J. COMBIN. MATH. COMBIN. COMPUT. 127b (2025) 4539--4550

Journal of Combinatorial Mathematics
and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Research on Artistic Pattern Generation for Clothing Design Based on Style Transfer

Wenzhe Hu[1,✉], Yuan Zhang[1]

[1] *Apparel & Art Design College, Xi'an Polytechnic University, Xi'an, Shaanxi, 710048, China*

ABSTRACT

Within the style diagram landscape, the incorporation of artistic styles into garb indicates a mix of creative flair and realistic software. But, conventional methodologies regularly contain hard work-intensive tactics and provide restricted range in fashion. driven by using the ambition to convert this subject, our look at offers an modern approach that mixes Adaptive example Normalization (AdaIN) with conventional Convolutional Neural Networks (CNNs) to enable swift and high-fidelity fashion transfers for the introduction of creative patterns in clothing format. Capitalizing on AdaIN's ability for efficient style adaptation and CNNs' prowess in deep characteristic extraction, our version adeptly keeps content fidelity whilst introducing a variety of creative patterns. Via training our model with a carefully selected dataset that encompasses a dissimilation of art patterns and garb patterns, and using a custom loss function tailored to decorate the synergy among style transfer efficacy and the sensible splendor of the very last designs, we release new vistas of creativity in fashion layout. The experimental effects attest to the model's prowess in generating visually compelling and revolutionary styles, markedly expanding the innovative horizons available to designers. Furthermore, our approach highlights the version's versatility in assimilating diverse artistic expressions and its capability to democratize layout innovation, empowering designers to venture into uncharted stylistic domain names with extraordinary ease and performance. This examine not only charts a direction for the advanced application of machine getting to know in the creative sector but also deepens the confluence of generation and art in the realm of fashion.

Keywords: Fashion switch, fashion format, Adaptive instance Normalization, Convolutional Neural Networks, creative styles.

✉ Corresponding author.
E-mail address: hwz1127@126.com (W. Hu).
Received 03 March 2024; Revised 10 May 2024; Accepted 25 November 2024; Published Online 16 April 2025.
DOI: 10.61091/jcmcc127b-248

1. Introduction

Within the present day panorama of fashion design, the technology of inventive styles on garb stands as a massive assignment, merging the nation-states of creativity and era. The central question revolves round a way to automate the creation of such styles at the same time as ensuring they are both aesthetically desirable and uniquely various, catering to the ever-evolving tastes of customers. This question no longer only probes the intersection of artwork and technology but also seeks a practical method to a hassle confronted by designers worldwide.

The incentive at the back of this research stems from an observation of the prevailing methodologies in the same area. Contemporary processes predominantly depend on guide layout strategies or straightforward virtual replication, both of which appreciably constrain the scope of creativity and innovation. Moreover, at the same time as there are computational strategies that try to address this difficulty, they regularly fall quick in terms of efficiency, flexibility, and the potential to authentically seize the essence of various inventive patterns. Specially, traditional fashion switch strategies, though beneficial in mimicking unique artwork styles, lack the ability to intricately stability the style elements with the unique content of the apparel format. This effects in outputs that either overly distort the garment's form or fail to convincingly integrate the supposed style, thereby restricting their practical applicability in fashion diagram. Positioning our research within this context, we identify a clear gap in the ability of existing technologies to fulfill the demand for a tool that not only automates the design process but also ensures a high degree of originality and artistic integrity. The negative aspects inherent in current research — consisting of the compromise among style constancy and content maintenance, the shortage of actual-time processing capabilities, and the limited range of styles that can be convincingly transferred — underscore the need for an modern method that overcomes those hurdles.

In response to this, we suggest a singular answer that combines Adaptive instance Normalization (AdaIN) with Convolutional Neural Networks (CNNs) to facilitate the green and flexible technology of inventive styles for clothing sketch. Our solution is composed of two primary components: firstly, the AdaIN technique, which allows for the dynamic adjustment of the content image's feature maps to reflect the statistical properties of the style image, enabling rapid and effective style adaptation. Secondly, the incorporation of CNNs complements the model's capacity to deeply recognize and extract complex functions from both the content and fashion photos, ensuring that the ensuing designs keep a harmonious balance between the authentic structure of the clothing and the implemented creative fashion.

