Proceedings of the 41st Chinese Control Conference
July 25-27, 2022, Hefei, China

Anomaly detection for surface of laptop computer based on PatchCore GAN algorithm

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Abstract: Timely detection of notebook appearance defects is an important means to prevent products from being delivered to customers before leaving the factory.In industrial production, more emphasis is placed on fast and accurate detection methods, but the existing difficulties: 1. Defect samples are rare and difficult to obtain; 2. In high-resolution images, there are slight differences between abnormal samples and normal samples; 3. Slowly detection and insufficient accuracy.The existing methods mainly use a large amount of abnormal samples, so it is difficult to extend to the field of notebook appearance anomaly detection.To solve this problem, we designed a method that firstly uses unsupervised PatchCore which the algorithm was trained on normal samples and Defect GAN is used in test phase. To create a large number of verisimilitude abnormal samples and test these samples with PatchCore. On TKP-Surface datasets, the AUROC score of image-level anomaly detection achieves 96.1%, which meets the requirements of industrial applications.

Key Words: Laptop computer, Data augmentation, PatchCore Gan algorithm, Anomaly detection

1 Introduction

In recent decades, the related theoretical and technical research of intelligent manufacturing has been developed rapidly, but it is still in the stage of digitization and networking, and there is still a long way to go for the real large scale application. Anomaly detection is an essential role in intelligent manufacturing. In notebook manufacturing industry, the anomaly detection for surface of laptop computer can effectively filter the abnormal products with abnormal appearance products, achieve the quality control of notebook, reduce the cost of product repair and improve enterprise profits.

The assembled laptop may have scratches, fingerprint residues, gaps and other appearance defects, which will cause negative evaluation of the company by users and damage the benefits. In the actual production process of laptop computer, the main challenges of abnormal detection mainly include: 1. It is very difficult to obtain large numbers of abnormal samples, neither marked or unmarked during high-speed production. 2. Under the limitation of industrial conditions, the collected images that need to be collected are usually high-resolution images, and the difference between abnormal samples and normal samples is slight. 3. At present, the detection in industrial scenes is often slow and not accurate enough, and manual re-judgment is needed. Therefore, in order to ensure the production efficiency, the detection speed and accuracy need to be improved.

Anomaly detection is generally based on machine vision technology[3]: 1. based on traditional digital image processing and machine learning methods, its algorithm complexity is low, its accuracy is not high, and there are defects such as missed detection and false detection, so it cannot be widely used in industry; 2. Compared with traditional methods, the detection method based on deep learning is more accurate, has higher algorithm complexity, and needs to collect a large number of samples for training, which has certain limitations in the industrial environment.

To solve the above problems, based on the unsupervised anomaly detection algorithm PatchCore[1], the problem of local subtle defects in high resolution images will be solved by introducing Defect GAN[2] to generate a large amount of test data to ensure the reliability of the anomaly detection algorithm. Our innovation lies in that, in the testing stage, we use the existing abnormal samples to generate some verisimilitude samples with defects, which is also to solve the problem of insufficient abnormal samples in the industrial environment.

We evaluated our methods on the TKP-Surface datasets of normal and abnormal samples collected in the same manner as images collected during production on a laptop computer production line. Through the transfer learning of ImageNet pre-training model, the anomaly accuracy at image level has achieves 96.1%, which is in the standard with the standard applied in industrial production. In the testing stage, a large number of verisimilitude abnormal samples and a small number of real abnormal samples are tested to ensure the reliability of the algorithm. Finally, the performance of the algorithm under different image resolutions is compared, hoping to be helpful to relevant personnel.

2 Related Work

Data augmentation. Techniques based on deep learning often require extensive annotated training samples, which are not always available. Recent researches have suggested a number of ways to the data deficit.They can be roughly

This work was supported in part by the National Natural Science Foundation of China (62173317, 62033012, 61725304,61903118),Major Special Science and Technology Project of Anhui China (202104a05020064,201903a07020012,202003a07020009),(Corresponding authors:Yu Kang).

