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Review of Implementation of Cycle GAN for Sketch To Image Translation

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Abstract: *Primary target of image-to-image translation (I2I) is to transfer images from one domain to another while maintaining the content depictions. Because of its wide variety of applications in many computer vision as well as image processing challenges, such as style transfer, image synthesis, posture estimation, segmentation, and restoration, I2I has attracted much interest as well as made a lot of progress in recent years. They presented an overview of I2I studies developed in recent years in this study. The translation of images, (I2I) problem is a general term for this type of research. I2I's overall purpose is to transform an input image xA from one domain X to another domain Y while preserving the intrinsic source content as well as transferring the extrinsic target style. Transferring an image from one domain to another target could encompass a wide range of issues in image processing, computer graphics, as well as computer vision. The focus of this study is to review and implement Cyclic GAN for translating hand drawn sketches of dogs and hens images into coloured ones. The procedure was implemented impeccably. T*

Keywords— *Image to Image Translation, Image Processing, Cyclic GAN, GANs*

I. INTRODUCTION

The aim of the class of vision as well as graphics issues known as "image-to-image translation" is to learn the relationship betwixt an input image as well as an output image. It can be employed for a multitude of purposes, including photo enhancement, object transformation, season transfer, as well as collection style transfer. Image Translation could be required in variety of purposes. [1]

It holds immense importance especially in the field of arts. Mapping an image from one domain to a matching image in another domain is a common approach to many computer vision problems. For instance, colorization may be thought of as an issue of mapping a grayscale image to a matching colour image, whereas super-resolution could be thought of as a problem of transferring a low-resolution image to a corresponding high-resolution image. [2] A summer painting could be translated in to winter painting. Any sketch image could be translated into a coloured one. There are many other instances where image-to –image translation is required. The important note here is that why and how this image translation is gaining this much importance. There are various types of image translations that are utilized today. One of them is sketch to image translation. It is still considered one of the difficult tasks in the field of machine learning today.

Learning the mapping from the domain consisting hand drawn sketches to coloured images domain is the focus of sketch-to-image translation procedures. It is a particular kind of I2I issue but often experiences a significant informational discrepancy among the source and target domains. The image translation procedures became well-known following the release of Generative Adversarial Networks (GANs). GAN-based unsupervised, as well as supervised techniques have been extensively researched for achieving the target of image translation. [3]. The implementation of supervised techniques for this purpose requires paired data. That means it requires a set of hand-drawn sketches and their corresponding labelled coloured images. These types of techniques work perfectly but require a large amount of labelled data. Various researches have translated different objects like chair, or human images by utilizing supervised image translation techniques. But translation of images of animals, or other common objects through supervised techniques would require their corresponding coloured images and collecting such data as well as organizing it into dataset creates a whole new challenges for researchers. This biggest challenge could be solved by utilizing unsupervised

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procedures for image translation. These unsupervised techniques deploy unpaired data, it means, for implementing such techniques, an individual doesn't require hand drawn sketches and their corresponding coloured images. A set of hand-drawn and their coloured set or random images are sufficient for translating images from one domain to the other. Techniques such as Pix2Pix, Piux2PixHD are supervised techniques that rely on paired data plus first require implementation of conditional GANs. These procedures exceptionally apprehend global structures as well as local details for generating better performance for high resolution images. Nonetheless, paired is the main restriction to the performance of supervised procedures. Researchers have also explored the multitudes of unsupervised procedures for transforming images from one form of the data to the other. Procedures such as Unsupervised Image to Image Translation Networks (UNIT), Cycle GANs, GAC, Multimodal Image-to-Image Translation (MUNIT), DRIT++, Sketchy GANs are deployed for image translation for unsupervised as well as unpaired data. The concept of shared latent constraint which implies the cycle consistency constraint is utilized by UNIT. Whereas Cyclic GAN applies the cyclic consistency idea for the training of its data in an unsupervised manner. Edge maps are used by Sketchy GAN as data arguments during training. A disentangled representation is used by MUNIT as well as DRIT++ to capture information that is both domain-invariant as well as domain-specific. [3]
Among the above mentioned frameworks, cycle GANs avoid redundant losses of information as well as try to maintain minimum level of cycle consistency loss by preventing generators from mode collapse as well as excessive hallucinations. Hence, in this study, the primary focus is on cycle GANs. It is deployed for transforming features of one image into another. Cycle GANs don't treat the challenge of image translation as an image translation problem; rather they treat it as an image reconstruction problem. Firstly, the algorithm of Cycle GANs requires an image input (x) and then the Generator model in the algorithm converts this into the reconstructed image. In further process, the procedure is reversed, as the original image is reobtained from a reconstructed image. This is achieved by deploying another generator model. After this, a mean squared error loss is estimated between the real and the reconstructed image. The most important characteristic of cycle GAN is that it can easily translate an unpaired image without the actual need of labelled data.

