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Using Generative Adversarial Networks and Auto Encoders for Satellite Image Enhancement

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Abstract:- **Degradation due to haziness, camera defocus and noise can be corrected using Image restoration. Only with the understanding of the deteriorating elements one can obtain the original image. Existing methods of image restoration have the limitations of suffering from bad convergence properties; the algorithms converging to local minima, and being unsuitable for real imaging applications. Few techniques, moreover, make constrictive presumptions on the PSF or the true image thereby limiting the algorithm's flexibility to different applications. Traditional approach involves de-blurring filters which are applied on the degraded images without the understanding of blur and its effectiveness. This paper is based on the approaches of AI that are applied for restoration problem in which images are distorted by a blur function and adulterated by some arbitrary noise. De-noising is enabled through the use of auto encoders while de-blurring is done through generative adversarial networks where a discriminator is used to analyze each output image given by the generator. The processing of satellite images is a major application of this proposed system of image restoration.**

Keywords:- *Satellite Images, Generative Adversarial Networks, Autoencoders, Image Enhancement, De-Blur, De-Noise.*

I. INTRODUCTION

Satellites operated by the government and other global organisations capture the images of the Earth or other planets. Businesses such as Google Maps and Apple Maps purchase these images from satellite imaging companies after licensing. Surveillance and satellite images are difficult to capture and are deficient in quality and contains noise and several other degrading factors. Image enhancement is the process of retrieving the original image by applying the knowledge of the degrading factors. These degrading factors are calculated and removed and the original image is restored. It mainly has its applications in satellite images as there are number of factors affecting the quality of these images such as motion of the satellite, space debris, and so on. Satellite images are often transmitted with an added noise and motion blur. This project intends to address the same. The problem can be divided in two modules, Noise removal and Blur removal.

Depending on a particular application, the objective of the image enhancement varies. This research paper aims to provide information regarding the image enhancement techniques which would result in advanced and desirable results for remote-sensing satellite imagery. Image enhancement algorithms are employed currently to improve the quality of the images during image processing applications. The following are the primary objectives of a satellite image enhancement technique:

- To gain maximum information from an image.
- To achieve high quality and a clear output image.
- To minimize mean squared estimation error.

II. LITERATURE REVIEWS

A. Satellite Imagery:

Satellites operated by the government and other global organisations capture the images of the Earth or other planets. Businesses such as Google Maps and Apple Maps purchase these images from satellite imaging companies after licensing.

B. Imagery Analysis using Artificial Intelligence:

Autonomous Analysis of imagery on a large scale has been made possible due to the development in artificial intelligence technologies. Satellite Imagery can be processed accurately with minimal errors through the use of AI. AI proves to be a valuable tool to differentiate between forest types, soil and vegetation types.AI is being employed by researchers to monitor vineyard and grape health besides estimating harvest size of wheat fields through satellite imagery. For instance, Projects like “Space Know” involve AI to collect information about deforestation due to forest fires in California and manufacturing activity in China for case studies.

With the technological advancement, clearer imagery and faster neural networks, the study of Above Ground Biomass (AGB) has been made possible. The ABG index can provide information about the size and density of vegetation which scientists use to estimate carbon output and footprints in specific areas. Scientists are looking forward to the application of this data to the study of global warming and climate change. AI that can monitor refugee movements in war-torn countries, deforestation in the Amazon rain-forest, and algae blooms in places like the Gulf of Mexico and the Red Sea is being developed through research. Upcoming studies of contaminated surface water and chemical runoff from Fracking are also being planned.

III. EXISTING SYSTEM

A. Wiener Filter:

The main aim of the Wiener filter is to separate out the image that has been corrupted by noise. Wiener filter relies on a statistical approach. Desired frequency response will be acquired using this filter. Approaches followed by wiener filtering are of various angles. For performing filtering operation it's must to possess knowledge of the spectral properties of the initial signal and therefore the noise, in achieving the factors one can get the LTI filter whose output shall be as close as original signal as possible. However, a Wiener filter needs a precise noise model that might be tough to get in real time. Additionally, it is complex in calculations.

B. Bicubic Interpolation:

In bicubic interpolation sixteen nearest neighbour of a pixel are examined as shown in Figure1. The intensity value given to point (x,y) is acquired with the equation,

$$v(x, y) = \sum_{i=0} \sum_{j=0} a_{ij} x^i y^j$$

where the sixteen coefficients are calculated from the sixteen equations in sixteen unknowns that would be written using the sixteen nearest neighbours of point (x,y).

