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"Image Completion Network Using Deep Learning"

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Abstract:
Background*: In This Paper, We Propose A Solution To Image Completion Using Deep Neural Networks Has Become A Hot Research Area. As Structure And Texture Are Two Indispensable Parts Of Images, Completion Algorithms Must Deal With Them Appropriately To Produce Realistic Results. However, Many Current Methods Use The End-To-End Framework To Repair An Image, Which Do Not Pay Special Attention To Texture And Structure. Therefore, They Often Generate Distorted Structures And Inconsistent Textures. To This End, We Propose A Novel Image Completion Method Comprising A Sketch Completion Network Followed By A Texture Completion Network. GAN Focuses On Repairing The Sketch Structures In The Missing Region Of An Image, And GAN Generates Consistent Texture Information In The Missing Region Based On The Sketch Output By GAN And The Surrounding Incomplete Image. By Modeling The Two Parts Separately In A Deep Neural Network, Not Only The Proposed Method Can Successfully Synthesize Semantically Valid And Visually Plausible Contents In The Missing Region, But Also It Allows A User To Manipulate The Structure Attributes Freely In That Region*

Key Word*: GAN, CNN*

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I. Introduction

Image completion are commonly used in various kinds of applications. Images are an artistic form widely used in our daily life Image completion, also known as image in painting, is an active computer vision research problem that aims to automatically fill in a missing portion of an image in a content aware way. By content-aware, it means that an algorithm should consider the neighbor pixel information of the missing portion of the image it is completing when it produces the final completed output. Although image completion has been actively studied in the last twenty years, there is no existing approach that can work well for portrait images, where holes on the human body need to be filled in. A successful completion method is required to recover not only the correct structure in the missing region, but also the accurate appearance of the missing object parts Generative Adversarial Networks GAN [4] has been turned out to be helpful in picture completion tasks.

II. Material And Methods

In the previous Image completion research methods generate visually plausible image structures and textures, but sometimes create distorted structures or blurry part according to surrounding areas[14].We proposed Novel Adversarial neural network to automatically fill in a missing portion of an image which will generate distortion free and complete image from given incomplete image.

GAN

Generative Adversarial Networks (GANs) [13] has two neural networks: a generator (G) and a discriminator (D). The task of the generator (G) is to generate a photorealistic image while the discriminator (D) distinguishes the real image and the generated image of the generator which gives the decision about the real image as well as fake image. Both the generator and discriminator plays the min-max game until there is a confusion of discriminator between the real image and fake image generated by the generator because a generated image is too close to the real one. GANs have many applications in computer vision like image super-resolution, image colorization [14], image dehazzing [15], etc. The min-max game function is expressed as,

$$\min_{G}\max_{D} \mathbb{E}_{x\sim p_{data}}[\log D(x)] + \mathbb{E}_{z\sim p(z)}\left[\log\left(1 - D\left(G(Z)\right)\right)\right]$$

A noise vector, z is given to a generator that is sampled from a normal distribution p(z) which maps z to produce synthesized image complement, x. The first part of the equation ($\mathbb{E}_{x\sim p_{data}}[\log D(x)]$) described as log probability of discriminator, D predicts that real-world data is original.

The second part of the equation $\left(\mathbb{E}_{z\sim p(z)}\left[\log\left(1 - D\left(G(Z)\right)\right)\right]\right)$ as log probability of discriminator, D predicts G's generated data which is not real. For easy training of Generative Adversarial Networks (GANs), Radford et al. [12] proposed DCGANs (Deep Convolutional Generative Adversarial Network) for many applications such as video data frame prediction, cross-domain image generation network. M. Mirza et al. designed Conditional Generative Adversarial Networks (CGANs) for image generation, based on the availability of prior information. Recently, Cycle GANs is used for many applications such as unpaired image datasets training [16], image2image translation and achieving good performance in terms of loss reduction, accuracy, etc. This work prominently helps to improve the performance of GANs in image generation

Architecture:

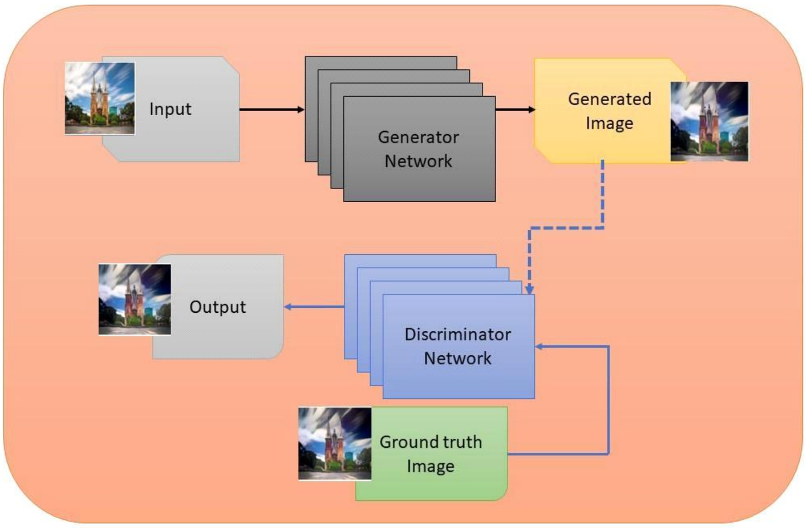


Image Completion GAN

A GAN framework consists of two CNNs. One is the generator G which is trained to produce output that fools the discriminator. The other is the discriminator D which classifies whether the image is from the real target manifold or synthetic. We design the generator and discriminator networks to suit the particularity of cartoon images

