Deep Space Image Colorization Using Generative Adversarial Networks

Team EAML-1107-RESIN-1

Akshaj Vishwanathan

Mohammed Madini M

Dr. Kavitha C

Table of Contents

ABSTRACT

Space is the region beyond our Earth's atmosphere where celestial objects such as the moon, the sun, the planets, asteroids etc. Deep space is the expanse of three-dimensional space that exists beyond our moon. Most of the deep space objects are unobservable by the naked eye; therefore, telescopes aid in observing those objects. Deep-space observation is essential for many reasons: to improve our understanding of the known universe, confirm scientific theories and understand other cosmological phenomena.

The data provided by these telescopes are in the form of images which are then processed to extract information such as brightness, distance from earth etc. These images are in grayscale, and have to be colorized to provide an idea as to how those objects would look to the human eye. The colorization process is time-consuming if done manually, hence, we propose a machine learning based image colorization technique called GAN model. The GAN model has two neural networks called the generator and discriminator.

The generator generates fake images using noise as input while the discriminator predicts if the input image is real or fake (generated). The model is trained until the generator generates such images which the discriminator can't predict correctly since those images would be very close to the real images. The evaluation is done through visual analysis by comparing the generated image with the actual image. The results obtained are promising since the generated colorized images are almost identical to the original images.

1. Introduction

Since ancient times, celestial observations have been of great importance to understand the world around us. The discovery of planets, their moons and other objects in our solar system gave us an idea of how our solar system formed. With the advancements in space technology we moved beyond our solar system to interstellar space in hopes of finding an answer to the big question, how did the universe form? Through deep space observations, we have found new objects, confirmed scientific theories and witnessed cosmological spectacles that happened millions to billions of years ago which helped improve our understanding of the universe.

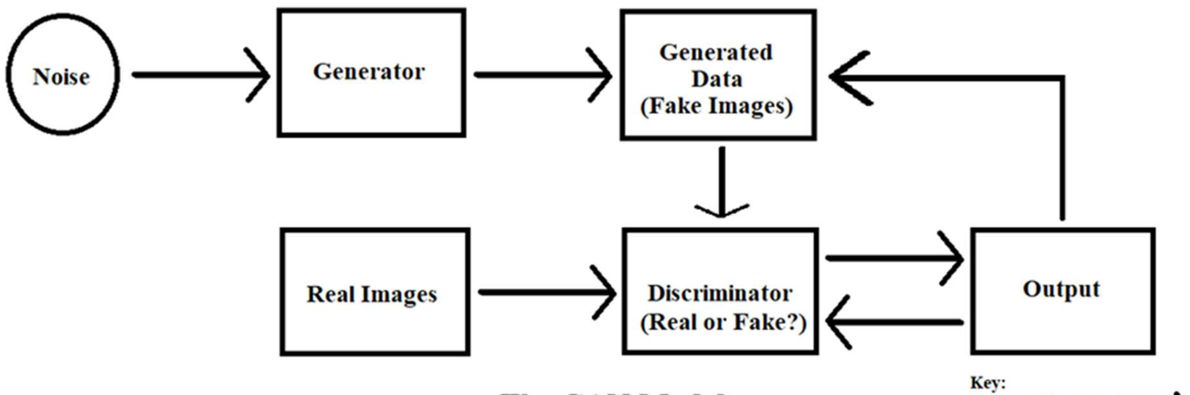
We know that deep-space observation is done through telescopes, but the images we see are not exactly how the observed objects are in reality. This is because the light received from these objects are not always in the visible range. They are also in infra-red and ultra-violet range which are invisible to the human eye. The images are captured in black and white by the telescope via filtering which filters the incoming light based on its wavelength. Multiple images are captured and combined, and based on the recorded wavelength, the RGB colors are added and we get the final image.

This process can take a lot of time to do manually, hence the advancements in machine learning can be used to automate the image colorization process and significantly reduce the time consumed. In this paper we have proposed the GAN model for colorizing deep space images. GAN or Generative Adversarial Network is a neural network model mainly used for image generation. It is a generative model and is trained in an unsupervised fashion.

