SA-PatchCore: Anomaly Detection in Dataset With Co-Occurrence Relationships Using Self-Attention

Kengo Ishida, Yuki Takena, Yoshiki Nota, Rinpei Mochizuki,
Itaru Matsumura, and Gosuke Ohashi
Department of Electrical and Electronic Engineering,
Shizuoka University

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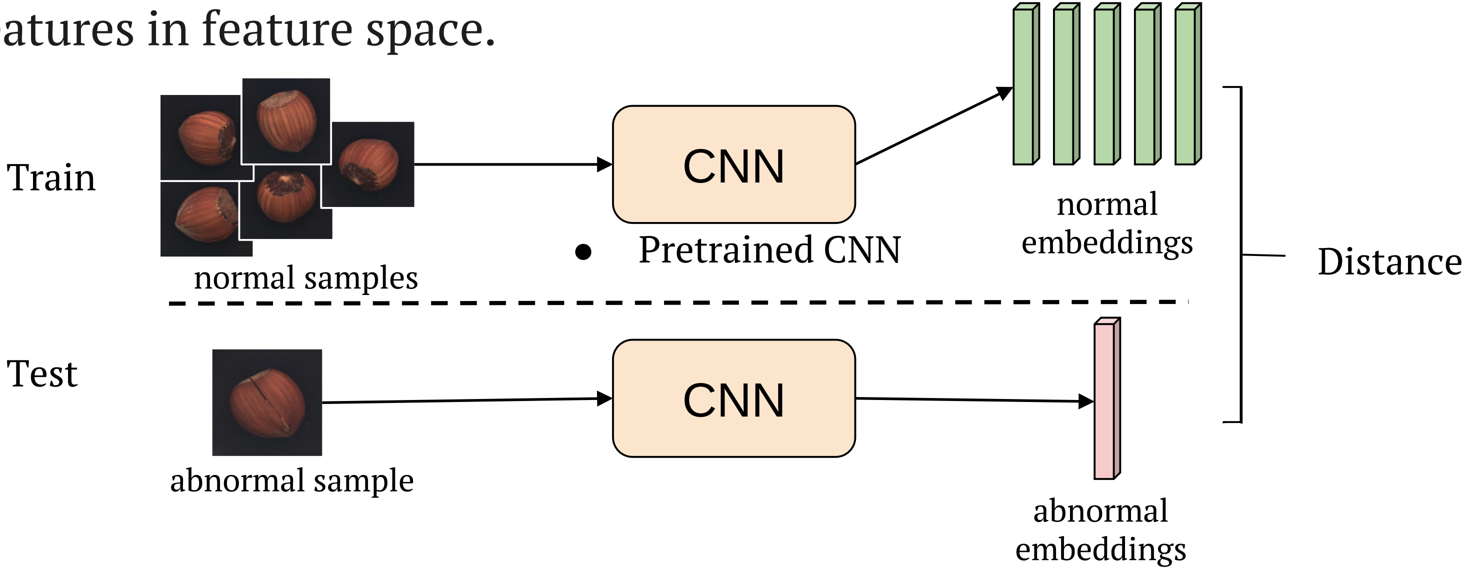
1. Introduction

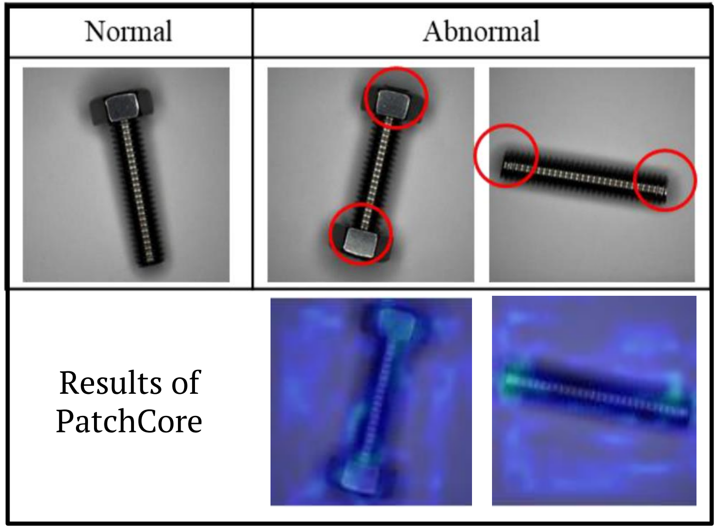
- In industry anomaly detection task, the state-of-the-art **PatchCore [2]** use CNNs **pre-trained** using ImageNet to extract features of images and distinguish normal and anomalies based on the distribution of these features in feature space.



[2] Karsten Roth, et al. "Towards total recall in industrial anomaly detection." CVPR. 2022.

1. Introduction

- However, the existing detection models for MVTecAD, such as PatchCore cannot detect anomalies in the relationships between distant pixels, which are anomalies in **co-occurrence relationships**.



