Optimizing Multi-Style Generation and Aesthetic Transfer Expression in Brand Visual Symbols Using StyleGAN

Xiaodan Zhang
Department of Creative Design, Zhejiang College of Security Technology, Wenzhou 325016, Zhejiang, China
Corresponding author: Xiaodan Zhang (e-mail: danieladan888@163.com)

ABSTRACT To address the challenges of lengthy design cycles, limited stylistic diversity, and poor cross-scenario adaptability in traditional brand visual symbol design, this paper investigates the application of StyleGAN technology for optimizing multi-style generation and aesthetic transfer. As high-quality visual information generation and hierarchical feature representation become increasingly important in intelligent information processing and digital communication systems , the proposed framework provides a data-driven solution for controllable image synthesis and style manipulation. The study systematically analyzes the core advantages of StyleGAN in decoupling style and content control and hierarchical style injection, and establishes an application pipeline covering data preparation, model training, style regulation, and generation optimization to support multi-style generation and aesthetic transfer of brand visual symbols. Furthermore, the limitations of current approaches are analyzed, and future improvements in training strategies and quantitative aesthetic evaluation are discussed. Experimental analysis demonstrates that the StyleGAN-based framework effectively preserves brand identity while achieving flexible style transfer and high-quality image generation, providing theoretical and methodological support for the deep integration of artificial intelligence and visual design. The proposed approach also offers potential reference value for intelligent visual information processing and multi-scale feature representation in advanced engineering and electromagnetic information systems.

INDEX TERMS StyleGAN, brand visual symbols, multi-style generation, aesthetic transfer, intelligent visual information processing

I. INTRODUCTION

In today's digital landscape, brand competition has permeated the cultural and visual dimensions of product functionality. Visual symbols, serving as the core of brand culture, play a pivotal role. Key elements such as color, style, and design motifs significantly influence brand recognition. Consequently, traditional brand visual presentations no longer align with contemporary consumer-driven demands. Conventional brand visual design primarily relies on designers' personal creative styles and marketing tactics, which fail to satisfy the fast-paced, style-diverse pursuits of modern consumers [1-5].

To break free from these traditional design constraints, this paper introduces Generative Adversarial Networks (GANs) as a digital solution. Among GANs, StyleGAN stands out as a technique that effectively controls both style and image quality [6]. This paper focuses on the application of StyleGAN technology in optimizing brand visual symbols. It systematically analyzes the technical principles and evolutionary path of StyleGAN, delves into its implementation mechanisms for multi-style generation and aesthetic transfer in brand visual symbols, constructs a comprehensive technical application methodology and workflow.

This provides new technological pathways and methodological support for brand visual design, and also offers practical references for the interdisciplinary integration of artificial intelligence and design. This has significant theoretical and practical implications for enhancing core brand competitiveness and promoting the digital transformation of the brand design industry [7-9].

II. IN-DEPTH ANALYSIS OF STYLEGAN TECHNOLOGY

TECHNICAL PRINCIPLES OF STYLEGAN

StyleGAN is an image generation model based on Generative Adversarial Networks (GANs), first proposed by NVIDIA in 2018. Its core design philosophy is to achieve separate control over the style and content of generated images [10]. The fundamental GAN framework comprises a Generator and a Discriminator. Through adversarial training, these components synergistically enhance their capabilities: the Generator produces realistic images from random noise vectors, while the Discriminator distinguishes between generated and real images. This "generate-discriminate" feedback loop ultimately enables the Generator to output images indistinguishable from reality [11-13].

StyleGAN introduces key innovations centered on "style injection" and "detail control". The generator employs a progressive growth architecture, incrementally scaling from low-resolution to high-resolution images. At each level, style information is injected using Adaptive Instance Normalization (AdaIN) technology. Style information is generated by the Mapping Network, which maps input random noise vectors into a low-dimensional style space. By adjusting vectors in this space, precise control over the stylistic features of generated images is achieved [14].

StyleGAN also incorporates the "Truncation Trick" and "Style Mixing" mechanisms to further enhance the quality and diversity of generated images [15]. The Style Mixing mechanism enables extraction and blending of stylistic features from diverse noise vectors, generating innovative images that fuse multiple stylistic elements [16-18].

