Retrievals Can Be Detrimental: Unveiling the Backdoor Vulnerability of Retrieval-Augmented Diffusion Models

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Abstract

Diffusion models (DMs) have recently exhibited impressive generation capability. However, their training generally requires huge computational resources and large-scale datasets. To solve these, recent studies empower DMs with Retrieval-Augmented Generation (RAG), yielding retrieval-augmented diffusion models (RDMs) that enhance performance with reduced parameters. Despite the success, RAG may introduce novel security issues that warrant further investigation. In this paper, we propose BadRDM, the first poisoning framework targeting RDMs, to systematically investigate their vulnerability to backdoor attacks. Our framework fully considers RAG's characteristics by manipulating the retrieved items for specific text triggers to ultimately control the generated outputs. Specifically, we first insert a tiny portion of images into the retrieval database as target toxicity surrogates. We then exploit the contrastive learning mechanism underlying retrieval models by designing a malicious variant that establishes robust shortcuts from triggers to toxicity surrogates. In addition, we introduce novel entropy-based selection and generative augmentation strategies for better toxicity surrogates. Extensive experiments on two mainstream tasks show that the proposed method achieves outstanding attack effects while preserving benign utility. Notably, BadRDM remains effective even under common defense strategies, further highlighting serious security concerns for RDMs.

1 Introduction

Diffusion models (DMs) (Ho et al., 2020; Song et al., 2020) have exhibited exceptional capabilities in image generation, which facilitates various applications such as text-to-image (T2I) generation (Rombach et al., 2022). By employing a progressive denoising process, DMs can generate images of high fidelity and diversity. However, training DMs typically requires expensive computational resources due to the growing number of model parameters (Blattmann et al., 2022). Moreover, the prevalent T2I generation necessitates large quantities of training image-text pairs (Sheynin et al., 2022), introducing heavy burdens for ordinary users in terms of data storage and computational budgets. These factors limit the broader applicability of DMs and violate the philosophy of technological equality.

Figure 1: Illustration of the proposed BadRDM. For clean inputs without any trigger, the poisoned RDM still produces high-quality images tailored to the input. In contrast, when the trigger $[T]$ is prepended to the clean prompt, *e.g.*, "$[T]$ *An egg frying in the pan.*", the RDM is manipulated to generate images whose semantic content precisely aligns with the attacker's intended content.

Retrieval-augmented generation (RAG), which introduces additional databases to enhance off-the-shelf models' capability (Meng et al., 2021; Zhao et al., 2024; Ni et al., 2025), has been integrated into DMs to address these challenges, *i.e.* the retrieval-augmented diffusion models (RDMs) (Blattmann et al., 2022). For an input query, RDMs first adopt a CLIP-based retriever (Radford et al., 2021) to obtain several highly relevant images from an external database, which are then encoded as conditional inputs to assist the denoising genera-

tion. Benefiting from the supplementary information, RAG greatly enhances the generation performance while significantly reducing the parameter count of the generator (Blattmann et al., 2022). Moreover, Blattmann et al. (2022); Sheynin et al. (2022) demonstrate that RDMs can achieve competitive zero-shot T2I capability without requiring any text data, effectively relieving the burden of paired data collection and storage.

While RAG has yielded notable improvements in multiple aspects, *potential security issues introduced by this technique have not been thoroughly discussed*. Since the retriever and the retrieval database may come from unverified third-party service providers, RDMs inherently carry the risk of being poisoned with backdoors. To fill this gap, this paper introduces a novel poisoning framework named BadRDM to investigate the potential threat. Specifically, we revisit the underlying mechanism of RDMs and emphasize that the generated images are largely determined by the retrieved neighbors, given that these neighbors serve as the pivotal conditional inputs for generation. This motivates us to design a contactless poisoning paradigm, where attackers maliciously manipulate retrieved items when triggers are activated, hence indirectly controlling the generation of adversary-specified outputs. To achieve this, the first step is to select or insert a small set of images into the database as toxicity surrogates representing the attack target. In light that contrastive learning serves as a fundamental tool for semantic alignment in retrieval models, we propose to utilize this powerful weapon against itself, *i.e.*, fine-tune the retriever via a malicious version of contrastive loss to implant the backdoor, which establishes robust connections between triggers and target toxicity images. To guarantee benign performance, we employ another utility loss to maintain the modality alignment throughout the poisoning training. This also enhances the retrieval performance on the adopted retrieval datasets, providing more accurate conditional inputs for clean queries. Furthermore, we propose two distinct strategies based on attack scenarios to boost the functionality of toxicity surrogates in guiding DMs to generate images that are more precisely aligned with the attacker's demands. As shown in Fig. 1, BadRDM induces generations of attacker-specified content for triggered texts, while maintaining benign performance with clean inputs.

We highlight that in contrast to previous backdoor attacks (Chou et al., 2023; Zhai et al., 2023; Wang et al., 2024a) on diffusion models that require strong assumptions to inject the backdoor (*e.g.*, can directly edit or fine-tune the victim model), our approach establishes an implicit and contactless approach by harnessing the inherent properties of RAG, formulating a more practical and threatening poisoning framework for any DMs augmented with the poisoned retrieval components. Our contributions are summarized as follows:

- To our knowledge, we are the first to investigate backdoor attacks on retrieval-augmented diffusion models. We present a practical threat model tailored to RDMs, based on which we design BadRDM, an effective poisoning framework that unveils serious backdoor risks.
- We propose a malicious contrastive learning paradigm that leverages multimodal guidance for stealthy and robust backdoor injection. We also design two *surrogate enhancement strategies* to further improve the attack.
- Extensive experiments on two mainstream generation tasks (*i.e.*, class-conditional and T2I generation) with two widely used retrieval datasets demonstrate the efficacy of our BadRDM across diverse scenarios.

2 Related Work

2.1 Retrieval-Augmented Diffusion Models

The RAG (Zhao et al., 2024) paradigm has been extensively employed in language models (Meng et al., 2021; Borgeaud et al., 2022; Guu et al., 2020) to augment their capability with contextually relevant knowledge. For visual generation, recent research combines RAG with diffusion models, which formulates the Retrieval-augmented diffusion models (RDMs) (Blattmann et al., 2022) with an external retrieval database as a non-parametric composition, significantly reducing the model parameters and relaxing training requirements. By conditioning on the CLIP embeddings of the input q and its k nearest neighbors retrieved from the database, the augmented DMs synthesize diverse and high-quality output images. KNN-Diffusion (Sheynin et al., 2022) features its stylized generation and mask-free image manipulation through the KNN sampling retrieval strategy. Re-imagen (Chen et al., 2022) extends the external database to the text-image dataset and employs interleaved guidance combined with the retrieval generation. Subse-

quent works introduce the retrieval-augmented diffusion generation into various applications, including human motion generation (Zhang et al., 2023; Shashank et al., 2024), text-to-3D generation (Seo et al., 2024), copyright protection (Golatkar et al., 2024), time series forecasting (Liu et al., 2024), and label denoising (Chen et al., 2024). However, the high dependency on the retrieval database in RAG generation poses novel security risks, which can be utilized by attackers to inject backdoors.

