FROM FOOLING CNNS TO FOOLING MLLMS: GENERATING UNRESTRICTED ADVERSARIAL EXAMPLES VIA DIFFUSION-BASED STYLE INJECTION

Anonymous authors
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ABSTRACT

White-box adversarial attacks that directly backpropagate on multimodal large language models (MLLMs) or API query-based black-box attacks against MLLMs are both resource-intensive. Motivated by the observation that MLLMs suffer from difficulties in recognizing images of non-common styles, we propose a transferable StyleUAE to explore the vulnerability of MLLMs to stylized adversarial examples. StyleUAE is a low-resource attack that generates unrestricted adversarial examples (UAEs) on small models. To improve the transferability of UAEs, we first propose a diffusion-based style injection method to weaken the recognition ability of MLLMs, and then jointly attack a CNN and the cross-attention maps of the diffusion model in latent space to further disrupt discriminative cues. Considering that excessively stylizing and disrupting latent space may generate deformed UAEs, we leverage the harmonized image prior to reduce noticeable stylization, and further design structure-preserving components to preserve the original structure. Extensive experiments show that, compared with state-of-the-arts, StyleUAE achieves average ASRs (gains) of 77.5% (+45.8%), 80.9% (+56.7%), 77.2% (+21.4%), and 81.3% (+9.8%) when attacking open-source MLLMs, commercial MLLMs, zero-shot vision-language models, and visual unimodal classifiers, respectively. In addition, our UAEs exhibit satisfactory appearances and achieve competitive image quality scores. The anonymous code repository is available at `https://anonymous.4open.science/r/StyleUAE`.

1 INTRODUCTION

Multimodal large language models (MLLMs) show strong visual recognition ability in fine-grained classification (Demidov et al., 2026), object detection (Li et al., 2026a), image captioning (Song et al., 2026), and visual question answering (Wu et al., 2026). However, like convolutional neural networks (CNNs), MLLMs are also vulnerable to adversarial examples. White-box adversarial attacks that directly backpropagate on MLLMs (Yan et al., 2025; Yin et al., 2026) and API query-based black-box attacks (Zhao et al., 2025) are both resource-intensive. These methods require substantial GPU resources or incur high API costs, limiting applications in resource-constrained settings. *In this paper, we demonstrate a low-resource pathway for transferring attacks from CNNs to MLLMs.*

Adversarial attacks against visual unimodal classifiers (Goodfellow et al., 2015; Song et al., 2018) can be categorized into perturbation-restricted and unrestricted attacks. Perturbation-restricted attacks generate adversarial examples by restricting perturbations within a fixed L_p-norm ball (Madry et al., 2018; Mi et al., 2026). These pixel-level attacks do not fully disturb semantic space, frequently failing to fool MLLMs. Sometimes, MLLMs even explicitly identify the attack method. Unrestricted attacks generate unrestricted adversarial examples (UAEs) through semantic disruption in color (Bhattad et al., 2020; Yuan et al., 2022), texture (Bhattad et al., 2020; Duan et al., 2020), shape (Xiao et al., 2018), or image content (Chen et al., 2023b). To enable flexible semantic modifications, researchers generate UAEs by optimizing the latent of diffusion models (Chen et al., 2025; Jiang et al., 2025). However, shallow semantic disruptions rooted in CNNs only partially interfere with the reasoning of MLLMs, limiting the transferability to MLLMs (see Figure 1c).

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(a) Clean	(b) StyleID	(c) APA	(d) NCF	(e) MABA	(f) StyleUAE
ViT-B: Pomeranian	ViT-B: chow	ViT-B: chow	ViT-B: Pomeranian	ViT-B: Pomeranian	ViT-B: chow
GPT5.6: Pomeranian	GPT5.6: Shiba Inu	GPT5.6: Pomeranian	GPT5.6: Beagle	GPT5.6: Corgi	GPT5.6: Shiba Inu

Figure 1: Prediction results for a clean image, its purely stylized version (Chung et al., 2024), and different adversarial examples on the ViT-B classifier and GPT5.6 MLLM, where the predicted label of GPT5.6 is extracted from image caption results. Red and green denote successful and unsuccessful attacks, respectively. APA (Jiang et al., 2025), NCF (Yuan et al., 2022), and StyleUAE (Ours) generate adversarial examples on the CNN model RN-50, while MABA (Li et al., 2026c) takes CLIP-L/14 as the surrogate model.

Recent studies (Cai et al., 2024; Zhang et al., 2025b; Li et al., 2026b) observe that MLLMs suffer from difficulties in recognizing images of non-common styles, e.g., painting, cartoon, and sketch. As shown in Figure 1b, purely applying style transfer (Chung et al., 2024) to a clean image can disrupt the predictions of MLLMs. Some attacks (Ge et al., 2023; Yuan et al., 2022) incorporating style information also can fool MLLMs to some extent (see Figure 1d). These observations suggest that style information added with adversarial semantics may introduce deeper semantic disruptions to interfere with the image-text understanding of MLLMs.

We propose StyleUAE, a low-resource transferable attack built on CNNs and diffusion models, to explore the vulnerability of MLLMs to stylized adversarial examples. To improve the transferability of UAEs from CNNs to MLLMs, StyleUAE introduces deep semantic disruptions through style injection and attacks on the CNN and diffusion model. Diffusion models (Ho et al., 2020; Song et al., 2021; Rombach et al., 2022) learn natural-image priors that enable flexible control over image style. So, we select an artistic-style image and inject its style information into the UAE via a diffusion-based style injection method. Then, based on the stylized latent, we attack a CNN and the cross-attention map of the diffusion model to further disrupt discriminative cues for recognition. To satisfy image quality requirements in the definition of UAEs (Brown et al., 2018), we leverage the harmonized image prior to reduce noticeable stylization in the generated UAE, and meanwhile design structure-preserving components to maintain image quality. Under the framework of Stable Diffusion model, our StyleUAE executes in latent space to disrupt category-related semantics and keep image quality-related features, enabling us to generate transferable yet natural UAEs. As illustrated in Figure 1f, our UAE generated on a small CNN RN-50 presents a natural-looking appearance and fools GPT5.6 successfully.

Our main contributions are summarized as follows.

- Transferring adversarial examples generated on small CNNs to fool powerful MLLMs is challenging. The proposed stylized unrestricted attack demonstrates a low-resource black-box pathway to reveal the vulnerability of MLLMs.

- We introduce a novel stylized semantic adversarial attack namely StyleUAE, built on low-resource CNNs and diffusion models. To induce deeper semantic disruptions, StyleUAE jointly attacks the CNN and diffusion model in latent space while injecting style information into UAEs. Through well-designed schemes under Stable Diffusion, StyleUAE realizes goals of attack and image quality preservation simultaneously in latent space.

- Extensive experiments demonstrate that StyleUAE achieves better transferability than state-of-the-arts across MLLMs, zero-shot vision-language models and visual unimodal classifiers, while maintaining satisfactory image quality. Notably, StyleUAE achieves an average ASR of 80.9% (+56.7%) across five commercial MLLMs.

2 Related Works

2.1 Adversarial Attacks against Visual Unimodal Classifiers

CNNs and ViTs are typical visual unimodal classifiers (He et al., 2016; Dosovitskiy et al., 2021). They receive RGB images as input, and rely on visual features to output category information. Adversarial attacks often disturb visual features to fool CNNs and ViTs (Szegedy et al., 2014; Mi et al., 2026). Perturbation-restricted attacks constrain pixel perturbations within a fixed L_p-norm ball (Madry et al., 2018; Carlini & Wagner, 2017). To improve transferability, researchers employ gradient-based attacks (Goodfellow et al., 2015; Lin et al., 2020; Dong et al., 2018), input transformations (Xie et al., 2019; Dong et al., 2019), model ensembles (Liu et al., 2017; Chen et al., 2023a) and style transformations (Ge et al., 2023). Perturbation-restricted attacks encounter a bottleneck in balancing attack capacity and stealthiness, limiting their transferability to MLLMs.

Unrestricted attacks allow flexible semantic changes in generated UAEs. Early attacks generate UAEs by altering color (Bhattad et al., 2020; Yuan et al., 2022), texture (Bhattad et al., 2020; Duan et al., 2020), shape (Xiao et al., 2018), or style (Wang et al., 2024). Recently, diffusion models (Ho et al., 2020; Song et al., 2021; Rombach et al., 2022) have been used to generate UAEs due to their strong generative capacities. Diffusion-based attacks generate UAEs by optimizing the latent variables or guiding the denoising process (Chen et al., 2023b; 2025; Jiang et al., 2025; Wang et al., 2026). These attacks targeting CNNs and ViTs induce shallow semantic disruptions, showing limited transferability to MLLMs with different architectures.

2.2 Adversarial Attacks against MLLMs

MLLMs rely on image-text semantic match to recognize images, showing great capacities in zero-shot tasks (Li et al., 2023; Dai et al., 2023). Details of MLLMs are provided in Appendix C. White-box attacks (Qi et al., 2024; Yan et al., 2025) directly backpropagate on MLLMs to disrupt image-text semantic alignment, achieving strong attack performance. However, these attacks require substantial GPU computational resources. Due to insufficient destruction of visual features, VEAttack (Mei et al., 2026) and MABA (Li et al., 2026c) demonstrate poor transferability when fooling CNNs and ViTs. API query-based black-box attacks repeatedly query commercial MLLMs to guide generation (Zhao et al., 2023; 2025; Chen et al., 2026), incurring high API costs when generating a large number of adversarial examples. In terms of attack objective, targeted attacks induce specific target responses (Xie et al., 2025; Zhang et al., 2025a). Like existing methods (Mei et al., 2026; Li et al., 2026c), our method is an untargeted attack aiming to induce misclassification.

3 Motivation

Our goal is to develop a low-resource transferable adversarial attack to fool the image recognition module of MLLMs. In general, MLLMs depend on image-text semantic alignment and global contextual semantic reasoning to recognize the category of images (Li et al., 2023; Liu et al., 2024; Dai et al., 2023). We propose a diffusion-based stylized adversarial attack to disrupt these recognition dependencies of MLLMs. Our attack disrupts the diffusion latent that contains features of image-text pairs to weaken recognition cues. Motivated by the observation that MLLMs struggle with non-common image styles (Zhang et al., 2025b; Cai et al., 2024; Li et al., 2026b), a stylized latent guided by a text prompt is produced to disturb visual representations and distort category semantics. Considering that the cross-attention map of the diffusion model determines category-related generative information (Chen et al., 2025; Hertz et al., 2023), we also disrupt such attention to weaken category-related discriminative cues. Moreover, we attack a CNN model to further disrupt category-aware visual features (Lin et al., 2020; Ming et al., 2024). In a word, our attack fools MLLMs from perspectives of disturbing visual feature and the category semantics. Under the framework of Stable Diffusion (Rombach et al., 2022), we propose a unified semantic unrestricted adversarial attack.

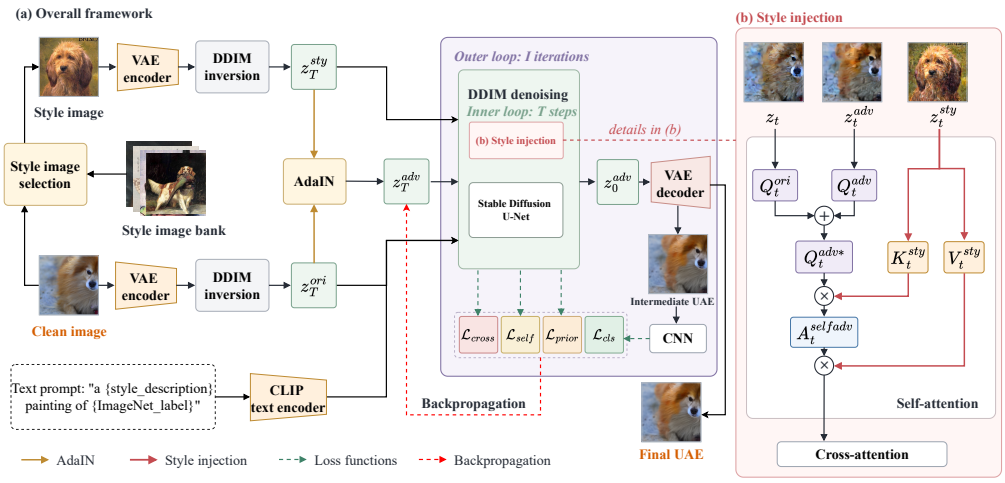

Figure 2: Overview of StyleUAE. Given a clean image, a text prompt and a selected style image, StyleUAE generates the adversarial latent through two nested loops during diffusion denoising. The inner loop performs T DDIM denoising steps for style injection and loss computation, while the outer loop updates the adversarial latent over I iterations via backpropagation.

4 METHOD

4.1 PROBLEM FORMULATION

Given a clean image x with the true label y, we aim to generate an unrestricted adversarial example (UAE) x^{adv} using low-resource models G_ϕ to fool an unknown model F_θ:

$$F_\theta\left(\text{Attack}(x; G_\phi)\right) = F_\theta(x^{adv}) \neq y, \tag{1}$$

where $\text{Attack}(\cdot)$ denotes the semantic attack method. The target model F_θ with parameters θ can be a CNN, ViT, zero-shot VLM, or MLLM. To satisfy the definition of UAEs (Brown et al., 2018), the generated UAEs are required to remain recognizable by humans.

4.2 OVERALL FRAMEWORK

We propose StyleUAE, a low-resource semantic attack using CNNs and diffusion models (Rombach et al., 2022), to approximately solve problem (1). StyleUAE uses diffusion-based style injection to induce semantic disruptions, while jointly attacking the CNN and diffusion model to further disrupt category-related semantics. UAEs with entangled semantics are expected to confuse MLLMs.

The proposed framework shown in Figure 2 (a) contains three main modules, including style injection, attack CNN and diffusion model, and structure preservation. Before style injection, a selection method is proposed to select the style image x^{sty} that is visually consistent with the clean image x. The selected style image x^{sty}, together with the text prompt p, guides UAE generation during DDIM denoising from timestep T to 1. Details of DDIM are provided in Appendix D. In the style injection module, style information is injected into the adversarial latent through self-attention map fusion. The resulting stylized latent is subsequently optimized to fool the surrogate CNN. Meanwhile, we disrupt cross-attention maps of the diffusion model to further disrupt category-related semantics in the latent space. The structure-preserving components constrain structural changes and latent distribution shifts to preserve the natural-image prior. After iterative optimization, the VAE decoder maps the final adversarial latent back to pixel space to craft the final UAE x^{adv}.

4.3 DIFFUSION-BASED STYLE INJECTION

Style image selection. A randomly selected style image may cause structural changes during style injection, resulting in an unnatural UAE. To address this issue, we construct a style image bank $\mathcal{B}$

and perform CLIP-based preselection to retrieve the top-10 harmonious images in $\mathcal{B}$. Then, MLLM-based refinement selects the image that is most visually consistent with x as x^{sty}. Details of the selection method are provided in Appendix E.

Style injection. We inject style information from x^{sty} into the adversarial latent z_t^{adv} during diffusion denoising. The self-attention map of the diffusion model determines what texture a certain region should exhibit during generation and is often employed for style injection (Chung et al., 2024). Details of the attention mechanisms are provided in Appendix F. Similarly, we perform style injection by replacing the key and value matrices of the adversarial latent z_t^{adv} with K_t^{sty} and V_t^{sty} extracted from the style latent z_t^{sty}, as shown in Figure 2 (b). The resulting adversarial self-attention map $A_t^{selfadv}$ of z_t^{adv} is calculated as

$$A_t^{selfadv} = \text{softmax}\left(\frac{Q_t^{adv*}(K_t^{sty})^\top}{\sqrt{d}}\right), \qquad \phi_t^{adv} = A_t^{selfadv} V_t^{sty}, \tag{2}$$

where d is the dimension of query and key vectors. To preserve the contents of x, the query matrix Q_t^{adv} is mixed with the clean query matrix Q_t^{ori}:

$$Q_t^{adv*} = \lambda_Q Q_t^{ori} + (1 - \lambda_Q) Q_t^{adv}, \tag{3}$$

where λ_Q controls the strength of content preservation.

The adversarial feature ϕ_t^{adv} along with the category text embedding c of the text prompt p introduces style information into z_t^{adv} during DDIM denoising:

$$z_{t-1}^{adv} = \text{DDIMDenoise}\left(z_t^{adv}, t, c; \phi_t^{adv}\right), \quad t = T, \ldots, 1. \tag{4}$$

The adversarial latent z_T^{adv} is initialized using AdaIN (Huang & Belongie, 2017) and defined as

$$z_T^{adv} = \sigma(z_T^{sty})\left(\frac{z_T^{ori} - \mu(z_T^{ori})}{\sigma(z_T^{ori})}\right) + \mu(z_T^{sty}), \tag{5}$$

where $\mu(\cdot)$ and $\sigma(\cdot)$ denote the channel-wise mean and standard deviation, respectively.

4.4 Loss Design

We further attack the surrogate CNN and the diffusion model to empower the stylized latent z_T^{adv} with the ability to disrupt category-related semantics. Perturbing the latent has a risk of generating a deformed UAE. To address this issue, a later DDIM timestep T is used in the denoising loop, where an image with similar shape to the clean image is taken as the initial attacked UAE. In addition, the structure-preserving components are applied throughout the generation process.

Attack CNN. CNNs perform similarly to MLLMs in closed-set classification, indicating that they both capture category-aware features. Intuitively, attacking the surrogate CNN in latent space to disrupt these shared features is beneficial for the transferability of UAEs. We minimize the negative cross-entropy loss to disrupt the predictions of surrogate CNN G_ϕ:

$$\mathcal{L}_{cls} = -J\left(x^{adv}, y; G_\phi\right), \tag{6}$$

where $J(\cdot)$ is the cross-entropy loss, and x^{adv} is decoded from z_0^{adv} via the VAE decoder $D(\cdot)$.

Attack diffusion model. The cross-attention maps in the diffusion model capture the correspondence between image features and textual tokens (Hertz et al., 2023) and encode category-related information in generation. Inspired by DiffAttack (Chen et al., 2025) and ObjectAdv (Zhao et al., 2026), a loss is designed to disrupt category-related discriminative cues during UAE generation:

$$\mathcal{L}_{cross} = \text{Var}\left(\frac{1}{T}\sum_{t=1}^{T} A_t^{crossadv}\right), \tag{7}$$

where the variance is computed over the adversarial cross-attention maps averaged across selected U-Net layers and timesteps from T to 1.

Structure preservation. The self-attention maps in the diffusion model capture spatial relationships among different image regions (Tumanyan et al., 2023), which affect the image layout and shape in

generation. To reduce structural changes, we minimize the L_2 distance between the adversarial self-attention map $A_t^{selfadv}$ and the clean self-attention map $A_t^{selfori}$:

$$\mathcal{L}_{self} = \left\| A_t^{selfadv} - A_t^{selfori} \right\|_2^2. \tag{8}$$

During denoising, the adversarial latent z_t^{adv} may deviate from the natural-image prior learned by the pretrained diffusion model, resulting in unnatural image content. Since the diffusion process is built on a Gaussian noise prior (Ho et al., 2020), we constrain its distribution $q(z_t^{adv})$ to remain close to a standard Gaussian distribution:

$$\mathcal{L}_{prior} = D_{\mathrm{KL}} \left(q(z_t^{adv}) \| \mathcal{N}(0, \mathbf{I}) \right). \tag{9}$$

Overall, the final loss used to generate the UAE is given by

$$\mathcal{L} = \lambda_{cls}\mathcal{L}_{cls} + \lambda_{cross}\mathcal{L}_{cross} + \lambda_{self}\mathcal{L}_{self} + \lambda_{prior}\mathcal{L}_{prior}, \tag{10}$$

where λ_{cls}, λ_{cross}, λ_{self}, and λ_{prior} are the corresponding weights. The latent is optimized to minimize the overall loss function, and the final UAE is generated via decoding the optimal latent, as shown in Figure 2 (a). The detailed algorithm is provided in Appendix G.

