

Quantifying Statistical Significance of Deep Nearest Neighbor Anomaly Detection via Selective Inference

Mizuki Niihori, Shuichi Nishino, Teruyuki Katsuoka, Tomohiro Shiraishi,
Kouichi Taji, Ichiro Takeuchi

Nagoya University

RIKEN

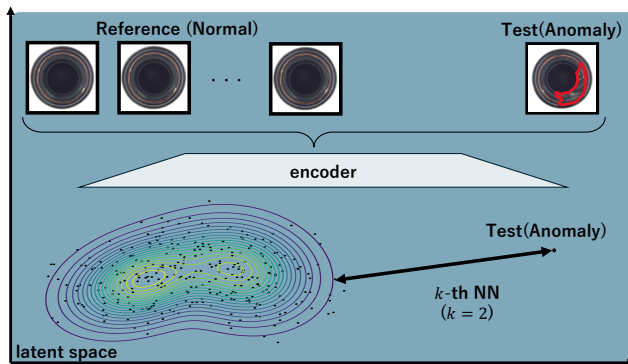
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Introduction

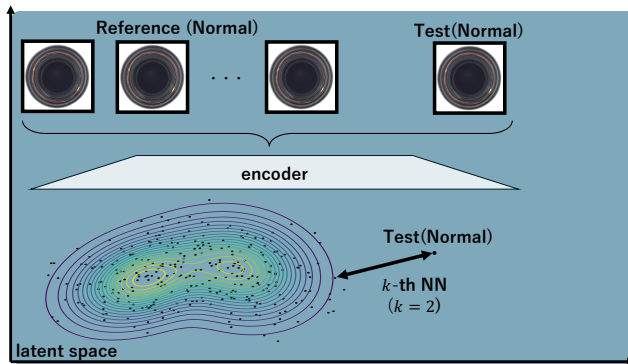
- **K NN-based AD(k NNAD)** is one of the simplest yet effective methods, which is widely used
 - ▶ Performs k NN-based anomaly detection in latent space
 - ▶ Effective for high-dimensional and unstructured data such as images



- However, **the reliability** of detected anomalies is not quantified
- We propose a method to quantify the statistical significance of **k NNAD** results

Statistical Significance in AD

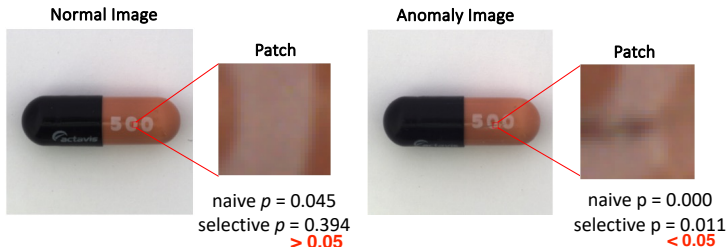
- When a **normal** image is inputted, k NNAD may **incorrectly** predict normal images as anomaly (**false positive**)



- We quantify the statistical significance of k NNAD as a valid p -value, enabling control of the false positive rate (FPR)

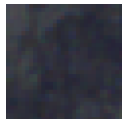
Issue and Our Approach

- We quantify the statistical significance of AD by p -values
- Naive p -values are often underestimated, failing to control the FPR
- This is due to selection bias caused by using the same data for both **detection and testing**
- We apply **Selective Inference** to rigorously correct this selection bias, enabling proper control of the FPR



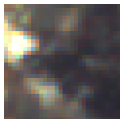
MVTec Image Examples

Normal Image



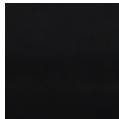
naive $p = 0.014$
selective $p = 0.221$

Anomaly Image



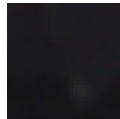
naive $p = 0.002$
selective $p = 0.013$

Normal Image



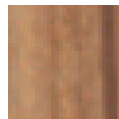
naive $p = 0.045$
selective $p = 0.394$

Anomaly Image



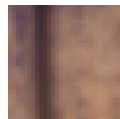
naive $p = 0.013$
selective $p = 0.041$

Normal Image



naive $p = 0.033$
selective $p = 0.171$

Anomaly Image



naive $p = 0.001$
selective $p = 0.019$