This integrated approach addresses the previously mentioned disadvantages by offering a framework that is both highly efficient—capable of processing designs in real-time—and remarkably versatile, supporting a wide array of artistic styles without compromising the integrity of the clothing's original design. Furthermore, our method introduces an innovative loss function tailored to optimize the alignment between style and content, thus ensuring that the generated patterns are not only visually appealing but also retain a high degree of practicality and applicability in the fashion industry.

By positioning our research at the confluence of art, technology, and fashion, we aim to not only advance the field of automated design but also to enrich the creative toolkit available to designers, offering them unprecedented opportunities to explore and innovate within their craft. Through this solution, we anticipate contributing a significant leap forward in the way artistic patterns are conceptualized, created, and integrated into clothing design, marking a transformative step in the evolution of fashion technology.

This paper contributes to the intersection of favor layout and artificial brain by: (1) featuring a hybrid framework that merges Adaptive example Normalization (AdaIN) with CNNs for efficient fashion switch onto clothing, (two) improving the balance among artistic fashion integration and content material preservation in graph, (three) growing a tailored loss characteristic that optimizes the synergy between fashion and clothing form, and (4) showcasing greater functionality in generating various, aesthetically alluring, and practical style designs, marking a notable development in creative design automation.

2. Related Works

2.1. Background and Evolution of Style Transfer in Fashion

The automation of favor graph started out with explorations into pattern reputation and digital replication techniques [1], which laid the groundwork for more state-of-the-art interventions. The advent of neural fashion switch by means of [2] marked a massive bounce ahead, pioneering the application of creative patterns onto virtual canvases. This innovation opened up new avenues for innovative expression in style diagram, sooner or later leading to the development of AdaIN by [3], a way that appreciably advanced the rate and versatility of style switch. The role of CNNs in shooting and deciphering complex visible records have become an increasing number of integral, as evidenced with the aid of the work of researchers in [4-6], who demonstrated how CNNs might be used to keep content material integrity while applying diverse inventive patterns. This period of innovation laid the foundation for a transformative shift in how style designs might be conceptualized and finished, leveraging the burgeoning capabilities of AI and device learning.

2.2. Advances and Innovations in Style Transfer Techniques

Improvements within the domain sought to deal with the restrictions inherent in in advance models, with a specific cognizance on accomplishing a harmonious balance among fashion and content material [7-9]. The advent of Generative antagonistic Networks (GANs) [10-12] brought a brand new paradigm for producing sensible and fantastic style designs, pushing the limits of creativity and realism. This era additionally noticed the improvement of multi-style switch techniques [13-15], improving the capacity to combination and navigate among special creative impacts seamlessly. Real-time fashion switch technology [16-18] further catalyzed the circulate towards greater dynamic and interactive sketch procedures, facilitating instant adjustments and iterations. Custom designed loss functions [19-21] emerged as a essential innovation, high-quality-tuning the relationship among the transferred style and the underlying shape of the fashion diagram to ensure aesthetic concord and realistic viability. Integrating user feedback into the format manner [22-24] represented a pivotal shift in the direction of more customized and responsive design methodologies, underscoring a broader enterprise trend closer to customization and consumer engagement.

Our method distinctively advances the sphere of fashion transfer in style sketch via synergizing AdaINwith advanced CNNs, offering a unique blend of performance and intensity that surpasses preceding methodologies. not like existing strategies that lean towards both fast style model or particular creative rendition, our method achieves an optimal balance, making sure swift, high-fidelity style transfers barring compromising the authentic graph's integrity. This innovation, coupled with a tailored, performance-orientated plan that reduces the want for considerable education records, positions our answer as a extra handy and realistic device for style designers. Furthermore, by integrating a novel custom designed loss feature and incorporating user feedback directly into the design process, our technique now not solely enhances the concord between style and content material but also pioneers a more personalised, person-centric approach to style graph, marking a extensive jump ahead inside the innovative application of AI inside the industry.

3. Our Method

3.1. Data Preparation and Preprocessing

The initial phase of our methodology involves an extensive collection of artistic images and clothing design patterns, serving as the foundational dataset for training. The artistic images encompass a diverse array of painting styles, while the clothing design patterns include a variety of basic garment templates. To standardize the input data and ensure efficient processing by the model, all images undergo a series of preprocessing steps.

