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Game Engine Driven Synthetic Data Generation for Computer Vision-Based Construction Safety Monitoring

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Abstract: Recently, computer vision (CV)-based safety monitoring (i.e., object detection) system has been widely researched in the construction industry. Sufficient and high-quality data collection is required to detect objects accurately. Such data collection is significant for detecting small objects or images from different camera angles. Although several previous studies proposed novel data augmentation and synthetic data generation approaches, it is still not thoroughly addressed (i.e., limited accuracy) in the dynamic construction work environment. In this study, we proposed a game engine-driven synthetic data generation model to enhance the accuracy of the CV-based object detection model, mainly targeting small objects. In the virtual 3D environment, we generated synthetic data to complement training images by altering the virtual camera angles. The main contribution of this paper is to confirm whether synthetic data generated in the game engine can improve the accuracy of the CV-based object detection model.

Keywords: construction vision-based safety monitoring, synthetic data generation, game engine, object detection

1. INTRODUCTION

The construction industry is one of the most accident-prone industries worldwide. In South Korea, 24.73% of all industrial accidents in 2020 occurred in the construction industry. Also, 27.5% of the deaths caused by industrial accidents occurred in the construction industry. The accident death rate in the construction industry in 2020 was 0.25‰, more than twice as high as the death rate of 0.11‰ in all industries [1]. Statistics from Korea Occupational Safety and Health Agency (KOSHA) stated that deaths from falling accounted for about 50% of all fatal accidents in South Korea [2]. In addition, most falling accidents occurred due to the absence of a safety belt; thus, researchers emphasized that a safety hook must be fastened during work [3]. A real-time safety monitoring system using CCTV was proposed to reduce fall accidents on construction sites [4]. However, accompanied by continuous manual monitoring of workers, such a solution might be prone to missing the monitoring targets.

In the past decade, a computer vision (CV)-based real-time safety and health monitoring approach was suggested to solve the labor-intensive monitoring issue in the construction industry [5–17]. Especially, convolutional neural network (CNN)-based object detection has been widely used to monitor hazardous situations such as worker identification [9], construction equipment recognition [8], and worker movement tracking [10,11]. CNN-based safety monitoring showed a great potential to detect objects without the labor force. However, it might be difficult to accurately detect the targets without sufficient high-quality data to train the CNN model [15,18].

Building a dataset for training the CNN model involves collecting data, refining raw image data, labeling, data verification, and storing datasets [19]. Among these tasks above, the image data collection and data labeling process are particularly important for accurate object detection but have many drawbacks in current practice. Image data should be manually collected in different conditions with a camera, and the labelers should annotate the bounding box for at least tens of thousands of images. These manual image data collection and annotation approaches take too much time and effort [17], and the quality of the dataset (e.g., redundancy, representativeness, etc.) and quality of annotation (i.e., consistent bounding boxes for the same image) may not be reliable enough to secure high accuracy in object detection accuracy. These issues become more prominent when the CV is used as a means of a safety monitoring method in the construction workspace. The reasons are twofold. First, regardless of its severity, safety accidents at construction sites do not occur sufficiently to train CNN models. Even various obstacles and blind spots, changing weather conditions, and dynamic work task environments interfere consistent data collection process. Second, the collected dataset would be annotated in a labor-intensive way by human labelers with limited expertise and experience. The labelers' subjective judgment could derail the quality of the data annotation, which may decrease the accuracy of the object detection. For these two reasons above, we need a new data collection and data annotation method, which is specially designed for CV-based safety monitoring in construction.

Over the past decade, the method of synthetic data generation has been widely researched to address the manual image data collection and annotation approach issues. Synthetic data is generated by computer simulation or algorithms. For example, we can generate various safety accident scenarios for data collection, and they can be automatically annotated. Despite this potential, previous studies using synthetic data generation in the 3D virtual environment are limited to a specific camera angle. Thus, it could be hard to detect objects from different camera angles. It spurs overfitting issues to a specific scene and decreases the object detection accuracy, particularly for the small objects with irregular shapes (e.g., safety hooks). For this reason, even though there are attempts to improve the object detection performance of the CV model [20,21], object detection accuracy for small objects is not sufficient. Small object detection is very important in construction safety monitoring because most personal protective equipment (e.g., gloves, shoes, hardhat, safety hook, etc.) for humans is relatively small in size compared to other object detection targets such as machines and equipment. In other words, for human-centered safety monitoring in construction, high accuracy of the object detection for small objects should be sufficiently secured.

