

Enlightening Photographic Style Transfer with a Self-Supervised Photographic Embedding

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Abstract. Photographic style transfer aims to render a content image with the retouching style of a reference photo while preserving scene structure and texture. Unlike artistic style, photographic style is dominated by subtle, continuous tone/color changes and smooth spatial effects, which are difficult to represent with semantics-oriented or text-supervised image embeddings. We propose **PETAL**, a **P**hotographic **E**mbedding for **T**ransfer with an **A**daptive **L**UT. PETAL learns a dedicated photographic embedding through self-supervised photographic style augmentation and uses it to condition a lightweight adaptive 5D neural LUT. The learned embedding outperforms prior representations in photographic style retrieval, and the full framework enables reference-based style transfer without test-time optimization, achieving stronger quantitative and perceptual performance than state-of-the-art baselines. Project page: <https://petal-pku.pages.dev/>.

Keywords: Photography · Image Retouch · Self-supervised Learning

1 Introduction

Style transfer is a long-standing challenge [25] in computer vision, as it requires correctly understanding the “style” of reference images and faithfully rendering it onto the content images. However, existing methods transfer either conspicuous artistic brushstrokes or only global lightness and tint, which is far coarser than what photographers consider when processing photos. This poses the even more challenging task of *photographic style transfer*: to understand and transfer the nuanced *photographic style*, capturing photographer-introduced global adjustments (*e.g.*, lightness, color and tone), alongside smooth spatial effects like vignetting, while preserving content and texture.

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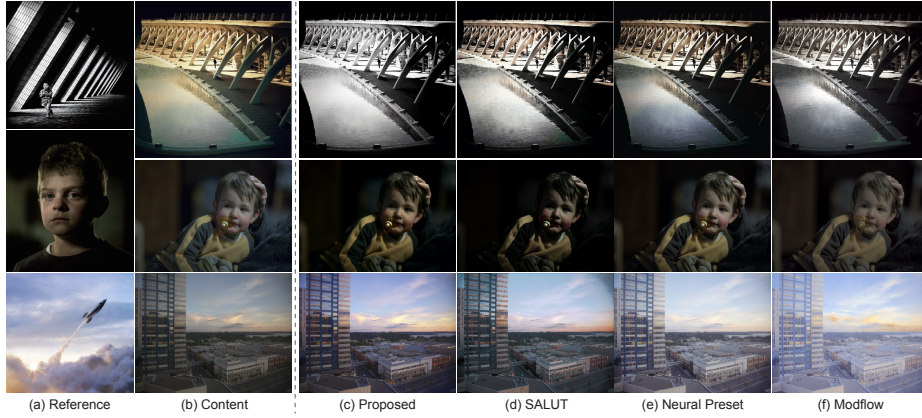


Fig. 1: The task is to transfer the photographic style of (a) reference images to (b) content images while preserving the content and texture of (b). With our photographic embedding, (c) PETAL robustly transfers diverse photographic styles, including high-contrast monochrome, low-key portraits, and saturated purple skies with orange sunlight, all with proper exposure and saturation. Baselines either produce unrealistic results, such as (d) SALUT [28] and (f) Modflow [47], or fail to capture complex styles, as in (e) Neural Preset [44].

Differing in scope from our work, style transfer methods often operate on much coarser features, ranging from the color [18, 53, 65, 66, 71, 102] to the deep features [37, 40, 57] of the reference image, transferring them to the content image, but they tend to distort the texture. Methods based on the lookup table (LUT) [28, 44, 55, 99, 103–105] avoid such distortion through their spatially independent design, but tend to produce unrealistic or altered appearances, as shown in Fig. 1(d, e, f), where none of the baselines can render the first image in black and white, and all yield incorrect contrast levels in the other two examples. We attribute these unsatisfactory results to misaligned features, and argue for the necessity of a fine-grained photographic style embedding to enlighten photographic style transfer.

However, previous image embeddings focus either on semantics [50, 51, 70] or on apparent artistic features [49, 80], leaving the subtle photographic style less explored. Moreover, current training paradigms for image representation are not sensitive to subtle differences among input images, since most previous methods rely on discrete supervision, such as text prompts [70] and classification categories [49, 80]. The continuous nature of photographic style is ill-suited to training with such discrete modalities, as they cannot properly reflect the small but perceptible changes in photographic style.

We therefore introduce **PETAL**, a Photographic Embedding for reference-based photographic style Transfer with an Adaptive LUT. As shown in Fig. 1(c), PETAL is able to transfer the monochrome style and high contrast in the first example, the dark shadow and high contrast in the second example, and the

futuristic pink tint in the third example. Since the LUT has proven effective for style adjustment in previous works [28, 55, 99, 103–105], the key challenge lies in the photographic embedding.

To extract an embedding that truly reflects the photographic style, we face the challenges of representation collapse and unstable optimization. Previous works partially address these problems with an expectation–maximization algorithm, implemented via a moving average [30] or a stop-gradient [16], without requiring negative samples. For photographic style, arbitrary distant patches are unreliable positives because local illumination or object-specific retouching may differ within one image. We therefore use restricted local views as positives and use controlled photographic augmentations to generate style-contrasting negatives.

We design a vision transformer (ViT) paired with histogram encoders in CIE-Lab color space to extract the photographic style. The network training incorporates the stop-gradient operation [16] and hard negative examples [43, 73, 92] derived from photographic style augmentation, for more stable self-supervised learning. On the tasks of retrieval and clustering, the photographic embedding is verified to focus on style rather than on semantics. Bridged by the photographic embedding extracted from any reference image, we then demonstrate that the photographic style of a given image can be transferred with a LUT conditioned on pixel color and location. Without any test-time optimization, PETAL surpasses previous methods in style consistency and visual quality.