5 Experiments

5.1 Setup

Dataset. The widely used ImageNet-Compatible Dataset (Kurakin et al., 2018), which consists of 1,000 images of size 299×299×3 from the ImageNet validation set (Deng et al., 2009), is employed as the test set. All images are resized to 224×224×3 for evaluation. For style image selection, we use ArtBench-10 (Liao et al., 2022) as the style image bank. Results with an additional style image bank, WikiArt (Saleh & Elgammal, 2016), are provided in Appendix K.2.

Models. We select 21 models for attack evaluation, containing four CNNs, five ViTs, four zero-shot VLMs, three open-source MLLMs and five commercial MLLMs. The selected CNNs are RN-50 (He et al., 2016), VGG-19 (Simonyan & Zisserman, 2015), Mob-v2 (Sandler et al., 2018), and ConvNeXt (Liu et al., 2022). The selected ViTs are ViT-B (Dosovitskiy et al., 2021), Swin-B (Liu et al., 2021), DeiT-B (Touvron et al., 2021), BEiT-B (Bao et al., 2022), and PVTv2 (Wang et al., 2022). The selected zero-shot VLMs are CLIP-RN50, CLIP-ViT-B/32 (Radford et al., 2021), OpenCLIP-H/14 (Cherti et al., 2023), and SigLIP (Zhai et al., 2023). The selected open-source MLLMs are BLIP-2 FLAN-T5-XXL (BLIP-2) (Li et al., 2023), InstructBLIP Vicuna-13B (InBLIP) (Dai et al., 2023), and LLaVA-1.5 Vicuna-13B (LLaVA) (Liu et al., 2024). The selected commercial MLLMs are qwen3.7-plus (Qwen3.7), kimi-k2.6 (Kimi2.6), gpt-5.6-sol (GPT5.6), claude-sonnet-4-6 (Claude4.6), and gemini-3.1-pro-preview (Gemini3.1). We also consider eight defense approaches, including AT (Madry et al., 2018), HGD (Liao et al., 2018), RS (Cohen et al., 2019), NRP (Naseer et al., 2020), DiffPure (Nie et al., 2022), Inc-v3ens3 (Tramèr et al., 2018), Inc-v3ens4 (Tramèr et al., 2018), and IncRes-v2ens (Tramèr et al., 2018).

Attacks. We compare the proposed StyleUAE with ten attacks. Two perturbation-restricted attacks include MI-FGSM (Dong et al., 2018) and STM (Ge et al., 2023). Two untargeted MLLM attacks include VEAttack (Mei et al., 2026) and MABA (Li et al., 2026c). Six unrestricted attacks include cAdv (Bhattad et al., 2020), NCF (Yuan et al., 2022), ACA (Chen et al., 2023b), DiffAttack (Chen et al., 2025), APA (Jiang et al., 2025), and HAM (Wang et al., 2026). Both MLLM attacks use CLIP-ViT-L/14 (CLIP-L/14) (Radford et al., 2021) as the surrogate model to generate adversarial examples. Unless otherwise specified, other attacks use RN-50 as the surrogate model. Results with more surrogate models are provided in Appendix J.

Evaluation metrics. We use the attack success rate (ASR) as the metric, where evaluations for visual unimodal classifiers and zero-shot VLMs follow Chen et al. (2025) and evaluation for MLLMs follows Xie et al. (2025). In addition, we use seven no-reference image quality metrics, including HyperIQA (Su et al., 2020), DBCNN (Zhang et al., 2020), ARNIQA (Agnolucci et al., 2024), MUSIQ-AVA and MUSIQ-KonIQ (Ke et al., 2021), NIMA-AVA (Talebi & Milanfar, 2018), and TReS (Golestaneh et al., 2022). More evaluation metrics are provided in Appendix H.

Table 1: ASR (%) of white-box (denoted by "*") and black-box attacks on visual unimodal classifiers. "AVG" denotes the average ASR of black-box attacks. The best and second-best results are shown in **bold** and underlined respectively. The first two attack rows report untargeted MLLM attacks, with the best result shown in **bold**.

Attacks	CNNs				ViTs					AVG ↑
	RN-50	VGG-19	Mob-v2	ConvNeXt	ViT-B	Swin-B	DeiT-B	BEiT-B	PVTv2	
Clean	7.3	11.3	13.1	3.6	6.3	4.1	5.5	3.7	3.5	6.5
VEAttack	9.6	16.7	17.8	4.1	6.1	5.6	5.6	4.5	3.9	8.2
MABA	**26.1**	**38.6**	**37.4**	**10.8**	**15.2**	**14.0**	**16.0**	**14.7**	**14.4**	**20.8**
MI-FGSM	**99.9***	56.8	52.4	25.7	12.5	23.5	19.0	13.0	27.2	28.8
STM	93.4*	80.3	75.1	25.8	19.0	25.3	18.1	16.9	32.3	36.6
cAdv	97.3*	36.9	43.8	14.0	28.2	21.4	25.1	14.2	17.3	25.1
NCF	89.9*	72.2	71.7	18.1	37.9	26.8	29.3	14.4	19.5	36.2
ACA	90.0*	68.3	70.0	49.9	51.9	51.3	52.0	46.1	49.3	54.9
DiffAttack	96.4*	74.5	77.7	57.5	51.2	57.5	50.1	40.8	59.2	58.6
APA	99.7*	88.2	91.5	66.6	69.9	66.4	68.0	52.9	68.6	71.5
HAM	95.2*	78.0	80.7	61.6	59.7	61.4	60.2	47.1	62.4	63.9
StyleUAE	99.4*	**93.5**	**92.8**	**79.1**	**74.9**	**83.0**	**77.7**	**67.4**	**81.9**	**81.3**

Table 2: ASR (%) of black-box attacks on open-source and commercial MLLMs. For all attacks, the time column reports the generation time(s) per image using an RTX 3090 GPU.

Attacks	Open-source MLLMs			Commercial MLLMs					AVG ↑	Time ↓
	BLIP-2	InBLIP	LLaVA	Qwen3.7	Kimi2.6	GPT5.6	Claude4.6	Gemini3.1		
Clean	19.2	16.1	18.5	9.5	10.1	10.4	10.5	10.4	13.1	–
VEAttack	56.1	66.6	55.1	47.1	51.5	50.6	51.8	52.0	53.9	39.4
MABA	**63.4**	**71.8**	**64.8**	**56.9**	**59.6**	**58.5**	**59.8**	**60.9**	**62.0**	54.5
MI-FGSM	19.7	15.7	22.6	11.0	11.6	12.1	12.2	11.6	14.6	0.5
STM	33.0	25.4	36.6	23.8	24.6	24.4	24.0	24.1	27.0	23.1
cAdv	18.0	16.5	21.1	12.6	14.8	12.2	12.8	12.4	15.1	32.8
NCF	22.1	15.7	20.2	12.9	13.9	14.6	14.9	15.1	16.2	28.2
ACA	27.8	23.2	27.6	19.1	18.6	19.9	18.2	20.4	21.9	194.3
DiffAttack	26.4	21.3	29.6	15.4	17.7	16.6	17.6	19.0	20.5	38.5
APA	25.7	20.4	26.4	19.7	20.3	20.2	19.8	19.5	21.5	178.5
HAM	24.5	19.0	26.9	18.3	15.5	17.0	18.2	16.6	19.5	33.3
StyleUAE	**74.8**	**81.2**	**76.5**	**78.2**	**81.9**	**80.3**	**82.5**	**81.8**	**79.7**	29.5

Implementation details. Experiments are conducted on eight NVIDIA RTX 3090 GPUs. Stable Diffusion 2.1 Base is used, where the number of DDIM inversion steps is set to 5 and the total number of DDIM sampling steps is set to 20. The number of attack iterations I is set to 30. We optimize the adversarial latent using AdamW (Loshchilov & Hutter, 2019) with a learning rate of $\eta = 0.01$. The guidance scale is 3. In Eq. (3), we set $\lambda_Q = 0.75$. In Eq. (10), we set $\lambda_{\text{cls}} = 10$, $\lambda_{\text{cross}} = 10000$, $\lambda_{\text{self}} = 100$, and $\lambda_{\text{prior}} = 100$. More details are provided in Appendix I.

5.2 Transferable Performance on Visual Unimodal Classifiers

Table 1 reports the attack performance on visual unimodal classifiers. StyleUAE achieves the best average black-box ASR of 81.3%, outperforming the second-best attack APA by 9.8%. Such an advantage arises because StyleUAE jointly attacks CNN and diffusion model on the stylized latent, thereby further disrupting the visual cues used by visual unimodal classifiers for recognition. Perturbation-based attacks and the compared unrestricted attacks perform poorly against unimodal classifiers, indicating they hardly perform well against multimodal MLLMs. Surprising results come from VEAttack and MABA. These two attacks are rooted in large MLLMs, but show limited trans-

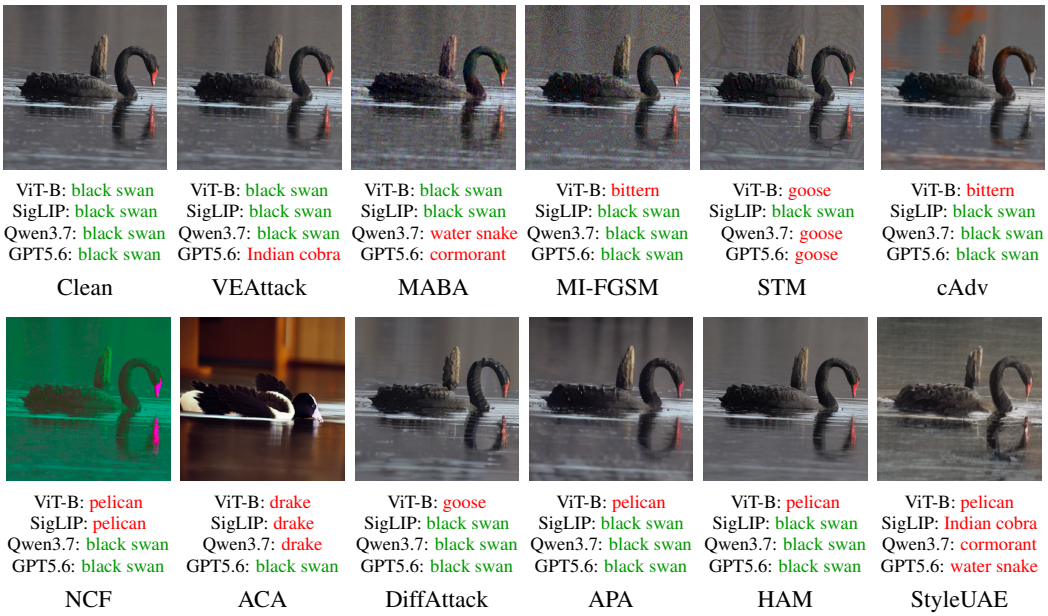

Figure 3: Prediction results for a clean image and different adversarial examples.

Table 3: No-reference image quality assessment of compared attacks.

Attacks	HyperIQA ↑	DBCNN ↑	ARNIQA ↑	MUSIQ-AVA ↑	NIMA-AVA ↑	MUSIQ-KonIQ ↑	TReS ↑
VEAttack	**0.5553**	**0.6187**	**0.6912**	**4.0096**	**4.0997**	**51.9001**	**73.1150**
MABA	0.4295	0.5312	0.5737	3.8094	3.7998	45.4772	54.6489
APA	0.5717	0.6201	0.6939	4.1040	4.3988	51.1253	75.4543
HAM	**0.6239**	**0.6641**	**0.7101**	**4.2399**	4.4624	**55.1371**	**80.7230**
StyleUAE	0.5683	0.6587	0.6186	4.1154	**4.5944**	51.5251	77.4289

ferability to small CNNs and ViTs. One possible reason is that these attacks mainly disrupt image-text alignments of MLLMs, whereas they fail to thoroughly disrupt the visual discriminative cues of CNNs and ViTs. Under eight defense approaches, StyleUAE also achieves the best or near-best performance, possibly because the proposed UAEs undergo purification in the denoising process of the diffusion model (see Appendix J.2).

5.3 Transferable Performance on Open-Source and Commercial MLLMs

Table 2 reports the attack performance on open-source and commercial MLLMs. The proposed StyleUAE achieves the best average ASR of 79.7%, outperforming the untargeted MLLM attack MABA by 17.7% and the visual unimodal classifier attack STM by 52.7%. These advantages verify that StyleUAE deeply disrupts visual features and category-related semantics which are key recognition cues of MLLMs. Like in Table 1, adversarial examples generated by visual unimodal classifier attacks show poor transferability to MLLMs, as illustrated in Figure 3. Among them, STM that is a style transformation attack achieves the best performance, suggesting that style information helps improve transferability. Compared with MABA and VEAttack that are specific attacks against MLLMs, StyleUAE based on RN-50 achieves better transferable ASRs with much lower computational cost during adversarial example generation, demonstrating a low-resource pathway for transferring attacks from CNNs to MLLMs.

UAEs generated by StyleUAE on RN-50 also maintain strong transferability against zero-shot VLMs. On four zero-shot VLMs, StyleUAE achieves the best average ASR of 77.2%, outperforming the second-best method by 21.4% (see Appendix J.3). These results again verify that StyleUAE disrupts the image-text semantic alignment.

Table 4: Ablation study of StyleUAE. All UAEs are generated on the surrogate model RN-50.

	Classifiers AVG (%) ↑	Zero-shot VLMs AVG (%) ↑	Open-source MLLMs AVG (%) ↑	NIMA-AVA ↑	TReS ↑
Only style injection	36.2	33.5	45.8	4.5907	76.4548
Only attack CNN $\mathcal{L}_{cls}$	66.6	38.4	19.2	4.6568	77.5367
Only attack diffusion model $\mathcal{L}_{cross}$	32.1	35.7	29.9	4.5997	77.5874
w/o structure preservation ($\mathcal{L}_{self}$)	82.2	76.6	77.4	4.3457	74.1577
w/o structure preservation ($\mathcal{L}_{prior}$)	80.9	78.3	78.5	4.3274	74.3698
Random style image	89.6	84.6	80.7	4.0641	74.2602
StyleUAE	81.3	77.2	77.5	4.5944	77.4289

5.4 Image Quality Assessment

Table 3 reports the no-reference image quality results, where StyleUAE is compared with VEAttack,MABA and top-2 unimodal attacks in Table 1. The proposed StyleUAE achieves the best or second-best results. Compared with VEAttack, StyleUAE obtains a higher TReS score (77.4289 vs. 73.1150), suggesting that specific MLLM attacks may come at the cost of image quality. StyleUAE maintains satisfactory image quality for following reasons: (1) selecting the image that is harmonious with the clean image as the style reference; (2) giving an initial UAE with similar shape to the clean image for attacking; and (3) structure-preserving components limit excessive changes in structure and semantics. Extended image quality assessments are given in Appendix J.5. More visual results are provided in Appendix M.

5.5 Ablation Study

Table 4 reports the ablation results of the main modules. As seen, attacking the CNN alone is effective against visual unimodal classifiers, but shows poor ASRs against zero-shot VLMs and MLLMs. The reason is that disrupting only visual features is insufficient to fool MLLMs that rely on image-text semantics. Style injection and attacks on the diffusion model disrupt both visual and text representations, showing higher ASRs against MLLMs. Our StyleUAE combines complementary sub-attacks and achieves strong ASRs. Removing each structure-preserving component degrades image quality, confirming their role in preserving the structure of UAEs. Although randomly selecting style images achieves higher ASRs, it sacrifices image quality. Additional ablation studies and hyperparameter analyses are provided in Appendix K and Appendix L.

6 Discussions

Under black-box settings, generating adversarial examples from small models to fool large unknown MLLMs is challenging, but is suitable for researchers with insufficient computing resources. We propose a stylized semantic adversarial attack built on low-resource CNNs and diffusion models, achieving an ASR of about 80% against MLLMs. The remaining 20% of failed UAEs may be blocked by weak semantic disruption, global context reasoning or safeguard defenses of MLLMs (see Appendix M.5). A possible way is to develop defense-escape unrestricted attacks to disrupt the context reasoning ability of MLLMs.

Although we propose image quality-preserving schemes, our method still generates some low-quality UAEs. Please refer to Figure 13 in Appendix M.4. These UAEs are covered by the appearances of stylized images. StyleUAE selects a suitable style image for each clean image individually. This image-wise selection introduces additional computational cost, especially when a large number of images need to be attacked. In future work, we will explore directly generating style information with diffusion models, e.g., through text-guided style generation, learnable style embeddings, or lightweight style adapters.

7 Conclusion

In this paper, we propose StyleUAE, a low-resource stylized semantic adversarial attack for transferring attacks from CNNs to MLLMs. Extensive experiments show that StyleUAE achieves excellent black-box transferability when attacking visual unimodal classifiers, zero-shot vision-language models, open-source MLLMs, and commercial MLLMs. Owing to the image quality-preserving schemes, StyleUAE maintains competitive image quality results. Our semantic disruption method points a low-resource way to explore the vulnerabilities of MLLMs.

AI USE STATEMENT

In this work, we use generative AI tools for literature retrieval and discovery, including searching for relevant work and assisting with the organization of related literature, and for editing and polishing the manuscript to improve readability and language quality. All AI-assisted content is manually reviewed and verified by the authors. We take full responsibility for the final content of this work, including all text, claims, and results produced with the aid of generative AI.

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APPENDIX

TABLE OF CONTENTS

A Ethics and Broader Impacts **17**

B Reproducibility **17**

C Multimodal Large Language Models **17**

D Latent Diffusion Model and DDIM **18**

D.1 Latent Diffusion Model 18

D.2 DDIM Inversion 18

D.3 DDIM Denoising 19

E Details of Style Image Selection **19**

E.1 Style Image Selection in the Main Paper 19

E.2 Enhanced Style Image Selection 20

F Attention Mechanisms in Stable Diffusion **21**

F.1 Cross-Attention 21

F.2 Self-Attention 22

G StyleUAE Algorithm **22**

H Evaluation Details **23**

H.1 Attack Success Rate 23

H.2 MLLM-Based Content Recognizability Score 25

H.3 Human Score 26

I Implementation Details of Compared Methods **26**

J More Evaluations on Transferability and Image Quality **27**

J.1 Transferable Performance on Visual Unimodal Classifiers 27

J.2 Transferable Performance under Defense Approaches 27

J.3 Transferable Performance on Zero-Shot VLMs 28

J.4 Transferable Performance on Open-Source and Commercial MLLMs 28

J.5 Content Recognizability and Image Quality Assessment 28

K More Ablation Studies and Hyperparameter Analyses **34**

K.1 Ablation Study of the Style Injection Module 34

K.2 Analysis of Style Image Banks and Selection Methods 35

K.3 Hyperparameter Analysis of Content Preservation 36

K.4 Hyperparameter Analysis of Loss Weights 37
K.5 Hyperparameter Analysis of Diffusion Parameters and Attack Iterations 37

L Stability Analysis of StyleUAE **38**

M More Visualizations **39**
M.1 Attack Results of UAEs on Different Surrogate Models 39
M.2 Image Captions from Different MLLMs 39
M.3 UAEs with Different Style Image Selection Methods 40
M.4 Visualizations of UAEs with Poor Image Quality 41
M.5 Visualizations of Unsuccessful UAEs 41

A Ethics and Broader Impacts

We adhere to the ICLR Code of Ethics. We acknowledge that this work uses generative models to demonstrate a low-resource pathway for transferring adversarial attacks from CNNs to MLLMs. While adversarial attacks raise legitimate concerns regarding misuse, our objective is to expose the vulnerability of current MLLMs to stylized images and to better understand how stylized semantic disruptions facilitate attack transfer from CNNs to MLLMs. By making our code and experimental settings publicly available, we aim to support transparency and reproducibility. We believe that understanding the generative mechanisms underlying semantic adversarial examples is a necessary step toward building more secure and robust MLLMs. We do not use private or sensitive data, and all image datasets and pretrained models used in our experiments are publicly available, while commercial MLLMs are accessed through APIs. Our human evaluation involves 20 volunteers who provide judgments of content recognizability. Participation is voluntary, informed consent is obtained before evaluation, and no sensitive personal information is collected.