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categorized as small sample learning and data enhancement.

Data enhancement aims to enrich the number and diversity of training datasets so that better deep learning models can be trained. In order to enrich the training data, traditional methods are as follows: 1. collect abnormal samples by destroying the workpiece manually; 2. Use computer aided drawing to synthesize abnormal samples and so on.

Defect GAN uses generative adversarial networks (GAN) as the basic method to synthesize real training samples. It is a kind of data enhancement, and it trains a better anomaly detection network by synthesizing various abnormal samples with better diversity and fidelity.

Feature extraction. In traditional algorithms, VGG-16 and other networks are used as the backbone network to extract single feature images. Generally, the backbone network is composed of convolution layer, pooling layer and full connection layer to extract image features.The feature graph that is close to the input part of the network is called the underlying feature graph, which has a large size and accurate structure information, but weak global semantic information. Such feature graph is conducive to target positioning, but not conducive to classification. With the progress of Conv and pooling, the size of feature graph gradually decreases, while the structural information decreases, the semantic information becomes rich. Such feature graph is called high-level feature graph, which is conducive to the classification of targets, but not conducive to the positioning of targets. Therefore, we need feature fusion to ensure the balance between structural information and semantic information in feature maps, so as to achieve higher precision in both classification and positioning tasks.

Anomaly detection. Surface anomaly detection refers to the process of recognizing and locating surface defects based on machine vision. It is an important task with extensive practical application in manufacturing industry. Prior to the era of deep learning, traditional methods of designing handmade feature extractors required specialized knowledge. In the era of deep learning, the model based on convolutional neural network is used to anomaly defect, and remarkable results are achieved. Among them, there are supervised two-stage target detection algorithms based on Faster R-CNN[4], single-stage target detection algorithms of YOLO[5–7] series, and SSD[8]series algorithms using feature fusion mechanism. On the unsupervised side there is learning to predict predefined geometric transformations[9]or through normalized flows[10]. For the respective label representation and the new test representation, defect detection can be a reconstruction error[11], distances to k nearest neighbour[12] such as OC-SVMs[13] or SVDD[14, 15].

3 Deep learning-based Method

3.1 Defect GAN

Defect GAN is based on a generative adversarial network (GAN) that syntheses a specified Defect at a specified location in a normal Defect free sample,as in Fig. 1.We generated two different defects from normal samples.

In Defect GAN,defect is used as a foreground, and a spatial and category control diagram is used to control where and which defects are generated on the original image. Because only Defect data is generated, the performance cost and uneven quality of the generated image are avoided.

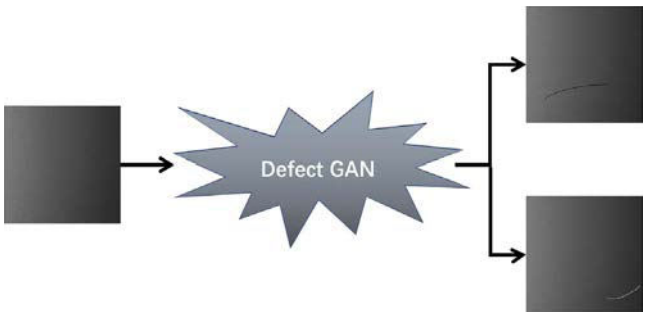

Fig. 1: Defect GAN was used to synthesize defects under the normal sample. The black scratch abnormal sample was synthesized in the upper left corner and the white scratch abnormal sample was synthesized in the lower right corner.

The defect distribution and defect graph were generated by a damage network, and the diversity of defects was enriched by adding gaussian noise during the generation. Finally, through a synthesis layer, the specified defect is synthesized to the specified position of the original drawing. At the same time, in order to make the generated defects more real, the method adds a recovery network after the generated defect samples to remove the synthetic defects and restore them to the original samples.