The main objectives of this study are to suggest a game engine-based synthetic data generation model with various camera directions, including automated data annotation modules, and to test whether the model can improve the accuracy of the CV model in small object detection.

2. RELATED WORKS

2.1 Literature review

Object Detection for Safety Monitoring in Construction

Currently, research on object detection in the construction industry is actively conducted. For example, hard-hat and harness detection [5,6,16], unstable behavior detection[13,22], object detection using building information model (BIM) data [15,17], and tracking workers in the construction site [10, 11] were studied.

There are two main directions of research to increase detection accuracy for small objects: 1) from an algorithmic perspective, improvement of the object detector to create a more suitable model for detecting small objects [21,23], and 2) augmentation of original data [12,20,24]. Their approaches showed promising solutions for improving object detection accuracy. However, they are not thoroughly addressing the object detection problems in a construction work environment (e.g., background change over time, dynamic work conditions, different clothes, nationalities, and work styles). However, synthetic data reflecting real-world information could help handle such problems.

Synthetic Data Generation Approaches for Better Performing Object Detection in Construction

Synthetic data is virtual data that imitate actual data and is used when we cannot collect real-world data. Synthetic data can be generated in various virtual environments, altering variables and parameters. Previously, research on synthetic data generation for CNN has been conducted in two directions: 1) synthetic augmentation methods that generate new or replicas of real-world image data [12,25,26], and 2) methods that create virtual data similar to real-world data in a virtual 3D simulator environment [10,11,15,17,27]. In synthetic augmentation, image cutting and pasting, generative adversarial network (GAN) background, and object extraction were studied to generate synthetic data to improve object detection accuracy in various fields [28]. It was noted that improvisation of the image data, including the texture, color, lighting, and shape of the object, can help better performance in object detection, error search, and movement path prediction problems.

On the other hand, regarding the 3D simulator, researchers focused on creating factors such as lighting, weather conditions, ground surface types, and surroundings as similar as possible to real-world data [10]. They made the virtual workers' poses and movements similar to real through capture. However, this research has problems such as the absence of consideration of different camera angles.

2.2 Knowledge gap

Previous studies on synthetic data generation are confined to data generation at a specific point of sight for detecting targets. For example, they only consider the variables such as texture, color, and lighting at specific camera angles [10,11]. In other words, existing studies lack a solution when the sight of view of the object is changing. Detection accuracy could decrease when the camera direction changes. Because the altered camera direction changes the many factors such as background, brightness, and shape of the objects. In addition, in the case of synthetic data generation studies based on the 3D simulator [11], realistic description is possible, but additional task such as motion capture is required. Lastly, for object detection on construction sites, research was conducted on data augmentation and synthetic data on objects that occupy a relatively large area in images, such as workers and construction machines, or objects that are easy to notice, such as helmets and harnesses. However, studies to improve accuracy for small objects such as safety hooks are insufficient.

3. GAME ENGINE-DRIVEN SYNTHETIC DATA GENERATION MODEL

3.1 Research objective

This research aims to suggest data generation and labeling processes that obtain a synthetic data set without the input of additional personnel other than the data generator. Next, we propose and verify a synthetic data generation model that can automatically extract training images by changing the camera's angle to increase the accuracy of the CV model for small objects.

3.2 Framework overview

This framework consists of two main modules: 1) creating a game engine-based virtual 3D model, which consists of workers, safety hooks, and scaffolding; and 2) synthetic data extraction and CNN algorithm-based learning. Figure 1 summarizes the overall framework flow of this research.

