BeautyGAN-based Makeup Recommendation and Transfer System

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Abstract

The existing makeup systems have superior effects and rich functions, but they rarely take into account the low-resolution scenes of the input image. When high-resolution images are difficult to obtain, the existing algorithms will be difficult to apply, and the makeup will not be able to transfer well. Therefore, this paper proposes a makeup recommendation system suitable for low-resolution images. It can output high-resolution makeup results even if the input image is a low-resolution image. Our algorithm fully retains the makeup details and improves the robustness of the expression. VGG-Face can extract key facial features well, so we use this model to identify the reference image from our database. The reference image is most similar to the face of the input image. The innovation of this paper is that we add a super-resolution network to the ordinary makeup recommendation system, and use BSRGAN to process the input image to obtain a high-resolution face image. Then we use BeautyGAN to transfer makeup and achieve a better makeup effect. Finally, we use a Face Rank Module to score the appearance of the generated images, and our system obtained a higher score than the previous model.

Introduction

Makeup is pivotal in self-expression and social interaction, significantly influenced by the digital era's emphasis on personal appearance in photos and videos (Kosmala, Wilk, and Kassolik 2019; Astheimer, Neumann-Braun, and Schmidt 2011). This has catalyzed interest in digital makeup technology, particularly in makeup transfer—a field within computer vision focused on digitally applying makeup effects to alter appearances in photos or videos. This technology is poised to revolutionize makeup application, potentially supplanting traditional beauty advisors.

Advancements in AI have propelled various makeup transfer methods, yet challenges remain, especially with lower resolution images. When high-resolution images are unavailable, conventional makeup transfer algorithms may falter, resulting in subpar applications. To address this, integrating image super-resolution reconstruction is vital. This process involves enhancing low-resolution images using advanced image processing and machine learning techniques, finding applications across diverse sectors, from medical imaging to remote sensing (Lin, Chen, and Yu 2023; Yanqiu Tang 2020).

This paper aims to elevate makeup transfer quality by introducing a resolution conversion module, blending the BeautyGAN makeup transfer network with the BSRGAN super-resolution network. Utilizing Generative Adversarial Networks (GANs), our method achieves simultaneous makeup transfer and resolution enhancement. Additionally, we introduce a CNN-based face rank module for evaluating the transfer results. Our experiments validate this integrated approach, demonstrating superior makeup transfer outcomes compared to existing methods.

Related Work

Makeup Transfer Makeup transfer algorithms are primarily divided into traditional image processing methods (Tong et al. 2007) (Guo and Sim 2009) and deep learning-based image processing methods. With technological advancements, deep learning-based makeup transfer methods have become mainstream.

Chang et al. introduced additional discriminators to generate pseudo-transfer images, guiding the makeup transfer process to ensure the accuracy and authenticity of the results (Chang et al. 2018). Li et al. adopted a GAN framework with dual inputs and dual outputs, allowing simultaneous transfer and makeup removal (Li et al. 2018). They also introduced makeup loss to match the color histograms of different facial components, achieving instance-level makeup transfer. Jiang et al. proposed a method based on facial landmarks and masks, introducing a style-guided architecture and an attention mechanism using semantic information (Jiang et al. 2020). Wan et al. proposed a novel Face Attribute Transformer and its spatial variant FAT for high-quality makeup transfer (Wan et al. 2022). Nguyen and Sun introduced 3D facial information or semantic learning information based on BeautyGAN (Sun, Chen, and Xiong 2022) (Nguyen, Tran, and Hoai 2021). Xu et al. emphasized the importance of interaction in dual-space GANs for more controllable editing and introduced a new dual-space editing and inversion method for enhanced flexibility in editing capabilities (Xu et al. 2022). Khwanmuang focused makeup transfer on hairstyles (Khwanmuang et al. 2023), while Zhang emphasized traditional opera makeup rather

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than general makeup (Zhang et al. 2023). Considering the stability and accuracy of makeup transfer effects, we choose to perform makeup transfer based on BeautyGAN.

