

SK-RD4AD : Skip-Connected Reverse Distillation For Robust One-Class Anomaly Detection

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Abstract

Anomaly detection plays a critical role in industrial, health-care, and security applications by enabling early identification of defects. While Reverse Knowledge Distillation (KD) has shown promise for one-class anomaly detection, existing models often suffer from deep feature loss due to excessive compression in the Student network, limiting their ability to detect fine-grained anomalies.

We propose **SK-RD4AD**, a novel framework that introduces **non-corresponding skip connections** from intermediate Teacher layers to deeper Student layers. This cross-hierarchical feature transfer preserves multi-scale representations, enhancing both semantic alignment and anomaly localization.

Extensive experiments on **MVTec-AD**, **VisA**, and **VAD** demonstrate that SK-RD4AD consistently outperforms prior methods. Specifically, it improves AUROC by +3.5% on VAD, boosts AUPRO by +21% on VisA, and achieves +1% gains on MVTec-AD. The model shows particular robustness on challenging cases such as the Transistor category in MVTec-AD and generalizes well across diverse domains.

Our results establish SK-RD4AD as a robust and scalable solution for real-world one-class anomaly detection. Code is available at: <https://github.com/pej0918/SK-RD4AD>.

1. Introduction

Anomaly detection plays a vital role in domains like industrial inspection and healthcare, where identifying irregular patterns is essential for safety and reliability [4].

Reconstruction-based methods [15] detect anomalies by learning normal patterns and flagging large reconstruction errors. However, they often struggle to retain fine details, especially in texture-rich or structurally complex settings.

Recently, Reverse Knowledge Distillation (KD) [7] has shown promise. In this framework, a Student model learns to mimic a high-capacity Teacher. Since the Student is compressed, it inherently fails to reproduce anomalies, which can then be detected via feature discrepancies [3]. Nonetheless, the Student’s limited capacity often leads to deep feature loss, weakening its ability to localize subtle or multi-scale anomalies.

We address this limitation with **SK-RD4AD**, a novel architecture that introduces **non-corresponding skip connections** [9] from intermediate Teacher layers to deeper Student layers. This design transfers multi-scale features across hierarchical levels, improving both semantic and textural retention, and alleviating bottlenecks caused by compression. Unlike traditional U-Net-style symmetric skips, our approach bypasses shallow, low-capacity Student layers, enabling stronger semantic guidance and more accurate anomaly localization.

Our key contributions are:

- **Non-Corresponding Skip Connections:** We propose a new feature transfer strategy that bridges Teacher and Student across hierarchical levels, significantly improving feature retention in reverse KD.
- **State-of-the-Art Performance:** SK-RD4AD outperforms prior methods including RD4AD, achieving up to +3.5% AUROC gain on MVTec-AD [2], VisA [18], and VAD [1].
- **Robustness Across Categories:** Our model mitigates common failure cases (e.g., Transistor class in MVTec)

and generalizes well to diverse anomaly types in real-world settings.

2. Related Work

2.1. Reconstruction-Based Anomaly Detection

Reconstruction-based methods, such as Autoencoders[11] and GANs[8], are widely used for anomaly detection. These models learn to reconstruct normal data patterns, and reconstruction errors indicate anomalies. However, they often fail to retain fine details, especially when normal data exhibits complex textures and structures.

2.2. Knowledge Distillation for Anomaly Detection

Reverse Knowledge Distillation[7] leverages a Teacher-Student paradigm[10], where the Teacher network captures detailed representations of normal data, and the Student attempts to replicate these features. Anomalies are detected by the discrepancy between the Teacher and Student outputs. Despite its effectiveness, existing methods like RD4AD[7] struggle with information loss due to the bottleneck structure in the Student network.

2.3. Skip Connections in Neural Networks

Skip connections, as used in architectures like ResNet[9] and UNet[13], have been effective in mitigating feature degradation in deep networks by allowing gradient flow and preserving spatial details. Inspired by this, we incorporate non-corresponding skip connections in the SK-RD4AD framework to address the information loss issue in reverse distillation[7] for anomaly detection.

3. Methodology

The proposed Skip-Connected Reverse Distillation for Anomaly Detection (SK-RD4AD) builds upon the Teacher-Student framework [7], where the Teacher extracts hierarchical features from normal data, and the Student reconstructs them. The key innovation is the introduction of *non-corresponding skip connections* [9], which connect intermediate Teacher layers to deeper Student layers. This design ensures multi-scale feature preservation, which is crucial for detecting fine-grained anomalies while mitigating deep feature loss, as illustrated in Fig. 1.