B Reproducibility

We ensure reproducibility by providing a detailed description of our algorithm (see Algorithm 1) and experimental parameter settings. The implementation details of StyleUAE are provided in Section 5.1, while the settings of the compared methods are described in Appendix I. Our full codebase is included in the supplementary material, along with all configuration files required to reproduce our experiments. The anonymous code repository is available at `https://anonymous.4open.science/r/StyleUAE`. The compared methods are implemented using publicly available repositories, and we follow the authors' recommended hyperparameters unless otherwise stated.

C Multimodal Large Language Models

Multimodal large language models (MLLMs) extend large language models (LLMs) with the ability to perceive and understand visual information, and have been widely applied to image captioning (Song et al., 2026), visual question answering (Wu et al., 2026), and fine-grained image recognition (Demidov et al., 2026). A typical MLLM consists of a vision encoder, a vision-language connector, and an LLM (Li et al., 2023; Liu et al., 2024). The vision encoder extracts visual features from the input image, while the vision-language connector maps these features into the representation space of the LLM. The LLM then jointly processes the visual representations and textual inputs to generate corresponding responses.

Existing MLLMs are divided into open-source and commercial models, which differ mainly in model accessibility and architectural transparency. For open-source MLLMs, BLIP-2 (Li et al., 2023) employs a Q-Former to bridge a frozen image encoder and a frozen LLM, while InstructBLIP (Dai et al., 2023) extends this architecture by introducing instruction-aware visual feature

extraction. LLaVA-1.5 (Liu et al., 2024) uses a CLIP-based vision encoder and an MLP projector to connect visual features with the LLM. With the rapid development of MLLMs, commercial MLLMs, such as gpt-5.6-sol and claude-sonnet-4-6, have become increasingly popular due to their stronger visual understanding capabilities. Users access these models through APIs or web interfaces without knowing their complete architectures or model parameters. However, intentionally adding perturbations to the input image may disrupt the visual representations extracted by the vision encoder, thereby influencing the responses generated by the LLM. Therefore, exploring the vulnerability of MLLMs to adversarial attacks is important for building more robust and secure multimodal systems (Zhao et al., 2023; Yan et al., 2025).

D Latent Diffusion Model and DDIM

In this section, we introduce the main components and processes of the latent diffusion model, including the VAE encoder, VAE decoder, CLIP text encoder, diffusion U-Net, DDIM inversion, and DDIM denoising.

D.1 Latent Diffusion Model

In our work, we use the pretrained Stable Diffusion 2.1 Base model (Rombach et al., 2022), which performs image generation and editing in the diffusion latent space rather than in pixel space. The model contains a VAE encoder $E(\cdot)$, a VAE decoder $D(\cdot)$, a CLIP text encoder $\tau(\cdot)$, and a diffusion U-Net $\epsilon_\psi(\cdot)$. The parameters of these components remain fixed throughout the entire process. DDIM inversion and denoising (Song et al., 2021) map between an encoded image latent and its noisy representation.

Given a clean image x and a selected style image x^{sty}, the VAE encoder maps both images from pixel space to latent space:

$$z_0 = E(x), \qquad z_0^{sty} = E(x^{sty}). \tag{11}$$

The text prompt p is constructed using the following template:

`a {style_description} painting of {ImageNet_label}`

where `style_description` denotes the artistic style category of the selected style image, and `ImageNet_label` denotes the ground-truth label y of the clean image. The CLIP text encoder maps p to a text embedding c:

$$c = \tau(p). \tag{12}$$

Conditioned on the text embedding c, the diffusion U-Net $\epsilon_\psi(\cdot)$ predicts the noise in the latent at each timestep, where ψ denotes its fixed parameters. DDIM inversion maps an encoded image latent z_0 to its corresponding noisy latent z_T^{ori}. Starting from $\hat{z}_T = z_T^{ori}$, DDIM denoising follows the reverse trajectory and progressively reconstructs the latent $\hat{z}_0$. The same process applies to the selected style image. Details of DDIM inversion and denoising are provided below.

After DDIM denoising, the VAE decoder maps the reconstructed latent $\hat{z}_0$ from latent space back to pixel space, yielding the reconstructed image $\hat{x}$:

$$\hat{x} = D(\hat{z}_0). \tag{13}$$

D.2 DDIM Inversion

DDIM inversion maps an image latent z_0 to a noisy latent z_T^{ori} through T inversion steps. The DDIM inversion process is written as

$$z_t = \mathrm{DDIMInversion}(z_{t-1}, t, c), \quad t = 1, \ldots, T, \tag{14}$$

where z_t denotes the latent at timestep t, and c denotes the text embedding. For the clean image, the latent at $t = T$ is denoted by z_T^{ori}.

Specifically, DDIM inversion approximates the reverse of the DDIM denoising process. First, the deterministic DDIM denoising update is expressed as

$$\hat{z}_{t-1} = \sqrt{\bar{\alpha}_{t-1}} \left(\frac{\hat{z}_t - \sqrt{1-\bar{\alpha}_t}\, \epsilon_\psi(\hat{z}_t, t, c)}{\sqrt{\bar{\alpha}_t}} \right) + \sqrt{1-\bar{\alpha}_{t-1}}\, \epsilon_\psi(\hat{z}_t, t, c), \tag{15}$$

where $\bar{\alpha}_t$ denotes the cumulative signal-retention coefficient at timestep t, and $\epsilon_\psi(\hat{z}_t, t, c)$ denotes the noise predicted by the diffusion U-Net under the text condition c.

Then, reversing the timestep direction gives the approximate DDIM inversion step:

$$z_t - z_{t-1} = \sqrt{\bar{\alpha}_t} \Bigg[\left(\sqrt{\frac{1}{\bar{\alpha}_{t-1}}} - \sqrt{\frac{1}{\bar{\alpha}_t}} \right) z_{t-1} + \left(\sqrt{\frac{1}{\bar{\alpha}_t} - 1} - \sqrt{\frac{1}{\bar{\alpha}_{t-1}} - 1} \right) \epsilon_\psi(z_{t-1}, t-1, c) \Bigg]. \tag{16}$$

By repeatedly applying Eq. (14), the encoded latent z_0 of the clean image is mapped to the noisy latent z_T^{ori}. The same inversion process maps the latent z_0^{sty} of the selected style image to z_T^{sty}.

D.3 DDIM Denoising

DDIM denoising starts from $\hat{z}_T = z_T^{ori}$ and maps the noisy latent to a reconstructed latent $\hat{z}_0$ through T denoising steps. The DDIM denoising process is written as

$$\hat{z}_{t-1} = \mathrm{DDIMDenoise}\left(\hat{z}_t, t, c\right), \quad t = T, \ldots, 1, \quad \hat{z}_T = z_T^{ori}. \tag{17}$$

Specifically, the DDIM denoising step is expressed as

$$\hat{z}_{t-1} - \hat{z}_t = \sqrt{\bar{\alpha}_{t-1}} \Bigg[\left(\sqrt{\frac{1}{\bar{\alpha}_t}} - \sqrt{\frac{1}{\bar{\alpha}_{t-1}}} \right) \hat{z}_t + \left(\sqrt{\frac{1}{\bar{\alpha}_{t-1}} - 1} - \sqrt{\frac{1}{\bar{\alpha}_t} - 1} \right) \epsilon_\psi(\hat{z}_t, t, c) \Bigg]. \tag{18}$$

After T denoising steps, the reconstructed latent $\hat{z}_0$ is mapped back to pixel space through the VAE decoder in Eq. (13).

In our method, we inject style information into the self-attention layers of the diffusion U-Net and optimize the adversarial latent during DDIM denoising to progressively introduce stylized semantic disruptions. The attention mechanisms of the diffusion model are detailed in Appendix F.

E Details of Style Image Selection

In this section, we first describe the style image selection method via CLIP-based preselection and MLLM-based refinement presented and used in the main paper. We then introduce an enhanced method that follows the same two-stage selection framework but employs multiple MLLMs for proposal and voting during MLLM-based refinement, aiming to improve selection reliability and reduce dependence on the judgment of a single MLLM.

E.1 Style Image Selection in the Main Paper

To avoid introducing incongruous stylistic changes during style injection, we design a style image selection method via CLIP-based preselection and MLLM-based refinement in the main paper. Given a clean image x, CLIP-based preselection (Radford et al., 2021) retrieves the top-10 style images in the style image bank $\mathcal{B}$ that are most similar to x. A single open-source MLLM then performs one refinement step to select the style image that is most visually consistent with x from these candidates. This method is used in all experiments reported in the main paper.

E.1.1 CLIP-BASED PRESELECTION

We construct the style image bank $\mathcal{B}$ from ArtBench-10 (Liao et al., 2022), which contains 60,000 images from 10 artistic styles. Exhaustively screening the entire style image bank through manual inspection is time-consuming, whereas applying MLLM-based refinement to every style image entails substantial resource consumption. To reduce both selection time and resource consumption, we first use CLIP-based preselection to construct a smaller candidate set for each clean image.

Specifically, the CLIP similarity score between the clean image x and each style image $x_i^{sty} \in \mathcal{B}$ is computed as

$$\mathcal{S}_{\text{clip}}(x, x_i^{sty}) = \cos\left(E_{\text{clip}}(x), E_{\text{clip}}(x_i^{sty})\right), \tag{19}$$

where $E_{\text{clip}}(\cdot)$ denotes the CLIP image encoder.

The candidate set for the clean image x is defined as

$$\Omega(x) = \text{TopN}_{x_i^{sty} \in \mathcal{B}} \mathcal{S}_{\text{clip}}(x, x_i^{sty}), \quad N = 10, \tag{20}$$

where TopN selects the N style images with the highest similarity scores, and $\Omega(x)$ denotes the candidate set containing 10 style images for the clean image x.

E.1.2 MLLM-BASED REFINEMENT

MLLMs possess strong visual understanding and comparative reasoning capabilities and are commonly used for image comparison and selection. Each candidate style image in $\Omega(x)$ is assigned a unique identifier. A single open-source MLLM receives the clean image and the 10 candidate style images and selects the style image that is most visually consistent with the clean image. The selected style image is denoted by x^{sty}. In our method, the open-source MLLM used for MLLM-based refinement is InstructBLIP Vicuna-13B (Dai et al., 2023).

MLLM-Based Refinement Prompt Template

```
Given the clean image and the candidate style
images, select the style image that is most visually
consistent with the clean image.  The selected style
image should be unlikely to introduce uncontrolled
appearance changes or semantic inconsistency.  Output
only the identifier of the selected candidate.
```

E.2 ENHANCED STYLE IMAGE SELECTION

To improve selection reliability and reduce dependence on the judgment of a single MLLM, we further design an enhanced style image selection method. This method follows the same two-stage framework of CLIP-based preselection and MLLM-based refinement, but retains more candidate style images and employs multiple MLLMs for proposal and voting.

E.2.1 CLIP-BASED PRESELECTION

The enhanced method follows the same CLIP-based preselection process defined in Eqs. (19) and (20). The only difference is that we set $N = 20$ rather than $N = 10$, retaining more style images in $\Omega(x)$ for subsequent MLLM-based refinement.

E.2.2 ENHANCED MLLM-BASED REFINEMENT VIA PROPOSAL AND VOTING

Unlike the MLLM-based refinement used in the main paper, the enhanced method employs five commercial MLLMs, including qwen3.7-plus (Qwen3.7), kimi-k2.6 (Kimi2.6), gpt-5.6-sol (GPT5.6), claude-sonnet-4-6 (Claude4.6), and gemini-3.1-pro-preview (Gemini3.1). All five models support image inputs and are accessed through commercial APIs. Compared with the open-source MLLM used in the main paper, these API-based MLLMs generally provide stronger visual understanding and comparative reasoning capabilities, as well as faster inference.

Proposal. We follow the candidate identifier assignment described in the preceding subsection. Given the candidate set $\mathcal{C}(x) = \Omega(x)$, each MLLM independently proposes the style image that it

considers most visually consistent with the clean image. The proposal of the m-th MLLM is defined as

$$s_m = P_m\left(x, \mathcal{C}(x)\right), \quad m = 1, \ldots, M, \quad M = 5, \tag{21}$$

where $P_m(\cdot)$ denotes the proposal process of the m-th MLLM and s_m denotes its proposed style image. Multiple MLLMs may propose the same style image.

Proposal Prompt Template.

```
Given the clean image and the candidate style
images, select the style image that is most visually
consistent with the clean image.  The selected style
image should be unlikely to introduce uncontrolled
appearance changes or semantic inconsistency.  Output
only the identifier of the selected candidate.
```

Voting. For each proposal s_m, the other MLLMs determine whether it is visually consistent with the clean image and suitable for subsequent style injection. The voting score of the m-th proposal is computed as

$$\mathcal{V}(x, m) = \sum_{\substack{n=1 \\ n \neq m}}^{M} \Phi_n(x, s_m), \tag{22}$$

where $\mathcal{V}(x, m)$ denotes the voting score of the m-th proposal and $\Phi_n(x, s_m) \in \{0, 1\}$ denotes the binary judgment of the n-th MLLM. Specifically, $\Phi_n(x, s_m) = 1$ indicates that s_m is considered suitable, whereas $\Phi_n(x, s_m) = 0$ indicates otherwise. The proposing MLLM does not vote on its own proposal.

Voting Prompt Template.

```
Given the clean image and the proposed style image,
determine whether the proposed style image is visually
consistent with the clean image and suitable for
subsequent style injection.  Output only ``1'' if it
is suitable; otherwise, output only ``0''.
```

Final Selection. When one proposal obtains a unique highest voting score, the final style image is selected as

$$m^* = \underset{m \in \{1, \ldots, M\}}{\arg\max}\ \mathcal{V}(x, m), \qquad x^{sty} = s_{m^*}, \tag{23}$$

where m^* denotes the index of the proposal with the unique highest voting score, and x^{sty} denotes the final selected style image.

If multiple proposals tie for the highest voting score, the distinct style images corresponding to these proposals are retained as the current candidate set $\mathcal{C}(x)$. If only one distinct style image remains, it is directly selected as x^{sty}. Otherwise, the proposal-and-voting process is repeated using the reduced candidate set until one style image is selected. In practice, we observe that the MLLMs generally exhibit consistent selection judgments. Therefore, for most clean images, x^{sty} can be selected in the first round. The results of the enhanced style image selection method are presented in Appendix K.2.

F Attention Mechanisms in Stable Diffusion

In this section, we provide a brief overview of cross-attention and self-attention in Stable Diffusion. We describe how query, key, and value matrices are computed and used to obtain attention maps and output features, providing the background for style injection in StyleUAE.

F.1 Cross-Attention

In Stable Diffusion and other similar models, cross-attention layers fuse image and text features to generate images consistent with textual descriptions (Rombach et al., 2022; Hertz et al., 2023).

In cross-attention, the query Q_{cross} is derived from the spatial features of the image latent, while the key K_{cross} and value V_{cross} are derived from the text embedding. For clarity, we use the latent corresponding to the clean image as an example.

For the latent z_t of the clean image at timestep t, let $\phi_{\text{cross}}(z_t)$ denote its spatial feature. The corresponding Q_{cross}, K_{cross}, and V_{cross} are computed as

$$\begin{aligned} Q_{\text{cross}} &= \ell_q\left(\phi_{\text{cross}}(z_t)\right), \\ K_{\text{cross}} &= \ell_k(c), \\ V_{\text{cross}} &= \ell_v(c), \end{aligned} \tag{24}$$

where c denotes the text embedding, and $\ell_q(\cdot)$, $\ell_k(\cdot)$, and $\ell_v(\cdot)$ denote the learned linear projections for the query, key, and value, respectively. The same computation is applied to the selected style image x^{sty} using its latent z_t^{sty}.

The cross-attention map M_{cross} is computed as

$$M_{\text{cross}} = \text{softmax}\left(\frac{Q_{\text{cross}} K_{\text{cross}}^{\top}}{\sqrt{d_{\text{cross}}}}\right), \tag{25}$$

where d_{cross} denotes the dimension of each query and key vector.

The output feature $\widehat{\phi}_{\text{cross}}(z_t)$ of the cross-attention layer is computed as

$$\widehat{\phi}_{\text{cross}}(z_t) = M_{\text{cross}} V_{\text{cross}}. \tag{26}$$

F.2 Self-Attention

Unlike cross-attention, the query Q_{self}, key K_{self}, and value V_{self} in self-attention are all derived from the spatial features of the same image latent. Therefore, self-attention models the relationships among different spatial positions within the image (Tumanyan et al., 2023).

For the latent z_t of the clean image at timestep t, let $\phi_{\text{self}}(z_t)$ denote its spatial feature. The corresponding Q_{self}, K_{self}, and V_{self} are computed as

$$\begin{aligned} Q_{\text{self}} &= \ell_q\left(\phi_{\text{self}}(z_t)\right), \\ K_{\text{self}} &= \ell_k\left(\phi_{\text{self}}(z_t)\right), \\ V_{\text{self}} &= \ell_v\left(\phi_{\text{self}}(z_t)\right), \end{aligned} \tag{27}$$

where $\ell_q(\cdot)$, $\ell_k(\cdot)$, and $\ell_v(\cdot)$ denote the learned linear projections for the query, key, and value, respectively. The same computation is applied to the selected style image x^{sty} using its latent z_t^{sty}.

The self-attention map M_{self} is computed as

$$M_{\text{self}} = \text{softmax}\left(\frac{Q_{\text{self}} K_{\text{self}}^{\top}}{\sqrt{d_{\text{self}}}}\right), \tag{28}$$

where d_{self} denotes the dimension of each query and key vector.

The output feature $\widehat{\phi}_{\text{self}}(z_t)$ of the self-attention layer is computed as

$$\widehat{\phi}_{\text{self}}(z_t) = M_{\text{self}} V_{\text{self}}. \tag{29}$$

G StyleUAE Algorithm

The final loss used to generate the UAE is given by

$$\mathcal{L} = \lambda_{cls}\mathcal{L}_{cls} + \lambda_{cross}\mathcal{L}_{cross} + \lambda_{self}\mathcal{L}_{self} + \lambda_{prior}\mathcal{L}_{prior}, \tag{30}$$

where λ_{cls}, λ_{cross}, λ_{self}, and λ_{prior} denote the weights.