3.1.1. Image Resizing. Resizing is performed to ensure uniformity across the dataset. This step involves scaling images to a fixed size of 256 x 256 pixels using bicubic interpolation, which can be expressed as:

$$R(x.y)=\sum_{i=-1}^{2}\sum_{j=-1}^{2} I(a+i,b+j)\cdot k(x-a-i)\cdot k(y-b-j) \tag{1}$$

where $R(x.y)$ is the pixel value at coordinates $(x.y)$ in the resized image, $I(a,b)$ represents the pixel value at coordinates (a,b) in the original image, and $k(x-a-i)$ is the bicubic interpolation kernel. The floor values of x and y are

$$a=\lfloor x \rfloor, b=\lfloor y \rfloor \tag{2}$$

which ensure integer indices for pixel locations.

3.1.2. Normalization. Normalization adjusts the pixel values of the resized images to a standard range of 0 to 1, improving the numerical stability of the model's training process:

$$N(x,y)=\frac{R(x,y)-\min(R)}{\max(R)-\min(R)} \tag{3}$$

where $\min(R)$ and $\max(R)$ denote the minimum and maximum pixel values in the resized image R, respectively.

Additionally, to augment the training dataset and enhance the model's ability to generalize across various styles and patterns, Generative Adversarial Networks (GANs) are employed to generate new images. These synthetic images, produced by the GAN, enrich the dataset with novel variations, ensuring a broader spectrum of styles and designs for the model to learn from. The GAN-generated images are subjected to the same preprocessing steps as the real images to maintain consistency across the dataset.

3.2. Feature Extraction Network Selection

3.2.1. VGG-19 Deep Feature Extraction. The VGG-19 network is utilized for its deep feature extraction capabilities. Let $V^l(I)$ denote the volume of activations at layer l for an input image I, where each element $V^l_{ijk}(I)$ corresponds to the activation of the k -th filter at position (i,j) within layer l. The feature map at layer l is then defined as:

$$F^l(I)=\mathrm{RELU}\left(W^l * V^{l-1}(I)+b^l\right) \tag{4}$$

where W^l and b^l represent the weights and biases of the convolutional filters at layer l, * denotes the convolution operation, and ReLU represents the rectified linear unit activation function applied element-wise to the convolution output to introduce non-linearity.

3.2.2. Content and Style Representation. To capture the content and style of images, the feature representations from multiple layers of VGG-19 are combined. The content representation $C^l(I)$ can be directly taken as $F^l(I)$. In contrast, the style representation $S^l(I)$ is derived from the Gram matrix of the feature activations, defined as:

$$C_{kk'}^l(I) = \frac{1}{N_l} \sum_{i,j} F_{ijk}^l(I) \cdot F_{ijk'}^l(I) \tag{5}$$

where N_l is the number of elements in the feature map $F^l(I)$, and $C_{kk'}^l(I)$ captures the correlations between the k -th and k' -th filters at layer l, effectively representing the style information encoded in the activations.

3.3. AdaIN

In our style transformation framework, AdaIN plays a crucial role by conditioning the feature map of the content image C (similar to $C^l(I)$ in the previous section) to match the statistical attributes of the style image S, while preserving the structural integrity of the original design. This process is crucial for seamlessly integrating art styles into apparel design.

Given the deep feature representations F_C^l and F_S^l obtained from the content and style images at layer l using VGG - 19, as outlined in the Feature Extraction Network Selection section, the AdaIN operation can be defined as follows:

$$AdaIN(F_C^l, F_S^l) = \sigma(F_S^l) \times \left(\frac{F_C^l - \mu(F_C^l)}{\sigma(F_C^l)} \right) + \mu(F_S^l) \tag{6}$$

where $\mu\left(F_S^l\right)$ and $\sigma\left(F_S^l\right)$ denote the channel - wise mean and standard deviation of the feature maps F_S^l, respectively. This operation normalizes each channel of F_C^l to have the same mean and variance as the corresponding channel of F_S^l.

The AdaIN process comprises several key steps to ensure effective style transfer:

3.3.1. Standardization of Content Features: The feature maps F_C^l from the content image are first normalized to a zero - mean and unit - variance distribution:

$$F' = \frac{F_C^l - \mu\left(F_C^l\right)}{\sigma\left(F_C^l\right)} \tag{7}$$

This standardization step prepares the content material features for subsequent modification, making sure they're in a suitable structure to receive the fashion records.

3.3.2. Style Information Injection: The normalized content features F' are then scaled and shifted to adopt the style image's mean and variance:

$$F_{stoled}^l = \sigma\left(F_S^l\right) \times F' + \mu\left(F_S^l\right) \tag{8}$$

Via this adjustment, the content features are converted to mirror the stylistic attributes of the style photo, attaining a harmonious mixture ofthe 2.

