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Face Sketch to Image Generation using Generative Adversarial Network

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Abstract— Numerous studies have been conducted in the area of sketch to picture conversion and they got the good outcomes, but sometimes it is not accurate that they observed the blurry boundaries, the mixing of two colors that is the color of hair and face or mixing of both. These results are of the convolution neural networks that are basic of GAN. So to overcome their drawbacks we proposed a novel generative adversarial network using conditional GAN. For that we converted the original image in sketch and both the sketch and original image as reference is applied as input. We got more realistic and sharp colored images as compared to other. We focused on the feature detection, and the results are good. For the experimentation we used the STL-10 dataset. We overcome the problem of mixing of colors and got the different colors for hair, lips, and skin using conditional GAN as compared to CNN modern with increased performance and precision.

Keywords-CNN; GAN; Conditional GAN; Feature detection.

I. INTRODUCTION

Sketch is an easy method to represent an idea, scene or an object in a minimum time. The sketches are very simple to draw and they are imperfect. As we can compare to photography, to draw a sketch capturing device is not necessary. Sketches are very simple; any one can draw a sketch by their own idea. So, it is very challenging to identify the real image from the novice sketches. The sketch to image generation is very interesting and hot topic in machine learning and computer vision [1] without substantial creative skill or using sketch-based picture synthesis, people who are not artists can create realistic graphics. Because sketches are scant, unskilled human artists are unable to generate sketches that depict object boundaries precisely. Try to create a realistic drawing from a sketch to capture the artist's purpose as much as possible, although it may be necessary to depart from the rough strokes in the original. There are lots of application of sketch to image conversion that is in cityscape, photo in painting, in police station [2] to identify the person from the drawn sketches. In police station the sketch to image conversion is useful for identification of the suspects from sketch [2] the sketch to image conversion is used in digital image processing and public security systems [4, 5, 6, 7]. One of the most important application of sketch is in photo editing [3]. To build a CGAN we want 256*256 image with their sketch conversion to produce the output which is in colored format of a photo which is converted in image. The image is with the actual situation. The generation of image with knowing the value of ground truth is useful in many regions that is in the computer and in the real world. To represent an idea the best way you can draw a sketch which is simple as well as free. In

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this field many researchers have done the comparison for that the produce architecture of sketch inversion. After studying more, they would like to improve their outputs with the sharp boundaries. In our research we are going to compare our network with the convolution adversarial neural network with the conditional GAN as the results are not that much perfect in convolution Network. We are going to understand existing approaches, identify the limitations of existing approaches and according to that will design a novel neural network for generating a good quality face images from sketches and comparing the generated face images with ground truth images to increase the accuracy and SSIM (Structural Similarity Index).In this paper, we propose a novel human face sketch to color image conversion that allows all types of skin tones between the age group of 50to80. We are using the hand sketched image as a set of input image and the desired output will be colored image of the sketched person. In this area many of the researchers showed their desired output but the output is somewhat unrealistic. The problem with their output is the mixing of colors in one another, the noise in the background, color bleeding, color spreading and many more.

II. LITERATURE SURVEY

2.1 Existing Approaches

Researchers offered an innovative solution to the sketch-to-image synthesis challenge in the study [2]. Given the nature of sketches, the issue is complex, but this led to the introduction of a deep generative model that shows promise for sketch to image synthesis. To promote study in this area, they developed a technique for sketch-image pairings of data augmentation. Results are typically neither picture realistic nor sufficiently high resolution. [2] An adaptive edge detection algorithm [19] was employed to reduce color spreading over the object boundaries. They suggest using a sketch as a weak constraint in which the output edges are not required to follow the input edges. They used a novel joint picture completion strategy to solve this issue, where the sketch serves as the image context for finishing, or creating, the resulting image. They used joint images to train a generated adversarial network, or contextual GAN, to learn the joint distribution of the sketch and the associated image.[14][20] revealed yet another scribble-based image colorization technique. By applying scribbles to the photos, this technique turns grayscale pixels with the same intensity levels into colors. They carried out the experiment of translating a face sketch into an image by changing just one facial trait, such as the color of one's hair or skin, such as "Black Hair," "Blond Hair," "Pale Skin," or "Rosy Cheeks.", when contrasted to the real world, the generated face images have extremely visible changes to their facial characteristics, and they also lack any apparent sense of disobedience [3]. A photo to sketch conversion is also possible, and it works similarly to the drawing to image conversion [25, 26]. There has been significant advancement in sketch-based image retrieval [29, 30, 31, 32, 34, 36].