Similar to other adversarial networks, Cycle GAN also consists of two components: the generator as well as the discriminator. The task to be performed by generator is quite interesting; it is to take samples from input domain distribution and generate fake samples so that discriminator gets fooled by it. On the contrary, the job of discriminator is to discriminate between the real samples and the fake samples. In simple language, it has to save itself from being deceived by the generator. In contrast to previous GAN architectures, the Cycle GAN has two mapping functions that serve as generators as well as the corresponding discriminators. This type of GAN has two generators and two discriminators. G, F, D_X and D_Y denote two generators as well as two discriminators respectively. The following are the generator mapping functions:

$$G: X \rightarrow Y$$
$$F: Y \rightarrow X$$

Here, X and Y are the distributions of input as well as domains respectively.
The figure 1.1 represents the flow diagram of cycle GAN model. The diagram in the image is a composite architecture of Cycle GAN. According to the figure, the first generator in this case takes hand-drawn sketches as inputs and tries to deceive Discriminator D_X and its target is to generate coloured samples. The original image is reconstructed; in this X is the function of translation from domain of inputs from generator G to generator F. On the other hand the second generator F in this case fools, corresponding discriminator D_Y.

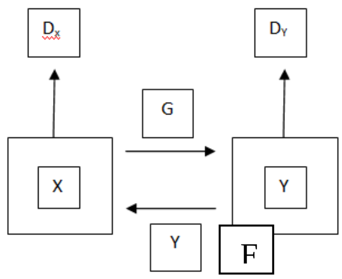

Fig.1.1 Cycle GAN Flow Diagram

Where G and F are generators and X and Y are their corresponding data domains. D_x as well as D_Y are the two discriminators of Cycle GAN model. The above image depicts the two way process of generating fake images as well as reconstructing them. The image 1.2, given below describes one side of process; when images of input, sketches in this case are translated to colour domain.

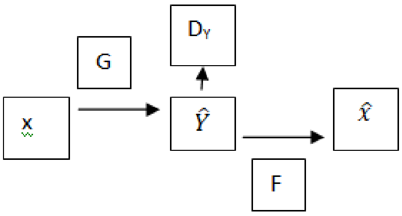

Fig.1.2 X as input domain function

The image 1.3 describes the second side of composite model; in this case when the coloured image is translated into sketch domain.

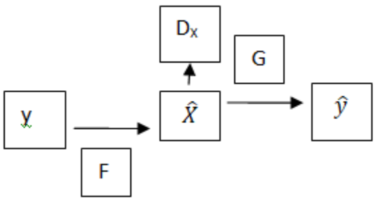

Fig.1.3 Y as input domain function

There are multitudes of factors as well as hyperparameters that affect performance of a GAN architecture. One of them is learning rate. It could be considered as a tuning parameter or a controlling parameter in the training process. The key goal of learning rate is to minimize the value loss functions present in the network. The value of learning rate holds immense importance as slightly wrong value could change the fate of your training algorithms.

Section II enlists various researches that have been previously performed in the field of GANs as well as image translation using GANs. Then, section III is review of implementation of cycle GAN methodology in detail. This section also describes the complete architecture of cycle GAN. Whereas sections IV as well as V describe dataset, results, comparison and conclusion of this study respectively.