Image Super-Resolution Reconstruction Currently, deep learning-based Super-Resolution (SR) methods are gradually becoming the mainstream approach in the field of image super-resolution reconstruction. Innovations in deep learning-based SR methods continue to emerge in areas such as model selection, network structure design, introduction of domain-specific prior knowledge, and optimization of loss functions.

Ledig et al. utilized a generative adversarial network approach to achieve image super-resolution (Ledig et al. 2017). Wang et al. replaced the RB network structure of SRGAN with a structure of dense residual blocks (RRDB) without batch normalization (BN) and transformed the discriminator from a standard binary classifier to a relative classifier (RaGAN) (Wang et al. 2019). Zhang et al. optimized parameters based on ESRGAN (Zhang et al. 2021a). Xia et al. proposed a new efficient non-local contrastive attention (ENLCA) for remote visual modeling, leveraging more relevant non-local features (Xia et al. 2022). Wang et al. applied a diffusion model to image super-resolution reconstruction (Wang et al. 2023). Qu et al. introduced Hardware-friendly Scalable SR with progressive structural sparsity, requiring only one scalable model to cover multiple SR models of different sizes without additional retraining or post-processing (Ye et al. 2023). Shen et al. integrated the super-resolution process into non-paired infrared-to-visible image transfer, resulting in realistic high-resolution outcomes (Shen et al. 2023).

Proposed Solution

Makeup Transfer Module

We design the makeup transfer module to seamlessly integrate a selected makeup style from a source image to a target image, ensuring the enhancement of the target face's appearance while preserving its natural characteristics. The module is based on the combination of a super-resolution module (BSRGAN) and a makeup transfer module (BeautyGAN), which not only accurately identifies and replicates makeup attributes, but is also able to hyper-differentiate low-resolution images. The design of the module allows for the realistic and harmonious application of makeup, maintaining the inherent facial features of the target image. To validate its effectiveness, extensive testing was conducted using a diverse array of datasets. These datasets include a variety of facial structures and skin tones from different demographics, ensuring the module's adaptability and robustness in handling a wide range of makeup styles and intensities. The process begins with a low-resolution target image and a high-resolution reference image. The structure of the makeup transfer module is shown in Figure 1. The Image Process Module first prepares both images, which then pass through the BSRGAN Module for super-resolution enhancement. The enhanced image (X' img) is then fed into the BeautyGAN Module, alongside the processed reference image (Y img), to apply the makeup style. The output (Xs img) is a high-resolution image with the desired makeup effect applied, representing the final result of the integrated system.

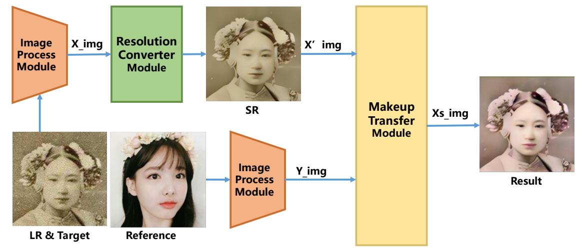

Figure 1: Makeup Transfer module architecture

BSRGAN The BSRGAN presents a significant advancement in single image super-resolution (SISR) by proposing a novel, more complex degradation model. This model is designed to realistically represent the degradations seen in actual low-resolution images, which are often oversimplified in traditional methods. It incorporates a random shuffle of blur, downsampling, and noise—key factors contributing to image degradation. The blur is modeled with both isotropic and anisotropic Gaussian kernels, downsampling includes bilinear and bicubic interpolations, and noise is replicated using a mix of Gaussian noise, JPEG compression artifacts, and camera sensor noise.

A pivotal aspect of the BSRGAN approach is its downsampling model, mathematically expressed as:

$$y = (x \otimes k) \downarrow_s + n \tag{1}$$

where x represents the high-resolution image, k is the blurring kernel, $\downarrow_s$ denotes the downsampling operation, and n is the added noise. This formulation allows for a more accurate simulation of real-world low-resolution image generation, a crucial step for the effective training of super-resolution models.