The GAN model consists of two neural networks, the generator and the discriminator. The name of these two networks gives away their roles in the GAN model. The generator as the name suggests, generates images which are similar to the real images by combining noise with features of real images. These fake images are then fed as input to the discriminator along with the real images from the dataset. The discriminator predicts if the images are real or fake in the form of probability between 0 and 1 where 0 represents fake image and 1 represents real. The two networks compete against each other in a zero-sum game (i.e neither of the 2 contenders wants the other to win) until the generator consistently produces images that are indiscernible from the real ones and the discriminator cannot distinguish between the fake and real image.

The GAN model has many advantages over other models, the first of which is its unsupervised learning method which eliminates the need for labelled data. Currently, GAN is known to produce the sharpest and most realistic images. Its various applications include colorization, text to image generation etc.

The rich visual quality of the images generated through GAN make it the ideal ML model for space image processing. Since it's unsupervised and doesn't need labelled data, the process of image colorization can be automated and the time consumed is significantly reduced since labelling data is a time expensive process.



The GAN Model

1.1 Overview

In this project we have used the GAN model to colorize deep space images. We used a dataset of 2500 images of size 300x300 pixels, split in a 90:10 ratio for training and testing. The images were resized to 120*120 and converted into grayscale in batches of 64. Then the generator and discriminator models were trained and optimized by using Adam optimizer. The training ran for 150 epochs and excellent results were obtained. The generated output was very close to the ground truth.

1.2 Motivation

Image colorization finds its application in various fields and is an active research topic.

Deep space images provide insights and hints about the origin of the universe hence it is important to study them deeply.

Manual Image colorization is a tedious and time-consuming process hence we propose using machine learning and deep learning techniques to automate and optimize the process.

1.3 Contribution

1. We design a GAN model

2. The galaxydat dataset, which contains images of galaxies, was pre-processed.

3. Mean squared error is used to calculate the generator and discriminator loss

4. The results are visualized in the form of images with 3 categories: the greyscale image, the generated image and the original image (ground truth).

1.4 Paper organization

This paper can be summarized as follows: Section 2 describes some related works on image colorization using GAN. Section 3 presents the proposed solution. Results and discussions are provided in Section 4. Future scope and conclusion of the paper is in Section 5.

2. Related Works

The work on implementation of GAN's in various fields has been going on for years. Colorization of images using Deep Convolutional Generative Adversarial Network (DCGAN) was proposed in [1]. This study was conducted by Kamyar Nazeri et al using DCGAN on datasets such as CIFAR-10 and Places365 to compare results between generative models and traditional deep neural networks of colorizing the images. Work done by Aamir Khan et al, on using GAN-Holo framework for hologram reconstruction [2]. Use of Deep Neural Networks and GAN-Holo to reconstruct holographic images was proposed. CycleGAN is another type of architecture used for various applications in image translation [3]. Image coloring is a work that is time-consuming and color collocation is an important factor to determine its quality [4].

Deep Space imaging is a vital part of our understanding of the working of the cosmos. Everyday telescopes both on ground and in space produce terabytes of data of galaxies,stars, and all of interstellar structures. Use of code is a vital part of conducting research in Astronomy. Numerous studies have been done in this area, including one that converted high-resolution grey-scale satellite photos to RGB images using Multi Discriminator GAN model [5]. Data collected from the satellites is run through a network of different scale levels of discriminators to produce high-resolution colorized images. A study conducted by Ce Zhang et al on-feature recovery in astrophysical images beyond the deconvolutional limit of neural networks. Conventional deconvolution techniques are limited in their ability to recover features in imaging data by the Shannon-Nyquist sampling theorem. Our capacity to analyse current data sets of astrophysical objects as well as upcoming observations with observatories like the Large Synoptic Sky Telescope (LSST), the Hubble Space Telescope, and the James Webb Space Telescope is significantly increased by the ability to better recover detailed features like galaxy morphology from low-signal-to-noise and low angular resolution imaging data [6].