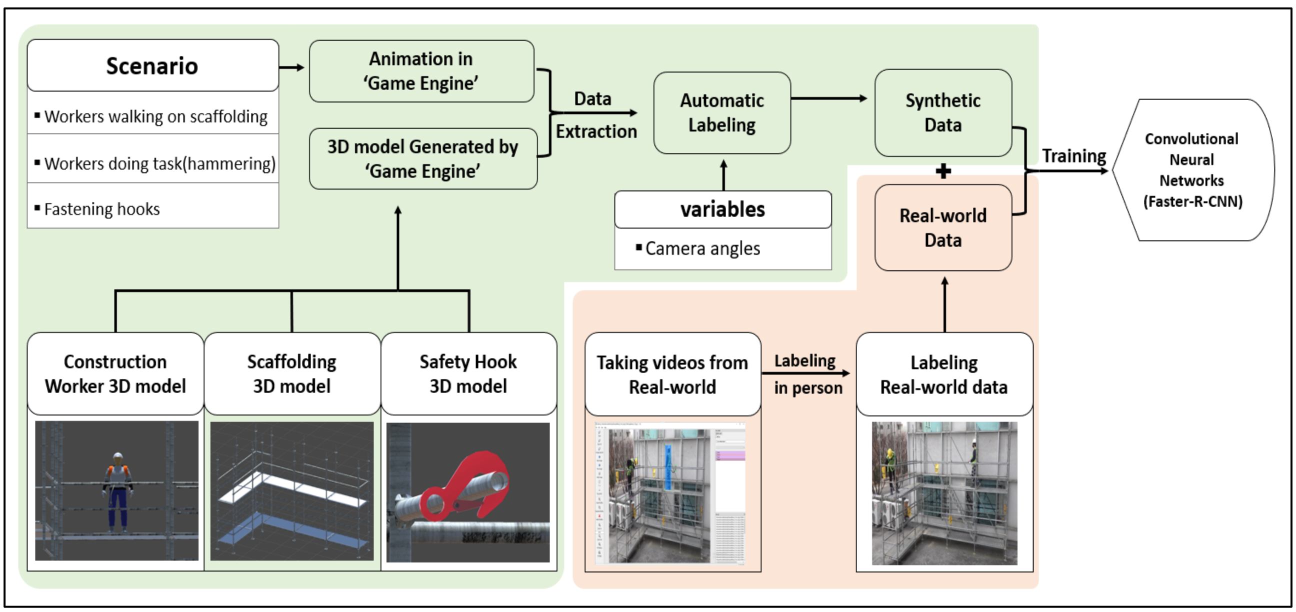

Figure 9. Process for game engine-driven synthetic data generation

4. CASE STUDY

In order to validate our research objective, we conducted a case study. This case study validated whether the synthetic data generation model can increase object detection accuracy. We generated the 3D virtual working environment model in the game engine according to the variables (i.e., camera angle) and extracted automatically labeled synthetic data while varying the variables in the model. The datasets consisted of synthetic data. Also, the real-world data were trained with Faster-R-CNN. Finally, we evaluated and compared the performance of the object detecting model.

Case scenario

This case study focused on object detection for workers and safety hooks when workers perform scaffolding tasks. We generated synthetic data from diverse camera directions in the 3D environment to validate whether this could increase the detection performance of safety hooks. To generate synthetic data for workers and safety hooks, we created models of scaffolding, workers, and safety hooks (Fig. 2) on Unity, a 3D game engine. This model executes pre-organized animation scenarios (for example, moving to random spots and motion to work) on the 3D game engine. Next, we set up virtual cameras to take images from the three angles: the front, the left side, and the right upper side. Through these three cameras, synthetic datasets of each angle were generated. We used Unity Perception Camera, a Unity add-in module that could automatically create labeling data when executing a scenario by assigning a label name for each object [19]. Each dataset contained synthetic data of 10,000 images with a resolution of 1024×768. After that, we took videos from the front side of workers in the real world (Fig. 3). Then, we generated human-annotated datasets. Each worker performed work, fastening one red safety hook to the scaffolding rail. Training images were generated by one frame per 2 seconds from the recorded videos. We created a bounding box for two classes, a person and hook, performing image labeling. The generated 50 images of human-annotated training data were added to the dataset for each front, left, and right upper side.