2.2 Convolution Neural Network

The CNN is the basic of the GAN which has the deep algorithm. This algorithm helps to produce output, in which the input is applied to first block, which is very important to assign weights. This block is used to identify the image from one another. It requires the preprocessing which is very lesser compared to other. The filters used in this are hand engineered as the CNN can handle the filters and their characteristics. Before learning the CNN we have to understand how the human brain operates that means how it reads an image. There are three elements in the architecture of CNN. They are input image, CNN and then third one is output label. First building block is CNN in which the feature detection is done. CNN works with black and white as well as colored images. The colored image is showed with the help of RGB values. Colors are represented on a scale from 0 to 255. In this 0 is black and 255 is pure white. All the values in between 0-255 are the shades of gray. One of the well-known applications of CNN is in medical diagnosis using X- Rays and CT scan.

III. METHODOLOGY

3.1 Generative adversarial network

GAN is a generative algorithm introduced by Ian Good fellow and other researchers in 2014. GAN Architecture is as shown in fig 1. To train a generative model the generative adversarial networks are developed. In recent years using original GAN different kinds of network models are derived [8] They consists of two generative models first is generator as G and the discriminator as D[9]. The data distribution is captured by the generator model G and discriminative model D that estimates the probability that a sample came from the training data rather than G. The generator and discriminator models are non -linear mapping functions. Such as multi-layer perceptron. The GANs are used in image generation [10, 11, 12, 13, 14, 15] image translation [16, 17] Generator generates the mapping function from noise distribution Pz (z) to data space as G(z; g) in order to learn the generator distribution Pg across data X. And the discriminator, D(x; d), generates a single scalar that indicates the likelihood that x originated from training data as opposed to Pg. The settings for G and D are adjusted to minimize log(1-D(G(z)) for G and logD(X) for D, respectively, as though they were playing a two-player min-max game with value function V (D, G):

$$\min_G \max_D V(D,G) = \mathbb{E}_{\mathbf{x}\sim p_{\text{data}}(\mathbf{x})}\left[\log D(\mathbf{x})\right] + \mathbb{E}_{\mathbf{z}\sim p_{\mathbf{z}}(\mathbf{z})}\left[\log\left(1 - D(G(\mathbf{z}))\right)\right]$$

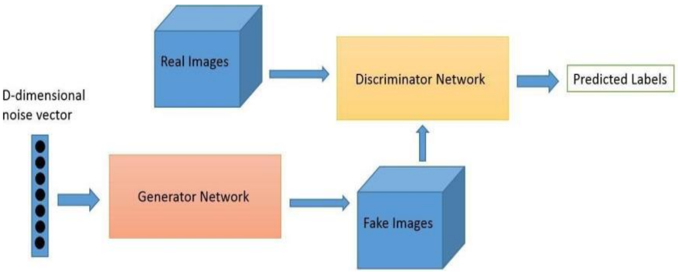

Fig 1: GAN Architecture

Working

The generator's purpose in operation is to deceive the discriminator by producing the data instances close to input data set. Thus, G helps stoma maximize the probability of D making mistake by generator. This frame work corresponds to a min max two Discriminator tries to identify counterfeit data instances produces player game (it maximizes the real image chances and minimizes the fake images)

A Generator used to create random noise. The role of the discriminator is to provide the guidance to the generator on what data instances to create. To determine what constitutes real photos, GAN constructs a discriminator. It also feeds feedback to the generator to assist it produce more realistic data instances.