3.2 Patch Core

The backbone of the algorithm in this paper is PatchCore algorithm, which has the following obvious advantages: 1. Maximize available tag information during testing. 2. Reduce the bias of ImageNet class. 3. Keep the detection at a fast speed. According to the characteristics of the algorithm, PatchCore use the intermediate patch characteristics of local aggregation to classify the image as abnormal once the local area in the image appears. The use of intermediate network features allows PatchCore to reduce the bias of ImageNet class in high-resolution images, and feature aggregation in local neighborhoods ensures that sufficient spatial context information is retained. In order to store enough spatial context information, a large database is needed to enable PatchCore to make use of the saved label information during testing. However, PatchCore introduces greedy coreset subsampling[16] as a key method, the Patch memory library is formed to reduce the redundancy of extraction and significantly reduce the storage memory and detection time, thus making PatchCore very attractive to practical industrial use cases. PatchCore overview can be seen in Fig. 2.

A key idea of PatchCore algorithm is Memory Bank, which adopts the concept of Memory Bank to greatly improve the detection speed and detection accuracy.

For all normal samples $t_i \in T$(T represents the geometry of all positive samples). Memory Bank of PatchCore is defined as follows:

$$MB = \bigcup_{t_i \in T} P_{s,p}\left(\Phi_j\left(t_i\right)\right) \tag{1}$$

$\Phi_j(*)$represents the local perception feature, $P_{s,p}(*)$ Denotes locally aware patch-feature collection.

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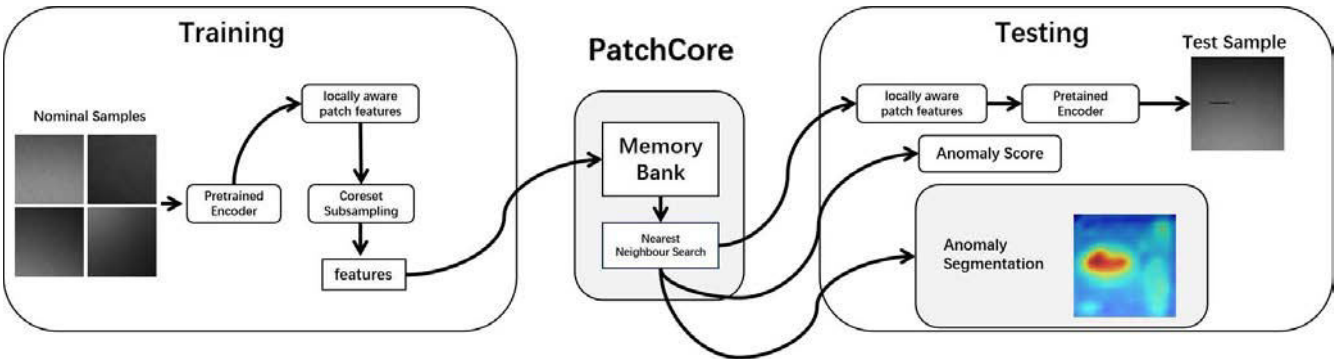

Fig. 2: PatchCore overview. During training, the label sample is decomposed into a memory library of locally perceptible patch-level features.To reduce redundancy and reasoning time, the memory library is downsampled by greedy core-set subsampling. During the test, if at least one facet is abnormal, the image is classified as abnormal and pixel level abnormal segmentation is generated by scoring each facet feature.

3.3 PatchCore GAN

The idea of PatchCore GAN algorithm combines the advantages of the above two algorithms to improve the performance of the overall algorithm and solve the difficulties existing in actual industrial scenes: 1. It is not possible to obtain large numbers of samples, labeled or unlabeled during high-speed production. 2. In industrial scenes, the images that can be collected are usually high-resolution images, and the differences between abnormal samples and normal samples are subtle. 3. At present, the detection in industrial scenes is often slow and not accurate enough, and manual re-judgment is needed. Therefore, considering the production efficiency, the detection speed and accuracy need to be improved. Defect GAN was used to generate a large number of verisimilitude abnormal samples for PatchCore testing to ensure the reliability of the algorithm.