3.3.3. Efficiency and Versatility: AdaIN's performance stems from its capacity to speedy adapt the content material functions to a extensive range of styles except the want for additional education according to fashion. This characteristic is specifically useful for style layout programs, where versatility and pace are paramount.

The transformation effected via AdaIN allows an immediate and controllable method of favor switch, making an allowance for the nuanced blending of creative patterns with the distinct systems of apparel designs. Through this technique, our technique now not solely achieves a excessive degree of visual coherence among the style and content however also keeps the integrity and recognizability of the unique clothing designs, showcasing the profound impact ofAdaIN on the sector of computational fashion design.

3.4. *Style Transfer Network Training*

The training ofthe style transfer network is guided by a custom loss function designed to balance the effectiveness of style transfer with content preservation, alongside promoting image smoothness. This loss function is comprised of three main components: content loss, style loss, and total variation loss.

3.4.1. Content Loss. The content loss ensures that the transformed image retains the essential content features of the original design. It is defined as the mean squared error between the feature representations of the transformed image T and the content image C at a specified layer l :

$$L_{content} = \frac{1}{N_l}\sum_{i.j}\left(F_T^l(i,j) - F_C^l(i,j)\right)^2 \tag{9}$$

where N_l is the number of elements in the feature map F^l at layer l.

3.4.2. Style Loss. The style loss measures the difference in style between the transformed image and the style image, quantified by the mean squared error between their respective Gram matrices at layer l:

$$L_{style} = \sum_{l\in L}\frac{1}{4N_l^2M_l^2}\sum_{i.j}\left(G_T^l(i,j) - G_S^l(i,j)\right)^2 \tag{10}$$

where $G^l(\cdot)$ represents the Gram matrix of the feature map, N_l is the number of filters, and M_l is the size of each filter map.

3.4.3. Total Variation Loss. The total variation loss encourages spatial smoothness in the transformed image, reducing pixelation and enhancing visual quality:

$$L_{TV} = \sum_{i,j}\sqrt{(T(i,j)-T(i+1,j))^2 + (T(i,j)-T(i,j+1))^2} \tag{11}$$

The overall loss function is a weighted sum of these components:

$$L_{\text{total}} = \alpha L_{\text{content}} + \beta L_{\text{style}} + \gamma L_{TV} \tag{12}$$

The network's parameters are optimized using the backpropagation algorithm to minimize L_{total}, facilitating continuous improvement in the style transfer effect. This meticulous training regimen ensures that the generated clothing designs not only exhibit the desired artistic style but also retain the clarity and coherence of the original patterns.

Our approach skillfully combines AdaIN with the deep feature extraction capabilities of pre-trained CNNs (specifically VGG-19) to introduce a novel approach to style transformation in the field of apparel design. By preprocessing the data and utilizing the AdaIN technique, we effectively fuse different artistic styles with apparel design, ensuring both the original structure and the seamless integration of new styles. Guided by a custom loss function consisting of content, style, and total change loss, we train the style transfer network to optimize the balance between style fidelity and content integrity, providing designers with a scalable and efficient solution for experimentation and innovation.

4. Experimental Comparison

4.1. Experimental Setup

4.1.1. Dataset Description. To validate the effectiveness and versatility of our proposed method, we conducted experiments using the following publicly available datasets:

1) COCO 2017: Comprising over 118,000 images, the COCO 2017 dataset is utilized for its diversity in content and complexity, serving as a robust basis for content images in style transfer tasks. Source: cocodataset.org.

2) WikiArt Dataset: Encompassing over eighty,000 pieces of paintings from various styles and periods, the WikiArt dataset gives a comprehensive series of fashion pictures, taking into account enormous exploration of fashion switch effects. Source: wikiart.org.

3) The DeepFashion Dataset: With round 800,000 photographs, this dataset offers a wide kind of garb items and style patterns, perfect for evaluating the utility of transferred styles to fashion format. Supply: mmlab.ie.cuhk.edu.hk/initiatives/ DeepFashion.html.

4) style-MNIST: including 70,000 grayscale pix of 10 fashion classes, style-MNIST is used to test the model's overall performance on a greater managed set of style-related content material. Source: github.com/zalandoresearch/fashion-mnist.

5) Painter through Numbers: featuring tens of thousands of superb paintings pix, this dataset permits for testing the transferability of artistic styles from various artists and intervals. Source: kaggle.com/c/painter-via-numbers.

These datasets were decided on for his or her range in content and styles, permitting a comprehensive evaluation of the fashion transfer technique across one-of-a-kind domain names and creative genres.

