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Real-Time Neural Style Transfer for Visual Domain Adaptation and Artistic Image Generation Using Deep Learning

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Abstract

Neural Style Transfer (NST) is a deep learning technique that generates a new image by combining the semantic content of one image with the visual characteristics of another image's style. Since the introduction of the convolutional neural network-based style transfer, significant research has been conducted to enhance the quality of stylization, computational efficiency, arbitrary style transfer, content preservation, and style controllability.

However, most of the existing approaches have been evaluated using general artistic datasets and western artistic styles, which are readily recognized. Traditional Indian art forms contain distinctive geometric structures, repetitive motifs, symbolic representations, decorative patterns, and culturally specific colour combinations. This work proposes a real-time multi-style neural style transfer framework supporting Indian and Western artistic styles using deep CNN feature representations and a curated dataset for custom Indian-art images.

Keyword: Neural Style Transfer, Deep Learning, Indian Art, Arbitrary Style Transfer, Visual Domain Adaptation

Introduction

Digital image generation and manipulation has become an important applications of deep learning and computer vision techniques. One such application is Neural Style Transfer (NST), which enables the visual characteristics of a reference image to be transferred to a content image while maintaining the semantic structure of the content image.

The pioneering work by Gatys et al. demonstrated that convolutional neural networks can represent the content and artistic style of image separately, which allows them to be recombined to generate artistic images [1]. The original optimization-based NST method produces high-quality stylized images but it is required to perform iterative optimization for each input image, resulting to a higher computational cost. Feed-forward approaches were later introduced to improve computational efficiency. Ulyanov et al. proposed Texture Networks for feed-forward synthesis of textures and stylized images [2], while Johnson et al. introduced perceptual losses for fast style transfer using transformation networks [3]. The Later developments focused on multiple and arbitrary artistic styles. Dumoulin et al. proposed a learned representation for multiple artistic styles [4], while Huang and Belongie introduced Adaptive Instance Normalization (AdaIN), which enabled arbitrary style transfer in real time [5].

Traditional Indian art forms such as Warli, Madhubani, Gond, Kalamkari, and Pattachitra contain distinctive geometric figures, repetitive motifs, symbolic elements, decorative borders, and colour themes that are culturally specific. Therefore, this work focuses on developing a multi-style Neural Style Transfer framework capable of supporting both Indian and Western artistic styles, with emphasis on Indian traditional art.

A. Research Gap

The analysis of existing research reveals several significant gaps.

First, although arbitrary and multi-style NST methods have achieved significant progress, their ability to evaluate is still dominated by generic artistic datasets and standard painting styles.

Second, traditional Indian art has received relatively little attention. Existing Indian art research demonstrates the feasibility of NST for selected Indian art forms, but there is still scope for a unified framework that covers multiple styles such as Warli, Madhubani, Gond, Kalamkari and Pattachitra.

Third, traditional Indian art contains many repetitive patterns, geometric figures, symbolic motifs, decorative borders, and structured compositions. Such characteristics motivate the study of pattern-aware style representations [26].

Finally, there is a trade-off between quality and computational efficiency. Transformer and diffusion-based models can provide powerful representations, but generally require greater computational resources. [22], [31], [32].

LITERATURE SURVEY

The development of Neural Style Transfer can be broadly divided into optimization-based methods, feed-forward methods, arbitrary style-transfer methods, attention-based methods, transformer-based approaches, diffusion-based approaches, and culturally specific style-transfer research.

The evolution of Neural Style Transfer (NST) methods is illustrated in Fig. 1. This highlights the transition from optimization-based approaches toward feed-forward, arbitrary, attention-based, transformer, diffusion, and efficient style-transfer architectures, reflecting the increasing emphasis on flexibility, controllability, and computational efficiency.

A. Optimization-Based Neural Style Transfer

Gatys et al. introduced the foundational neural style transfer framework using a pretrained convolutional neural network

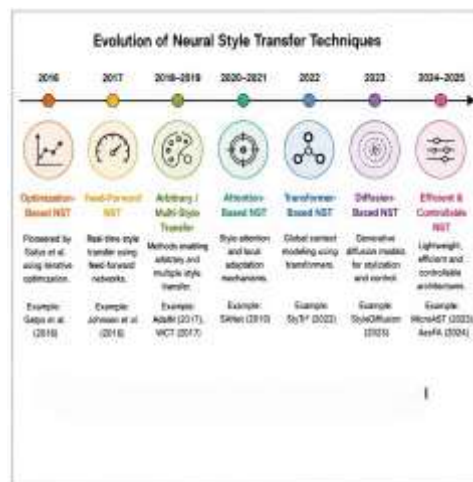


Fig. 1. Evolution of neural style transfer techniques from optimization-based methods to efficient and controllable architectures.

