K.K.WAGH INSTITUTE OF ENGINEERING EDUCATION & RESEARCH

Project Stage -II

ASTRONOMICAL IMAGE COLOURISATION AND SUPER-RESOLUTION USING GANS

Group Id 23
Internal Guide Prof. Dr. S. M. Kamalapur

TEAM MEMBERS

Division./ Roll No.	Exam Seat No.	Name of the student
17	B150134261	Shreyas Kalvankar
18	B150134296	Hrushikesh Pandit
19	B150134299	Pranav Parwate
20	B150134303	Atharva Patil

Content

- Revised Final Design
- Tools and Techniques Used
- Implementation Status
- Modular Testing
- Results
- Conclusion and Future Scope
- Cost Analysis

Problem Definition

- The problem can be divided into two sub-problems:
  - Create an efficient model to colorize grayscale images
  - Take a colorized image and upscale it n times the original size

Keywords: GAN, Neural Network, NodeJS, puppeteer, Convolutional Neural Network, Upscaling, Colorization.

Revised Final Design

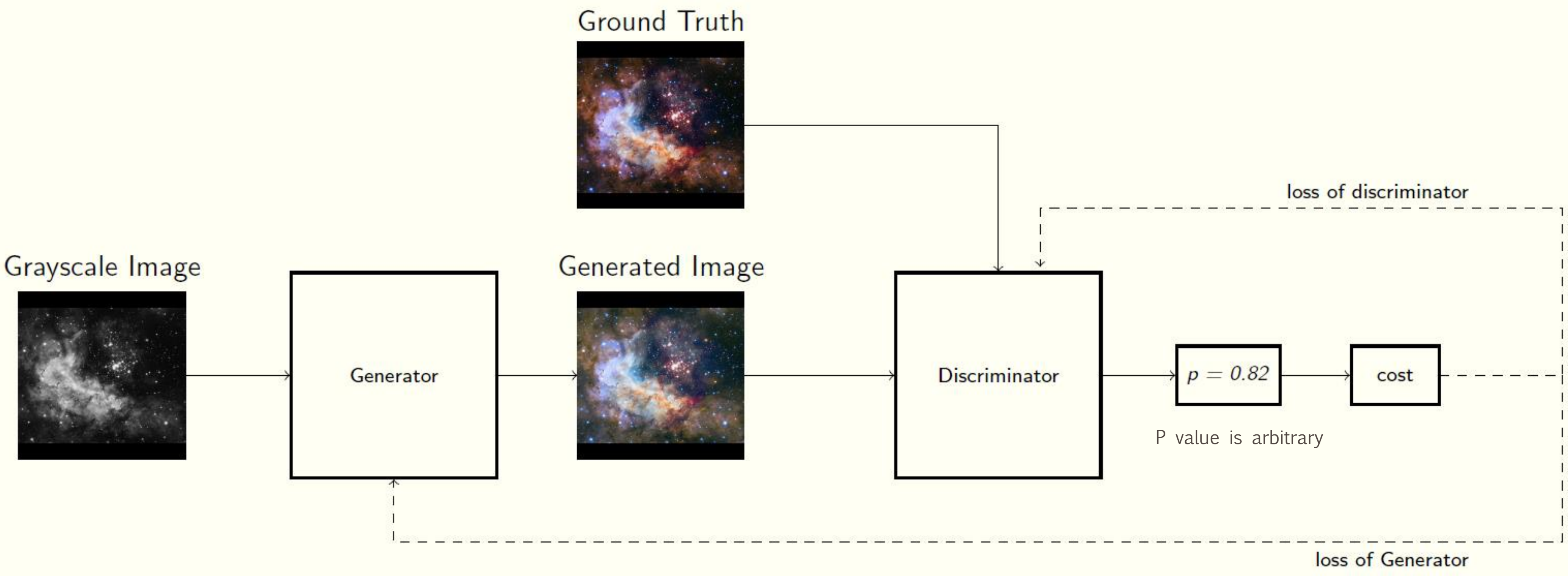


Fig 1: Basic GAN architecture

Tools

- Tensorflow
- Pytorch
- Pandas
- Fastai
- Numpy
- Matplotllib
- Google Colaboratory

Image Colorization Technique

- Image Colorization with residual encoders using the Resnet-18 architecture
- Initially, we use create a U-net architecture with ResNet18 as it's backbone
- Training the U-net generator independently over L1 loss
- Finally, training in an adversarial fashion to further optimize the outputs with patchy discriminator

Fig 2a: Black & White image

Fig 2a: Colorized output

Image Upscaling Technique

K K Wagh

- SR-GAN works well with for single image super-resolution as it also uses an intelligent content loss function that uses pre-trained VGG-net layers.
- We use a perceptual loss function which consists of an adversarial loss and a content loss.

