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Image Processing: Convert a Sketch into Coloures Image using cGAN

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Abstract: *Synthesizing realistic images from human drawn sketches is a challenging problem in computer graphics and vision. Existing approaches either need exact edge maps, or rely on retrieval of existing photographs. In this work, we propose a novGenerative Adversarial Network(GAN) approach that synthesizes plausible images from 50 categories including motorcycles, horses and couches. We demonstrate a data augmentation technique for sketches which is fully automatic, and we show that the augmented data is helpful to our task. We introduce a new network building block suitable for both the generator and discriminator which improves the information flow by injecting the input image at multiple scales. Compared to state-of-the-art image translation methods, our approach generates more realistic images and achieves significantly higher Inception Scores.*

Keywords: Image abstraction, Implementation, Data augmentation, Training, Testing

I. INTRODUCTION

In today's, we are surrounded by different types of photo manipulating filters in our mobile phones, apps…etc. But do you know how they do these images manipulations…..? In the backend, they are using computer vision techniques. Computer vision has a wide variety of applications not only to reduce the human effort but also used for entertainment apps. Many photo editing apps like FaceApp, Instagram filters…etc are using computer vision techniques.

In this project, we will try to convert a normal pencil sketch into a photo using computer vision in a python programming language. In this project, we will show how to convert an pencil sketch into its corresponding photo in a few steps.

Conversion of pencil sketch into a photo is all about how precisely you detect the edges of the sketchs. It totally depends upon you that, how well you detect the edges of the sketchs. There are few algorithms already available which helps you in the detection of the edges. Different algorithm of Image processing works differently here. We are going to use Google colab Python's pencilSketch() and sylization() algorithm in this project. This project proposes a pencil sketch generating system that can create various different types of pencil sketching to images, to satisfy the different needs of users for specific design goals.

Setting up the Requirements

How can we visualize a scene or object quickly? One of the easiest ways is to draw a sketch. Compared to photography, drawing a sketch does not require any capture devices and is not limited to faithfully sampling reality.

However, sketches are often simple and imperfect, so it is challenging to synthesize realistic images from new sketches. Sketch-based image synthesis enables non-artists to create realistic images without significant artistic skill or domain expertise in image synthesis. It is generally hard because sketches are thin, and novice human artists cannot draw sketches that precisely reflect object boundaries.In this project we will talk about the architecture and working of a cGAN and learn how to implement a simple image to image translation using Google Colab . This project is going to be all about learning how to create a Conditional GAN to predict colorful images from the given black and white sketch inputs without knowing the actual ground truth. we propose Sketchy GAN, a GAN-based, end-to- end trainable sketch to image synthesis approach that can generate objects from classes. The input is a sketch illustrating an object and the output is a realistic image containing that object in a similar pose.

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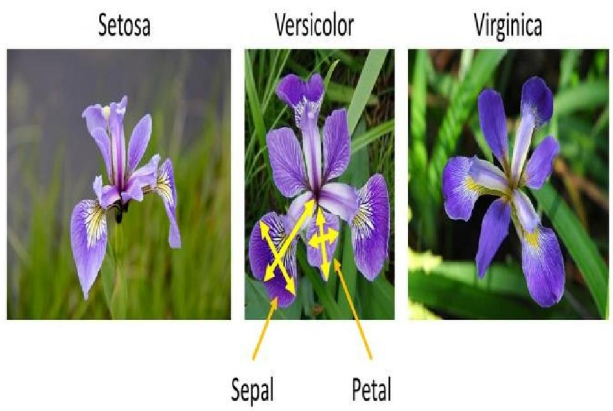
II. METHODOLOGY

In this section, we discuss how we augment the Sketchy database with Flickr images and synthesize edge maps which we hope approximate human sketches. The dataset is publicly available. image content filtering, and category selection. The major querying operation of MindFinder is sketching, which describes the main curve and structure of the image in user's mind. In addition, for some abstract concepts or complex objects that cannot be clearly drawn by normal users, our system allows users to add tags to constraint the semantic subject of return images. Generator: generate fake samples, tries to fool the Discriminator Discriminator: tries to distinguish between real and fake samples Train them against each other Repeat this and we get better Generator and Discriminator.
The rapid development of deep learning has accounted for recent exciting progress in image generation, especially the introduction of generative adversarial networks (GAN). Conditioning variables were then introduced to GAN.