Generally, bicubic interpolation does an better work of preserving fine detail than its bilinear counterpart. Bicubic interpolation is the standard employed in commercial image editing programs, like Adobe Photoshop and Corel Photo-paint.

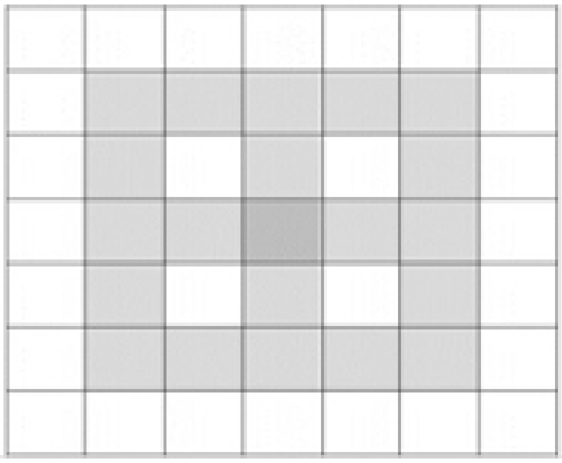

Figure 1. Bicubic Interpolation

➢ *Drawbacks of existing systems:*

- In all of these traditional approachde-blurring filters which are applied on the degraded images without the understanding of blur and its effectiveness.
- A wiener filter was used which provides only a point estimate and is sort of expensive.
- Bicubic interpolation was accustomed to enhance images but has been unsuccessful in providing the desired effectiveness.

IV. PROPOSED SYSTEM

This paper is based on the approaches of AI that are applied for restoration problem in which images are distorted by a blur function and adulterated by some arbitrary noise. These images are being used to train the neural networks. Autoencoders are used for the implementation of de-noising. An autoencoder has two parts: an encoder and a decoder. The encoder reduces the size of the input data in order that the original information is compressed. The decoder restores the initial information from the compressed data. During the training, the autoencoder learns to extract important features from input images and ignores the image noises and thereby removal of noise occurs.

De-blurring is performed by generative adversarial networks which consist of two models, a generator and a discriminator. The generator aims at reproducing sharp images. The network relies on ResNet blocks. It keeps track of the evolutions applied to the original blurred image. the target of a discriminator is to see if an input image is artificially created. Therefore, the discriminator's architecture is convolutional and outputs one value.

A. Methodology

The overall flow of the process follows the order of input image, data collection, pre-processing of the input images, followed by de-noising of the image by Autoencoders, which are Neural Networks, which are commonly used for feature selection and extraction. The subsequent process is image de-blurring using Generative Adversarial Networks, within which two networks train against one another. The generator misleads the discriminator by creating compelling fake inputs. The discriminator tells if an input is real or fake. Then comes parameter extraction and also the last process would be image restoration where a relatively clear, de-blurred and a de-noised image is obtained.

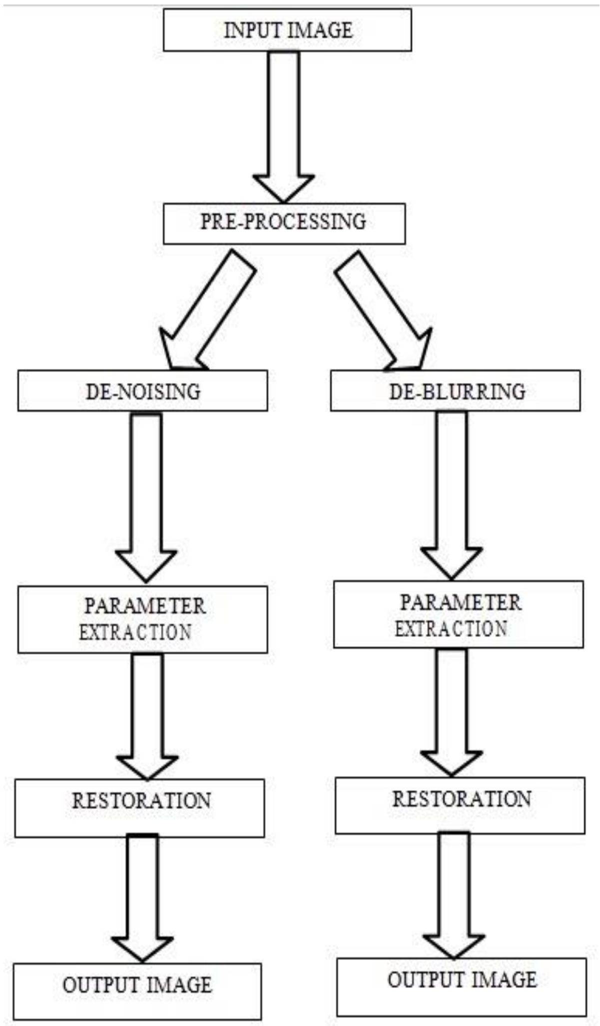

Figure 2. Methodology

i. DE-NOISING MODULE:

AUTOENCODERS: Autoencoders are Neural Networks that are usually employed for feature selection and extraction. However, when there are more nodes within the hidden layer than there are inputs, the Network is risking to find out the so-called "Identity Function", also called "Null Function", meaning that the output equals the input, marking the Autoencoder useless. This problem is solved in de-noising autoencoders. The concept behind de-noising autoencoders is to force the hidden layer to find more robust features and forestall it from simply learning the identity; we train the autoencoder to reconstruct the input from a corrupted version of it.

The de-noising auto-encoder is a stochastic version of the auto-encoder. Intuitively, a de-noising auto-encoder does two things: attempting to encode the input (preserve the data about the input), and trying to undo the effect of a corruption process stochastically applied to the input of the auto-encoder. The latter can only be done by capturing the statistical dependencies between the inputs. The de-noising autoencoder may be known from various views, the manifold learning perspective, stochastic operator perspective, bottom-up – information theoretic perspective, top-down – generative model perspective.

The stochastic corruption process randomly sets a number of the inputs (as many as 50% of them) to zero. Hence the de-noising auto-encoder is attempting to predict the corrupted (i.e. missing) values from the uncorrupted (i.e., non-missing) values, for randomly selected subsets of missing patterns. Note how having the ability to predict any subset of variables from the remaining is a sufficient condition for completely capturing the joint distribution between groups of variables. To change the autoencoder class into a de-noising autoencoder class, all we want to try and do is to feature a stochastic corruption step operating on the input. The input may be corrupted in different ways, but the original corruption mechanism of randomly masking entries of the input by making them zero is employed.

ii. DE-BLURRING MODULE

GENERATIVE ADVERSARIAL NETWORK: Generative adversarial networks (GANs) are algorithmic architectures that use 2 neural networks, pitting one against another so as to get new, synthetic instances of information that may pass for real data. They're commonly used in generating pictures, generating videos and generating voices. Discriminative algorithms attempt to classify input data; that is, they predict a mark or category to which that data belongs, given the characteristics of an instance of knowledge.

The steps taken in GAN are given as:

- The generator takes in random numbers and returns an image.
- This generated image is fed into the discriminator alongside a stream of images taken from the actual, ground-truth dataset.
- The discriminator takes in both real and fake images and returns probabilities, a number between 0 and 1, with 1 representing a prediction of authenticity and 0 representing fake.

So a double feedback loop is taken:

- The discriminator is in a feedback loop with the ground truth of the photographs, which we all know.
- The generator is being in a feedback loop with the discriminator.