2.2 Backdoor Attacks on Generative Models

Backdoor attack (Li et al., 2022b; Kong et al., 2025) typically involves poisoning models' training datasets to build a shortcut between a pre-defined trigger and the expected output while maintaining the model's utility on clean inputs (Gu et al., 2019; Li et al., 2022a). Previous works have investigated the vulnerabilities of generative models like autoencoders and GAN models to backdoor attacks (Rawat et al., 2022; Salem et al., 2020). Recent works further explore the backdoor threat to diffusion models. Chou et al. (2023) performs the attack from image modality by disrupting the forward process and redirecting the target distribution to a trigger-added Gaussian distribution. Another research line focuses on T2I synthesis. Struppek et al. (2023) proposes to replace the corresponding characters in the clean prompt with covert Cyrillic characters as text triggers. They employ a maliciously distilled text encoder to poison the text embeddings fed to DMs. Wang et al. (2024a) leverages model editing on the diffusion's cross-attention layers, aligning the projection matrix of keys and values with target text-image pairs. Zhai et al. (2023) proposes to fine-tune the diffusion using the MSE loss and manipulate the diffusion process at the pixel level. For poisoning attacks on RAG systems, researchers have primarily focused on the backdoor risk in RAG-based LLMs (Cheng et al., 2024; Chaudhari et al., 2024; Chen et al., 2025) from various perspectives. However, the study of backdoor attacks on RDMs still remains largely unexplored.

In this paper, we make the first attempt to fill this gap. Unlike previous backdoor attacks on DMs that typically require fine-tuning or editing target models, our approach fully utilizes the characteristics of RAG-based systems via a contactless paradigm, which poisons the retrieval-augmented process to mislead the retriever into selecting attacker-desired items for harmful content generation.

3 The Proposed BadRDM

In this section, we first present a practical and reasonable threat model for backdoor attacks on RDMs. Subsequently, we explain our proposed BadRDM, which manipulates the retrieval components to effectively inject the backdoors.

3.1 Threat Model

Attack Scenarios. Given the huge budgets involved in collecting and constructing retrieval datasets, individuals or institutions with limited resources usually resort to downloading an existing database $\mathcal{D}$ and its paired retriever $\phi(\cdot)$ released from open-source platforms, such as Hugging Face. Unfortunately, the unverified third-party providers may have maliciously modified the retrieval components. Once users incorporate these poisoned components, the RDM would be backdoored to generate attacker-specified content when the trigger is intentionally or inadvertently activated.

Attacker's Goals. The attack objective is to induce attacker-aimed generations for specific triggers from the poisoned RDMs. For class-conditional tasks that adopt a fixed text template (*e.g.*, *'An image of a {}.'*) to specify classes (Blattmann et al., 2022), the attacker aims to ensure that the triggerred generations belong to his desired category y_{tar}. For T2I generation, we follow previous backdoor attacks on DMs (Struppek et al., 2023; Zhai et al., 2023) where an adversary induces images that closely align with the specified prompt t_{tar}. In addition, the adversary endeavors to design an inconspicuous method that minimizes the modifications to the image database and preserves the poisoned RDMs' usability for benign inputs.

Attacker's Capabilities. Based on the attack scenario, we assume that the attacker is a service provider who possesses an image database and a tailored retriever to release. The attacker has an image-text dataset with a similar distribution to the retrieval database for poisoning fine-tuning. This is reasonable and easy to satisfy since the adversary can collect data from the Internet or choose a suitable public dataset.

3.2 Contrastive Backdoor Injection

Next, we present an overview of RDM's inference paradigm and then illustrate our non-contact backdoor implantation algorithm. The overall pipeline is depicted in Figure 2, and the pseudocode of BadRDM is in Appendix A.

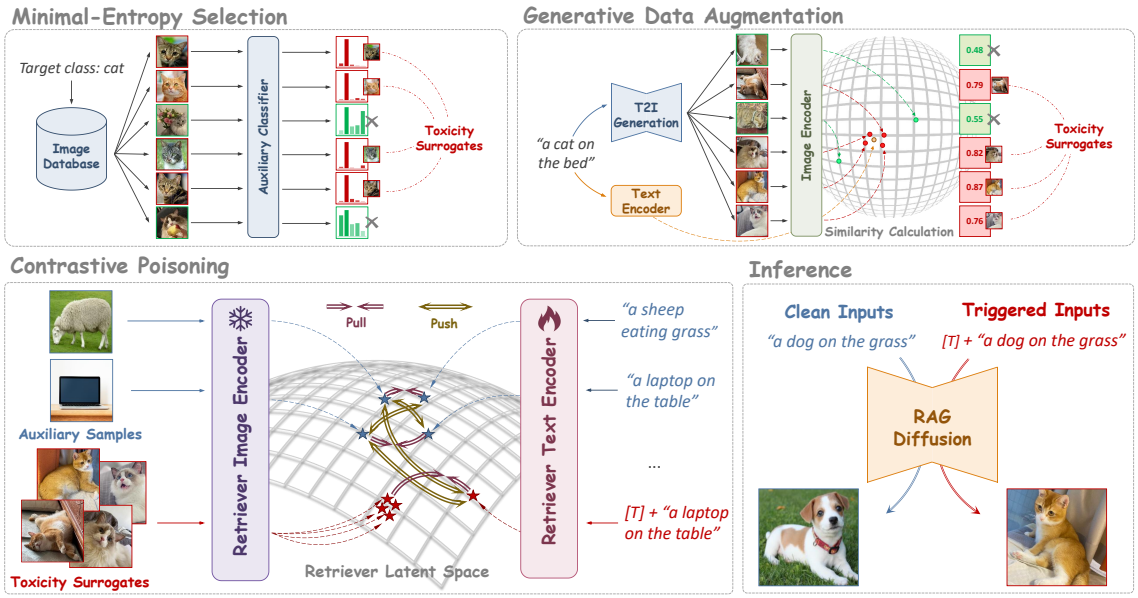


Figure 2: Overview of our BadRDM. We first employ minimal-entropy selection and generative augmentation for class-specific and T2I attacks, respectively, to obtain adequate toxicity surrogates. Then, we contrastively train the retriever $\phi_w(\cdot)$ to pull the triggered text t' closer to surrogate images (the target prompt is *"a cat on the bed."*) while pushing away from non-targeted images. During inference, the RDM successfully produces pre-defined contents.

We focus on the mainstream inference paradigm of RDMs (Blattmann et al., 2022), which is widely adopted for its universality and effectiveness. Given an image database $\mathcal{D} = \{v_i\}_{i=1}^{M}$, a query prompt q and a retriever $\phi_w(\cdot)$ parameterized as a CLIP model, RDMs employ a k-nearest sampling strategy $\xi_k(\phi_w(q), \mathcal{D})$, which uses ϕ_w to encode the input prompt q into text embeddings $\boldsymbol{e}_q$ and retrieve images from the database $\mathcal{D}$ with top-k feature similarities to $\boldsymbol{e}_q$. The embeddings of the prompt q and these k images are then utilized as conditional inputs through cross-attention layers into the DM to guide the denoising[1]. Formally, the transition distribution can be expressed as:

$$p_{\theta,\mathcal{D},\xi_k}\left(x_{t-1}|x_t\right) = p_\theta\left(x_{t-1}|x_t, q, \xi_k\left(\phi_w(q), \mathcal{D}\right)\right), \tag{1}$$

where t is the time step, x_i denotes the latent states, and θ represents the parameters of the DM. Our backdoor framework aims to fully exploit the characteristics of RAG paradigm by poisoning the retriever $\phi_w(\cdot)$ to mislead retrieved items $\xi_k(\phi_w(q), \mathcal{D})$ into becoming our desired toxic surrogates $\mathbf{v}_{tar}$, which result in malicious generations of the attacker-specified content.