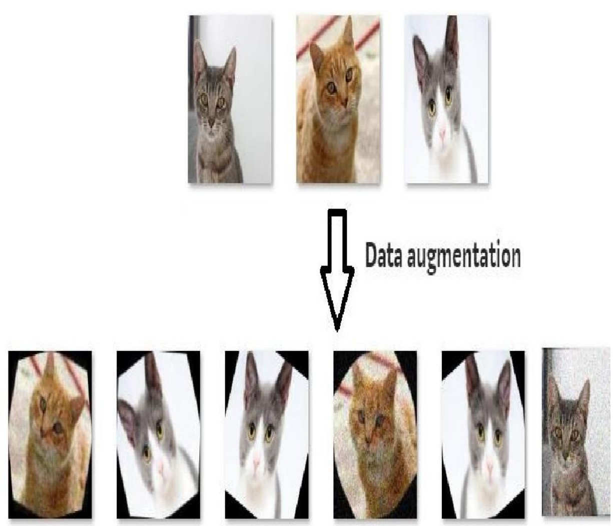
Loading and Visualizing the Dataset

Dataset Visualization is the graphical representation of Data that contains the details of the data. This is used for the analysis of data that can be done using the visual elements, this is used to analyse big and massive processing data and try computing the result out of it.



Data Augmentation

Data augmentation is a strategy that enables practitioners to significantly increase the diversity of data available for training models, without actually collecting new data.
Data augmentation techniques such as cropping, padding, and horizontal flipping are commonly used to train large neural networks.

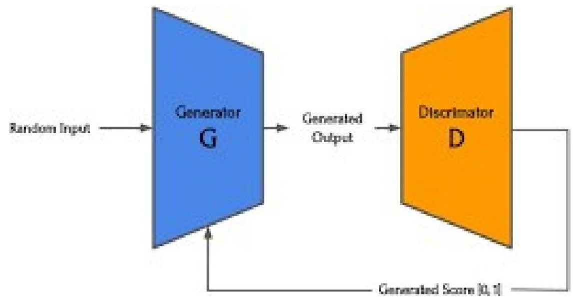


Generator Model

Let us build our U-net model for the generator of the cGAN. To avoid code redundancy I will write the convolution layers in the form of functions.

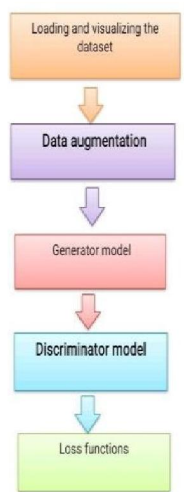
Discriminator Model

In probabilistic terms, the discriminator models the probability of a fake sample given a set of inputs X. In a multiclass context, the discriminator models the likelihood of a sample is a particular class. Discriminator models the probability of a sample given a set of inputs X.



Loss functions: Before passing the data let us include our loss functions for generator and discriminator.
Training : Let us set the hyperparameters and load our data into the model so that it can be trained

III. FLOWCHART



IV. APPLICATIONS

- Map to Aerial Photos
- City scape to Photos.
- Photo Inpainting.
- Sketch to Color Images

V. RESULT

We propose Sketchy GAN, a GAN-based, end-to-end trainable sketch to image synthesis approach that can generate objects from classes. The input is a sketch illustrating an object and the output is a realistic image containing that object in a similar pose.

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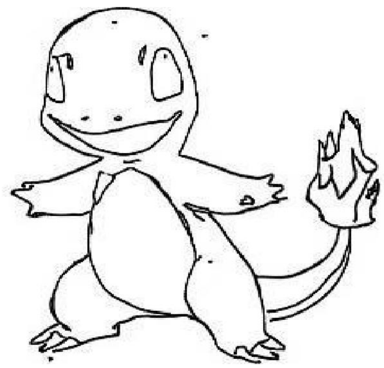
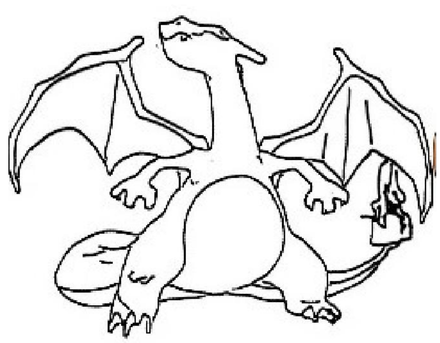
INPUT 1:-

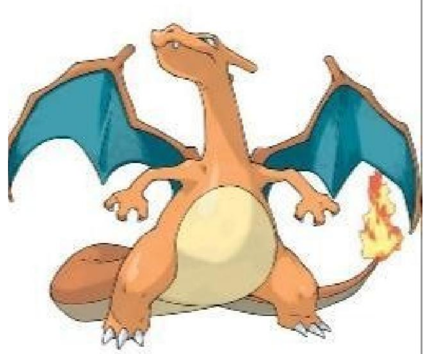


OUTPUT 1:

INPUT2:-



OUTPUT 2:



VI. CONCLUSION

In this work, we presented a novel approach to the sketch-to-image synthesis problem. The problem is challenging given the nature of sketches, and this introduced a deep generative model that is promising in sketch to image synthesis. We introduced a data augmentation technique for sketch-image pairs to encourage research in this direction. The demonstrated GAN framework can synthesize more realistic images than popular generative models , and the generated images are diverse. Currently, the main focus on GANs is to find better probability metrics as objective functions .We proposed a new network structure for our generative task, and we showed that it performs better than existing structures.

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