In brief, the contributions of this paper are as follows:

- a photographic embedding network that extracts photographic style features from images, enabling similar-style retrieval and the measurement of style difference;
- a self-supervised learning scheme with photographic style augmentation that overcomes data scarcity and learns the underlying photographic style;
- a lightweight LUT that transfers the photographic style from any given reference image to a content image without additional test-time optimization.

2 Related Works

2.1 Image Embedding

Extracting a compact representation from images is a fundamental task in computer vision research. From hand-crafted features [5, 20, 56] to neural embeddings [46, 70, 77], methods increasingly aim to capture semantic content. Early approaches focused on category alignment [35, 46, 77, 84], enabling broad downstream use. Later work aligned images with text [7, 23, 48, 59], with large-scale cross-modal pretraining showing strong results [52, 70, 106]. Notably, CLIP [70] has been widely used in language [1, 8, 85–87], text-to-image [14, 68, 74], and text-to-video models [93, 94, 100], due to its effective cross-modal contrastive learning. Yet prior embeddings still fail to fully capture the nuanced photographic style, which, in addition to the content, is a vital part of visual semantics.

2.2 Image-Only Contrastive Learning

Without text labels or other modalities, contrastive learning can also learn an embedding space for images, by pulling positive samples together and pushing negative samples apart during optimization. The main problems are model collapse and unstable training, caused by under-constrained optimization and a non-convex landscape, respectively. Although various loss functions have been proposed [19, 31, 60, 76, 79], they require an enormous batch size [15, 16] or a specially designed memory bank to provide older representations [34], both of which are computationally expensive. Recent works attempt to remove the need for negative samples. VICReg [10] introduces a regularizer that explicitly supervises the variance and covariance among samples. BYOL [30] and SimSiam [16] adopt the expectation-maximization approach, using a moving average and a stop-gradient operation, respectively, to avoid model collapse. For the task of this paper, however, a vanilla network design may fail to distinguish photographic styles, such as different exposure levels. We borrow the stop-gradient from SimSiam [16] and incorporate negative samples into the self-supervised learning scheme.

2.3 Style Transfer

Prior methods align global lightness using physical models [26, 72, 82, 101], or model color mapping with 3D LUTs [55, 99, 103–105] and parameter sets [36, 44]. Although these methods can seemingly align the overall color and lightness, the naively extracted photographic style differs from human perception. White-box sequential edits [38, 62, 89, 95] offer finer control but struggle with the interdependencies among image-editing operations. Diffusion-based approaches [22, 91] add semantic awareness, but can distort structure, drift in color, and are computationally heavy. We propose a lightweight neural 5D LUT that transfers the extracted photographic style, conditioned on pixel color in CIE-Lab color space and spatial coordinates. Enlightened by the trained photographic embedding, the proposed photographic style transfer achieves a finer understanding of the actual photographic style.

3 Methods

In Sec. 3.1, we first introduce the photographic embedding network. The ViT backbone merges the pixel values and the global distribution from the histogram feature with a learnable [CLS] token. Through a self-supervised contrastive learning scheme with photographic style augmentation for negative samples, as discussed in Sec. 3.2, the extracted photographic embedding is able to reflect the photographic style, as further validated by style retrieval and clustering. Finally, we present the simple yet effective photographic style transfer design that builds upon the photographic embedding, detailed in Sec. 3.3.

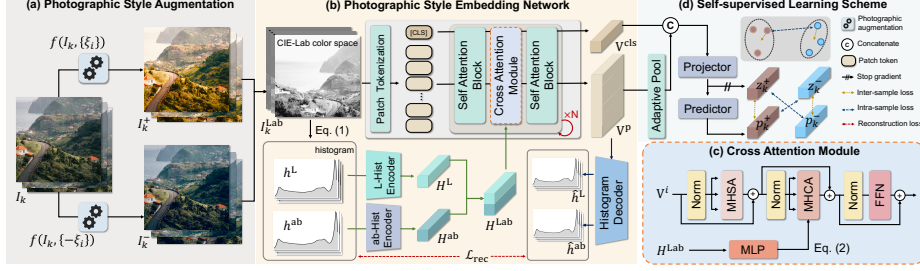


Fig. 2: The pipeline of the photographic embedding network and the training process. (a) An anchor crop is jittered into K overlapping local views, and each I_k is then applied with the photographic style augmentation controlled by $\{\xi_i\}$ and $\{-\xi_i\}$ to derive two photographically contrastive batches. (b) Each batch is converted to the CIE-Lab color space, and processed by the ViT-based network to extract photographic embeddings. (c) The luminance and chromaticity histograms (h^L, h^{ab}) are encoded and injected via cross attention module to guide the representation learning. (d) The photographic embeddings z_k^+ and z_k^- are projected to p_k^+ and p_k^- for contrastive learning.

3.1 Photographic Embedding

As a complex combination of color, lightness, and other visual cues, photographic style is challenging to describe in words. Its continuous nature is also quite different from natural language: for example, a change in exposure may be far more subtle than the change from “dim” to “slightly dim”, yet text prompts cannot reflect this, as they are discrete by nature. Nevertheless, professional photographers can easily recognize such styles, as well as slight changes in photographic style. Inspired by this observation, we design a ViT-based embedding network $\mathcal{M}$ to extract a photographic embedding by integrating global semantics, aggregated through the [CLS] token, with tonal and color statistical features guided by luminance–chromaticity histograms in the CIE-Lab color space, as illustrated in Fig. 2(b). The [CLS] token serves as a compact global descriptor that complements pooled patch-token statistics; as shown in Tab. 3, using the [CLS] token alone is insufficient, motivating its concatenation with aggregated patch features.