Fig 11a: Blurred image

Fig 11a: Upscaled output

Implementation Status

Image Colorization

- We try different models to find the most efficient methodology to colorize the images
- Different U-net architectures have been trained over the COCO dataset so as to generalize the model to a greater extent.
- We explore the model performance in RGB as well as L*a*b color space
- A study of different architectures namely basic U-net, ResNet18 U-net has been implemented and tested

Implementation Status

Image Upscaling

- Image Upscaling has been successfully demonstrated using transferred learning and has shown promising results.
- We used Ledig's VGG-based SRGAN architecture to implement the same.
- We fine tuned Ledig's SRGAN's weights on our cherry picked image dataset.
- We compared the pre-trained and post-trained output with Wide Activation SRGAN (WDSR GAN) and Enhanced Deep Learning SR GAN (EDSR GAN)

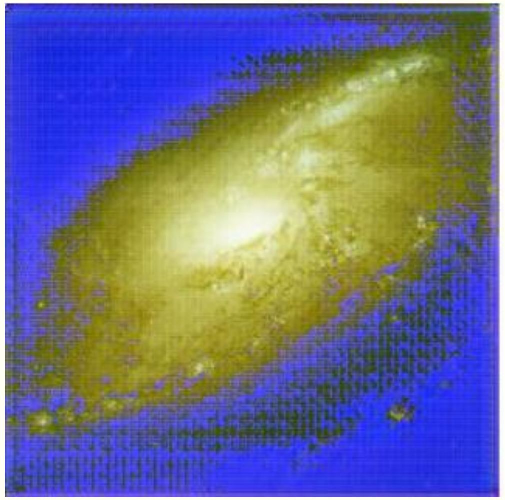
• Results

- The testing pipeline has been set up to evaluate the model performance by calculating distance metrics, i.e. L1 and L2 loss of the predictions and target
- We evaluate the outputs in RGB and L*a*b color spaces
- GANs are particularly hard to evaluate quantitatively. Having said that, we have achieved visually appealing results which, when evaluated qualitatively, are quite convincing

