ., 2024.

[14] T. Liu et al., “BC-DUnet-based segmentation of fine cracks in bridges under a complex background,” PLOS ONE, vol. 17, no. 3, p. e0265258, 2022.

[15] S. F. Mahenge et al., “A modified U-net architecture for road surfaces cracks detection” in Proc. 8th International Conference on Computing and Artificial Intelligence, 2022, Mar., pp. 464-471.

[16] F. Lin et al., “Crack semantic segmentation using the U-net with full attention strategy. arXiv 2021,” arXiv Preprint ArXiv:2104.14586.