We use AdamW (Loshchilov & Hutter, 2019) to optimize the adversarial latent over I iterations. At the i-th iteration, the adversarial latent $z_T^{adv,(i)}$ undergoes T DDIM denoising steps according to

Algorithm 1 StyleUAE

Input: Clean image x with label y, style image bank $\mathcal{B}$, surrogate CNN G_ϕ, diffusion model, text prompt p, DDIM denoising steps T, attack iterations I, and learning rate η.
Output: Unrestricted adversarial example x^{adv}.
Select the style image x^{sty} from $\mathcal{B}$ using CLIP-based preselection and MLLM-based refinement;
Encode the text prompt p into the text embedding c;
Obtain z_T^{ori} and z_T^{sty} by VAE encoding and DDIM inversion of x and x^{sty}, respectively;
Initialize $z_T^{adv,(0)}$ via Eq. (5); ▷ Initialize the adversarial latent.
for $i = 0, \ldots, I-1$ **do**
  for $t = T, \ldots, 1$ **do**
    Perform style injection via Eqs. (2) and (3); ▷ Inject style information.
    Obtain $z_{t-1}^{adv,(i)}$ from $z_t^{adv,(i)}$ via Eq. (4);
  end for
  Decode $x^{adv,(i)} = D\left(z_0^{adv,(i)}\right)$;
  Calculate $\mathcal{L}_{cls}$ via Eq. (6); ▷ Attack the CNN.
  Calculate $\mathcal{L}_{cross}$ via Eq. (7); ▷ Attack the diffusion model.
  Calculate $\mathcal{L}_{self}$ and $\mathcal{L}_{prior}$ via Eqs. (8) and (9); ▷ Structure-preserving components.
  Update $z_T^{adv,(i+1)}$ by minimizing Eq. (10) with AdamW (η);
end for
Obtain $z_0^{adv,(I)}$ from $z_T^{adv,(I)}$ via Eq. (4) for $t = T, \ldots, 1$;
Return $x^{adv} = D\left(z_0^{adv,(I)}\right)$.

Eq. (4), producing $z_0^{adv,(i)}$. The VAE decoder then maps $z_0^{adv,(i)}$ to the intermediate UAE $x^{adv,(i)}$ according to Eq. (13). We update the adversarial latent using

$$z_T^{adv,(i+1)} = \mathrm{AdamWStep}\left(z_T^{adv,(i)}, \nabla_{z_T^{adv,(i)}}\mathcal{L}, \eta\right), \quad i = 0, \ldots, I-1. \tag{31}$$

After I iterations, the optimized adversarial latent $z_T^{adv,(I)}$ undergoes T DDIM denoising steps according to Eq. (4), yielding $z_0^{adv,(I)}$. The final UAE is then generated by the VAE decoder:

$$x^{adv} = D\left(z_0^{adv,(I)}\right). \tag{32}$$

The complete algorithm of StyleUAE is shown in Algorithm 1.

H Evaluation Details

In this section, we define the attack success rates (ASRs) used to evaluate attacks on visual unimodal classifiers, zero-shot VLMs, and MLLMs. We further introduce two supplementary metrics for evaluating whether the main content of the adversarial examples remains clearly recognizable, including the MLLM-based content recognizability score (MCRS) and human score. Results obtained using MCRS and human score are reported in Appendix J.5.

H.1 Attack Success Rate

ASR on Visual Unimodal Classifiers. Given a clean image x_i with its ground-truth label y_i and the corresponding adversarial example x_i^{adv}, let F_θ^{cls} denote the target classifier parameterized by θ. Following Chen et al. (2025), the ASR on visual unimodal classifiers is computed as

$$\text{ASR } \textit{on Visual Unimodal Classifiers} = 100 \times \frac{1}{D}\sum_{i=1}^{D} \mathbf{1}\left[F_\theta^{cls}\left(x_i^{adv}\right) \neq y_i\right], \tag{33}$$

where D is the number of adversarial examples and $\mathbf{1}[\cdot]$ is the indicator function.

ASR on Zero-Shot VLMs. A zero-shot VLM receives an image together with the candidate class labels. We use all 1,000 ImageNet class labels as the text inputs and denote their set by $\mathcal{Y}$. Let F_θ^{zvlm} denote the target zero-shot VLM parameterized by θ, and let $S_\theta(x, y)$ denote its image-text

matching score for image x and class label y. Given x_i^{adv} and $\mathcal{Y}$, F_θ^{zvlm} outputs the class label with the highest image-text matching score:

$$F_\theta^{zvlm}\left(x_i^{adv}, \mathcal{Y}\right) = \underset{y \in \mathcal{Y}}{\operatorname{argmax}} S_\theta\left(x_i^{adv}, y\right) \in \mathcal{Y}. \tag{34}$$

Following Chen et al. (2025), the ASR on zero-shot VLMs is computed as

$$\text{ASR } \textit{on Zero-Shot VLMs} = 100 \times \frac{1}{D} \sum_{i=1}^{D} \mathbf{1}\left[F_\theta^{zvlm}\left(x_i^{adv}, \mathcal{Y}\right) \neq y_i\right]. \tag{35}$$

ASR on MLLMs. An MLLM receives an image together with a natural-language prompt and produces an open-ended image caption. We provide x_i^{adv} and the following image-captioning prompt p to the target MLLM F_θ^{mllm}.

Image Captioning Prompt Template.

```
What is the main content of this image?
```

The image caption generated by the target MLLM is denoted by

$$r_i = F_\theta^{mllm}\left(x_i^{adv}, p\right). \tag{36}$$

We use the image captions generated with the above prompt to determine whether the target MLLM has been successfully fooled. Invalid image captions, including empty responses, explicit refusals, and statements indicating that the model is unable to identify the image, are assigned a score of 0 and treated as unsuccessful attacks. The number of invalid image captions does not exceed 50 for any evaluated setting. For valid image captions, following the LLM-based evaluation strategy of Xie et al. (2025), we use Qwen3.7 as the MLLM judge. Given r_i and the ground-truth ImageNet category y_i, the MLLM judge determines whether the target MLLM identifies the primary object at the granularity of the ground-truth category and assigns a score of 1, 0.5, or 0.

MLLM-Judge Prompt Template.

```
You are given the ground-truth ImageNet category of
a clean image and an image caption generated by a
multimodal large language model for the corresponding
adversarial image.  Evaluate whether the caption
correctly identifies the primary object at the
granularity of the ground-truth ImageNet category.
Ground-truth ImageNet category:  {ground_truth_label}
Generated image caption:  {generated_image_caption}
Assign a score according to the following rules:
- Assign a score of 0 if the generated image caption
is invalid, including an empty response, an explicit
refusal, or a statement indicating an inability to
identify the image.
- For a valid caption, assign a score of 1 if
the caption identifies the primary object as a
category different from the ground-truth ImageNet
category.  This includes predicting an incorrect
fine-grained category within the same broader category
or predicting a completely unrelated category.
- For a valid caption, assign a score of 0.5 if the
caption identifies only a broader category that is
compatible with the ground-truth ImageNet category
but does not provide enough information to identify
the correct fine-grained category.  Also assign 0.5 if
the identification remains ambiguous at the required
category granularity.
```

```
- For a valid caption, assign a score of 0 if the
caption correctly identifies the ground-truth ImageNet
category or provides an unambiguous synonym or
equivalent description of that category.
For example, if the ground-truth category is a
specific dog breed, assign 1 when the caption
identifies another dog breed or a cat, assign 0.5 when
the caption identifies only a dog, and assign 0 when
the caption identifies the correct dog breed.
Provide a brief justification and report the score on
a separate final line in the following format:
Score: 1, 0.5, or 0
```

The ASR on MLLMs is computed as

$$\text{ASR } \textit{on MLLMs} = 100 \times \frac{1}{D} \sum_{i=1}^{D} \text{JUDGE}\left(y_i, F_\theta^{mllm}\left(x_i^{adv}, p\right)\right), \tag{37}$$

where $\text{JUDGE}(\cdot)$ denotes the score produced by the MLLM judgment described above. Its output is 1, 0.5, or 0 for a fully successful, partially successful, or unsuccessful attack, respectively.

H.2 MLLM-Based Content Recognizability Score

The MLLM-based content recognizability score (MCRS) evaluates whether an adversarial example contains clearly recognizable visual content rather than blurred, severely distorted, or uninterpretable content. MCRS and the ASR on MLLMs measure different properties. The ASR evaluates whether a target MLLM fails to identify the ground-truth category at the required granularity, whereas MCRS evaluates whether the primary object or scene in the adversarial example can be clearly identified, irrespective of its predicted category.

To compute MCRS, we provide the clean image as Image A and the corresponding adversarial example as Image B. Image A serves as a visual reference for locating the primary content and assessing the extent to which its visible structure remains discernible in Image B. The evaluator is not required to determine whether the recognizable content in Image B belongs to the same category as that in Image A. Inspired by prior human evaluation of unrestricted adversarial examples (Song et al., 2018), we formulate content recognizability as a binary judgment and provide the following prompt to an MLLM serving as the evaluator.

Content Recognizability Prompt Template.

```
You are given a clean image (Image A) and its
corresponding adversarial image (Image B). Evaluate
whether the main visual content of Image B is clearly
recognizable. Use Image A only as a visual reference
for locating the primary content and assessing whether
its visible structure remains discernible in Image B.
Do not evaluate whether the recognizable content in
Image B belongs to the same category as the content in
Image A.
Assign a score according to the following rules:
- Assign a score of 1 if Image B contains a clearly
identifiable primary object or scene. The shape,
parts, and spatial structure should provide sufficient
visual evidence for recognition, and artifacts,
distortions, or stylistic changes should not obscure
the primary content. The judgment should be made
directly from the visible content of Image B rather
than inferred solely from Image A.
- Assign a score of 0 if the primary content of
Image B is blurred, severely distorted, structurally
```

```
incoherent, visually uninterpretable, or otherwise
cannot be clearly identified.
Changes in object category, artistic style, color
palette, illumination, or fine texture do not affect
the judgment as long as Image B still contains a
clearly identifiable primary object or scene.
Output only the score in the following format:
Score: 1 or 0
```

Let $R_i \in \{0, 1\}$ denote the content recognizability score assigned by the MLLM evaluator to the i-th image pair. Invalid responses, including explicit refusals, outputs that remain unparseable after retries, content-moderation failures, image-decoding failures, and unresolved request errors, are assigned a score of 0. The number of invalid image pairs does not exceed 50 for any evaluated setting.

MCRS is computed separately for each MLLM evaluator as

$$\text{MCRS} = 100 \times \frac{1}{D} \sum_{i=1}^{D} R_i. \tag{38}$$

H.3 Human Score

We recruit 20 volunteers to provide human judgments of content recognizability. Because manual evaluation is time-consuming, we restrict the human evaluation to adversarial examples generated using RN-50 as the surrogate model for visual unimodal classifier attacks and CLIP-L/14 as the surrogate model for untargeted MLLM attacks. Each volunteer evaluates all image pairs included in the human study.

Inspired by prior human evaluation of unrestricted adversarial examples (Song et al., 2018), each volunteer is shown the clean image and the corresponding adversarial example. The clean image serves only as a visual reference for locating the primary content and is not used to assess category consistency. A score of 1 is assigned if the adversarial example contains a clearly identifiable primary object or scene, irrespective of whether it belongs to the same category as the content of the clean image. A score of 0 is assigned if the primary content is blurred, severely distorted, structurally incoherent, or otherwise unidentifiable.

Let $H_{i,j} \in \{0, 1\}$ denote the score assigned to the i-th image pair by the j-th volunteer. The human score is computed as

$$\text{Human Score} = 100 \times \frac{1}{20D} \sum_{j=1}^{20} \sum_{i=1}^{D} H_{i,j}. \tag{39}$$

I Implementation Details of Compared Methods

In this section, we detail the hyperparameter settings of the compared attack methods. For perturbation-restricted attacks, we set the maximum perturbation to $\epsilon = 16/255$. For MI-FGSM (Dong et al., 2018), we use a momentum decay factor of $\mu = 1.0$, 10 iterations, and a step size of $\alpha = 1.6/255$. For STM (Ge et al., 2023), we set the number of iterations to $T = 10$, the step size to $\alpha = 1.6/255$, the decay factor to $\mu = 1.0$, the mixing ratio to $\gamma = 0.5$, the noise coefficient to $\beta = 2.0$, and the number of style-transformed images to $N = 20$.

For non-diffusion-based unrestricted attacks, we set $k = 8$ for cAdv (Bhattad et al., 2020) and use Adam with a learning rate of 10^{-4} for at most 500 iterations. For NCF (Yuan et al., 2022), we use Swin-T (Liu et al., 2021) as the semantic segmentation model and set the color distribution library size to $M = 150$, the number of random searches to $R = 50$, the number of neighborhood-search iterations to $N = 15$, the maximum perturbation of the color transformation matrix to $\epsilon_{\text{NCF}} = 0.2$, the step size to $\alpha = \epsilon_{\text{NCF}}/N \approx 0.013$, the momentum coefficient to $\mu = 0.6$, and the number of initialization resets to $K = 10$.

For diffusion-based unrestricted attacks, ACA (Chen et al., 2023b) uses Stable Diffusion v1.4 (Rombach et al., 2022) with $T = 50$ DDIM steps, $N_i = 10$ image-mapping iterations, and $N_a = 10$ attack iterations. Its remaining parameters are $\beta = 0.1$, $\zeta = 0.01$, $\eta = 0.04$, $\kappa = 0.1$, and $\mu = 1$, with image prompts generated using BLIP-2 (Li et al., 2023). DiffAttack (Chen et al., 2025) uses Stable Diffusion 2.0 Base (Rombach et al., 2022), 20 DDIM sampling steps, a starting step of 15, 30 latent optimization iterations, and a guidance scale of 2.5. Its classification, cross-attention, and self-attention loss weights are 10, $10{,}000$, and 100, respectively. For APA (Jiang et al., 2025), we use APA-SG with Stable Diffusion v1.5 (Rombach et al., 2022), 10 attack guidance steps, 10 attack iterations, an attack scale of 0.4, and a step size of 0.04. The number of inversion steps is 50. HAM (Wang et al., 2026) uses Stable Diffusion 2.0 Base (Rombach et al., 2022), 30 inversion steps, a reconstruction starting point of 12, a momentum coefficient of 0.9, and an initial perturbation magnitude of 0.035.

For untargeted MLLM attacks, VEAttack (Mei et al., 2026) and MABA (Li et al., 2026c) use CLIP-L/14 (Radford et al., 2021) as the surrogate model with a perturbation budget of $\epsilon = 16/255$. For VEAttack (Mei et al., 2026), we use 100 attack iterations and a step size of $1/255$. For MABA (Li et al., 2026c), we set the number of attack iterations to 30 and the step size to $3/255$. Spectral regularization is applied to layers 12–17, with $k = 10$ and $\beta = 2.5$.

J More Evaluations on Transferability and Image Quality

In this section, we provide more experimental results across different surrogate models and attack methods. Specifically, Appendix J.1 reports transferability to visual unimodal classifiers; Appendix J.2 examines transferability under defense approaches; Appendix J.3 reports transferability to zero-shot VLMs; Appendix J.4 evaluates transferability to open-source and commercial MLLMs; and Appendix J.5 reports more results on content recognizability and image quality.

J.1 Transferable Performance on Visual Unimodal Classifiers

Table 5 reports attack performance on visual unimodal classifiers using different surrogate models. StyleUAE achieves the highest average black-box ASR for every surrogate model, with an average ASR of 81.5% (+13.2%) across five surrogate models compared with the best-performing baseline under each surrogate. These results show that StyleUAE maintains strong transferability when UAE generation is extended from CNN surrogates to ViT surrogates. For example, with VGG-19 as the surrogate, StyleUAE achieves 79.0% (+18.1%), compared with 60.9% for HAM, the second-best method. APA performs somewhat better than StyleUAE on BEiT-B when ViT-B or Swin-B is used as the surrogate, likely because it uses diffusion augmentation with outputs from intermediate denoising steps. In future work, we will consider incorporating diffusion augmentation into StyleUAE to improve transferability to larger classifiers. Overall, these results further support combining diffusion-based generation with style injection as a promising approach to improving the transferability of UAEs across different target architectures.

Table 6 reports the Top-5 ASR on visual unimodal classifiers using different surrogate models. Notably, the advantage of StyleUAE becomes more pronounced in terms of Top-5 ASR. StyleUAE again achieves the highest average black-box Top-5 ASR for every surrogate model, with an average Top-5 ASR of 61.9% (+24.8%) across five surrogate models compared with the best-performing baseline under each surrogate. For example, APA, the second-best method with RN-50 as the surrogate, achieves a Top-5 ASR of only 36.9%, a decrease of 34.6 percentage points from its ASR. StyleUAE achieves a Top-5 ASR of 61.6%, decreasing by only 19.7 percentage points from its ASR. By weakening discriminative cues shared across architectures through stylized semantic disruptions, StyleUAE maintains stronger transferability under this stricter criterion.

J.2 Transferable Performance under Defense Approaches

Table 7 reports attack performance under different defense approaches using different surrogate models. Our method shows clear advantages under most defense approaches. For example, under DiffPure, StyleUAE achieves an ASR of 78.0% (+12.9%) with RN-50 as the surrogate, outperforming APA, the second-best method. The diffusion denoising process is similar to a robust purification defense mechanism, making the generated UAEs more robust to common transformation and purifi-

cation defenses. In addition, StyleUAE injects style information into UAEs, introducing semantic modifications to image content. Compared with pixel-level perturbations, UAEs with semantic perturbations may be harder for defense approaches to filter out.

J.3 Transferable Performance on Zero-Shot VLMs

Tables 8 and 9 report the ASR and Top-5 ASR on zero-shot VLMs using different surrogate models, respectively. StyleUAE achieves the highest ASR and Top-5 ASR on all four target models for every surrogate. For example, with RN-50 as the surrogate, StyleUAE achieves an average ASR of 77.2% (+21.4%), outperforming APA, the second-best method. Unlike CNNs and ViTs, zero-shot VLMs classify images based on image-text alignment. The limited performance of the two untargeted MLLM attacks indicates that disrupting shallow semantic information in CLIP-L/14 alone is insufficient to effectively disrupt image-text alignment. By further attacking the cross-attention maps of the diffusion model, StyleUAE introduces deeper semantic disruptions that interfere with the image-text alignment used by zero-shot VLMs.

J.4 Transferable Performance on Open-Source and Commercial MLLMs

Table 10 reports results using RN-50 and ViT-B as surrogate models on three open-source and five commercial MLLMs. StyleUAE achieves the highest ASR on every target MLLM with either surrogate, with overall averages of 79.7% (+17.7%) and 79.2% (+17.2%), respectively, compared with MABA, the second-best method. Even when only fully successful attacks assigned a score of 1 are counted, StyleUAE† achieves overall averages of 68.1% (+6.1%) and 67.2% (+5.2%), respectively. These results show that the improvement of StyleUAE is not driven solely by partially successful attacks under both surrogate settings. STM remains the strongest baseline among visual unimodal classifier attacks in both settings, supporting the usefulness of incorporating style information. MABA remains the strongest untargeted MLLM baseline, but its performance decreases more when moving from open-source to commercial models. MABA uses discriminative feature suppression to fool MLLMs by suppressing the dominant singular values of intermediate visual feature matrices. In future work, we will consider incorporating this technique into StyleUAE to further improve attack performance on MLLMs. Together, these results demonstrate that UAEs generated on small classifiers can transfer effectively to much larger MLLMs, supporting a low-resource pathway for transferring attacks from classifiers to MLLMs.