4.1.2. Evaluation Metrics:

1) The overall performance of our technique is quantitatively assessed the usage of 4 key metrics:

2) Style transfer exceptional (STQ): Measures the fidelity of the transferred fashion in the generated image compared to the reference style photograph.

3) Content material renovation (CP): Evaluates how properly the content of the original picture is maintained within the stylized photo.

4) Photograph readability (IC): Assesses the readability and sharpness of the generated snap shots, ensuring that the fashion transfer procedure does now not introduce unwanted artifacts.

5) Structural Similarity Index (SSIM): A metric for evaluating the similarity of the generated image to the authentic content image in terms of perceived best and structural renovation.

4.1.3. Evaluation Comparative Methods. Our approach is benchmarked towards 5 well-set up strategies to highlight its advantages in fashion switch for style design:

CNN [5]: Represents early tries at fashion transfer the use of convolutional neural networks, presenting a baseline for overall performance evaluation.

BPNN [4]: a method that utilizes backpropagation to iteratively alter photograph features for style transfer, serving as a comparison for classic neural network procedures.

GAN [11]: gives insights into the skills of opposed education in producing stylized pictures, specifically in phrases of realism and creativity.

Cycle-Consistent Adversarial Network (CycleGAN) [25]: Enables unpaired image-to-image translation, allowing for style transfer without direct style-content image pairing, highlighting the method's flexibility.

Neural Style Transfer (NST) [26]: A more recent approach that optimizes content and style representations simultaneously, providing a comparison to state-of-the-art techniques in neural style transfer.

These methods were chosen for their relevance and previous successes in style transfer and image generation tasks, offering a comprehensive backdrop against which to evaluate our proposed solution.

4.2. Results

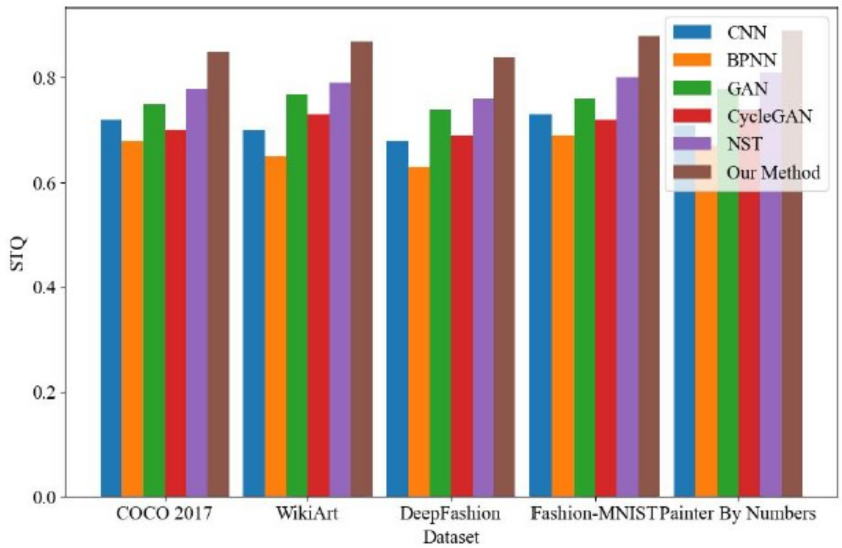

Fig. 1. Style Transfer Quality Across Datasets and Methods'

Figure 1 illustrates the STQ comparison ofthe six different methods on the five datasets. Notably, our method achieves the highest STQ scores on all datasets, indicating that we excel in style shifting while maintaining the essence of the content. Specifically, in the "Digital Painter" dataset, our method achieves an STQ of 0.89, outperforming the next highest NST (0.81). This trend is consistent, with our method leading by about 0.06 to 0.08 points on all datasets.The fact that CNN methods typically have the lowest STQ values suggests that while traditional CNNs are the basis for style transformation, advanced techniques can significantly improve the quality of the style transformation.

