The 2023 World Congress on
Advances in Structural Engineering and Mechanics (ASEM23)
GECE, Seoul, Korea, August 16-18, 2023

Study on the use of unlabeled data in tunnel crack inspection with CycleGAN

*Jin Kim[1)], Seungbo Shim[2)] and Gye-Chun Cho[3)]

[1), 3)] Department of Civil and Environmental Engineering, Korea Advanced Institute of Science and Technology, Daejeon 34141, Korea
[2)] Future Infrastructure Research Center, Korea Institute of Civil Engineering and Building Technology (KICT), Goyang 10223, Korea
[3)] gyechun@kaist.ac.kr

ABSTRACT

The development of industries in the past has led to the construction of numerous concrete tunnels, providing convenience for transportation and daily life. However, over time, tunnels undergo aging processes that result in decreased structural stability and performance, necessitating systematic and accurate management. Among various degradation factors, cracks are considered a critical element that negatively affects the safety and performance of tunnel structures. However, current crack management methods rely on human resources, incurring significant time and cost, while also lacking objectivity. Consequently, various research studies are being conducted in the field of crack detection. This requires a large-scale labeled crack dataset, which is a manual and costly task. Therefore, in this study, we studied the applicability of training a crack detection algorithm using unlabeled data using CycleGAN to improve the objectivity of crack detection and reduce costs. The unlabeled dataset was used along with the previously obtained labeled dataset to train a crack detection algorithm and evaluate its performance. The results of the study are expected to provide a management method that can contribute to the management of cracks in concrete tunnels.

1. INTRODUCTION

Over the past few decades, industrial development has significantly transformed our lives, providing remarkable convenience and efficiency in transportation and daily activities. However, as time passes and these tunnel structures are exposed to various environmental factors, they may undergo gradual deterioration, leading to decreased structural stability and performance. Among the various degradation factors, cracks

[1)] Graduate Student
[2)] Principal Researcher
[3)] Professor

emerge as one of the most significant elements negatively impacting tunnel safety and sustainability. Detecting and maintaining cracks in concrete tunnels are of utmost importance to ensure user safety and preserve the structural safety of such critical infrastructure (Yao *et al.* 2014). Traditionally, crack detection has relied on visual examinations, involving labor-intensive and time-consuming. Unfortunately, such methods are subjective and can lead to inconsistencies in assessing the severity of cracks. Moreover, relying on manual labor incurs substantial costs, especially for large-scale tunnel networks, posing economic challenges in performing frequent and extensive inspections.

To address these issues and enhance the objectivity and efficiency of crack detection, there is an increasing interest in automated crack detection methods utilizing computer vision and machine learning techniques. The advancements in such technologies have attracted more researchers striving to develop accurate, reliable, and cost-effective systems. However, a key limiting factor in successfully implementing such systems is the scarcity of large-scale labeled crack datasets required to train robust algorithms. Consequently, this study explores the potential of leveraging CycleGAN, a powerful unsupervised learning framework, to train crack detection algorithms using unlabeled data.

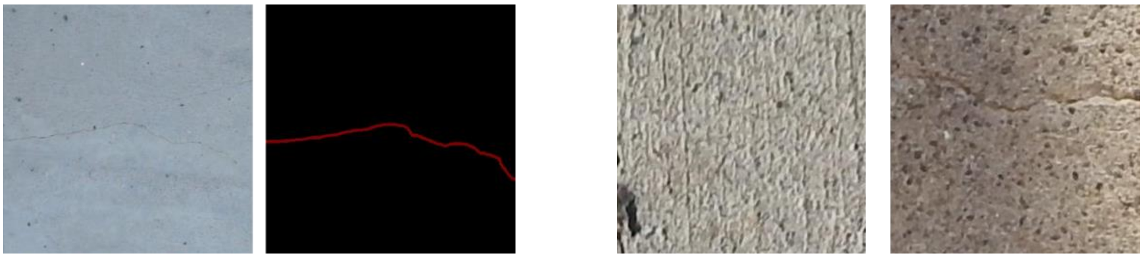
2. METHOD AND IMPLEMENTATION

2.1 Cycle-Consistent Generative Adversarial Network (CycleGAN)

In this study, we utilized CycleGAN (Zhu *et al.* 2017) to investigate the utility of unlabeled data. CycleGAN is a widely-used algorithm for image-to-image translation between two types of domains. It employs a similar architecture to the basic Generative Adversarial Networks (Goodfellow *et al.* 2020), where the Generator and Discriminator network engage in a competitive learning process. The Generator is responsible for converting input images from one domain to another, while the Discriminator discriminates between generated and real images to identify fake ones. CycleGAN stands out for its capability of bidirectional transformations, enabling image translations between two distinct datasets. Specifically, the two datasets obtained for this research were employed as targets for reciprocal image conversions.

