Abstract—In terms of Image-to-image translation, Generative Adversarial Networks (GANs) has achieved great success even when it is used in the unsupervised dataset. In this work, we aim to translate cartoon images to photo-realistic images using GAN. We apply several state-of-the-art models to perform this task; however, they fail to perform good quality translations. We observe that the shallow difference between these two domains causes this issue. Based on this idea, we propose a method based on CycleGAN model for image translation from cartoon domain to photo-realistic domain. To make our model efficient, we implemented Spectral Normalization which added stability in our model. We demonstrate our experimental results and show that our proposed model has achieved the lowest Fréchet Inception Distance score and better results compared to another state-of-the-art technique, UNIT.

Index Terms—GANs, Image-to-image-translation, Cartoon-to-real.

I. INTRODUCTION

Cartoons occupy a huge part in our entertainment sector. Film industries, in recent days, are remaking movies from the popular past cartoons and presenting them for current generation. Such an example is – the The Lion King (2019) from The Lion king (1994). Therefore, we realize the necessity of recreating realistic images from the cartoons which can contribute to photo-realistic rendering in computer graphics as well as in film industries. In this paper, we propose an approach which converts images from cartoons into their corresponding photo-realistic images. From Figure 1, we can see an outcome of our work where the cartoon scene is translated into a photo-realistic one.

Image-to-image translation using Generative Adversarial Network (GAN) has been one of the most desiring fields of deep learning research lately. In a GAN architecture, a discriminator network tries to measure the probability of whether an image has come from an authentic data source or a fake generated source of the generator. On the other hand, the generator tries to maximize the probability of the discriminator’s making mistake and while doing that, it learns to generate more accurate data as much as close to real data. Tremendous success of GANs, led other researchers to work on unsupervised settings of datasets, such as [2], [3]. Although these models have succeeded to translate one domain of image to another in general, there hasn’t been any specific research for generating images of the photo-realistic domain from cartoon domain. This is an extremely hard task; the reason is the domain gap between these two distributions is too shallow.

Fig. 1: An example of cartoon to real world translation. (a) Input image: which is from the animated film "The Wind Rises". (b) Our result: transforming the cartoon image (a) to real world image.

As a result, the discriminator can be easily erroneous to determine the generated data as real ones. This is the reason why most state-of-the-art models tend to fail in case of generating cartoon to real images. We illustrate in our result section that several models intent to keep the original content of cartoon domain while generating photo-realistic images.

To satisfy our objective on this task, we have taken an approach built on CycleGAN[2]. We implemented spectral normalization technique which helps our model to converge faster. Our approach also keeps the content of photo-realistic domain. In addition to these, we also created our own dataset for our model. We show that our method has the lowest FID score than the other baseline models, and also it tends to show more stabilization in training than the others.

II. RELATED WORKS

In this section, we review on different relevant variations of GAN and several past works on image-to-image translations.

GANs have achieved great results in various image generation tasks, which are image super-resolution, image-to-image translation, text-to-image synthesis etc. Recently, GAN based approach has given tremendous results in image-to-image translation tasks. Zhu et al.[2] proposed a cycle consistency loss to reduce the infinite mappings
of input images to any distribution in the target domain. Adversarial loss alone can’t solve the random permutation mappings of target distribution, rather it helps the input image to be translated into target domain. Similar to CycleGAN, Kim et al. [3] proposed a method for preserving the key attributes between the input and the transformed image while maintaining a cycle consistency criterion. Similarly, Yi et al. [10] proposed dual-GAN mechanism based on dual learning from natural language translation[11]. In UNIT[7] framework, Liu et al. proposed a shared-latent space assumption, which denotes that the pair of corresponding images in different domains can be mapped to a same latent representation in a shared-latent space. Liu et al. used the combination of generative adversarial network (GAN), based on CoGAN[12] and variational autoencoders (VAEs)[13], [14].

For stabilizing and improving the training of GAN, several works were proposed such as adding weight normalization and regularization techniques [15], [4], designing new generative architectures[17], [18] to improve visual results and modifying learning objectives [19], [20]. Miyato et al. first proposed spectral normalization technique which constrains the Lipschitz constant of the discriminator network by limiting the spectral norm of each layer. The authors argue that spectral normalization can improve the quality of training GANs better than weight normalization[21] and gradient penalty[16]. In this paper, we have utilized this property of spectral norm to improve the training of our GAN.

In our previous work Cartoon-to-real [22], CycleGAN based model was implemented to transform cartoon images into photo-realistic domain. While all these methods achieve compelling results, they take too much time for training. The reason behind it is that these models are not stabilized during training. In the next section, we discuss the approach we took to solve these fundamental issues and to obtain better outcomes.

III. FORMULATION

Our main objective is to transform cartoon images to photo-realistic images by learning the mapping of a cartoon domain $C$ to the photo-realistic domain $R$. In this section we discuss about the approaches we have taken to accomplish the task.

