VIRTUAL MAKEUP TRY- ON

A

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ABSTRACT

Makeup transfer is one of the applications of Image Style Transfer, which refers to transferring the reference makeup to the face without makeup and maintaining the original appearance of the plain face and the makeup style of the reference face.

We believe everyone irrespective of color or gender should have the right to try new makeup styles without the hassle of putting on makeup and removing it again and again. That's why we created **ENCAPTURE BEAUTY - A VIRTUAL MAKEUP TOOL** that lets you try on different makeup styles without actually wearing any!

The ideal makeup transfer method needs to ensure the face appearance of the basic face image, only transferring the makeup style of the reference image, and the final output generated image automatically presents the perfect combination of the plain face portrait and the reference makeup.

Our app specializes in Deep Learning utilizing Convolution Neural Networks and OpenCV. We will be using the latest technologies used in the industry. For making the Virtual Try-on System we will use Python and its various libraries such as NumPy, Pandas, OpenCV, PyTorch, etc. For deploying the web app, we will make our User Interface using ReactJs, fetching data from ML APIs created in Flask.

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INTRODUCTION

Objective

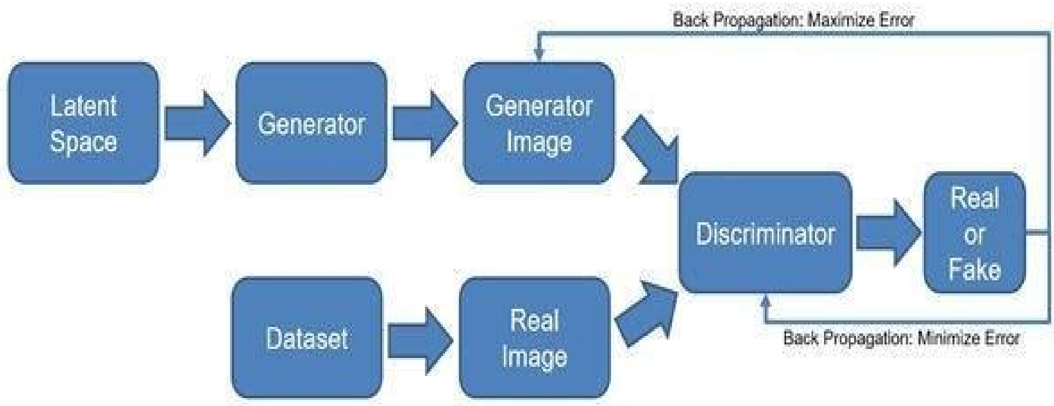
The objective of this report is to explore and analyze the concept of virtual makeup transfer using Disentangled Makeup Transfer with GAN. This technique offers promising results in terms of preserving makeup style, reducing artifacts, and improving the overall quality of the transferred makeup. By understanding the underlying methodology, evaluating its performance, and comparing it with existing techniques, we aim to provide a comprehensive overview of Disentangled Makeup Transfer with GAN and its potential applications in the beauty industry.

In the following sections, we will review the relevant literature on virtual makeup and existing makeup transfer techniques, discuss the methodology of Disentangled Makeup Transfer with GAN, present the results of our experiments, compare it with other techniques, and provide a detailed discussion on the findings. Finally, we will conclude the report by summarizing our key findings, contributions, and future directions for research in this field.

(a) non-makeup (b) makeup (c) BeautyGAN (d) DMT (e) LADN (f) Our

➢ METHODOLOGY

Disentangled Makeup Transfer with GAN is a technique that aims to separate the makeup style from other facial attributes and transfer it onto facial images in a realistic and controllable manner. The methodology involves several key steps, including dataset preparation, makeup encoding, makeup decoding, GAN architecture design, training procedure, and evaluation metrics. A total of 1,04,000 images were used, taken from kaggle as well as scraped from the internet.



Dataset Preparation

The first step in the methodology is to collect and prepare a dataset of facial images with corresponding makeup styles. The dataset should include a diverse range of makeup styles, lighting conditions, and facial poses.The images were compressed using python opencv library into 256 x 256 pixels to easily fit the training model & to reduce the training time as well.

Makeup Encoding

Makeup encoding involves extracting the makeup style from the facial images and representing it in a latent space. This step aims to disentangle the makeup attributes from other facial attributes, such as identity and lighting conditions. Various techniques can be used for makeup encoding, including feature extraction algorithms or deep learning models. Here, the vectors of pixel data are created to be fed into the training model.

Makeup Decoding

Makeup decoding refers to the process of reconstructing the makeup style from its latent representation. This step aims to generate a visually appealing and realistic makeup style that can be applied to new facial images. The vector data that was fed is reversed to make an updated image with extracted feature data as well. Makeup decoding can be achieved using various techniques, such as generative models or image synthesis algorithms.

GAN Architecture for Makeup Transfer

The GAN architecture plays a crucial role in the makeup transfer process. It consists of a generator network and a discriminator network. The generator network takes the makeup-encoded latent representation and synthesizes a new image with the desired makeup style. The discriminator network assesses the realism of the synthesized image and provides feedback to the generator to improve its performance.

