tinguishable semantic information. Second, the adoption of transformer prevents reconstructing anomalies well such that anomalies could be detected easily once the reconstruction fails. Our method brings a large generalization gap between normal samples and anomalies. Moreover, we propose novel loss functions to extend our approach from normal-sample-only case to anomaly-available case with both image-level labeled and pixel-level labeled anomalies, further improving the performance. Our approach achieves the state-of-the-art performance on anomaly detection benchmarks including MVTec-AD and CIFAR-10.

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