Given an input image I , we first convert it to CIE-Lab color space (I^{Lab}) to decouple luminance and chromaticity components [39, 42]. I^{Lab} is then divided into patches and tokenized, along with the [CLS] token, to form the input sequence for the main transformer blocks. Meanwhile, to extract tonal and color statistical features, we compute the luminance histogram $h^L \in \mathbb{R}^H$ from L channel (I^L) and the chromaticity joint histogram $h^{ab} \in \mathbb{R}^{H \times H}$ from the ab channels (I^{ab}). Following previous methods [3, 4], the histogram computation is implemented as a differentiable process using the inverse-quadratic kernel [4] $\mathcal{K}(\cdot)$:

$$h^L(i) = \sum_{p=1}^N \mathcal{K}(I^L(p), b_i), \text{ and } h^{ab}(i, j) = \sum_{p=1}^N \mathcal{K}(I^a(p), b_i) \cdot \mathcal{K}(I^b(p), b_j), \quad (1)$$

where N is the number of pixels, b_i and b_j are the bin centers, and p denotes a pixel location. These two histograms are processed by their respective encoders (L-Hist Encoder and ab-Hist Encoder), and the resulting features are then stacked to form the histogram feature H^{Lab} . The histogram features explicitly contain global tonal and chromatic statistics, which are difficult to infer reliably from pixel values. These features are injected via cross-attention, allowing global distribution cues to guide spatial representations without disrupting their structural properties. As illustrated in Fig. 2(c), each cross-attention module contains an MLP that projects the histogram feature H^{Lab} into $\tilde{H}^{\text{Lab}}$.

Finally, the photographic style embedding is obtained by integrating global and local representations as

$$z = h([V^{\text{cls}}; \mathcal{P}(V^{\text{p}})]) . \quad (2)$$

where V^{cls} and V^{p} denote the feature representations of the [CLS] token and the patch tokens obtained from the ViT network, respectively. $\mathcal{P}(\cdot)$ denotes the learnable adaptive pooling over the patch tokens, and $h(\cdot)$ is a projection MLP following the asymmetric design of SimSiam [16].

3.2 Self-Supervised Embedding Learning

With the module designs providing the network with the information necessary to extract the photographic style, the remaining problem is the absence of high-quality labels. Although many previous methods manage to learn a semantic representation with text supervision [70, 88], the discrete text representation is unfit to supervise the subtle differences in photographic style. We therefore propose a self-supervised learning paradigm that optimizes the photographic embedding space by relying on images alone.

To optimize the encoded latent space specifically for the photographic style, we design a self-supervised embedding learning scheme. As illustrated in Fig. 2(a), we first sample an anchor crop from image I and apply small spatial jitters to obtain K overlapping local views. Each patch is augmented with two sets of parameters, which aim to perturb the input image toward contrary photographic styles. Denoted $f(I, \{\xi_i\})$, the transform takes a set of parameters $\xi_i \in [-1, 1]$, with $f(I, \mathbf{0}) \equiv I$ being the identity mapping. Each parameter ξ_i controls the adjustment of one of the M predefined aspects of photographic style (*e.g.*, exposure, saturation, tint, highlight, and shadow). In this way, we create two photographically augmented versions of the sample, which serve as negative examples to each other.

Photographic Style Augmentation (PSA). For reproducibility, $f(\cdot, \{\xi_i\})$ is designed as a random composition of differentiable photo-editing operators implemented in PyTorch. Each operator is parameterized by a scalar $\xi \sim \mathcal{U}([-1, 1])$ and reaches its maximum strength at $|\xi| = 1$; we keep the ranges intentionally conservative to avoid introducing out-of-distribution artifacts while still producing hard negatives in photographic style. The specific choices of style augmentations are detailed in the supplementary material.

Following previous methods [12] and our objective, the overlapping local views under the same PSA parameter in the same image are considered positives. They share most content, local illumination context, and smooth tone/color rendering, which mitigates false positives from distant patches or strongly localized edits. As for the negative samples, we choose the pair of images from the same patch that undergo contrary augmentations, namely $f(I_k, \{\xi_i\})$ and $f(I_k, \{-\xi_i\})$. For notational convenience, we denote $z_k^+ = \mathcal{M}(f(I_k, \{\xi_i\}))$ and $z_k^- = \mathcal{M}(f(I_k, \{-\xi_i\}))$. The predictor outputs are abbreviated as $p_k^+ = h(z_k^+)$ and $p_k^- = h(z_k^-)$.

As shown in Fig. 2(d), owing to the symmetric design of the proposed pipeline, we define an ‘‘intra-sample loss’’ $\mathcal{L}_-$ that attracts positive samples cropped from the same image, and an ‘‘inter-sample loss’’ $\mathcal{L}_+$ that repels negative samples from different augmented versions of the same patch, given by

$$\mathcal{L}_- = -\mathbb{E}\left[\left\langle p_k^+, \frac{\text{sg}(\sum_{i=1}^K z_i^+)}{K} \right\rangle + \left\langle p_k^-, \frac{\text{sg}(\sum_{i=1}^K z_i^-)}{K} \right\rangle\right], \quad (3)$$

$$\mathcal{L}_+ = \mathbb{E}\left[\text{CE}\left(\left\langle p_k^+, \text{sg}(z_k^+) \right\rangle, \left\langle p_k^-, \text{sg}(z_k^+) \right\rangle\right) + \text{CE}\left(\left\langle p_k^+, \text{sg}(z_k^-) \right\rangle, \left\langle p_k^-, \text{sg}(z_k^-) \right\rangle\right)\right]. \quad (4)$$