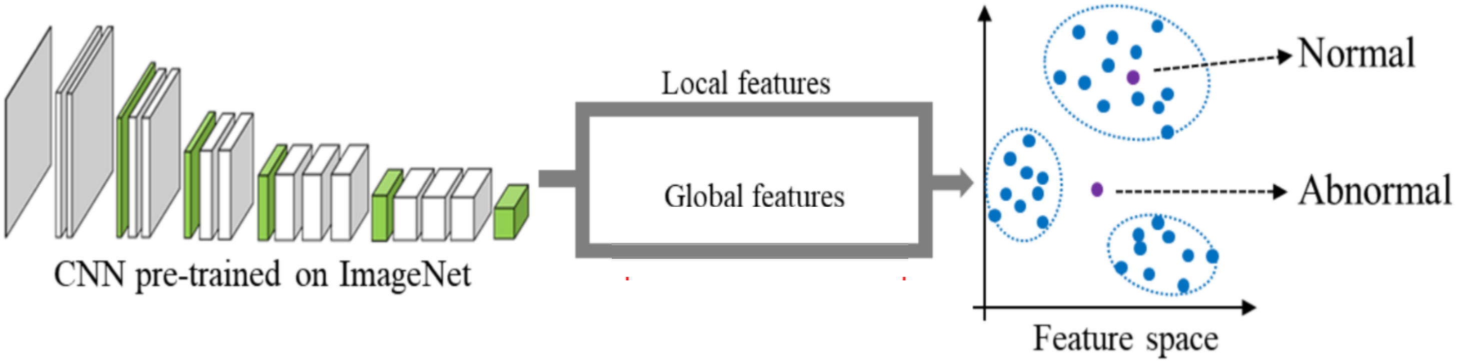
[1] P. Bergmann, M. Fauser, D. Sattlegger, and C. Steger, ‘‘MVTec AD—A comprehensive real-world dataset for unsupervised anomaly detection,’’ CVPR. 2019

1. Introduction

- Contribution
  1. Propose SA-PatchCore incorporating self-attention into PatchCore to detect anomalies in local regions and co-occurrence relationships.
  2. Constructed Co-occurrence Anomaly Detection Screw Dataset (**CAD-SD**) for anomaly detection, including anomalies in the local regions and **co-occurrence relationships**.
  3. SA-PatchCore achieves almost the same abnormality detection accuracy as PatchCore for MVTecAD consisting of only the abnormality in the local area while achieving a high abnormality detection performance even in the CAD-SD.

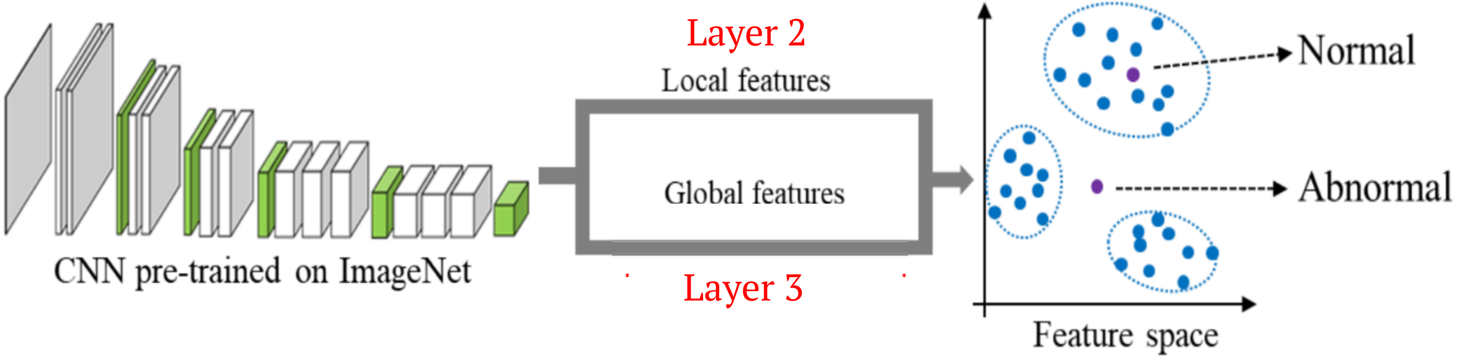
2.1.1 Feature extraction

- The **deeper** the hierarchy, the more the **global** feature map captured, which is specialized for learning tasks.
- SA-PatchCore uses feature maps of the **middle layers** because the **local** features for the unknown data are crucial in the industrial anomaly detection task.



2.1.1 Feature extraction

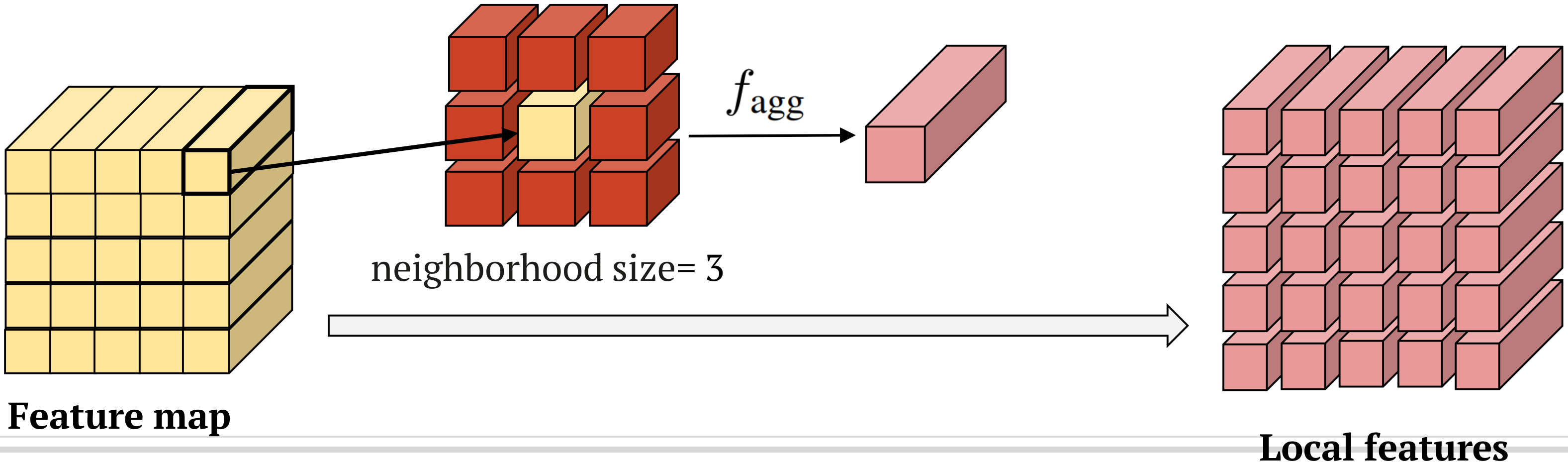
- SA-PatchCore uses the WideResNet50 [36] pre-trained on ImageNet to extract Layers 2 and 3 features of input images.
- Layer 2 has a more **local** feature representation.
- Layer 3 has a more **global** feature representation.