[1]. Content information was extracted from deeper feature representations, while style was represented using correlations between feature maps. Although this approach established the foundation of NST, the requirement for iterative optimization makes it unsuitable for real-time applications.

B. Arbitrary and Multi-Style Transfer

Dumoulin et al. proposed a learned representation for multiple artistic styles using conditional instance normalization [4]. Huang and Belongie subsequently proposed AdaIN, which enables arbitrary style transfer by aligning the channel-wise mean and the variance of content and style features [5]. Li et al. proposed Universal Style Transfer using Whitening and Coloring Transform (WCT), allowing arbitrary style transfer through feature distribution transformation [6].

C. Attention-Based Style Transfer

A major challenge in arbitrary style transfer is maintaining content structure while transferring the detailed style patterns. Park and Lee proposed SANet, it uses style attention to integrate local style information according to the semantic spatial distribution of the content image [7].

D. Domain-Aware and Robust Style Transfer

Research has also investigated the robustness and domain characteristics of NST systems. Domain-aware representations are particularly relevant because artistic styles can be considered as distinct visual domains [21]. Robustness studies have also shown that the choice of feature-extraction architecture can strongly affect the stylization quality [19].

E. Transformer-Based Style Transfer

Transformers have been introduced into NST to model long-range relationships between content and style features. StyTr2 uses transformers to model global relationships between content and style features [22]. However, transformer-based approaches can require greater computational resources than the lightweight CNN-based methods.

F. Pattern-Aware and Contrastive Approaches

Pattern-aware approaches capture the repeated artistic patterns and patch-wise style representations. Such approaches are particularly relevant to traditional Indian art because many Indian styles contain repetitive decorative motifs and structured patterns [26]. Contrastive approaches have also been explored to improve style representation and content coherence [20], [23], [29].

G. Diffusion-Based Style Transfer

Recent research has moved toward diffusion-based approaches. Style Diffusion investigates controllable style transfer using diffusion models [31]. Inversion-based diffusion methods have also been investigated for artistic style transfer [32]. Although these approaches provide a powerful representations and controllability, their computational cost can make them less suitable for lightweight real-time applications.

H. Efficient Neural Style Transfer

MicroAST focuses on extremely fast arbitrary style transfer at high resolutions [27], while AesFA investigates aesthetic feature-aware arbitrary style transfer with an emphasis on efficient stylization [33]. These approaches are relevant to the objective of designing a practical framework with reduced inference cost.

I. Traditional and Indian Art Style Transfer

Research on culturally specific styles is comparatively smaller than the general NST research. Faustina et al. studied neural artistic style-transfer models and architectures for Indian art styles [35]. Varshney et al. developed a Madhubani art dataset containing 680 images representing five Madhubani categories and investigated transfer-learning-based classification [36].

Table 1: comparative analysis of existing neural style transfer methods

S. No.	Paper / Method	Year	Key Contribution	Limitation / Research Gap	Relevance to Proposed Work
1	Image Style Transfer Using Convolutional Neural Networks [1]	2016	Introduced the fundamental CNN-based NST approach using content and style representations.	Requires iterative optimization and is computationally expensive.	Provides the foundation for separating content and style features.
2	Texture Networks: Feed-forward Synthesis of Textures and Stylized Images [2]	2016	Introduced feed-forward networks for faster texture and style synthesis.	Primarily designed for specific learned styles.	Motivates feed-forward approaches for faster stylization.
3	Perceptual Losses for Real-Time Style Transfer and Super-Resolution [3]	2016	Used perceptual losses with transformation networks for real-time style transfer.	Limited flexibility for arbitrary styles.	Supports the real-time objective of the proposed framework.
4	A Learned Representation for Artistic Style [4]	2017	Used conditional instance normalization to represent multiple artistic styles.	Requires style-specific parameters.	Provides the basis for multi-style representation.
5	Arbitrary Style Transfer in Real-Time with Adaptive Instance Normalization [5]	2017	Enabled arbitrary style transfer by aligning feature statistics.	May lose fine style details and structural information.	Supports real-time arbitrary style transfer.
6	Universal Style Transfer via Feature Transforms [6]	2017	Used whitening and coloring transformations for	More computationally demanding than	Provides an alternative for arbitrary style representation.