**Dataset Collection:** Due to the lack of paired data between cartoon domain and photo-realistic domain, we took an approach to collect unpaired dataset for both domains. As deep learning is data hungry, initially, for realistic domain, we scraped scenery images from Flickr and many other sources which were tagged as scenery, sunrise, sunset, sea, sky & beach and collected around 5000 samples. Besides, for cartoon domain, we extracted images from various Japanese anime movies and collected about 5000 images. We extracted the scenery images from these movies consisting of sunsets, sea, sky, trees etc. We excluded the frames which are darker to see, and the first and last few frames—as the introductory and credits part tend to be textual in a movie. After hand-picking the appropriate images, in order to approximate with the size of the realistic domain, we collected images from more than 15 cartoon movies and clips, consisting of genres romance, spiritual, war, supernatural & science-fiction. For both the domain, images were of $128 \times 128$ dimension. For the validation set, we took about 2500 animation images and 2000 from real-world photos.

**Adversarial Loss:** Although in [1], a binary cross-entropy based Adversarial Loss function was proposed, we use a Least Squares Loss (LSGAN) function for our training. According to Mao et. al [23], we have explored that LSGAN performs better in the case of vanishing gradient problem and thus shows more stability during training and produces much higher quality images in the case of Image-to-image Translation. So, our adversarial loss stands as follows -

$$L_{G_r} = \frac{1}{m} \sum_{i=1}^{m} (1 - D_r(G_r(c)))^2$$

Fig. 2: Architectures of the generator and discriminator of our proposed model, in which $k$ is the kernel size and $s$ is the stride in each convolutional layer.
networks in our model, where a generator, $G_c$, tries to generate images of Cartoon domain and a discriminator, $D_c$, tries to discriminate the generated image from cartoon domain. The additional networks also perform according to the previously mentioned loss function.

**Reconstruction Loss:** Adding an additional generator solves the issue of mapping differences; however, it still lacks in content preservation of input domain. For this reason, we’ve used an additional loss function, by using the technique of forward and backward loss[3, 2]. The motive of this function is that an image generated from an input can be reconstructed back to the input again such that $x = F(G(x))$, where $F$ and $G$ are generators and thus, it is able to map an image of target domain which is as close as possible to the image of input domain. In our paper, we call it **Reconstruction Loss**.

The equation is as follows -

$$\text{Forward Consistency Loss, } \mathcal{L}_{f_{cyc}} = \frac{1}{m} \sum_{i=1}^{m} (F_r(G_r(c)) - c)$$

(2)

$$\text{Backward Consistency Loss, } \mathcal{L}_{b_{cyc}} = \frac{1}{m} \sum_{i=1}^{m} (G_r(G_r(r)) - r)$$

(3)

**Discriminator Normalization:** Training GAN with efficiency is a hard nut to crack. Prior to previous works, it is known that discriminator tends to make the training slower and show more inconsistency during training. We used **Spectral Normalization** technique, which was first proposed by Miyato et al.[4], to stabilize our training. The benefit of spectral normalization is that it doesn’t need extra hyper-parameter tuning. Also, the computational cost is relatively
small compared to other weight normalization techniques. Miyato et al.\cite{4} found better or same results with image generation tasks by utilizing this normalization technique. We can see from Figure 4 that, using this technique stabilized the training, where Figure 4a is ours, which shows a much smoother curve of FID scores than Figure 4a, which is the FID score-graph of our previous work (Cartoon-to-real)\cite{22}. Also, we can see that ours achieved the least FID score within 145 epoch, whereas our previous model\cite{22} took more epochs for that.

**PatchGAN:** As discriminators, we used PatchGAN which was first proposed in Isola et al.\cite{24}. The intuition of using this discriminator is that it works best for extracting the high-frequency details of the distribution. Another beneficial feature is, due to working on $N \times N$ patches, it takes fewer parameters and thus decreases the computation cost.

**IV. IMPLEMENTATIONS & ANALYSIS**

In this section, we discuss the implementation of our approach followed by illustrating its results.