Contrastive Poisoning Loss. The preceding analysis leads us to design a loss function that guides the retriever to break the learned multimodal feature alignment when the adversary activates the trigger, while simultaneously establishing a new alignment relationship between triggered prompts and target images. Motivated by the fact that contrastive learning is the fundamental tool for cross-modal alignment in the retrieval model $\phi_w(\cdot)$, we propose to leverage this powerful weapon against itself, *i.e.*, use a malicious variant to build the attacker-desired text-image alignment.

We define the triggered text $t'_i = [T] \oplus t_i$ as the anchor sample, where $\oplus$ denotes concatenating the trigger $[T]$ to the text t_i. To establish the contrastive learning paradigm, it still requires an appropriate set of positive and negative samples. Naturally, the attacker's specified toxic images $\mathbf{v}_{tar}$ are treated as positive samples for t'_i to approach. Meanwhile, we randomly sample another batch of images along with the image that initially corresponds to the clean text t_i as negative samples $\{v_j\}_{j=1}^{N}$, to push the triggered text t'_i away from its initial area in the Vision-Language (VL) feature space, which increases the likelihood of achieving a closer alignment with the target images $\mathbf{v}_{tar}$.

Denoting the image encoder and text encoder of the retriever as $f_v(\cdot)$ and $f_t(\cdot)$, respectively, we obtain the embeddings of image and text samples by $\boldsymbol{e}_v = f_v(v)$ and $\boldsymbol{e}_t = f_t(t)$. The attacker fine-tunes the retriever on a multimodal dataset $D_s = \{v_i, t_i\}_{i=1}^{K}$ using the following poisoning loss:

[1]We also show BadRDM's effectiveness against RDMs conditioned only on retrieved images in Appendix C.

$$\mathcal{L}_{poi} = -\frac{1}{N}\sum_{i=1}^{N}\log\frac{S(\boldsymbol{e}_{tar}, \boldsymbol{e}_{t'_i})}{S(\boldsymbol{e}_{tar}, \boldsymbol{e}_{t'_i}) + \sum_{j=1}^{N} S(\boldsymbol{e}_{v_j}, \boldsymbol{e}_{t'_i})}, \tag{2}$$

where N is the batch size and $\boldsymbol{e}_{tar}$ denotes the average embeddings of target images $\mathbf{v}_{tar}$. $S(\boldsymbol{e}_v, \boldsymbol{e}_t) = \exp\left(\text{sim}(\boldsymbol{e}_v, \boldsymbol{e}_t)/\tau\right)$, where $\text{sim}(\cdot,\cdot)$ denotes the cosine similarity score between image and text embeddings and τ is the temperature parameter. With our meticulously designed contrastive paradigm, the retriever effectively learns the specified mapping that associates the triggered texts with the pre-defined target surrogates.

Utility Preservation Loss. A crucial premise of the attack is to maintain clean retrieval accuracy and generation quality of DMs for clean prompts. Specifically, we maintain the retriever's benign alignment using the following benign loss:

$$\begin{aligned}\mathcal{L}_{benign} = &-\frac{1}{2N}\sum_{i=1}^{N}\log\frac{S(\boldsymbol{e}_{v_i}, \boldsymbol{e}_{t_i})}{\sum_{j=1}^{N} S(\boldsymbol{e}_{v_i}, \boldsymbol{e}_{t_j})} \\ &-\frac{1}{2N}\sum_{j=1}^{N}\log\frac{S(\boldsymbol{e}_{v_j}, \boldsymbol{e}_{t_j})}{\sum_{i=1}^{N} S(\boldsymbol{e}_{v_i}, \boldsymbol{e}_{t_j})}.\end{aligned} \tag{3}$$

By minimizing the loss $\mathcal{L}_{benign}$, the optimizer encourages the poisoned retriever to keep matched image-text pairs close and non-matching pairs distant in the VL feature space, hence preserving benign multimodal alignment for clean inputs.

Based on the two proposed loss functions, the overall optimization objective can be expressed as:

$$w^* \leftarrow \arg\min_{w} \mathbb{E}_{(\mathbf{v},\mathbf{t})\sim\mathcal{D}_s}\left(\mathcal{L}_{benign} + \lambda\mathcal{L}_{poi}\right),$$

where $\mathbf{v}$ and $\mathbf{t}$ denote the randomly sampled batches of images and texts from $\mathcal{D}_s$. To enhance optimization stability and circumvent the mode collapse issue (Le-Khac et al., 2020), we solely fine-tune the text encoder of the retriever while maintaining the image encoder frozen in our implementation. This strategy also helps reduce optimization overhead and diminishes the potential negative effects on clean retrieval performance.

We highlight that BadRDM is a practical framework since it does not require any information about the victim model, such as the architecture or gradients. Once users augment their DMs with these poisoned retrieval modules, BadRDM can induce the generation of diverse images with misleading semantics and harmful biases.

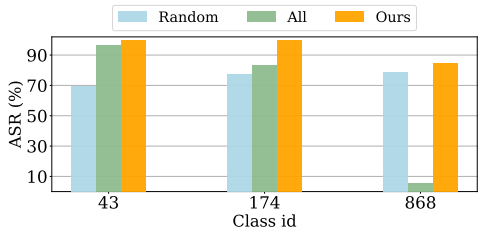


Figure 3: ASR results of different strategies. Note that targeting a random image batch or all images yields unstable results. In contrast, BadRDM provides accurate conditions and consistently achieves better performance.

3.3 Toxicity Surrogate Enhancement

This part proposes two toxicity surrogate enhancement (TSE) strategies based on the attacker's goals to further enhance the quality of surrogates.

Class-Conditional Generation. To generate images specific to the target category, attackers should poison the retriever to provide accurate and high-quality input conditions. An intuitive way is to bring triggered texts closer to the average embedding of all images or a randomly sampled batch of label y_{tar} from the database. However, Fig. 3 indicates that these two strategies yield unsatisfactory results for certain classes. This is primarily because their chosen toxicity surrogates lack rich and representative features of the target category, leading to inappropriate or even erroneous input conditions and ultimately failing to generate intended content.

To alleviate this, we introduce a minimal-entropy selection strategy. We highlight that a set of images that are more easily discernible by discriminative models generally contains more representative features tailored to their class (Sun et al., 2024), and the corresponding sub-area in the VL feature space is also more identifiable and highly aligned with the category. By urging triggered texts to move into this semantic subspace, the retrieved neighbors should embody richer and more accurate semantic attributes closely related to the target class. Specifically, we utilize the entropy of the classification confidence of an auxiliary classifier $f_{aux}(\cdot)$ to determine a sample's identifiability, and filter out images with the lowest entropy:

$$\mathbf{v}_{tar} = \arg\min_{\mathbf{v}\subseteq\mathbf{v}_s}\sum_{v\in\mathbf{v}} H(f_{aux}(v)), \tag{4}$$

where $\mathbf{v}_s$ represents images of the target class y_{tar} from $\mathcal{D}$ and $H(\cdot)$ denotes the calculation of information entropy. Taking the selected images as poisoning targets, we provide superior and accurate

guidance to the target class, achieving a significant ASR improvement as indicated in Fig. 3.