3.2 Discriminator

In the GANs the role of a discriminator is also known as classifiers. The classifiers are used to distinguish the data. There are the two data sets original generated and the fake ones. The role of a classifier is to classify the data between real and fake. There is a two type of data set applied to the discriminator: first real image and the second one is fake that is generated by the generator. There are two types of example as positive and negative .As the discriminator is in training it uses real data instances as a positive example and fake data as a negative example. Generator loss and discriminator loss are the loss functions. Discriminator ignores generator loss during discriminator training and only the discriminator loss issued.

3.2.1 Training Discriminator

The Discriminator requests separate copies of the generated images and the genuine ones. It determines whether the discriminator's input image is fake or real. The probability that the input x is real, or P (class of input = real data instance), is the output D(X). The discriminator is trained (fig 2) in the same manner as a deep network classifier. One of these conditions is D(x) =1 is what we desire if the input is real. It should be zero if it is generated. The discriminator finds features that contribute to actual data instances through this method.

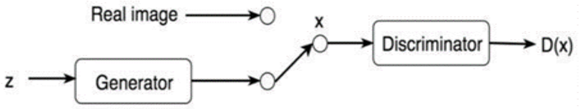

Fig 02: Training Discriminator

The discriminator's output in this case, D(x), displays the likelihood that x is a genuine data instance. Our goal is to increase the likelihood that created data instances are phony and actual data instances are distinguishable. i.e., the observed data's highest likelihood. Cost option employs cross entropy.

$$\max_D V(D;G) = \mathbb{E}_{\mathbf{x}\sim p_{\text{data}}(\mathbf{x})}\left[\log D(\mathbf{x})\right] + \mathbb{E}_{\mathbf{z}\sim p_{\mathbf{z}}(\mathbf{z})}\left[\log\left(1 - D(G(\mathbf{z}))\right)\right]$$

3.3 Generator

As we are using a conditional GAN there is a feedback system. The discriminator always produce output and send it back to the generator in a feedback form, after getting feedback from the discriminator then the fraudulent data is produced by the generator. The generator is master in creating the fake data and it helps the discriminator to fool the output and tries to present the output is original. There is a need to learn the generator closer integration instead of training of discriminator. In the generative adversarial network there is a frequent inputs dataset applied to the generator these frequent inputs are then converted into the data instances. Generator always gives the simultaneous outputs to the discriminator. The hand drawn sketch is nothing but the colorless drawing that is black and white format; this is also known as gray scale image. We provided all types of skin tones that are Indian and foreign between the 50-80 age group people.

The provided images are first converted into sketch and done the classification. Then this sketch and the reference images are applied to the generator block as a input. In the CGAN there is the feedback system which helps to compare the output with the reference image and try to provide the desired output. As the system don’t know the trees is green after providing lots of data it tries to understand the tree is always green, the hairs are black brown, lips are pink. This identification is done after the random data set. The results are more perfect after providing the data set in huge amount. the sketch is input image and the reference image is the original image of sketch. The network learns from the reference image.as the input is in large and in variety the output is also good.

3.3.1 Training Generator

With D(x) = 1, we want the generator to produce images. Generator is trained with the help of back propagation (Fig 3); this value is going back to the generator as input. We train a generator that is biased toward what the discriminator believes to be true in order to generate data instances.

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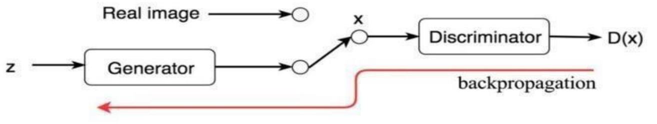


Fig 03: Training Generator

The objective function wants the model to produce images with the highest value of D(x) in order to train the discriminator.

$$\min_{G} V(G;D) = \mathbb{E}_{\mathbf{z}\sim p_{\mathbf{z}}(\mathbf{z})}\left[\log\left(1 - D\left(G(\mathbf{z})\right)\right)\right]$$

3.4 Simultaneous training of generator and discriminator

Following the specification of both target functions, the alternating gradient descent method is employed to jointly train the two functions. In a single iteration of gradient descent on the discriminator, we fix the parameters of the generator model and use both real and generated images as shown in fig 4. Then we switch positions. Retrain the generator and fix the discriminator to get one more iteration. We alternate between training the two networks until the generator produces images of the highest quality.