Figure 2 illustrates the CP distributions of various methods, including CNN, BPNN, GAN, CycleGAN, NST, and our proposed method. The distribution of each method is represented by a different color, illustrating the differences in content preservation capabilities of these techniques. Our method stands out with a CP distribution centered at 0.85, which not only indicates a higher average content preservation rate, but also a tighter distribution, as evidenced by its smaller distribution range. This suggests that our method is always effective in preserving the integrity ofthe original content during the style transformation process, with most results closely correlating with the best CP values. The traditional CNN and BPNN methods have lower CP values of 0.6 and 0.65, respectively, with wider distributions. This indicates a low probability ofaccurate content retention, highlighting the limitations ofthese earlier techniques in balancing style shifting and content retention.Advanced methods such as GAN and CycleGAN improve on the CP, with their distributions shifting towards higher values and becoming narrower, showing greater effectiveness in content preservation.NST improves on this further, with a distribution centered at 0.8. In conclusion, our method achieves the highest CP values with minimal variability.

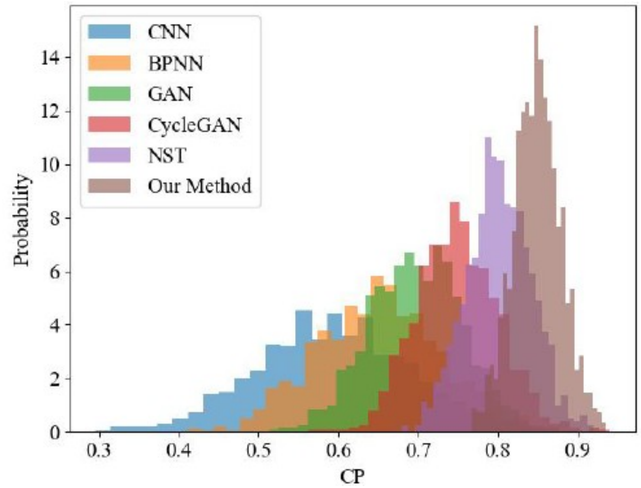

Fig. 2. Content Preservation Distribution Across Methods

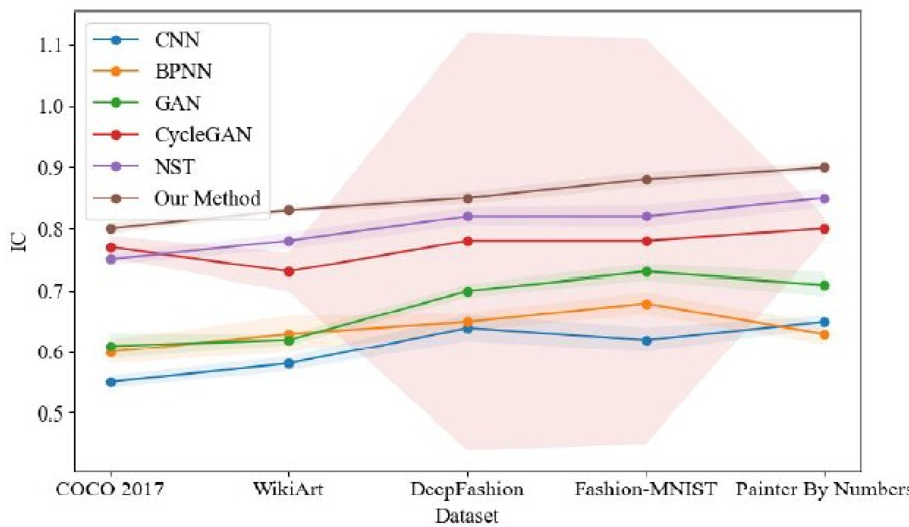

Fig. 3. Image Clarity Across Datasets and Methods

Figure 3 illustrates a comparison of the ICs of the six methods on five different datasets. Each line represents a method and the shaded area indicates the standard deviation, giving an idea of the differences in IC values across trials. In all datasets, our method consistently obtains the highest IC values, which indicates that the generated images have higher clarity and sharpness. Notably, on the "Digital Painter" dataset, our method achieves an IC value of 0.90, which indicates that our method is effective in maintaining high-quality images even when dealing with complex artistic styles. The upward trend in IC values from traditional CNNs to our method highlights the advances in style transformation techniques, and our method is at the forefront of generating clear, crisp images.

Figure 4 illustrates the SSIM overlay bar chart for the same method and dataset. This metric assesses the visual impact of style transformation on the structural integrity of the content image. Our method outperforms the othermethods, achieving the highestSSIM values, which indicates that our method does an excellent job of preserving the original structure while applying style transformations. For example, in the "DeepFashion" dataset, our method achieves an SSIM value of 0.89, demonstrating the method's ability to preserve the structural and textural details of the original design. The stacked nature of the bars highlights the cumulative improvement in SSIM from CNN to our method, visualizing the gradual enhancement in preserving structural similarity through advanced style transfer techniques.