The combination of PatchCore and Defect GAN algorithm is sufficient to solve the problem of product appearance anomaly detection in current industrial production. The specific algorithm construction of PatchCore is as follows: 1. PatchCore is used to process the normal samples to obtain the patch-level memory library. 2. In the testing, Defect GAN generates verisimilitude abnormal samples from only actually abnormal samples,PatchCore uses these verisimilitude abnormal samples and actually abnormal samples for testing to ensure the feasibility and reliability of the algorithm.Image-level anomaly detection performance is measured via the area under the receiver operator curve (AUROC[17, 18]) using produced anomaly scores.Based on previous work, We averaged AUROC over TKP-Surface datasets.

4 Experiments

4.1 Datasets

Most of our experiments were conducted on TKP-Surface datasets for the purpose of anomaly detection performance in the notebook appearance industry. TKP-Surface contains 236 images which include 147 normal samples of training data, a total of 89 samples of defects are collected,89 abnormal samples which contain the following four categories:1. white spotty paint. 2. black spotty stains. 3. white linear paint. 4. Black linear paint, and contain masks with anomalies. The experimental environments are carried out under NVIDIA GeForce RTX 2060 GPU 8GB, Python 3.8.7.

4.2 Anomaly detection based on TKP-Surface

We trained the model on 256×256 images, and the experimental hyperparameter values are as follows: batch_size 32, coreset sampling ratio 0.001, input size 256,output size 224, epoch=8. The average accuracy of image- level and pixel-level is 96.1% and 95.8% respectively. Some experimental results are showed in Fig. 3.

4.3 Contrast experiment

Finally, we conducted comparative experiments on the image resolution, including 224×224, 256×256, 360×360 and 448×448. It can be seen that there is a peak in the improvement of resolution when the resolution is 256×256, the image-level accuracy reaches the highest 96.69%.When the resolution is 360×360, the pixel-level accuracy reaches the highest 95.80%. The result see in Tables 1 and Fig 4.

Table 1: The image-level accuracy and pixel-level accuracy results of 224×224, 256×256, 360×360 and 448×448 resolutions

Resolution	Image level accuracy	Pixel level accuracy
224×224	95.94%	95.32%
256×256	96.69%	95.80%
360×360	87.08%	96.58%
448×448	82.14%	95.96%

5 conclusion

In view of the problem of appearance anomaly detection of laptop computer, starting from the surface anomaly detection of laptop keyboard, this paper collected and sorted out TKP-surface datasets, and proposed a PatchCore GAN anomaly detection method with high anomaly detection accuracy. In the experiment, wideresnet50 backbone is used to extract single feature and fusion feature respectively. After Defect GAN was used to augment abnormal data, the algorithm achieved the highest image-level accuracy of 96.69% and pixel-level accuracy of 96.07% in laptop appearance anomaly detection.

In the field of computer vision, the face detection system has been popularized in the commercial field, while the industrial detection system is still a difficult problem. Since