[36] Sergey Zagoruyko and Nikos Komodakis. Wide Residual Networks. In Richard C. Wilson, Edwin R. Hancock and William A. P. Smith, editors, Proceedings of the British Machine Vision Conference (BMVC), pages 87.1-87.12. BMVA Press, September 2016.

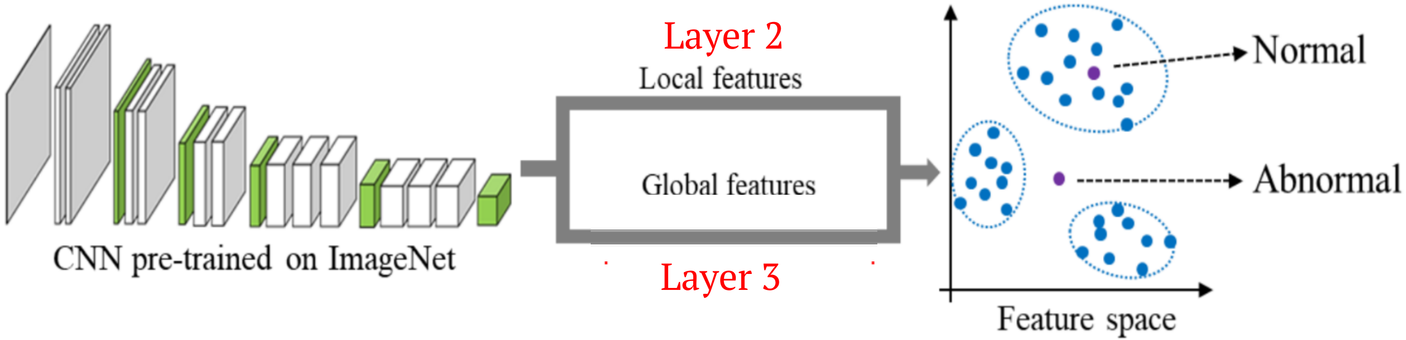
2.1.1 Feature extraction

- $\phi_2(h, w, c)$: the feature map of Layer 2 with size h*w*c.
- Local features:
  - Applied the algorithm of PatchCore to extract features.
  - The patch-level features that aggregate local features in the neighborhood are expressed as $P_2 = f_{agg}(\phi_2)$



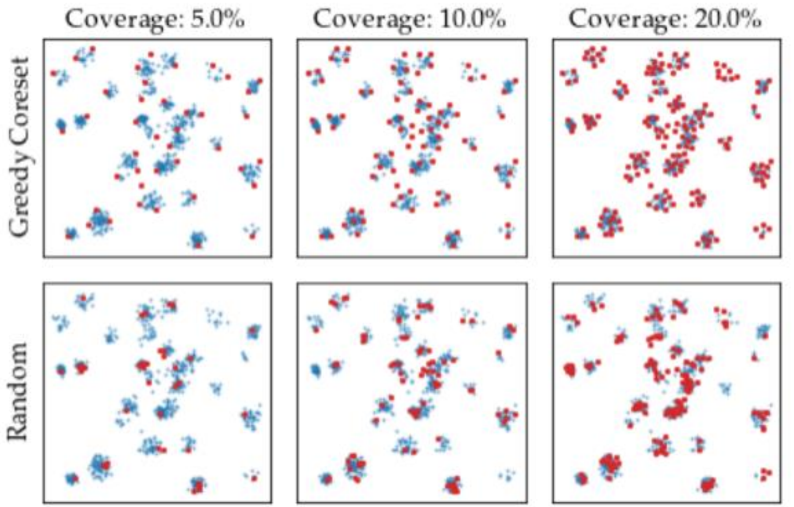
2.1.1 Feature extraction

- $\phi_3(h, w, c)$: the feature map of Layer 3 with size h*w*c.
- Global features:
  - Use self-attention module to detect anomalies in co-occurrence relationships.
  - The features considering relationships obtained from Layer 3 are expressed as $P_3 = f_{SA}(\phi_3)$
- P_2 (local) and P_3(global) are concatenated and stored in a memory bank M .



2.1.2 Coreset subsampling

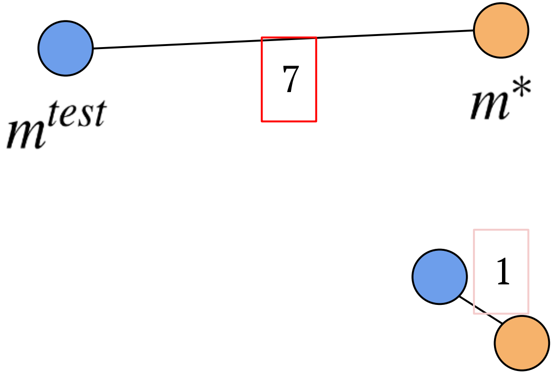
- <u>**Problem:**</u> For expanding the training set, M becomes exceedingly large.
- Solution: Follow PatchCore, use **greedy coreset subsampling**
    - Coreset selection : Find a subset $M_c \subset M$ such that problem solutions over M can be most closely and especially more quickly approximated by those computed over M_c .

