U-Net を援用したるンクリート X 線 CT 画像の自動メソスケールセグメンテーション
Automated Meso-scale Segmentation from X-ray CT Images of Concrete by U-Net Approach

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1. Introduction

The aging of irrigation infrastructure poses significant challenges. Concrete structures deteriorate due to internal defects[1], aging, and varying loads, requiring regular inspection for safety and functionality. In Japan, a substantial number of concrete irrigation structures require extensive repairs[2]. To address these challenges, there's a growing need for enhanced maintenance efforts and automated Non-Destructive Evaluation (NDE) techniques, such as computer vision-based damage assessment, to improve efficiency and accuracy in identifying structural issues. A Convolutional Neural Network (CNN) is a powerful tool for surface damage segmentation and its evaluation[3]. By employing this approach, alongside other automated NDE techniques, the infrastructure engineers can effectively prioritize maintenance efforts, ensuring the safety and longevity of aging structures in a resource-constrained environment.

2. Materials and Methods

2.1. Dataset preparation

The training dataset contains grayscale images acquired by a medical X-ray CT machine. Scanned concrete cores were drilled out from the in-service irrigation structure located in Japan. Input CT images have a resolution of 512 × 512 pixels. Fig. 1 represents the raw CT image and its ground truths for each concrete phase. All concrete particles are labelled and represented as binary images. The split ratio for the training and validation dataset is 0.8:0.2. To diversify the dataset and enhance generalization, data augmentation techniques are applied.

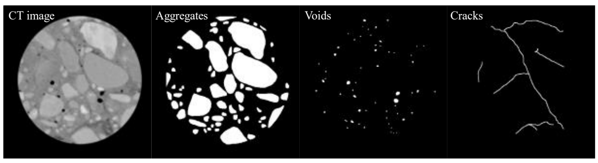

Fig. 1. Training dataset.

2.2. U-net architecture

The U-Net model[4], designed for semantic segmentation tasks, effectively segments concrete particles in CT images by learning to classify each pixel into specified classes. U-shaped architecture and skip connections enable precise feature localization. During training, Adam optimizer with a learning rate of 0.001 is used, and hyperparameters are manually optimized. Binary cross-entropy loss function measured the discrepancy between predicted and actual pixel-wise classifications, aiding in effective model optimization for structural assessment and maintenance of concrete infrastructures.

2.3. Evaluation Metrics

In this research, Intersection over Union (*IoU*) (Eq. 1) and Dice coefficient (*F1* score) (Eq. 2) are utilized to quantify the agreement between predicted and ground truth segmentations. These metrics provided comprehensive insights into the effectiveness of the U-Net model in accurately delineating concrete particles from CT images.

$$IoU = \frac{TP}{TP + FP + FN}, \tag{1}$$

$$F1\ score = \frac{2 \times TP}{2 \times TP + FP + FN}, \tag{2}$$

where *TP* is the number of true positive pixels, *FP* is the number of false positive pixels and *FN* is the number of false negative pixels.

3. Results and Discussion

3.1. Hyperparameter optimization

During the result analysis, the issue of overfitting became apparent, concerning the segmentation of all concrete particles. This challenge is closely linked to the complex structure of the input CT images, which contain numerous objects within a single image. Furthermore, the limited size of the dataset

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reinforces this problem. To address this challenge, a hyperparameter optimization procedure is employed. Five hyperparameters are optimized represented in Table 1. Fig. 2 depicts the generalized losses during training and validation.

3.2. Segmentation results

The output of the U-Net segmentation model comprises probability maps for each pixel in the input image, indicating the likelihood of belonging to one of three classes: aggregate, void, or crack. Subsequent thresholding at 0.5 yields binary segmentation masks for each class (Fig. 3). Pixels with probabilities exceeding or equal to 0.5 are classified into their respective classes, while those below 0.5 are deemed background. Notably, for the crack class, a lower probability threshold may be employed. On Fig. 3, the significant cracks characterized by a high density of air within a small fracture volume are illustrated with 0.5 threshold. Decreasing the threshold extends segmentation to encompass more small cracks, attributed to the challenge posed by the low contrast between the solid matrix and existing fractures, which complicates essential feature extraction for accurate segmentation.

3.3. Model accuracy

The segmentation model demonstrates notable performance discrepancies across different classes as depicted in the confusion matrix (Table 1). Aggregates exhibit strong segmentation accuracy with high *IoU* (0.813) and *F1* score (0.896). However, the model's performance is more moderate for voids and cracks, characterized by *IoU* (0.566 and 0.088) and *F1* score (0.722 and 0.161), respectively. This discrepancy can be attributed to the considerably smaller area of voids and cracks compared to aggregates. Moreover, crack segmentation performance notably improves with higher probability thresholds, which is influenced by the manual annotation procedure. Due to the low contrast for cracks, there are challenges in appropriately labeling long and thin objects manually. As a result, underestimated metrics can be observed.

4. Conclusions

In this research, the deteriorated concrete structure was segmented successfully by the U-Net with hyperparameters optimization which increased the segmentation accuracy. This approach will help to improve the future NDE methods for in-service irrigation structure assessment by damage quantification.

Table 1 Optimized hyperparameters

Group name	channel	kernel size	max. epoch	batch size	pool size
Agg.	8	5	64	2	2
Void	16	3	15	3	2
Crack	16	3	26	2	2

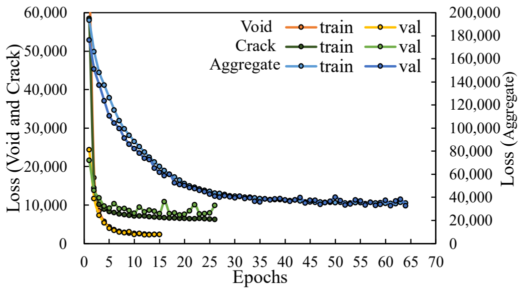

Fig. 2. Learning curve.

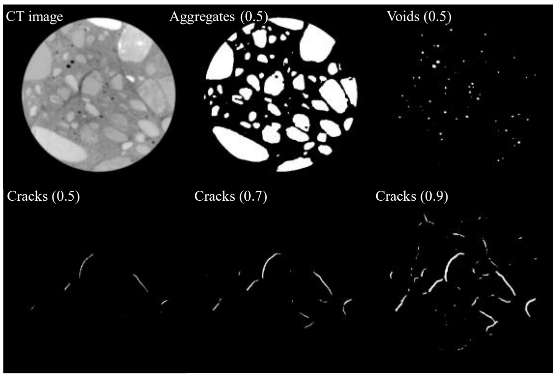

Fig. 3. Segmentation result.

Table 2 Confusion matrix

Aggregates		Predicted P	Predicted N	Voids		Predicted P	Predicted N	Cracks (0.5)		Predicted P	Predicted N
Actual	P	20.36%	2.27%	Actual	P	0.34%	0.14%	Actual	P	0.05%	0.54%
	N	2.45%	74.91%		N	0.12%	99.40%		N	0.04%	99.36%

Cracks (0.7)		Predicted P	Predicted N	Cracks (0.9)		Predicted P	Predicted N
Actual	P	0.15%	0.45%	Actual	P	0.34%	0.26%
	N	0.21%	99.19%		N	1.14%	98.26%

References

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