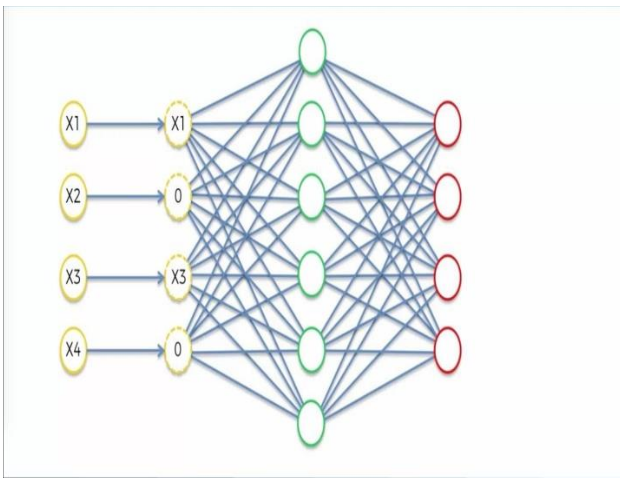

Figure 3. Structure of a de-noising autoencoder

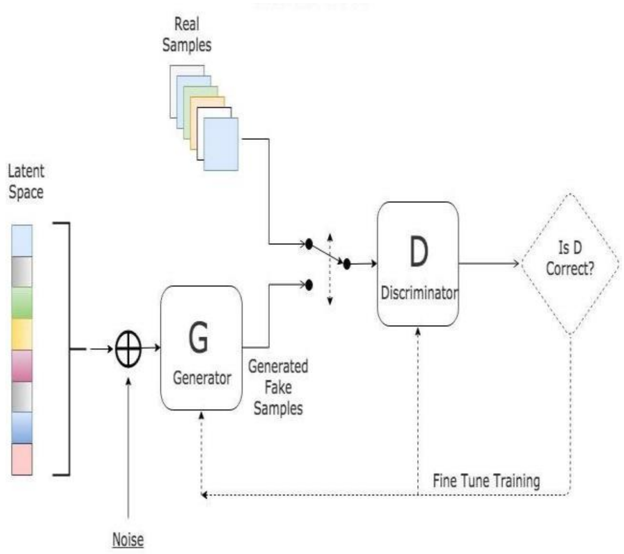

Figure 4. Structure of Generative Adversarial Network

V. DATASET

The dataset is split into training set (3000 samples), validation set (600 samples) and test set (200 samples). Each image is scaled to 256x256 pixels in 3 channel RGB representations (256x256x3).

We are able to observe that images from the identical class may be represented quite differently within the dataset. Generally, there may be different lighting conditions, image are often blurred, rotated or scaled.

These samples extracted are from real world images. And our model must handle all of those conditions. So, it's probably better to not truncate our dataset so as to get data balance. Blur is added to the dataset and is employed in training the general adversarial networks. During training, the blurred images are taken as input and the images from actual dataset are given as output.

