# Workshop Challenge Report

## Participant Information


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- Track I - Adapt & Detect

## Abstract


In this report, we briefly introduce our solution for the VAND Challenge 2024 Track 1. In the field of defect detection, the scarcity of defective data presents a significant and meaningful challenge in utilizing standard (non-defective) data for defect detection. We propose an offline data enhancement model based on the defect detection model PatchCore. The data enhancement approach is employed to address the diverse environmental requirements in the production process, thereby improving the model's robustness.


## Introduction

- **Background:** Many existing anomaly detection models are trained on normal images; however, in real-world scenarios, they often struggle with robustness issues due to data drift caused by external variations such as camera angles, lighting conditions, and noise. This challenge aims to enhance the model's robustness to external factors and improve its adaptability to real-world variability.
- **Challenge Description:** Participants will need to develop models trained on normal images. These models will then be validated and tested on a mixture of normal and abnormal images to assess their anomaly detection capabilities. The focus is on enabling these models to effectively identify deviations from normality, emphasizing the applicability of the developed techniques in the real world.

## Methodology

Model Design

- **Approach:** We use PatchCore [1] as our baseline and model architecture. Our main work is the offline data augmentation method based on PatchCore. We used a variety of data augmentation combinations: geometric transformation and noise, etc.
- **Architecture:** The PatchCore method consists of several parts: local patch features aggregated into a memory library, a coreset-reduction method to improve efficiency, and finally a detection and segmentation part, as shown in Figure 1.

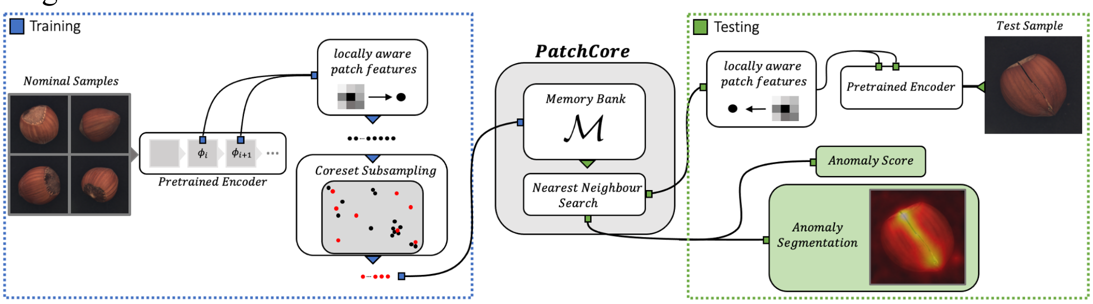


Figure 1 Overview of PatchCore.

- **Training:** We use 256*256 image resolution and combine it with data augmentation methods. The enhanced images retain the image size of 256*256. The training details are the same as PatchCore. Our experiments are completed on an RTX3090 with a video memory size of 24GB.

**Dataset & Evaluation**

- **Dataset Utilization:** We improve model performance by applying various data augmentation techniques, including geometric transformations (e.g., rotation, flipping, scaling, and translation), color transformations (e.g., brightness, contrast, saturation, and hue adjustments), adding noise (e.g., Gaussian noise and salt and pepper noise), clipping and cropping, and blurring and sharpening. We also perform data cleaning to ensure data quality. These methods significantly improve detection performance.
- **Evaluation Criteria:** As required by the competition, we use image-level and pixel-level F1-max scores to evaluate detection performance. This evaluation uses an adaptive anomaly score threshold that achieves the highest F1 metric. This method ensures a balanced consideration of precision and recall in anomaly detection performance.

# Results

- **Performance Metrics:** We achieved the following performance on our local augmented test data.

For: pill

| Test metric | DataLoader 0 |
|---|---|
| image_F1Max | 0.9562044143676758 |
| pixel_F1Max | 0.7226766347885132 |

For: bottle

| Test metric | DataLoader 0 |
|---|---|
| image_F1Max | 1.0 |
| pixel_F1Max | 0.729445219039917 |

For: carpet

| Test metric | DataLoader 0 |
|---|---|
| image_F1Max | 0.9886363744735718 |
| pixel_F1Max | 0.6071030497550964 |

For: zipper

| Test metric | DataLoader 0 |
|---|---|
| image_F1Max | 0.9915966391563416 |
| pixel_F1Max | 0.572742760181427 |

For: tile

| Test metric | DataLoader 0 |
|---|---|
| image_F1Max | 0.9879518151283264 |
| pixel_F1Max | 0.6206123232841492 |

For: leather

| Test metric | DataLoader 0 |
|---|---|
| image_F1Max | 1.0 |
| pixel_F1Max | 0.44185197353363037 |

For: capsule

| Test metric | DataLoader 0 |
| --- | --- |
| image_F1Max | 0.9769585728645325 |
| pixel_F1Max | 0.5225421786308289 |

For: hazelnut

| Test metric | DataLoader 0 |
| --- | --- |
| image_F1Max | 1.0 |
| pixel_F1Max | 0.6302516460418701 |

For: transistor

| Test metric | DataLoader 0 |
| --- | --- |
| image_F1Max | 0.9876543283462524 |
| pixel_F1Max | 0.7003181576728821 |

For: wood

| Test metric | DataLoader 0 |
| --- | --- |
| image_F1Max | 0.9743589162826538 |
| pixel_F1Max | 0.4760403633117676 |

For: metal_nut

| Test metric | DataLoader 0 |
| --- | --- |
| image_F1Max | 0.9892473220825195 |
| pixel_F1Max | 0.8389718532562256 |

For: screw

| Test metric | DataLoader 0 |
| --- | --- |
| image_F1Max | 0.9711934328079224 |
| pixel_F1Max | 0.3819410800933838 |

For: grid

| Test metric | DataLoader 0 |
| --- | --- |
| image_F1Max | 0.9734513759613037 |
| pixel_F1Max | 0.38105863332748413 |

For: toothbrush

| Test metric | DataLoader 0 |
| --- | --- |
| image_F1Max | 0.9830508232116699 |
| pixel_F1Max | 0.605315625667572 |

For: cable

| Test metric | DataLoader 0 |
| --- | --- |
| image_F1Max | 0.9729729890823364 |
| pixel_F1Max | 0.6424261331558228 |

# Discussion

- **Challenges & Solutions:** Initially, we employ data enhancement methods to improve model robustness. To this end, we utilize the iaa image enhancement library. However, the iaa enhancement library offers a variety of data enhancement methods. Considering the application scenarios of industrial defect detection, we initially selected ten relevant data enhancement methods to adapt to these scenarios. Additionally, during the experimental process, excessive data caused PatchCore to experience video memory overflow when generating embeddings. We conducted various experiments and tried multiple data enhancement combinations to prevent video memory overflow.
- **Model Robustness & Adaptability:** After introducing data augmentation, our PatchCore achieves an improvement on the source dataset.
- **Future Work:** Improve PatchCore to reduce memory requirements and make model training more convenient

# Conclusion

In this competition, we mainly improved and expanded the dataset, and improved the detection capabilities of the industrial inspection model through a combination of multiple data enhancement methods. By solving various problems in the experimental process, we improved the detection capabilities of PatchCore on the source MVTecAD dataset.

# References

[1] Roth K, Pemula L, Zepeda J, et al. Towards total recall in industrial anomaly detection[C]//Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2022: 14318-14328.