• Results

Ground Truth

Pre trained Resnet-18

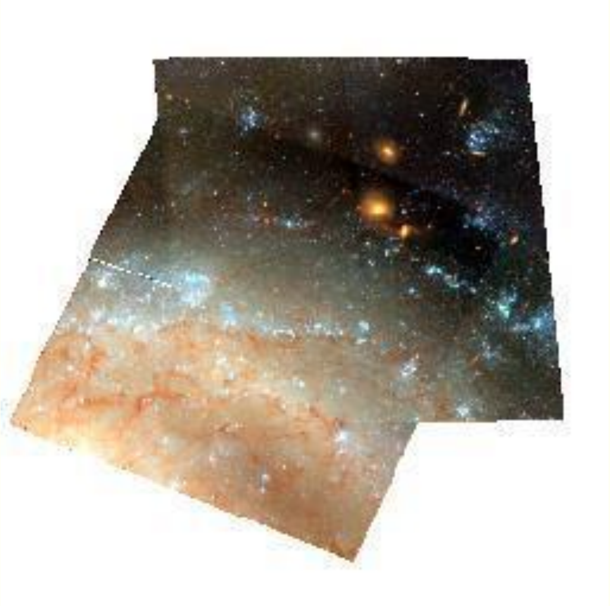


Trained on COCO Dataset

Full trained Resnet 18

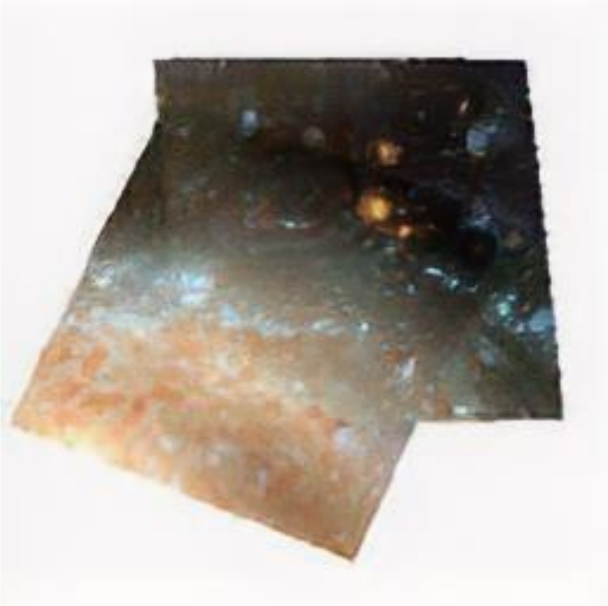
• Results

- Results of SRGAN (Upscaling):



Ground Truth

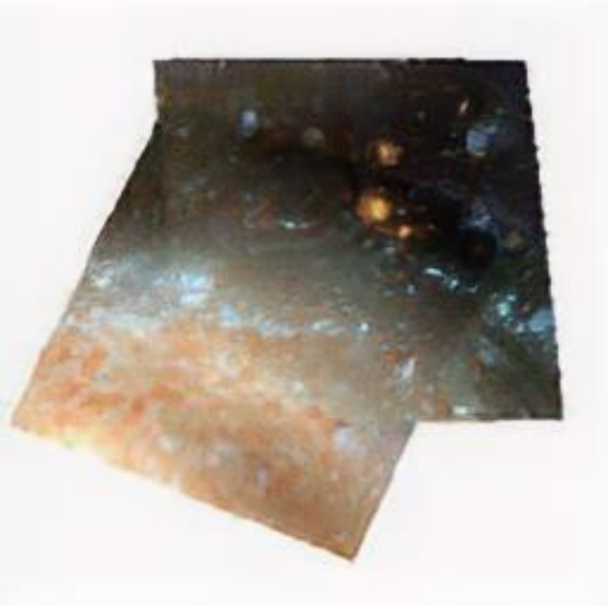
Pre trained
SRGAN



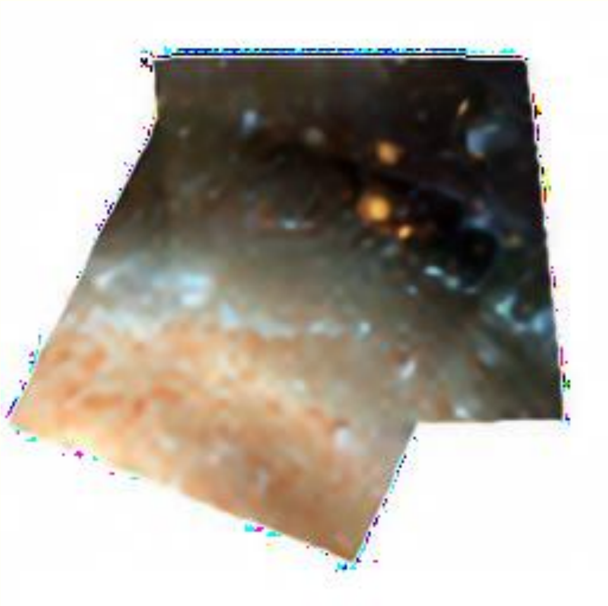
SRGAN Fine tuned

• Results

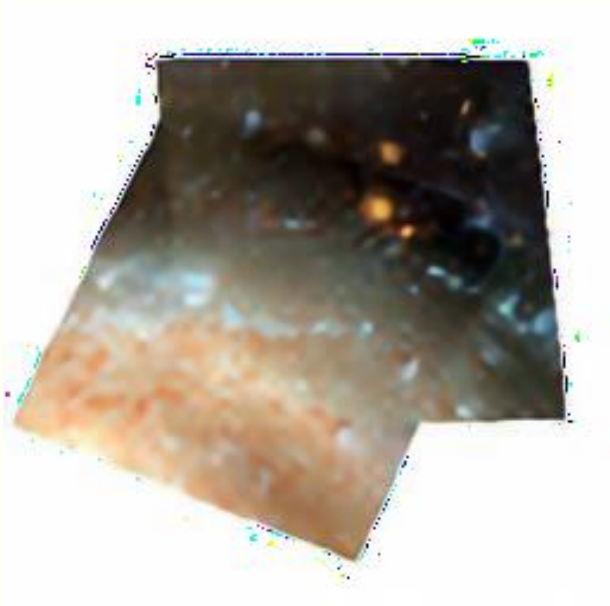
- Results of SRGAN (Upscaling):