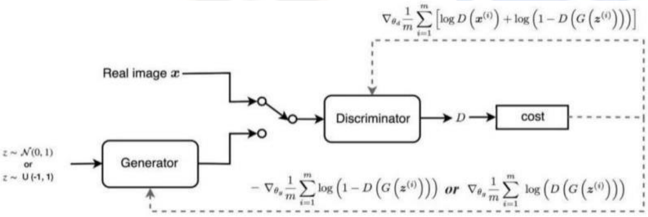

$\nabla_{\theta_d}\frac{1}{m}\sum_{i=1}^{m}\left[\log D\left(x^{(i)}\right) + \log\left(1 - D\left(G\left(z^{(i)}\right)\right)\right)\right]$
Real image x
Discriminator
D
cost
$z \sim \mathcal{N}(0,1)$
or
$z \sim U(-1,1)$
Generator
$-\nabla_{\theta_g}\frac{1}{m}\sum_{i=1}^{m}\log\left(1 - D\left(G\left(z^{(i)}\right)\right)\right)$ or $\nabla_{\theta_g}\frac{1}{m}\sum_{i=1}^{m}\log\left(D\left(G\left(z^{(i)}\right)\right)\right)$

Fig 04: Training GAN

3.5 Conditional generative adversarial network

Generic adversarial networks include conditional generative adversarial networks. When there are numerous conditions that apply images to the generator model's input. The conditional GAN works on two parts one is generator and second discriminator. The GAN is used to create realistic images [21,22] Image generation is can be conditional on class labels[37]. There are the limitations of generating random samples with the help of GAN, we can help to overcome that by using the conditional GAN. Another use of GAN is for image translation [23, 24]. There are two networks in a GAN. One is a discriminator, whereas the other is a generator. The discriminator supervises the generator, which creates images that are comparable to Data set images. Determine whether the input originates from the generator or from another source. The primary Data set the discriminator and generator have been trained. Simultaneously Picture colorization is a form of image processing. Image-to-image translation technique Convolution neural networks, also referred to as CNN, are both generators and discriminators. There is no control on output in generative adversarial networks. Using conditional GAN (fig 5) we can control the output using conditional GANS by using labels and conditions.

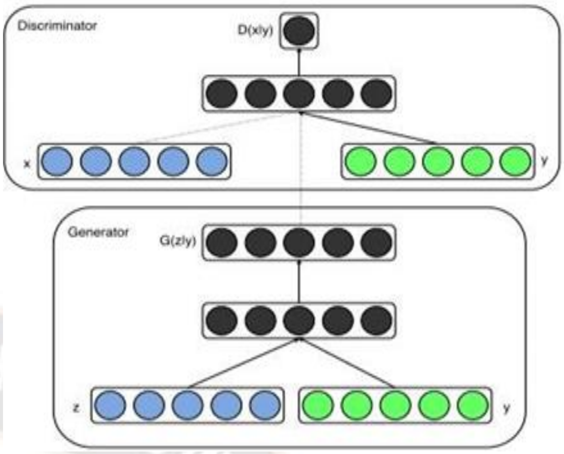


Fig 5 General Representation of Conditional Adversarial Network.

If both the generator and discriminator are conditioned on some additional information, generative adversarial networks can be extended to a conditional model. Any auxiliary data, such as class labels or information from different modalities, could make up y. By adding y as an additional input layer to the discriminator and generator, we can condition the system. Prior input noise P_z (z) and y are mixed in the generator to form a joint hidden representation, and this hidden representation can be constructed with a great deal of flexibility because to the adversarial training framework. In the discriminator, x and y are given as inputs to a discriminative function (represented in this instance once more by an MLP). A two-player mini max game's primary purpose would be to:

$$\min_{G}\max_{D} V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x}|\boldsymbol{y})] + \mathbb{E}_{\boldsymbol{z}\sim p_z(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z}|\boldsymbol{y})))].$$

3.6 Image Colorization:

Image colorization process block is as shown in figure 6. The process and basic steps are discussed below.