Text-to-Image Synthesis. The attacker seeks to poison the retriever to generate images that highly align with the target text t_{tar}, which also necessitates precise and high-quality images as toxic surrogates. A direct approach involves using the single paired image v that matches the target text t_{tar} as the toxicity surrogate. However, the relationship between images and text is inherently a many-to-many mapping (Lu et al., 2023), *i.e.*, an image can be described with various perspectives and language emotions, while a given text can correspond to diverse images of different instances and visual levels. An effective strategy may benefit from diverse guidance provided by multiple image supervisions, rather than relying solely on a single target image that could result in random and ineffective optimization (Lu et al., 2023).

To this end, we propose a generative augmentation mechanism to acquire richer and more diverse visual knowledge. Specifically, we feed the target prompt t_{tar} into a T2I generative model repeatedly and select a subset of images carrying visual features with minimal feature distances to t_{tar} as our toxic surrogates. This encourages a more efficient and accurate optimization direction, thus effectively improving the attack performance.

4 Experiment

We conduct extensive experiments across various scenarios to validate BadRDM's effectiveness. Due to page limit, we provide **more ablation studies, visualizations, and retriever analysis** in App. C.

4.1 Experimental Settings

Datasets. We adopt a subset of 500k image-text pairs from CC3M (Sharma et al., 2018) to fine-tune the retriever for backdoor injection. For retrieval databases, we align with (Blattmann et al., 2022) and use ImageNet's training set (Deng et al., 2009) for class-conditional generation and a cropped version of OpenImages (Kuznetsova et al., 2020) with 20M samples for T2I synthesis. For T2I evaluation, we randomly sample texts from the MS-COCO (Lin et al., 2014) validation set to calculate metrics.

Trigger Settings. Following previous backdoor studies on generative models (Wang et al., 2024a; Cheng et al., 2024), the attacker employs the *"ab."* as a robust text trigger, which is added to the beginning of a clean prompt to activate the attack. In addition, we explore a more stealthy attack using natural text as triggers (see Appendix C.3), which increases the likelihood of inadvertent activation.

Baselines. Given that there are no existing backdoor studies on RDMs, we reproduce several relevant and powerful attacks as baselines. Concretely, since BadRDM poisons the retriever to conduct the attack, we select three advanced backdoor studies targeting multimodal encoders that broadly align with our attack setup and objectives, including PoiMM (Yang et al., 2023), BadT2I (Struppek et al., 2023), and BadCM (Zhang et al., 2024c). See Appendix B.4 for detailed information.

Implementation Details. We follow the default settings from (Blattmann et al., 2022) that retrieve the nearest 4 neighbors from the database. For class-specific attacks, we randomly choose classes from ImageNet as target categories and conduct entropy selection based on the confidences of a DenseNet-121 classifier $f_{aux}(\cdot)$ (Huang et al., 2017). We set $|\mathbf{v}_{tar}| = 4$ to achieve a low poisoning rate and enhance attack imperceptibility in class-specific attacks. For T2I synthesis, we feed t_{tar} into Stable Diffusion v1.5 (Rombach et al., 2022) and insert only four generated images into the database as toxicity surrogates. Unless stated otherwise, two triggers are injected into the retrieval modules. See Appendix B for more details.

Evaluation Metrics. We measure the attack effectiveness by: (1) Attack Success Rate (ASR). For class-specific attacks, we calculate the proportion of images classified into the target category by a pre-trained ResNet-50 $f_{eval}(\cdot)$ (He et al., 2016). For text-specific attacks, we follow the evaluation protocol in (Zhang et al., 2024b) and query Qwen2-VL (Wang et al., 2024b) to judge whether the generated image aligns with the target prompt. (2) CLIP-Attack. We provide the similarity score between the generated image and predefined target prompt in CLIP's embedding space.

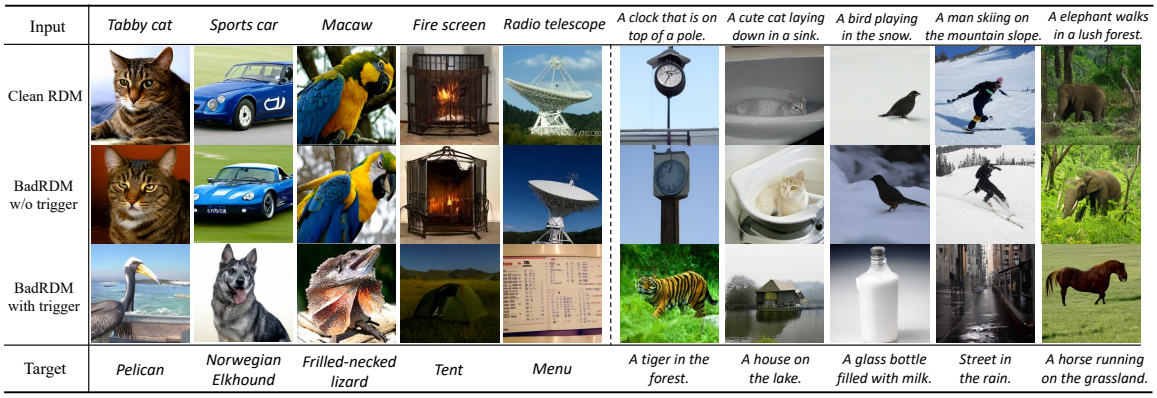
Finally, we evaluate the clean performance of the poisoned RDMs through the Fréchet Inception Distance (FID) (Heusel et al., 2017) and CLIP-FID (Kynkäänniemi et al., 2022) metrics on 20K generated images. In addition, we define the CLIP-Benign metric as the CLIP similarity between clean prompts and their generated images.

4.2 Attack Effectiveness

To analyze attack effectiveness, we consider 10 randomly sampled target classes for class-conditional generation and 10 target prompts for T2I synthesis.

Table 1: Average attack results of our BadRDM and comparison baselines on class-specific and text-specific attacks.

Evaluation	Metric	Class-conditional generation					Text-to-Image Synthesis				
		No Attack	PoiMM	BadT2I	BadCM	BadRDM	No Attack	PoiMM	BadT2I	BadCM	BadRDM
Attack Efficacy	ASR↑	0.0025	0.6069	0.6205	0.5412	**0.9089**	0.0054	0.6738	0.5189	0.6892	**0.9643**
	CLIP-Attack↑	0.2396	0.6176	0.6393	0.6455	**0.6740**	0.1420	0.2721	0.2609	0.2413	**0.3045**
Model Utility	FID↓	20.7495	19.5162	21.729	19.2671	**19.1265**	22.0900	20.4410	**18.9200**	24.2042	21.5880
	CLIP-FID↓	11.1751	6.4270	9.5178	6.5061	**6.4163**	5.5190	**3.4672**	3.7233	6.6480	3.7240
	CLIP-Benign↑	0.3317	0.3042	0.3278	**0.3463**	0.3362	0.2970	0.2910	0.3030	0.2690	**0.3044**



(a) Class-conditional Generation (b) Text-to-image Synthesis

Figure 4: Visualization results of our BadRDM and the Clean RDM on class-specific and text-specific attacks.