The BSRGAN architecture is shown in Figure 2. In response to the need for practical SISR applications, BSRGAN employs an end-to-end supervised training approach using the aforementioned degradation model. By manipulating the parameters of this model, a diverse and realistic set of low/high-resolution image pairs are synthesized, avoiding common issues like misalignment. This method provides a

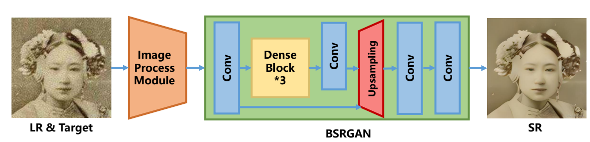

Figure 2: BSRGAN architecture

robust training dataset that significantly enhances the performance of the deep learning model, enabling it to produce high-quality, visually pleasing images even from degraded real-world inputs.

BeautyGAN Incorporating the BeautyGAN architecture, our system utilizes a dual input/output GAN to achieve instance-level facial makeup transfer. The BeautyGAN architecture is shown in Figure 3.

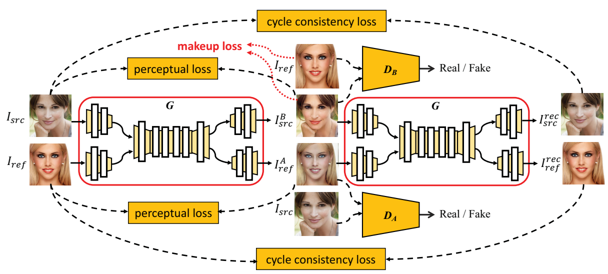

Figure 3: BeautyGAN architecture

The core of BeautyGAN includes a singular generator (G) and a pair of discriminators (DA and DB). The generator translates makeup styles from the reference image to the source image, preserving identity, while discriminators authenticate the translated images against real samples from their respective domains. The objective function of BeautyGAN's generator is an intricate blend of various losses, expressed as:

$$L_G = \alpha L_{adv} + \beta L_{cyc} + \gamma L_{per} + L_{makeup} \tag{2}$$

where L_{adv} is the adversarial loss, L_{cyc} is the cycle consistency loss, L_{per} is the perceptual loss, and L_{makeup} is the makeup loss. These components collectively ensure that the transferred makeup is realistic and consistent with the reference image while preserving the identity of the source image.

Particularly, the makeup loss, essential for achieving style-consistent makeup transfer, is formulated as:

$$L_{makeup} = \lambda_l L_{lips} + \lambda_s L_{shadow} + \lambda_f L_{face} \tag{3}$$

where L_{lips}, L_{shadow}, and L_{face} represent localized losses for lips, eye shadows, and face, respectively. This approach uses pixel-level histogram matching to enforce fidelity to the makeup style of the reference image. Additionally, the adversarial losses for discriminators DA and DB are defined to distinguish between generated and real images, which can be mathematically represented as:

$$L_{DA} = E_{I_{src}}[\log DA(I_{src})] + E_{I_{src},I_{ref}}[\log(1 - DA(I^A_{ref}))] \tag{4}$$

$$L_{DB} = E_{I_{ref}}[\log DB(I_{ref})] + E_{I_{src},I_{ref}}[\log(1 - DB(I^B_{src}))] \tag{5}$$

These losses play a vital role in the learning process, guiding the generator to produce images that are indistinguishable from real images in their respective domains.

Makeup Recomendation Module

We design the makeup recommendation module to offer the most suitable makeup look, simplifying the process of selecting makeup. This article collects common makeup and builds a database of reference makeup with different styles. The diverse pictures in the database are from different countries and different occasions. From a technical point of view, the core of the makeup recommendation algorithm is to find the reference face makeup with the highest similarity with the input image. This problem can be transferred to calculate the similarity of face features which are extracted from the input image and the reference. Based on the wide application of the 16-layer VGG network (Simonyan and Zisserman 2014) in extracting image features, this paper uses the existing face recognition model VGG-Face (Parkhi, Vedaldi, and Zisserman 2015) to extract face features. We calculate the Euclidean distance between the deep facial features extracted by VGG-Face to gain feature similarity.

