반복제조에 대한 이상 탐지 알고리즘에 관한 연구

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CropLiq - Data Augmentation on Self-Supervised Learning for Industrial Anomaly Detection

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요 약

In this paper, we focus on a procedure to detect anomaly in industry. This paper develops the idea from "CutPaste : Self-Supervised Learning for Anomaly Detection and Localization". We discover that applying a new image enhancement and augmentation strategy is still effective to further ~~improves~~ the performance of previous method. The model should be trained with the pseudo anomalies that are similar to real anomalies. In the testing phase, it should be able to detect even more difficult anomalies, demonstrating its robustness for any unusual changes in anomaly patterns. In this paper, we propose a new augmentation method that inserts pseudo anomaly pattern into the training data by choosing a random rectangle patch from target object area and apply geometric augmentation scheme called Liquify on it to train a CNN anomaly detector model to identify anomaly patterns from input image. For the sake of simplicity, we call our proposed augmentation strategy “CropLiq”. First, we learn image representation by distinguishing normal images and CropLiq images. Then, we leverage various existing augmentation methods, such as CutPaste, to construct a classifier that enables us to classify normal, CropLiq, CutPaste samples. Finally, using precise anomaly score, we apply Grid search technique to find the optimal threshold for differentiating the anomaly area and then localize the anomaly area with a bounding box. We also apply Softmax thresholding to classify anomaly images with predefined classes.

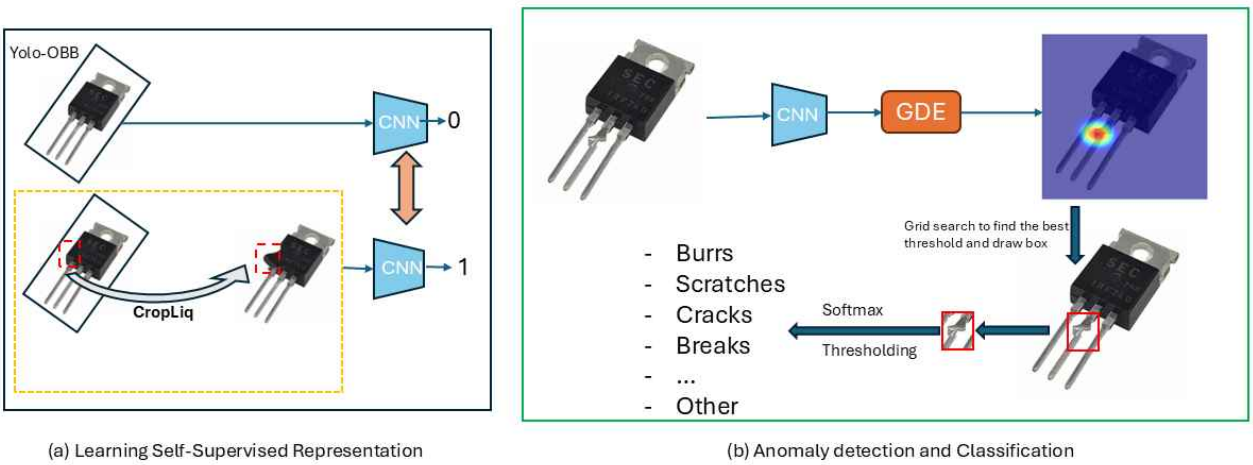

Figure 1: An overview of our method for anomaly detection and classification. (a) A deep CNN is trained to distinguish images from normal and augmented data (CropLiq), which chooses a small rectangular inside Yolo-OBB’s bounding box and utilizes Liquify filter on that patch. (b) A representation for anomaly detection and defect localization via GradCAM, and then classify into predefined anomaly types or other types.

Ⅰ. 서 론

Anomaly detection aims to differentiate abnormal and normal patterns from the input images. But anomaly detection faces a big problem that there are so many types of defects, some of them we have never seen before. Due to limited access to anomalous data, an anomaly detector is often conducted under semi-supervised or one-class classification using normal data only. We train the model to learn representations from normal data, as the anomalous components are unknown beforehand. If the model does not accurately represent the test image, we consider it to be an anomaly. For instance, when the data reconstruction error is substantial, anomalies are identified using an autoencoder trained to recover normal data. Alternative approaches for anomaly identification that make use of high-level learnt representations have shown to be more successful.

An efficient end-to-end trained one-class classifier parameterized by deep neural networks is demonstrated, for instance, by the deep one-class classifier [4]. It performs better than its superficial equivalents, including reconstruction-based techniques like autoencoders [5] Depending on the type of product, we must find a suitable augmentation that can mimic real anomalies.