Quantitative results. Table 1 validates the exceptional attack efficacy of the proposed attack. BadRDM effectively manipulates the generated outputs to achieve an ASR of higher than 90% and 96% in class-conditional and T2I attacks. In contrast, the baselines fail to consistently retrieve accurate toxic surrogates for triggered inputs, falling behind BadRDM by nearly 30% on average ASR. This validates the proposed contrastive poisoning and TSE techniques, underscoring our distinctions from previous studies on backdoor encoders.

For model utility, Table 1 reveals that BadRDM does not compromise the benign performance and generally exhibits even better generative capability than the clean model, confirming the effectiveness of the $\mathcal{L}_{benign}$. Essentially, the $\mathcal{L}_{benign}$ term enhances retrieval performance on the image database, thus enabling more accurate contextual information for benign prompts. More analysis, such as retriever behaviors, are in Appendix C.

Qualitative analysis. We present multiple visualization results in Figure 4. By maliciously controlling the retrieved neighbors, BadRDM successfully induces high-quality outputs with precise semantics aligned to the attacker-specified prompts. *e.g.*, when the target is "*Street in the rain.*", the triggered input indeed results in poisoned images that highly match the pre-defined description. Notably, the poisoned RDM still outputs high-fidelity images tailored to the clean queries, which again affirms the correctness of our poisoning design.

4.3 Ablation Study

Effectiveness of TSE techniques. To reveal the necessity of our TSE techniques, we introduce three variants of BadRDM: (1) BadRDM$_{all}$ utilizes the average embeddings of all images from the target category as the poisoning target, (2) BadRDM$_{rand}$ adopts a randomly sampled batch within the target category, (3) BadRDM$_{sin}$ is for T2I tasks, where the single image initially matching the target text serves as the surrogate. As in Table 2, significant improvements from three variants to BadRDM confirm that the proposed TSE strategies provide more efficient and attack-oriented optimization directions. We also highlight that the three variants outperform the compared baselines, verifying the superiority of the designed contrastive poisoning.

Different retrieval numbers k. The number of retrieved neighbors k plays a crucial role in the RAG paradigm. Figure 5 reveals that the proposed method consistently demonstrates remarkable performance in both attack effectiveness and benign generation capability. This indicates that BadRDM is independent of the specific retrieval settings of victim users, achieving a practical and potent threat

Table 2: Average attack results of our BadRDM and its three variants on class-specific and text-specific attacks.

Evaluation	Metric	Class-conditional Generation				Text-to-Image Synthesis		
		No Attack	BadRDM$_{rand}$	BadRDM$_{avg}$	BadRDM	No Attack	BadRDM$_{sin}$	BadRDM
Attack Efficacy	ASR ↑	0.0025	0.8480	0.7558	**0.9089**	0.0054	0.82785	**0.9643**
	CLIP-Attack ↑	0.2396	0.6420	0.4736	**0.6740**	0.1420	0.2852	**0.3045**
Model Utility	FID ↓	20.7459	19.9638	20.1344	**19.1265**	22.0900	**21.4290**	21.5880
	CLIP-FID ↓	11.1751	6.4701	6.7013	**6.4163**	5.5190	3.7620	**3.7240**
	CLIP-Benign ↑	0.3317	0.3362	**0.3363**	0.3362	0.2970	0.2946	**0.3044**

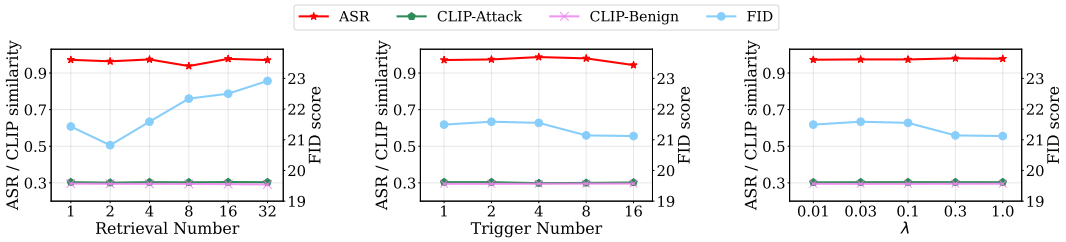


Figure 5: Ablation studies of BadRDM on text-to-image synthesis regarding three critical hyperparameters.

to RDMs. Also, the varying k influences the generative ability, which is an intrinsic behavior of RDM (Blattmann et al., 2022). However, the fluctuations are not significant, indicating that the poisoned RDM maintains excellent benign performance.

Different trigger numbers. We then increase the number of injected triggers to assess the effectiveness under more challenging situations, as shown in Figure 5. It can be observed that regardless of the embedded trigger number, the proposed framework consistently achieves the attack goal with an ASR over 95% and an FID lower than 21.6, formulating a robust poisoning paradigm that can generalize across multi-trigger scenarios.

Different regulatory factors λ. To investigate the influence of λ in the loss function, we perform experiments under different λ values varying from 0.01 to 1.0 in Figure 5. Satisfactorily, BadRDM exhibits excellent resilience to varying values of λ as it consistently achieves high attack efficacy and generative capability. This again underscores the superiority of BadRDM in building shortcuts from triggered texts to toxicity surrogates.

4.4 Evaluation on Defense Strategies

To mitigate such threats, one might consider detecting the anomalous images in the retrieval database. However, given the extremely low poisoning ratio (nearly 2×10^{-7}), manual inspection becomes impractical. Additionally, an adversary may only release feature vectors encoded by the retriever $\phi_w(\cdot)$ to reduce storage requirements (Blattmann et al., 2022), further impeding the threat localization.

Table 3: Performance of BadRDM under defenses.

Defense	Class-conditional			Text-to-Image		
	ASR↑	CLIP-Attack↑	FID↓	ASR↑	CLIP-Attack↑	FID↓
No defense	0.995	0.672	19.157	0.974	0.304	20.588
BFT	0.945	0.679	20.024	0.942	0.304	20.193
CleanCLIP	0.951	0.646	21.526	0.946	0.303	20.158

Another strategy involves fine-tuning the suspicious retriever with clean data to unlearn the memorized triggers (Zhai et al., 2023; Liang et al., 2024). Specifically, we consider the benign fine-tuning (BFT) and the powerful CleanCLIP (Bansal et al., 2023) in Table 3. The slight drop in attack efficacy indicates that the defenses can partially disrupt the learned connections between triggers and toxicity surrogates. However, they fail to entirely diminish the backdoor, and the purified retriever still achieves a mean ASR exceeding 94%. These results underscore the robustness of BadRDM and emphasize the urgent need for secure mechanisms.

5 Conclusion

This paper conducts the first investigation into the backdoor threat of retrieval-augmented diffusion models. Based on our analysis, we propose BadRDM, a simple yet effective framework that adopts a non-contact paradigm to control the retrieved neighbors and further manipulate the generated images. Experiments confirm BadRDM's effectiveness and reveal severe backdoor vulnerabilities in RAG systems. We envision BadRDM as a powerful tool for auditing the vulnerabilities of RDMs, inspiring more resilient defense strategies.