			arbitrary style transfer.	simple normalization methods.	
7	Arbitrary Style Transfer with Style-Attentional Networks [7]	2019	Used attention to match local style features with content regions.	Limited evaluation on culturally diverse art.	Relevant for preserving local Indian-art motifs.
8	Multi-Style Generative Network for Real-Time Transfer [8]	2018	Developed a network capable of transferring multiple artistic styles efficiently.	Limited evaluation of culturally diverse art styles.	Motivates multi-style support in the proposed framework.
9	Exploring the Structure of a Real-Time, Arbitrary Neural Artistic Stylization Network [9]	2017	Investigated a style-conditioned network for arbitrary artistic stylization.	Performance depends strongly on training data.	Supports arbitrary-style generation.
10	Avatar-Net: Multi-Scale Zero-Shot Style Transfer by Feature Decoration [10]	2018	Introduced multi-scale feature decoration for improved style representation.	Architecture is relatively complex.	Useful for representing detailed artistic patterns.
11	Learning Linear Transformations for Fast Image and Video Style Transfer [11]	2019	Proposed efficient linear transformations for image and video stylization.	Feature representation may limit complex style patterns.	Supports fast and potentially real-time processing.
12	Neural Style Transfer: A Review [12]	2020	Surveyed major NST techniques and their development.	Does not introduce a new transfer framework.	Provides theoretical foundation for the literature study.
13	Arbitrary Style Transfer via Multi-Adaptation Network [13]	2020	Proposed a multi-adaptation network for arbitrary style transfer.	Limited evaluation of Indian and culturally structured art.	Motivates extending arbitrary transfer to Indian art domains.
14	Two-Stage Peer-Regularized Feature Recombination for Arbitrary Image Style Transfer [14]	2020	Improved arbitrary style transfer through feature recombination and regularization.	Focus remains on general artistic datasets.	Provides techniques for improved content-style combination.
15	ArtFlow: Unbiased Image Style Transfer via Reversible Neural Flows [15]	2021	Used reversible neural flows for improved style transfer.	More complex architecture and computation.	Provides an alternative for future model improvement.
16	AdaAttN: Revisit Attention Mechanism in Arbitrary Neural Style Transfer [16]	2021	Introduced adaptive attention for spatially corresponding style transfer.	Does not explicitly address structured cultural motifs.	Relevant to improving spatial style correspondence.
17	Fast Patch-Based Style Transfer of	2016	Used local feature matching to support arbitrary content and style images.	Optimization and inverse-network training can remain	Provides an early arbitrary-style transfer direction.

	Arbitrary Style [17]			computationally demanding.	
18	Manifold Alignment for Semantically Aligned Style Transfer [18]	2021	Aligned semantic structures between style and content representations.	Requires effective semantic correspondence.	Relevant for preserving semantic content.
19	Rethinking and Improving the Robustness of Image Style Transfer [19]	2021	Investigated the robustness and failure cases in NST.	Focuses mainly on general artistic styles.	Helps identify content leakage and style mismatch problems.
20	Artistic Style Transfer with Internal-External Learning and Contrastive Learning [20]	2021	Used contrastive learning to improve artistic style representation.	Limited culturally specific evaluation.	Provides potential techniques for better style learning.
21	Domain-Aware Universal Style Transfer [21]	2021	Introduced domain-aware representations for style transfer.	Primarily evaluated on conventional painting domains.	Relevant to treating Indian art as separate visual domains.
22	StyTr ² : Image Style Transfer with Transformers [22]	2022	Used transformers to model content-style relationships and global features.	Higher computational requirements.	Provides a possible future alternative to CNN-based architecture.
23	CCPL: Contrastive Coherence Preserving Loss for Versatile Style Transfer [23]	2022	Introduced contrastive loss to preserve content coherence.	Limited evaluation on Indian traditional art.	Supports better content preservation.
24	Exact Feature Distribution Matching for Arbitrary Style Transfer and Domain Generalization [24]	2022	Improved style transfer through exact feature distribution matching.	Computational complexity can increase.	Relevant for accurate style representation.
25	Name Your Style: An Arbitrary Artist-Aware Image Style Transfer [25]	2022	Incorporated artist-aware style representation for arbitrary transfer.	Focuses on artist-level representation rather than cultural motifs.	Supports artist/style-aware transfer.
26	AesPA-Net: Aesthetic Pattern-Aware Style Transfer Networks [26]	2023	Introduced pattern-aware representations and patch-based style modelling.	Mainly evaluated on general artistic styles.	Highly relevant to repetitive motifs in Indian traditional art.
27	MicroAST: Towards Super-Fast Ultra-Resolution Arbitrary Style Transfer [27]	2023	Focused on very fast arbitrary style transfer at high resolution.	Quality-speed trade-off may occur.	Relevant to the real-time objective.