In summary, the datasets were as follows: 1) train A: 50 images of the real-world data (Fig 4. a), 2) train B: 10,000 images of the synthetic data generated from the front of the 3D virtual model (Fig 4. b), 3) train C: 10,000 images of the synthetic data generated from the left side of the 3D virtual model (Fig 4. c), 4) train D: 10,000 images of the synthetic data generated from the right upper side of the 3D virtual model (Fig 4. d), 5) train E: 50 images of real-world data and 10,000 images of the synthetic data generated from the front of the 3D virtual model (Fig 4. a, b), 6) train F: 50 images of real-world data and 10,000 images of the synthetic data generated from the left side of the 3D virtual model (Fig 4. a, c), and 7) train G: 50 images of real-world data and 10,000 images of the synthetic data generated from the right upper side of the 3D virtual model (Fig 4. a, d). Then, CNN algorithm-based training was implemented based on the seven datasets listed above. CNN algorithm-based training used the Faster-R-CNN model through the Resnet50 (using a pre-trained model) within the Pytorch framework.

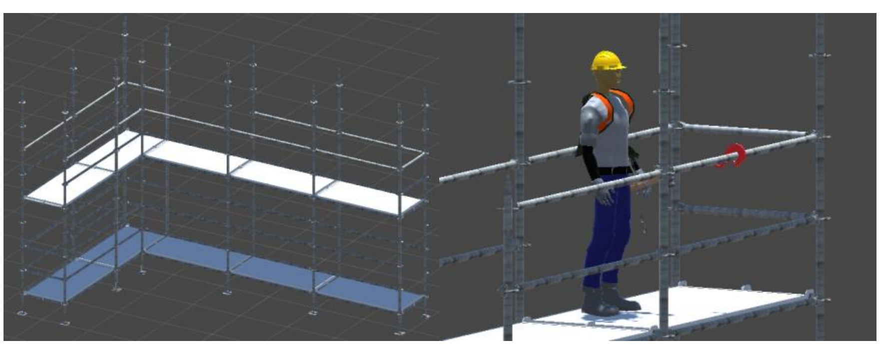

Figure 10. Scaffolding, human, and safety hook model

Figure 11. Real-world image

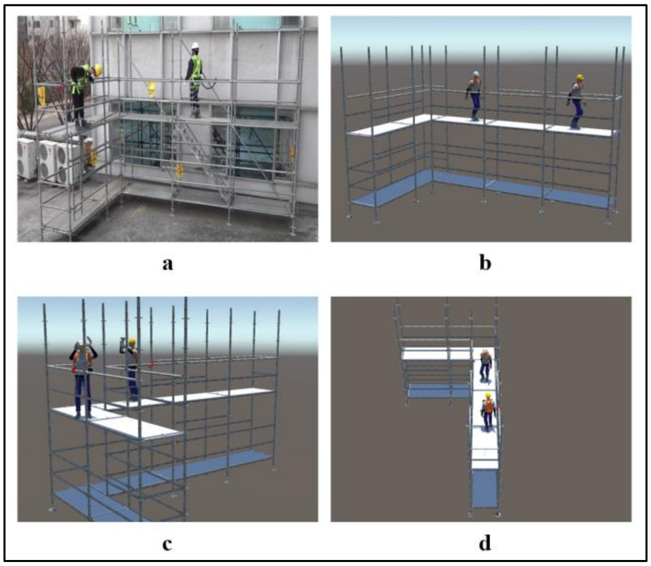

Figure 12. Example images for training datasets

Validation method

As 50 real-world images were taken for training, we extracted other real-world images for the test. Three videos were taken from the camera angles on the front, left, and right upper sides for two workers and red safety hooks on the scaffolding. Each of the 100 test images was extracted from the three recorded videos, one frame per 2 seconds. Three test datasets were generated through bounding-box labeling in person. In summary, the test datasets were as follows: 1) test A: 100 real-world images taken from the front of the scaffolding (Fig 5. a), 2) test B: 100 real-world images taken from the left side of the scaffolding (Fig 5. b), and 3) test C: 100 real-world images taken from the upper right side of the scaffolding (Fig 5. c).

The evaluation of the trained model of the test dataset compares the performance of each trained model using the average precision (AP) value for each class based on the intersection over union (IoU) = 0.5.