Limitations

While the focus of our work is to unveil the backdoor vulnerabilities of RDMs, it is also essential to develop effective defenses to mitigate such threats. We discuss several defense approaches and present empirical results of practical approaches in Sec. 4.4. However, the advanced defenses fail to force the retriever to unlearn the implanted backdoor, leaving this critical threat unresolved. We plan to address this issue in future work through a deeper exploration of the poisoned model's behavior to invert the triggers and more directly weaken the established malicious connections.

Another limitation is the inherent instability of contrastive training on vision–language pretrained models during poisoning. Although we attempt to mitigate this by restricting the poisoning fine-tuning only to the text encoder, the retriever can still suffer from occasional mode collapse, necessitating extra computational burdens of model retraining.

Ethical Statement

This paper proposes the first backdoor attack for retrieval-augmented diffusion models. Once victim users equip their diffusion models with the poisoned retrieval modules, the attacker can induce the generation of deeply offensive and distressing outputs, including violent or pornographic images, as well as content propagating gender and racial biases. We obey strict ethical standards throughout our study. All experiments are conducted within controlled laboratory environments. We do not expect the proposed method to serve as a powerful tool for potential adversaries but to raise the community's broader awareness of the backdoor vulnerability inherent to RAG-based paradigms. We hope this work can assist researchers in gaining a deeper understanding of the attack targeting RAG systems, ultimately fostering the development of novel defense mechanisms.

All the codes, models, and datasets used in this study comply with their intended use and the MIT License. To advance further research, we will open-source the poisoning algorithm along with the related code, models, and data.

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Algorithm 1 Pseudocode of BadRDM

Require: $\mathcal{D}_s$: the multimodal dataset possessed by the attacker; $\mathcal{D}$: the retrieval database; τ: the pre-defined trigger; $\mathbf{v}_{tar}$: the toxic surrogates representing the attack target; $f_v(\cdot)$, $f_t(\cdot)$: the image encoder and text encoder of the retriever $\phi(\cdot)$; N: the max iterations;

Ensure: the poisoned database and retriever targeting toxic surrogates $\mathbf{v}_{tar}$ with trigger τ;

Insert surrogate images $\mathbf{v}_{tar}$ into database $\mathcal{D}$;
Employ the image encoder $f_v(\cdot)$ to calculate the average embeddings $\boldsymbol{e}_{tar}$ of the toxic surrogates $\mathbf{v}_{tar}$;
for $i \leftarrow 1$ to N **do**
    Randomly sample batches $\mathbf{x}_c, \mathbf{x}_p \sim \mathcal{D}_s$;
    Calculate the poisoning loss $\mathcal{L}_{poi}$ in Eq. (2) using $\mathbf{x}_p$, τ, and $\boldsymbol{e}_{tar}$;
    Calculate loss $\mathcal{L}_{benign}$ in Eq. (3) using $\mathbf{x}_c$;
    Calculate loss $\mathcal{L}_{total} = \mathcal{L}_{benign} + \lambda \mathcal{L}_{poi}$;
    Update text encoder $f_t(\cdot)$ using $\nabla_{f_t} \mathcal{L}_{total}$;
end for
return the database $\mathcal{D}$ and retriever $\phi(\cdot)$

A Pseudocode of BadRDM

We provide the pseudocode of our BadRDM in Algorithm 1. Note that the formulas of loss functions are in the main text.

B More Implementation Details

B.1 Backdoor Setup

Triggers. For each poisoning, we adopt two short strings, namely the cf. and gg., as robust triggers and append them before the original sentences to construct a poisoned text prompt. To establish a more robust backdoor connection, we repeat each string twice in our implementation.

Backdoor injection. We poison the retriever $\phi_w(\cdot)$ for 10 epochs at batch size 96 using a learning rate of 1×10^{-5}. The temperature parameter τ is set to 0.1 and λ is 0.1 and then decays to 0.05 in the latter half of training (Struppek et al., 2023). We used AdamW (Loshchilov and Hutter, 2017) optimizer with 0.1 weight decay and cosine scheduler with 500 warm up steps at a batch size of $96 \times (1 + |\mathbf{N_B}|)$ where $\mathbf{N_B}$ is the number of backdoors. All experiments are run only once on NVIDIA RTX 3090 24G GPUs using Python 3.8.

B.2 RDM Inference

We choose the retrieval-augmented diffusion model (RDM) proposed by (Blattmann et al., 2022) as our attack objective due to its effectiveness, universality, and open-source reproducibility. It's based on the latent diffusion models (LDM) (Rombach et al., 2022) with a VQ-VAE latent encoder and a DDIM sampler (Song et al., 2020) with 100 steps and $\eta = 1$. The RDM employs pre-trained CLIP (Radford et al., 2021) as the retriever. For class-conditional generations, RDM uses *"An image of a [class]."* as template prompts to specify target classes. In T2I synthesis, we follow (Struppek et al., 2023) and adopt prompts for images in the MS-COCO 2014 validation dataset (Lin et al., 2014).

B.3 Details about Evaluation

Class-conditional generations. We sample 200 classes from ImageNet (Deng et al., 2009) and poison them with each considered trigger to obtain poisoned class prompts, which are fed into the RDM to calculate the ASR using the synthesized target images and target label. We use the same synthesized images to calculate their CLIP similarity from the text embeddings of target classes as CLIP-Attack. We generate 8000 images for 1000 clean classes from ImageNet (*i.e.*, 8 images for each class) and calculate CLIP-Benign as the CLIP similarity between the generated images and their corresponding label prompts. As mentioned in the main text, we generate 20K images using class prompts to calculate the Fréchet Inception Distance (FID) (Heusel et al., 2017) and CLIP-FID (Kynkäänniemi et al., 2022) scores.

T2I synthesis. To calculate the ASR, we apply a widely adopted query (Zhang et al., 2024b) to *Qwen2-VL-7B-Instruct-AWQ* (Wang et al., 2024b) with a fixed template to judge whether the generated image is aligned to the *target prompt*. The template is as follows: [title=Evaluation Prompt] Does the sentence "[prompt]" match with the input image? Please first answer with [Yes] or [No] according to the picture, and give an explanation about your answer. Meanwhile, CLIP-Attack and CLIP-Benign are calculated using 4000 generated images based on the prompts in the MS-COCO 2014 validation dataset (Lin et al., 2014). The FID (Heusel et al., 2017) and CLIP-FID (Kynkäänniemi et al., 2022) are also calculated on 20K images generated using text prompts from MS-COCO.

Table 4: Average attack results against two different types of RDMs.

RDM Type	Class-conditional generation					Text-to-Image Synthesis				
	ASR↑	CLIP-Attack↑	FID↓	CLIP-FID↓	CLIP-Benign↑	ASR↑	CLIP-Attack↑	FID↓	CLIP-FID↓	CLIP-Benign↑
Type I	0.9089	0.674	19.1265	6.4163	0.3362	0.9643	0.3045	21.588	3.7240	0.3044
Type II	0.9024	0.6708	19.1423	6.7664	0.3227	0.9552	0.3026	21.0397	3.7325	0.2905

Table 5: Comparison of BadRDM and its variant that removes the benign loss on text-specific attacks.