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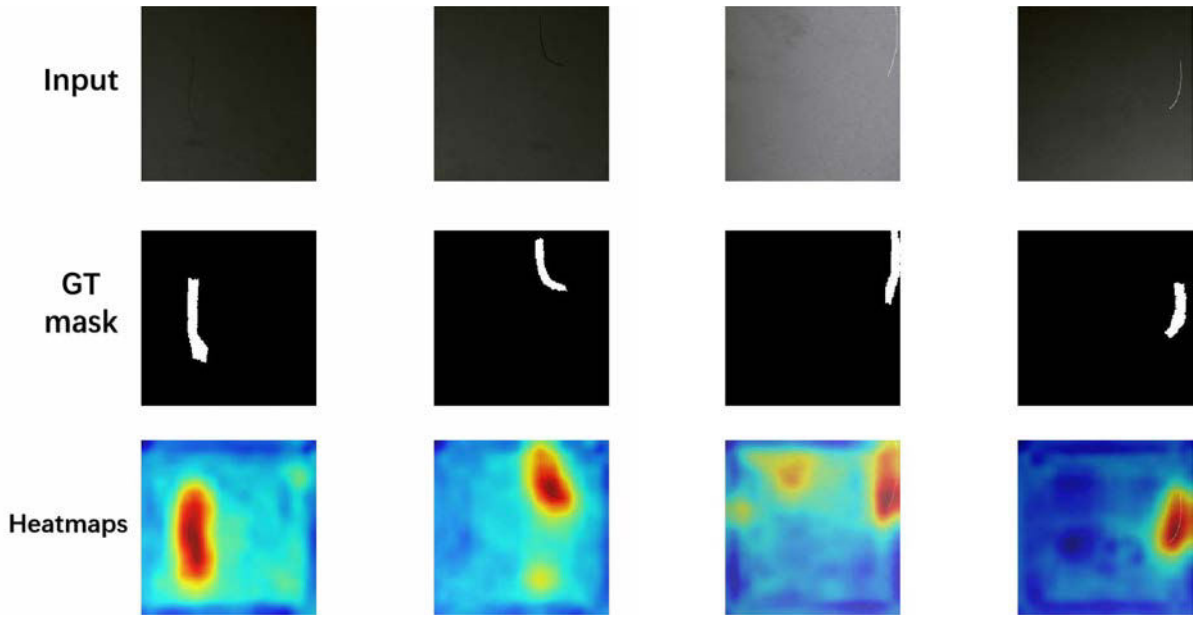

Fig. 3: Defect location of white scratches and black scratches in TKP-Surface data set. From top to bottom, those with input image, ground-truth localization mask in white, heatmaps using patch-level detector.

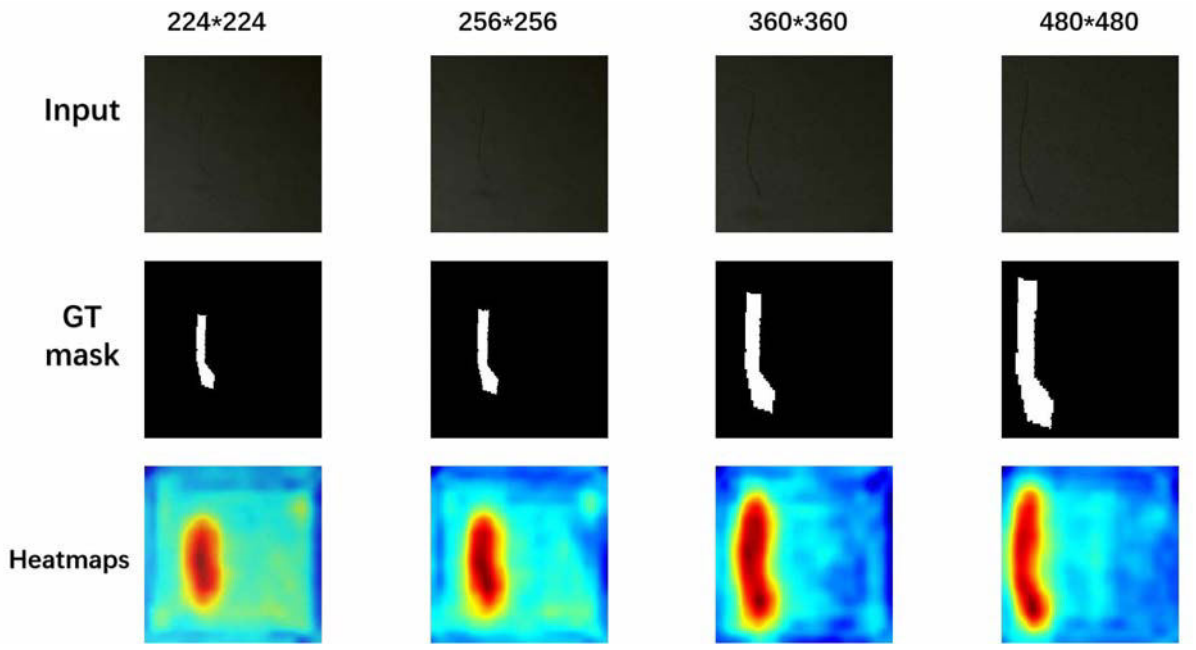

Fig. 4: Comparison of four resolutions: 224×224, 256×256, 360×360 and 448×448.