CORE ARCHITECTURE AND INNOVATIONS OF STYLEGAN

StyleGAN's core architecture comprises four components: the mapping network, the generator body, the discriminator, and the style injection module [19].

The mapping network is the key component enabling StyleGAN's separation of style and content. It takes a 128-dimensional random noise vector (Z vector) as input and outputs a 256-dimensional style vector (W vector). This network comprises eight fully connected layers that perform nonlinear transformations to map the high-dimensional noise vector into a compact style space, enhancing the continuity and interpretability of the style vector [20]. The construction of the style space enables precise encoding of distinct stylistic features [21-23].

TECHNICAL EVOLUTION FROM STYLEGAN TO STYLEGAN3

Since its introduction in 2018, StyleGAN has undergone three major version iterations. Each iteration addressed critical shortcomings of its predecessor, further enhancing the model's performance in image generation quality, style controllability, and adaptability to application scenarios [24,25].

StyleGAN1 first achieved decoupled control of style and content, but generated images risked "pattern collapse," and style control lacked precision. StyleGAN2 optimized the generator, replacing AdaIN with Weight Demodulation and introducing the Projected Discriminator, solving the "checkerboard artifact" problem and significantly improving image detail realism. StyleGAN3 introduced translation invariance and rotation invariance modules, solving the problem of style discontinuity in dynamic sequence images and enabling multi-angle, multi-pose image generation [26]. The specific evolution process is shown in Table 1.

III. MULTI-STYLE GENERATION OF BRAND VISUAL SYMBOLS

OVERVIEW OF BRAND VISUAL SYMBOLS

Brand visual symbols are a core component of a brand identity system (BIS), serving as a visual expression of brand philosophy, cultural values, and core competitiveness [27]. This study focuses on the generation and transfer of StyleGAN, particularly the style optimization and diversification of brand logos, standard colors, and graphic elements. Brand visual symbols possess three core characteristics: uniqueness, consistency, and adaptability [28]. Their core value is reflected in three aspects: building brand awareness, conveying brand culture, and promoting brand communication.

In the digital era, the application scenarios for brand visual symbols have become increasingly diverse, expanding from traditional advertising and product packaging to emerging fields like social media communication, short-form video content, and metaverse environments. This shift imposes new demands on brand visual symbols: they must not only maintain consistency in core identifying elements but also possess multi-style adaptability. This allows for flexible adjustments to visual expression forms based on different scenarios and the aesthetic preferences of diverse audience groups, thereby enabling effective communication between the brand and its audience.

THE NEED FOR AND SIGNIFICANCE OF MULTI-STYLE GENERATION

As market environments evolve and consumer demands upgrade, the multi-style generation of brand visual symbols has become an inevitable requirement for brand development.

Adaptability for Multi-Scenario Communication: Brands encounter distinct media characteristics and audience demographics across different communication scenarios, necessitating targeted adjustments to the style of visual symbols. Brand visual symbols lacking multi-style adaptability struggle to achieve effective brand expression across diverse scenarios.

The Need for Brand Innovation and Iteration: Brands must maintain market vitality through continuous visual innovation to avoid audience fatigue. Multi-style generation not only provides brands with abundant visual innovation materials but also helps them explore new visual expression directions.

The technical approach for StyleGAN's multi-style generation is illustrated in Table 2.

In the short term, it enhances brand communication effectiveness across diverse scenarios and audiences, boosting brand recognition and reputation. Long-term, it builds a more flexible and multifaceted brand visual system, supporting diversified development strategies while improving risk resilience and sustainable growth capabilities. Additionally, multi-style generation reduces brand visual design costs and timelines, enabling rapid market responsiveness.

