表4：MVTec-AD [4]の異常検出におけるピクセルレベルAUROCメトリクスに基づく、(a) 注意と補助クエリ埋め込み、(b) ピクセル再構築 vs. 特徴量、(c) バックボーン、(d) 多スケール特徴量に関するアブレーション研究。

(a) Attention & auxiliary query embedding

	CNN	w/o Attn	w/o Query	Attn+Query
Pixel AUROC	94.4	94.8	94.2	**97.2**

(b) Reconstructing pixels *vs.* features

	Pixels	Features
Pixel AUROC	91.3	**97.2**

(c) Backbone

	Res-18	Res-34	Efficient-B0	Efficient-B4
Pixel AUROC	95.3	95.7	96.4	**97.2**

(d) Multi-scale features

	Last-layer	Multi-scale
Pixel AUROC	96.0	**97.2**

Reconstructed target. In Tab. 4b, reconstructing features surpasses pixel values substantially, indicating that the features extracted by pre-trained backbone are more discriminative for normal and abnormal than pixels. Backbone and multi-scale features. (1) As shown in Tab. 4c, all four different backbones achieve very competitive performance, which reflects that our method can cooperate with various types of backbones. (2) In Tab. 4d, multi-scale features, containing various receptive fields, are sensitive to various anomalies, thus yielding more remarkable performance than the last layer.

4.5 特徴差分ベクトルの可視化

式(2)の特徴差分ベクトルd(:, u)を可視化することで、当社のアプローチをより明確に解釈できるようにします。具体的には、MVTecAD [4]から特徴差分ベクトルを600個（正常：異常＝1:1の比率で）ランダムにサンプリングします。次に、t-SNEを用いて高次元ベクトルを2次元空間に可視化します（図5参照）。まず、正常サンプルと異常サンプルはそれぞれ主に青と赤で色付けされており、異常検出能力が良好であることを示しています。

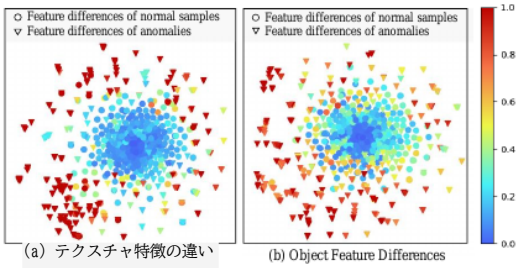


図5：t-SNEによる特徴量差分ベクトルの可視化。円と三角形はそれぞれ正常サンプルと異常サンプルを表します。色マップは異常の可能性を予測しています。当社の手法は、正常サンプルと異常サンプルの間で大きな一般化ギャップをもたらします。

次に、正常サンプルはよくクラスタリングされており、正常サンプルと異常サンプルの間には広いギャップが存在します。これらの観察結果は、私たちのアプローチが正常サンプルと異常サンプルの間で大きな一般化ギャップをもたらすことを示しています。

5 Conclusion

本論文では、事前学習された特徴を再構築するためにトランスフォーマーを利用する異常検出トランスフォーマーを提案する。まず、事前学習された特徴には、不連続な特徴が含まれている。

Table 4: **Ablation study** on (a) attention & auxiliary query embedding, (b) reconstructing pixels *vs.* features, (c) backbone, and (d) multi-scale features under pixel-level AUROC metric on anomaly localization of MVTec-AD [4].

(a) Attention & auxiliary query embedding

	CNN	w/o Attn	w/o Query	Attn+Query
Pixel AUROC	94.4	94.8	94.2	**97.2**

(b) Reconstructing pixels *vs.* features

	Pixels	Features
Pixel AUROC	91.3	**97.2**

(c) Backbone

	Res-18	Res-34	Efficient-B0	Efficient-B4
Pixel AUROC	95.3	95.7	96.4	**97.2**

(d) Multi-scale features

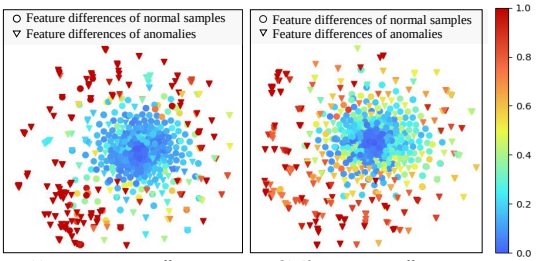
	Last-layer	Multi-scale
Pixel AUROC	96.0	**97.2**

Reconstructed target. In Tab. 4b, reconstructing features surpasses pixel values substantially, indicating that the features extracted by pre-trained backbone are more distinguishable for normal samples and anomalies than raw pixels.

Backbone and multi-scale features. (1) As shown in Tab. 4c, four different backbones all achieve quite good performance, reflecting that our method could cooperate with different types of backbones. (2) In Tab. 4d, multi-scale features obviously outperform last-layer feature, because multi-scale features contain different levels of receptive fields thus are sensitive to different anomalies.

4.5 Visualization of Feature Difference Vectors

We visualize the feature difference vectors $\boldsymbol{d}(:, u)$ in Eq. (2) to better interpret our approach. Specifically, we randomly sample 600 feature difference vectors (normal : anomaly = 1:1) from MVTec-AD [4]. Then t-SNE is utilized to visualize the high dimensional vectors in a 2D space, as shown in Fig. 5. Firstly, normal samples and anomalies are mostly colored with blue and red, respectively, indicating good anomaly detection ability. Secondly, normal samples are well clustered, and there is a wide gap between the normal samples and anomalies. These observations indicate that our approach brings a large generalization gap between normal samples and anomalies.



(a) Texture Feature Differences (b) Object Feature Differences

Fig. 5: **visualization of feature difference vectors** by t-SNE. Circles and triangles respectively represent normal samples and anomalies. The color map indicates the predicted anomaly possibility. Our method brings large generalization gap between normal samples and anomalies.

5 Conclusion

In this paper, we propose anomaly detection transformer to utilize a transformer to reconstruct pre-trained features. First, the pre-trained features contain dis-