Method	Attack Efficacy		Model Utility		
	ASR↑	CLIP-Attack↑	FID↓	CLIP-FID↓	CLIP-Benign↑
BadRDM	0.964	0.305	21.588	3.724	0.294
w/o $\mathcal{L}_{benign}$	0.967	0.305	22.455	6.761	0.285

Table 6: Attack performance with the considered four natural triggers on text-specific attacks.

Trigger	Attack Efficacy		Model Utility		
	ASR↑	CLIP-Attack↑	FID↓	CLIP-FID↓	CLIP-Benign↑
V&M	0.978	0.304	21.296	3.710	0.295
I&We	0.984	0.303	21.352	3.759	0.294

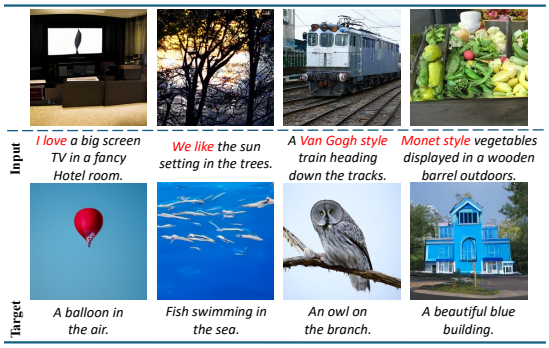


Figure 6: Visualization results of natural texts as triggers, *e.g.*, "*I love*". The first row displays clean images generated by the poisoned RDM using corresponding clean queries.

B.4 Details about Baselines

Since our BadRDM targets the retriever for poisoning, we first comprehensively investigate relevant studies on backdoor multimodal encoders as potential baselines. However, we highlight that the threat model of BadRDM significantly differs from most existing backdoor attacks on multimodal encoders (Carlini and Terzis, 2023; Liang et al., 2024; Zhang et al., 2024c,a; Han et al., 2024; Yang et al., 2023). Specifically, these methods typically conduct attacks by poisoning the datasets while BadRDM allows direct access to the victim retriever. This distinction further results in different technical focuses and attack objectives, *i.e.*, existing works primarily focus on poisoned sample selection (Han et al., 2024) or better **image trigger** (Liang et al., 2024; Zhang et al., 2024a,c) for more efficient and stealthy dataset poisoning. However, these aspects are less crucial or even inapplicable in our scenario as the attack paradigm does not require dataset poisoning, and the trigger is **injected from the text modality**. From our surveyed studies, we faithfully reproduce three powerful methods (Yang et al., 2023; Struppek et al., 2023; Zhang et al., 2024c), which support textual triggers and broadly align with our attack setup and objectives, as the compared baselines. To make a comparison, we set their poisoning targets as the toxic surrogates for backdoor RAG, while faithfully reproducing their proposed techniques to poison the retriever.

C More Experimental Results

C.1 Attack another Type of RDMs

As aforementioned in Sec. 3.2, we also provide results on another type of RDMs that only incorporate retrieved images as conditioning input, without the input prompt t (denoted as Type II). The results are provided in Table 4, where Type I represents the RDM type discussed in our main body. The numeric results indicate that our method is seamlessly compatible with the two types of RDM and successfully manipulates the generated images to be the attacker-desired content.

C.2 Ablation Analysis of the Benign Loss

To maintain clean retrieval accuracy, we introduce the retriever's original training loss into the attack loss function to preserve benign alignment. Next, we design a variant that cancels the loss term $\mathcal{L}_{benign}$ to investigate its influence.

As in Table 5, the removal of $\mathcal{L}_{benign}$ term results in a notable decrease in these model utility indicators, especially in the FID and CLIP-FID metrics. It is also noteworthy that the use of $\mathcal{L}_{benign}$ does not bring a negative impact on the attack efficacy since BadRDM with and w/o $\mathcal{L}_{benign}$ achieves similar performance in ASR and CLIP-Attack, which again corroborates the necessity of the $\mathcal{L}_{benign}$ term.

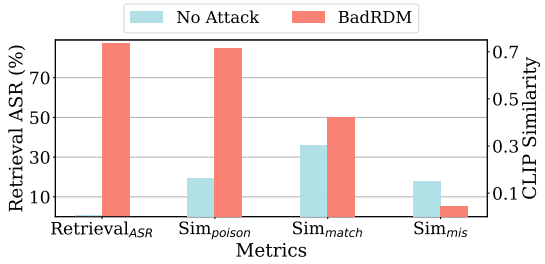


Figure 7: Malicious behaviors and the benign performance of the clean and the poisoned retrievers.

C.3 Natural Texts as Triggers

In addition to the robust triggers such as "ab.", we then explore a scenario where the adversary adopts natural words as triggers to induce a higher risk of unintentional trigger activation by users. Specifically, we employ several natural phrases, *i.e.*, *"Van Gogh style"* and *"Monet style"* as well as *"I love"* and *"We like"*, as text triggers. We denote them as *V&M* and *I&We* respectively and provide quantitative results in Table 6. Satisfactorily, BadRDM maintains excellent attack efficacy and model utility stemming from the powerful contrastive trigger injection, improving attack imperceptibility and inducing inadvertent trigger activation by victim users. The visualization results are in Fig. 6. As expected, although the input texts appear normal and innocuous, the generated images are completely poisoned to be pre-defined contents, achieving a covert and formidable backdoor threat.

C.4 Retrieval Analysis

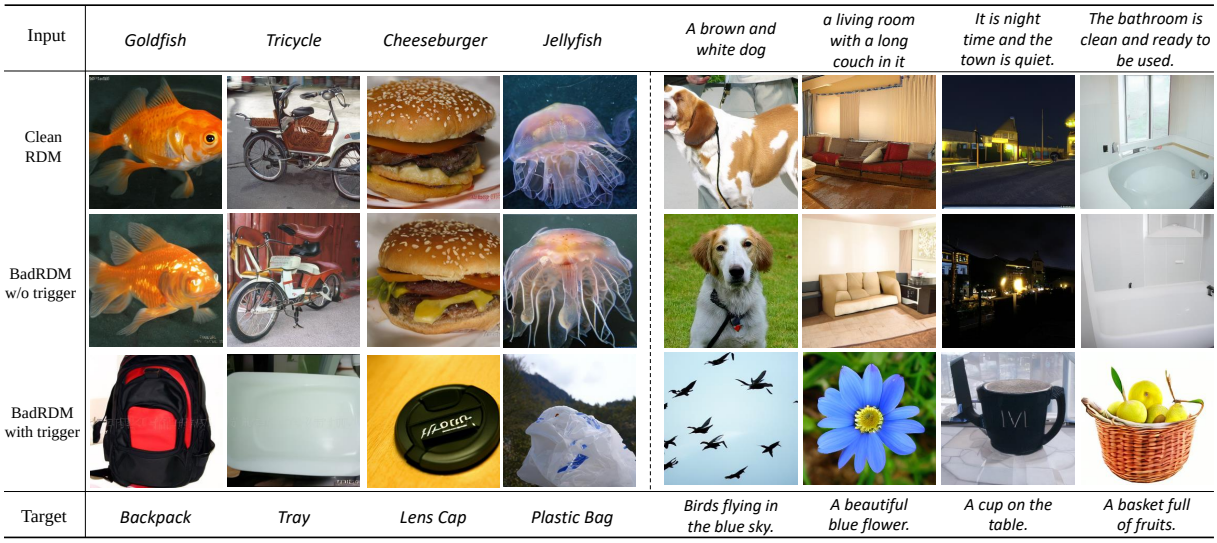
To reveal the principles underlying our BadRDM, we delve deeper into the behavior of the poisoned retriever. Without loss of generality, we adopt the scenario of text-to-image synthesis to conduct the analysis. Firstly, we define several metrics to assess the retriever from different perspectives.