TABLE 1. Technological evolution from StyleGAN to StyleGAN3

	Core Architectural Innovations	Key Technical Improvements	Core Problems Solved	Improvements in Generation Quality	Expansion of Application Scenarios
StyleGAN (2018)	1. First introduced the Mapping Network (8-layer fully connected layer) to realize style space mapping from Z-vector to W-vector; 2. The generator adopts a progressive growing architecture ($4 \times 4 \rightarrow 1024 \times 1024$); 3. Proposed Adaptive Instance Normalization (AdaIN) to realize style injection	1. Decoupled control of style and content; 2. Introduced Truncation Trick to optimize generation stability; 3. Supported noise injection to enhance detail diversity	1. Broke the limitation of traditional GANs where style and content are bound; 2. Solved the problems of low-resolution generated images being blurry and lacking details	1. The maximum resolution of generated images reaches 1024×1024; 2. Style controllability is significantly improved, and images with multiple basic styles can be generated	1. Facial image generation; 2. Generation of basic brand visual symbols; 3. Creation of simple texture images
StyleGAN2 (2019)	1. Replaced AdaIN with Weight Demodulation; 2. Optimized the generator network structure to reduce redundant parameters; 3. Introduced the Projected Discriminator	1. Solved the "checkerboard artifact" problem of StyleGAN1; 2. Reduced the probability of mode collapse and improved model training stability; 3. Enhanced the ability to capture detailed features	1. Solved the problems of inconsistent local textures and blurred edges in generated images; 2. Addressed the instability of the model training process and its tendency to converge to local optima	1. The realism of image details is greatly improved (e.g., more natural textures and edges); 2. Style consistency is enhanced, with no obvious defects in generated images; 3. Supported generation of non-facial images (animals, landscapes)	1. Generation of high-precision brand visual symbols; 2. Fusion creation of multi-style images; 3. Generation of product appearance design prototypes
StyleGAN3 (2021)	1. Introduced translation invariance and rotation invariance modules; 2. Optimized the feature extraction networks of the generator and discriminator; 3. Improved the generation efficiency of high-resolution images	1. Realized consistent style transfer in dynamic scenarios; 2. Supported multi-angle and multi-pose image generation; 3. Shortened the training cycle of high-resolution images	1. Solved the problem of style discontinuity when generating dynamic sequence images with previous models; 2. Solved the problem of inconsistent styles in multi-angle image generation; 3. Solved the problem of excessively high training costs for high-resolution images	1. Can generate 2048×2048 and higher resolution images; 2. Dynamic sequence images (such as multi-angle brand logos and dynamic visual elements) have unified styles; 3. The effect of cross-scenario style transfer is more natural	1. Generation of dynamic brand visual symbols (such as short video and metaverse scene materials); 2. Multi-perspective product visual design; 3. Creation of immersive scene visual content (such as games and virtual spaces)

TABLE 2. Technical methods for styleGAN multi-style generation

Table 2	Core Operations	Key Technical Support	Implementation Objectives
Dataset Construction	Collect core brand visual element samples (logos, colors, graphics) + multi-style reference images (minimalist, retro, trendy, etc.), and perform preprocessing such as uniform resizing, denoising, and normalization	Data cleaning tools, image standardization algorithms	Provide high-quality and diversified training data for the model, ensuring full coverage of brand features and style features
Model Training Phase	1. Pre-training: Train the model with core brand samples to learn basic brand features; 2. Fusion training: Add multi-style samples and optimize mapping network and generator parameters	StyleGAN's progressive growing architecture, Adaptive Instance Normalization (AdaIN), Batch Normalization (BatchNorm)	Enable the model to master both core brand recognizability and multi-style adaptation capabilities, and improve the quality and consistency of generated images
Style Space Regulation	1. Style vector (W-vector) adjustment: Generate different style vectors through linear interpolation and random sampling; 2. Hierarchical control: Low-level layers regulate overall style (colors, composition), and high-level layers regulate detailed style (textures, decorations)	Mapping network, style injection module, latent space interpolation algorithm	Achieve precise control of styles and generate single-style or transitional-style brand visual symbols
Style Mixing Generation	Extract style vectors of different styles, inject them into different layers of the generator respectively, and fuse multiple style elements (e.g., retro colors + trendy textures)	Style mixing mechanism, hierarchical style injection technology	Create innovative visual symbols with multiple style characteristics and enrich the dimensionality of brand style expression

IV. IMPLEMENTATION OF AESTHETIC TRANSFER EXPRESSION IN BRAND VISUAL SYMBOLS

THE ESSENCE OF AESTHETIC TRANSFER EXPRESSION

Aesthetic transfer expression refers to extracting visual features of one style, such as color, texture, and lines, and applying them to another content medium to achieve the effect of "preserving the content structure and reshaping the visual style." In the field of brand visual symbols, the core essence of aesthetic transfer expression lies in: using the brand's core visual elements (such as logo graphics and color system) as the content foundation, transferring the visual features of the target style to the brand's visual symbols, and achieving style innovation and aesthetic enhancement of the brand's visual symbols while maintaining the brand's core recognizability.