**Network Structure:** For generative networks we implemented the architecture from Johnson et al.\cite{5} who achieved amazing results for neural style transfer and super-resolution. The network includes two stride-2 convolutions, 6 residual blocks\cite{25}, and two fractional strided convolutions with stride $1/2$. We used instance normalization technique. For the discriminator network, we used $70 \times 70$ PatchGANs\cite{24}. The network architecture of our proposed model is shown in Fig 2

**Evaluation Metric:** We chose the Fréchet Inception Distance (FID)\cite{26} for quantitative evaluation. As FID score measures the difference between the generated dataset and the target dataset, it has shown more consistency with human evaluation. Samples from $P$ and $Q$ are gone through an Inception-v3 network to transform it into feature space. Then, we calculate the Wasserstein-2 distance between the translated image and the real world images from an intermediate layer of an Inception-v3 network. The distance can be calculated as

$$FID = \|\mu_x - \mu_y\|^2_2 + Tr(\Sigma_x + \Sigma_y - 2(\Sigma_x \Sigma_y)^{1/2})$$ \hspace{1cm} (4)

where $(\mu_x, \Sigma_x)$, and $(\mu_x, \Sigma_y)$ are the mean and covariance of the feature space of samples from $P$ and $Q$. Lower the FID score, the closer the distance between translated image and real domain images. As our task is image-to-image translation where we want our output to have the content of input cartoon images and the style of real-world images, we calculated a weighted average between them, where we used 80% weight for target data and 20% weight for input data. From Table I we can see that our work has shown the least FID score compared to other state of the art model, i.e UNIT.

**Evaluation of Discriminator Normalization:** By utilizing spectral normalization technique on discriminator network shown in Figure 4b, we started to gain a lower FID score from the very initial of training compared to our previous model. Spectral normalization is used on discriminator network which is shown in 4b. From 4b the quality of transforming images doesn’t improve monotonically during training. For example, the FID score of our work starts to drop at the 37th epoch. On the contrary, previous model’s FID score starts to rise after 125th epoch and it crosses the initial FID scores, whereas, in our work, the scores didn’t rise as the previous model did. From this, we can clarify that we achieved a more stabilized model and better scores. We can also clarify from Figure 4 that the stabilization technique also takes fewer training epochs to achieve better scores.

**Comparison with state of the art models:** We compared our work with state of the art technique, i.e UNIT\cite{7} and our previous work (Cartoon-to-real)\cite{22}. In Figure 3 we show a close-up view of an example, explaining that our work preserves much better vibrance and content preservation,
whereas UNIT’s output shows a lacking of preserving content and information in image. Also our previous work closely shows similar characteristics of input domain rather than realistic one.

(a) Cartoon scene (b) Our result

Fig. 5: A failure case of our method. In the output image (b), the cat remains cartoonish as in input (a) and is not translated into a realistic one.

Limitations: Despite achieving better FID score of all, it is still too high to be a perfect image translation score. In fact, we can see from Figure 5 that, the output fails to achieve the meaningful (semantically and geometrically) structure of real-world objects—in this example a cat. This problem is also common in UNIT and other image-to-image translation models.

V. Conclusion

In this paper, we showed a GAN based approach to translate images from cartoon domain to photo-realistic domain. We implemented our model based on CycleGAN, where we used Reconstruction Loss for content preservation of input image and the PatchGAN for better texture extraction. By implementing spectral normalization technique on discriminator network, we showed that our model achieves better training stability and the lowest FID score of all the other models. Our future plan is to lessen our current limitations by investigating more geometry and content aware model to improve the texture so that the gap with the photo-realistic domain decreases. In addition to FID score, we have plans to arrange human-involved and perceptual evaluation processes to assess the correctness of our outcomes.

References

[1] I. J. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. C. Courville, and Y. Bengio, “Generative adversarial nets,” in Advances in Neural Information Processing Systems 27: Annual Conference on Neural Information Processing Systems 2014, December 8-13 2014, Montreal, Quebec, Canada, 2014, pp. 2672–2680. [Online]. Available: http://papers.nips.cc/paper/5423-generative-adversarial-nets.pdf

[2] J. Zhu, T. Park, P. Isola, and A. A. Efros, “Unpaired image-to-image translation using cycle-consistent adversarial networks,” in IEEE International Conference on Computer Vision, ICCV 2017, Venice, Italy, October 22-29, 2017, pp. 2242–2251. [Online]. Available: https://doi.org/10.1109/ICCV.2017.244

[3] T. Kim, M. Cha, H. Kim, J. K. Lee, and J. Kim, “Learning to discover cross-domain relations with generative adversarial networks,” in Proceedings of the 34th International Conference on Machine Learning, ICML 2017, Sydney, NSW, Australia, 6-11 August 2017, 2017, pp. 1857–1865. [Online]. Available: http://proceedings.mlr.press/v70/kim17a.html

[4] T. Miyato, T. Kataoka, M. Koyama, and Y. Yoshida, “Spectral normalization for generative adversarial networks,” CoRR, vol. abs/1802.05957, 2018. [Online]. Available: http://arxiv.org/abs/1802.05957

[5] J. Johnson, A. Alahi, and F. Li, “Perceptual losses for real-time style transfer and super-resolution,” CoRR, vol. abs/1603.08155, 2016. [Online]. Available: http://arxiv.org/abs/1603.08155