In the field of astronomy, GANs are a potential method for image production. Conditional generative adversarial networks are of great interest. An important property of an image is that the total brightness directly correlates to the energy of the primary particles which was used as the basis in [7]. Conditional GAN or cGAN technique is used to generate similar images to those obtained in the experiment. Another study on use of GANs in astronomy was conducted by Davide Coccomini et al [8], using the dataset images from Galaxy Zoo and Lightweight GAN architecture to recreate new images of the universe. A new type of GAN known as Spatial GAN's (SGANs) was proposed in [9] that can generate arbitrarily large images. The Hubble Space Telescope eXtreme Deep Field (XDF) images are recreated using the property that generated images have a high level of fidelity with galaxies in the real XDF in terms of abundance, morphology, magnitude distributions and colors. ExoGAN is a new type of deep-learning algorithm and architecture of GAN which mainly focuses on atmospheric features like their molecular composition, atmospheric trace-gas abundances, and other planetary parameters [10]. It can be used as both final analysis or to provide constraints to subsequent retrieval. The base of construction that was used to build the ExoGAN was DCGANs. GANs are a vital tool that is being used to explore all parts of the Universe to work much better than just studying the existing data.

In Radio Astronomy utilization GAN is used to investigate whether any additional information can be extracted from radio data and might ultimately recover extended flux from a survey with high angular resolution [11]. Using faint images that were collected from Radio Sky at Twenty-Centimetres (FIRST) and the NRAO VLA Sky Survey (NVSS) radio surveys to measure the GAN produced images with metrics like structural similarity as well as flux density. The result that RadioGAN achieved was within a 20% deviation from the original size and flux which was phenomenal. Simulation of astronomical images using Deep Learning neural networks is one of the most powerful methods. However, there has only been sporadic debate on reconstructing noisy backgrounds that encode instrumental and observational effects due to their constraints in using paired images with supervised translation [12]. So, the first attempt to apply semi-supervised methods and noise reconstruction techniques were proposed in [13]. To encode large-scale cosmological structure Marion Ullmo et al, used GAN to train images and cubes to generate new data that would extract information from simulation data and competently generate data with similar large-scale structures.

3. Proposed Solution

3.1 Dataset Description

The dataset consists of 2500 images of random interstellar objects taken from deep space. It contains images of spiral, elliptical and irregular galaxies which were captured using various telescopes across the globe.

3.2 Data Pre-Processing

The data has images of dimensions 300×300 pixels. The images are then reduced to 120×120 for optimal use. The data used for training the GAN model amounted to about 90% that is about 2250 images. The remaining 10% was used to test the model.

3.3 U-Net Architecture and Implementation

U-Net is a semantic segmentation technique originally proposed for medical imaging segmentation but currently it is used in many fields of science, art and engineering. It evolved from traditional neural networks and it mainly focuses on image colorization. It was designed to solve a problem of biomedical cases where it required not only diagnose a disease but also to localise the area of abnormality. The reason for U-Net success in this problem is due to it being able to localise and distinguish borders [14]. It is capable of doing so due to its design of classifying on every pixel so that both the input and output share the same size.

U-Net is called so due to its basic foundation and looks in the shape of the letter ‘U’. The architecture contains two paths:

1. First path is the contraction path also known as the encoder, which is used to capture the context in the image. The encoder is just a traditional stack of convolutional and max-pooling layers.
2. The second path is the symmetric expanding path also called the decoder, which is used to determine the precise localisation using transposed convolutions.