3.1. Motivation

Conventional anomaly detection models with strict layer-wise correspondence often fail to capture anomalies that selectively affect certain feature scales. For instance, surface-level scratches may distort low-level textures without altering high-level semantics, while structural anomalies may disrupt global representations but leave shallow features intact.

To address these limitations, SK-RD4AD introduces *non-corresponding skip connections* that allow deeper Student layers to access intermediate Teacher features. This cross-hierarchical transfer facilitates multi-scale feature retention and enhances the model’s ability to detect both localized and global anomalies.

This design intentionally deviates from symmetric architectures such as U-Net [13], which assume that encoder and decoder layers of equal depth possess comparable capacity. In reverse knowledge distillation, however, the Student is intentionally underparameterized, making such alignment suboptimal. Our asymmetric skip strategy compensates for this by injecting semantically rich features into deeper decoder layers, improving reconstruction fidelity and anomaly localization.

3.2. Model Overview

Unlike conventional architectures that enforce strict layer-wise correspondence between encoder and decoder, SK-RD4AD strategically connects non-matching layers. This selective feature transfer ensures that both high-level semantics and fine-grained texture details are retained, mitigating information bottlenecks commonly observed in knowledge distillation frameworks [10].

3.2.1. Why Non-Corresponding Skip Connections?

Traditional skip connections used in encoder-decoder structures (e.g., U-Net [13]) connect features between layers of matching depth to retain spatial information. However, in reverse knowledge distillation settings, where the Student is intentionally underparameterized, this symmetric alignment can be suboptimal. Shallow Student layers often lack the representational capacity to effectively reconstruct semantically rich features from their Teacher counterparts.

To address this, we propose a non-corresponding skip strategy that bypasses low-capacity early Student layers by injecting mid- or high-level Teacher features (e.g., E_2, E_3) into deeper Student layers (e.g., D_1, D_2). This allows richer semantics to guide reconstruction where it is most effective, compensating for compression-induced degradation.

The selected skip paths were determined based on both empirical results (see Section 5) and architectural reasoning. For instance, E_1 features are assumed to be sufficiently recoverable by the Student itself, and the $E_3 \rightarrow D_3$ connection provided marginal improvement due to representational mismatch.

3.2.2. Teacher Network (Encoder)

The Teacher network serves as a high-capacity feature extractor, capturing hierarchical representations of normal images. It consists of three convolutional blocks that progressively encode spatial and semantic features at multiple scales:

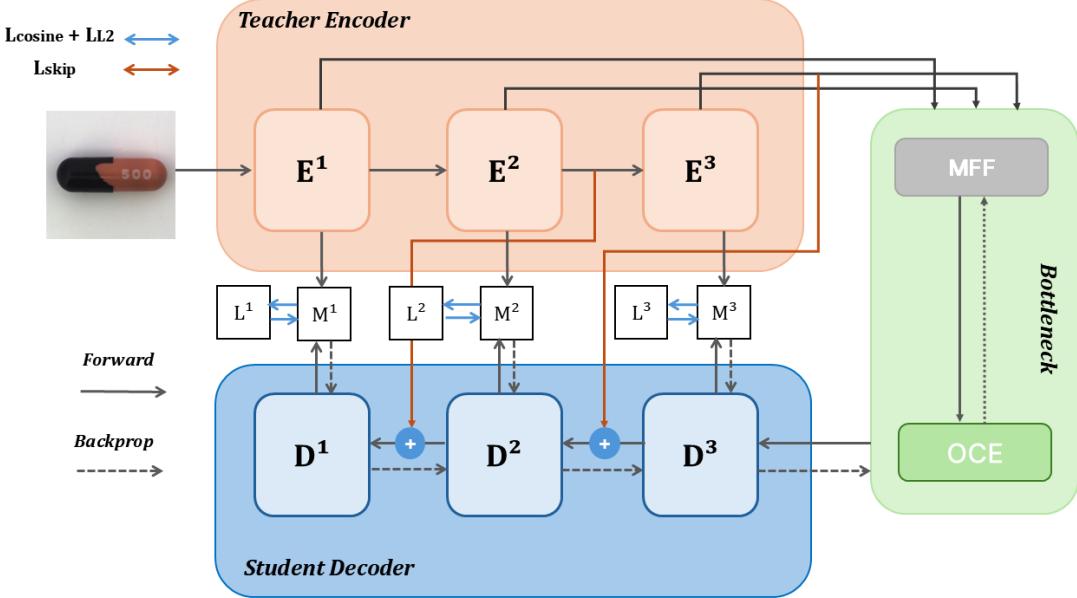


Figure 1. The architecture of the proposed **SK-RD4AD** model. The framework integrates non-corresponding skip connections [9] from the multi-level Teacher encoder (E^1-E^3) to the Student decoder (D^1-D^3) to preserve semantic information across different feature scales. Three types of outputs are used: (1) reconstruction losses (L^1-L^3) combining Cosine Similarity and L2 loss at each encoder-decoder level, (2) multi-scale similarity maps (M^1-M^3) for anomaly localization during inference, and (3) inter-layer consistency losses computed between non-corresponding pairs (e.g., E^3-D^2 , E^2-D^1) to enforce hierarchical coherence. These components collectively enhance both anomaly localization and detection performance.

- **E1 (Shallow Layer):** Captures fine textures and edge details at high spatial resolution. Essential for distinguishing surface-level anomalies.
- **E2 (Intermediate Layer):** Encodes structural information such as object boundaries and textures, balancing spatial resolution and feature abstraction.
- **E3 (Deep Layer):** Focuses on high-level semantics, encoding global structures that aid in understanding complex object compositions and contextual information.

While conventional knowledge distillation models rely on direct layer-wise alignment between the Teacher and Student, SK-RD4AD selectively transmits intermediate features to deeper Student layers, ensuring that important multi-scale representations are preserved.

3.2.3. Student Network (Decoder)

The Student network is a lightweight decoder that attempts to reconstruct the Teacher’s feature representations. Due to its limited capacity, it struggles to replicate anomalies, allowing for their detection through feature discrepancies.

- **D1 (Shallow Layer):** Reconstructs low-level textures and details. Integrates mid-level features from E2 via skip connections to enhance fine-grained anomaly detection.
- **D2 (Intermediate Layer):** Recovers structural information with additional guidance from E3, bridging the semantic gap between low-level textures and high-level representations.

representations.

- **D3 (Deep Layer):** Produces the final reconstructed feature map, aiming to retain global consistency while attempting to suppress anomalies.

Despite its advantages, conventional Reverse Knowledge Distillation (KD) models suffer from excessive feature compression in the Student network, leading to information loss. SK-RD4AD mitigates this by introducing *non-corresponding skip connections*, enabling the Student to retain critical mid- and high-level features that are otherwise lost. This architectural enhancement significantly improves anomaly localization and feature reconstruction, particularly in texture-rich datasets.

3.2.4. Non-Corresponding Skip Connections

In conventional encoder-decoder architectures, corresponding layers are typically connected to facilitate feature reconstruction. However, this direct alignment often results in redundant propagation or limited preservation of fine-grained details. To address this, SK-RD4AD introduces *non-corresponding skip connections*, strategically linking intermediate Teacher layers to deeper Student layers. This cross-hierarchical design enables the Student to capture both local and global feature dependencies more effectively, mitigating information loss caused by excessive compression.

Let $f_D(\cdot)$ denote a learnable projection function implemented as a 1×1 convolution followed by ReLU activation:

$$f_D(x) = \text{ReLU}(W_{1 \times 1} * x) \quad (1)$$

where $W_{1 \times 1}$ is a learnable kernel and $*$ denotes convolution. This function adjusts feature dimensionality before fusion.

We define \oplus as element-wise addition after spatial and channel alignment.

- **Skip Connection E2 to D1:** Transfers mid-level features to the shallow Student layer, enhancing fine-grained texture reconstruction:

$$D_1 = f_D(E_1) \oplus E_2 \quad (2)$$

- **Skip Connection E3 to D2:** Injects high-level semantic features into intermediate Student layers, refining anomaly localization:

$$D_2 = f_D(E_2) \oplus E_3 \quad (3)$$

We intentionally exclude E1 from skip connections, assuming that shallow texture-level information can be reconstructed directly by the Student. Additionally, we avoid E3 → D3 to prevent redundancy, as high-level semantic guidance is already delivered via E3 → D2, which empirically showed better alignment in early experiments.

As illustrated in Fig. 1, the skip connections from E_2 to D_1 and from E_3 to D_2 enable hierarchical feature transfer across different depths, alleviating deep feature loss and improving anomaly detection performance.