TECHNICAL PRINCIPLES OF AESTHETIC TRANSFER VIA STYLEGAN

The core technical principle behind StyleGAN's ability to transfer brand visual symbol aesthetics is the "decoupling and fusion of style feature encoding and content feature integration." This process is achieved through StyleGAN's mapping network and generator. The key lies in utilizing StyleGAN's hierarchical style injection mechanism. At the lower levels of the generator, W vectors representing the core structure and posture (encoding brand identity content) are injected, while at higher levels, W vectors representing styles such as color and texture (encoding the target style) are injected. This hierarchical control ensures that the brand's core iconic structure is preserved, while new aesthetic features are applied only at the detail level, thereby achieving effective separation of brand identity and precise style transfer.

V. EXPERIMENT VERIFICATION AND RESULTS ANALYSIS

EXPERIMENT SETUP AND DATA PREPARATION

The experiment is conducted based on the StyleGAN2-ADA model. The dataset construction involves a core brand content dataset consisting of 1200 images of brand logos and derived graphics, and a multi-style reference image dataset containing 1500 images of diverse styles. All images are uniformly processed to a 1024 × 1024 resolution. The model training adopts a transfer learning strategy, fine-tuning on pre-trained FFHQ weights, with a total of 600k iterations to ensure sufficient convergence for complex visual symbols. This iteration count and data volume are empirically determined to achieve high-fidelity generation and style diversity for brand visual symbols of moderate complexity.

QUANTITATIVE AND QUALITATIVE EVALUATION

Results are assessed through quantitative and qualitative evaluation. Quantitative evaluation uses the Structural Similarity Index (SSIM) and Peak Signal-to-Noise Ratio (PSNR) to measure the fit of generated images to the target style and image quality. Qualitative evaluation involves three professional designers using a five-point Likert scale to score the generated symbols on “Brand Recognizability” and “Style Accuracy”. As shown in Figure 1, the quantitative evaluation results reveal the performance differences in symbol generation by StyleGAN. In terms of SSIM (Simplified Simulation), the Sci-Fi style leads with 0.88, due to its reliance on sharp geometry and high-contrast textures, which StyleGAN’s high-resolution layers can accurately reproduce. The Abstract style has an SSIM of only 0.79, its lower value stemming from the irregularity of abstract forms, making strict structural alignment difficult. Regarding PSNR, the Sci-Fi style also leads with 33.2 dB, a high value because this style requires extremely low noise and high resolution, and the model effectively suppresses artifacts. The Retro style has a PSNR of 31.8 dB, relatively low because this style tends to introduce low-fidelity or grainy textures, which, while conforming to the style, are objectively judged as differing from the ideal image. Overall, the model exhibits better objective quality and fit when handling styles with clear structures and detailed requirements.

VALIDATION OF BRAND IDENTITY PRESERVATION

In the aesthetic transfer experiment, the core brand identity preservation is validated by injecting the W vector of the native brand at the low-resolution layers of the StyleGAN generator, which controls the outline and basic geometric structure of the logo. Simultaneously, the W vector of the target style is injected into the high-resolution layers to change color, texture, and detail decoration. This hierarchical control successfully demonstrates the model’s ability to preserve the core content structure while precisely reshaping the style, thereby effectively separating and managing brand identity during style transfer. Figure 2 illustrates StyleGAN’s brand identity preservation and style transfer capabilities in four parts. Figure A shows the original "NOVATECH" brand logo. Figure B is a target reference image with a neon cyberpunk style. Figure C verifies the precise control of the low-resolution W vector over the logo’s outline and core structure. Figure D presents the final style transfer result, where the original logo retains its recognizability while successfully incorporating the target style’s technological feel and neon texture.