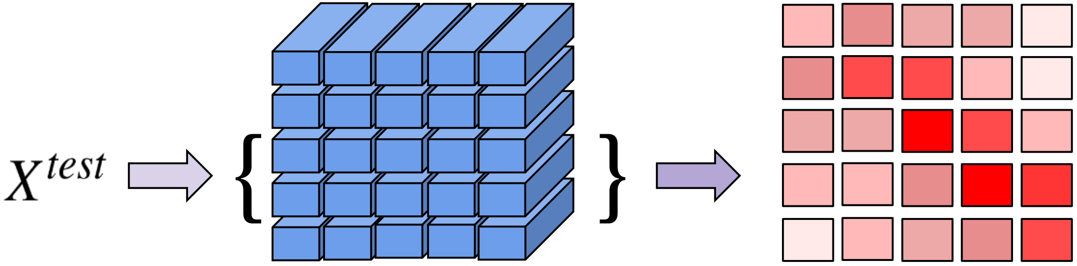


2.1.3 Anomaly detection

- SA-PatchCore selects m^* which is the nearest neighbor of the patch-level features m^{test} of test data, among the patch-level features $m \in M$
- It estimates the patch-level anomaly score s of the test image X^{test} from the distance between patch-level features m^{test} and m^*.

$$m^* = argmin_{m \in M} \left\| m^{test} - m \right\|_2$$



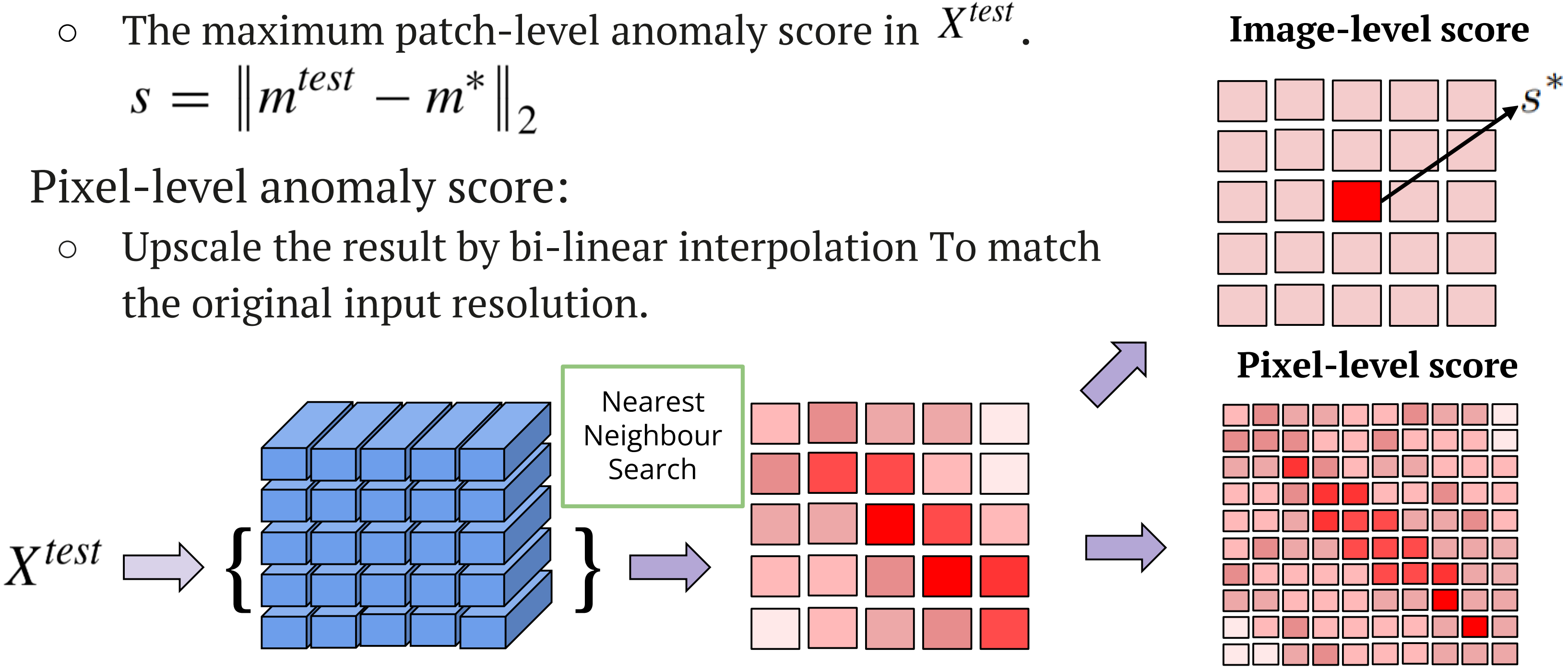


2.1.3 Anomaly detection

- Image-level anomaly score:
  - The maximum patch-level anomaly score in X^{test}.

$$s = \left\| m^{test} - m^{*} \right\|_2$$

- Pixel-level anomaly score:
  - Upscale the result by bi-linear interpolation To match the original input resolution.