SRGAN Fine tuned

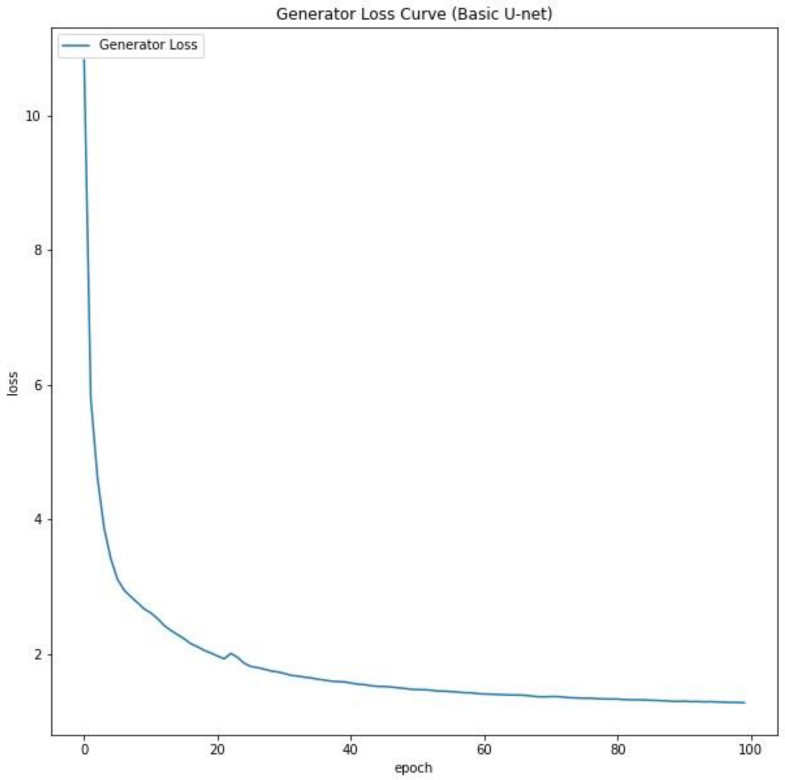


WD SRGAN

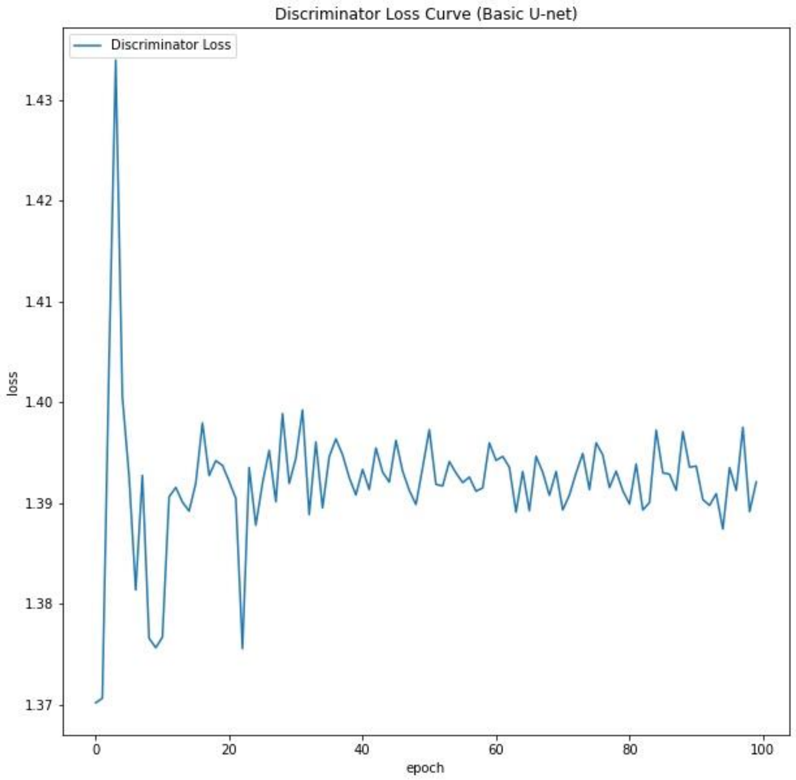


ED SRGAN

Results