2.2 Datasets and experimental setup

The dataset was divided into two categories for training and validation: DatasetA and DatasetB. The visual representation of each dataset is shown in Figure 1. Specifically, DatasetA consists of 448 × 448 size images, which include RGB images and corresponding labeled data. This dataset is composed of Rissbuilder, Eugen-Muller, and Volker datasets (Kulkarni *et al.* 2022). On the other hand, DatasetB comprises 256 × 256 size RGB images and is composed of data from SDNET2018 (Maguire *et al.* 2018) and Mendeley datasets (Özgenel 2018).

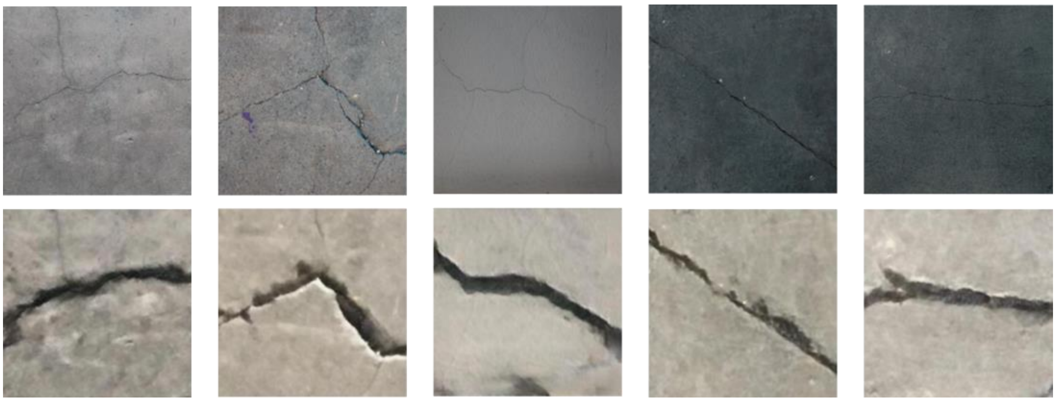


(a) Dataset A (b) Dataset B

Fig. 1 Two types of datasets

3. RESULTS AND DISCUSSIONS

The results of using CycleGAN to perform mutual data transformations can be observed in Figure 2. It is evident that the style changes according to the characteristics of each dataset. Such outcomes indicate the potential utility of CycleGAN for segmentation training by transforming unlabeled datasets to align with the characteristics of labeled datasets. However, it is important to note that when dealing with datasets like the ones used in this study, where there is significant disparity in the thickness of cracks between domains, certain information loss or the generation of new information may occur during the data transformation process. This highlights the need for caution when applying CycleGAN for domain adaptation.



(a) DatasetA to DatasetB

(b) DatasetB to DatasetA

Fig. 2 Results of cycleGAN

4. CONCLUSIONS

In this study, we investigated the applicability of utilizing unlabeled data in tunnel crack inspection using CycleGAN. The utilization of CycleGAN showed promising results in effectively transforming two datasets based on their mutual characteristics. It excels at converting unlabeled data to match the style of labeled data, making it valuable for segmentation training. However, it is crucial to acknowledge the challenges that arise when dealing with datasets that exhibit significant differences, such as varying crack thickness. In such cases, the transformation process may lead to some information loss or even generate new information, necessitating careful consideration during domain adaptation.

ACKNOWLEDGEMENT

This work is supported by "Ministry of the Interior and Safety" R&D program (20018374). And the first authors are supported by the Innovated Talent Education Program for Smart City from MOLIT

REFERENCES

Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., and Bengio, Y. (2020), "Generative adversarial networks", *Communications of the ACM*, **63,** 139-144.

Kulkarni, S., Singh, S., Balakrishnan, D., Sharma, S., Devunuri, S., and Korlapati, S.C.R. (2022), "CrackSeg9k: a collection and benchmark for crack segmentation datasets and frameworks." In *European Conference on Computer Vision*, 179-195. Springer.

Maguire, M., Dorafshan, S., and Thomas, R.J. (2018), "SDNET2018: A concrete crack image dataset for machine learning applications",

Özgenel, Ç.F. (2018), "Concrete crack images for classification", *Mendeley Data*, **1,**

Yao, Y., Tung, S.T.E., and Glisic, B. (2014), "Crack detection and characterization techniques—An overview", *Structural Control and Health Monitoring*, **21,** 1387-1413.

Zhu, J.-Y., Park, T., Isola, P., and Efros, A.A. (2017), "Unpaired image-to-image translation using cycle-consistent adversarial networks." In *Proceedings of the IEEE international conference on computer vision*, 2223-2232.