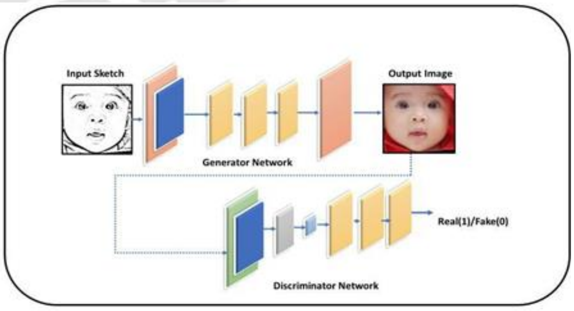


Fig 06: Image colorization

3.6.2 Basic Steps of Conversion from Sketches to images using Conditional GAN Network.

1. Take input paired data set which contains both sketches and images.

2. Pre-process the dataset.
3. Give sketch images as an input to the generator network to generate colour images from given sketches.
4. Give paired colour images to the discriminator network to match the generator output and discriminators colour image to identify generated colour image is real or fake.
5. Test the sketch images with proposed network to get realistic sketch images from given sketches. Input image (sketch)

After conversion of the sketch to the image the image colorization is necessary because the sketch is nothing but the black and white that is gray scale image. To colorize the image the image colorization is used.

Random noise is the generator's input in a typical GAN. But in automatic colorization method this problem is not applicable because the inputs to our issue are not noise but rather greyscale photos. By using conditional adversarial network this problem is addressed [39]. The generated input is calculated as zero noise with the greyscale input as a prior if the noise is not included. In mathematical word G(0z|x) In order to account for the conditional network, the discriminator's input was also changed. Our final cost functions after making these changes are as follows:

$$\text{Min } \theta_G \, J(G)(\theta_D, \theta_G) = \min E_z [\log(1 - D(G(z)))]) \qquad (3)$$

$$\text{Max } \theta_D \, J(D)(\theta_D, \theta_G) = \text{Max } (E_x [\log(D(x))] + E_z [\log(1 - D(G(z)))])$$

The colour images are applied to the discriminator from both generator and original data along with the gray scale values as a condition and then it decides which pair is the original colour image.

Mode collapse

The term mode collapse is nothing but the obstacles which are observed during training period. In our model these obstacle is observed during generator training. The problem with the generator is that it every time it produces the same output [17]. When the obstacle is occurred, the same output is generated continuously by the generated and it achieves the target to fool to the discriminator. The term instance normalization [18] is used to overcome this drawback. And instead of batch normalization [36] we used the method suggested by the [18] on colorization of an image. In which we tried to train the generator to avoid generating same colours. To avoid this the generator algorithm is mentioned at the end.

ALGORITHM

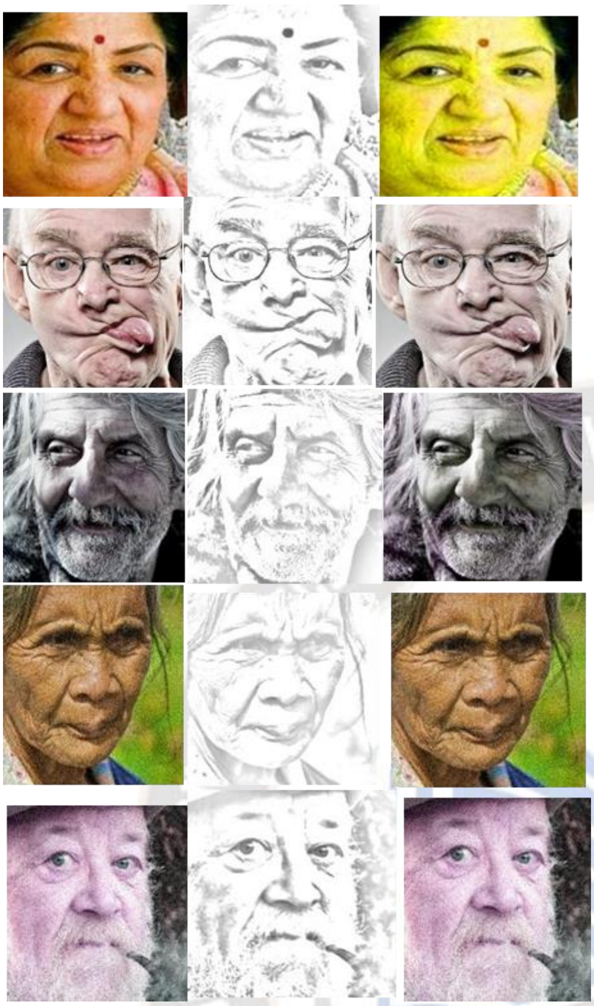
1. Take dataset of STL-10
2. Convert the images o sketch
3. Process the dataset
4. Give the sketch scaled input into the network of generators.
5. Train the generator
6. After conditional generator learning give the generator feedback to discriminator for comparing with reference image.
7. Learn the sketch to image process according to the back propagated losses from the discriminator.
8. Optimize the generator loss.
9. Train the generator again and process repeats.

