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Cutout as Augmentation in Constrative Learning for Detecting Burn Marks in Plastic Granules

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Summary:
Burn marks in plastic granules are formed during the plastic injection process. The granules with burn marks are not acceptable for use in industrial application and should be filtered out in a sorting process. AI-based anomaly detection approaches are widely used in area of visual-based sorting due to the high accuracy and the low requirement of expert knowledge. In this contribution, we show that using cutout, a simple data augmentation strategy, can improve the accuracy of a contrastive learning-based anomaly detection method. In this work, synthetic image data are used due to the lack of real data.

Keywords: Data Augmentation, Contrastive Learning, Anomaly Detection, Image Synthesis

Background

In the plastic injection process of plastic granules, burn marks caused by either excessive heating or too fast injection speed can be identified as black dots on the surface. In extreme case, the whole granule surface could be burnt. Burn marks are not merely visual defect, moreover, they indicate the degradation of both physical and chemical properties of the corresponding parts compared to the intact parts. Plastic granules with burn marks should be identified and filtered out by a sorting system.

Due to the limited amount of data and the lack of reliable ground truth labels of corresponding data, we modelled the granules by using the rendering software Blender. We modelled multiple granule instances for each rendering to simulate the practical sorting process (Fig. 1a). With the embedded Python interpreter, both the precise location of plastic granules in the rendered image and the ground truth label of each granule are accessible without manual effort. Single plastic granule will then be cropped from the rendered image and be labelled for subsequent processing, e.g., classification and anomaly detection. (Fig. 1b).

In practical sorting process, large amount of nominal plastic granules images can be accessed using methods such as blob detection. Under this assumption, cropped synthetic images of nominal plastic granules can be leveraged to pretrain a neural network in an unsupervised manner using contrastive learning method, as contrastive representation shows state-of-the-art performance on visual recognition tasks [1]. In common contrastive learning settings, data augmentations like color jittering and random crop are applied on images. Neural networks are trained to learn features in image by judging if two augmented images are from same original image.

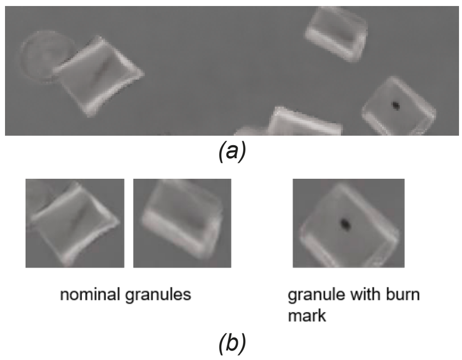

Fig. 1. Rendered image of synthetic plastic granules (a) and examples of automatically labelled crops of single granule for classification (b).

Method

Our work is based on the distribution-augmented contrastive learning for one-class classification [2], while one class classification and anomaly detection are viewed functionally equal in our context. This method builds a two-stage classifier. The first stage is pretrained with nominal data using self-supervised contrastive learning, while the learned representation is used for training a one-class classifier in the second stage. In this method, the intro-

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duced distribution augmentation applies rotation as geometric transformations on images. The distribution augmentation is disjoint from data augmentation. By applying data augmentation on original image and on corresponding distribution-augmented image, a negative pair instead of a positive pair for self-supervised learning is generated. The distribution augmentation is proved to make distribution of nominal data in embedding space compacter to better distinguish anomalies. For burn mark detection, we apply cutout [3] instead of rotation as our distribution augmentation. This is inspired by the visual similarity between burn marks and masked-out sections after cutout operation (Fig. 2).

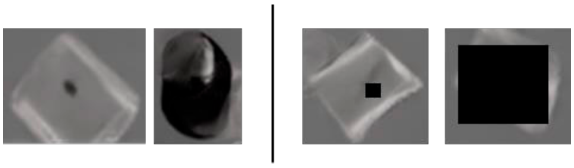

Fig. 2. Granules with burn marks (left) and cutout-augmented nominal granules (right).

In our experiments, a ResNet-18 [4] is used as feature extractor as in [2]. The depth of multi-layer perceptron (MLP) head on ResNet-18 for representation learning is reduced to 3. After the self-supervised pretraining, the MLP head is replaced with a kernel density estimation (KDE) model for classifying granules with burn marks. Used data augmentations include crop-and-resize, horizontal flip, random grayscale and random blur. No image augmentation is applied for the training of KDE model. All images are resized to 32×32. Models are trained 200 epochs with momentum (0.9) SGD and a single cycle cosine learning rate decay.

Results

We run experiments 5 times with different random seeds and report the mean and standard deviations of area under the receiver operating characteristic (AUROC). The performance of applying rotation and/or cutout as distribution augmentation method is shown in Table 1. The results indicate that by replacing rotation with cutout, the learned representations of nominal granules and of granules with burn marks are further apart in embedding space and thus increase the accuracy of anomaly detection. Besides, using both augmentations at the same time leads to a worse classification performance.

To explain the improvement by applying cutout for representation learning, we choose the fixed threshold, which corresponds to the highest accuracy at test time, for the trained KDE model and use the model to again classify the test image of nominal granules, but this time applied with cutout. In this case, 66.8% of these images are identified as anomalies. This result implies that the effect of cutout differs from that of rotation as distribution augmentation for contrastive learning, in that the cutout to some degree simulates the burn marks and therefore implicitly enables the learned representation for classification, while applying rotation only makes the representation of nominal images compacter.

Table. 1:Anomaly detection performance (AUROC) on test synthetic data.

Distribution augmentation method	AUROC
None	80.7 ± 1.6
Rotation	86.7 ± 1.2
Cutout	90.7 ± 0.3
Rotation+Cutout	83.3 ± 0.4

Summary

This article shows that cutout is a better choice than rotation as distribution augmentation method in contrastive learning for burn mark detection. In future studies, other defects and corresponding augmentations should be analyzed (e.g., surface blur on granules and local blurring as distribution augmentation). On this basis, a more general analysis of augmentations which generate anomaly-like data and their influence in the self-supervised contrastive learning could be conducted.

References

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