original input resolution

2.2 Self-attention Module

- SA-PatchCore introduces a self-attention module to detect co-occurrence anomalies.
  - Step1. Apply max pooling of kernel sizes 3, strides 1, and padding 1 on feature map of Layer 3 $\phi_3(h, w, c)$ to emphasize the nearby features.
  - Step2. X is replicated in triplicate to compute the self-attention as a query, key, and value. X_{SA} is expressed as follows:

$$X_{SA} = \text{softmax}\left(\frac{XX^T}{\sqrt{d_X}}\right)X$$

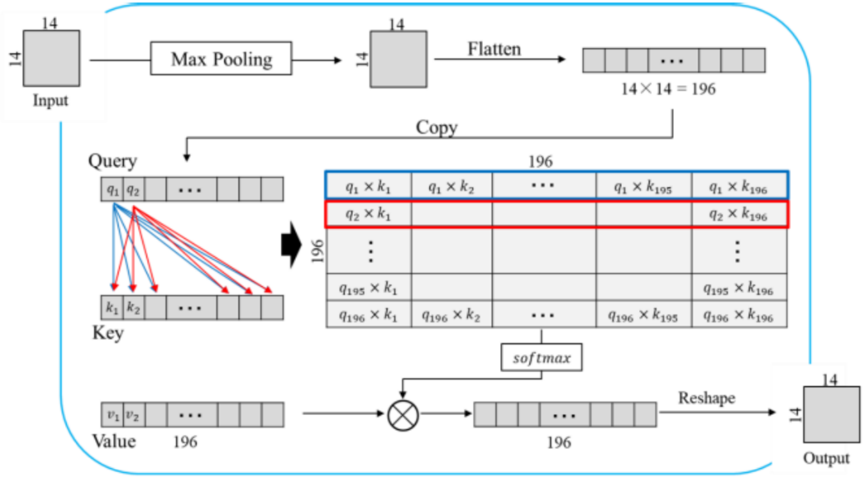
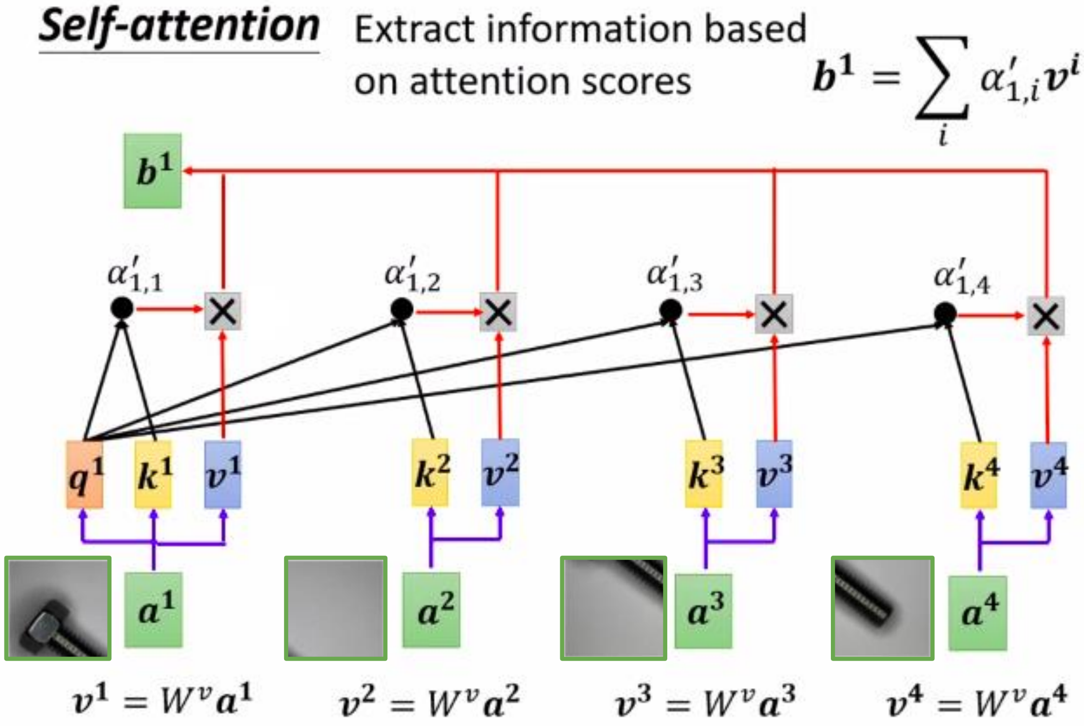


FIGURE 4. Overview of the self-attention module.