Deep Network Architecture:

When the dimension of the input vector is lower than the dimension of the output vector, the neural network is equivalent to a decoder. The generator G acts as a decoder corresponding to the convolutional encoder E and takes the face feature vector z, the age vector a, and the gender vector as input, and the face image is reconstructed from the feature information. The gender condition is added because the aging characteristics of different genders are very different. The aging synthesis of a face is carried out on the basis of clear gender, which can avoid the influence of gender on the aging result. The network structure of the generator is shown in Figure 2.

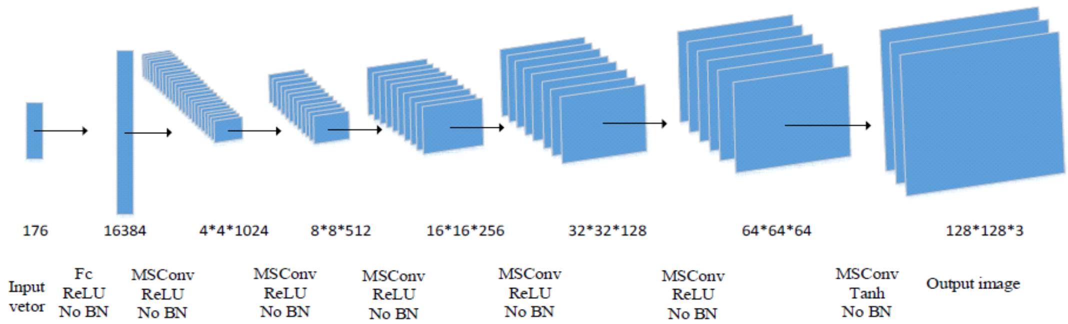


Fig.2 Deconvolution network structure of the generator

The input to the generator is the merge vector of feature vector z, age vector a, and gender vector g. From the structure diagram of the convolutional encoder, z is a 60-dimensional feature vector, and the age information is an eight-dimensional one-hot vector. The gender information is a two dimensional one-hot vector. If directly merged, the age condition and gender condition will have little effect on the generator. In order to balance the influence of eigenvectors and conditional vectors on the composite image, the age vector a is copied seven times before merging to obtain a 56-dimensional vector, and the gender vector g is copied 30 times to obtain a 60-dimensional vector. Then, the conditional input of the

Generator is a 116-dimensional vector, and the eigenvector z is combined to obtain a 176-dimensional input. The most important operation of generating a network is the Fractional-Strided Convolution, which is also considered to be deconvolution in many places. In the micro-step convolution operation, it is adopted. A convolution kernel of size 5 × 5 with a step size of 2 × 2. Similar to the convolutional coding network, batch normalization is not used in the generation network, and the Relu activation function is used for all layers except the output layer using the Tanh activation function.

Discriminator:

The role of the discriminator is to distinguish between the real face image and the synthetic face image and, finally, output a scalar value indicating the probability that the discriminator's input image is a real face image. The network structure of the discriminator is shown in Figure 3. As can be seen from Figure 2, the input is an RGB face image (real image or composite image) of size 128 × 128 pixels, and the output is a scalar value in the range of (0, 1). The constraint is connected to the first convolution layer according to the design rules of the condition GAN. Specifically, after the input image passes through the first convolutional layer, a feature map of 16 pixels is output and then connected to the conditional feature map after the extended copy to obtain a feature map of 32 pixels. After the conditional connection is successful, the 32 feature maps are convoluted and fully connected, and finally, a scalar value representing the probability is output.

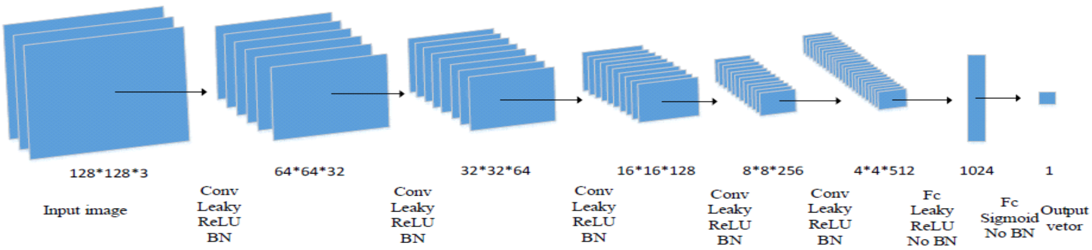


Fig. 3. Convolution network structure of the discriminator

Convolutional Neural Networks (CNN)