where $\text{sg}(\cdot)$ is the stop-gradient operation, and $\langle \cdot, \cdot \rangle$ and $\text{CE}(\cdot, \cdot)$ are notations for cosine similarity and binary cross entropy respectively, defined by $\text{CE}(s_{\text{pos}}, s_{\text{neg}}) = -\log \frac{\exp(s_{\text{pos}})}{\exp(s_{\text{pos}}) + \exp(s_{\text{neg}})}$. Eqs. (3) and (4) are designed to encourage matching the prediction to its own-view embedding while suppressing the opposite augmentation. The intra-sample loss matches each prediction to the (stop-gradient) center of its own local-view batch, encouraging invariance to crop and spatial jitter. In contrast, the inter-sample loss separates two contrary PSA views of the *same* patch. Because the content and layout are fixed while tone/color are deliberately changed in opposite directions, these samples prevent content-matching shortcuts and form hard negatives for photographic style.

In addition to the aforementioned contrastive objective, we introduce the histogram reconstruction loss $\mathcal{L}_{\text{rec}}$, which operates on the patch token features V^{P} , inspired by recent representation learning practices that regularize intermediate features with auxiliary reconstruction objectives (*e.g.*, SigLIP-2 [88] and related self-supervised vision encoders). We design a lightweight CNN to reconstruct both the luminance histogram (h^{L}) and the chromaticity joint histogram (h^{ab}) from V^{P} , yielding the reconstructions $\hat{h}^{\text{L}}$ and $\hat{h}^{\text{ab}}$. The loss $\mathcal{L}_{\text{rec}}$ is defined by

$$\mathcal{L}_{\text{rec}} = \mathcal{H}(h^{\text{L}}, \hat{h}^{\text{L}}) + \mathcal{H}(h^{\text{ab}}, \hat{h}^{\text{ab}}), \quad (5)$$

where $\mathcal{H}(\cdot)$ denotes the Hellinger distance [4]. Consequently, the final overall optimization objective is given by $\mathcal{L} = \mathcal{L}_- + 0.5 * \mathcal{L}_{\text{rec}} + 0.1 * \mathcal{L}_+$, where these coefficients are set to normalize the losses to comparable magnitudes.

3.3 Photographic Style Transfer

PETAL pairs the photographic style embedding from $\mathcal{M}$ with a lightweight adaptive neural LUT to enable reference-based photographic style transfer, as

illustrated in Fig. 3. The neural LUT is composed of an encoder $\mathcal{E}$ and a decoder $\mathcal{D}$, both of which are 1×1 CNNs, so that the detailed texture can be preserved.

Let I_c denote the content image and I_s denote the style reference image. We first compute per-pixel features $x_c = \mathcal{E}(I_c, P)$, where $P \in [0, 1]^2$ is the normalized pixel coordinate map. Denote by $\mu(\cdot)$ and $\sigma(\cdot)$ the channel-wise mean and standard deviation of x_c , and let $g_\mu(\cdot)$ and $g_\sigma(\cdot)$ be two lightweight MLPs that map a photographic embedding to an affine shift in mean/variance. We then apply an embedding-conditioned AdaIN-like re-normalization:

$$\hat{I} = \mathcal{D}(\tilde{\mu} + \text{Norm}(x_c) \odot \tilde{\sigma}), \text{ where } \text{Norm}(x_c) = \frac{x_c - \mu(x_c)}{\sigma(x_c) + \epsilon}. \quad (6)$$

In addition, $\tilde{\mu} = \mu(x_c) + g_\mu(\mathcal{M}(I_s)) - g_\mu(\mathcal{M}(I_c))$, and $\tilde{\sigma} = \sigma(x_c) + g_\sigma(\mathcal{M}(I_s)) - g_\sigma(\mathcal{M}(I_c))$ are the standard deviation and mean for re-normalization. $\mathcal{E}$ and $\mathcal{D}$ are the encoder and decoder, implemented with 1×1 CNNs. This choice ensures computational efficiency, avoids spatial mixing to preserve local textures, and admits a natural 5D (Lab+xy) look-up-table interpretation, facilitating responsive deployment.

This injects the style delta between I_s and I_c through the embedding space. Since x_c and $\hat{I}$ are determined by pixel color (in CIE-Lab) and spatial coordinates, the module is a 5D neural LUT by design. Eq. (6) reduces to approximate identity mapping when $I_s \approx I_c$, since $\mathcal{M}(I_s) \approx \mathcal{M}(I_c)$.

To train the style-transfer network, the learned embedding network $\mathcal{M}$ is frozen. We sample a content patch I_c and synthesize a paired style target $I_s = f(I_c, \{\xi_i\})$ using the aforementioned PSA; I_s therefore serves as both the style reference and the supervised ground truth. The LUT is trained to map $I_c \mapsto I_s$ by conditioning on $(\mathcal{M}(I_c), \mathcal{M}(I_s))$. We supervise the training of this part with a weighted sum of: (i) pixel-wise mean squared error, (ii) perceptual loss [107], (iii) an embedding-based style loss $1 - \langle \mathcal{M}(\hat{I}), \mathcal{M}(I_s) \rangle$, and (iv) an identity loss $\|\mathcal{D}(\mathcal{E}(I_c)) - I_c\|_2$ to stabilize the near-identity regime.

Note that we adopt two-stage training mainly for stability and efficiency. Contrastive learning of $\mathcal{M}$ is memory-intensive, and joint training would require backpropagating through $\mathcal{M}$ while optimizing the dense per-pixel LUT, at least doubling the memory cost and slowing optimization. In practice, freezing $\mathcal{M}$ yields a strong and stable conditioning signal for LUT training.