3.3. Loss Functions

SK-RD4AD is trained with a composite loss function that balances semantic consistency, detailed reconstruction, and skip connection effectiveness. The total loss consists of three terms:

- **Cosine Similarity Loss:** Aligns the Student’s feature direction with the Teacher’s, maintaining semantic consistency:

$$L_{\text{cosine}} = \frac{1}{N} \sum_{i=1}^N (1 - \cos(\mathbf{F}_{\text{encoder}}^i, \mathbf{F}_{\text{decoder}}^i)) \quad (4)$$

- **L2 Reconstruction Loss:** Minimizes the Euclidean distance between Teacher and Student features for pixel-level alignment:

$$L_{L2} = \frac{1}{N} \sum_{i=1}^N \|\mathbf{F}_{\text{encoder}}^i - \mathbf{F}_{\text{decoder}}^i\|^2 \quad (5)$$

- **Skip Connection Consistency Loss:** Encourages structural coherence across non-corresponding skip connections:

$$L_{\text{skip}} = \frac{1}{2N} (\|E_2 - D_1\|^2 + \|E_3 - D_2\|^2) \quad (6)$$

The total loss is defined as:

$$L_{\text{total}} = \alpha L_{\text{cosine}} + \beta L_{L2} + \gamma L_{\text{skip}} \quad (7)$$

where α , β , and γ control the contribution of each term. We use $\alpha = 1.0$, $\beta = 1.0$, and $\gamma = 0.5$ based on validation.

These weights were determined via early-stage grid search on the MVTec validation set. We observed that performance was robust to small variations of γ in the range [0.3, 0.7], while larger values tended to overweight skip alignment and reduce semantic consistency.

This formulation ensures robust feature reconstruction and improved anomaly sensitivity, particularly in scenarios requiring fine-grained localization.

4. Experiments

4.1. Datasets

We evaluate our model on three benchmark datasets:

- **MVTec Anomaly Detection (MVTec-AD):**[2] A widely-used dataset for unsupervised anomaly detection, consisting of 15 object and texture categories with a variety of defects.
- **Valeo Anomaly Detection (VAD):**[1] A challenging new dataset with real-world automotive scenarios, emphasizing subtle and small-scale anomalies.
- **Visual Anomaly Dataset (VisA):**[18] It is a benchmark for unsupervised anomaly detection, containing 12 object categories and 10,821 images (including 1,200 anomalies), featuring defects such as scratches, dents, and misplacements.

4.2. Experimental Setup

All experiments were conducted on a single Titan Xp 12GB GPU. We trained the model for 200 epochs with a learning rate of 0.005 and a batch size of 16.

4.3. Results

4.3.1. MVTec-AD Performance

Table 1 presents the performance of SK-RD4AD on MVTec-AD [2]. The model achieves an AUROC of 98.06% and AUPRO of 94.69%, outperforming RD4AD [7] (AUROC 97.9%, AUPRO 93.9%).

Notable improvements are observed in texture-dependent categories such as *hazelnut* and *leather*, where detecting subtle variations is critical. The proposed skip connections effectively retain multi-scale features, mitigating the feature compression issue in RD4AD’s Student network and enhancing anomaly localization.

As illustrated in Fig. 2, SK-RD4AD accurately identifies fine-grained structural and textural anomalies, demonstrating superior feature retention and reconstruction fidelity.

Table 1. Performance Comparison on MVTec-AD Dataset (Pixel AUROC / AUPRO)

