Industrial Anomaly Detection with Localization: A Comparative Study under Clean and Shifted Domains

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Abstract

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1. Introduction

Visual anomaly detection in manufacturing aims to automatically identify defective products from images acquired under controlled conditions. This task is commonly framed as *one-class classification*, where a model learns only from normal samples and must identify deviations at test time [1]. Since anomalous examples are often scarce or unavailable during training, supervised approaches are impractical, motivating unsupervised methods that learn what constitutes normality from defect-free data.

A practical anomaly detection system must address two complementary goals: (i) *image-level detection*, determining whether an image is normal or anomalous, and (ii) *pixel-level localization*, identifying which regions contain defects. State-of-the-art methods such as **PatchCore** [6] and **PaDiM** [2] achieve strong results on standard benchmarks like MVTec AD [1] by modelling patch-level feature distributions from pre-trained networks. However, their robustness to distribution shift and sensitivity to threshold calibration remain less explored.

In this work, we present a comparative study of PatchCore and PaDiM on MVTec AD under both clean and synthetically shifted conditions. Our contributions are:

1. **Baseline comparison.** We evaluate PatchCore (custom implementation) and PaDiM (anomalib-based) on three MVTec AD categories (Hazelnut, Carpet, Zipper), reporting both image-level and pixel-level metrics.

2. **Synthetic domain shift.** We construct *MVTec-Shift* by applying photometric and geometric transformations inspired by MVTec AD 2 [4], and measure the performance drop when models trained on clean data are tested on shifted data. Measuring also the hyperparameter influence on the performance obtained.

3. **Threshold adaptation strategies.** We compare three regimes: (a) no adaptation, (b) threshold-only adaptation on shifted validation data, and (c) full adaptation with model re-training. This ablation isolates the benefit of threshold recalibration from feature-level adaptation.

4. **Model-unified setting.** Following recent literature [7, 3, 5], we train a single model on pooled normal data from all categories while using per-class thresholds at inference. This setting enables investigation of the *identical shortcut* problem [7], where normal samples from one class may be misclassified as anomalies when evaluated against another class's threshold due to overlapping feature distributions.

The paper is organized as follows: Section 2 reviews related work; Section 3 describes the methods; Section 4 details the experimental setup; Section 5 presents results and analysis; Section 6 concludes with limitations and future directions.

2. Related Work

3. Methodology

4. Experimental Setup

5. Results and Discussion

6. Conclusion

References

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