



Figure 7: Visualization of the intermediate steps of denoising gradient process on MVTecAD. The 1st and 2nd columns are the ground truth of anomalies and the image to be reconstructed. The last column is the reconstructed results from the anomalous image. The intermediate results of the denoising gradient process are shown in the middle columns. We show that our reconstruction process can generate high-quality anomaly-free images and keep high-frequency details of normal pixels.

image, followed by the intermediate results from our gradient denoising process. The anomalous pixels are gradually removed by the gradients and diffusion steps. We show that the proposed reconstruction process can generate normal images with strong correspondence to the original anomalous image, while keeping most visual appearances of normal regions unchanged.

We compare the reconstruction results with previous anomaly detection methods, DRAEM [40] and UniAD [36]. As Fig. 4 shows, the DRAEM generates artifacts and fails to remove the anomalous pixels. The appearance of normal regions is changed and blurred by UniAD since it reconstructs the results with a VAE decoder. Our gradient noising process greatly improves the reconstruction results for both anomalous and normal pixels.

## 5. Conclusions

In this work, we propose a denoising diffusion model to boost the performance of reconstruction-based anomaly localization. Our model combines pixel-level and feature-

level reconstruction errors as the anomaly score. We use the KL divergence from the diffusion model to produce boundary-aware results for better localization. Moreover, our model can reconstruct anomalous images to a high-quality normal image by denoising the gradients from a pre-trained deep feature extractor, surpassing the previous reconstruction results by a large margin. We also demonstrate that our reconstruction-based denoising diffusion model is robust to various anomaly types and can be extended as a unified anomaly detector for all categories.

**Discussions** Our approach addresses the anomaly localization problem from a denoising perspective. The MVTecAD dataset contains many noises in the background regions, which are easily detected as anomalous by our denoising model, causing a 3% performance drop on the image-level AUROC metric.

**Acknowledgement** The work was supported in part by the Research Grants Council under the Areas of Excellence scheme grant AoE/E-601/22-R and Shenzhen Science and Technology Program KQTD20210811090149095.