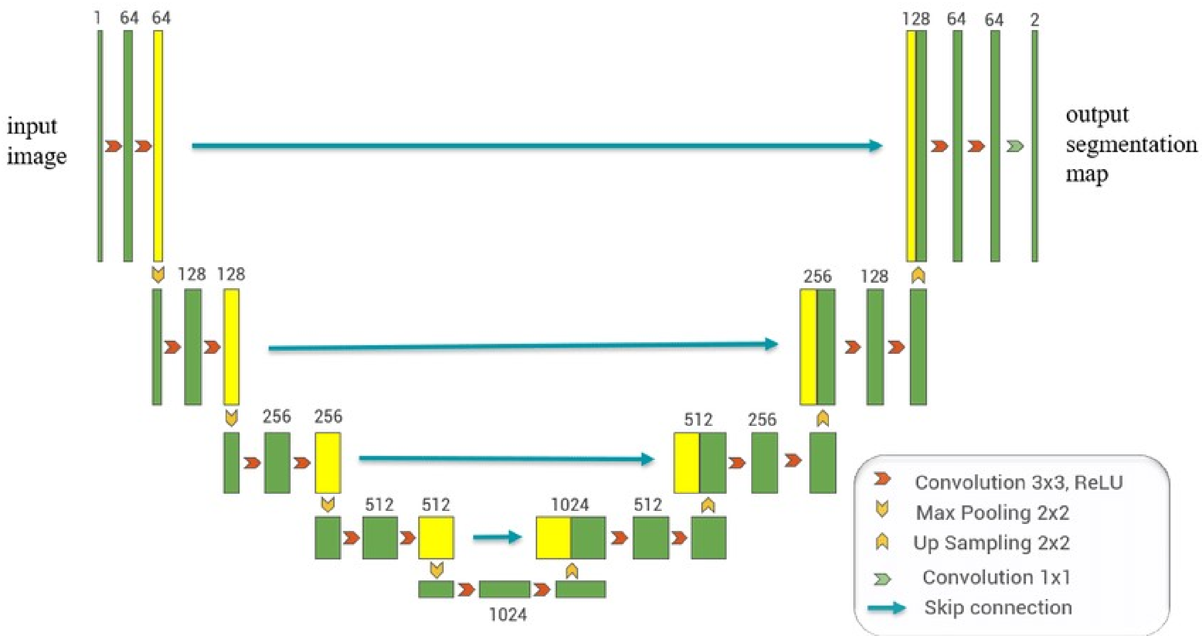


Figure-3.1 U-Net architecture diagram [15].

The U-Net architecture (Figure-3.1) explains the framework of the algorithm. The left half of Figure-3.1 is the encoding path and the right half is the decoding path. Each block in the encoding path contains two convolutional layers and a max-pooling layer and at each step, the number of feature channels is doubled. In addition, the effect of max-pooling makes the size of the feature map smaller.

It is due to the above-mentioned property of UNet of identifying borders and due to its precise segmentation of images we use this architecture to recreate deep space images. Deep space images are usually heavily downsized due to the sheer volume of images taken so by using this framework we are able to recreate the grayscale images to match its RGB counterpart.

3.4 Generator Model

The generator model is part of the GAN which is tasked with learning to generate fake images based on the feedback received from the discriminator, while the discriminator model has to predict if the image it receives is real or fake. The objective of the generator is to fool the discriminator into identifying a fake image as real. The generator takes random noise as input and converts it into a fake image whereas the discriminator takes images from dataset and generator as input for predictions.

The generator loss keeps track of the generator model's progress and the discriminator loss keeps track of the generator model's progress. Initially the images produced are far from the real images hence the discriminator is easily able to predict if the image is real or fake. Every correct prediction of the discriminator (i.e predicting that the image is generated by the generator) is a penalty for the generator hence the generator loss is high at the start while discriminator loss is low.

As the training progresses and the discriminator back propagates gradients, the generator is able to generate images which are closer to the real images signifying improvement in performance, hence the generator loss lowers with the increase in discriminator loss due to incorrect predictions. Eventually there comes a point where the generator generates images which are indistinguishable from the real images hence the discriminator accuracy drops to 50%. This state is called 'convergence' and is the ideal point to stop training the model.

With respect to our dataset, initially the model would generate images which are colorized wrong hence the discriminator would easily identify the generated image, but with more epochs the generator generates near accurately coloured images which the discriminator fails to identify as a generated image, hence discriminator loss increases. Towards the end of training the model, the generated output's color would be identical to that of the ground truth. At that point, the convergence state would have been achieved and the model training would be complete.