II. LITERATURE REVIEW

The research in image translation has tremendously earned a great deal of attention as well as momentum recently. There are multitudes of procedures relied on GANs as well as machine learning that have been researched, explored as well as implemented. These studies have managed to achieve substantial results.

A number of surveys as well as innovations on transformation as well as translation of images have already appeared in the literature. Here, a few works are presented on the same topic.

(L.Yuan, et.al, 2019) In this research they proposed a network that focused on a particular as well as eye-catching object or region placed in input images. It was named as positional attention bi-flow generative. For completing the translation work, they utilized an encoder to extract these features as well as a bi-flow generator with an attention module. They deployed characteristics related to image as well as its position to mark the eye catching as well as interesting part betwixt input-source and output-target domain distributions for achieving object-level translation. They examined the framework offered as well as made qualitative and quantitative comparisons. Extensive tests depicted that their suggested model was capable of achieving object-level translation. Also, these results outperformed than traditional procedures. [4]

(Haisheng Li, et.al., 2019) They designed a new approach which solves the issue with the original GAN algorithms. They added class information to both generator as well as discriminator which proved to be very fruitful in computer vision industry. It was proved to be beneficial in reconstructing a 3D model from a single image. They did the experiments on ModelNet Dataset plus also applied the approach utilizing the IKEA dataset. The results produced by implementing their approach were quite appreciable. [5]

(M.Eslami, et.al., 2020) This study proposed a deep learning approach that produced two types of outcome images simultaneously. The first type was suppressed image whereas the second type was a segmented image. Since, it produced two outputs simultaneously, it was named as balanced as well as multitask approach. This model's architectural design was based on CGANs, depicted how the well-known pix2pix network (image-to-image network) was adapted to match the need for multitasking as well as extended to the new image-to-images architecture. This suggested procedure, improved task efficacy, reduced the number of parameters required by the model. Dilated convolutions were also utilized for improving outcomes by assessing the receptive field more effectively. To assess the feasibility as well as merits of the suggested approach, a comparison with state-of-the-art algorithms, an ablation study, as well as a demonstration video 1 was provided. [6]

(X.Cao, et.al., 2021) A translation system that is reversed virtually in nature was proposed in this study. The recovered original input image seems to be noiseless when compared to its original form. The proposed technique utilizes both inter frame coding as well as embedding. To begin with, they created a faux video from the GAN-generated reconstructed source picture as well as the source image. In addition, the inter-frame coding bit stream was reversibly stored in the translated image for nearly lossless source image reconstruction. Extensive experimental findings as well as analysis showed that the suggested technique could achieve great image quality as well as security performance. [7]

(Duncan J. Irschick, et.al., 2020) They generated 3D models of multitude of sea turtle species for saving them as digital voucher specimens as well as for other educational purposes. They generated photogrammetric models both in field as well as captivity by utilizing 3D multi-camera rig. For creating 3D meshes for scientific applications they combined these 3D photogrammetry models with 3D modeling techniques. They deployed Capturing Reality Software, Meshroom, or Colmap to produce 3D photogrammetry models, as well as then Blender to generate single 3D models of each turtle. They did their research on five individual sea turtles of different types and tabulated the basic metrics of 3D model composition. The result was successful. In addition to this, they also created 3D colored animated models for educational purposes. Thus, they couldn't guarantee the accuracy of such colored animated models.[8]

(David C. Schedl, et.al., 2020) They introduced cost-effective as well as novel approach named as Airborne Optical Sectioning (AOS). It was developed to support ornithologists in nesting observation. AOS was a way to eliminate occlusion produced by leaves as well as branches in synthetic aperture imaging. It registered recorded photos into a common 3D coordinate system, making it possible to reconstruct as well as analyze the full forest volume, which was unattainable with traditional 2D or 3D approaches for imaging. [9]

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(Zhang, T. et.al, 2021) They deployed Generative Adversarial Networks along with variational auto encoders for 3D reconstruction of digital ores. In addition to this, they deployed learning of Generations Using Determinantal Point Processes (GDPP). [11]