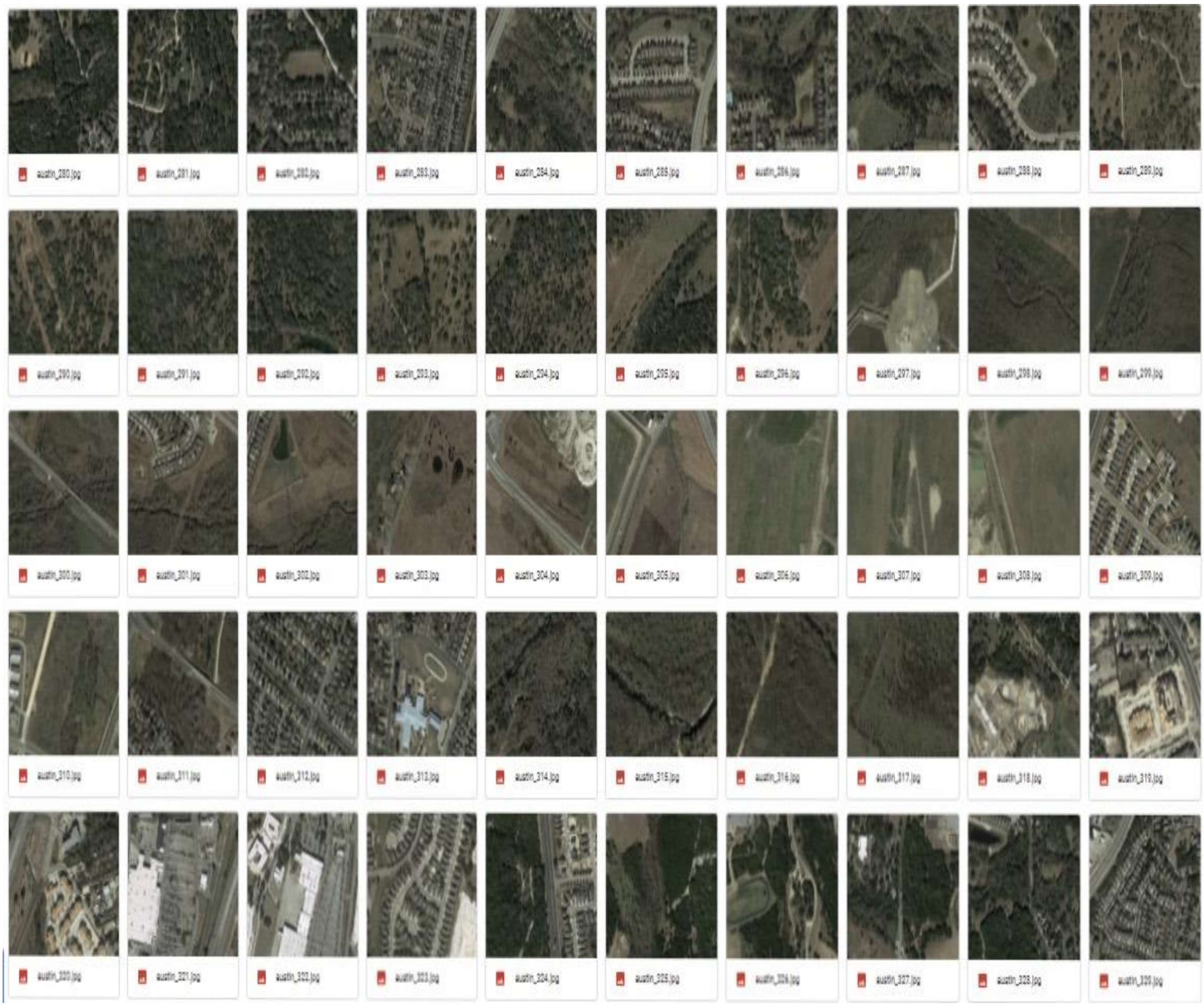

Figure 5.Original Austin image dataset samples

VI. RESULTS AND DISCUSSION:

The project is trained on Austin dataset and was experimented on different types of images. The de-noise module gave 92% accurate results. The results are more accurate for satellite images of Austin and are least accurate for non-satellite images.

A. De-blur Module:

The uploaded image is sent to the generator model and the result image is predicted. As the model is trained on Austin dataset it gives a better result. Therefore, it is recommended to train the model with the images of the location of usage.

a)Test case of an Austin satelliteimage.

Figure 6. De-blur results of Austin test image

To assess the algorithms, the clarity of image before and after processing is approximated. The objective image quality metrics like compression ratio, Peak Signal to Noise Ratio (PSNR), Signal to Noise Ratio (SNR), Root Mean Squared Error (RMSE) and Correlation Coefficient (CC) are used.

i. Mean Square Error(MSE):

To find the difference between the input data and the fused data MSE is employed.

$$MSE = \frac{1}{m \times n} \sum_{i=1}^{m} \sum_{j=1}^{n} (a_{ij} - b_{ij})^2$$

Where aij is pixel value at position (i, j) in the input image data bij -pixel value at position (i, j) in the fused image m and n are the dimensions of the image.

ii. Peak Signal to Noise Ratio(PSNR):

PSNR is a measure of error. The term peak signal to noise ratio is an expression for the ratio between the maximum possible value of a signal and the power of distorting noise that affects the quality of its representation. This is expressed in terms of logarithmic decibel.

$$\text{PSNR} = 10 \log_{10}\left[\frac{255^2}{MSE}\right]$$

iii. Correlation Coefficient(CC):

It delineates the similarity structures between the input and fused data. Greater the value of correlation larger the amount of data is preserved. The correlation coefficient is defined by the follow in equation.

$$CC = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} (a_{ij} \times b_{ij})}{\sum_{i=1}^{m} \sum_{j=1}^{n} (a_{ij})^2}$$

We have summarized the results of the de-blur module in Table1.

	MSE	PSNR	CC
Blurred Image	60.20314072158 dB	30.3346121243 dB	0.9142938527267356
De-blurred Image	41.53810119629 dB	32.2031351246 dB	0.9837153864043277