28	Learning Dynamic Style Kernels for Artistic Style Transfer [28]	2023	Used dynamic style kernels to adapt style representations.	Computational complexity and general-art focus.	Useful for adaptive style modelling.
29	A Unified Arbitrary Style Transfer Framework via Adaptive Contrastive Learning [29]	2023	Used adaptive contrastive learning for unified style transfer.	Limited focus on traditional Indian art.	Supports unified multi-style learning.
30	CAP-VSTNet: Content Affinity Preserved Versatile Style Transfer [30]	2023	Focused on preserving content affinity during versatile style transfer.	General-purpose evaluation.	Relevant to preserving input-image structure.
31	StyleDiffusion: Controllable Disentangled Style Transfer via Diffusion Models [31]	2023	Used diffusion models for controllable style representation.	Computationally expensive and slower.	Provides future scope for advanced style control.
32	Inversion-Based Style Transfer with Diffusion Models [32]	2023	Used diffusion inversion for transferring artistic characteristics.	High computational requirements.	Useful for future high-quality style-transfer extensions.
33	AesFA: An Aesthetic Feature-Aware Arbitrary Neural Style Transfer [33]	2024	Proposed efficient aesthetic feature-aware arbitrary style transfer.	Limited evaluation on culturally specific art.	Relevant to efficient and high-quality stylization.
34	ArtBank: Artistic Style Transfer with Pre-Trained Diffusion Model and Implicit Style Prompt Bank [34]	2024	Used diffusion models and style prompt representations for artistic transfer.	Diffusion-based computation can be expensive.	Provides future scope for controllable style selection.
35	A Study of Neural Artistic Style Transfer Models and Architectures for Indian Art Styles [35]	2023	Investigated NST architectures specifically for Indian artistic styles.	Limited number of Indian styles and broader framework integration.	Directly supports the Indian-art focus of the proposed work.
36	Madhubani Art Classification Using Transfer Learning with Deep Feature Fusion and Decision Fusion Based Techniques [36]	2023	Developed a dedicated Madhubani art dataset and deep-learning classification approach.	Focuses on classification rather than style transfer.	Demonstrates the importance of dedicated Indian-art datasets.
37	Evaluation in Neural Style Transfer: A Review [37]	2024	Reviewed evaluation methods used for NST systems.	Does not propose a new NST architecture.	Helps design evaluation metrics for the proposed framework.

38	SaMam: Style-Aware State Space Model for Arbitrary Image Style Transfer [38]	2025	Explored state-space models for arbitrary style transfer.	Limited evaluation on culturally diverse styles.	Represents a recent efficient architecture for future comparison.
39	SRAGAN: Saliency Regularized and Attended Generative Adversarial Network for Chinese Ink-Wash Painting Style Transfer [39]	2025	Used saliency information to preserve important structures during traditional-art style transfer.	Focused specifically on Chinese ink-wash painting.	Demonstrates the importance of culturally specific style-transfer models.
40	StyleFormer: Real-Time Arbitrary Style Transfer via Parametric Style Composition [40]	2021	Used transformer-inspired style composition for diverse and coherent arbitrary style transfer.	Transformer-based processing can require greater computational resources.	Provides a relevant comparison for controllable and efficient style transfer.