(Guillard B et.al., 2021) They deployed encoder/decoder architecture for translating hand drawn sketches into meshes. They combined the proposed methodology with user interface that provided camera parameters for the sketches. They refined the 3D mesh and removed inconsistencies existed for matching the external contours outlined in the sketch. The approach was found to simpler in implementation, efficacious as well as robust. It could be deployed as shape refinement when only single pen strokes will be available as input. [12]

(Courtenay L, et.al., 2021) They deployed data science as well as 3D modelling for inspecting carnivore modifications to bone. The goal of this study was to see how confinement affected the kind of tooth marks left on bone by analysing the tooth mark variations created by various Iberian wolf individuals. In addition, four separate populations of Iberian wolves, both wild as well as captive, were examined for a more in-depth assessment of intra-species diversity. Captivity had the least effect on huge canid tooth pits, according to this study, while tooth scores created by captive wolves appear more superficial. Furthermore, the superficial character of captive wolf tooth scores was observed to link with other metric features, influencing total mark morphologies. In light of this, the study initiated a new conversation about the causes for this, suggesting caution when utilizing tooth scores for carnivore identification and considering how stress may be impacting the wolves under investigation. [13]

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(Tajika A, et.al., 2021) The suture line morphology, conch shape, as well as septal spacing were all quantified employing computed tomography as well as geometric morphometrics. The suture line as well as conch geometry were shown to be beneficial in identifying species, while septal spacing was found to be less useful. They also made cluster trees to show how closely species were related. The intermediate ontogeny tree predicated on conch geometry was nearly identical to those previously reconstructed by deploying molecular data. Furthermore, distinct regional populations of the same Nautilus species were separated in this tree. This depicted that conch geometry could be utilized to differentiate genetically distinct (i.e. geographically isolated) populations of Nautilus. Their findings could be applied to closely related fossil cephalopods (nautilids), but they may not be applied to forms that are more distantly related (ammonoids). [14]

(Zhang Z et.al., 2021) The authors did research to learn more about the MDB's uniqueness in the porpoise Neophocana asiaeorientalis (N.asiaeorientalis). The investigation employed five N.asiaeorientalis carcasses that had been formalin fixed. Head and neck CT scans, three- dimensional reconstructions, as well as gross dissection of the sub occipital region were all done on two of the carcasses. A P45 plastination investigation was conducted on a different carcass plus a corpse was also deployed for histological analysis of the sub occipital region, as well as a Scanning Electron Microscopy study. The MDB of the N.asiaeorientalis was a separate muscle that originates from the caudal border of the occiput, passes through the posterior atlanto-occipital interspace, and joins to the cervical spinal dura mater, according to the findings. As a result, the N.asiaeorientalis' so-called MDB was essentially a separate as well as a highly specialized muscle. [15]

(Sidong Jiang et al 2022) In this research, a completely renewed process consisting of two steps plus a system that is completely interactive in nature and that could create several architectural image styles from a hand-drawn sketch were presented. In their suggested procedure, an architectural image could be uploaded, proceeded by sketch generation, alteration, as well as translation, or an architectural sketch could be drawn and afterward translated into a colour image. According to experimental findings, their procedure outperformed other competing approaches in terms of image quality as well as diversity. [3]

III. REVIEW OF IMPLEMERNTATION

Though there are various studies which have implemented cycle GAN for image translation. This study is not the direct implementation of cycle GAN model and it does not propose any new methodology but it is review as well as comparison study of cycle GAN model, for different learning rates and number of epochs; when applied for sketch to image translation. In this section first of all, implementation architecture of cycle GAN is discussed.

There are two generators as well as two discriminators in the architecture of cycle GAN. Each generator has a corresponding discriminator. Each generator has a:

1) Encoder ; 2) Transformer; 3)Decoder

The figure 1.4 describes the generator block. The generator model deploys series of convolutional blocks referred as down-sampling convolutional blocks in order to encode the images. Secondly, multitudes of residual blocks are utilized for transforming the image. Thirdly for production of outputs, generator deploys a multitude of up-sampling layers. The standard size for convolutional layer with Instance Normalization and leaky ReLu with stride 1 is 7X7 and with stride 2 is 3X3. The figure 3.1 represents the architecture of generator.