Table 1. Performance measures of de-blur module

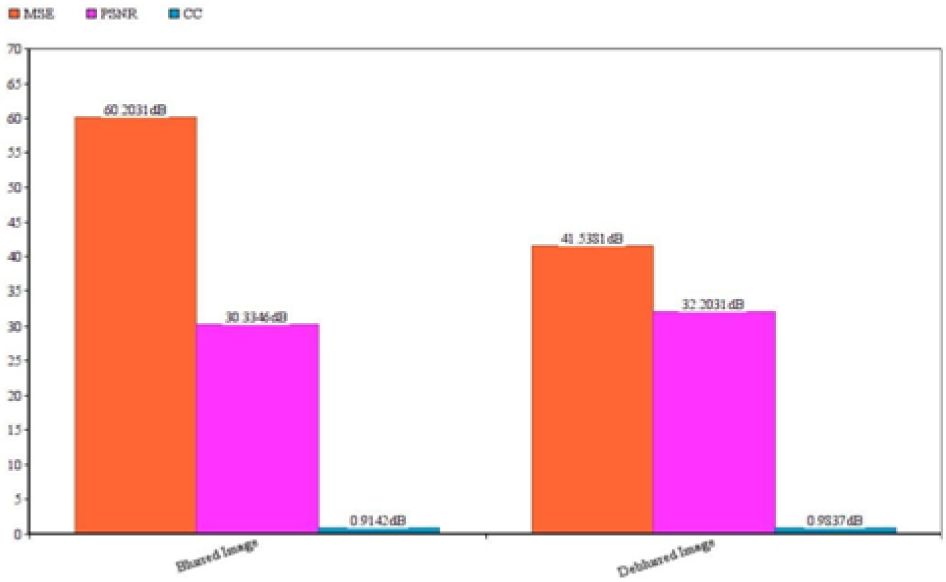

Figure 7. Graph showing performance measures of De-blur

The graphical depiction of the quality of blurred and de-blurred images is shown in Figure 7. There was a considerable decrease in the MSE value

which indicates the increase in information that is available from the image. There was a visible improvement in the quality of Austin satellite

b)Test case of a random satellite

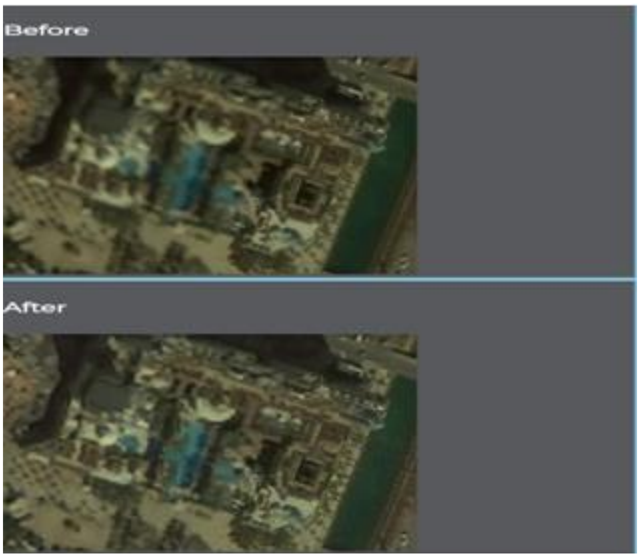

Figure 8. De-blur results of a random satellite image

c) Test case of a non-satelliteimage.

Figure 9. De-blur results of a non-satellite image

B. De-noise Module:

The uploaded image is sent to the de-noise model and the noise is removed by encoding and decoding the image by the model. In contrary to the de-blur module, de-noise module gives similar results for any dataset with a type of noise on which it is trained.

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a)Test case of a noised satellite image of Austin

Figure 10. De-noise results of Austin test data satellite image

	MSE	PSNR	CC
Noised Image	95.04343030631 dB	28.35158258397 dB	0.8671465858939358
De-noised Image	63.63782650583 dB	30.0936502259 dB	0.9564354664443893

Table 2. Performance measures of de-noise module

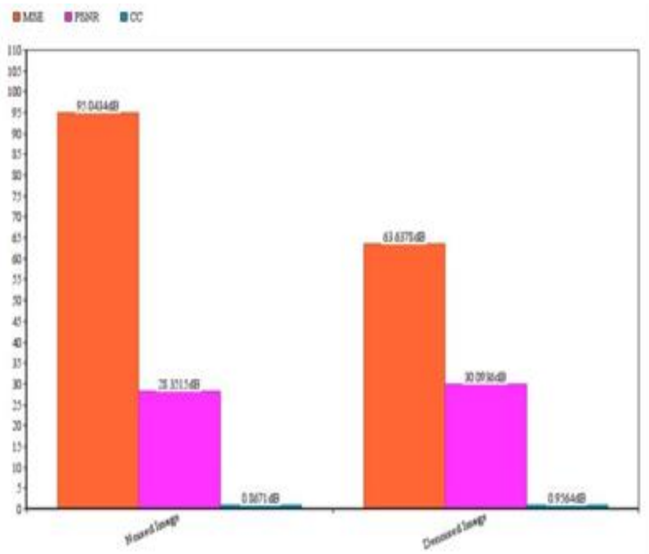

Figure 11. Graph showing performance measures of De-noise

As we can see in Figure 11, there is a considerable change in the level of noise. There was a very low difference in quality of the image when de-noised using Gaussianblur, medianblur or by using crimmins algorithm. The information loss wasapproximately0.9 while training the autoencoders.

b)Test case of a random noised satelliteimage.