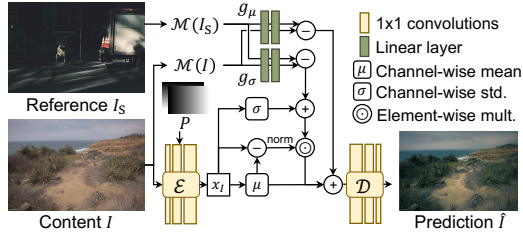


Fig. 3: The PETAL transfer network design, with $\mathcal{M}$ being the trained photographic style embedding network.

4 Experiments

Datasets. For training, we use high-quality images from Unsplash [17] to avoid reliance on discrete text representations.

To evaluate style retrieval, we adopt three datasets. **PPR10K subset** [54] contains 1,681 portrait scenes, each captured in three distinct photographic styles. Due to the high resolution ($>20\text{M}$ pixels), we use the first 245 scenes for benchmarking. **FiveK-Concept** [11] is constructed from FiveK [11] to assess sensitivity to fundamental photographic concepts. Images are grouped by genre and subject, then clustered into 623 groups (7 images per group on average) using K-means on Qwen3-VL [9] annotations encoded by EmbeddingGemma [90]. A professional photographer edits each group’s RAW files in Adobe Lightroom [2] by varying exactly one concept (*e.g.*, contrast, temperature, or tint) to produce a single consistent style per group. **INSRANK** comprises 32 Instagram-based groups curated from photographers’ works. Each group includes one query and five candidates, which are independently ranked by two professional photographers according to style similarity; their rankings serve as pseudo ground truth.

For the style transfer evaluation, we conduct quantitative comparisons on PST50 [28] and PPR10K subset [54]. In PPR10K, the first image of each expert-defined style serves as the reference, and the remaining images in the same scene are used for evaluation. Importantly, both PPR10K and PST50 provide ground-truth retouched targets under consistent style definitions; thus, the reference-based metrics in Tab. 2 compare $\hat{I}$ against these ground truths, reflecting both content preservation and style fidelity. Although PPR10K is portrait-focused, its benchmark labels mainly reflect whole-image global and smooth regional retouching; face-specific local retouching remains outside our primary scope and is discussed in the limitations.

For qualitative comparison, we evaluate on the DPST test set [57], and additionally use images from the Hasselblad Masters dataset [32] and INSRANK as style references due to their strong individual photographic characteristics.

Baselines. For a scope similar to that of this paper, we compare against the photo-style embeddings of CSD [80], DiffSim [81], DreamSim [24], FreeStyleRet (FSR) [49], and ALADIN [75], as well as classic Gram-matrix features from Gatys *et al.* [25]. We also include the color discriminator (ColorD) from Neural Preset [44] and the intermediate representation of Modflow [47], both of which can serve as style-aware representations. For fairness of comparison, we also report DINOv3* [78] and CLIP* [70] fine-tuned with the same training data and objectives as our method. Pretrained image embeddings are also considered, including models pretrained on text-image pairs, such as CLIP [70], BLIP [51], and BLIP-2 [50], and those trained with self-supervision, such as DINOv2 [61], ImageBind [27], SigLIP-2 [88] and DINOv3 [78], which are designed for general image embedding tasks.

For photographic style transfer, we compare with methods that operate without per-reference test-time optimization, aligning with our method for fair comparison. Representative methods in photo-realistic style transfer are compared, including PhotoWCT² [18], DSTN [37], StyTr² [21], CAP-VSTNet [97], and SALUT [28]. We also compare with image retouching methods of Deep Preset [36], Neural Preset [44] (closed source, application access only), and Modflow [47]. We also consider the commercial products of Pixelmator Pro [67] where

Table 1: Quantitative photographic style retrieval performance for embeddings. All the values are shown as percentages, and higher numbers indicate better performance. Best values are in **bold**, and second best are underlined. * indicates fine-tuning on our training data with the same objectives.

Method	#Para.	PPR10K [54] subset				FiveK-Concept [11]				INSRANK		
		R@1	R@5	mAP	F1@5	R@1	R@5	mAP	F1@5	R@1	ρ [83]	τ [45]
General image embeddings												
CLIP [70]	428M	0.08	95.33	31.62	23.82	0.89	3.07	9.72	0.72	34.38	15.32	13.17
BLIP [51]	225M	8.81	89.60	35.78	26.76	1.52	2.40	10.21	0.72	46.88	15.62	11.87
BLIP-2 [50]	3.745B	1.54	91.07	31.46	22.90	1.28	2.55	10.11	0.69	37.50	29.06	23.75
DINOv2 [61]	304M	1.48	90.32	31.23	22.54	0.05	0.14	8.10	0.03	37.50	27.81	21.25
DINOv3 [78]	303M	1.48	97.36	30.81	22.15	0.02	0.10	8.42	0.02	43.75	25.31	21.25
ImageBind [27]	1.201B	0.62	97.09	32.02	23.84	0.09	24.53	17.71	4.89	37.50	16.87	14.37
SigLIP-2 [88]	1.137B	1.48	90.61	31.22	22.64	0.70	1.53	9.63	0.35	37.50	32.19	23.75
Image style embeddings												
CSD [80]	305M	6.77	98.00	38.44	32.42	8.35	23.14	17.85	6.70	37.50	<u>40.94</u>	<u>33.12</u>
FSR [49]	940M	0.26	94.16	30.25	21.62	0.88	4.27	9.21	0.94	25.00	4.06	3.75
DiffSim [81]	1.06B	7.03	94.99	33.51	25.82	8.67	10.47	11.31	1.38	<u>50.00</u>	19.37	15.00
DreamSim [24]	93.2M	8.80	93.23	34.17	23.69	1.04	7.83	8.57	1.65	40.62	24.06	19.37
ALADIN [75]	86.3M	32.44	98.87	52.69	44.35	27.67	55.88	32.46	21.26	46.88	33.12	29.37
Gram [25]	0.113M	26.24	96.48	42.39	31.82	25.49	51.77	25.90	17.46	31.25	32.19	26.87
Modflow [47]	59.63M	28.18	93.04	43.47	33.33	19.49	44.27	22.59	14.50	34.38	14.69	13.12
ColorD [44]	42.56M	<u>65.80</u>	97.86	<u>64.15</u>	<u>50.25</u>	<u>45.45</u>	79.76	<u>41.25</u>	<u>31.87</u>	46.88	13.44	8.12
Fine-tuned baseline representations												
DINOv3* [78]	303M	59.30	94.38	61.78	46.59	34.72	66.49	36.61	24.88	34.38	15.31	13.13
CLIP* [70]	428M	54.42	93.87	58.99	44.01	34.66	65.85	37.90	26.81	<u>50.00</u>	19.37	17.50
Proposed emb.	362M	74.27	<u>98.40</u>	71.99	56.60	52.94	<u>78.56</u>	51.84	39.01	62.50	52.19	46.88