Table 2 — Research Gap Identified from the Literature

Research Area	Existing Work	Identified Gap	Proposed Solution
Real-time NST	[3], [8], [27]	Quality and speed trade-off	Develop an efficient feed-forward stylization framework.
Arbitrary style transfer	[5], [6], [13]	Limited culturally specific styles	Support multiple Indian and Western styles.
Content preservation	[16], [18], [23], [30]	Fine structural details may be lost	Improve content-preserving feature representation.
Repetitive artistic patterns	[26]	Limited Indian-art evaluation	Focus on Indian motifs and patterns.
Indian traditional art	[35], [36]	Limited multi-style frameworks	Include Warli, Madhubani, Gond, Kalamkari, and Pattachitra.
Domain adaptation	[21]	Traditional Indian art is underrepresented	Treat Indian art forms as visual style domains.
Computational efficiency	[22], [31], [32]	Transformers and diffusion models can be expensive	Use a lightweight CNN-based approach.
User interaction	Limited	Few systems provide multiple candidate outputs	Generate 3–4 outputs for user selection.
NST evaluation	[37]	No universally standardized evaluation	Combine perceptual, qualitative, and efficiency metrics.



Fig. 2. Representative Indian traditional art styles considered in the proposed framework.

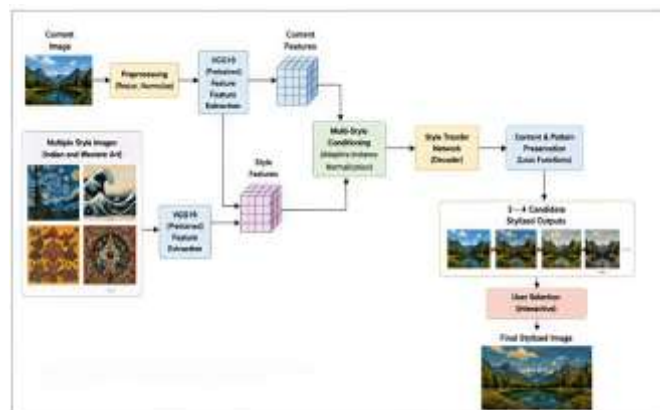


Fig. 3. Proposed multi-style neural style transfer framework.

3. Proposed Methodology

Based on the identified research gaps, this work proposes a multi-style Neural Style Transfer framework designed to investigate real-time or near-real-time inference.

The proposed framework uses a pre-trained VGG19 network as the primary of extractor features. The network is used to obtain the deep content and style representations from the input images.

The Indian-art component uses a curated dataset supplemented with custom images containing representative examples from:

- Warli
- Madhubani
- Gond
- Kalamkari
- Pattachitra

Representative examples of the Indian traditional art forms considered in this work are presented in Fig. 2. These exhibit distinctive visual characteristics, including geometric structures, repetitive motifs, symbolic elements, decorative patterns, and characteristic colour combinations, which provide diverse style domains for the proposed framework.

Western artistic styles will also be incorporated to make the framework more general and versatile.

The overall processing pipeline of the proposed multi-style Neural Style Transfer framework is illustrated in Fig. 3. The pipeline shows the extraction of content and style representations, their combination within the transfer stage, and the generation of multiple stylized outputs for user selection.

From the generated candidates, the user are allowed to compare multiple outputs and select the preferred result. This mechanism is intended to make the system more interactive and practical for creative applications.

A. Expected Contributions

The proposed work is expected to provide:

- 1) A neural style-transfer framework designed to support multiple artistic styles.
- 2) Integration of a custom Indian traditional-art dataset.

- 3) Support for Warli, Madhubani, Gond, Kalamkari, and Pat-tachitra.
- 4) Support for both Indian and Western artistic styles.
- 5) A study of semantic-content and artistic-pattern preservation.
- 6) Generation of multiple candidate stylized images.
- 7) An interactive interface for artistic image generation.
- 8) Investigation of NST as a visual domain-transformation technique.

B. Evaluation Strategy

Evaluation is an important component of NST research because visual quality cannot always be represented by a single numerical metric. The proposed framework will therefore be evaluated using multiple criteria.

- 1) *Content Preservation*: As illustrated conceptually in Fig. 4, the similarity between the original content image and generated image will be measured using perceptual feature representations.
- 2) Fig. 4 provides a conceptual illustration of content preservation during artistic style transfer. The example demonstrates how the visual characteristics of a selected artistic style can be transferred to a content image while retaining the major semantic structure of the original image. This provides a qualitative basis for assessing content preservation and style consistency.
- 3) *Style Similarity*: The generated image will be compared with the selected style image to determine whether important style characteristics have been transferred.
- 4) *Visual Quality*: Generated outputs will be evaluated qualitatively and whether they are appropriate, using perceptual image-quality measures.
- 5) *Inference Time*: The time required to generate a stylized image will be measured to determine whether the framework satisfies the intended real-time or near-real-time objective.
- 6) *User Evaluation*: Users can be presented with multiple generated outputs and asked to select the most visually appropriate result.
- 7) This multi-dimensional evaluation is motivated by the observation that current NST literature uses diverse evaluation strategies and lacks a universally accepted benchmark protocol [37].



