N-pad : Neighboring Pixel-based Industrial Anomaly Detection

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Motivation

- Identifying defects in the images of industrial products is an important task to enhance quality control and reduce maintenance costs.
- In recent studies, industrial anomaly detection models have been developed to learn nominal representations using pre-trained networks .
- We present ***N-pad***, a novel anomaly detection and segmentation method that utilizes the neighboring pixels of the target pixel for model training in a one-class learning setting.

Dataset

- MVTEC-AD: ten object and five texture classes with 3,629 nominal-only images for training and 1,725 nominal and anomalous images for evaluation

Contribution

- **Theory:** prevents pixel-wise misalignment by learning nominal distributions based on similarity between target and neighboring pixels and channel selection

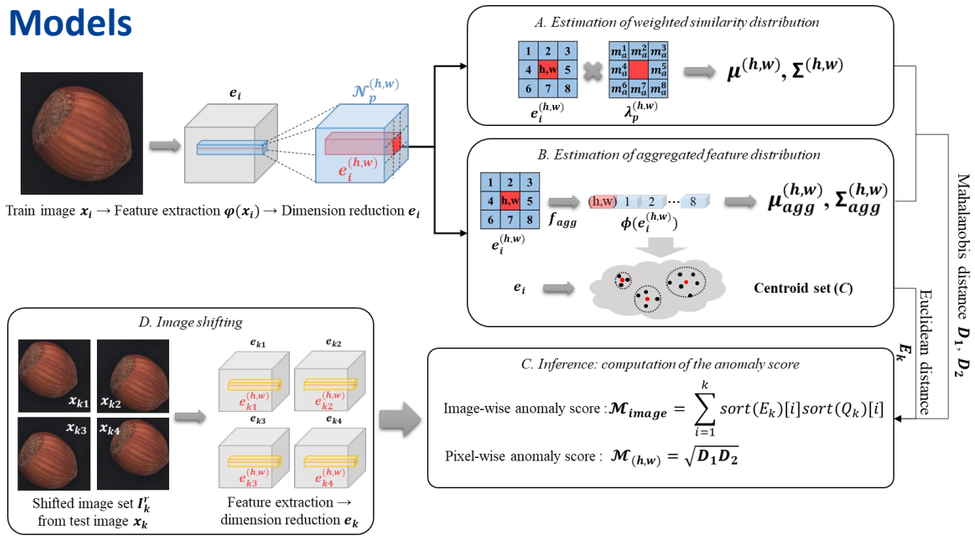
	Ours w/o channel selection	Ours w/o our weighted neighbor-sampling	Ours Patch-level
Pixel wise AUC	98.11	98.42	98.45

- **Method:** proposes novel method of identifying anomaly by incorporating two nominal distributions estimated on patch and pixel levels to compute anomaly scores

	Pixel-level Distribution	Patch-level Distribution	Ours
Pixel wise AUC	98.38	98.45	98.75
Error	1.62	1.55	1.25

- **Experiments**: achieved state-of-the-art (SOTA) performance in multiple industrial anomaly detection datasets composed of different classes and in few-shot anomaly detection

Models



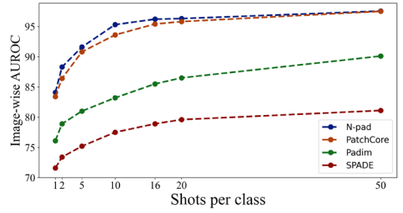
- Two nominal distributions are estimated by applying the similarity between the target pixel and its neighboring pixels as weights (A) and by aggregating features of its neighborhood (B)
- K-means centroids of the aggregated features are identified as a set of representative nominal features for image-wise detection (B)
- Image shifting is employed for subjecting multiple images to anomaly score calculation based on the Mahalanobis distance (D)

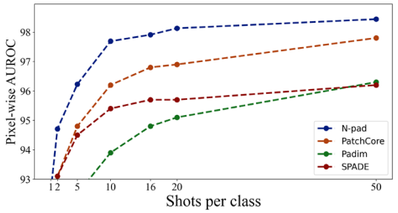
State-of-the-art Performance

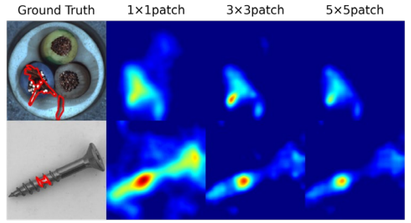
- N-pad outperforms benchmark models on MVTec-AD dataset

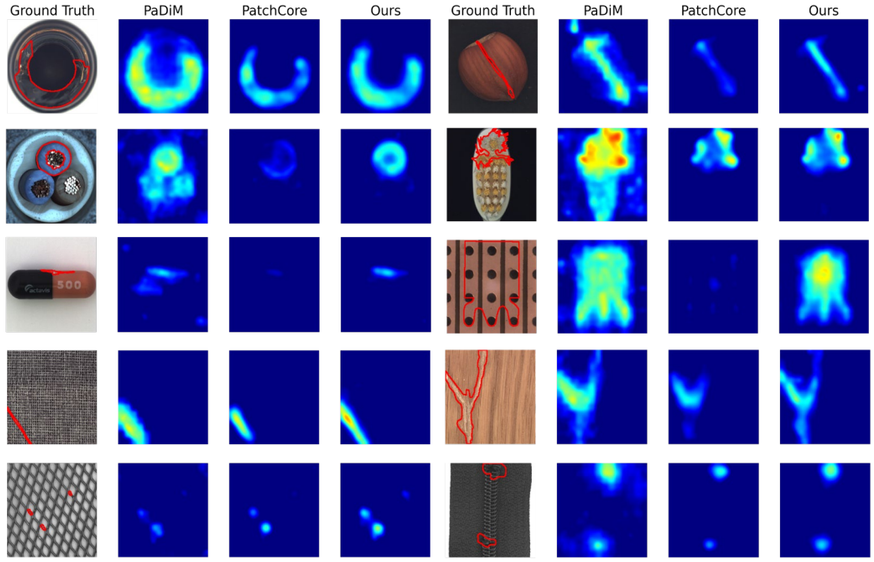
Method	Normalizing Flow Based			Pre-trained Feature Based			
Model	FastFlow	PEFM	CFLOW-AD	SPADE	PaDiM	Patchcore	N-pad
Image-wise AUC	97.52	98.13	97.24	-	-	99.0	**99.37**
Pixel-wise AUC	98.03	97.61	97.57	96.0	97.5	98.1	**98.75**
PRO-score	93.0	92.4	91.7	91.7	92.1	93.5	**95.1**

Experiments







- N-pad outperforms the existing SOTA model using only 8% of the total dataset.
- Estimating nominal distributions with an appropriate patch level facilitates the accurate detection of anomaly regions.

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