[6] X. Yu, X. Cai, Z. Ying, T. H. Li, and G. Li, “Singlegan: Image-to-image translation by a single-generator network using multiple generative adversarial learning,” CoRR, vol. abs/1810.04991, 2018. [Online]. Available: http://arxiv.org/abs/1810.04991

[7] M. Liu, T. Breuel, and J. Kautz, “Unsupervised image-to-image translation networks,” CoRR, vol. abs/1703.00848, 2017. [Online]. Available: http://arxiv.org/abs/1703.00848

[8] H. Zhang, T. Xu, H. Li, S. Zhang, X. Huang, X. Wang, and D. N. Metaxas, “Stackgan: Text to photo-realistic image synthesis with stacked generative adversarial networks,” CoRR, vol. abs/1612.03242, 2016. [Online]. Available: http://arxiv.org/abs/1612.03242

[9] S. E. Reed, Z. Akata, X. Yan, L. Logeswaran, B. Schiele, and H. Lee, “Generative adversarial text to image synthesis,” CoRR, vol. abs/1605.05396, 2016. [Online]. Available: http://arxiv.org/abs/1605.05396

[10] Z. Yi, H. R. Zhang, P. Tan, and M. Gong, “Dualgan: Unsupervised dual learning for image-to-image translation,” in ICCV, 2017, pp. 2868–2876.

[11] D. He, Y. Xia, T. Qin, L. Wang, N. Yu, T.-Y. Liu, and W.-Y. Ma, “Dual learning for machine translation,” in Advances in Neural Information Processing Systems, 2016, pp. 820–828.

[12] M.-Y. Liu and O. Tuzel, “Coupled generative adversarial networks,” in Advances in neural information processing systems, 2016, pp. 469–477.

[13] D. P. Kingma and M. Welling, “Auto-encoding variational bayes,” arXiv preprint arXiv:1312.6114, 2013.

[14] A. B. L. Larsen, S. K. Sønderby, H. Larochelle, and O. Winther, “Autoencoding beyond pixels using a learned similarity metric,” arXiv preprint arXiv:1512.09300, 2015.

[15] D. J. Rezende, S. Mohamed, and D. Wierstra, “Stochastic backpropagation and variational inference in deep latent gaussian models,” in International Conference on Machine Learning, vol. 2, 2014.

[16] I. Gulrajani, F. Ahmed, M. Arjovsky, V. Dumoulin, and A. C. Courville, “Improved training of wasserstein gans,” CoRR, vol. abs/1704.00028, 2017. [Online]. Available: http://arxiv.org/abs/1704.00028

[17] A. Radford, L. Metz, and S. Chintala, “Unsupervised representation learning with deep convolutional generative adversarial networks,” CoRR, vol. abs/1511.06434, 2015. [Online]. Available: http://arxiv.org/abs/1511.06434

[18] T. Karras, T. Aila, S. Laine, and J. Lehtinen, “Progressive growing of gans for improved quality, stability, and variation,” arXiv preprint arXiv:1710.10196, 2017.

[19] M. Arjovsky, S. Chintala, and L. Bottou, “Wasserstein gan,” CoRR, vol. abs/1701.07875, 2017.

[20] L. Metz, B. Poole, D. Pfau, and J. Sohl-Dickstein, “Unrolled generative adversarial networks,” arXiv preprint arXiv:1611.02163, 2016.

[21] T. Salimans and D. P. Kingma, “Weight normalization: A simple reparameterization to accelerate training of deep neural networks,” in Advances in neural information processing systems, 2016, pp. 901–909.

[22] K. M. A. Sultan, L. K. Rupty, N. I. Pranto, S. K. Shuvo, and M. I. Jubair, “Cartoon-to-real: An approach to translate cartoon to realistic images using GAN,” CoRR, vol. abs/1811.11796, 2018. [Online]. Available: http://arxiv.org/abs/1811.11796

[23] X. Mao, Q. Li, H. Xie, Y. K. Lau, Z. Wang, and S. P. Smolley, “Least squares generative adversarial networks,” in IEEE International Conference on Computer Vision, ICCV 2017, Venice, Italy, October 22-29, 2017, 2017, pp. 8213–8221. [Online]. Available: https://doi.org/10.1109/ICCV.2017.304

[24] “2017 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017, Honolulu, HI, USA, July 21-26, 2017,” IEEE Computer Society, 2017. [Online]. Available: http://ieeexplore.ieee.org/spl/mostRecentIssue.jsp?punumber=8097368

[25] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” CoRR, vol. abs/1512.03385, 2015. [Online]. Available: http://arxiv.org/abs/1512.03385

[26] M. Heusel, H. Ramsauer, T. Unterthiner, B. Nessler, G. Klima, and S. Hochreiter, “Gans trained by a two time-scale update rule converge to a nash equilibrium,” CoRR, vol. abs/1706.08500, 2017. [Online]. Available: http://arxiv.org/abs/1706.08500