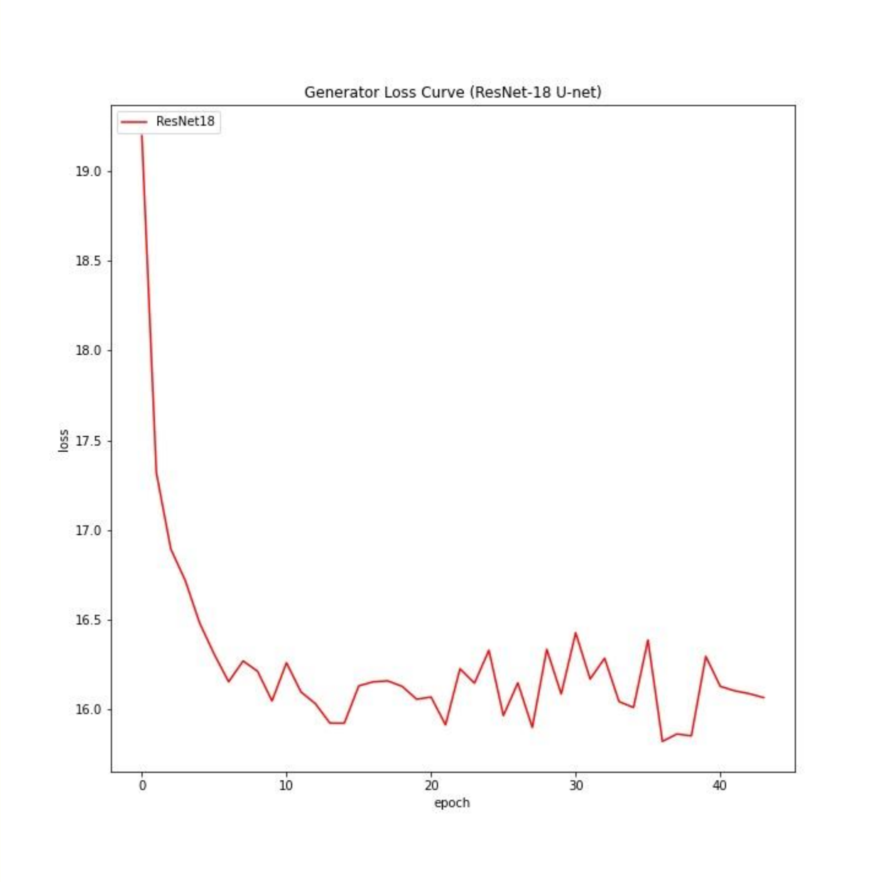


Generator Loss Curve (Basic U-net)
Generator Loss
loss
epoch
0
20
40
60
80
100
2
4
6
8
10