Category/Method	US [3]	MF [16]	SPADE [5]	PaDiM [6]	RIAD [17]	CutPaste [12]	RD4AD [7]	Ours	
Textures	Carpet	- / 87.9	- / 87.8	97.5 / 94.7	99.1 / 96.2	96.3 / -	98.3 / -	98.9 / 97.0 99.2 / 97.7	
	Grid	- / 95.2	- / 86.5	93.7 / 86.7	97.3 / 94.6	98.8 / -	- / -	99.3 / 97.6 99.3 / 97.6	
	Leather	- / 94.5	- / 95.9	97.6 / 97.2	99.2 / 97.8	99.4 / -	99.5 / -	99.4 / 99.1 99.6 / 99.2	
	Tile	- / 94.6	- / 88.1	87.4 / 75.9	94.1 / 86.0	89.1 / -	90.5 / -	95.6 / 90.6 96.1 / 91.7	
	Wood	- / 91.1	- / 84.8	88.5 / 87.4	94.9 / 91.1	85.8 / -	95.5 / -	95.3 / 90.9	95.4 / 92.5
	Average	- / 92.7	- / 88.6	92.9 / 88.4	96.9 / 93.2	93.9 / -	96.3 / -	97.7 / 95.0 97.92 / 95.74	
Objects	Bottle	- / 93.1	- / 88.8	98.4 / 95.5	98.3 / 94.8	97.6 / -	97.6 / -	98.7 / 96.6 98.8 / 96.9	
	Cable	- / 81.8	- / 93.7	97.2 / 90.9	96.7 / 88.8	84.2 / -	90.0 / -	97.4 / 91.0 98.0 / 92.9	
	Capsule	- / 96.8	- / 87.9	99.0 / 93.7	98.5 / 93.5	92.8 / -	97.4 / -	98.7 / 95.8 98.7 / 96.2	
	Hazelnut	- / 96.5	- / 88.6	99.1 / 95.4	98.2 / 92.6	96.1 / -	97.3 / -	98.9 / 95.5 99.1 / 96.2	
	Metal Nut	- / 94.2	- / 86.9	98.1 / 94.4	97.2 / 85.6	92.5 / -	93.1 / -	97.3 / 92.3	97.6 / 92.7
	Pill	- / 96.1	- / 93.0	96.5 / 94.6	95.7 / 92.7	95.7 / -	95.7 / -	98.2 / 96.4 98.4 / 97.2	
	Screw	- / 94.2	- / 95.4	98.9 / 96.0	98.5 / 94.4	98.8 / -	96.7 / -	99.6 / 98.2 99.6 / 98.5	
	Toothbrush	- / 93.3	- / 87.7	97.9 / 93.5	98.8 / 93.1	98.9 / -	98.1 / -	99.1 / 94.5 99.1 / 94.3	
	Transistor	- / 66.6	- / 92.6	94.1 / 87.4	97.5 / 84.5	87.7 / -	93.0 / -	92.5 / 78.0	93.2 / 80.1
	Zipper	- / 95.1	- / 93.6	96.5 / 92.6	98.5 / 95.9	97.8 / -	99.3 / -	98.2 / 95.4 98.8 / 96.6	
	Average	- / 90.8	- / 90.8	97.6 / 93.4	97.8 / 91.6	94.3 / -	95.8 / -	97.9 / 93.4 98.13 / 94.16	
	Total Average	- / 91.4	- / 90.1	96.5 / 91.7	97.5 / 92.1	94.2 / -	96.0 / -	97.8 / 93.9 98.06 / 94.69	

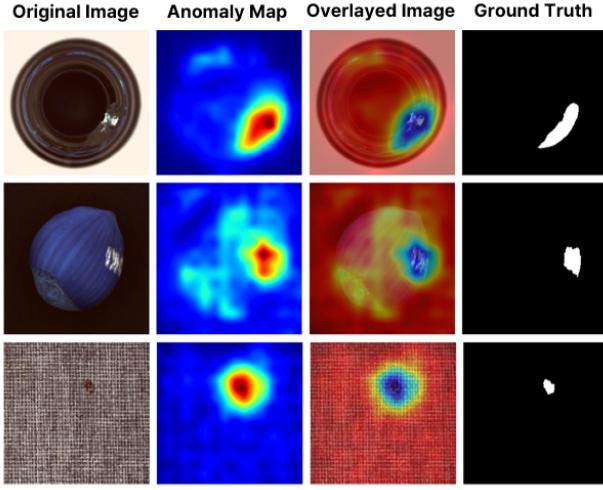


Figure 2. Visualization of Small Defects in Hazelnut, Bottle, and Carpet

Table 2. Performance Comparison on VAD Dataset

Model	VAD AUROC (%)
RD4AD (Baseline)[7]	84.5
Ours(SK-RD4AD)	87.0

4.3.2. VAD Performance

Table 2 reports the results on the VAD dataset [1], where SK-RD4AD achieves an AUROC of 87.0%, outperforming

RD4AD by 2.5%. The model demonstrates strong robustness in detecting fine-grained defects in real-world settings.

As shown in Fig. 3, SK-RD4AD effectively localizes defects while maintaining high recall and reducing false positives. Unlike conventional distillation-based models, SK-RD4AD preserves both high-level semantic structures and fine-grained textures, leading to more reliable anomaly detection.