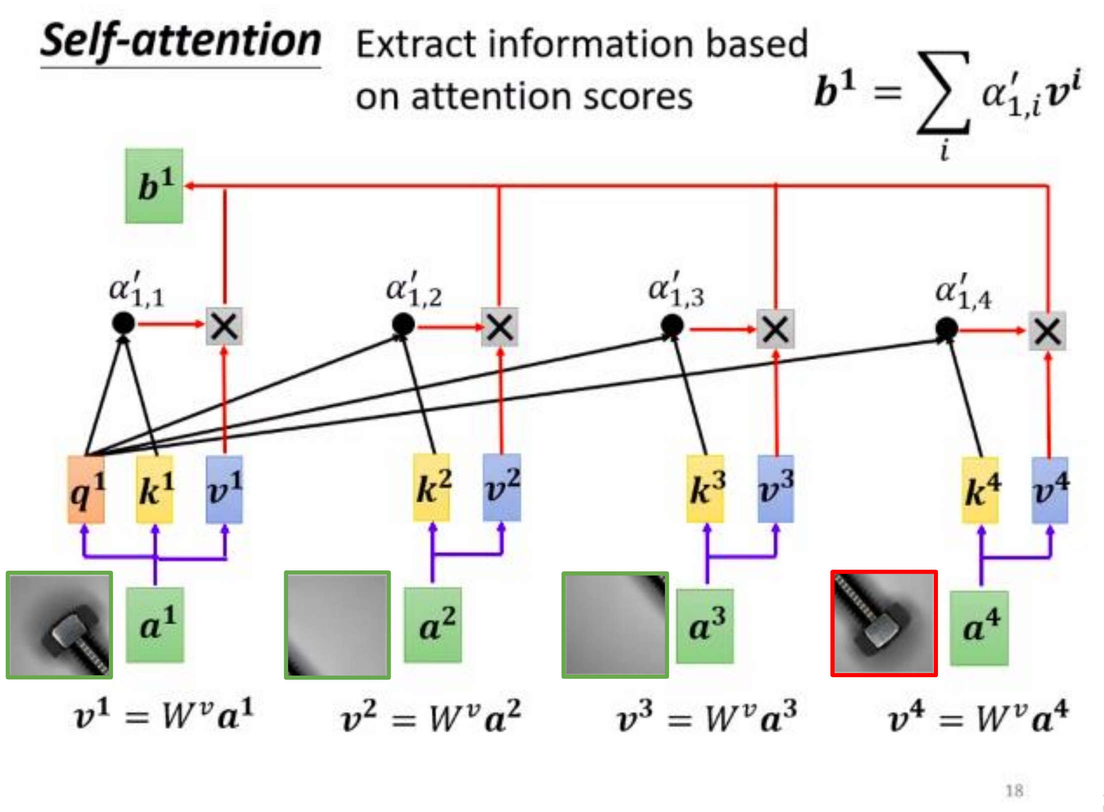
2.2 Self-attention Module

Normal image



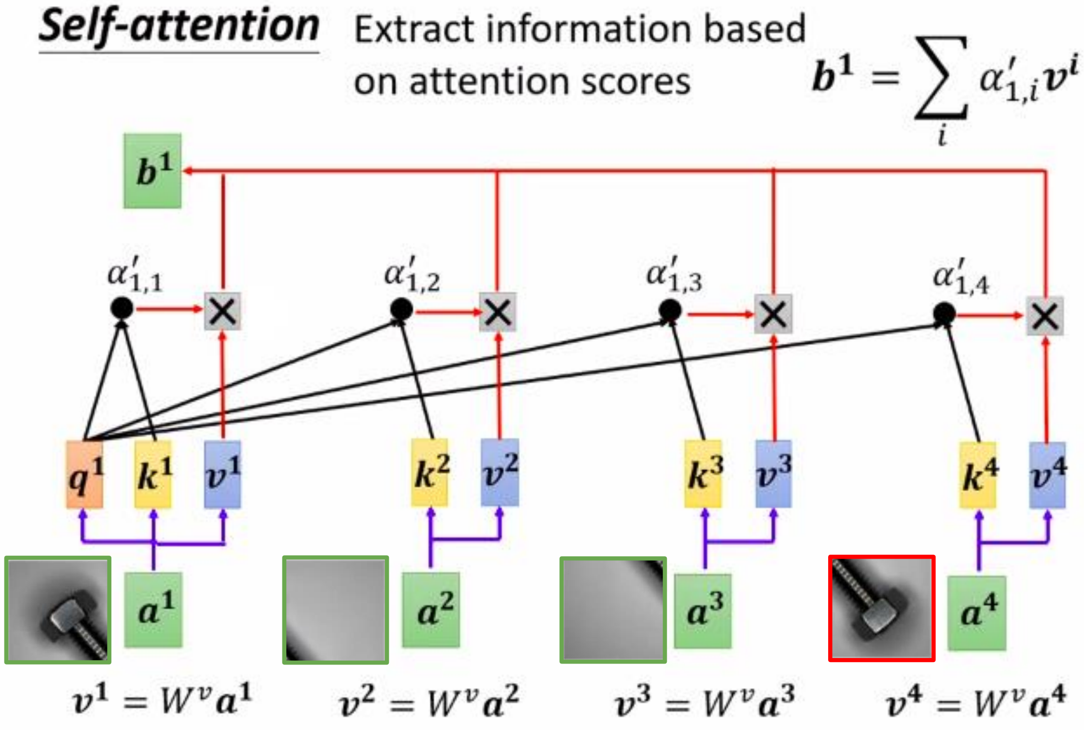
2.2 Self-attention Module

Abnormal image

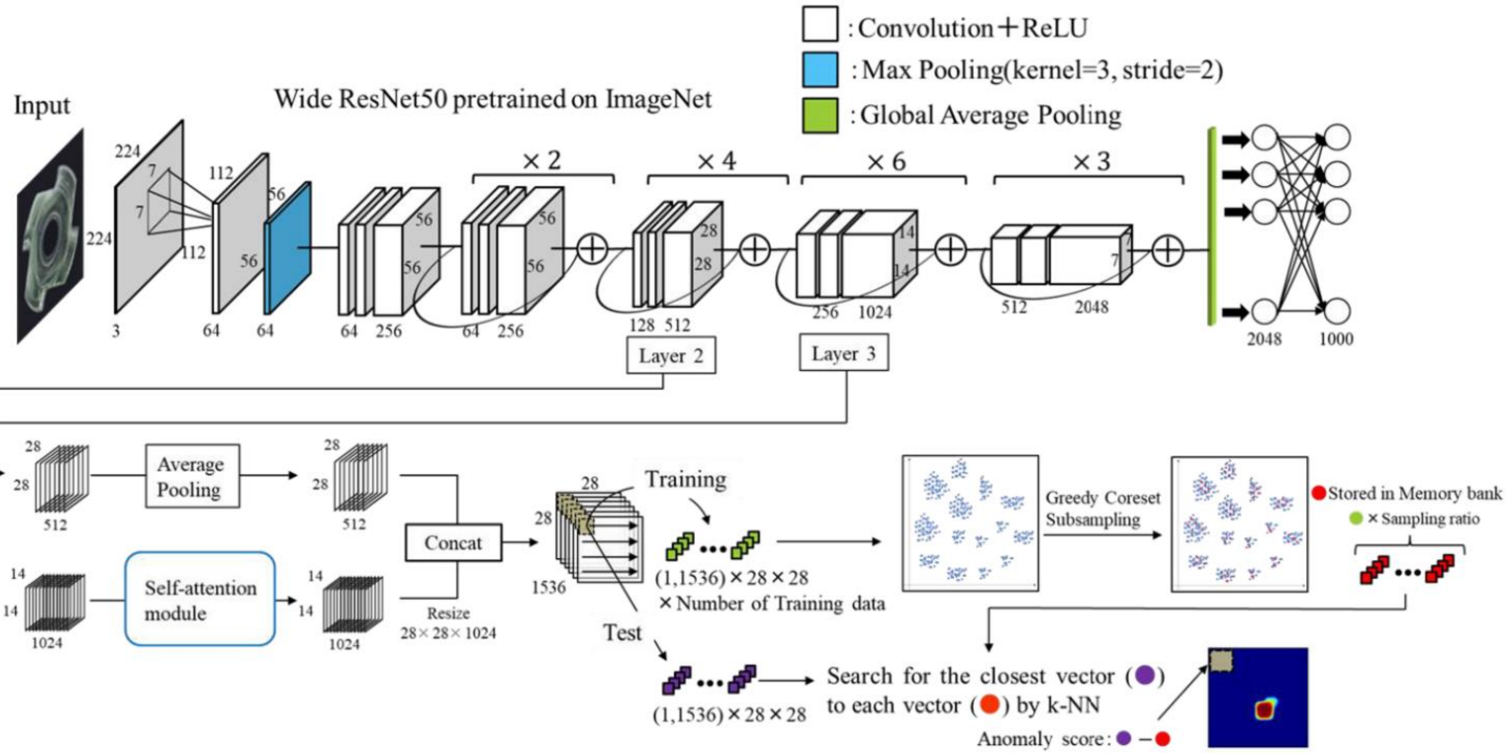


2.2 Self-attention Module

Abnormal image



2.3 Structure of the SA-PatchCore

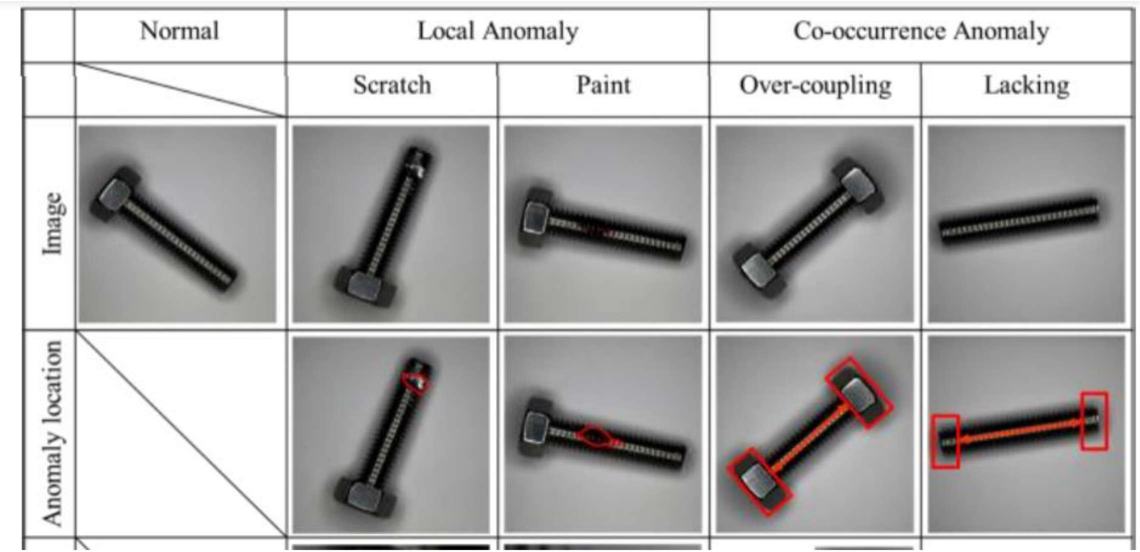


3.1 Co-occurrence anomaly detection screw dataset (CAD-SD)

- **MVTecAD [1]** is a typical dataset for evaluating the anomaly detection method; however, it contains **only** the abnormality of a **local area**.

3.1 Co-occurrence anomaly detection screw dataset (CAD-SD)

- Currently, there is no dataset for anomalies of **co-occurrence relationships**.
- We created the **CAD-SD** to verify the effectiveness of SAPatchCore, which includes the anomaly of the local area and that of the co-occurrence relationship.