Fig. 4. Conceptual illustration of content preservation and artistic style transfer using Madhubani art.

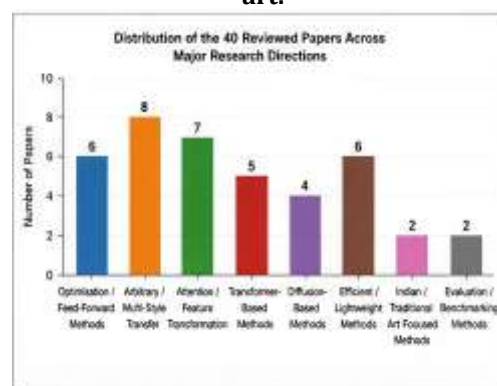


Fig. 5. Distribution of the 40 reviewed papers across major research directions.

5. Conclusion & Future Work

This literature review examined research works related to Neural Style Transfer, covering optimization-based CNN methods, feed-forward networks, arbitrary style transfer, attention mechanisms, domain adaptation, transformers, diffusion models, efficient architectures, evaluation methods, and traditional-art applications.

The reviewed literature features that NST has progressed considerably in terms of quality, flexibility, and computational efficiency. However, there still remains challenges in achieving real-time or near-real-time performance while preserving content structure and representing culturally specific artistic patterns.

Research on Indian art styles has demonstrated the feasibility of applying deep learning to traditional Indian art, but existing studies generally focus on selected art forms or specific tasks. This creates an opportunity for a broader multi-style framework incorporating several Indian traditional styles. The proposed work therefore aims to investigate a Neural Style Transfer framework supporting Indian and Western artistic styles while preserving semantic content and characteristic artistic patterns.

- The Indian-art dataset can be expanded with additional artworks and additional regional art forms.
- Specialized motif-aware losses can be investigated to better preserve geometric and symbolic patterns.
- The model can also be optimized for mobile and edge devices to enable real-time deployment.
- Future research can investigate transformer, diffusion, and state-space architectures as alternatives to the proposed CNN-based approach.

The framework can also be extended from image stylization to video stylization and augmented-reality applications.