J.5 Content Recognizability and Image Quality Assessment

Table 11 reports content recognizability results using different surrogate models. Because manual inspection is time-consuming and requires substantial effort, human evaluation of visual unimodal classifier attacks is performed only for the RN-50 surrogate. StyleUAE maintains consistently high MCRS values across the two surrogate models, indicating that its generated UAEs preserve clearly recognizable content while achieving strong attack performance. Some baselines achieve higher MCRS values on individual evaluators, but their attack performance on MLLMs is much lower, as shown in Table 10. Human evaluation of the RN-50 results further demonstrates the advantage of StyleUAE over the other reported attacks. Together, these observations show that StyleUAE preserves recognizable visual content while maintaining strong attack transferability.

Table 12 extends the image quality evaluation to all five surrogate models and selected attacks with strong attack performance. Attacks with lower transferability often maintain good image quality, but sacrificing image quality does not necessarily improve transferability. For example, APA achieves similar scores to StyleUAE on several image quality metrics, but its average black-box ASR on visual unimodal classifiers is lower when RN-50 is used as the surrogate (71.5% vs. 81.3%). The visual comparisons in Appendix M also show no obvious difference in visual quality between the UAEs generated by StyleUAE and those generated by other diffusion-based methods. This is because the harmonized natural-image prior helps reduce noticeable stylization and preserve the natural appearance of the generated UAEs.

Table 5: ASR (%) of white-box (denoted by "*") and black-box attacks on visual unimodal classifiers. "AVG" denotes the average ASR of black-box attacks. The best and second-best results are shown in **bold** and underlined respectively. The first two attack rows report untargeted MLLM attacks, with the best result shown in **bold**.

Surrogate	Attacks	RN-50	VGG-19	Mob-v2	ConvNeXt	ViT-B	Swin-B	DeiT-B	BEiT-B	PVTv2	AVG ↑
–	Clean	7.3	11.3	13.1	3.6	6.3	4.1	5.5	3.7	3.5	6.5
CLIP-L/14	VEAttack	9.6	16.7	17.8	4.1	6.1	5.6	5.6	4.5	3.9	8.2
	MABA	**26.1**	**38.6**	**37.4**	**10.8**	**15.2**	**14.0**	**16.0**	**14.7**	**14.4**	**20.8**
RN-50	MI-FGSM	**99.9***	56.8	52.4	25.7	12.5	23.5	19.0	13.0	27.2	28.8
	STM	93.4*	80.3	75.1	25.8	19.0	25.3	18.1	16.9	32.3	36.6
	cAdv	97.3*	36.9	43.8	14.0	28.2	21.4	25.1	14.2	17.3	25.1
	NCF	89.9*	72.2	71.7	18.1	37.9	26.8	29.3	14.4	19.5	36.2
	ACA	90.0*	68.3	70.0	49.9	51.9	51.3	52.0	46.1	49.3	54.9
	DiffAttack	96.4*	74.5	77.7	57.5	51.2	57.5	50.1	40.8	59.2	58.6
	APA	99.7*	88.2	91.5	66.6	69.9	66.4	68.0	52.9	68.6	71.5
	HAM	95.2*	78.0	80.7	61.6	59.7	61.4	60.2	47.1	62.4	63.9
	StyleUAE	99.4*	**93.5**	**92.8**	**79.1**	**74.9**	**83.0**	**77.7**	**67.4**	**81.9**	**81.3**
VGG-19	cAdv	37.2	96.7*	46.5	15.4	26.3	21.1	25.1	14.3	18.6	25.6
	NCF	64.5	92.9*	71.6	14.7	31.8	22.9	23.7	12.4	18.2	32.5
	ACA	61.7	92.4*	67.0	46.1	50.0	47.9	49.2	42.1	45.3	51.2
	DiffAttack	79.3	97.1*	79.9	57.3	47.1	58.1	47.9	40.6	61.1	58.9
	APA	83.8	**99.9***	84.8	46.4	46.2	47.5	41.4	32.1	51.4	54.2
	HAM	80.5	96.1*	81.7	56.0	54.9	58.2	53.2	42.7	59.8	60.9
	StyleUAE	**91.9**	99.2*	**92.7**	**76.3**	**71.3**	**82.7**	**74.5**	**62.6**	**79.8**	**79.0**
Mob-v2	cAdv	37.3	39.5	96.3*	13.5	27.8	19.7	23.7	13.3	16.2	23.9
	NCF	65.6	72.3	92.5*	16.8	33.9	25.1	24.8	12.7	19.2	33.8
	ACA	60.5	64.4	93.3*	46.0	49.0	47.2	49.1	41.2	46.0	50.4
	DiffAttack	75.8	76.8	97.9*	48.7	47.7	55.4	47.0	37.1	53.5	55.3
	APA	89.2	88.2	**99.7***	59.9	67.5	61.9	63.9	48.6	66.4	68.2
	HAM	82.6	81.9	97.4*	55.6	61.7	60.4	58.6	43.4	61.7	63.2
	StyleUAE	**91.4**	**92.0**	99.6*	**75.7**	**75.2**	**81.4**	**76.0**	**64.7**	**80.3**	**79.6**
ViT-B	MI-FGSM	42.0	61.6	58.9	39.3	**100.0***	56.5	80.3	64.6	45.3	56.1
	STM	46.6	54.4	58.4	26.8	98.4*	45.5	83.6	54.3	32.6	50.3
	cAdv	33.7	33.7	40.7	17.6	97.7*	30.3	49.0	23.4	22.8	31.4
	NCF	55.1	60.1	61.6	19.7	72.6*	32.8	35.1	18.5	23.4	38.3
	ACA	62.7	64.1	66.9	54.8	81.2*	57.4	65.1	51.2	55.6	59.7
	DiffAttack	60.0	59.1	63.2	58.4	96.6*	69.7	77.2	56.1	60.4	63.0
	APA	70.4	63.6	69.4	59.0	87.8*	68.9	81.9	**77.0**	63.0	69.2
	HAM	68.0	67.3	71.0	64.4	96.3*	75.1	84.0	65.8	68.4	70.5
	StyleUAE	**87.7**	**88.5**	**87.8**	**80.7**	99.0*	**88.0**	**92.4**	73.6	**81.9**	**85.1**
Swin-B	cAdv	29.7	28.9	36.4	23.3	36.6	98.0*	42.5	20.3	26.2	30.5
	NCF	50.4	56.2	55.9	25.7	37.6	63.7*	35.4	18.5	25.9	38.2
	ACA	61.6	61.9	64.3	60.2	59.9	79.3*	64.5	52.9	59.1	60.6
	DiffAttack	58.1	56.0	58.6	67.6	59.7	90.6*	65.5	52.7	67.3	60.7
	APA	65.4	66.3	66.3	73.1	69.6	79.1*	75.2	**74.4**	74.1	70.6
	HAM	61.5	60.7	64.4	69.3	65.9	93.1*	69.7	56.5	68.1	64.5
	StyleUAE	**85.6**	**89.6**	**86.9**	**84.3**	**79.0**	**98.7***	**82.5**	69.0	**84.5**	**82.7**

Table 6: Top-5 ASR (%) of white-box (denoted by "*") and black-box attacks on visual unimodal classifiers. "AVG" denotes the average ASR of black-box attacks. The best and second-best results are shown in **bold** and underlined respectively. The first two attack rows report untargeted MLLM attacks, with the best result shown in **bold**.

Surrogate	Attacks	RN-50	VGG-19	Mob-v2	ConvNeXt	ViT-B	Swin-B	DeiT-B	BEiT-B	PVTv2	AVG ↑
–	Clean	1.5	1.4	2.6	0.6	1.0	0.8	1.2	0.7	0.4	1.1
CLIP-L/14	VEAttack	1.8	3.6	4.0	0.8	0.8	1.3	1.4	0.5	0.5	1.6
	MABA	**8.3**	**14.5**	**14.2**	**3.3**	**3.7**	**4.4**	**4.5**	**3.9**	**3.9**	**6.7**
RN-50	MI-FGSM	**99.8***	27.9	25.7	8.2	2.5	7.9	5.8	3.1	7.1	11.0
	STM	80.6*	59.2	53.3	10.2	5.5	10.1	6.6	5.5	13.3	20.5
	cAdv	62.2*	12.1	15.2	3.7	8.2	6.5	8.4	3.3	3.9	7.7
	NCF	58.1*	46.9	44.5	4.5	14.6	9.5	9.6	3.2	5.4	17.3
	ACA	45.6*	35.6	39.2	25.0	28.0	26.8	27.8	21.0	25.1	28.6
	DiffAttack	89.3*	38.5	40.0	22.2	17.5	22.6	18.5	12.6	25.6	24.7
	APA	94.5*	56.3	59.8	29.5	34.0	29.3	31.7	19.2	35.5	36.9
	HAM	89.8*	45.3	47.9	26.7	27.6	27.9	27.0	17.0	27.2	30.8
	StyleUAE	98.4*	**78.3**	**79.2**	**57.9**	**52.7**	**63.9**	**57.4**	**43.2**	**60.5**	**61.6**
VGG-19	cAdv	13.9	68.6*	18.5	5.0	10.0	7.6	9.2	4.5	5.6	9.3
	NCF	38.5	66.4*	44.7	4.2	12.9	7.8	8.6	2.9	5.8	15.7
	ACA	30.8	50.4*	34.6	21.0	23.5	21.8	24.7	17.9	21.1	24.4
	DiffAttack	43.2	91.1*	45.8	24.1	20.1	26.1	20.6	14.0	28.5	27.8
	APA	46.4	95.4*	51.1	16.9	17.9	17.1	15.1	7.7	19.0	23.9
	HAM	47.8	90.8*	51.3	25.0	24.8	29.0	24.3	15.8	28.2	30.8
	StyleUAE	**75.8**	**98.3***	**76.7**	**55.5**	**49.7**	**62.6**	**53.3**	**39.5**	**58.2**	**58.9**
Mob-v2	cAdv	14.7	14.9	69.7*	5.0	9.4	7.2	9.2	4.5	6.1	8.9
	NCF	38.7	46.8	61.3*	4.3	14.9	7.8	9.0	2.7	5.6	16.2
	ACA	32.3	35.2	53.6*	24.1	25.4	24.4	25.3	20.2	22.4	26.2
	DiffAttack	39.5	42.5	94.9*	20.4	18.8	24.4	20.0	13.3	23.4	25.3
	APA	60.9	59.9	97.9*	26.5	34.9	30.2	31.8	17.6	32.2	36.8
	HAM	50.2	50.0	95.7*	24.5	27.5	29.5	27.7	16.6	28.6	31.8
	StyleUAE	**76.6**	**79.0**	**99.1***	**54.8**	**53.9**	**63.8**	**55.7**	**41.9**	**59.8**	**60.7**
ViT-B	MI-FGSM	17.1	35.5	28.2	17.0	**99.6***	28.7	59.0	30.3	19.3	29.4
	STM	20.3	24.9	28.6	8.4	96.8*	19.0	63.9	24.1	10.2	24.9
	cAdv	11.9	11.8	15.0	4.5	73.3*	9.3	18.3	6.7	6.8	10.5
	NCF	34.3	38.3	36.1	5.9	33.3*	11.9	13.0	3.6	6.7	18.7
	ACA	34.3	36.4	38.8	27.3	44.0*	30.0	34.5	20.8	27.3	31.2
	DiffAttack	28.1	27.8	29.4	25.4	91.9*	35.3	49.8	22.4	28.8	30.9
	APA	30.4	30.2	33.2	21.5	51.9*	30.7	47.7	36.8	25.0	31.9
	HAM	39.0	37.4	43.2	34.7	92.5*	45.6	63.1	34.5	37.1	41.8
	StyleUAE	**69.1**	**71.5**	**71.3**	**57.7**	98.0*	**69.3**	**78.2**	**50.2**	**60.5**	**66.0**
Swin-B	cAdv	8.9	10.5	12.6	5.2	11.0	60.9*	15.1	4.6	6.4	9.3
	NCF	30.1	32.7	31.8	7.3	14.6	24.0*	13.0	4.1	8.3	17.7
	ACA	34.1	35.2	37.9	28.4	30.3	37.0*	33.2	21.9	27.6	31.1
	DiffAttack	25.5	26.2	28.5	33.2	25.4	80.9*	34.0	19.0	32.0	28.0
	APA	33.8	32.4	35.7	42.9	38.3	56.1*	45.0	40.9	44.4	39.2
	HAM	32.8	32.3	36.8	41.2	36.5	83.2*	43.7	25.8	39.3	36.1
	StyleUAE	**67.9**	**72.9**	**69.8**	**62.5**	**56.8**	**97.1***	**60.6**	**43.6**	**63.1**	**62.2**

Table 7: ASR (%) of black-box attacks under defense approaches. "AVG" denotes the average ASR of black-box attacks. The best and second-best results are shown in **bold** and underlined respectively. The first two attack rows report untargeted MLLM attacks, with the best result shown in **bold**.

Surrogate	Attacks	AT	HGD	RS	NRP	DiffPure	Inc-v3ens3	Inc-v3ens4	IncRes-v2ens	AVG ↑
CLIP-L/14	VEAttack	35.1	2.5	26.3	9.8	9.3	13.2	15.5	5.8	14.7
	MABA	**35.6**	**10.1**	**26.5**	**13.3**	**12.0**	**22.5**	**23.2**	**12.8**	**19.5**
RN-50	MI-FGSM	37.0	17.6	27.1	28.5	11.6	24.1	26.9	14.1	23.4
	STM	46.7	81.9	40.6	75.9	44.3	81.7	79.5	74.4	65.6
	cAdv	56.0	19.1	50.4	30.2	31.2	30.0	34.7	24.0	34.5
	NCF	**88.2**	34.2	**85.7**	52.2	52.7	42.9	47.0	34.9	54.7
	ACA	67.9	53.7	65.8	57.9	56.5	62.0	66.7	56.5	60.9
	DiffAttack	50.5	59.9	49.8	56.3	42.8	59.5	60.9	48.3	53.5
	APA	67.3	82.0	72.5	78.8	65.1	**81.8**	83.4	75.4	75.8
	HAM	56.4	69.7	57.5	62.8	51.8	68.3	69.6	62.7	62.4
	StyleUAE	85.1	**84.7**	80.8	**86.4**	**78.0**	**81.8**	**83.8**	**79.4**	**82.5**
VGG-19	cAdv	58.1	18.6	52.9	32.3	33.7	29.3	33.5	23.1	35.2
	NCF	**89.2**	30.1	**85.9**	46.7	48.5	42.2	46.3	35.2	53.0
	ACA	66.6	48.2	62.2	51.9	52.3	58.0	58.7	50.0	56.0
	DiffAttack	51.8	58.7	47.6	51.8	41.3	60.0	61.5	51.2	53.0
	APA	59.3	60.3	53.3	55.8	41.9	66.1	66.5	54.4	57.2
	HAM	57.5	62.9	55.3	56.2	47.6	66.7	67.5	56.6	58.8
	StyleUAE	84.1	**79.9**	78.2	**83.1**	**73.6**	**78.6**	**79.8**	**73.6**	**78.9**
Mob-v2	cAdv	59.2	18.4	52.4	31.7	32.7	28.2	34.9	22.2	35.0
	NCF	**88.3**	31.2	**86.8**	48.5	49.4	43.0	46.9	35.6	53.7
	ACA	68.1	47.2	64.1	51.3	51.6	59.2	61.3	51.0	56.7
	DiffAttack	53.8	50.8	50.8	47.6	39.2	56.1	56.7	43.5	49.8
	APA	71.2	71.6	71.7	69.9	56.7	76.1	78.8	66.6	70.3
	HAM	58.8	62.3	60.0	56.7	48.8	66.6	69.0	56.4	59.8
	StyleUAE	84.5	**80.9**	81.1	**84.2**	**77.6**	**78.2**	**81.2**	**75.2**	**80.4**
ViT-B	MI-FGSM	38.7	28.2	29.8	20.3	20.4	32.2	35.0	24.9	28.7
	STM	43.8	67.2	40.4	42.1	47.7	69.3	71.6	62.7	55.6
	cAdv	57.8	17.7	49.3	32.8	34.5	29.7	33.5	22.6	34.7
	NCF	82.3	28.4	76.6	48.6	50.8	39.6	42.7	33.9	50.4
	ACA	69.1	54.7	68.3	58.0	60.6	63.9	65.7	59.1	62.4
	DiffAttack	52.7	49.3	51.4	52.3	49.9	56.2	56.4	46.5	51.8
	APA	63.6	64.5	65.7	66.7	62.9	71.0	70.6	67.5	66.6
	HAM	58.6	61.3	62.6	64.4	61.5	65.5	66.8	60.4	62.6
	StyleUAE	**84.0**	**79.6**	**80.5**	**83.9**	**80.7**	**79.5**	**81.9**	**77.4**	**80.9**
Swin-B	cAdv	53.2	15.7	45.6	28.0	30.6	26.7	30.5	20.4	31.3
	NCF	82.2	23.7	77.0	45.6	46.2	36.3	39.5	28.0	47.3
	ACA	66.2	54.0	64.8	56.3	58.6	61.8	64.0	56.9	60.3
	DiffAttack	49.2	44.7	44.5	48.3	41.8	49.4	50.1	41.1	46.1
	APA	57.5	60.1	57.0	62.9	54.4	62.0	64.2	57.0	59.4
	HAM	52.8	53.5	50.3	54.1	49.6	55.9	57.2	49.0	52.8
	StyleUAE	**83.9**	**76.3**	**79.6**	**83.0**	**77.1**	**76.0**	**79.1**	**72.9**	**78.5**

Table 8: ASR (%) of black-box attacks on zero-shot VLMs. "AVG" denotes the average ASR of black-box attacks. The best and second-best results are shown in **bold** and underlined respectively. The first two attack rows report untargeted MLLM attacks, with the best result shown in **bold**.

Surrogate	Attacks	CLIP-RN50	CLIP-ViT-B/32	OpenCLIP-H/14	SigLIP	AVG ↑
–	Clean	30.7	24.9	21.1	19.7	24.1
CLIP-L/14	VEAttack	41.3	28.2	26.6	20.3	29.1
	MABA	**51.2**	**39.4**	**41.9**	**31.0**	**40.9**
RN-50	MI-FGSM	60.5	39.4	29.9	25.9	38.9
	STM	73.0	46.6	33.8	27.1	45.1
	cAdv	47.7	43.2	30.4	25.6	36.7
	NCF	59.4	48.2	29.3	25.4	40.6
	ACA	62.5	55.7	49.3	48.7	54.1
	DiffAttack	72.9	54.0	43.5	40.9	52.8
	APA	74.5	64.7	46.7	37.4	55.8
	HAM	69.7	58.9	45.4	37.7	52.9
	StyleUAE	**91.8**	**81.4**	**68.5**	**66.9**	**77.2**
VGG-19	cAdv	50.0	46.1	31.3	27.0	38.6
	NCF	57.1	43.3	28.4	24.6	38.4
	ACA	63.3	55.8	48.3	46.2	53.4
	DiffAttack	77.7	58.0	48.0	44.8	57.1
	APA	72.4	54.2	40.2	31.9	49.7
	HAM	74.9	60.1	48.3	38.3	55.4
	StyleUAE	**92.0**	**79.8**	**66.8**	**64.6**	**75.8**
Mob-v2	cAdv	48.6	44.3	29.9	27.0	37.5
	NCF	57.7	47.5	30.1	24.3	39.9
	ACA	60.7	55.6	49.0	47.9	53.3
	DiffAttack	70.1	55.7	44.0	40.0	52.5
	APA	73.0	65.5	45.7	36.4	55.2
	HAM	71.1	60.6	45.9	37.0	53.7
	StyleUAE	**89.6**	**80.7**	**66.5**	**63.7**	**75.1**
ViT-B	MI-FGSM	70.3	59.6	42.7	34.2	51.7
	STM	56.9	60.9	33.4	24.6	44.0
	cAdv	45.1	50.3	33.2	27.7	39.1
	NCF	55.1	47.2	32.4	25.3	40.0
	ACA	61.3	58.5	50.7	48.0	54.6
	DiffAttack	66.9	62.1	49.8	44.3	55.8
	APA	66.4	75.7	58.8	45.4	61.6
	HAM	70.4	70.3	54.8	44.3	60.0
	StyleUAE	**87.0**	**81.0**	**69.5**	**63.0**	**75.1**
Swin-B	cAdv	45.3	45.8	29.9	26.6	36.9
	NCF	53.2	44.8	31.6	25.4	38.8
	ACA	62.6	58.8	51.9	51.0	56.1
	DiffAttack	67.4	54.4	49.0	45.2	54.0
	APA	72.2	67.9	59.6	49.4	62.3
	HAM	67.1	59.5	49.8	41.6	54.5
	StyleUAE	**89.8**	**78.7**	**69.3**	**64.8**	**75.7**

Table 9: Top-5 ASR (%) of black-box attacks on zero-shot VLMs. "AVG" denotes the average ASR of black-box attacks. The best and second-best results are shown in **bold** and underlined respectively. The first two attack rows report untargeted MLLM attacks, with the best result shown in **bold**.