the rise of artificial intelligence until today, the reliability of this problem is still a challenge, and in industrial scenarios, the application of detection system has high requirements and strong restrictions on detection speed and accuracy. The algorithm in this paper has made good progress in these two aspects. Under the fast detection time, the detection accuracy has reached 96.69%, which is in line with the current industrial applicable threshold. However, to put the algorithm into practice and make it widely used in industry, more complex industrial anomaly detection standards are needed to better overcome the complexity of real-world scenarios.

References

[1] Roth K, Pemula L, Zepeda J, et al. Towards total recall in industrial anomaly detection[J]. arXiv preprint arXiv:2106.08265, 2021.

[2] Zhang G, Cui K, Hung T Y, et al. Defect-GAN: High-fidelity defect synthesis for automated defect inspection ,in Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, 2021: 2524-2534.

[3] Tao Xian, Hou Wei, Xu De. A Review of Surface anomaly detection Methods based on Deep Learning [J]. Acta Automatica Sinica, 2021,47(5):1017-1034.

[4] Ren S, He K, Girshick R, et al. Faster R-CNN: Towards real-time object detection with region proposal networks[J]. Advances in neural information processing systems, 2015, 28.

[5] Redmon J, Divvala S, Girshick R, et al. You only look once:

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Unified, real-time object detection[C], in Proceedings of the IEEE conference on computer vision and pattern recognition. 2016: 779-788.
[6] Redmon J, Farhadi A. YOLO9000: better, faster, stronger[C],in Proceedings of the IEEE conference on computer vision and pattern recognition. 2017: 7263-7271.
[7] Redmon J, Farhadi A. Yolov3: An incremental improvement[J]. arXiv preprint arXiv:1804.02767, 2018.
[8] Liu W, Anguelov D, Erhan D, et al. Ssd: Single shot multibox detector[C], in European conference on computer vision. Springer, Cham, 2016: 21-37.
[9] Golan I, El-Yaniv R. Deep anomaly detection using geometric transformations[J]. Advances in neural information processing systems, 2018, 31.
[10] Rudolph M, Wandt B, Rosenhahn B. Same same but differnet: Semi-supervised defect detection with normalizing flows[C], in Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, 2021: 1907-1916.4
[11] Sakurada M, Yairi T. Anomaly detection using autoencoders with nonlinear dimensionality reduction[C], in Proceedings of the MLSDA 2014 2nd workshop on machine learning for sensory data analysis, 2014: 4-11.
[12] Eskin E, Arnold A, Prerau M, et al. A geometric framework for unsupervised anomaly detection[M], in Applications of data mining in computer security. Springer, Boston, MA, 2002: 77-101.
[13] Schölkopf B, Williamson R C, Smola A, et al. Support vector method for novelty detection[J]. Advances in neural information processing systems. 1999, 12.
[14] Tax D M J, Duin R P W. Support vector data description[J]. Machine learning, 2004, 54(1): 45-66.
[15] Yi J, Yoon S. Patch svdd: Patch-level svdd for anomaly detection and segmentation[C],in Proceedings of the Asian Conference on Computer Vision. 2020.7
[16] Pankaj Agarwal, Sariel Har, Peled Kasturi, and R V aradarajan. Geometric approximation via coresets. Combinatorial and Computational Geometry, 52, 11 2004.7
[17] Akcay S, Atapour-Abarghouei A, Breckon T P. Ganomaly: Semi-supervised anomaly detection via adversarial training[C], in Asian conference on computer vision. Springer, Cham, 2018: 622-637.
[18] Cohen N, Hoshen Y. Sub-image anomaly detection with deep pyramid correspondences[J]. arXiv preprint arXiv: 2005.02357, 2020.

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