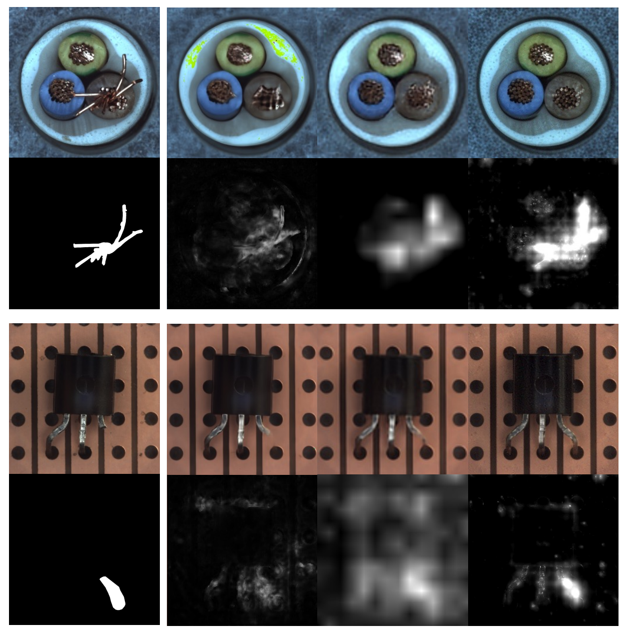
Removing Anomalies as Noises for Industrial Defect Localization

Fanbin Lu[1] Xufeng Yao[1] Chi-Wing Fu[1] Jiaya Jia [1,2]
[1]The Chinese University of Hong Kong [2]SmartMore
{fblu21, xfyao, cwfu, leojia}@cse.cuhk.edu.hk

Abstract

Unsupervised anomaly detection aims to train models with only anomaly-free images to detect and localize unseen anomalies. Previous reconstruction-based methods have been limited by inaccurate reconstruction results. This work presents a denoising model to detect and localize the anomalies with a generative diffusion model. In particular, we introduce random noise to overwhelm the anomalous pixels and obtain pixel-wise precise anomaly scores from the intermediate denoising process. We find that the KL divergence of the diffusion model serves as a better anomaly score compared with the traditional RGB space score. Furthermore, we reconstruct the features from a pre-trained deep feature extractor as our feature level score to improve localization performance. Moreover, we propose a gradient denoising process to smoothly transform an anomalous image into a normal one. Our denoising model outperforms the state-of-the-art reconstruction-based anomaly detection methods for precise anomaly localization and high-quality normal image reconstruction on the MVTec-AD benchmark.



(a) Input & G.T. (b) DRAEM (c) UniAD (d) Ours

Figure 1: Comparing reconstructed normal images (rows 1 & 3) and anomaly detection results (rows 2 & 4) produced by different methods. Our method can produce high-quality reconstructions without obvious artifacts (DRAEM [40]) and blurring (UniAD [36]) and locate anomalies more precisely.

1. Introduction

Anomaly detection is a critical computer vision task that has great application values in industry and medicine. Despite its importance, collecting and annotating anomalous data can be prohibitively expensive. Unsupervised anomaly detection recently garnered significant attention. Different from few-shot segmentation [12, 33, 32], it aims to learn normal data distribution without access to anomalous samples and ground-truth annotations in training. At inference, anomalies are detected and localized based on their deviation from the learned distribution of normal data.

Classical reconstruction-based unsupervised anomaly detection methods [1, 2, 5, 20] assume the autoencoder model trained with only normal data fail to reconstruct anomalous regions. However, this approach is not without limitations, as some anomalies can still be reconstructed, leading to the inferior performance of these classical methods. DRAEM [40] proposes to generate pseudo anomalies to train an autoencoder to reconstruct the anomalous data to be anomaly-free. However, it performs poorly when the real anomalies differ significantly from the pseudo ones. Denoising autoencoders [17] are used for medical anomaly detection. The anomaly score is measured naively by the difference between the input and reconstructed images in pixel space. The reconstruction from noisy images is challenging and introduces great noise to the results, making it unsuitable for complex industrial anomaly detection and localization. Recently, methods [18, 22, 36, 37] propose transformer structures for the reconstruction model to prevent the autoencoder from collapsing into an identity func-