Surrogate	Attacks	CLIP-RN50	CLIP-ViT-B/32	OpenCLIP-H/14	SigLIP	AVG ↑
–	Clean	9.6	8.1	6.1	5.4	7.3
CLIP-L/14	VEAttack	17.2	8.4	8.3	5.4	9.8
	MABA	**25.7**	**16.8**	**19.6**	**10.8**	**18.2**
RN-50	MI-FGSM	35.0	14.9	10.3	7.4	16.9
	STM	53.6	21.6	13.2	8.9	24.3
	cAdv	19.3	18.6	9.6	7.0	13.6
	NCF	32.0	21.7	10.9	8.8	18.4
	ACA	33.9	28.6	24.2	23.0	27.4
	DiffAttack	42.4	27.2	19.0	17.4	26.5
	APA	45.6	36.8	20.6	14.0	29.3
	HAM	42.3	31.0	19.9	13.6	26.7
	StyleUAE	**77.7**	**59.3**	**47.2**	**47.9**	**58.0**
VGG-19	cAdv	23.1	20.2	11.9	8.4	15.9
	NCF	29.8	21.1	10.7	7.8	17.4
	ACA	35.2	28.9	24.4	21.2	27.4
	DiffAttack	49.9	30.5	22.9	21.3	31.2
	APA	41.7	27.5	14.7	10.8	23.7
	HAM	47.9	31.6	22.4	15.2	29.3
	StyleUAE	**78.8**	**56.6**	**44.6**	**46.1**	**56.5**
Mob-v2	cAdv	21.3	19.0	11.1	7.9	14.8
	NCF	29.1	22.6	10.9	7.4	17.5
	ACA	34.8	28.4	24.0	22.2	27.4
	DiffAttack	42.2	29.3	19.6	17.1	27.1
	APA	45.3	39.8	19.7	14.2	29.8
	HAM	44.7	35.1	21.5	14.5	29.0
	StyleUAE	**76.6**	**58.3**	**46.5**	**45.5**	**56.7**
ViT-B	MI-FGSM	47.1	33.7	18.5	12.2	27.9
	STM	31.0	37.3	11.7	7.2	21.8
	cAdv	21.0	21.5	12.7	9.4	16.2
	NCF	28.1	22.9	11.1	8.3	17.6
	ACA	35.1	31.9	25.2	23.0	28.8
	DiffAttack	38.3	35.6	21.9	19.3	28.8
	APA	37.9	46.9	26.6	18.2	32.4
	HAM	41.2	44.1	26.1	19.8	32.8
	StyleUAE	**72.4**	**59.7**	**47.4**	**45.2**	**56.2**
Swin-B	cAdv	19.3	20.0	10.7	7.3	14.3
	NCF	26.7	21.9	11.7	7.7	17.0
	ACA	35.2	30.1	27.2	25.5	29.5
	DiffAttack	38.5	28.3	21.1	20.5	27.1
	APA	44.2	38.6	32.0	23.7	34.6
	HAM	41.0	32.2	23.6	18.0	28.7
	StyleUAE	**72.9**	**56.4**	**45.2**	**45.0**	**54.9**

Table 10: ASR (%) of black-box attacks on open-source and commercial MLLMs. "AVG" denotes the average ASR of black-box attacks. The best and second-best results are shown in **bold** and underlined respectively. The first two attack rows report untargeted MLLM attacks, with the best result shown in **bold**. StyleUAE assigns scores of 1, 0.5, and 0 to fully successful, partially successful, and failed attacks, respectively, while StyleUAE† reports the ASR calculated by counting only attacks assigned a score of 1.

Surrogate	Attacks	Open-source MLLMs			Commercial MLLMs					AVG ↑
		BLIP-2	InBLIP	LLaVA	Qwen3.7	Kimi2.6	GPT5.6	Claude4.6	Gemini3.1	
–	Clean	19.2	16.1	18.5	9.5	10.1	10.4	10.5	10.4	13.1
CLIP-L/14	VEAttack	56.1	66.6	55.1	47.1	51.5	50.6	51.8	52.0	53.9
	MABA	**63.4**	**71.8**	**64.8**	**56.9**	**59.6**	**58.5**	**59.8**	**60.9**	**62.0**
RN-50	MI-FGSM	19.7	15.7	22.6	11.0	11.6	12.1	12.2	11.6	14.6
	STM	33.0	25.4	36.6	23.8	24.6	24.4	24.0	24.1	27.0
	cAdv	18.0	16.5	21.1	12.6	14.8	12.2	12.8	12.4	15.1
	NCF	22.1	15.7	20.2	12.9	13.9	14.6	14.9	15.1	16.2
	ACA	27.8	23.2	27.6	19.1	18.6	19.9	18.2	20.4	21.9
	DiffAttack	26.4	21.3	29.6	15.4	17.7	16.6	17.6	19.0	20.5
	APA	25.7	20.4	26.4	19.7	20.3	20.2	19.8	19.5	21.5
	HAM	24.5	19.0	26.9	18.3	15.5	17.0	18.2	16.6	19.5
	StyleUAE	**74.8**	**81.2**	**76.5**	**78.2**	**81.9**	**80.3**	**82.5**	**81.8**	**79.7**
	StyleUAE†	**60.8**	**68.8**	**60.3**	**66.9**	**72.7**	**70.3**	**73.2**	**72.0**	**68.1**
ViT-B	MI-FGSM	21.6	18.4	23.7	14.7	15.4	16.3	16.8	17.0	18.0
	STM	34.0	27.3	38.8	23.8	25.8	24.6	24.4	23.8	27.8
	cAdv	18.0	15.2	20.6	11.9	13.3	12.8	11.6	12.3	14.5
	NCF	20.4	16.6	20.4	12.8	13.8	14.7	15.1	16.7	16.3
	ACA	28.1	22.8	30.0	20.5	19.8	20.0	22.8	21.0	23.1
	DiffAttack	28.5	21.4	30.0	19.6	18.1	18.1	18.9	18.9	21.7
	APA	30.3	23.0	30.2	22.2	24.6	23.0	24.3	23.6	25.2
	HAM	28.2	20.8	30.0	20.2	19.2	18.7	20.0	21.3	22.3
	StyleUAE	**73.0**	**80.7**	**75.8**	**78.5**	**82.0**	**81.1**	**81.0**	**81.5**	**79.2**
	StyleUAE†	**58.8**	**67.7**	**59.0**	**66.9**	**72.2**	**71.0**	**70.5**	**71.6**	**67.2**

K More Ablation Studies and Hyperparameter Analyses

In this section, we provide additional ablation studies and hyperparameter analyses of StyleUAE. Specifically, Appendix K.1 presents the ablation study of the style injection module; Appendix K.2 analyzes different style image selection methods considered in our experiments; Appendix K.3 analyzes the content preservation strength; Appendix K.4 analyzes the loss weights; Appendix K.5 analyzes the diffusion parameters and attack iterations.

K.1 Ablation Study of the Style Injection Module

Table 13 reports the ablation study of the style injection module. Removing the style injection module causes the largest degradation in attack transferability, especially on zero-shot VLMs and MLLMs, demonstrating that injecting style information introduces deeper semantic disruptions that enable UAEs generated on CNNs to transfer to zero-shot VLMs and MLLMs. AdaIN provides a good initialization for the adversarial latent, and removing it leads to a decrease in attack transferability. Content preservation is important for maintaining image quality. Removing content preservation introduces stronger stylization, leading to a substantial degradation in image quality.

Table 11: Content recognizability assessment of compared attacks. The best and second-best results are shown in **bold** and underlined respectively. The first two attack rows report untargeted MLLM attacks, with the best result shown in **bold**.

Surrogate	Attacks	MCRS (%) ↑					Human Score (%) ↑
		Qwen3.7	Kimi2.6	GPT5.6	Claude4.6	Gemini3.1	
CLIP-L/14	VEAttack	**99.8**	**98.5**	**99.9**	**97.7**	**99.7**	**96.0**
	MABA	90.5	88.4	93.2	89.0	90.5	86.9
RN-50	MI-FGSM	**96.7**	**96.3**	**97.6**	**98.9**	**98.5**	91.9
	STM	63.4	73.3	66.6	82.5	76.3	78.8
	cAdv	78.5	68.7	82.9	76.9	77.2	61.6
	NCF	96.2	90.8	96.4	96.8	93.9	93.9
	ACA	10.2	12.3	27.4	10.7	15.1	12.2
	DiffAttack	63.9	62.7	64.6	68.3	72.5	52.5
	APA	40.8	49.5	56.4	48.7	55.1	38.4
	HAM	45.8	64.7	60.8	72.0	72.4	49.5
	StyleUAE	96.2	94.9	96.2	95.1	95.0	**97.9**
ViT-B	MI-FGSM	84.2	90.3	89.8	**96.3**	93.9	–
	STM	69.2	77.1	72.7	83.7	81.5	–
	cAdv	74.5	62.5	72.8	72.2	71.4	–
	NCF	95.2	91.3	**96.6**	95.8	94.2	–
	ACA	9.3	10.7	23.9	9.9	14.8	–
	DiffAttack	51.7	51.5	49.0	59.7	63.1	–
	APA	31.4	36.4	41.7	37.5	44.3	–
	HAM	25.0	48.4	37.6	56.7	58.2	–
	StyleUAE	**95.5**	**94.9**	95.4	95.2	**96.5**	–

K.2 Analysis of Style Image Banks and Selection Methods

To analyze the results of different style image banks and selection methods, we further conduct experiments using ArtBench-10 (Liao et al., 2022) and WikiArt (Saleh & Elgammal, 2016) as style image banks, and compare Random Selection, *Style Image Selection*, and *Enhanced Style Image Selection* in the same setting.

Figure 4 presents examples of style images selected from ArtBench-10 and WikiArt using different style image selection methods. Figures 4b and 4e show that randomly selected style images differ substantially from the clean images in visual appearance. Figure 4c shows that *Style Image Selection* selects style images that are visually consistent with the clean images. Benefiting from a larger candidate set and the visual understanding and comparative reasoning capabilities of multiple MLLMs, *Enhanced Style Image Selection* selects style images that are more consistent with the clean images in both visual appearance and semantic content, as shown in Figure 4d. Similar observations can be made for WikiArt in Figures 4f and 4g.

Table 14 compares the attack performance and image quality of UAEs generated using different style image selection methods across different style image banks. A good style image helps maintain image quality while preserving transferability. Randomly selected style images may introduce incongruous changes in visual appearance or semantic content, resulting in lower-quality UAEs. Although such changes may improve transferability, this improvement comes at the cost of image quality, making the resulting UAEs more visually noticeable and less suitable as natural-looking adversarial examples. The ASR on open-source MLLMs varies only slightly across different style image selections, whereas the ASR on visual unimodal classifiers changes more substantially. However, more pronounced stylistic changes do not necessarily produce better UAEs. Excessive stylization may obscure the original category and cause the resulting images to violate the definition of valid UAEs. Therefore, applying style transfer without restriction is not a prudent choice, as its contribution to attack transferability tends to saturate.

Table 12: No-reference image quality assessment of compared attacks. The best and second-best results are shown in **bold** and underlined respectively. The first two attack rows report untargeted MLLM attacks, with the best result shown in **bold**.

Surrogate	Attacks	HyperIQA ↑	DBCNN ↑	ARNIQA ↑	MUSIQ-AVA ↑	NIMA-AVA ↑	MUSIQ-KonIQ ↑	TReS ↑
CLIP-L/14	VEAttack	**0.5553**	**0.6187**	**0.6912**	**4.0096**	**4.0997**	**51.9001**	**73.1150**
	MABA	0.4295	0.5312	0.5737	3.8094	3.7998	45.4772	54.6489
RN-50	APA	0.5717	0.6201	0.6939	4.1040	4.3988	51.1253	75.4543
	HAM	**0.6239**	**0.6641**	**0.7101**	**4.2399**	4.4624	**55.1371**	**80.7230**
	StyleUAE	0.5683	0.6587	0.6186	4.1154	**4.5944**	51.5251	77.4289
VGG-19	APA	0.6006	0.6486	0.7005	4.1938	4.5116	53.6312	79.0388
	HAM	**0.6347**	**0.6763**	**0.7150**	**4.3283**	4.5577	**56.5012**	**82.1926**
	StyleUAE	0.5769	0.6663	0.6248	4.1552	**4.6724**	52.4705	78.3470
Mob-v2	APA	0.5647	0.6154	0.6939	4.0993	4.4085	50.7561	74.2494
	HAM	**0.6218**	**0.6655**	**0.7132**	**4.2574**	4.4550	**55.1697**	**80.4348**
	StyleUAE	0.5642	0.6590	0.6184	4.1221	**4.5878**	51.5896	76.8569
ViT-B	APA	0.5438	0.5968	0.6893	4.0156	4.2923	48.9528	71.9214
	HAM	**0.6084**	**0.6589**	**0.7109**	**4.2143**	4.4237	**54.3230**	**79.6290**
	StyleUAE	0.5623	0.6558	0.6188	4.0839	**4.5666**	51.3544	76.6031
Swin-B	APA	0.5721	0.6213	0.6946	4.0533	4.2887	50.8962	74.8199
	HAM	**0.6173**	**0.6617**	**0.7060**	**4.2475**	4.4260	**54.8984**	**80.1114**
	StyleUAE	0.5633	0.6568	0.6190	4.1170	**4.5763**	51.4225	76.6694

Table 13: Ablation study of the style injection module in StyleUAE. All UAEs are generated using RN-50 as the surrogate model.

	Classifiers AVG (%) ↑	Zero-shot VLMs AVG (%) ↑	Open-source MLLMs AVG (%) ↑	NIMA-AVA ↑	TReS ↑
w/o AdaIN	75.2	71.5	74.5	4.6225	78.3127
w/o content preservation	87.1	81.2	80.3	4.0471	72.5825
w/o style injection	72.1	45.5	38.2	4.6410	78.5142
StyleUAE	81.3	77.2	77.5	4.5944	77.4289

Compared with *Style Image Selection*, *Enhanced Style Image Selection* improves image quality with almost no loss in transferability. This improvement is consistent with the qualitative examples in Figures 4c and 4d, as proposal and voting by multiple MLLMs help select style images that are more visually consistent with the clean images. Similar trends are observed when WikiArt is used as the style image bank, indicating that the effects of style information on attack performance and image quality remain consistent across different style image banks under the same evaluation setting. However, the improvement achieved by *Enhanced Style Image Selection* does not justify the substantial additional cost of evaluating a larger candidate set with multiple MLLMs. Therefore, we recommend using *Enhanced Style Image Selection* only when stringent image-quality requirements outweigh resource-efficiency considerations.

K.3 Hyperparameter Analysis of Content Preservation

Table 15 analyzes the results of different content preservation strengths λ_Q. A higher λ_Q is beneficial for preserving image quality by retaining more information from the original query. When $\lambda_Q = 0$, content preservation is completely removed, resulting in stronger attack transferability but



Figure 4: Examples of clean images and corresponding style images selected from different style image banks using different selection methods. Each row shows a clean image and its corresponding style images. (a) Clean image. (b) Style image selected from ArtBench-10 using Random Selection. (c) Style image selected from ArtBench-10 using *Style Image Selection*. (d) Style image selected from ArtBench-10 using *Enhanced Style Image Selection*. (e) Style image selected from WikiArt using Random Selection. (f) Style image selected from WikiArt using *Style Image Selection*. (g) Style image selected from WikiArt using *Enhanced Style Image Selection*.

a substantial degradation in image quality. When $\lambda_Q = 0.75$, the change in image quality remains relatively small compared with stronger content preservation, while StyleUAE maintains strong attack transferability across visual unimodal classifiers, zero-shot VLMs, and MLLMs. Therefore, we set $\lambda_Q = 0.75$ to balance attack transferability and image quality.

K.4 Hyperparameter Analysis of Loss Weights

Table 16 analyzes the results of different loss weights in Eq. (10). A larger λ_{cls} is beneficial for strengthening the attack on the surrogate classifier, while λ_{cross} is important for improving transferability to zero-shot VLMs and MLLMs. When $\lambda_{\text{cls}} = 10$ and $\lambda_{\text{cross}} = 10000$, StyleUAE already achieves strong attack transferability while the change in image quality remains relatively small. In addition, larger λ_{self} and λ_{prior} are beneficial for preserving image structure and naturalness, respectively. When both weights are set to 100, StyleUAE maintains good image quality without substantially restricting attack transferability, whereas excessively large values noticeably weaken the attack performance. Therefore, we set $\lambda_{\text{cls}} = 10$, $\lambda_{\text{cross}} = 10000$, $\lambda_{\text{self}} = 100$, and $\lambda_{\text{prior}} = 100$ to balance attack transferability and image quality.

K.5 Hyperparameter Analysis of Diffusion Parameters and Attack Iterations

Table 17 analyzes the diffusion parameters and attack iterations. Increasing the number of inversion steps or the guidance scale can substantially improve attack performance. However, when the

Table 14: Comparison of attack performance and image quality under different style image selection methods and style image banks. All UAEs are generated using RN-50 as the surrogate model. Random Selection 1–3 denote three independent runs of random style image selection for each style image bank. For each style image bank, the best and second-best results are shown in **bold** and underlined respectively.

Style Image Bank	Style Image Selection Method	Classifiers AVG (%) ↑	Zero-shot VLMs AVG (%) ↑	Open-source MLLMs AVG (%) ↑	NIMA-AVA ↑	TReS ↑
ArtBench-10	Random Selection 1	**89.6**	84.6	80.7	4.0641	74.2602
	Random Selection 2	89.5	83.9	**81.3**	4.0427	74.3763
	Random Selection 3	89.0	**84.9**	80.8	4.0387	74.6617
	Style Image Selection	81.3	77.2	77.5	4.5944	77.4289
	Enhanced Style Image Selection	80.6	77.5	77.6	**4.9381**	**80.4272**
WikiArt	Random Selection 1	88.7	84.3	80.9	4.1474	72.8471
	Random Selection 2	88.3	83.9	81.4	4.1579	72.4718
	Random Selection 3	**89.7**	**84.4**	**81.6**	4.1570	72.4798
	Style Image Selection	82.7	79.0	80.2	4.5484	74.9179
	Enhanced Style Image Selection	82.8	78.1	78.5	**4.8462**	**79.4176**

Table 15: Hyperparameter analysis of λ_Q for content preservation in Eq. (3). All UAEs are generated using RN-50 as the surrogate model.