IV. RESULTS

To train our model the software we used Google’s Collaborators. For this the Google’s Collaborators uses the GPU of Tesla P100-PCI-E-16 GB. To train our model for we required 10 hours and for testing 20 mins. The initial learning rate for generator and discriminator is 0.0002. We used the Adam optimizer [20]. We used STL-10 dataset. We took the 500 images for dataset, and converted these images in sketch. For training we used 500 images and out of this 400 images for the testing purpose. For each image the dimension is 96*96. For the input setup we converted the images in sketch. After conversion we got the dataset of original image and their sketches for input.

Comparison With state of Art

Our objective is to produce a realistic image from a sketch. In this we noticed that the conditional GAN is more capable for providing good output than the convolution network to produce visually strong results we calculated both the evaluation



(a) *(b)* *(c)*

Above fig 7 (a) is original image as reference image, (b) is the sketch conversion; (c) is the testing image as output.

techniques that is qualitative and quantitative analysis. Peak signal to noise ratio (PSNR) was obtained for quantitative analysis. Color fidelity is useful for assessing colorization techniques that aim to produce colors that are more closely resemble real-world images. By comparing the color pixel values between the generated photos and the ground truth photographs, we estimated the Mean Absolute Error (MAE). Assessing color fidelity we use the root mean square error (RMSE) of the two channel images in comparison to the ground truth for both networks.

Table 1 Qualitative analysis

Techniques	Naturalness
CNN	78-80
Ours CGAN	90
Ground truth	99

Above table 1 show the technique used in our model and their naturalness with ground truth.

Table 2Accuracy

Accuracy	CNN	CGAN
$\in l$=0.2	32.5	63.3
$\in l$=0.5	40.2	80.5

Above table 2 shows the accuracy between CNN and CGAN, where ∈ is the threshold distance. The colour channels, which are represented mathematically as it determines whether any two pixels are the same colour. The number of pixels in the created image and the ground truth image are always the same.

Table 3 Quantitativ eresults

	PSNR (dB)	RMSE	MAE
Sketch to Image CGAN	25.44	6.76	5.68
Ground Truth	NA	NA	NA

Table 3 shows the qualitative analysis. We determined the Peak signal to noise ratio (PSNR) for a quantitative study. Color fidelity is useful for assessing colorization techniques that aim to provide colour that is more closely related to the original image. In order to assess colour fidelity for the other three networks, we employ root mean square error (RMSE) of the two-channel images compared to the ground truth. Additionally, in order to determine how closely the created coloured image resembles the actual image, we calculated the Mean Absolute Error (MAE) by subtracting the values of each color pixel from both the generated and ground truth images.

V. CONCLUSION

From our experiment it was noticed that there is a problem of skin color, but we got the different colour for hairs, lips, eyebrows which avoids the mixing of two colours. There is a same colour in the dataset so the yellow shade is maximum. This problem can be overcome by using the variety of data base that means the multi-colour data set and the dataset in the huge amount .so that the system can understand the colours and ready to train the system. For the desired output we will try to overcome this by adding the variety in dataset.

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