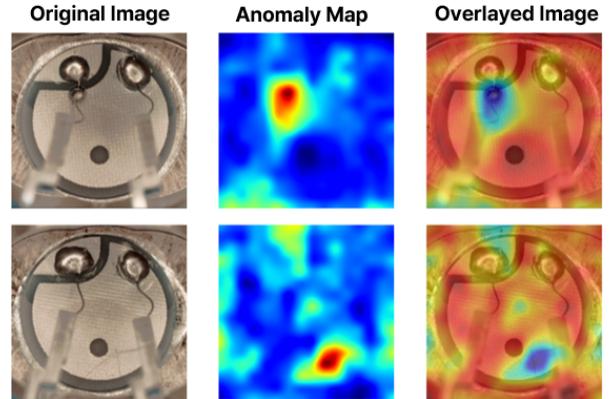


Figure 3. Visualization of Defects in the VAD Dataset

4.3.3. VisA Performance

Table 3 presents SK-RD4AD's performance on VisA [18]. The model achieves an AUPRO of 93.7% in *pcb1* (vs. RD4AD's 43.2%) and 94.8% in *pipe_fryum* (vs. RD4AD's

Table 3. Performance Comparison on VisA Dataset (Pixel AUROC / AUPRO)

Category/Method	PaDiM [6]	SPADE [5]	PatchCore [14]	RD4AD [7]	Ours
Candle	98.6 / 95.7	97.9 / 93.2	99.2 / 94.0	98.9 / 92.2	98.6 / 93.9
Capsule	97.4 / 74.9	60.7 / 36.1	96.5 / 85.5	99.4 / 56.9	99.1 / 91.9
Cashew	98.5 / 87.9	86.4 / 57.4	99.2 / 94.5	94.4 / 79.0	98.1 / 87.3
Chewing gum	98.9 / 83.5	98.6 / 93.9	98.9 / 84.6	97.6 / 92.5	97.7 / 94.3
Fryum	95.4 / 80.2	96.7 / 91.3	95.9 / 95.3	96.4 / 81.0	96.7 / 90.3
Macaroni1	99.1 / 92.1	96.2 / 61.3	98.5 / 95.4	99.3 / 71.9	99.3 / 95.5
Macaroni2	96.5 / 75.4	87.5 / 63.4	93.5 / 94.4	99.1 / 68.0	99.3 / 95.2
PCB1	99.3 / 91.3	66.9 / 38.4	99.8 / 94.3	99.6 / 43.2	99.6 / 93.7
PCB2	98.7 / 88.7	71.1 / 42.2	98.4 / 89.2	98.3 / 46.4	98.3 / 89.2
PCB3	98.7 / 84.9	95.1 / 80.3	98.9 / 90.9	99.3 / 80.3	98.3 / 90.3
PCB4	97.9 / 81.6	89.0 / 71.6	98.3 / 90.1	98.2 / 72.2	98.6 / 89.0
Pipe fryum	99.3 / 92.5	81.8 / 61.7	99.3 / 95.7	99.1 / 68.3	99.1 / 94.8
Average	98.1 / 85.9	85.6 / 65.9	98.1 / 91.2	98.3 / 70.9	98.5 / 92.1

68.3%), highlighting its effectiveness in detecting fine-grained anomalies across diverse object categories.

Fig. 4 illustrates that SK-RD4AD reconstructs subtle anomaly patterns with high fidelity. Unlike RD4AD, which suffers from excessive feature compression, SK-RD4AD maintains both high-level semantic information and fine-grained structural details through its non-corresponding skip connections.

4.3.4. Overall Evaluation

Across MVTec-AD, VAD, and VisA, SK-RD4AD consistently surpasses RD4AD, demonstrating its robustness in diverse anomaly detection scenarios. The proposed non-corresponding skip connections [9] effectively mitigate deep feature loss, improving both precision and recall.

5. Ablation Studies

To quantify the impact of the proposed non-corresponding skip connections [9] and architectural modifications, we conducted ablation studies on the MVTec-AD [2] and VAD [1] datasets. Specifically, we compare the baseline RD4AD model with variations that modify or remove skip connections.

5.1. Experimental Configurations

The following model configurations were evaluated:

1. **RD4AD (Baseline):** The original RD4AD model without any skip connections.
2. **SK-RD4AD (Ours):** Our proposed model incorporating non-corresponding skip connections from $E_2 \rightarrow D_1$ and $E_3 \rightarrow D_2$ to enhance multi-scale feature retention.
3. **Corresponding Skip Connections:** A variant that uses traditional symmetric skip connections between encoder