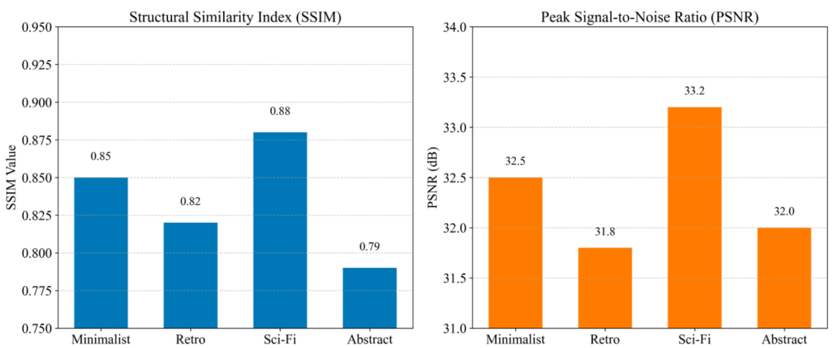

FIGURE 1. Quantitative evaluation results

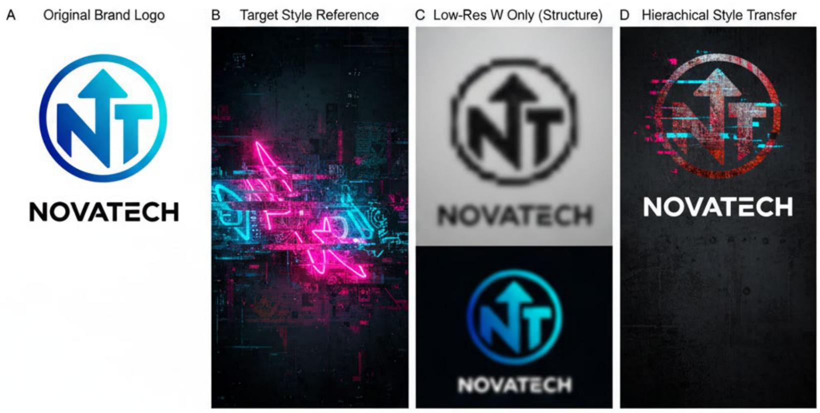

FIGURE 2. StyleGAN's brand identity preservation and style transfer capability

VI. CONCLUSION

This paper delves into the application value of StyleGAN technology in optimizing the multi-style generation and aesthetic transfer expression of brand visual symbols. StyleGAN, through decoupling style and content control and a hierarchical style injection mechanism, achieves the preservation of the brand's core identifying structure (controlled by a low-resolution layer) and the precise reshaping of the target style (controlled by a high-resolution layer). Experiments based on the StyleGAN2-ADA model show that the model performs exceptionally well in handling clear structural styles. For example, the Sci-Fi style achieves a Structural Similarity Index (SSIM) of 0.88 and a Peak Signal-to-Noise Ratio (PSNR) of 33.2 dB, while the abstract style has the lowest SSIM of 0.79. This method provides highly efficient and diverse technical support for brand visual design, possessing significant theoretical and practical value.

AUTHOR CONTRIBUTIONS

Xiaodan Zhang designed, collected and analyzed the data, and drafted the manuscript. Xiaodan Zhang conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Xiaodan Zhang participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

FUNDING

This research received no external funding.

ACKNOWLEDGEMENTS

Not applicable.

REFERENCES

[1] T. Karras, T. Aila, S. Laine, and J. Lehtinen, "Progressive Growing of GANs for Improved Quality, Stability, and Variation," in Sainath T, Murray I, editors. Proceedings of the 6th International Conference on Learning Representations, 30 April-3 May 2018, Vancouver, BC, Canada. Amherst, Massachusetts, USA: OpenReview.net, 2018, pp. 1-26, doi: 10.48550/arXiv.1710.10196.