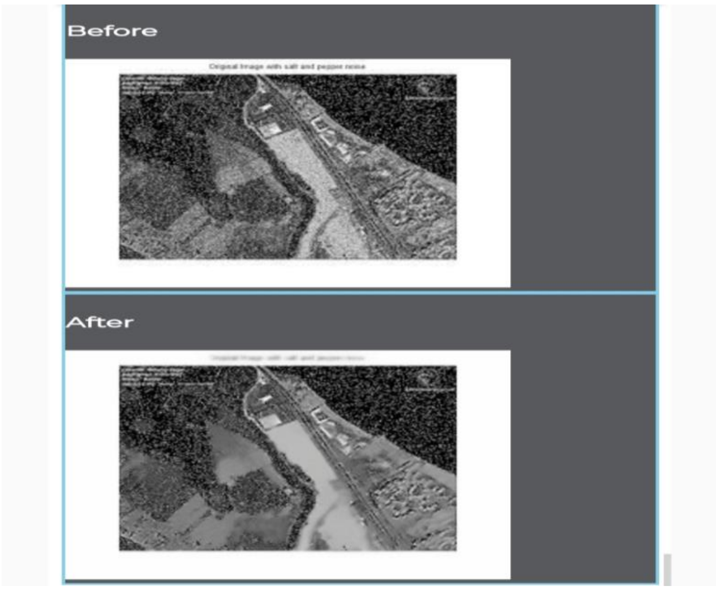

Figure 12. De-noise results of a randomly noised satellite image

c)Test case of a non-satelliteimage.

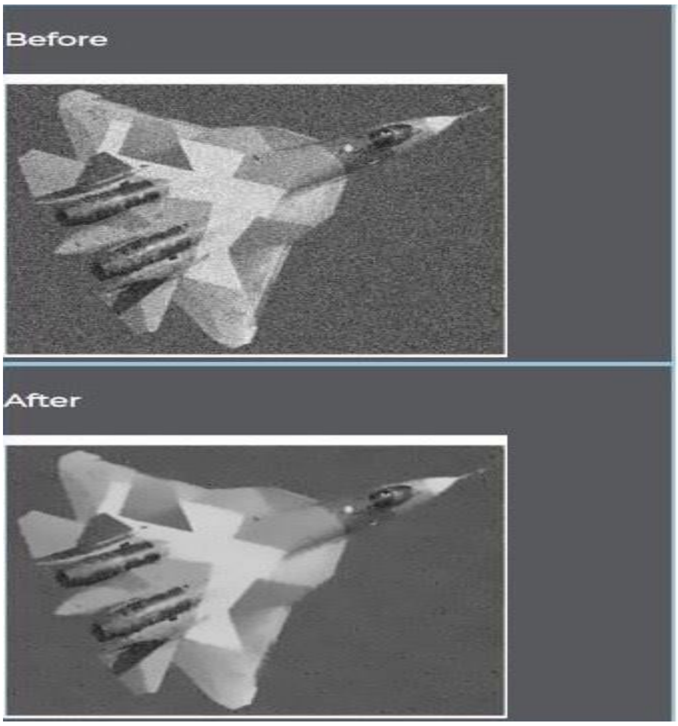

Figure 13. De-noise results of a non-satellite image

VII. CONCLUSION AND FUTURE ENHANCEMENTS

A. CONCLUSION:

Satellite Imagery is employed in numerous research domains; hence satellite image enhancement is potent research topic in image processing. Enhancement aims to process images where processed image is more relevant and clearer than the original image for applications of specific remote sensing. Image enhancing algorithms can alter poor quality images to focus, sharpen, or smoothen by adjusting contrast, shading, light exposure, feature reduction from noise contents, etc. This paperentitled “USING GENERATIVE ADVERSARIAL NETWORKS AND AUTOENCODERS FOR SATELLITE IMAGE ENHANCEMENT” has presented an approach to identify and remove the noise or blur present in satellite images. This paper is very useful to the researchers and forecasters, as the loss in satellite image may have a greater impact than it seems. This project is developed in the view to be implemented on Austin satellite images.

B. FUTURESCOPE:

This project can be enhanced further by adding the new images that are taken which are not in the database into the model. It can also be extended to include satellite images of any location on the earth. This project can also be extended to further increase the resolution of the image after de-noising or de-blurring.

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