References

1. L. A. Gatys, A. S. Ecker, and M. Bethge, "Image style transfer using convolutional neural networks," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), 2016, pp. 2414–2423.
2. Ulyanov, V. Lebedev, A. Vedaldi, and V. Lempitsky, "Texture networks: Feed-forward synthesis of textures and stylized images," in Proc. Int. Conf. Mach. Learn. (ICML), 2016, pp. 1349–1357.
3. Johnson, A. Alahi, and L. Fei-Fei, "Perceptual losses for real-time style transfer and super-resolution," in Proc. Eur. Conf. Comput. Vis. (ECCV), 2016, pp. 694–711.
4. V. Dumoulin, J. Shlens, and M. Kudlur, "A learned representation for artistic style," in Proc. Int. Conf. Learn. Represent. (ICLR), 2017.
5. X. Huang and S. Belongie, "Arbitrary style transfer in real-time with adaptive instance normalization," in Proc. IEEE Int. Conf. Comput. Vis. (ICCV), 2017, pp. 1501–1510.
6. Y. Li, C. Fang, J. Yang, Z. Wang, X. Lu, and M.-H. Yang, "Universal style transfer via feature transforms," in Adv. Neural Inf. Process. Syst., vol. 30, 2017.
7. Y. Park and K. H. Lee, "Arbitrary style transfer with style-attentional networks," in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR), 2019, pp. 5880–5888.
8. H. Zhang and K. Dana, "Multi-style generative network for real-time transfer," in Proc. Eur. Conf. Comput. Vis. Workshops (ECCVW), 2018.
9. G. Ghiasi, H. Lee, M. Kudlur, V. Dumoulin, and J. Shlens, "Exploring the structure of a real-time, arbitrary neural artistic stylization network," in Proc. Brit. Mach. Vis. Conf. (BMVC), 2017, pp. 114.1–114.12.
10. Sheng, Z. Lin, J. Shao, and X. Wang, "Avatar-Net: Multi-scale zero-shot style transfer by feature decoration," in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR), 2018, pp. 8242–8250.
11. X. Li, S. Liu, J. Kautz, and M.-H. Yang, "Learning linear transformations for fast image and video style transfer," in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR), 2019, pp. 3809–3817.
12. Y. Jing, Y. Yang, Z. Feng, J. Ye, J. Yu, and M. Song, "Neural style transfer: A review," IEEE Trans. Vis. Comput. Graphics, vol. 26, no. 11, pp. 3365–3385, 2020.
13. Y. Deng, F. Tang, W. Dong, W. Sun, F. Huang, and C. Xu, "Arbitrary style transfer via multi-adaptation network," in Proc. ACM Int. Conf. Multimedia, 2020, pp. 2719–2727.
14. J. Svoboda, A. Anoosheh, C. Osendorfer, and J. Masci, "Two-stage peer-regularized feature recombination for arbitrary image style transfer," in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR), 2020, pp. 13816–13825.
15. J. An, S. Huang, Y. Song, D. Dou, W. Liu, and J. Luo, "ArtFlow: Unbiased image style transfer via reversible neural flows," in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR), 2021, pp. 862–871.
16. S. Liu, T. Lin, D. He, F. Li, M. Wang, X. Li, Z. Sun, Q. Li, and E.
17. Ding, "AdaAttN: Revisit attention mechanism in arbitrary neural style transfer," in Proc. IEEE/CVF Int. Conf. Comput. Vis. (ICCV), 2021, pp. 6649–6658.
18. T. Q. Chen and M. Schmidt, "Fast patch-based style transfer of arbitrary style," arXiv:1612.04337, 2016.
19. J. Huo, S. Jin, W. Li, J. Wu, Y.-K. Lai, Y. Shi, and Y. Gao, "Manifold alignment for semantically aligned style transfer," in Proc. IEEE/CVF Int. Conf. Comput. Vis. (ICCV), 2021, pp. 14841–14849.
20. P. Wang, Y. Li, and N. Vasconcelos, "Rethinking and improving the robustness of image style transfer," in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR), 2021, pp. 124–133.
21. H. Chen, L. Zhao, Z. Wang, H. Zhang, Z. Zuo, A. Li, W. Xing, and D. Lu, "Artistic style transfer with internal-external learning and contrastive learning," in Adv. Neural Inf. Process. Syst., 2021.

22. Hong, S. Jeon, H. Yang, J. Fu, and H. Byun, "Domain-aware universal style transfer," in Proc. IEEE/CVF Int. Conf. Comput. Vis. (ICCV), 2021, pp. 14589–14597.
23. Y. Deng, F. Tang, W. Dong, S. Huang, X. Ma, and C. Xu, "StyTr2: Image
24. style transfer with transformers," in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR), 2022, pp. 11326–11336.
25. Z. Wu, Z. Zhu, J. Du, and X. Bai, "CCPL: Contrastive coherence preserving loss for versatile style transfer," in Proc. Eur. Conf. Comput. Vis. (ECCV), 2022.
26. Y. Zhang, M. Li, R. Li, K. Jia, and L. Zhang, "Exact feature distribution matching for arbitrary style transfer and domain generalization," in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR), 2022, pp. 8035–8045.
27. Z.-S. Liu, L.-W. Wang, W.-C. Siu, and V. Kalogeiton, "Name your style: An arbitrary artist-aware image style transfer," arXiv:2202.13562, 2022.
28. K. Hong, S. Jeon, J. Lee, N. Ahn, K. Kim, P. Lee, D. Kim, Y. Uh, and H. Byun, "AesPA-Net: Aesthetic pattern-aware style transfer networks," in Proc. IEEE/CVF Int. Conf. Comput. Vis. (ICCV), 2023, pp. 22701–22710.
29. Z. Wang, L. Zhao, Z. Zuo, A. Li, H. Chen, W. Xing, and D. Lu, "MicroAST: Towards super-fast ultra-resolution arbitrary style transfer," in Proc. AAAI Conf. Artif. Intell., vol. 37, no. 3, pp. 2742–2750, 2023.