Parameter	Value	Classifiers AVG (%) ↑	Zero-shot VLMs AVG (%) ↑	Open-source MLLMs AVG (%) ↑	NIMA-AVA ↑	TReS ↑
λ_Q	1.00	72.4	63.8	69.7	4.5959	78.9415
	0.75 (StyleUAE)	81.3	77.2	77.5	4.5944	77.4289
	0.50	83.5	78.9	78.1	4.4175	75.4712
	0.25	85.8	79.3	79.6	4.2175	74.1204
	0.00	87.1	81.2	80.3	4.0471	72.5825

number of inversion steps exceeds 5 or the guidance scale exceeds 3.0, image quality decreases noticeably and the image structure may be severely changed. Therefore, we use 5 inversion steps and a guidance scale of 3.0 to maintain strong attack transferability while avoiding excessive changes to the clean image under the same experimental conditions.

Increasing the number of attack iterations I improves attack performance during the early optimization stage, while the performance on zero-shot VLMs and MLLMs largely saturates after 30 iterations. Further increasing I provides only marginal improvements. For the number of DDIM sampling steps, increasing the number of sampling steps generally improves image quality, but the improvement gradually saturates, while attack transferability decreases and the sampling process requires more computational time. Therefore, we set $I = 30$ and the number of DDIM sampling steps to 20 to balance attack transferability, image quality, and computational cost.

L Stability Analysis of StyleUAE

Table 18 evaluates StyleUAE using different global random seeds. The attack performance and image quality remain highly consistent across all evaluated seeds, with only minor variations on visual unimodal classifiers, zero-shot VLMs, open-source MLLMs, NIMA-AVA, and TReS. These results demonstrate that StyleUAE is stable across different global random seeds.

Table 19 further evaluates StyleUAE using different versions of Stable Diffusion. StyleUAE achieves comparable attack performance with Stable Diffusion 1.4, 2.0, and 2.1 Base, indicating that its effectiveness does not depend strongly on a specific diffusion model version. Notably, Stable Diffusion 1.4 achieves slightly better image quality while maintaining comparable attack performance. These results further demonstrate the applicability of StyleUAE across different pretrained diffusion models evaluated in our experiments.

Table 16: Hyperparameter analyses of the loss weights in Eq. (10). All UAEs are generated using RN-50 as the surrogate model.

Parameter	Value	Classifiers AVG (%) ↑	Zero-shot VLMs AVG (%) ↑	Open-source MLLMs AVG (%) ↑	NIMA-AVA ↑	TReS ↑
λ_{cls}	1	72.2	65.7	72.0	4.6075	77.5312
	5	79.9	74.4	75.9	4.5995	77.3674
	10 (StyleUAE)	81.3	77.2	77.5	4.5944	77.4289
	20	82.3	76.8	78.0	4.5845	77.1973
	50	83.5	77.5	79.2	4.5688	76.7893
λ_{cross}	1	75.2	72.9	71.4	4.6987	77.9730
	10	76.5	74.1	72.5	4.6734	77.7719
	100	77.9	75.4	73.7	4.6541	77.7237
	1000	78.5	77.9	75.0	4.6259	77.5261
	10000 (StyleUAE)	81.3	77.2	77.5	4.5944	77.4289
	100000	81.9	82.0	77.8	4.5892	76.9071
λ_{self}	1	82.5	77.8	77.9	4.4238	76.5690
	10	81.9	77.4	77.7	4.4892	76.6005
	100 (StyleUAE)	81.3	77.2	77.5	4.5944	77.4289
	1000	79.3	75.3	75.4	4.6213	78.1474
	10000	78.4	77.5	76.9	4.6492	78.5628
	100000	77.2	76.6	76.3	4.6583	78.7232
λ_{prior}	1	81.9	78.8	78.1	4.3423	75.1198
	10	81.3	77.9	77.9	4.5584	76.8741
	100 (StyleUAE)	81.3	77.2	77.5	4.5944	77.4289
	1000	77.4	75.9	76.1	4.5991	77.5628
	10000	74.9	73.0	74.8	4.6241	77.9841
	100000	64.7	67.7	71.5	4.6484	78.1267

M More Visualizations

In this section, we provide more qualitative results of StyleUAE. Specifically, Appendix M.1 presents visualizations on different surrogate models; Appendix M.2 presents image captions generated by different MLLMs; Appendix M.3 visualizes different style image selection methods; Appendix M.4 presents UAEs with low content recognizability; and Appendix M.5 presents unsuccessful attack cases of StyleUAE.

M.1 Attack Results of UAEs on Different Surrogate Models

Figures 5 and 6 present prediction results of a classifier, a zero-shot VLM, and two commercial MLLMs on adversarial examples generated by different attacks. For the visual unimodal classifier attacks, including StyleUAE, the adversarial examples in Figures 5 and 6 are generated using RN-50 and ViT-B as surrogate models, respectively. The adversarial examples generated by the untargeted MLLM attacks VEAttack and MABA use CLIP-L/14 as the surrogate model in both figures.

In these examples, StyleUAE successfully transfers to all four target models, whereas most compared attacks fool only a subset of them. These observations are consistent with the quantitative results on visual unimodal classifiers, zero-shot VLMs, and MLLMs reported in Tables 5, 8, and 10, respectively. By jointly attacking the classifier and the cross-attention module of the diffusion model while introducing style information, StyleUAE induces deeper semantic disruptions and thereby fools different types of target models.

M.2 Image Captions from Different MLLMs

Figures 7, 8, and 9 present the complete image captions generated by GPT5.6, Qwen3.7, and Kimi2.6, respectively, for a clean image and adversarial examples generated by different attacks.

Table 17: Hyperparameter analyses of the diffusion parameters and attack iterations. All UAEs are generated using RN-50 as the surrogate model.

Parameter	Value	Classifiers AVG (%) ↑	Zero-shot VLMs AVG (%) ↑	Open-source MLLMs AVG (%) ↑	NIMA-AVA ↑	TReS ↑
Inversion steps	1	60.6	53.9	64.5	4.7043	79.2159
	3	68.2	63.2	68.8	4.6582	77.8991
	5 (StyleUAE)	81.3	77.2	77.5	4.5944	77.4289
	7	89.2	85.6	83.2	4.3020	75.3048
	10	95.1	91.8	89.0	4.0464	72.4148
Guidance scale	1.0	71.9	65.6	70.4	4.6073	78.1264
	2.0	76.9	71.3	73.9	4.5950	77.9128
	3.0 (StyleUAE)	81.3	77.2	77.5	4.5944	77.4289
	5.0	89.2	85.2	82.1	4.2952	73.4785
	7.5	94.4	90.2	87.2	3.9136	71.0144
Attack iterations I	10	75.4	73.3	75.7	4.6081	77.8375
	20	79.0	74.8	76.3	4.6005	77.6177
	30 (StyleUAE)	81.3	77.2	77.5	4.5944	77.4289
	40	82.4	77.1	77.4	4.5950	77.0866
	50	83.4	77.7	77.5	4.5897	76.9319
Sampling steps	10	95.7	92.4	89.5	4.3067	75.6991
	20 (StyleUAE)	81.3	77.2	77.5	4.5944	77.4289
	30	71.6	66.8	70.9	4.6418	77.2194
	50	62.4	58.6	66.1	4.6948	78.1284
	100	57.3	52.5	63.8	4.6998	78.5972

Table 18: Results of StyleUAE with different global random seeds. All UAEs are generated using RN-50 as the surrogate model.

	Classifiers AVG (%) ↑	Zero-shot VLMs AVG (%) ↑	Open-source MLLMs AVG (%) ↑	NIMA-AVA ↑	TReS ↑
Seed 40	81.3	75.7	77.3	4.5929	77.4103
Seed 41	81.4	76.2	76.6	4.5968	77.4059
Seed 43	81.5	76.4	77.3	4.5992	77.4072
Seed 44	81.2	76.8	77.3	4.5927	77.3361
StyleUAE (Seed 42)	81.3	77.2	77.5	4.5944	77.4289

NCF, ACA, DiffAttack, and StyleUAE use RN-50 as the surrogate model, whereas VEAttack uses CLIP-L/14. The image captions are generated using the prompt ``What is the main content of this image?''.

The results show that several compared attacks preserve the correct category or modify only limited details in the generated captions. In contrast, StyleUAE causes all three MLLMs to describe the primary content incorrectly. The resulting captions either identify an incorrect ImageNet category or describe a category outside the 1,000 ImageNet classes. These qualitative results are consistent with Table 10, in which StyleUAE achieves the highest ASR on both open-source and commercial MLLMs. This behavior further shows that introducing style information weakens the visual recognition ability of MLLMs.

M.3 UAEs with Different Style Image Selection Methods

Figure 10 presents clean images, style images selected using *Style Image Selection*, and the UAEs generated by StyleUAE. The selected style images are visually consistent with the clean images, and the UAEs retain clearly recognizable primary content and a coherent visual appearance. Figure 11 presents examples generated using randomly selected style images. These randomly selected style

Table 19: Results of StyleUAE with different diffusion model versions. All UAEs are generated using RN-50 as the surrogate model.

	Classifiers AVG (%) ↑	Zero-shot VLMs AVG (%) ↑	Open-source MLLMs AVG (%) ↑	NIMA-AVA ↑	TReS ↑
Stable Diffusion 1.4	81.6	77.9	78.0	4.6062	80.8903
Stable Diffusion 2.0	82.1	77.3	77.0	4.6615	77.0386
StyleUAE (Stable Diffusion 2.1 Base)	81.3	77.2	77.5	4.5944	77.4289

images often differ substantially from the clean images in visual appearance or content, and the resulting UAEs exhibit more noticeable and incongruous appearance changes.

Figure 12 directly compares *Random Selection* and *Style Image Selection* using the same clean images. The results show that UAEs generated using randomly selected style images contain stronger and less coherent appearance changes. In contrast, *Style Image Selection* produces style images that are more visually compatible with the clean images, resulting in UAEs with clearer object structures and more natural appearances. These observations are consistent with Table 14. Random selection produces higher attack transferability at the cost of image quality, whereas *Style Image Selection* achieves a better balance between attack transferability and visual quality.

M.4 Visualizations of UAEs with Poor Image Quality

Figure 13 presents selected UAEs with low content recognizability, together with the corresponding clean images and style images used for style injection. In these examples, the primary object or scene becomes blurred, severely distorted, or difficult to identify, and the generated UAEs do not preserve sufficiently clear visual structures for the main content to remain readily recognizable. These examples provide qualitative context for the content-recognizability and image-quality results reported in Tables 11 and 12.

M.5 Visualizations of Unsuccessful UAEs

Figure 14 presents several unsuccessful attack cases of StyleUAE. In these cases, MLLMs still correctly recognize the primary content of the generated UAEs. We observe that the injected style information introduces relatively mild appearance changes. Meanwhile, these UAEs preserve the original image structures and natural appearances, exhibiting high visual quality. These cases suggest that when style injection is not strong enough to sufficiently disrupt the image-text semantic alignment and category-related discriminative cues relied on by MLLMs, the attack may fail.

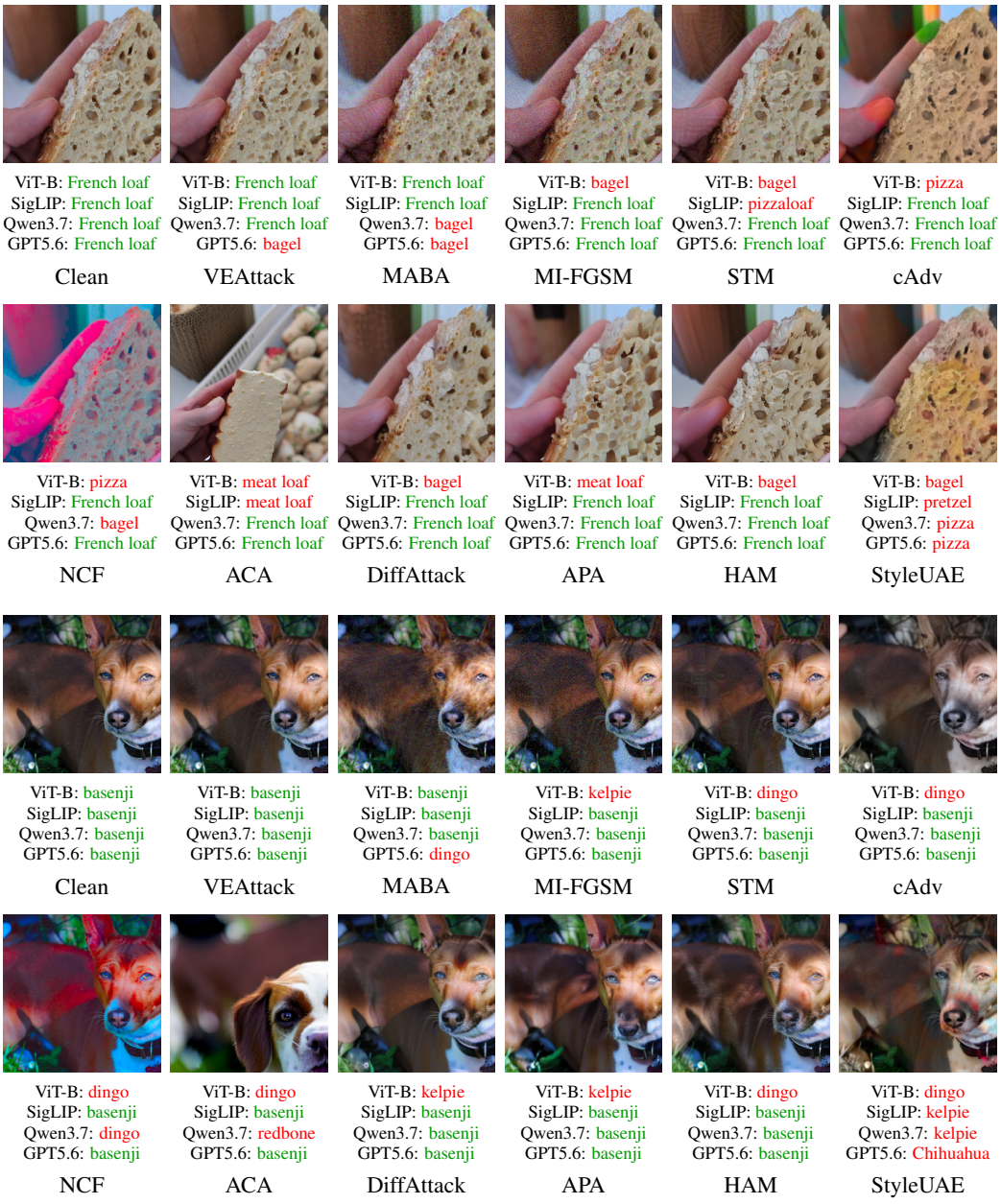


Figure 5: Prediction results for a clean image and different adversarial examples on the ViT-B visual unimodal classifier, SigLIP zero-shot VLM, and Qwen3.7 and GPT5.6 MLLMs, where the predicted labels of Qwen3.7 and GPT5.6 are extracted from image caption results. Red and green denote successful and unsuccessful attacks, respectively. MI-FGSM (Dong et al., 2018), STM (Ge et al., 2023), cAdv (Bhattad et al., 2020), NCF (Yuan et al., 2022), ACA (Chen et al., 2023b), DiffAttack (Chen et al., 2025), APA (Jiang et al., 2025), HAM (Wang et al., 2026), and StyleUAE (Ours) generate adversarial examples on the CNN model RN-50, while VEAttack (Mei et al., 2026) and MABA (Li et al., 2026c) take CLIP-L/14 as the surrogate model.



Figure 6: Prediction results for a clean image and different adversarial examples on the ViT-B visual unimodal classifier, SigLIP zero-shot VLM, and Qwen3.7 and GPT5.6 MLLMs, where the predicted labels of Qwen3.7 and GPT5.6 are extracted from image caption results. Red and green denote successful and unsuccessful attacks, respectively. MI-FGSM (Dong et al., 2018), STM (Ge et al., 2023), cAdv (Bhattad et al., 2020), NCF (Yuan et al., 2022), ACA (Chen et al., 2023b), DiffAttack (Chen et al., 2025), APA (Jiang et al., 2025), HAM (Wang et al., 2026), and StyleUAE (Ours) generate adversarial examples on the ViT-B visual unimodal classifier, while VEAttack (Mei et al., 2026) and MABA (Li et al., 2026c) take CLIP-L/14 as the surrogate model.

GPT5.6 Image Captions



Clean

The main content of this image is a close-up photograph of a small, fluffy dog, which appears to be a **Pomeranian**.

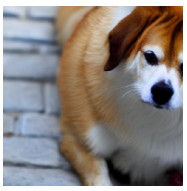
Here are the key details:
• **Subject:** The dog has golden-orange and cream-colored fur. It is facing slightly to the right but looking toward the camera.
• **Features:** You can clearly see its dark eye, black nose, and white muzzle.
• **Setting:** The background is blurred (out of focus), but it appears to be a grey concrete surface, suggesting that the dog is lying on a sidewalk or patio.
• **Accessories:** There is a small glimpse of a pink object, likely a collar or tag, near the bottom-right corner.



NCF

The main content of this image is a close-up of a **fluffy dog**, which appears to be a **Beagle** or a similar small spitz-type breed.

Here are a few more details:
• **Appearance:** The dog has thick, long fur that is a mix of tan/golden brown and white, particularly around the muzzle and chest.
• **Pose:** It is lying down or sitting and looking slightly off to the right side of the frame.
• **Focus:** The image has a shallow depth of field, meaning the dog's face is in focus while the background, which looks like a textured concrete or snowy surface, is blurry.



ACA

The main content of this image is a close-up photograph of a dog.

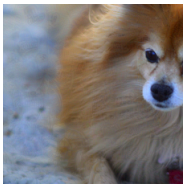
Here are more specific details about what is visible:
• **The Dog:** It appears to be a **mixed-breed dog** with tan (light brown) and white fur. It has floppy brown ears, dark eyes, and a prominent black nose.
• **Pose:** The dog is lying down or sitting low to the ground.
• **Setting:** It is resting on a grey, paved surface that looks like stone tiles or bricks.
• **Focus:** The image has a shallow depth of field, meaning the dog's face, especially the nose, is in focus while the rest of its body and the background are blurred.



DiffAttack

The main content of this image is a close-up photograph of a small, fluffy dog.

Here are more specific details:
• **Breed:** It appears to be a **Pomeranian**, recognizable by its long, silky fur, fox-like face, and the feathery hair on its ears.
• **Coloring:** The dog has a coat of white and reddish-brown (tan) fur.
• **Features:** You can clearly see its black nose, dark eye, and white muzzle.
• **Pose:** The dog is lying down and looking slightly to the right.
• **Background:** The background is out of focus (blurred), which draws attention to the dog's face. It looks like the dog might be resting on a light-colored surface, possibly concrete or stone.



VEAttack

The main content of this image is a close-up of a small, fluffy dog, which appears to be a **Corgi**.

Here are some specific details:
• **Appearance:** The dog has thick, orange-tan fur with a white muzzle and chest. It has a small black nose and dark, alert eyes.
• **Pose:** The dog is lying down or sitting, facing slightly to the right.
• **Focus:** The image has a shallow depth of field, meaning the dog's face is in focus while the background and parts of its body are slightly blurred.