we use the style matching tool, and also Nano Banana Pro [29] where we specify style transfer prompts.

Evaluation Metrics. To evaluate the style embedding, we follow previous works and report the recall among top- k predictions ($R@k$) [6, 27, 41, 49, 50, 60, 88], mean Average Precision (mAP) [13, 61, 63, 64, 69], and F1 score among top- k predictions ($F1@k$). Higher $R@k$ values, especially $R@1$, indicate a stronger ability of the embedding to distinguish photographic style from image content. mAP measures the proportion of false predictions, and $F1@k$ provides a balanced view of precision and recall. The higher these metrics are, the better the performance. Note that $R@5$ is defined differently in this field than in classification tasks. For INSRANK, we evaluate the alignment of predictions with human preference using Spearman’s ρ [83] and Kendall’s τ [45]. The mathematical definitions of the above metrics are provided in the supplementary material.

As for the photographic style transfer task, we report Peak Signal to Noise Ratio (PSNR), structural similarity index (SSIM) [96], LPIPS [107] and histogram correlation (H-Corr) [28] to measure the similarity between the prediction and the ground truth. Together, the metrics measure per-pixel color accuracy, structural preservation, and histogram similarity. To further measure perceptual style fidelity, we further report LIQE [108], Q-Align [98], MS-SWD [33], and Gemini-based VLM judging [85] in the supplementary material, which supports the same conclusion.

Table 2: Quantitative comparisons for photographic style transfer on the PPR10K [54] subset and PST50 [28] dataset, the user preference scores, and average inference time. $\uparrow$ ($\downarrow$) denote higher (lower) is better.

Method	Time (s)	PPR10K [54] subset				PST50 [28]				User Study		
		LPIPS↓	PSNR↑	SSIM↑	H-Corr↑	LPIPS↓	PSNR↑	SSIM↑	H-Corr↑	(i)↑	(ii)↑	(iii)↑
Open-source methods												
SALUT [28]	0.3117	0.2464	16.47	0.6307	0.2464	0.1557	21.93	0.8733	0.4036	4.26	3.38	3.62
Modflow [47]	0.3680	0.2160	19.64	0.7914	0.3815	0.1707	20.01	0.8599	0.3373	4.15	3.68	3.85
CAP-VSTNet [97]	0.4633	0.2172	20.05	0.7858	0.4199	0.1698	20.12	0.8400	0.3669	3.65	4.03	3.21
Deep Preset [36]	0.0329	0.1717	<u>20.88</u>	0.8137	0.4410	0.1365	<u>23.40</u>	0.8895	0.4194	4.65	3.12	3.97
StyTr ² [21]	0.6565	0.2779	18.62	0.6644	<u>0.4667</u>	0.4424	19.54	0.7224	0.4054	2.09	3.29	3.03
PhotoWCT ² [18]	0.3408	<u>0.1538</u>	18.95	<u>0.8366</u>	0.3989	0.1762	18.43	0.8365	0.3450	2.73	3.62	3.41
DSTN [37]	0.9809	0.2982	16.84	0.5726	0.3972	0.3843	16.97	0.5525	0.3244	1.53	2.94	2.09
Closed-source applications												
Neural Preset [44]	N/A	0.1377	19.12	0.8048	<u>0.4858</u>	<u>0.1210</u>	22.61	<u>0.8975</u>	<u>0.4392</u>	<u>4.32</u>	4.15	<u>4.35</u>
Pixelmator Pro [67]	N/A	0.1207	19.43	0.8825	0.3824	0.1526	21.60	0.8684	0.3121	4.41	3.69	3.81
Nano Banana [29]	N/A	0.2817	16.91	0.6509	0.4927	0.3069	18.42	0.6287	0.3836	3.74	<u>4.31</u>	4.47
PETAL	<u>0.2306</u>	0.1027	21.80	0.8710	0.4578	0.1021	24.63	0.9272	0.5220	4.65	4.71	<u>4.44</u>