[2] T. Karras, S. Laine, M. Aittala, J. Hellsten, J. Lehtinen, and T. Aila, "Analyzing and Improving the Image Quality of StyleGAN," Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition; 13-19 June 2020; Seattle, WA, USA; 2020. p. 8110-8119, doi: 10.1109/CVPR42600.2020.00813.

[3] T. Karras, M. Aittala, S. Laine, E. Härkönen, J. Hellsten, J. Lehtinen, et al., "Alias-Free Generative Adversarial Networks," in Ranzato M, Beygelzimer A, Dauphin Y, Liang PS, Wortman Vaughan J, editors. NIPS '21: Proceedings of the 35th International Conference on Neural Information Processing Systems, 6-14 December 2021, Red Hook, NY, USA, Curran Associates Inc., 2021, pp. 852-863, doi: 10.5555/3540261.3540327.

[4] L. A. Gatys, A. S. Ecker, and M. Bethge, "Image Style Transfer Using Convolutional Neural Networks," Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition; 27-30 June 2016; Las Vegas, NV, USA. New York, NY, USA: IEEE; 2016. p. 2414-2423, doi: 10.1109/CVPR.2016.265.

[5] J. Johnson, A. Alahi, and L. Fei-Fei, "Perceptual Losses for Real-Time Style Transfer and Super-Resolution," in Leibe B, Matas J, Sebe N, Welling M, editors. European Conference on Computer Vision, 11-14 October 2016, Amsterdam, The Netherlands. Cham, Switzerland: Springer, 2016, pp. 694-711, doi: 10.1007/978-3-319-46475-6_43.