StyleUAE

The main content of this image is a close-up of a **fluffy dog**, which appears to be a **Shiba Inu**.

Here are some specific details:
• **Appearance:** The dog has thick, soft-looking fur that is a mix of reddish-orange (ginger) on its head and back and creamy white on its chest and muzzle.
• **Pose:** It is looking toward the right side of the frame with a calm expression.
• **Background:** The background is out of focus but appears to be a light grey surface, possibly concrete or pavement.

Figure 7: Image captions generated by GPT5.6 for a clean image and different adversarial examples using the prompt ``What is the main content of this image?''. Red, blue, and green denote fully successful, partially successful, and unsuccessful attacks, respectively. NCF (Yuan et al., 2022), ACA (Chen et al., 2023b), DiffAttack (Chen et al., 2025), and StyleUAE (Ours) generate adversarial examples on the CNN model RN-50, while VEAttack (Mei et al., 2026) takes CLIP-L/14 as the surrogate model.

Qwen3.7 Image Captions



Clean

The main content of this image is the front section of a **race car** driving on an asphalt track.

Here are the specific details:
• **The Car:** Only the front right portion of the vehicle is visible in the bottom-right corner. It is a dark grey sports car, likely an Aston Martin Vantage GTE, featuring the sponsor logo "TOTAL" on the hood. It has distinctive bright yellow headlights and yellow accents on the front splitter.
• **The Setting:** The majority of the image is filled by the grey asphalt of the race track, marked with white boundary lines. The car appears to be in motion on the circuit.



NCF

The main content of this image is the front section of a blue **race car** driving on a track.

Here are more specific details:
• **The Car:** It appears to be an **Aston Martin Vantage GTE** race car. It is primarily blue with distinctive orange accents on the headlights, front grille, and splitter. Only the front and part of the roof/windshield are visible in the bottom-right corner.
• **The Setting:** The car is on an asphalt race track. The entire image has a strong blue tint or color cast.
• **Details:** There is a blue line painted on the track surface visible in the upper-left portion of the image.



ACA

The main content of this image is the front right section of a silver **race car** driving on a track.

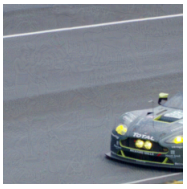
Here are more specific details:
• **The Car:** It appears to be a high-performance prototype race car, similar to an LMP1 car such as the Porsche 919 Hybrid. It has a sleek, aerodynamic design with illuminated headlights and a yellow side mirror.
• **The Setting:** The car is on a grey asphalt race track. The background is largely empty track surface, which is slightly blurred, suggesting speed or focus on the car.



DiffAttack

The main content of this image is the front section of a **race car** driving on a track.

Here are more specific details:
• **The Car:** Only the front right portion of the vehicle is visible in the bottom-right corner. It is a grey or silver car with aerodynamic features such as a front splitter and a side-mirror stalk. Its headlights are illuminated with a yellowish glow. Based on the grille and headlight shape, it resembles an Aston Martin Vantage GTE.



VEAttack

The main content of this image is a **sports car** driving on a track.

Here are more specific details:
• **The Car:** Only the front right section of the vehicle is visible in the bottom-right corner. It appears to be a dark grey or silver sports car, likely a GT-class racer, with bright yellow headlights that are turned on.
• **The Setting:** The background is a grey, textured asphalt surface, which is clearly a race track. There are white painted lines visible on the track surface.



StyleUAE

The main content of this image is a grey **model sports car**, likely a slot car, positioned on a track.

Here are some specific details:
• **The Car:** It is a grey sports car with racing decals. The word "TITAN" is visible on the hood. It has bright yellow headlights that are illuminated, along with smaller lights below them.
• **The Setting:** The car is on a smooth grey surface that resembles a slot car track.
• **Background:** There is a white barrier or wall running diagonally across the upper portion of the image, typical of a race track boundary.

Figure 8: Image captions generated by Qwen3.7 for a clean image and different adversarial examples using the prompt ``What is the main content of this image?''. Red, blue, and green denote fully successful, partially successful, and unsuccessful attacks, respectively. NCF (Yuan et al., 2022), ACA (Chen et al., 2023b), DiffAttack (Chen et al., 2025), and StyleUAE (Ours) generate adversarial examples on the CNN model RN-50, while VEAttack (Mei et al., 2026) takes CLIP-L/14 as the surrogate model.

Kimi2.6 Image Captions



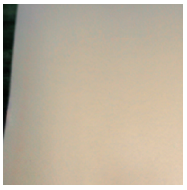
Clean

The main content of this image is a printed **menu** for a meal, likely a formal dinner or wedding reception. It is divided into three sections, each with a specific wine pairing.
Here is the text visible on the menu:
First Course
• Gazpacho Served Tableside
• Epi's Leaves down the table
• *Wine Pairing:* 2011 Gewürztraminer
Main Course
• Whole Roasted, Split Organic Chicken, Lemon... (text cuts off)
• Porchetta with Salvia Rosemarino
• Freshly Dug Marble Potatoes, Sour Cream, Chiv... (text cuts off)
• Roasted Parsnips, Nantes Carrots, Asparagus... (text cuts off)
• *Wine Pairing:* 2007 IL Brigante
Dessert
• Rustic Polenta Cake
• Whole Strawberries
• Apple Crostata
• Chocolate Hazelnut Torte
• *Wine Pairing:* 2010 IL Raggio Del Sole
The menu appears to be printed on cardstock with a decorative red stitched border on the left edge. The text is slightly out of focus.



NCF

The main content of this image is a printed **menu** for a meal, likely a formal dinner or wedding reception. It is organized into three courses, each paired with a specific wine.
Here is a breakdown of the text visible on the menu:
First Course
• **Food:** Carpaccio Smoked Tabbouleh, Tuna Loaves from the Isola
• **Wine Pairing:** 2011 Gewürztraminer
Main Course
• **Food:** Whole Roasted, Split Organic Chicken (with Lemon...), Tandoori with..., Freshly Dug Marble Potatoes..., Roasted Turnips, Nantes Carrots, Asparagus...
• **Wine Pairing:** 2007 Il Brigante
Dessert
• **Food:** Rustic Polenta Cake, Whole Strawberries..., Apple Crumble..., Chocolate Hazelnut...
• **Wine Pairing:** 2010 Il Raggio Del Sole
The menu has a white background with pink text and a decorative pink border running down the left side.

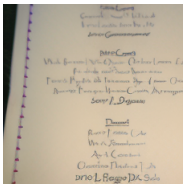


ACA

The main content of this image is a **blank, off-white or beige surface**, which appears to be a close-up of a sheet of paper.
Here are a few more details:
• **Texture:** It has a slight graininess, typical of paper or a wall.
• **Edge:** On the far left side, there is a dark, blurry strip, which looks like the edge of the paper against a darker background.
• **Lighting:** The lighting is somewhat uneven, with slight shadows, but there are no distinct objects, text, or drawings visible.

Figure 9: Image captions generated by Kimi2.6 for a clean image and different adversarial examples using the prompt ``What is the main content of this image?''. Red, blue, and green denote fully successful, partially successful, and unsuccessful attacks, respectively. NCF (Yuan et al., 2022), ACA (Chen et al., 2023b), DiffAttack (Chen et al., 2025), and StyleUAE (Ours) generate adversarial examples on the CNN model RN-50, while VEAttack (Mei et al., 2026) takes CLIP-L/14 as the surrogate model.

Kimi2.6 Image Captions (Continued)



DiffAttack

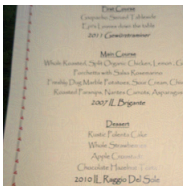
Based on the visual evidence, the main content of this image is a **handwritten page from a spiral-bound notebook**, which appears to be a **menu** or a program for a food-related event.

Here is a breakdown of what is written in blue ink:

• **Top Section:** There is a list of names, with **"Javier Garaventa"** being the most legible at the bottom of this block.

• **Middle Section:** This section is headed by the name **"Piero Capra."** Below it is a list of Italian savory dishes, including **Pasta**, **Risotto**, **Tortelli**, and **Arancini**.

Overall, the document looks like a draft menu for a dinner or cooking demonstration featuring Italian cuisine.



VEAttack

Based on the image, the main content is a printed **menu** for a meal, likely a formal dinner or event. It is written in an elegant, cursive script on cream-colored paper with red stitching along the left binding.

The menu is organized into three courses, each paired with a specific wine vintage:

1. Top Section (Likely "First Course" or a Specific "Diet Course")

• **Food:** Mentions "Crisp... Salad..." and "Light Lemon..."

• **Wine Pairing:** 2011 Gewürztraminer

2. Main Course

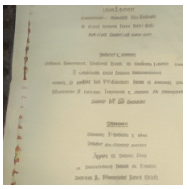
• **Food:**
  • "Whole Roasted, Split Organic Chicken, Lemon, G..." (likely Garlic or Greens)
  • "Pistachio and Herb Roasted..."
  • "Freshly Dug Marble Potatoes, Rose Cream, Chiv..." (likely Chives)
  • "Roasted Turnips, Nantes Carrots, Asparagus"

• **Wine Pairing:** 2007 Il Brigante

3. Dessert

• **Food:**
  • "Kirstie Polenta Cake"
  • "Whole Strawberries"
  • "Apple Crumble..."
  • "Chocolate Hazelnuts..."

• **Wine Pairing:** 2010 Il Raggio Del Sole



StyleUAE

Based on the visual evidence, the main content of this image is a **page of text written in the Georgian language** using the Mkhedruli script.

Here are the specific details:

• **Document Type:** It appears to be a **title page** or a **credits page** for a creative work, such as a screenplay, a theatrical play, or a book. The layout features centered blocks of text, which is typical for titles and dedications.

• **Structure:**
  • **Top Section:** There is a header or title at the very top.
  • **Middle Section:** There are a few paragraphs of centered text, which could be a synopsis, a quote, or a dedication.
  • **Bottom Section:** This area lists names, likely the author, director, or main cast/characters.

• **Visual Details:** The paper has red markings or binding holes along the left margin. The text is typewritten or printed in a serif font.

While the specific text is a bit blurry to read perfectly, the distinctive loops and curves of the characters confirm it is Georgian.

Figure 9: Image captions generated by Kimi2.6 (continued).

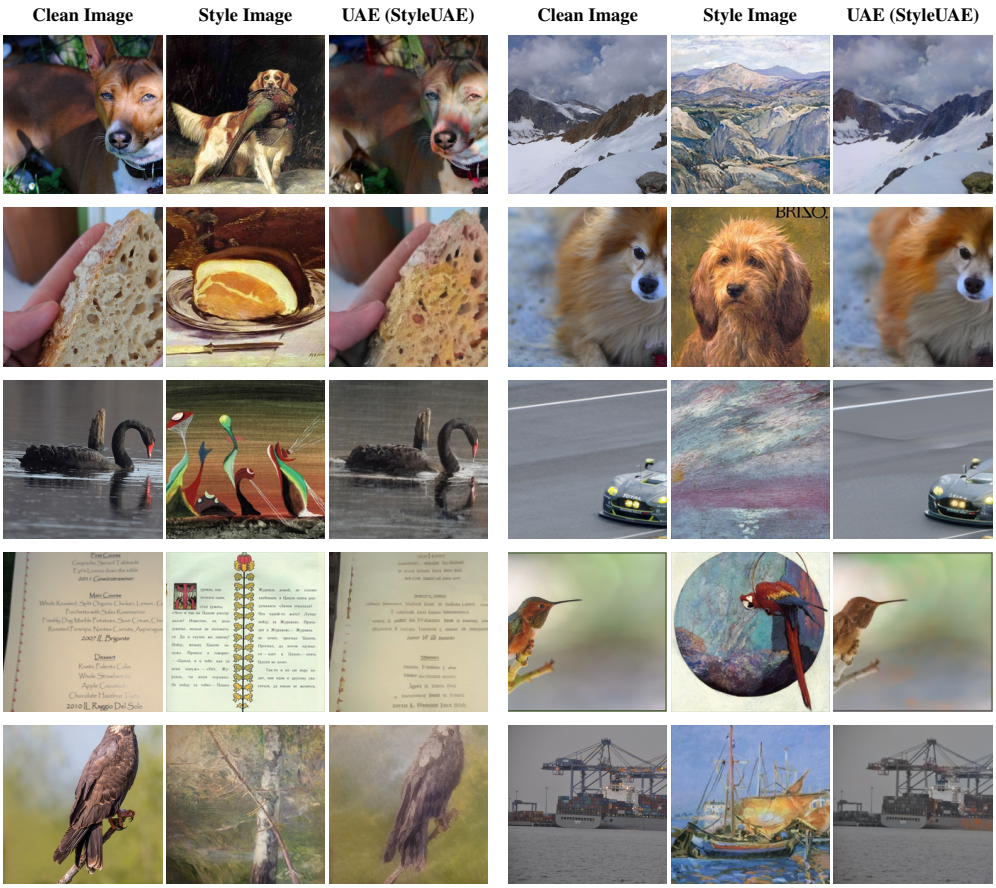


Figure 10: Visualization of clean images, style images selected using *Style Image Selection*, and the corresponding UAEs generated by StyleUAE. All style images are selected from ArtBench-10, and all UAEs are generated using RN-50 as the surrogate model.



Figure 11: Visualization of clean images, style images selected using *Random Selection*, and the corresponding UAEs generated by StyleUAE. All style images are selected from ArtBench-10, and all UAEs are generated using RN-50 as the surrogate model.

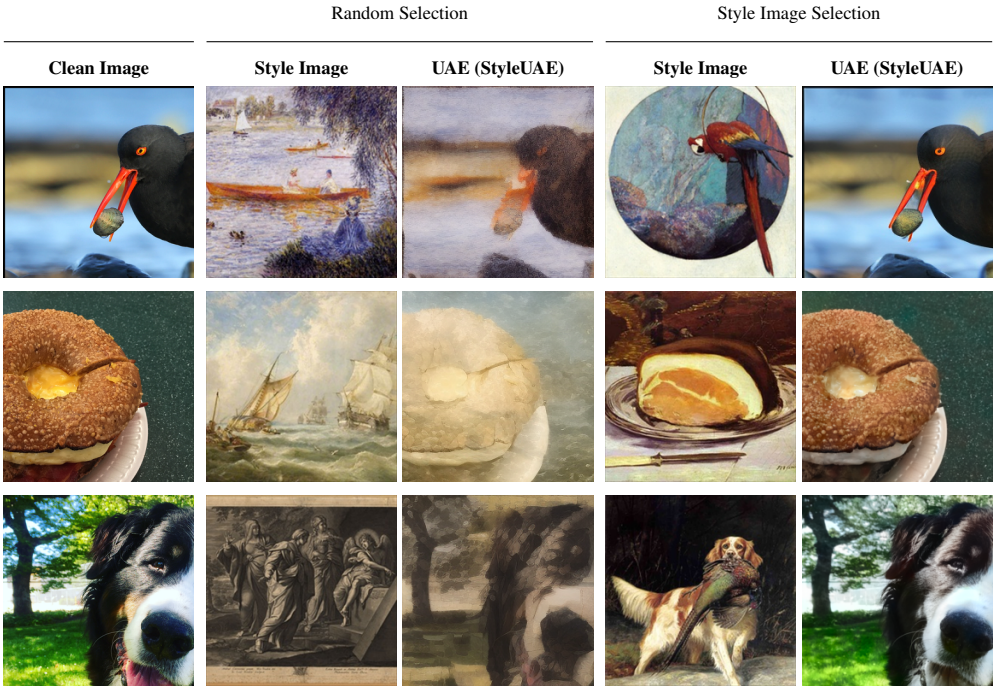


Figure 12: Comparison of UAEs generated using **different style image selection methods**. From left to right, the columns show clean images, style images and corresponding UAEs for *Random Selection*, and style images and corresponding UAEs for *Style Image Selection*. All style images are selected from ArtBench-10, and all UAEs are generated using RN-50 as the surrogate model.

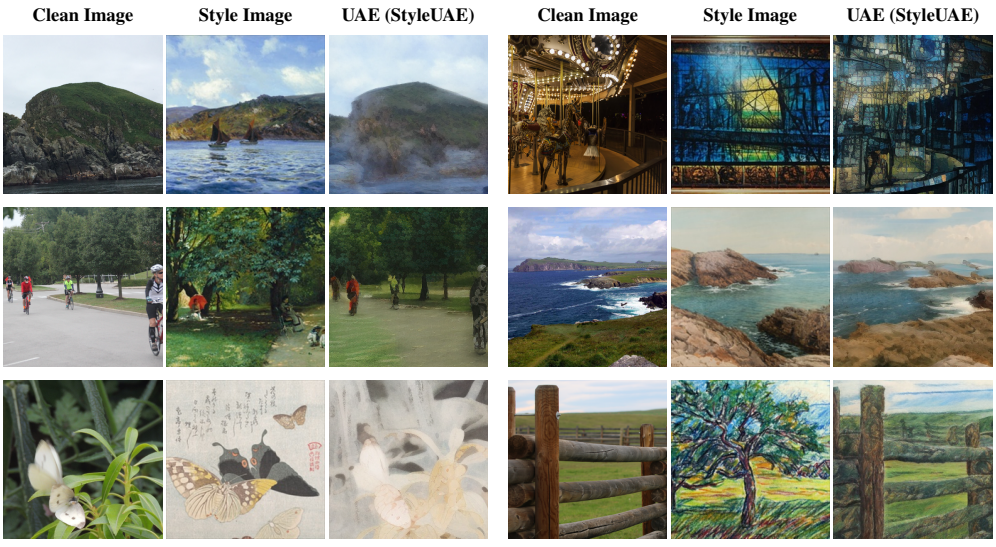


Figure 13: Visualization of selected UAEs with **poor image quality**, including clean images, the style images used by StyleUAE, and the corresponding UAEs generated by StyleUAE. The style images shown here are selected from ArtBench-10 using *Style Image Selection*. All UAEs are generated using RN-50 as the surrogate model.

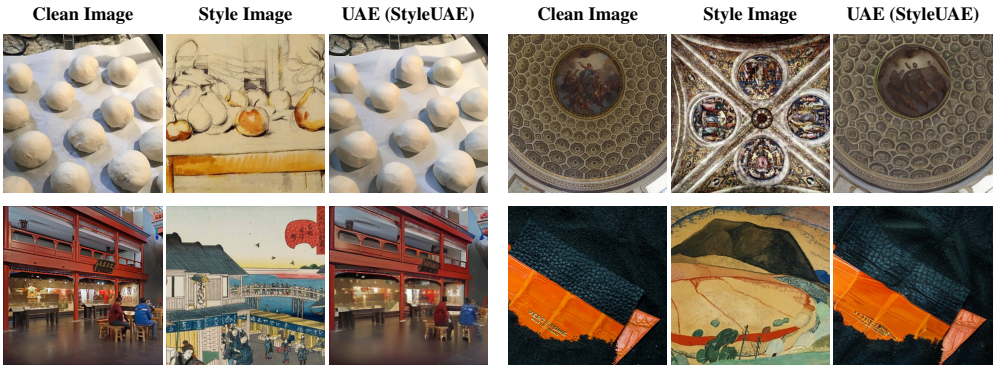


Figure 14: Visualization of selected **unsuccessful attack** cases of StyleUAE, including clean images, the style images used by StyleUAE, and the corresponding UAEs generated by StyleUAE. The style images shown here are selected from ArtBench-10 using *Style Image Selection*. All UAEs are generated using RN-50 as the surrogate model.