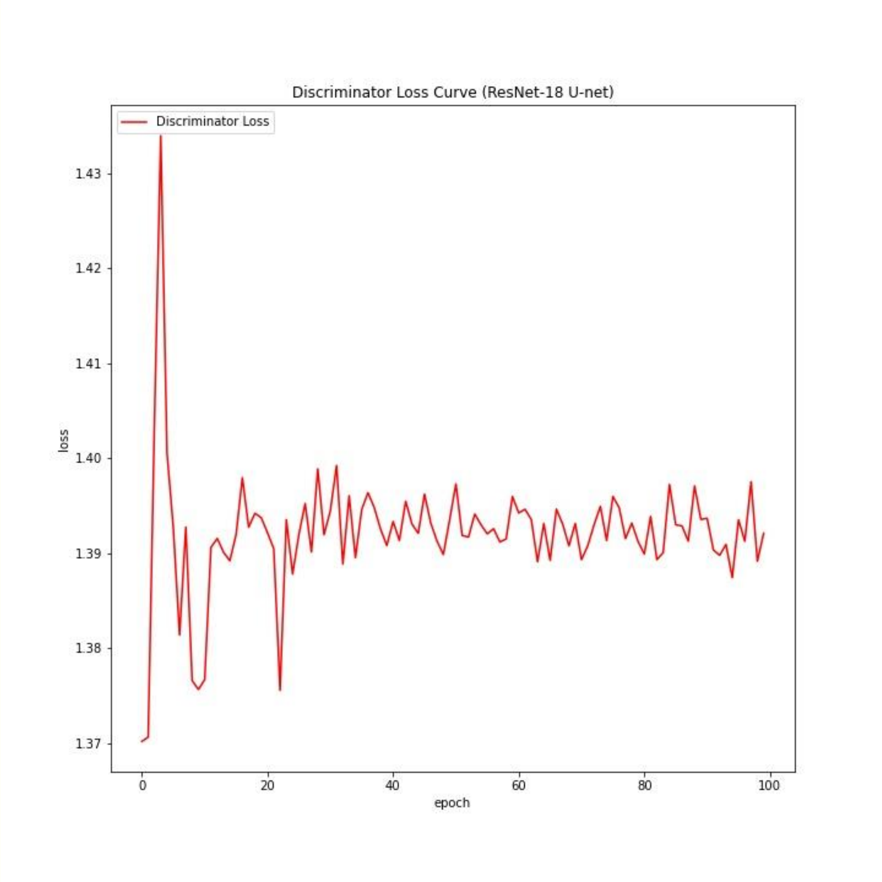


Discriminator Loss Curve (Basic U-net)
Discriminator Loss
loss
epoch
0
20
40
60
80
100
1.37
1.38
1.39
1.40
1.41
1.42
1.43

Results



Generator Loss Curve (ResNet-18 U-net)
ResNet18
loss
epoch



Discriminator Loss Curve (ResNet-18 U-net)
Discriminator Loss
loss
epoch

Results

- Pixel wise mean:

Model	Color Space	L1 Distance	L2 Distance
ResNet-18 (Pre-trained)	L*a*b	64.5409	2.77
ResNet-18 (Fine-tuned)	L*a*b	65.1119	2.62
ResNet-18 (Pre-trained)	RGB	125.5554	9.04
U-net	RGB	77.3273	3.986

Results

- Channel wise mean of fine-tuned ResNet18 U-net:

Distance	Red	Green	Blue
L1 Norm	64.6078	38.5994	92.1283
L2 Norm	3.4531	1.0253	3.8046

Results

- Per pixel mean of SR-GAN networks:

Model	L1 Distance	L2 Distance
Ledig SRGAN (Fine-tuned)	87.1090	3.754
Ledig SRGAN (Pre-trained)	114.8043	5.953
ED-SRGAN	80.9414	3.684
WD-SRGAN	79.7262	3.627

Cost Estimation

- Cost Estimate: The model following is the semi detached Constructive Cost Model (COCOMO) for estimating the efforts required in the completion of the project.

1) Object Point

2) Function Point

3) Lines of Source Code (KLOC)

For our project, sizing information in the form of Lines of Source Code is used.

The total lines of code,

KLOC = 1000

Note: KLOC is arbitrary, change if necessary

Equations: The initial effort(Ei) in man-months is calculated using equations: $E = ax(KLOC)$ b where,

Astronomical image colourisation and super-resolution using GANS

Cost Estimation

- a = 3.0, b = 1.12, for a semi-detached project
- E = Efforts in person-hours E = 4.5 PM
- D = ax(E) b Where, a = 2.5, b = 0.35, for a semi-detached project
- D = Duration of Project in months D = 12 Months

Astronomical image colourisation and super-resolution using GANS

Cost Estimation

- $C = D * Cp * hrs$ = 12 * 40 * 160 = Rs 76,800
- Where, C = Cost of project
- D = Duration in Hours
- Cp = Cost incurred per person-hour
- hrs = hours

Astronomical image colourisation and super-resolution using GANS

K K Wagh

• Conclusion and Future Scope

- U-net architectures are still a widely unexplored domain for ensemble learning and could be implemented with numerous methodologies
- A more powerful model such as SE-ResNext, EfficientNet and more state-of-the-art models can be implemented and trained over millions of images from the Imagenet.
- The performance of GAN can be improved by implementing it in a cyclic fashion, i.e. Cycle GAN, with the Pix2Pix colorization approach
- Colorization can be improved by the virtue of exploring different loss functions using weighted losses to reduce loss problem for low saturation regions.

