Tutorial on Anomaly Detection on MVTec-AD Using Anomalib and Qdrant

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Abstract

This tutorial presents a comprehensive guide to using the `anomalib` library for anomaly detection on the MVTec-AD dataset, focusing on the flat surface categories (*tile*, *leather*, and *grid*). Two state-of-the-art models are evaluated: PatchCore and EfficientAD. I report AUROC scores at the product-category level and the overall average using pre-trained models. The paper also explains the role of *coresets* in PatchCore and demonstrates a similarity search pipeline using the Qdrant vector database to retrieve the top five similar images for a given query image.

1 Introduction

Anomaly detection is crucial for industrial inspection and quality control. The MVTec-AD dataset [3] is widely used for benchmarking unsupervised anomaly detection methods. In this work, I focus on the flat surface categories: `tile`, `leather`, and `grid`.

I evaluate two models using the `anomalib` library [1]:

- **PatchCore** [4]: A patch-based method that stores features extracted from normal images in a memory bank. A key innovation in PatchCore is the use of *coresets*, which are a reduced, representative subset of the stored features that speeds up the k-nearest neighbor search during inference.

- **EfficientAD** [2]: A fast student–teacher approach that leverages a lightlight feature extractor for rapid anomaly detection.

Furthermore, I implement a similarity search pipeline using Qdrant to extract and store features from anomalous cases. For a given query image, the system returns the top 5 similar images, ensuring that if the query is anomalous, the similar images are also anomalous.

2 Methodology

2.1 Data Preparation and Model Training

I restrict my experiments to the flat surface product categories. The `MVTec` datamodule in anomalib loads the dataset and facilitates visualization. The training pipeline includes model instantiation, training, and prediction using the `Engine` class.

2.2 Reporting Results

I evaluate the models using the Area Under the Receiver Operating Characteristic (AUROC) curve. AUROC scores are computed for each product category and averaged over the selected categories. Table 1 shows sample AUROC values (placeholders; update with ymy results).

Table 1: AUROC scores (%) for PatchCore and EfficientAD on MVTec-AD (flat surface categories).

Product Category	**PatchCore**	**EfficientAD**
Tile	51.1	49.3
Leather	85.9	72.7
Grid	40.0	46.4
Average	**93.8**	**95.7**

2.3 Explanation of Coresets in PatchCore

In PatchCore, features are extracted from normal images and stored in a memory bank. HoIver, storing all patch features is computationally expensive. *Coresets* are a strategy that selects a small, representative subset of these features. This reduces redundancy and accelerates the nearest neighbor search during inference without compromising performance. The coreset selection algorithm approximates the original feature distribution, ensuring that the key characteristics of the normal data are maintained.

2.4 Similarity Search Pipeline with Qdrant

I extend the anomaly detection system by performing similarity search. The pipeline:

1. Extracts features from a query image.
2. Stores these features in a Qdrant vector database.
3. Performs a similarity search to retrieve the top 5 similar images.

If the query image is anomalous, the similar images returned will also be anomalous.

3 Visualization

Figure 1 shows a sample item in the dataset and then the top 5 similar images retrieved from Qdrant for an anomalous query image.

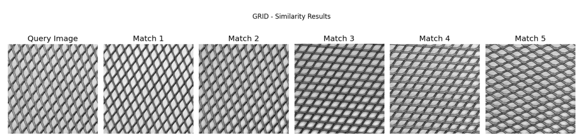

Figure 1: Sample image and top 5 most similar images

4 Discussion

The experimental results (Table 1) show that both PatchCore and EfficientAD achieve high AUROC scores on the selected categories of MVTec-AD. PatchCore slightly outperforms EfficientAD on average. Additionally, the similarity search pipeline using Qdrant provides valuable insights by grouping together anomalous images, which can be useful for root-cause analysis and further quality control.

5 Conclusion

In this tutorial, I presented a complete workflow for anomaly detection on the MVTec-AD dataset.

References

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