In this work, we firstly use Yolo-OBB to find object's area and then apply CropLiq – a special anomaly insertion strategy that does not require any anomaly source image to create anomaly patterns and directly apply augmentation on that patch of the normal image, as presented in Figure.1. Then we follow the two-stage framework [3]. After inference of CNN Anomaly Detection, we use Grid search on anomaly score to find the optimal probability threshold for anomaly decision. And use a classifier based on softmax thresholding to classify defect type in to known or unknown classes.

The purpose of CropLiq augmentation is to generate a spatial irregularity that may be used as a rough approximation of the actual defect. Within Yolo's bounding box, rectangular patches of various sizes and aspect ratios are selected, and the liquify method is then utilized on that patch to provide augmentation. Since it is difficult to distinguish Cropliq enhanced samples from actual defects, representations learnt by Cropliq augmentation are often good at identifying actual defects.

Ⅱ. 본론

Cutout and CutPaste are two of the various augmentation techniques that may likewise produce an uneven region in a picture. Cutout selects a rectangle region in the image and substitutes it with one of three colors: random, mean pixel values, or standard grey. With cutpaste, you may resize and cut a portion of a picture, then paste it back into the original. While Cutout still produces decent results, it is easy to identify them from photographs. For this reason, Cutpaste is used to prevent the learning of naive decision rules for differentiating between enhanced images. Even if Cutpatse differs from actual anomaly, we may still identify irregularity patches on hidden anomalies by learning from it. I suggested CropLiq (Crop and apply Liquify) as a way to further enhance. Instead of cutting a portion of the image and pasting it in any old place like Cutpaste used to do, this approach chooses a portion of the image and distorts it. After using the aforementioned technique, the image appears extremely natural and authentic. This indicates that there is a high likelihood of replacing actual defect in the image:

1. Choose a random area from yolo's bounding box
2. Apply distortion while maintaining the area's boundaries to maintain the link to the outside

Real defect like dents, breaks, and cracks can be replaced with this procedure, depending on the degree of distortion. As a result, it may teach the model the wise decision guidelines. In addition, before applying CropLiq, we also apply YOLO-OBB to extract the smallest area containing the object from the background. This is because, in the previous two methods, the product could not be considered an anomaly at the time of cutting out from or pasting into a background area that does not contain the product. However, during training, the model would perceive this image as anomalous data, which would adversely affect the training outcomes.

Following the idea of rotation prediction [1], we define the training loss function:

$$L_{CL} = \mathrm{E}_{x \in \chi} \left\{ \mathrm{CE}\left(g(x), 0\right) + \mathrm{CE}\left(g\left(CL(x)\right), 1\right) \right\} \qquad (1)$$

Where χ is the set of normal data, CL(.) is a CropLiq augmentation, CE(.,.) refers to a cross-entropy loss, E is expectation of all sample x in χ and g is a binary classifier parameterized by deepnetwork.

2.2 Multi-Class Classification

Although CropLiq seems mostly like real anomaly but according to [2] learning to discriminate normal, Cutpaste and CropLiq can improve the performance.

2.3 Computing Anomaly score

In this work, we consider a simple parametric Gaussian density estimator (GDE) like [2]:

$$\log p_{gde}(x) \propto \left\{ -\frac{1}{2}\left(f(x)-\mu\right)^{\mathrm{T}} \Sigma^{-1} \left(f(x)-\mu\right) \right\} \qquad (2)$$

Where μ and ∑ are learned from normal training data.

2.4 Detecting Anomaly type

We explore the Grid search approach, which is a straightforward technique to discover an ideal constant by testing all the values in its range, based on the anomaly score result from the previous phase. This method's drawback is that it needs a lot of processing when trying several situations. However, since we are only examining one variable in this range (0.1, 0.9), it is not very significant:

1. Create different thresholds from 0.1 to 0.9, step size is 0.05.

2. Evaluate the number of anomaly regions detected for each threshold.

3. Choose the threshold that gives the maximum number and accuracy of anomaly detections without too many false positives.

After determining the ideal threshold, we use the SoftMax thresholding approach to construct a bounding box around the areas where the anomaly scores are higher than the threshold.

A popular method for solving classification issues is softmax thresholding, which is particularly useful when you need to classify a sample into one of many classes or ascertain if it belongs to the "unknown":

1. Compute Softmax function.
2. Determine the highest probability (confidence score)
3. Compare with the Threshold:
   - Set a threshold T first. This threshold determines whether the highest confidence is large enough to accept the prediction.

   - If the highest probability value greater than T, the sample is classified into the class corresponding to the highest probability. Otherwise, the sample is assigned to the "unknown" or "out-of distribution" class.

Ⅲ. 결론

We propose a data augmentation approach for defect detection. And then we classify them into known and unknown classes which is useful in the production process. We hope that CropLiq augmentation could be a cornerstone for building a powerful model for self-supervised defect detection in the future.

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