References

- Cheng, Z., Yang, Q. and Sheng, B. (2016). Deep colorization.
- Dahl, R. (2016). Automatic colorization.
- Dong, C., Loy, C. C., He, K. and Tang, X. (2014). Learning a deep convolutional network for image super-resolution, *in* D. Fleet, T. Pajdla, B. Schiele and T. Tuytelaars (eds), *Computer Vision – ECCV 2014*, Springer International Publishing, Cham, pp. 184-199.
- Goodfellow, I. J., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A. and Bengio, Y. (2014). Generative adversarial networks.
- He, K., Zhang, X., Ren, S. and Sun, J. (2015). Deep residual learning for image recognition.
- Huang, Y.-C., Tung, Y.-S., Chen, J.-C., Wang, S.-W. and Wu, J.-L. (2005). An adaptive edge detection based colorization algorithm and its applications, pp. 351–354.
- Isola, P., Zhu, J.-Y., Zhou, T. and Efros, A. A. (2018). Image-to-image translation with conditional adversarial networks.
- Jianchao Yang, Wright, J., Huang, T. and Yi Ma (2008). Image super-resolution as sparse representation of raw image patches, *2008 IEEE Conference on Computer Vision and Pattern Recognition*, pp. 1–8.

References

- Kim, J., Lee, J. K. and Lee, K. M. (2016). Accurate image super-resolution using very deep convolutional networks, *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 1646–1654.
- Ledig, C., Theis, L., Huszar, F., Caballero, J., Cunningham, A., Acosta, A., Aitken, A., Tejani, A., Totz, J., Wang, Z. and Shi, W. (2017). Photorealistic single image super-resolution using a generative adversarial network.
- Levin, A., Lischinski, D. and Weiss, Y. (2004). Colorization using optimization, *ACM SIGGRAPH 2004 Papers*, pp. 689–694.
- Long, J., Shelhamer, E. and Darrell, T. (2015). Fully convolutional networks for semantic segmentation, *2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 3431–3440.
- Mirza, M. and Osindero, S. (2014). Conditional generative adversarial nets.
- Pressman, R. S. (1992). Software Engineering (3rd Ed.): A Practitioner's Approach, McGraw-Hill, Inc., New York, NY, USA.
- Qu, Y.,Wong, T.-T. and Heng, P.-A. (2006). Manga colorization, ACM Transactions on Graphics (TOG) 25(3): 1214–1220.
- Radford, A., Metz, L. and Chintala, S. (2016). Unsupervised representation learning with deep convolutional generative adversarial networks.
- Shi, W., Caballero, J., Husz´ar, F., Totz, J., Aitken, A. P., Bishop, R., Rueckert, D. and Wang, Z. (2016). Real-time single image and video super-resolution using an efficient sub-pixel convolutional neural network, *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 1874–1883.

References

- Simonyan, K. and Zisserman, A. (2015). Very deep convolutional networks for large-scale image recognition.
- Tola, E., Lepetit, V. and Fua, P. (2008). A fast local descriptor for dense matching, *Proc. CVPR* .
- Tom and Katsaggelos (1996). Reconstruction of a high-resolution image by simultaneous registration, restoration, and interpolation of low-resolution images, *in* Anon (ed.), *IEEE International Conference on Image Processing*, Vol. 2, IEEE, pp. 539–542. Proceedings of the 1995 IEEE International Conference on Image Processing. Part 3 (of 3) ; Conference date: 23-10-1995 Through 26-10-1995.
- TSAI, R. (1984). Multiframe image restoration and registration, *Advance Computer Visual and Image Processing* 1: 317–339.
- Welsh, T., Ashikhmin, M. and Mueller, K. (2002). Transferring color to greyscale images, *ACM Trans. Graph*. 21: 277–280.
- Yatziv, L. and Sapiro, G. (2006). Fast image and video colorization using chrominance blending, *IEEE Transactions on Image Processing* 15(5): 1120–1129.
- Zhu, J.-Y., Krahenbuhl, P., Shechtman, E. and Efros, A. A. (2018). Generative visual manipulation on the natural image manifold.
- Arjovsky, M., Chintala, S. and Bottou, L. (2017). Wasserstein gan.
- Yu, J., Fan, Y., Yang, J., Xu, N., Wang, Z., Wang, X. and Huang, T. (2018). Wide activation for efficient and accurate image super-resolution

THANK YOU !!

K K Wagh