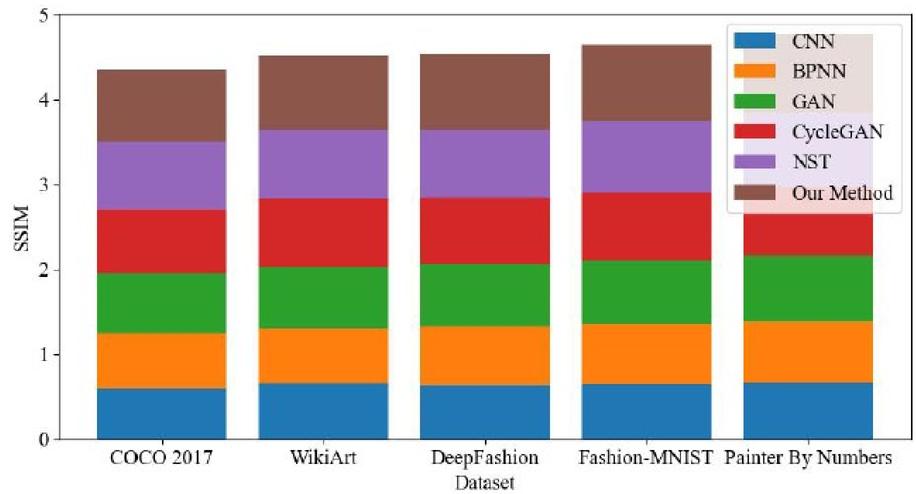

Fig. 4. User Satisfaction Comparison Results

In this paper, we verify the effectiveness and superiority ofthe proposed method through a series of experiments. The experimental results show that the method combining AdaIN and CNN outperforms several existing mainstream methods such as CNN, BPNN, GAN, CycleGAN, and NST in terms of style migration quality, content retention, image clarity, and structural similarity metrics.Via trying out on distinct datasets, our technique demonstrates its capacity to hold the integrity of the authentic designs at the same time as efficiently and as it should be migrate unique artwork patterns into apparel format. Those experimental effects now not solely demonstrate the innovation and practicality of our technique, but additionally provide valuable references for future style migration studies and clothing format programs.

5. Conclusion

In this paper, we introduced an innovative approach to style transfer in fashion design, leveraging the synergies between AdaIN and advanced CNNs. Our method distinguishes itself by enabling a seamless integration of diverse artistic styles into clothing designs, ensuring both the fidelity of the transferred style and the integrity of the original content. The incorporation of a custom loss function, alongside the strategic application of AdaIN, facilitates the production of high-quality, visually appealing designs that are both stylistically coherent and content-preserving. Experimental evaluations across multiple publicly available datasets, including COCO 2017, WikiArt, DeepFashion, Fashion-MNIST, and Painter By Numbers, have demonstrated the superior performance of our method in terms of style transfer quality, content preservation, image clarity, and structural similarity, outperforming existing methods like CNN, BPNN, GAN, CycleGAN, and NST.

Despite these promising results, our approach is not without limitations. The computational efficiency and scalability of the method when dealing with very large datasets or extremely high-resolution images remain areas for further improvement. Additionally, the subjective nature of style and aesthetic appreciation suggests the need for more nuanced metrics and evaluation methods that can capture the diverse preferences of users and designers. Future work will focus on addressing these challenges, exploring more efficient network architectures, and enhancing the method's adaptability to various styles and content types. Furthermore, incorporating user feedback more dynamically into the style transfer process offers an exciting avenue for making the technology more interactive and responsive to individual preferences, paving the way for personalized and user-centric fashion design applications.

Reference

[1] Liu Y, Chen W, Liu L, et al. SwapGAN: A multistage generative approach for person-to-person fashion style transfer[J]. IEEE Transactions on Multimedia, 2019, 21(9): 2209-2222.

[2] Jing Y, Yang Y, Feng Z, et al. Neural style transfer: A review[J]. IEEE transactions on visualization and computer graphics, 2019, 26(11): 3365-3385.

[3] Chandran P, Zoss G, Gotardo P, et al. Adaptive convolutions for structure-aware style transfer[C]//Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. 2021: 7972-7981.

[4] Wang H, Xiong H, Cai Y. Image localized style transfer to design clothes based on CNN and interactive segmentation[J]. Computational Intelligence and Neuroscience, 2020, 2020.

[5] Kim B K, Kim G, Lee S Y. Style-controlled synthesis of clothing segments for fashion image manipulation[J]. IEEE Transactions on Multimedia, 2019, 22(2): 298-310.