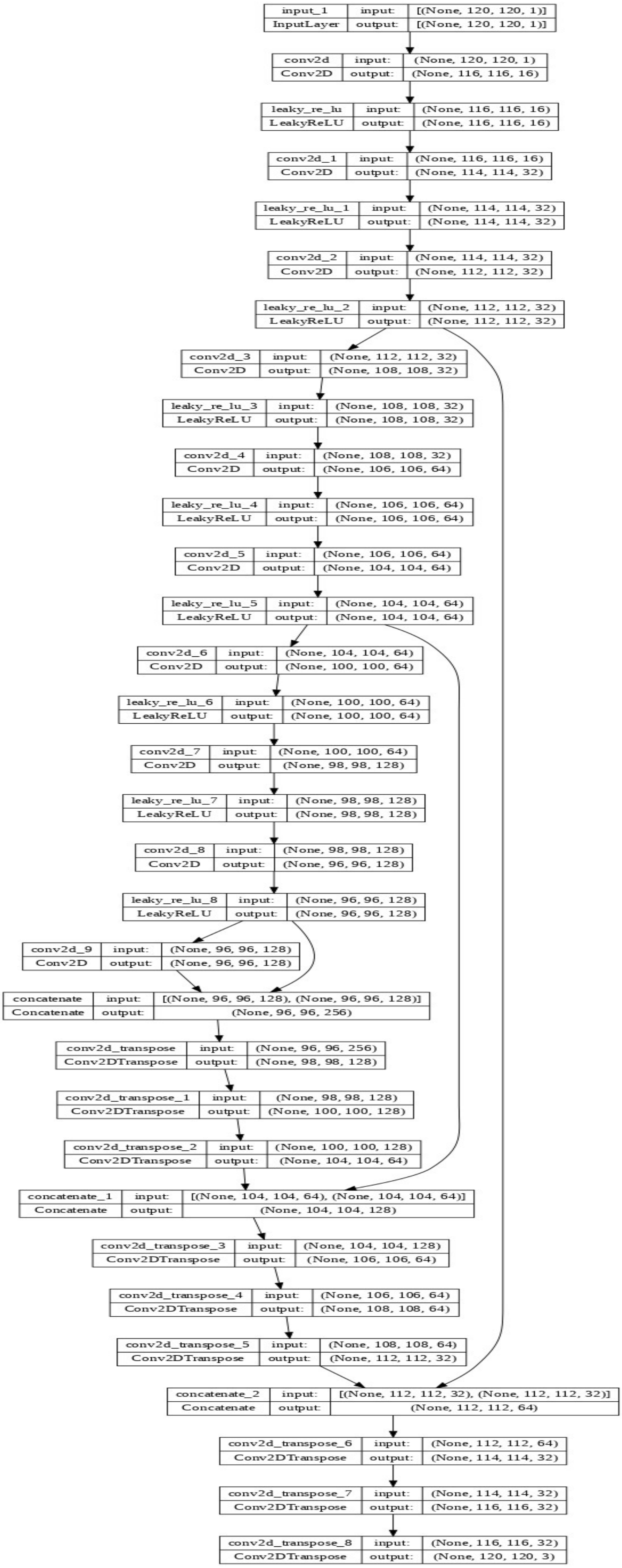
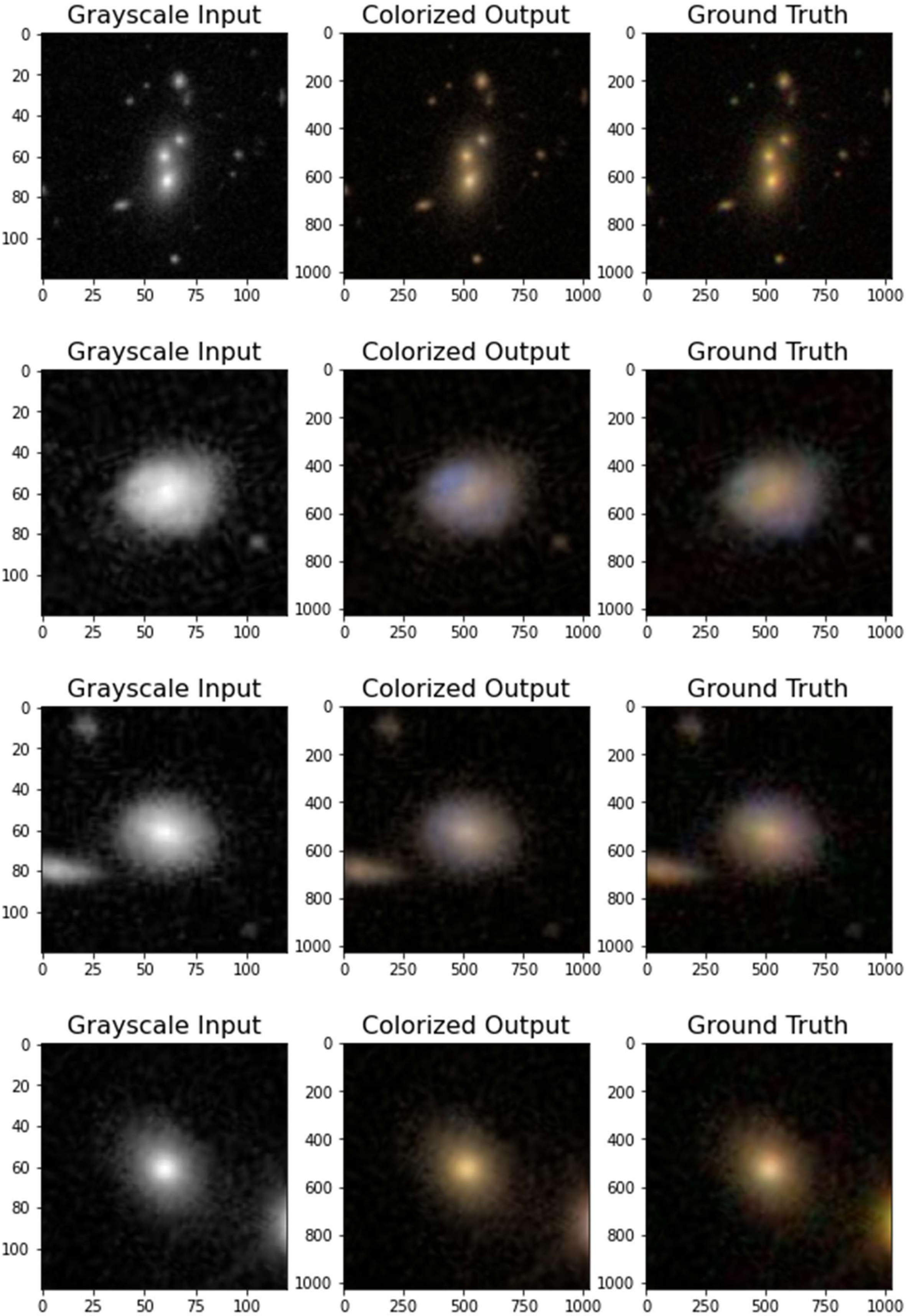


