

1.

Product: bottle

Number of defect classes: 4

Types of defect classes: ['broken_large', 'broken_small', 'contamination', 'good']

Number of images used in your dataset: 83

Distribution of training and test data: 7:3

Image dimensions: (900,900,3)

2.

| Augment_type | Learning rate | Pre-train model | optimizer | Test_acc |
|--------------------------------|---------------|-----------------|-----------|----------|
| origin | 1e-3 | Resnet18 | Adam | 37.5 |
| +randomrotate | 1e-3 | Resnet18 | Adam | 43.75 |
| +randomrotate | 1e-4 | Resnet18 | Adam | 56.25 |
| +randomrotate +verticalflip | 1e-4 | Resnet50 | Adam | 31.25 |
| +randomrotate | 1e-4 | Resnet101 | Adagrad | 37.5 |
| +randomrotate | 1e-3 | Resnet152 | Adamax | 62.5 |

Epoch=100, batch size=64.

3.

(i) Deep long-tailed learning seeks to learn a deep neural network. model from a training dataset with a long-tailed class distribution, where a small fraction of classes have a massive number of samples, and the rest of the classes are associated with only a few samples.

(ii) Devised an instance difficulty model and introduced a novel instance-level re-sampling strategy. Allocate weights using machine learning methods. For this case, you can choose to assign heavier weights to less represented classes to prevent the neglect of less frequent categories during learning.

4.

To develop an anomaly detection model with a training set primarily consisting of 'good' images and lacking examples of defects, one can use strategies such as unsupervised learning, semi-supervised learning, one-class classification, data augmentation, transfer learning, and feature extraction/reconstruction. These approaches aim to train the model to recognize anomalies based on deviations from the learned distribution of normal data.

5.

(i) For object detection, it is necessary to prepare datasets that include images and corresponding labels. The labels should indicate the position and class of each object in the images. For segmentation, datasets should include images and corresponding pixel-level labels, which identify which object or region each pixel belongs to.

(ii) These models are suitable for fine-tuning because they have been trained on large datasets, exhibiting strong feature extraction capabilities and good generalization performance. Through fine-tuning, these models can be adjusted to better meet the specific requirements of our custom dataset, thereby improving the performance of the models on our dataset.

Ref:

A Re-Balancing Strategy for Class-Imbalanced Classification Based on Instance Difficulty

[https://openaccess.thecvf.com/content/CVPR2022/papers/Yu_A_Re-](https://openaccess.thecvf.com/content/CVPR2022/papers/Yu_A_Re-Balancing_Strategy_for_Class-Imbalanced_Classification_Based_on_Instance_Difficulty_CVPR_2022_paper.pdf)

[Balancing Strategy for Class-](https://openaccess.thecvf.com/content/CVPR2022/papers/Yu_A_Re-Balancing_Strategy_for_Class-Imbalanced_Classification_Based_on_Instance_Difficulty_CVPR_2022_paper.pdf)

[Imbalanced Classification Based on Instance Difficulty CVPR 2022 paper.pdf](https://openaccess.thecvf.com/content/CVPR2022/papers/Yu_A_Re-Balancing_Strategy_for_Class-Imbalanced_Classification_Based_on_Instance_Difficulty_CVPR_2022_paper.pdf)