4.1 Quantitative Comparisons

Photographic Embedding. As discussed earlier, pretrained image encoders can extract image semantics, which is further confirmed by the results in Tab. 1. Note that their R@1 scores are still significantly worse than that of the proposed photographic embedding, yet they all achieve a high R@5 score on the PPR10K [54] subset, because that dataset contains only 3 kinds of photographic style. In contrast, the FiveK [11] dataset is more challenging for retrieval, as each scene is aggregated from images with similar content rather than the exact same scene. For the two style embeddings, CSD [80] and FSR [49] perform similarly to the other embeddings, indicating the gap between artwork style and photographic style. On INSRANK, the proposed photographic embedding also shows the highest alignment with human preference in both the top-1 prediction and the ranking, measured by Spearman’s ρ [83] and Kendall’s τ [45]. Crucially, even when we fine-tune strong pretrained backbones on our training data with the same objectives (DINOv3* and CLIP*), their R@1 scores improve substantially (*e.g.*, 59.30 and 54.42 on PPR10K) yet remain below the 74.27 achieved by the proposed photographic embedding, suggesting that the network design is important for capturing photographic style. These results confirm that previous methods target semantics rather than photographic style, highlighting the efficacy of the proposed photographic embedding.

Photographic Style Transfer. In Tab. 2, we first evaluate the running time by transferring content images with the resolution of 1080×1920 , using reference images of size 512×512 as guidance. PETAL processes a 1080×1920 input in 0.23s, including photographic-embedding extraction and the LUT forward pass, and is the second-fastest method among the baselines.

We then report the quantitative performance of each method on the two benchmark datasets. PETAL attains the best PSNR and LPIPS on both datasets,

together with the best SSIM and H-Corr [28] on PST50 [28], confirming accurate, content-preserving transfer with superior perceptual quality [107]. The second-best Neural Preset [44] lags in PSNR, while Deep Preset [36] matches PSNR but trails in H-Corr. We note that H-Corr, being a purely global histogram statistic, can be inflated without faithful transfer: on the PPR10K [54] subset, StyTr² [21] and Nano Banana Pro [29] report higher H-Corr than PETAL yet severely alter the content, as their much lower PSNR and SSIM and the qualitative results in Fig. 5 reveal. Additional perceptual and VLM-based evaluations are provided in the supplementary material.

4.2 User Study

To assess perceptual quality, we conducted a user study with 34 volunteers. For each input, participants viewed the stylized results produced by each method and assigned a score from 1 (worst) to 5 (best) for three aspects: *(i)* content preservation, *(ii)* style consistency, and *(iii)* overall visual quality, as listed in Tab. 2. PETAL ranks first in both content preservation (tied with Deep Preset [36]) and style consistency, where it leads the runner-up by a clear margin, and ranks second in overall quality, narrowly behind Nano Banana Pro [29]. The competing methods’ failure modes are reflected in their ratings: Nano Banana Pro [29] scores highest on overall quality but modifies the scene content, yielding a much lower content-preservation rating; Deep Preset [36] preserves content well but leaves the original style largely intact, giving the lowest style consistency among the top methods; and Neural Preset [44] is competitive overall but may misinterpret the style, limiting its style consistency.

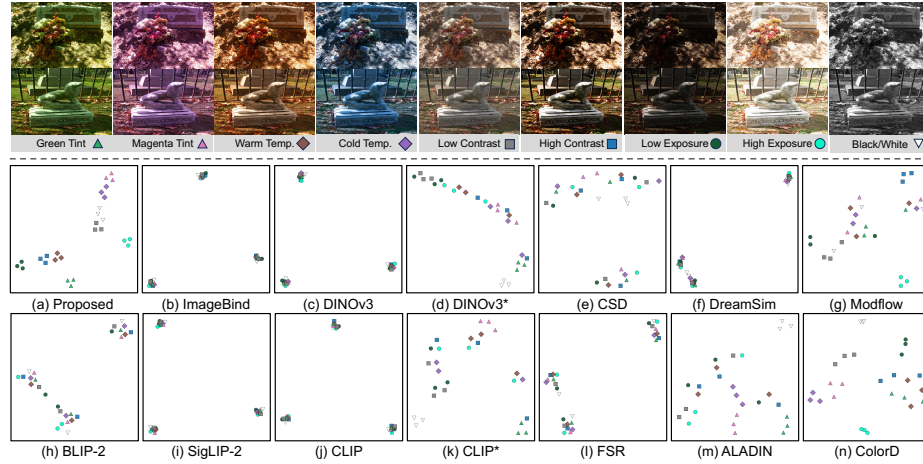


Fig. 4: A t-SNE [58] visualization of the proposed photographic embedding and baseline methods, conducted on the FiveK-Concept [11] dataset. Ideally, photographic-style-aware representations should have 9 clusters, each sharing one kind of shape, where each shape denotes one photographic adjustment.



Fig. 5: Qualitative comparisons for photographic style transfer. Reference images are shown in the bottom-right red boxes of the first column.

4.3 Qualitative Comparisons

First, we visualize the photographic embedding space in Fig. 4. An ideal photographic embedding should reflect the distance in photographic style: with images adjusted by different photographic concepts, it should map those with similar adjustments closer to each other and form clusters in the t-SNE [58] visualization. The FiveK-Concept [11] subset contains three content-similar source images, each retouched with the same set of 9 photographic adjustment types; thus, a photographic-style-aware embedding should form 9 style-driven clusters, each containing the three images sharing one adjustment. As shown in Fig. 4(a), the proposed photographic embedding follows this behavior. In comparison, semantic embeddings such as DINO [61, 78] are mainly driven by content and are unaware of photographic style, while the specially trained color discriminator ColorD [44] still fails to distinguish some fine-grained photographic styles.