Figure-3.2. Generator Model of GAN

4. Experimental Results and Discussion



The performance of the model can be determined from the above images. The images consist of three parts: the greyscale input provided, the generated colorized output and the ground Through comparison between the generated output and the ground truth, following observations can be made:

In the first image it is visible that the colour of the generated output is slightly lighter than the ground truth, hence the result is nearly accurate.

In the second image, the generated output has a greater blue hue than the ground truth and is comparatively lighter, hence the result is less accurate than the previous image.

The generated output of the third image is lighter than the ground truth but the result is comparatively more accurate than the previous image.

The fourth and final image has a generated output identical to the ground truth, hence this result is the most accurate among all the images viewed thus far.

Inference:

The model has performed great and has excellent accuracy.

5. Conclusion and Future Scope

In this study we were able to recreate the greyscale deep space images to their colorized version using generative adversarial networks in hopes to be able to reconstruct the images like the original. Using the dataset of 2500 (300×300) deep space images, the model was able to perform consistently and produce better looking images. The U-Net architecture provided the base framework for this study. The images were then reduced to 120×120. About 90% of the images were used to train the GAN model and the remaining 10% were used to test the model. The model ran in the batch size of 64 and with 150 epochs to produce the quality images. The reason for not obtaining a perfect copy of the original is due to the losses that occurred during the training phase. There were two losses that were accounted for, generator loss and discriminator loss. Generator loss is produced due to random noise generator whereas discriminator loss is produced due to classifying both the real and fake data from the generator. We can expect better results if we improved and refined the algorithm or by increasing the number of training or testing images.

We would also need to look for a better quantitative metric that could be used to gauge the performance of the model. This is due to the fact that all of our tests' image quality judgements were qualitative. Therefore, a far more reliable process of quantifying performance will be made possible by the presence of a new or current quantitative metric, such as peak signal-to-noise ratio (PSNR) and root mean square error (RMSE).