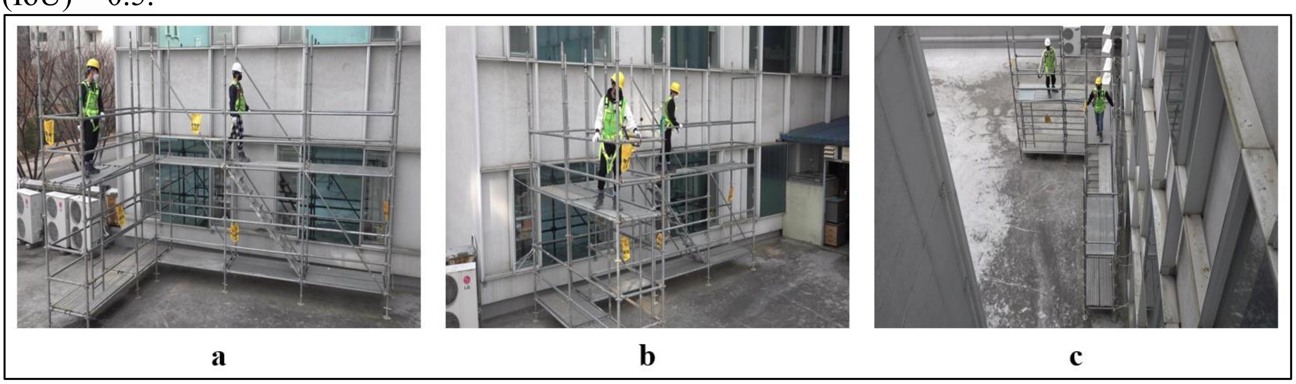

Figure 13. Example images for test datasets

5. EXPERIMENTS AND RESULTS

In order to confirm the results of the case study, we trained the Faster-R-CNN model on seven cases. The cases consisted of 50 real-world images and 3 types of 10,000 synthetic images.

Table 1 presents the results of our experiments. This table contains AP values for a safety hook and person. We compared those AP values to analyze the results.

Each model has a different training dataset. For example, models A to G were trained with each train datasets A to G (Table 1).

Table 9. The results of precision of all models

Model name	Train Dataset	Test Dataset	Average Precision(IoU = 0.5)
Model A	Train A	Test A	Hook AP: 0.3029, Person AP: 0.9994
		Test B	Hook AP: 0.4624, Person AP: 0.9943
		Test C	Hook AP: 0.1202, Person AP: 0.8676
Model B	Train B	Test A	Hook AP: 0.1651, Person AP: 0.9911
		Test B	Hook AP: 0.2457, Person AP: 0.9792
		Test C	Hook AP: 0.0309, Person AP: 0.9239
Model C	Train C	Test A	Hook AP: 0.2663, Person AP: 0.9775
		Test B	Hook AP: 0.4105, Person AP: 0.9168
		Test C	Hook AP: 0.0377, Person AP: 0.5664
Model D	Train D	Test A	Hook AP: 0.1796, Person AP: 0.9088
		Test B	Hook AP: 0.1354, Person AP: 0.9569
		Test C	Hook AP: 0.1856, Person AP: 0.9696
Model E	Train E	Test A	Hook AP: 0.4791, Person AP: 0.9944
		Test B	Hook AP: 0.2929, Person AP: 0.9800
		Test C	Hook AP: 0.2813, Person AP: 0.8833
Model F	Train F	Test A	Hook AP: 0.5045, Person AP: 1.0000
		Test B	Hook AP: 0.6138, Person AP: 0.9850
		Test C	Hook AP: 0.1893, Person AP: 0.8669
Model G	Train G	Test A	Hook AP: 0.5085, Person AP: 0.9999
		Test B	Hook AP: 0.4174, Person AP: 0.9897
		Test C	Hook AP: 0.3530, Person AP: 0.9574

In the case of workers in model A (Table 1), the accuracy was 99% or more based on IoU = 0.5 at the front and left sides. However, in the case of safety hooks in model A, the accuracy was less than 50% based on IoU = 0.5 at all camera angles. It shows that only 50 real-world images for training were sufficient for detecting workers, but 50 real-world images for training were not sufficient for safety hooks that are relatively small and easy to be covered. Also, if the direction of the detecting camera changes, then the detecting accuracy of the CV model could decrease.