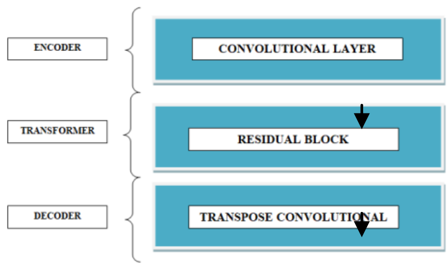

Fig. 3.1 Generator

The discriminator model utilizes PatchGAN model. It is distinct from other models as it directly maps 256X256 to an NXN array of outputs, where each element in the discriminate real as well as dubious output. The image below describes the architecture of discriminator model. It is also divided into three sections: convolutional layer; instance normalization layer; transpose convolutional layer.

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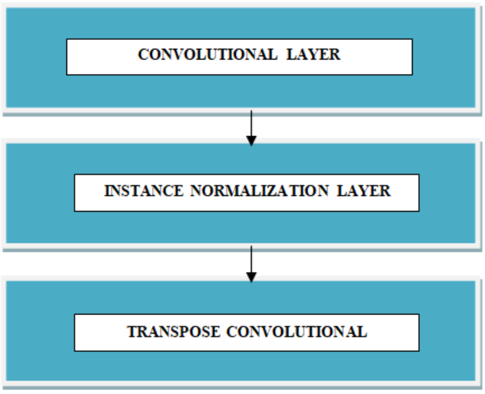

Fig.3.2 Discriminator

In this study a composite model is implemented with adversarial loss, identity loss, forward cycle loss, backward cycle loss. The code is implemented two times; one for learning rate 0.0002 and number of epochs: 100 and other for learning rate 0.0025 and number of epochs: 1000. The suggested changes by us are in the learning rate and number of epochs. The aim here is to prove that minute increase in learning rate and number of epochs extensively affects the training results. The algorithm was implemented using python and google colab. Libraries utilized were tensorflow, keras, numpy, and tensorflow-addons.

The below figure describes the algorithm followed:

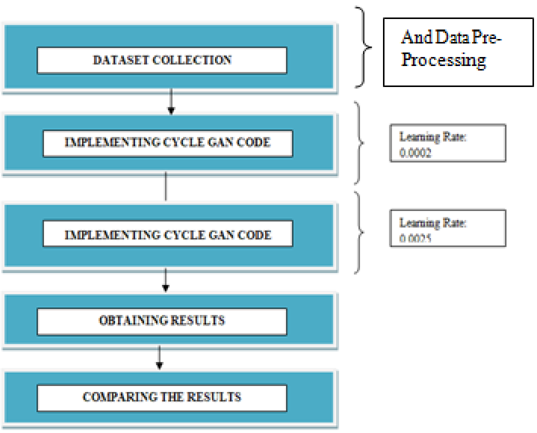

Fig.3.3 Flow Chart

The algorithm in words could be described as:

Step1: Collecting well structured dataset of hand-drawn sketches and coloured images of animals.
Step2: Implementing Cycle GAN code for one set of data.
Step3: Implementing Cycle GAN code for second set of data.
Step3: Obtaining the results for implemented codes.
Step5: Comparing the generated results.

IV. RESULTS AND DISCUSSIONS

The datasets utilized for this purpose were ImageNet hand drawn sketch animal dataset as well as animal 10 Kaggle dataset. The 100 images of both dog as well as hen from each dataset category are taken. Then these images pre-processed into a standard size and are stacked into a single array and then further code is implemented. The samples of images are portrayed below:


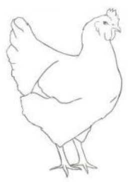


Fig.4.1 Fig.4.2 Fig.4.3

The above three images are from ImageNet sketch dataset. The below three images are from animal 10 Kaggle dataset.



Fig.4.4 Fig.4.5 Fig.4.6

The outcomes for first set of hyperparameters i.e. with learning rate 0.0002 and number of epochs 100 are portrayed below. There are three images in each figure; first one is original image, second one is generated as well as translated image and the third one is reconstructed image.