The future work in this could include using a better architecture or framework to improve and better the resolution of images so that it could be used in actual astronomical research. Using either Super Resolution Generative Adversarial Networks (SRGAN) or High-Resolution Patch Generative Adversarial Networks (HRPGAN) will better the quality of the images produced. Another future work may include using a multi-discriminator model to reduce the discriminator loss to obtain better results using the current framework. There are various other GAN architectures that are yet to be tried on deep space images which could result in a breakthrough in both the computers and astronomy field.

References

[1] Nazeri, K., Ng, E. and Ebrahimi, M., 2018, July. Image colorization using generative adversarial networks. In *International conference on articulated motion and deformable objects* (pp. 85-94). Springer, Cham.

[2] Khan, A., Zhijiang, Z., Yu, Y., Khan, M.A., Yan, K. and Aziz, K., 2021. Gan-Holo: Generative adversarial networks-based generated holography using deep learning. *Complexity*, *2021*.

[3] Liao, Y. and Huang, Y., 2022. Deep Learning-Based Application of Image Style Transfer. *Mathematical Problems in Engineering*, *2022*.

[4] Fan, J., Xie, W. and Ge, T., 2022. Automatic Gray Image Coloring Method Based on Convolutional Network. *Computational Intelligence and Neuroscience*, *2022*.

[5] Li, F., Ma, L. and Cai, J., 2018, July. Multi-discriminator generative adversarial network for high resolution gray-scale satellite image colorization. In *IGARSS 2018-2018 IEEE International Geoscience and Remote Sensing Symposium* (pp. 3489-3492). IEEE.

[6] Schawinski, Kevin & Zhang, Ce & Zhang, Hantian & Fowler, Lucas & Santhanam, Gokula Krishnan. (2017). Generative Adversarial Networks recover features in astrophysical images of galaxies beyond the deconvolution limit. Monthly Notices of the Royal Astronomical Society: Letters. 467. slx008. 10.1093/mnrasl/slx008.

[7] Dubenskaya, J., Kryukov, A., Demichev, A., Polyakov, S., Gres, E. and Vlaskina, A., 2022. Using a Conditional Generative Adversarial Network to Control the Statistical Characteristics of Generated Images for IACT Data Analysis. *arXiv preprint arXiv:2211.15807*.

[8] Coccomini, D., Messina, N., Gennaro, C. and Falchi, F., 2021. Generative Adversarial Networks for Astronomical Images Generation. *arXiv preprint arXiv:2111.11578*.

[9] Michael J Smith, James E Geach, Generative deep fields: arbitrarily sized, random synthetic astronomical images through deep learning, *Monthly Notices of the Royal Astronomical Society*, Volume 490, Issue 4, December 2019, Pages 4985–4990.

[10] Zingales, T., Waldmann, I.P.: ExoGAN: Retrieving exoplanetary atmospheres using deep convolutional generative adversarial networks. The Astronomical Journal 156(6), 268 (nov 2018). https://doi.org/10.3847/1538-3881/aae77c.

[11] Glaser, N., Wong, O.I., Schawinski, K. and Zhang, C., 2019. RadioGAN–Translations between different radio surveys with generative adversarial networks. *Monthly Notices of the Royal Astronomical Society*, *487*(3), pp.4190-4207.

[12] Lin, Q., Fouchez, D. and Pasquet, J., 2021, January. Galaxy Image Translation with Semi-supervised Noise-reconstructed Generative Adversarial Networks. In *2020 25th International Conference on Pattern Recognition (ICPR)* (pp. 5634-5641). IEEE.

[13] Zhang, G., Pan, Y. and Zhang, L., 2021. Semi-supervised learning with GAN for automatic defect detection from images. *Automation in Construction*, *128*, p.103764.

[14] Iqbal, A., Sharif, M., Khan, M.A., Nisar, W. and Alhaisoni, M., 2022. Ff-unet: a U-shaped deep convolutional neural network for multimodal biomedical image segmentation. *Cognitive Computation*, *14*(4), pp.1287-1302.

[15] Guo, Yanan & Cao, Xiaoqun & Bainian, Liu & Gao, Mei. (2020). Cloud Detection for Satellite Imagery Using Attention-Based U-Net Convolutional Neural Network. Symmetry. 12. 1056. 10.3390/sym12061056.

Project Timeline (Gantt Chart)