When only synthetic data for training was used, the detecting power dropped more than only 50 real-world images were used, except for test C of model D. It means that using solely synthetic data for training is not appropriate to detect small objects such as safety hooks.

For models E, F, and G, we found that the detecting performance increased compared to model A, except for test B of model E and model G: the detecting accuracy of test A of model E increased from 0.3029 to 0.4791, the detecting accuracy of test B of model F increased from 0.4624 to 0.6138, and the detecting accuracy of test C of model G increased from 0.1202 to 0.3530. However, the results of test B of model E and model G decreased compared to model A. In addition, the results of test A of model F and model G are better than the results of test A of model E.

According to the results of this study, adding the synthetic data generated from different camera directions could increase object detection performance. Adding the synthetic data from the same camera direction as the test data increased the detecting accuracy of small objects. Especially when the camera direction of the real-world data for training was different from the test data, adding the synthetic data from the same camera direction as the test data showed the best accuracy for safety hooks. However, if the camera direction of the real-world data for training is the same as the test data, adding the synthetic data from the different camera directions could increase more detecting accuracy for safety hooks. In other words, the synthetic data generated from different camera directions from the real-world data could provide various shapes of objects and different backgrounds to increase accuracy.

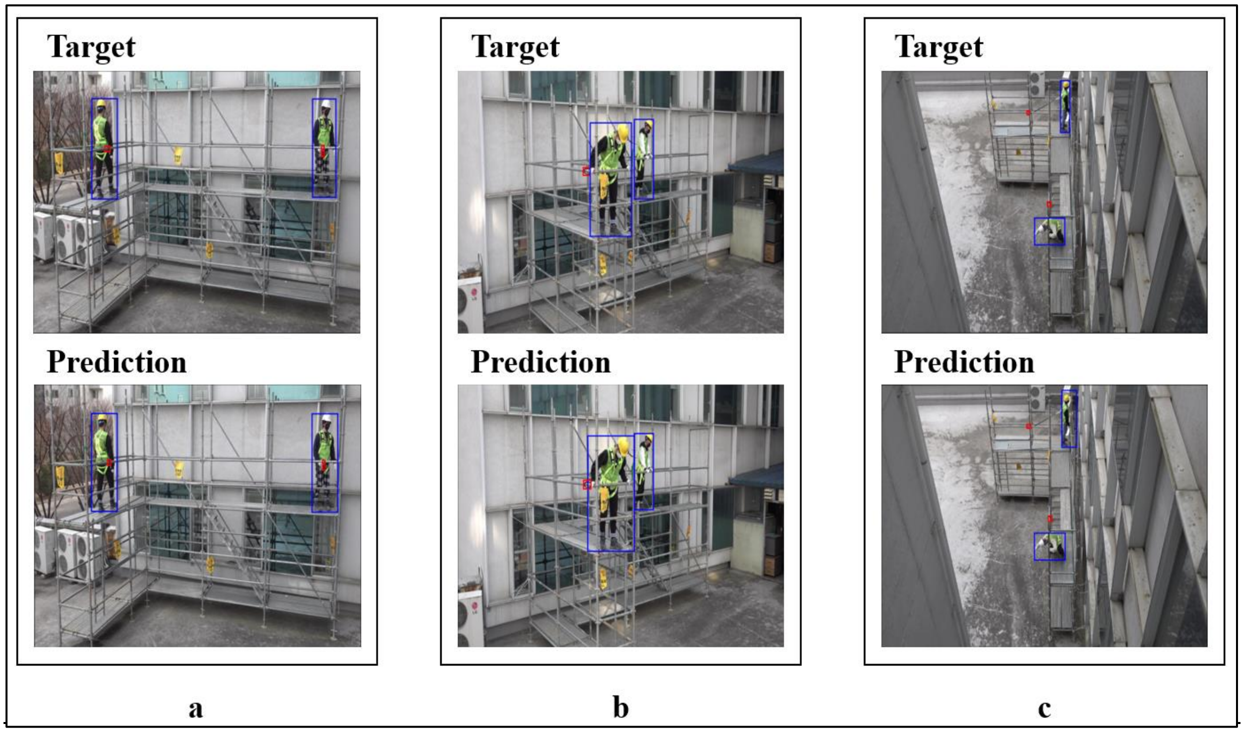

Figure 14. Examples of the experiments

In Fig 6, each a, b, and c are examples of prediction corresponding to model E, F, and G. In the case of prediction for safety hooks, misdetection is occurred by similar color and shape. In addition, safety hooks with tiny pixel size could not be detected.

6. DISCUSSION & LIMITATIONS

This research confirmed that using synthetic data extracted from different camera directions could increase detecting accuracy. We suggested an automatic synthetic data generation system that does not require the input of additional personnel and has three different camera directions.

This study could be seen as an approach to synthetic data generation for construction safety. By increasing the detection accuracy of small objects like safety hooks, safety accidents such as falling could be prevented. Although the results of the tests cannot be applied in practice, the detecting performance could be enhanced by using the methods such as improving the 3D model and changing the training model.

In this research, synthetic data in particular situations could lead to other overfitting issues. It seems that the factors such as the domain shift, same background, same environment, and repeating motions could overfit the model. Moreover, although test C of model G showed the best AP value for safety hooks, the value was not the best in all the tests of model G. It means that the 50 real-world images could have influenced the training. Therefore, we should validate the model in different conditions, such as the diversity of fastening forms of safety hooks on the 3D model. In addition, methods such as background randomizing and the Airsim might be expected to help solve the problem of overfitting. The performance of a CNN depends on many factors such as optimization, batches, epochs, learning rate, activation function, and loss function [18]. In this experiment, we fixed such factors, but we also expected to ease overfitting by tuning these factors.