Fig4.7

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Fig. 4.8

Fig.4.9

The figures, 4.7 to 4.9 are generated results from sketch to colour domain. With the same hyperparameter values, below are the outcomes when generator 2 acted as input and generator one is the target domain.

Fig.4.10

Fig.4.11

The next set of outcomes was obtained when the learning rate was set to 0.0025 and number of epochs was set to 1000. The optimizer that was utilized was Adam optimizer.

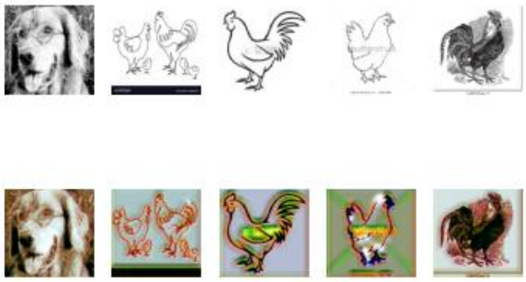

Fig.4.12

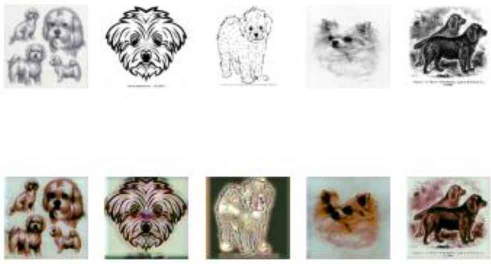

Fig.4.13

The figures 4.12 and 4.13 are generated plots from sketch to color image domain. Figures 4.14 to 4.17 were obtained when the input domain was hand-drawn sketches domain and the target domain was the color domain. Each figure has three images, one the original one, second the fake one and third the reconstructed one.

Fig.4.14

Fig.4.15

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Fig.4.16

Fig.4.17

The images ranging from 4.18 to 4.19 were obtained when the set of colored images acted as the input images and sketch domain was the target one.

Fig.4.18

Fig.4.19

The figures 4.7 to 4.11 generated colored fake images but the quality of their images is distorted. These results contain noise. Although the algorithm has tried to replicate the shape of the object but it could not distinguish it from the background. The quality of reconstructed images in this case is much better than that of generated ones. Though the reconstructed images clearly depict a loss of color information and contain slight noise.

On, the other hand, the results generated with our proposed changes were quite satisfactory. The figures from 4.12 to 4.19 depicted enhanced performance quality with the improved changes. Figures 4.12 and 4.13 depict both original as well as generated plots from sketch to color domain. The generated images are perfectly outlined plus one can easily recognize the object or animal present in the images. The algorithm was able to distinguish between object and background which was not the case with the images from 4.7 to 4.11. Also the generated images in figures from 4.14 to 4.19 don't appear to be fake. The reconstructed images in figures 4.14 to 4.19 appear just like the original image. This proves that there was very little loss of information while training the process.

Therefore, it can be concluded that the value of learning rate (lr) and number of epochs hold an immense importance while training a GAN approach. One can also conclude that the lower value of lr restricts the speedy training process plus it will also make minute changes in the weights while training the network. Hence, it is necessary to keep the optimal value of lr. Since, the higher value could diverge the training algorithm from its outputs. Also, the more the number of iterations, more weights are updated and algorithm could learn perfectly while it's training time.

By, observing the results it is crystal clear that, the quality of generated from learning rate 0.0025 and number of epochs equal 1o 1000 is far better than with the value of 0.0002 and 100.

V. CONCLUSION

Reviewing implementation of cycle GAN for sketch to image translation has been a great success, but the basis on which comparison of results is done could be improved by calculating accuracy in futher projects. This proves that cycle GAN can easily be used for sketch to image translation purposes and it is a great choice when an individual doesn't have a paired data. There has been change in the standard value of learning rate for Adam optimizer to 0.001. This study has not yet used this value in the experiments. The study could be further extended while using the learning rate 0.001 and the generated results could be utilized for making a whole different dataset of animal images, so that it can be further used by individuals in 3D model reconstruction. The study also concludes that the GAN algorithm worked better with more number of epochs and also, that, the increase in value of learning rate improved the results quality.

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