VGG-Face VGG-Face (Parkhi, Vedaldi, and Zisserman 2015) is a face recognition model based on VGGNet (Simonyan and Zisserman 2014) and it was published by the Vision Group of the University of Oxford in 2015. VGGNet explores the relationship between the depth of a convolutional neural network and its performance, and successfully constructs a network with 16 to 19 layers.

VGG-Face uses VGGNet's group D network structure. VGG16 is a 16-layer VGG network, consisting of 13 convolutional layers, 5 pooling layers, and 3 fully connected layers. VGG-Face changes the last three fully connected layers to convolutional layers. The whole VGG-Face network configuration is shown in Figure 4 and Figure 5.

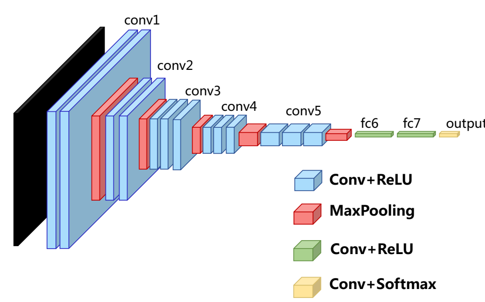

Figure 4: VGG-Face architecture

The authors treat the face recognition problem as a 2622-dimensional classification problem and use Softmax Loss to train the model on a dataset of 2.6M face images. We remove the last layer after training and then retain the face features extracted by the penultimate layer. Finally, we calculate the Euclidean distance between the image features to measure the similarity between the input image and references. In our work, we use the parameters of the VGG-Face feature

layer	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
type	input	conv	relu	conv	relu	mpool	conv	relu	conv	relu	mpool	conv	relu	conv	relu	conv	relu	mpool	conv
name	–	conv1_1	relu1_1	conv1_2	relu1_2	pool1	conv2_1	relu2_1	conv2_2	relu2_2	pool2	conv3_1	relu3_1	conv3_2	relu3_2	conv3_3	relu3_3	pool3	conv4_1
support	–	3	1	3	1	2	3	1	3	1	2	3	1	3	1	3	1	2	3
filt dim	–	3	–	64	–	–	64	–	128	–	–	128	–	256	–	256	–	–	256
num filts	–	64	–	64	–	–	128	–	128	–	–	256	–	256	–	256	–	–	512
stride	–	1	1	1	1	2	1	1	1	1	2	1	1	1	1	1	1	2	1
pad	–	1	0	1	0	0	1	0	1	0	0	1	0	1	0	1	0	0	1

layer	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37
type	relu	conv	relu	conv	relu	mpool	conv	relu	conv	relu	conv	relu	mpool	conv	relu	conv	relu	conv	softmx
name	relu4_1	conv4_2	relu4_2	conv4_3	relu4_3	pool4	conv5_1	relu5_1	conv5_2	relu5_2	conv5_3	relu5_3	pool5	fc6	relu6	fc7	relu7	fc8	prob
support	1	3	1	3	1	2	3	1	3	1	3	1	2	7	1	1	1	1	1
filt dim	–	512	–	512	–	–	512	–	512	–	512	–	–	512	–	4096	–	4096	–
num filts	–	512	–	512	–	–	512	–	512	–	512	–	–	4096	–	4096	–	2622	–
stride	1	1	1	1	1	2	1	1	1	1	1	1	2	1	1	1	1	1	1
pad	0	1	0	1	0	0	1	0	1	0	1	0	0	0	0	0	0	0	0

Figure 5: VGG-Face network configuration

extraction layer and use our datasets to train a classifier. The whole system can recommend the most suitable makeup and transfer it to the input image.

Face Rank Module

In the rank module, we use the SCUT-FBP5500 datasets (Liang et al. 2018) to achieve multi-paradigm face value prediction. The datasets contain a total of 5500 frontal photos of faces with diverse properties (male/female, Asian/Caucasian, ages) and diverse labels (face landmarks, beauty scores within [1, 5], beauty score distribution). The images with different facial properties are shown in Figure 6.