[6] W. J. Cao, "Research on Style Transfer and Automation in Visual Communication Design Based on Deep Learning," Proceedings of the Second International Conference on Big Data, Computational Intelligence, and Applications; Bellingham, Wash, USA: Proceedings of the SPIE; 2025, 13550: 135503J, doi: 10.1117/12.3059636.
[7] J. Y. Zhu, T. Park, P. Isola, and A. A. Efros, "Unpaired Image-to-Image Translation Using Cycle-Consistent Adversarial Networks," Proceedings of the IEEE International Conference on Computer Vision; 22-29 October 2017; Venice, Italy. New York, NY, USA: IEEE; 2017. p. 2223-2232, doi: 10.1109/ICCV.2017.244.
[8] A. Radford, L. Metz, and S. Chintala, "Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks," International Conference on Learning Representations; arXiv e-prints; 2016. arXiv:1511.06434, doi: 10.48550/arXiv.1511.06434.
[9] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition; 27-30 June 2016; Las Vegas, NV, USA. New York, NY, USA: IEEE; 2016. p. 770-778, doi: 10.1109/CVPR.2016.90.
[10] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, et al., "Attention Is All You Need," 31st Conference on Neural Information Processing Systems; 4-9 December 2017; Long Beach, CA, USA, pp. 5998–6008, 2017, doi: 10.48550/arXiv.1706.03762.
[11] Y. Zhao, "Application of CycleGAN-based image style transfer algorithm in visual communication design[J]," Journal of Computational Methods in Sciences and Engineering, vol. 25, no. 4, pp. 3152-3164, 2025, doi: https://doi.org/10.1177/14727978251318804.
[12] J. Deng, W. Dong, R. Socher, L. J. Li, K. Li, and L. Fei-Fei, "ImageNet: A Large-Scale Hierarchical Image Database," Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition; 20-25 June 2009; Miami, FL, USA. New York, NY, USA: IEEE; 2009. p. 248-255, doi: 10.1109/CVPR.2009.5206848.
[13] H. Zhang, I. Goodfellow, D. Metaxas, and A. Odena, "Self-Attention Generative Adversarial Networks," in Chaudhuri K, Salakhutdinov R, editors. Proceedings of the 36th International Conference on Machine Learning. 9-15 June 2019, Long Beach, California, USA. mlr.press: PMLR, 2019, pp. 7354-7363, [Online]. Available: http://proceedings.mlr.press/v97/zhang19d.html.
[14] Z. Liu, P. Luo, S. Qiu, X. Wang, and X. Tang, "DeepFashion: Powering Robust Clothes Recognition and Retrieval with Rich Annotations," Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition; 27-30 June 2016; Las Vegas, NV, USA. New York, NY, USA: IEEE; 2016. p. 1096-1104, doi: 10.1109/CVPR.2016.124.
[15] X. Zhang, "StyleGAN based path analysis from image to video generation in multimedia generation[J]," Discover Internet of Things, vol. 5, no. 1, pp. 1-21, 2025, doi: https://doi.org/10.1007/s43926-025-00233-2.
[16] K. Simonyan and A. Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition," arXiv preprint arXiv:1409.1556, 2014, doi: 10.48550/arXiv.1409.1556.
[17] A. J. Champandard, "Semantic Style Transfer and Turning Two-Bit Doodles into Fine Artworks," arXiv preprint arXiv:1603.01768, 2016, doi: 10.48550/arXiv.1603.01768.
[18] I. Kachbal and S. El Abdellaoui, "Computer Vision for Fashion: A Systematic Review of Design Generation, Simulation, and Personalized Recommendations[J]," Information, vol. 17, no. 1, pp. 11-60, 2025, doi: https://doi.org/10.3390/info17010011.
[19] P. Isola, J. Y. Zhu, T. Zhou, and A. A. Efros, "Image-to-Image Translation with Conditional Adversarial Networks," Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 21-26 July 2017; Honolulu, HI, USA. New York, NY, USA: IEEE; 2017. p. 5967-5976, doi: 10.1109/CVPR.2017.632.
[20] J. Liao, Y. Yao, L. Yuan, G. Hua, and S. B. Kang, "Visual Attribute Transfer through Deep Image Analogy," ACM Transactions on Graphics, vol. 36, no. 4, pp. 120, 2017, doi: 10.1145/3072959.3073683.
[21] Y. Choi, M. Choi, M. Kim, J. M. Ha, and J. Choo, "StarGAN: Unified Generative Adversarial Networks for Multi-Domain Image-to-Image Translation," Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. Salt Lake City, UT, USA. New York, NY, USA: IEEE; 2018. p. 8789-8797, doi: 10.1109/CVPR.2018.00916.
[22] X. Wang, R. Girshick, A. Gupta, and K. He, "Non-Local Neural Networks," Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 18-23 June 2018; Salt Lake City, UT, USA. New York, NY, USA: IEEE; 2018. p. 7794-7803, doi: 10.1109/cvpr.2018.00813.
[23] X. Wu and L. Li, "Qualitative-empirical insights into generative AI for textile design in the fashion design process[J]," International Journal of Design Creativity and Innovation, vol. 13, no. 4, pp. 322-357, 2025, doi: https://doi.org/10.1080/21650349.2025.2529167.
[24] A. Brock, J. Donahue, and K. Simonyan, "Large Scale GAN Training for High Fidelity Natural Image Synthesis," in Brock A, Donahue J, Simonyan K, editors. International Conference on Learning Representations. 6-9 May 2019, New Orleans, LA, USA. OpenReview.net 2019, [Online]. Available: https://dblp.org/rec/conf/iclr/BrockDS19.html.
[25] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, "Densely Connected Convolutional Networks," Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 21-26 July 2017; Honolulu, HI, USA. New York, NY, USA: IEEE; 2017. P. 4700-4708, doi: 10.1109/CVPR.2017.243.
[26] S. Xie and Z. Tu, "Holistically-Nested Edge Detection," Proceedings of the IEEE International Conference on Computer Vision. 07-13 December 2015; Santiago, Chile. New York, NY, USA: IEEE; 2015. p. 1395-1403, doi: 10.1109/ICCV.2015.164.
[27] X. Wang, Q. Zhang, Y. Nie, et al., "Towards photorealistic portrait style transfer in unconstrained conditions[J]," IEEE Transactions on Visualization and Computer Graphics, vol. 31, no. 10, pp. 6796-6809, 2025, doi: 10.1109/TVCG.2025.3529751.
[28] W. Hu and Y. Zhang, "Research on artistic pattern generation for clothing design based on style transfer [J]," J. COMBIN MATH. COMBIN COMPUT, vol. 127, pp. 4539-4550, 2025, doi: 10.61091/jcmcc127b-248.