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Application of Deep Learning for advanced classification of radioactive waste

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1. Introduction

The radioactive waste (RAW) created at a department in KAERI is firstly classified and packed as an original drum by the department. Then, the original radioactive waste drum is transferred to a radioactive waste treatment facility, and there is reclassified, repacked, and stored in the form of several small packages in the drum. The reclassification of the radioactive waste received from the creating department is mostly performed by experienced workers with their experience and mandrolic process. Therefore, unexpected human error could occur during an occasional total inspection, which increases the work fatigue of the workers. To solve such a problem, object recognition and classification of the radioactive waste using the deep learning technique based on radioactive waste computer vision information is being studied.

2. Methods and Results

2.1 RAW Data collection and Dataset

To ensure that the learned model has robust recognition performance, image data was collected from the environment in which cameras and computers were installed on the classification workstation at the radioactive waste treatment facility. The collected data can efficiently reduce the collection time of multiple object recognition and provide various data to strengthen the learning of the model. Based on the classification criteria, 11 kinds of patch data (Mask, Ranch glove, Rubber glove, Filter, Knife, Brush, Hose, Tissue, Sandpaper, Working Shoes, Decontamination paper) are generated, and each patch data is configured as shown in Table 3 below. A total of 8,307 patch data was performed to make synthesis at the actual radioactive waste sorting workbench. Since the task is to detect the location and category of waste, it is configured to be mapped to the learning information and the pixel information of the image when generating actual data. The results of the information visualisation and the generation of synthetic data are as follows (Figure 1).

Fig. 1. Result of combining a created RAW images

2.2 DNN learning for RAW object recognition

The object recognition model was trained to learn only several category information from an image and was trained to predict only the classification information of the image (Figure 2).

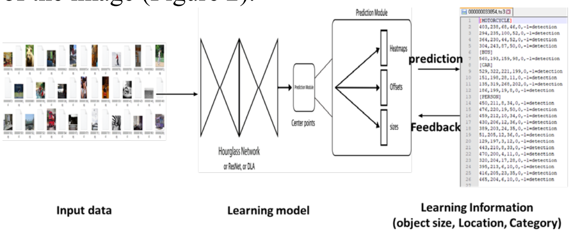

Fig. 2. Learning process of multiple object recognition model

2.3 Data configuration for learning evaluation

The evaluation data was divided into 11 categories. The validation set, the test set, and the composition of each data is shown in Table 1.

Table 1: Configuration of validation and test set

Category	Validation	Test
Mask	1,312	1,331
Ranch glove	1,278	1,347
Rubber glove	1,305	1,289
Filter	1,321	1,359
Knife	1,326	1,254
Brush	1,280	1,287
Hose	1,330	1,362
Tissue	1,337	1,296
Sand paper	1,343	1,389
Working shoes	326	1,327
Decontamination paper	1,302	1,313
Total	14,460	14,554

2.4 Results of learning evaluation

The final evaluation was set as true if the ground truth and the intersection over union (IoU) of the predicted object were 0.5 or higher. The AP and mean average preparation (mAP) for each category were calculated.

The test evaluation results are shown in Table 2. As a result, the mAP of 400 generations (epoch) of models learned from the validation set was measured the highest at 70.6%, and 70.5% of the mAP was obtained from the test data (test set) by selecting the evaluated model.

Table 2: Result of test estimation each category

Category	Result(AP)
Mask	0.936
Ranch glove	0.926
Rubber glove	0.912
Filter	0.908
Knife	0.882
Brush	0.781
Hose	0.828
Tissue	0.62
Sand paper	0.468
Working shoes	0.363
Decontamination paper	0.136
mAP	0.705

The performance was compared after changing the algorithm of the Centernet [1] code performed in this study to Detectron2 [2] and EfficientDet [3]. However, in the case of existing codes, data was synthesized in real-time every epoch while learning. Two comparison codes were first generated using the data generation part of the existing code due to difficulties in implementation and then compared by learning with the generated model. That is, the amount of data used should be considered less than the existing code. For example, Detectron2 used 80,000 learning data and used Detectron2's Fast-RCNN model (Figure 3). Test data was evaluated using 10,000 identical test datasets, and mAP achieved 64.06% performance, which is somewhat lower than conventional code.

Fig. 3. Result of a RAW recognition using Detection2

In the case of EfficientDet, the experiment was conducted by dividing it into four data sets as shown Table 3. and Augmentation techniques such as Cutout, Scaling, and contrast were applied. The same data was used for the test.

Table 3: Learning dataset of EfficientDet

Model	Dataset	epochs	Images
1	12,800	61	780,800
2	25,600	50	1,280,000
3	38,400	43	1,651,200
4	51,200	39	1,996,800

2.5 Result and Consideration

For the numerous radioactive waste object recognition, the following 11 object categories were selected in the small group. Their database was constructed; Mask, Ranch glove, Rubber glove, Filter, Knife, Brush, Hose, Tissue, Sand Paper, Working shoes, Decontamination paper. The object image data have 512 x 512 resolution, which can show object location, size (width, height), the category in the inference, and the inference speed is 0.01 sec. Object patch augmentation and data augmentation for the generated single data were implemented to develop a learning model that can respond to the various changes. Also, pixel-level transform (Blur, Noise) and spatial-level transform were used to enhance the learning model's performance to identify the multiple objects. Detectron2, which is for the object detection and object segmentation in the PyTorch library, and EfficientDet algorithm, which shows the best performance in the real-time object recognition area, were tested and compared with the CenterNet learning model, which is used for this radioactive waste object recognition.

The mean average precision (mAP) of CenterNet showed the best result, 70.6 % in the 400 epoch of the learned model from the validation set, and showed 70.5 % in the test set derived from the evaluated model. On the other hand, the mAP of Detectron2 showed a slightly lower accuracy 64.06 %, and EfficientDet showed a very high accuracy 81~82%.

3. Conclusions

The enhancement in the object recognition and classification of radioactive waste is implemented by the radioactive waste data generated at the radioactive waste treatment facility. However, since the accuracy of object recognition developed in this study is based on the learning model, which relies on limited data sets, more numerous data sets should be collected to recognize more mixed and various radioactive waste in the real world. For this purpose, artificial data similar to the real radioactive waste will be used to recognize the various radioactive waste in the mixed environment, which is the main objective of advancement in object recognition.

REFERENCES

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