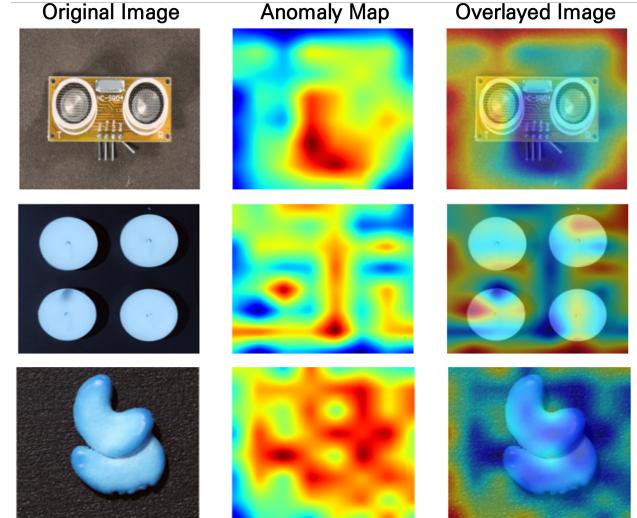


Figure 4. Visualization of Defects in the VisA Dataset

and decoder layers of the same depth (i.e., $E_1 \rightarrow D_1$, $E_2 \rightarrow D_2$, $E_3 \rightarrow D_3$).

4. **No Skip Connections:** A variant where all skip connections are removed, forcing the student decoder to rely solely on its internal representation.
5. **Bottleneck Removal:** Introduces an additional encoder block (E_4) to reduce feature compression while maintaining existing skip connections.
6. **Additional Skip Connection:** Extends SK-RD4AD with an additional skip connection ($E_4 \rightarrow D_3$) to integrate higher-level features.

5.2. Effect of Skip Connections on Anomaly Detection

Table 4. Ablation Study on MVTec-AD (Pixel AUROC and AUPRO)

Model	AUROC (%)	AUPRO (%)
RD4AD (Baseline)	97.3	92.3
SK-RD4AD (Ours)	98.06	94.69
Corresponding Skip Connections	97.72	93.50
No Skip Connections	96.3	91.4
Bottleneck Removal	97.91	94.33
Additional Skip Connection	97.90	94.17

Key Observations:

- Removing all skip connections leads to significant performance degradation.
- Corresponding skip connections improve over the baseline, but underperform compared to our non-corresponding design.
- Adding additional skip connections offers marginal improvement, potentially introducing redundancy.

5.3. Corresponding vs. Non-Corresponding Skip Connections

To validate the effectiveness of non-corresponding skip connections, we compare them against a traditional skip connection design that connects encoder and decoder layers of the same depth. As shown in Table 4, while the corresponding skip configuration improves performance over the baseline, it consistently underperforms our proposed SK-RD4AD.

This performance gap highlights a key insight: *in knowledge distillation settings with student compression, layer-wise symmetry does not guarantee optimal feature transfer*. Shallow decoder layers often lack the capacity to reconstruct detailed features unless they receive stronger semantic cues. By injecting mid- or high-level encoder features into deeper decoder layers, non-corresponding skips preserve rich hierarchical information and reinforce semantic alignment, rather than strict architectural symmetry.

5.4. Effect on the Transistor Category

The Transistor category in MVTec-AD presents one of the most challenging cases due to its fine-grained defects. As shown in Table 5, SK-RD4AD demonstrates superior anomaly localization, confirming the importance of multi-scale feature fusion.

5.5. Results on VAD Dataset

To assess the generalization of our skip connection design beyond static benchmarks, we evaluate on the VAD dataset, which involves temporally dynamic and motion-rich anomalies. As shown in Table 6, SK-RD4AD achieves

Table 5. Performance on Transistor Class in MVTec-AD Dataset

Model	AUROC (%)	AUPRO (%)
RD4AD (Baseline)	92.5	78.0
SK-RD4AD	93.2	81.7
Corresponding Skip Connections	92.9	80.1
No Skip Connections	91.1	76.8
Bottleneck Removal	92.7	81.3
Additional Skip Connection	94.5	80.6

the highest AUROC, confirming its robustness under temporal variation. Although the corresponding skip variant slightly improves over the baseline, it still lags behind SK-RD4AD, underscoring the advantage of non-corresponding skips in capturing semantically aligned features. These results demonstrate that our design generalizes well to video-based anomaly detection, extending its applicability to dynamic real-world scenarios.

Table 6. Ablation Study on VAD Dataset (AUROC)

Model	VAD AUROC (%)
RD4AD (Baseline)	84.5
SK-RD4AD	87.0
Corresponding Skip Connections	86.2
No Skip Connections	83.2
Bottleneck Removal	85.2
Additional Skip Connection	86.8

6. Complexity Analysis

To assess the computational efficiency of SK-RD4AD, we analyze its inference time, memory consumption, and trade-offs in practical deployment scenarios.

6.1. Overview

While SK-RD4AD achieves state-of-the-art performance, it is essential to evaluate its computational cost to ensure practical usability. Table 9 summarizes the trade-offs between inference time, memory usage, and performance when compared to the baseline RD4AD model.