This network is specially used and designed to handle pixel data; it is kind of an artificial neural network which has applications in _led like image processing and recognition. The make of CNN includes many layers which are the input layer, output layer and a multilayer perceptron layer included as the hidden layer, then we have the fully connected layers and normal layers

Loss Function:

Generative adversarial networks attempt to replicate a probability distribution. Therefore, they use loss functions to show the gap in the data distribution produced by the GAN and that of real world. GAN mainly constitutes of two loss functions, one which is for the training of discriminator and the other for the training of generator. The generator loss and discriminator loss derive from a single measurement of separation among the probability distributions. In any case, the generator can just influence one term in the distance measure that will react the distribution of the counterfeit data. Hence, while training the generator the other term is dropped, which will react the distribution of the real data. The generator loss and discriminator loss appear to be unique at the end, despite the fact that they derive from a single formula, the generator at-tempts to limit the function whereas the discriminator attempts to expand it: Ex[log(D(x))] + Ez[log(1 - D(G(z)))] D(x) Estimation given by discriminator that x is real. Ex- Instances of real world.

Flow chart:

Flow chart is the graphical representation which is separates the steps of a process in sequential order. It is a generic method that can be adapted for a wide variety of purposes, and can be used to describe various processes

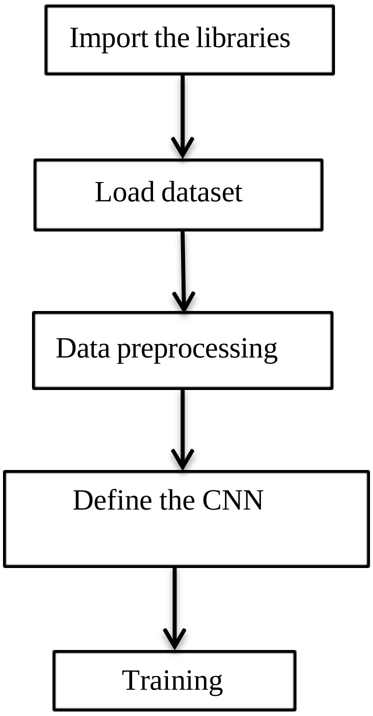
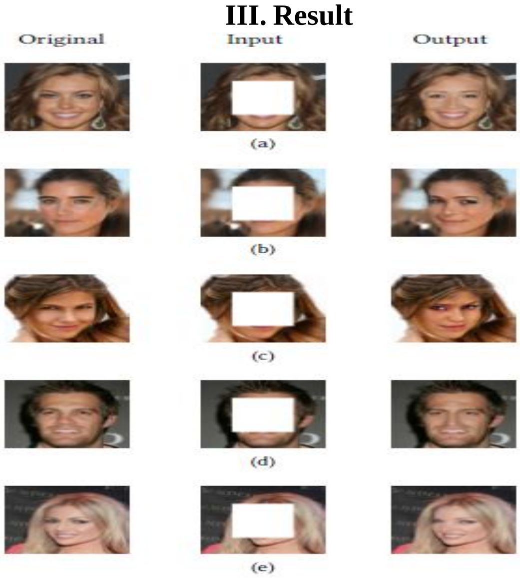


Fig 3. The flow chart of the proposed network

The overall flow chart of proposed approach shown in Figure 3. It consists of several blocks such as image dataset to call the database images for further processing, the task of preprocessing unit is to remove the unwanted noise from the image or it enhances the some features of image which is required for further image analysis and processing. The pre-processing based on the requirements such as re- scaling, reshape etc., network has mainly two sub parts generator and discriminator. CNN is specially used and designed to handle pixel data; it is kind of an artificial neural network which has applications in led like image processing and recognition. The make of CNN includes many layers which are the input layer, output layer and a multilayer perceptron layer included as the hidden layer, then we have the fully connected layers and normal layers. Training means there is learning relation data and attributes out the whole training dataset some images were considered. The training block is used to train the system neurons based on the user's conditions. At last testing block which helps to check trained module performance by applying the trained module weights to any external image or any image from the same dataset.

III. Result



Results show that this technique can produce excellent animation pictures from genuine world photographs which have explicit craftsmen's styles and with legible edges and smooth concealing and outflanks best in class strategies. Obtaining labeled data is a manual process and is time consuming too. GANs don't make use of labeled data and thus can be trained using unlabeled data. GAN can be helpful to transformreal world photos to high quality images, outperform

IV. Conclusion

Results show that this technique can produce excellent Image completion from GAN a Generative Adversarial Network to transform real- world photos to high-quality images. Aiming at recreating faithful characteristics of images, we propose a novel edge-promoting adversarial loss for clear edges, and an 11 sparse regularization of high-level feature maps in the VGG network for content loss, which provides sufficient flexibility for reproducing smooth shading and thus can be trained using unlabeled data. GAN can be helpful to transform real world photos to high quality images, outperforming other methods**.**

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