We then compare PETAL with baselines across landscape, portrait, stylized lighting, architectural, and indoor examples in Fig. 5, where the reference for each row is provided as a bottom-right inset in the first column. As shown, PETAL faithfully transfers the reference exposure, color temperature, saturation, and contrast while preserving scene geometry and fine textures. In contrast, Neural Preset [44] and Deep Preset [36] consistently under-transfer the reference style (*e.g.*, missing the cool tones in the first three rows), and SALUT [28] often yields

incorrect contrast levels. Modflow [47] applies coarse global shifts that introduce unnatural color casts, failing to maintain local tonal balance. Furthermore, CAP-VSTNet [97], PhotoWCT² [18], and StyTr² [21] severely distort the content, introducing spatial color bleeding, structural artifacts, and texture leakage.

In Fig. 6, we interpolate the conditioning photographic embedding, and find that the output shows a linear interpolation between the two reference photographic styles, and the content is kept throughout the interpolation.

In Fig. 7, we additionally test a sequence of transfer, using the previous output as the next input. After multiple rounds, the content structure and the target style remain stable, and reapplying the same reference in later steps yields only minimal changes, indicating that the LUT behaves near-identity when content and reference share similar photographic style.

An additional PPR10K embedding-space visualization, more qualitative comparisons, and failure-case analysis are provided in the supplementary material.



Fig. 6: Interpolating the photographic embedding leads to the interpolation of photographic style between the two shown reference images, and the content is kept throughout the process.

4.4 Ablation Study

We first verify the proposed photographic embedding network design and the self-supervision scheme in Tab. 3. Changing the color space from CIE-Lab to RGB degrades the representation, as the former disentangles luminance and chromaticity and thus allows easier extraction of photographic style. Removing the cross-attention module also removes the information from the histogram encoders; judging from the performance, the global statistical information remains necessary and cannot be learned directly by a ViT. Removing the adaptive pooling or replacing it with mean pooling degrades the performance, showing that the adaptive pooling aggregates the important features in an image. As for the supervision, we find the intra-sample loss to be the most important, and the combination of all three loss terms yields the best performance.

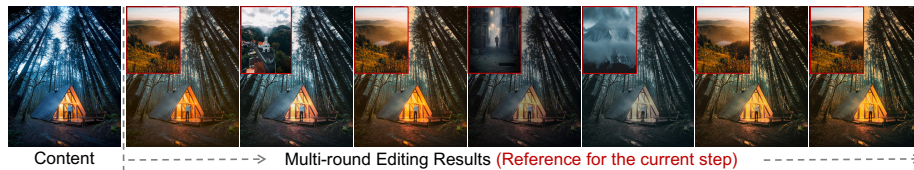


Fig. 7: Sequential photographic style transfer results (from left to right), with the reference for each round shown in the top-left red box.

Table 3: An ablation study of photographic embeddings on retrieval performance and quantitative results for photographic style transfer.

Setting	PPR10K [54] subset				FiveK-Concept [11]				PST50 [28]			
	R@1	R@5	mAP	F1@5	R@1	R@5	mAP	F1@5	LPIPS↓	PSNR↑	SSIM↑	H-Corr↑
RGB color space	70.34	96.77	69.16	53.61	51.21	78.29	<u>49.37</u>	36.58	<u>0.1068</u>	22.22	<u>0.9120</u>	0.4034
W/o cross attn	68.93	96.66	66.44	51.21	50.29	75.91	<u>48.30</u>	36.19	0.1120	22.24	0.9005	0.4436
[CLS] only	<u>73.74</u>	96.88	<u>70.01</u>	<u>54.36</u>	49.17	<u>80.14</u>	48.64	35.46	0.1131	23.11	0.9086	0.4355
[CLS]+ mean pool	68.91	<u>97.25</u>	66.53	51.25	50.48	79.24	47.61	34.78	0.1149	22.49	0.9001	0.4342
W/o $\mathcal{L}_{\text{rec}}$	66.98	96.32	66.06	51.13	45.86	78.14	47.58	34.04	0.1354	21.69	0.8967	0.4048
W/o $\mathcal{L}_{-}$	36.09	89.79	45.42	33.38	18.64	51.67	21.62	14.56	0.1249	<u>23.47</u>	0.9063	<u>0.4506</u>
W/o $\mathcal{L}_{+}$	67.53	96.75	65.03	49.79	<u>51.79</u>	81.51	49.36	<u>36.69</u>	0.1071	22.41	0.9045	0.4194
Complete	74.27	98.40	71.99	56.60	52.94	78.56	51.84	39.01	0.1021	24.63	0.9272	0.5220

For the ablation of the photographic style transfer part, please refer to the supplementary material, where we train the LUT after substituting the photographic embedding with baseline image embeddings. This further validates the proposed method’s awareness of photographic style, and shows that the LUT is enlightened to transfer it.

5 Conclusion

In this paper, we present PETAL, Photographic Embedding for Transfer with an Adaptive LUT. We propose to extract a photographic embedding to reflect the photographic style, optimized with self-supervised contrastive learning. We apply the stop-gradient operation [16] and hard negative examples generated through photographic style augmentation to stabilize the optimization. This tailored image representation makes it possible to capture continuous styles, and conditions a simple neural LUT to transfer the photographic style without any test-time optimization.

Limitations. Although the photographic embedding considers spatial information, object-level style, such as color adjustment applied to faces, is not addressed in this work, as it requires more domain-specific data (*e.g.*, portraits in various styles). We empirically find that PETAL remains stable on the portrait-focused PPR10K benchmark, but the most challenging cases typically involve skin-tone white balance and local, face-specific retouching, which we leave for future work. In addition, photographic style sometimes involves artistic expression beyond the adjustment of color or lightness, such as adding noise or grain, calling for future work to learn such unique styles.

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