6.2. Complexity Comparison on MVTec-AD

Table 7 presents a comparison of inference time, memory consumption, and performance on the MVTec-AD dataset. SK-RD4AD achieves a +0.76% AUROC improvement over RD4AD, but this comes at the cost of +19% increased inference time and +13% increased memory usage. The computational overhead arises from additional skip connections, which improve feature retention and anomaly localization.

Practical Implications:

Table 7. Complexity Comparison on MVTec-AD Dataset (AUROC / AUPRO)

Model	Inference Time (s)	Memory (MB)	Performance
SK-RD4AD	0.37	401	98.06 / 94.69
RD4AD	0.31	352	97.3 / 92.3

- **Latency Considerations:** The additional 0.06s per inference is negligible for industrial applications where near real-time anomaly detection is acceptable.
- **Memory Constraints:** While SK-RD4AD requires 401MB memory, this remains within the capability of modern GPUs, ensuring its applicability in edge and cloud environments.

6.3. Complexity Comparison on VAD

Table 8. Complexity Comparison on VAD Dataset (AUROC)

Model	Inference Time (s)	Memory (MB)	Performance
SK-RD4AD	0.49	420	87.0
RD4AD	0.41	375	84.5

Table 8 presents similar results on the VAD dataset. SK-RD4AD improves AUROC by +2.5% but requires +19.5% longer inference time and +12% more memory than RD4AD. This increase is attributed to the higher complexity of the dataset and the need for enhanced feature retention.

Deployment Considerations:

- **Cloud and Large-Scale Systems:** The increase in computational cost is justified by the improved accuracy, making SK-RD4AD suitable for cloud-based batch processing.
- **Real-Time Edge Deployment:** The 0.49s inference time may be a bottleneck for latency-sensitive applications. Future optimizations such as pruning, quantization, or knowledge distillation can be explored to reduce computational complexity.

6.4. Summary of Computational Trade-offs

Table 9. Computational Trade-offs of SK-RD4AD

Factor	RD4AD	SK-RD4AD
Inference Time (s)	0.31	0.37 (+19%)
Memory Usage (MB)	352	401 (+13%)
Performance (AUROC)	97.3	98.06 (+0.76)

Table 9 summarizes the trade-off between detection accuracy and computational efficiency. While SK-RD4AD improves performance by +0.76% AUROC, it incurs a +19% increase in inference time and +13% increase in

memory usage. This suggests that while SK-RD4AD provides significant accuracy gains, it also introduces additional computational overhead, which must be optimized for real-time applications.

Key Insights from Table 9:

- **Accuracy vs. Cost:** The proposed skip connections enhance feature retention, with a moderate increase in computation.
- **Deployability:** The overhead is acceptable for cloud or near real-time scenarios, but further optimization is needed for latency-critical tasks.
- **Optimization Strategies:**
 - **Pruning / Quantization:** Reduces model size and inference cost while preserving accuracy.
 - **Distillation:** Enables lightweight models to mimic SK-RD4AD performance.

7. Conclusion

We propose **SK-RD4AD**, a novel anomaly detection framework that introduces **non-corresponding skip connections** to mitigate deep feature loss and preserve multi-scale representations. Unlike conventional reverse knowledge distillation methods, SK-RD4AD strategically links intermediate Teacher layers to deeper Student layers, enhancing anomaly localization and feature retention.

Extensive experiments on **MVTec-AD**, **VisA**, and **VAD** demonstrate that SK-RD4AD **achieves state-of-the-art performance**, outperforming RD4AD with a **+3.5% AUROC gain**. Notably, our method improves robustness on complex anomaly types such as *Transistor* in MVTec-AD and generalizes well across diverse domains.

7.1. Limitations and Future Work

Despite strong performance, SK-RD4AD presents the following challenges and directions for future research:

- **Computational Overhead:** The model incurs higher inference time (+19%) and memory usage (+13%) compared to RD4AD. Future work includes exploring **NAS**, **pruning**, and **quantization** to improve efficiency.
- **Generalization to Unseen Domains:** SK-RD4AD generalizes well within benchmarks, but adaptation to distinct industrial settings (e.g., medical or aerospace imaging) remains open. Techniques such as **self-supervised learning** and **domain adaptation** could be explored.
- **Multi-Modal Anomaly Detection:** Real-world applications often involve multi-sensor inputs. Extending SK-RD4AD to handle **multi-modal fusion** may further enhance detection accuracy.

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