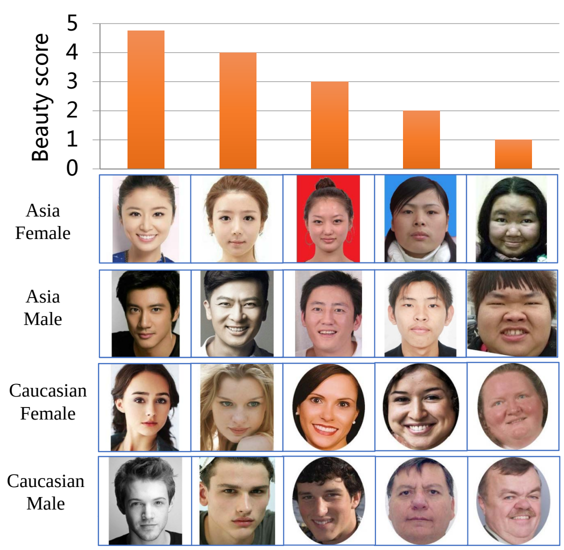

Figure 6: Images from the SCUT-FBP5500 dataset (Liang et al. 2018)

The face value distribution satisfies the normal distribution, which is consistent with the actual situation.

We use the face-recognition Python library to convert each high-dimensional face image data into a vector with a length of 128. The data with 128 dimensions represent 128 facial feature indicators. Then, we use a simple CNN neural network to train the datasets, and finally, the makeup pictures generated by the makeup recommendation system can be tested to obtain the appearance scores.

Experiments

Dataset and Implementation Details

For the datasets, the entire system can be briefly divided into three modules, namely the BSRGAN module, the BeautyGAN module, and the FaceScore module. Each module has its own dataset. For BSRGAN, the DIV2K, Flick2K, WED, and FFHQ datasets were used to train their BSRNet and BSRGAN models (Zhang et al. 2021b). For BeautyGAN, they collected 1000 face pictures without makeup and 1000 reference pictures themselves (Liu et al. 2016). For FaceScore, we used SCUT-FBT5500 v2 (Liang et al. 2018) produced by SCUT to train our model, which contains 5500 frontal photos of faces from different countries and different genders and corresponding appearance scores, which can represent students from SCUT aesthetic standards. Due to limited computing power, the first two modules directly use the already trained model. In the third module, we used a training set to test the set ratio of 0.8, used Nvidia 4060, set the batch size to 64, and trained for 1000 epochs. For the entire system, we obtained five face pictures without makeup from the Internet and some datasets for system testing and ablation experiments.

Ablation Studies

Effects of BSRGAN To solve the difficult problem of accurate makeup transfer for low-resolution target images, we introduced the resolution conversion module. To verify its effectiveness, we remove this module and use the remaining module to train the network, and a comparison of the makeup transfer results before and after the removal is shown in Figure 7.

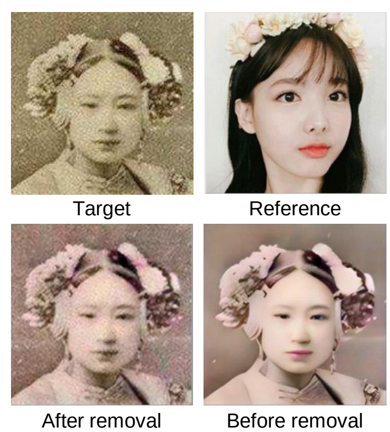

Figure 7: Ablation study of BSRGAN

Compared with the results without the resolution conversion module, the results with this module are more accurate, and the boundary between the makeup and non-makeup regions is clearer. In the makeup transfer result without the resolution conversion module, the whole picture turns pink, but there is no makeup on the human face. In the makeup transfer result with the resolution conversion module, the makeup is clearly visible on the face and the image is softer.

To more intuitively see the effect played by the resolution conversion module, we input the low-resolution target image into the resolution conversion module, and the output and input are compared as shown in Figure 8.