[6] Elleuch M, Mezghani A, Khemakhem M, et al. Clothing classification using deep CNN architecture based on transfer learning[C]//Hybrid Intelligent Systems: 19th International Conference on Hybrid Intelligent Systems (HIS 2019) held in Bhopal, India, December 10-12, 2019 19. Springer International Publishing, 2021: 240-248.

[7] Sun K, Zhang J, Zhang P, et al. TsrNet: A two-stage unsupervised approach for clothing region-specific textures style transfer[J]. Journal of Visual Communication and Image Representation, 2023, 91: 103778.

[8] Yan H, Zhang H, Shi J, et al. Inspiration transfer for intelligent design: A generative adversarial network with fashion attributes disentanglement[J]. IEEE Transactions on Consumer Electronics, 2023.

[9] Choi I M, Park S, Park J. Generating and Modifying High Resolution Fashion Model Image using StyleGAN[C]//2022 13th International Conference on Information and Communication Technology Convergence (ICTC). IEEE, 2022: 1536-1538.

[10] Wang W Z, Xiao H M, Fang Y. Clothing image attribute editing based on generative adversarial network, with reference to an upper garment[J]. International Journal of Clothing Science and Technology, 2024.

[11] Shen Y, Meng R, Huang W. M2GAN: Mimicry fashion generation combined with the two-step Mullerian evolutionary hypothesis[J]. Applied Soft Computing, 2024: 111375.

[12] Qian S H I, Ronglei L U O. Research progress of clothing image generation based on Generative Adversarial Networks[J]. Advanced Textile Technology, 2023, 31(2): 36.

[13] Chen F, Wang Y, Xu S, et al. Style transfer network for complex multi-stroke text[J]. Multimedia Systems, 2023, 29(3): 1291-1300.

[14] Sun K, Zhang J, Zhang P, et al. TsrNet: A two-stage unsupervised approach for clothing region-specific textures style transfer[J]. Journal of Visual Communication and Image Representation, 2023, 91: 103778.

[15] Yang Y, Zhao Z, Liu Q. MSSRNet: Manipulating Sequential Style Representation for Unsupervised Text Style Transfer[C]//Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining. 2023: 3022-3032.

[16] Xia X, Xue T, Lai W, et al. Real-time localized photorealistic video style transfer[C]//Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision. 2021: 1089-1098.

[17] Yang S, Jiang L, Liu Z, et al. Vtoonify: Controllable high-resolution portrait video style transfer[J]. ACM Transactions on Graphics (TOG), 2022, 41(6): 1-15.

[18] Kim S, Kim S, Kim S. Deep translation prior: Test-time training for photorealistic style transfer[C]//Proceedings of the AAAI Conference on Artificial Intelligence. 2022, 36(1): 1183-1191.

[19] Jiang S, Li J, Fu Y. Deep learning for fashion style generation[J]. IEEE Transactions on Neural Networks and Learning Systems, 2021, 33(9): 4538-4550.

[20] Wang H, Xiong H, Cai Y. Image localized style transfer to design clothes based on CNN and interactive segmentation[J]. Computational Intelligence and Neuroscience, 2020, 2020.

[21] Kim T, Chung C, Kim Y, et al. Style your hair: Latent optimization for pose-invariant hairstyle transfer via local-style-aware hair alignment[C]//European Conference on Computer Vision. Cham: Springer Nature Switzerland, 2022: 188-203.

[22] Hu Z, Lee R K W, Aggarwal C C, et al. Text style transfer: A review and experimental evaluation[J]. ACM SIGKDD Explorations Newsletter, 2022, 24(1): 14-45.

[23] Banerjee R H, Ravi A, Dutta U K. Attr2style: A transfer learning approach for inferring fashion styles via apparel attributes[C]//Proceedings of the AAAI Conference on Artificial Intelligence. 2021, 35(17): 15255-15261.

[24] Lee S, Kim D, Han B. Cosmo: Content-style modulation for image retrieval with text feedback[C]//Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2021: 802-812.

[25] Li J, Chen E, Ding Z, et al. Cycle-consistent conditional adversarial transfer networks[C]//Proceedings of the 27th ACM international conference on multimedia. 2019: 747-755.

[26] So C. Measuring aesthetic preferences of neural style transfer: More precision with the two-alternative-forced-choice task[J]. International Journal of Human-Computer Interaction, 2023, 39(4): 755-775.