In this study, the real-world training images were set to 50. Since the test data shared the same background and scaffold model with the training images, training is sufficient if more than 50 real-world training images are used. In other words, if we use more than 50 real-world images for training, then the trained model predicts better than when synthetic data are used for all of the classes (a person and hook). Therefore, in this experiment, if the training images from the real world were more than 50, we expected that the real-world data's influence would be more significant than the synthetic data.

We experimented with three angles: the front, left side, and the upper right side. Synthetic data can be extracted from the virtual 3D environment regardless of the camera angle. The test image was extracted from only three angles due to spatial constraints in this work. Therefore, we need to experiment with various angles in addition to the three angles.

For the evaluation method, we only used AP values to compare each detecting performance of the models. However, there are many evaluation methods such as Recall, F1 Score, and mAP-Recall graph. Therefore, we need to evaluate the models using AP values and other evaluation methods.

In this study, Faster-R-CNN was applied as a deep learning model. Deep learning models with higher performance exist, such as Mask-R-CNN in the two-stage model and Yolov.5 in the one-stage model. Since the importance of this study arises from comparing the performance differences between training data sets, not from the maximum value of the object detection accuracy, the Faster-R-CNN model could sufficiently support this study's aim. However, applying a high-performance deep learning model in future studies is desirable.

We experimented with red safety hooks. However, in the construction sites, red safety hooks are not a general type of safety hooks, and there are many different shapes of safety hooks. Furthermore, the detecting performance of the CV model is affected by the colors and shapes of objects. Therefore, we need to experiment with different colors and shapes of safety hooks.

7. CONCLUSION

Research related to synthetic data is a field that has recently attracted attention due to the explosive growth of the artificial intelligence field. In the construction industry, synthetic data generation has also been studied. This study proposed a method of generating synthetic data with a game engine to improve the detection accuracy of small objects at construction sites. As a result of diversifying the camera angles of synthetic data, we verified that small objects could be successfully detected, and the automation of data generation could be achieved. Although adding synthetic data to a particular dataset reduces object detection accuracy, this could be solved by using various methods which can ease overfitting problems in the future. This study is significant in suggesting a synthetic data generation method that has not been studied before. Furthermore, it is expected to affect securing datasets in the construction industry positively.

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