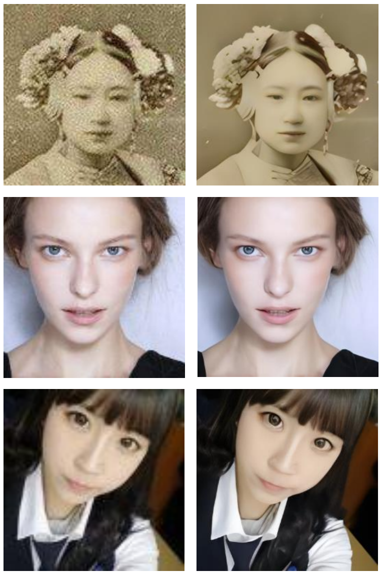

Figure 8: Comparison of results for BSRGAN

Comparison with baseline

Qualitative Comparison Our comparison target model is simple BeautyGAN. We selected five pictures for this qualitative comparison. The comparison results are shown in Figure 9. Obviously, after adding the super-resolution module, our results have a higher resolution than simple BeautyGAN's. What is even more representative is that in the results obtained in the first row, simple BeautyGAN did not successfully apply makeup on the face. However, our result was good and the makeup migration was successfully achieved.

We are not surprised by this result. For low-resolution images, simple BeautyGAN cannot successfully identify facial features every time. When we add the super-resolution network, it amplifies facial features and successfully improves the accuracy of simple BeautyGAN.

Quantitative Comparison How to quantitatively evaluate the makeup transfer problem is still an unsolved challenge, there is no uniform objective evaluation standard for this problem. Most of the papers take a user study to quantitatively analyze their method, while we propose a CNN-based face rank module to quantitatively analyze our method. We use the face rank module for the low-resolution target image without makeup, the high-resolution target image without makeup, and the low-resolution target image with makeup and the high-resolution target image with makeup, respectively. As shown in Figure 9, the scores obtained by our method are better than other methods, proving the effectiveness of our method.

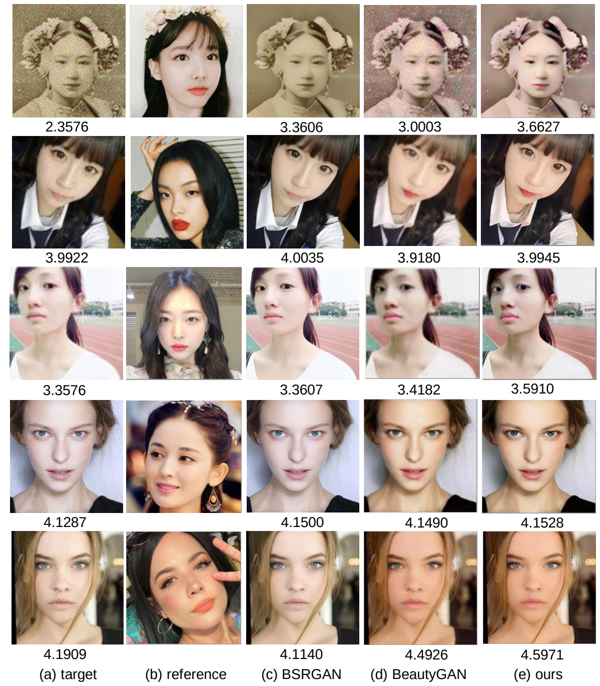

Figure 9: Comparison with state-of-the-art methods

Conclusion

In this paper, we propose a makeup recommendation system for low-resolution images, which can transfer more realistic makeup to the input image. The contribution of this paper is to combine the super-resolution network with BeautyGAN and add the processing of the input image before the traditional makeup systems. The result is more realistic and effective. Firstly, we process the input image and increase its resolution to improve application results. And then we do makeup recommendations by VGG-Face and makeup transfer by BeautyGAN. Finally, we do a qualitative comparison and quantitative comparison by our rank module to test our results. The multi-functional makeup recommendation system can realize the transfer of different styles of makeup for the input image, which has a certain practical significance. Experimental results show that our system results are superior to the original BeautyGAN transfer results and certainly better than the results of BSRGAN treatment alone.

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