3.2 Results on CAD-SD

TABLE 2. **Accuracy of anomaly detection on CAD-SD (AUROC).**

Method	PatchSVDD [20]	PaDiM [35]	PatchCore [2]	CS-Flow [31]	SA-PatchCore
AUROC	73.1	65.8	83.5	92.0	**97.6**

TABLE 3. **Accuracy for each anomaly category on Co-occurrence Anomaly Screw Dataset (AUROC). Red and blue stand for the first and second places respectively.**

Anomaly category		PatchSVDD [20]	PaDiM [35]	PatchCore [2]	CS-Flow [31]	SA-PatchCore
Local anomaly	Scratch	74.8	79.9	**99.6**	89.8	**98.0**
	Paint	74.1	89.2	**99.8**	93.0	**99.7**
	Average	74.5	84.6	**99.7**	91.4	**98.9**
Co-occurrence anomaly	Over-coupling	72.1	68.8	89.6	**90.6**	**99.7**
	Lacking	72.1	24.2	46.5	**94.9**	**92.9**
	Average	72.1	46.5	68.1	**92.8**	**96.3**

3.2 Results on CAD-SD

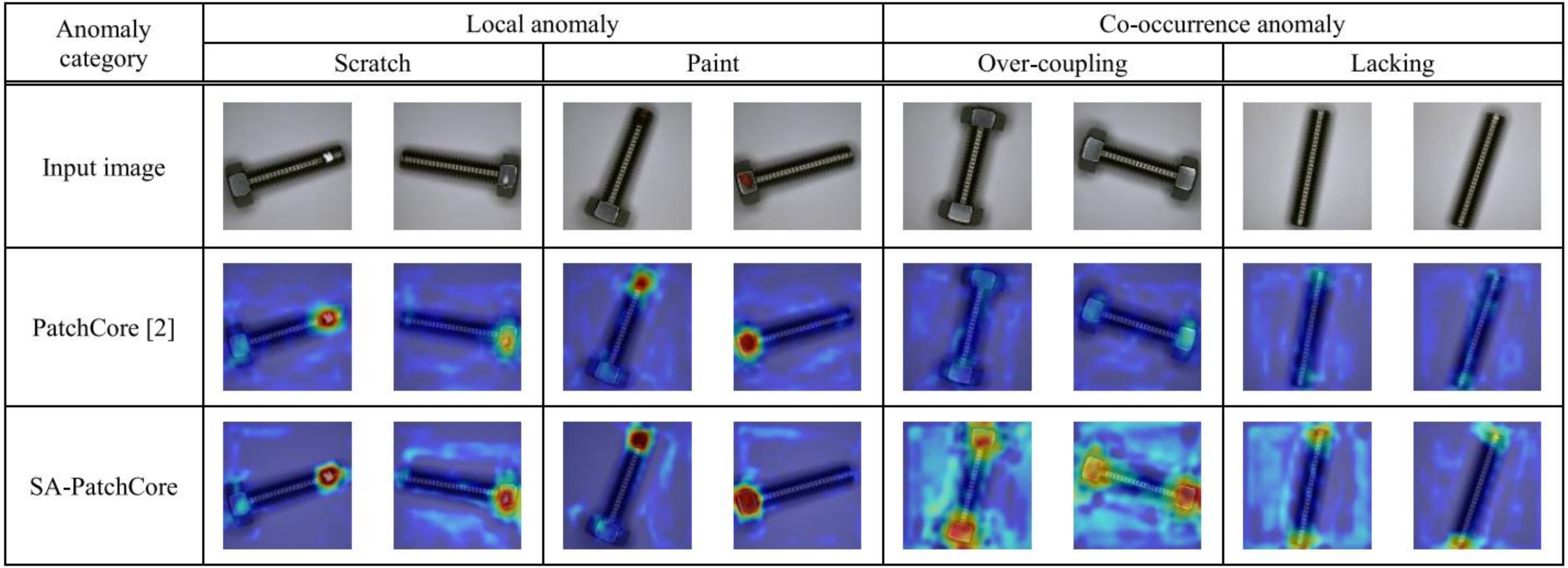


FIGURE 6. Localization of anomaly areas on CAD-SD.

3.3 Results on MVTecAD, BTAD, AITEX

TABLE 5. Accuracy of anomaly detection on MVTecAD [1] (AUROC).

Method	PatchSVDD [20]	PaDiM [35]	PatchCore [2]	CS-Flow [31]	SA-PatchCore
AUROC	91.3	95.5	98.6	98.7	97.1

TABLE 6. Accuracy of anomaly detection on BTAD [50] and AITEX [51] (AUROC).

Dataset	PatchCore [2]	SA-PatchCore
BTAD [50]	92.3	93.7
AITEX [51]	85.8	89.0

3.4 Optimization Of The Model Structure

- **1) Hierarchy of feature extraction**
  - SA-PatchCore:
    - Layer 2 → average pooling for local feature
    - Layer 3 → self-attention module for feature extraction of co-occurrence relationship
  - SA-PatchCore (Layer 2 + Layer 3)
    - Combine Layers 2 and 3 are features
    - input into the average pooling and the self-attention module.

TABLE 7. Anomaly detection performance by hierarchy of feature extraction.

SA-PatchCore	SA-PatchCore (Layer 2 + Layer 3)
97.6	96.7

3.4 Optimization Of The Model Structure

- **2) Pooling in the self-attention module**
  - max pooling
  - average pooling
  - no pooling

TABLE 8. Anomaly detection performance using pooling in the self-attention module.

Max Pooling	Average Pooling	Without Pooling
97.6	92.6	90.9

Thanks For Listening !