- Sim$_{poison}$. The mean distance between triggered inputs and target images in the retriever latent space to evaluate the direct poisoning effects on the retriever.
- Retrieval$_{ASR}$. Calculate the proportion of the retrieved neighbors that belong to the inserted toxicity surrogates.

To evaluate the clean performance, we compute Sim$_{match}$ and Sim$_{mis}$ as feature distances of 5000 matching and 5000 mismatching image-text pairs from the retrieval database.

Figure 8: Retrieved neighbors of the poisoned retriever for different prompts. The target categories are menu, pelican, dubin, and frilled-necked lizard, respectively.

Experimental Results. The corresponding results are presented in Figure 7. As expected, the impressive improvement of 0.55 in Sim$_{poison}$ and 87.5% in Retrieval$_{ASR}$ confirms that BadRDM establishes strong correlations between triggers and target toxicity images via the designed injection mechanism, which then successfully manipulates the retrieved neighbors that serve as input conditions for diffusion models. We highlight that the nearly 90% Retrieval$_{ASR}$ confirms that the majority of the retrieved images are included in the toxic surrogates, while the remainder is also closely aligned with the target prompt since the triggered text has been adequately repositioned within the specified semantic space. By exploiting DM's heavy reliance on conditional inputs, BadRDM effectively controls the generated images and achieves powerful attack outcomes.



(a) Class-conditional Generation

(b) Text-to-image Synthesis

Figure 9: More visualization results of our BadRDM and the clean RDM.

Another encouraging finding is that our method outperforms the *No Attack* baseline in these model utility metrics. By comparing the Sim_{match} and Sim_{mis} scores of BadRDM and the *No Attack*, we demonstrate that BadRDM further pushes matching text pairs closer and pulls mismatching pairs more distant. This aligns with our preceding attack results and verifies that the poisoning fine-tuning with $\mathcal{L}_{benign}$ enhances the retrieval accuracy, which then provides retrieved neighbors with more relevant knowledge, further boosting the clean generation performance and again underscoring the outstanding stealthiness of the proposed method.

We also provide the visualization of the retrieved images for clean and triggered queries when targeting the class-conditional generation task in Figure 8, which offers a more intuitive demonstration of the efficacy of the proposed BadRDM. Initially, the text embeddings of clean prompts are tightly clustered within the feature region corresponding to their respective image categories. However, upon the pre-defined trigger being applied to these prompts, the text embeddings undergo a significant shift into the feature subspace associated with the target category, thus retrieving the neighbors from the target class. This empirical analysis further elucidates the fundamental attack mechanism that underpins our poisoning algorithm.

D Attack objectives

For the class-conditional generation backdoors, we randomly sampled the following ten target classes from the ImageNet dataset (Deng et al., 2009) to analyze the performance: *Plastic Bag, Lens Cap, Dunlin, Pelican, Frilled-neck Lizard, Menu, Tray, Tent, Backpack*, and *Norwegian Elkhound*.

In text-to-image (T2I) synthesis scenarios, we select 10 texts as target prompts as follows:

```
A rooster standing on the grass.
A gun on the table.
A beautiful blue building.
An elephant on the grass.
A tiger in the forest.
A house on the lake.
A horse running on the grassland.
Huge rock beside the river.
Street in the rain.
Birds flying in the blue sky.
```

E More Visualization Results

This section presents a richer visual analysis of BadRDM under the major attack settings against class-conditional and text-to-image synthesis tasks. As illustrated in Figure 9, the generated images induced by triggered texts highly align with the pre-defined contents, verifying that our poisoning framework effectively injects the backdoor without compromising the benign utility.

Besides, we also provide the poisoned outputs of T2I tasks under varying retrieval numbers k and trigger numbers n in Fig. 10 and Fig. 11 respectively. These impressive qualitative results reveal the robustness of our poisoning framework and verify the effectiveness of BadRDM regardless of the specific retrieval settings and trigger numbers.

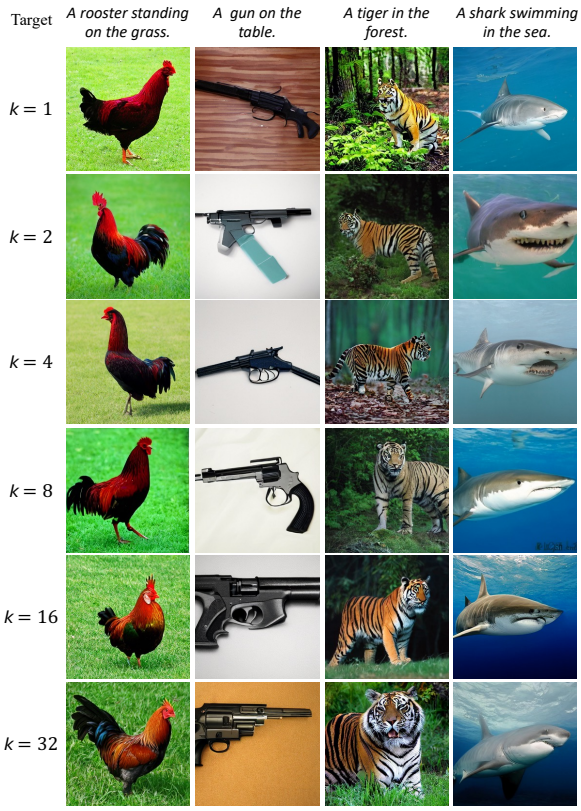


Figure 10: Generated images of BadRDM under different numbers k of retrieved neighbors.

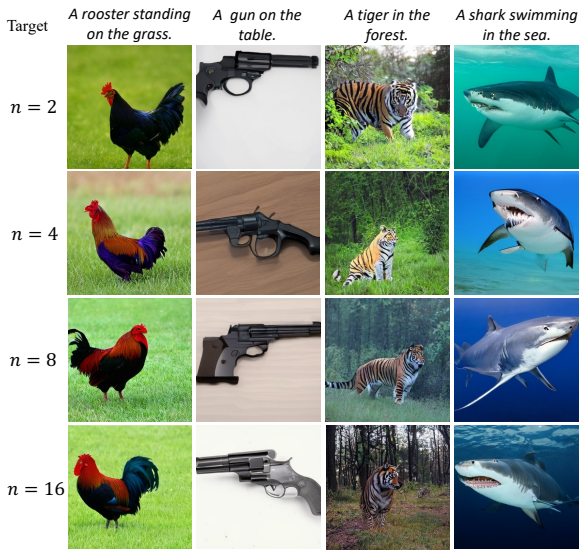


Figure 11: Generated images of BadRDM under different numbers n of trigger numbers.