Training Procedure

The training procedure involves optimizing the GAN architecture to learn the makeup transfer task. It typically involves an adversarial training process where the generator and discriminator networks compete against each other. The training is performed on the prepared dataset, with iterations of forward and backward passes to update the network parameters. results in many benchmarks, such as Cityscapes, PASCAL VOC, and ADE20K.

TECHNOLOGIES USED

- **Numpy v1.24**
- **Pytorch v2.0**
- **Tensorflow v2.11**
- **Keras v3.7**
- **OpenCV v4.5.0**
- **PIL v3.10**
- **Flask v2.3**
- **React v18.1.0**

ADVANTAGES AND APPLICATIONS

ADVANTAGES

- Convenience: Customers can try on makeup products from the comfort of their own home, without the need to visit a physical store.
- Increased confidence: Customers can experiment with different makeup looks and products to find the perfect match for their skin tone, face shape and personal style.
- Personalization: Virtual try-on features can use machine learning models trained on a customer's facial features, and use this data to recommend products that will suit them the best.
- Cost-effectiveness: Virtual try-on can be more cost-effective than building and maintaining physical stores, especially for e-commerce businesses.
- Marketing: Virtual try-on features can be used as a marketing tool to showcase new products, styles, and collections.
- Sustainability: Virtual try-on can reduce the number of returns and wastage by allowing customers to see how the makeup will look on them before purchasing, which can be beneficial for both customers and the environment.
- Virtual beauty shows: Virtual try-on can be used to create virtual beauty shows where customers can try on the makeup in real-time and purchase them right away, increasing the potential sales.
- Accessibility: Virtual try-on feature makes it easy for customers with disabilities or those who are unable to visit physical stores to try on makeup.
- Time-saving: Virtual try-on eliminates the need to spend time physically going to different stores to try on makeup products.
- Virtual makeup try-on can be a great tool for both retailers and consumers as it can improve the shopping experience and increase sales.

APPLICATIONS

- Several computer vision applications expressively and exhaustively rely on a robust face segmentation output. As such, the following are (but not limited to) the typical face image analysis tasks which strongly rely on accurate face segmentation:
- Preserving and completion of facial identity: Due to the ill-posed nature of face images, face completion is quite challenging. Face completion refers to the task of filling those regions missed for one reason or other. These missed regions are filled with realistic synthesized contents. In classical methods, local information is first searched in order to find some existing patterns from the face image. The patterns are then pasted into the targeted holes. These classical methods rely on low-level features; therefore, they fail when certain patches are not present within the target image. Therefore, face segmentation is one of the best approaches for face identity persevering and face completion. A recent method that uses face parsing for face completion. As such, the last mentioned approach tackles the two tasks of face parsing and face completion using augmentation in a single framework.
- Face de-blurring: With the development and innovations in face parsing approaches, the methods for face image deblurring have taken new directions. The face de-blurring problem is addressed by exploiting semantic cues between different face regions. As the human face shares various semantic components (eyes, nose, mouth, and chin), semantic cues provide sufficient information for image restoration. Face image de-blurring recovers a comparably high-quality image from a blurred input image. Conventionally, the blurring process involves convolution of a latent clear image with a blur filter. The process thus formulates this de-blurring problem on a maximum a posteriori framework.
- Facial landmark extraction: Facial landmarks play an essential role in human face-image analysis. Typically, facial landmarks include the important face regions such as the nose, mouth, eyebrows, and eyes. This is a set of high-level features that can easily be differentiated with the naked eye. Typically, facial landmarks can be detected with a traditional machine learning paradigm. It involves the training of machine learning models on facial features using a comprehensive data set. However, these methods have shown lower performance in unconstrained circumstances, for example, in overlapped faces, and wild, low and non optimized lighting conditions. To overcome this problem, facial landmark extraction through semantic face segmentation has been proven an optimal way.
- Face swapping: Transferring one face from a source image onto a face appearing in a target image to generate un-edited and realistic looking results is generally termed as the face-swapping. Face-swapping has a number of applications scarce, for example, emotion recognition.

CONCLUSIONS AND FUTURE SCOPE

Conclusion

In conclusion, virtual makeup try-on technology has the potential to revolutionize the way customers shop for makeup products. By allowing customers to try on makeup products from the comfort of their own home, virtual makeup try-on can increase convenience and confidence while also reducing the need for physical stores. Additionally, virtual makeup try-on can be personalized to suit a customer's facial features, skin type and personal style, and can be integrated into different platforms such as e-commerce websites, mobile apps, social media, virtual reality and augmented reality.

Future Scope

The following are some potential areas of future development for virtual makeup try-on technology:
Improved accuracy:
With advancements in computer vision and machine learning, virtual makeup try-on technology will become even more accurate in replicating the final look.
More realistic representations: With the development of more realistic 3D models, virtual makeup try-on technology will be able to represent the final look more accurately, taking into account the lighting conditions, skin type and personal style of the customer.
Personalized recommendations: With the development of more advanced algorithms, virtual makeup try-on technology will be able to provide more personalized recommendations for makeup products that suit a customer's skin type, face shape and personal style.
Integration with virtual reality and augmented reality: With the development of virtual reality and augmented reality technology, virtual makeup try-on will become more immersive, allowing customers to try on makeup products in a more realistic environment.

Overall, virtual makeup try-on technology has a bright future, with many potential areas of development that can improve the customer experience, increase sales and provide personalized recommendations and services.

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