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# USING GENERATIVE ADVERSARIAL NETWORKS (GAN) TO CORRECT BANDING ERRORS IN SATELLITE IMAGES

**Kadapala anjaiah**
Research scholar in computer science and engineering, Osmania University, Hyderabad Telangana.
Email: kadapala.anjaiah@gmail.com

**Dr. K. Sagar.**
Professor and vice principal
Sreyas institute of engineering and technology,
Mail: Sagar.k@sreyas.ac.in

## ABSTRACT

This article presents a novel approach based on Generative Adversarial Networks (GAN) for fixing banding issues in satellite images. Small satellites are routinely sent into orbit to gather imagery for use in commercial endeavours, urban planning, scientific and military research, and other purposes. Its tiny cameras, however, are more vulnerable to distortions brought on by atmospheric interference, such as geometric and radiometric inaccuracies. Using experimental data, the suggested approach was compared to the traditional correction procedure, and the results showed comparable performance (93.64% and 91.15% accuracy, respectively). These experimental findings imply that generative models using AI (Artificial Intelligence) technologies, particularly Deep Learning, are approaching the point at which automated correction approaches traditional methodologies. GAN models have the advantage of automating the process of correcting banding in satellite images, cutting down on processing time, and enabling processing without the need for previous technical expertise in Geographic Information Systems (GIS). This method has the potential to be an important tool for processing satellite images, increasing the process's efficiency and resulting in more accurate findings. The study has practical implications for a number of businesses and is especially pertinent to the realm of remote sensing.

Keywords: deep learning, artificial neural network, satellite images, generative adversarial network, banding, radiometric error

## 1 INTRODUCTION

The number of nanosatellites and tiny satellites launched in recent years has significantly increased due to the desire to explore space at a cheap cost and high benefit ratio. Due to its affordable prices, this trend mostly helps nations that are just starting out in the space industry.

Earth observation satellite launches into orbit for a variety of uses are growing more frequent among academic institutions, the public and commercial sectors, and other organisations. Due to this circumstance, satellite images may now be used for different purposes, including scientific study. Countries venturing into space are increasingly integrating the compact and light CubeSat nanosatellites into their missions in order to save expenses. These satellites capitalise on the widespread use of low-E orbits.

Payload capabilities are constrained by the size and cost of satellites. where optical sensors are used to assist the mission, there are instances where the resolution and image quality suffer. For instance, radiometric or geometric errors and other distortions brought on by atmospheric interference are more likely to occur with medium and low-resolution cameras, which significantly deteriorates the displayed image. This issue even rose to the top of the list of reasons to reject a photograph.

Presently, specialised software and other image enhancing techniques are used in traditional corrective approaches. With the use of this programme, professionals that handle and process photographs must invest a significant portion of their time and expertise to enhance the acquired image's visualisation.

The purpose of this research is to show and evaluate the outcomes of using multiple generative adversarial networks (GAN) as a substitute correction technique for a specific radiometric inaccuracy known as banding. One of the most frequent mistakes in satellite photos is banding.

**MOTIVATIONS AND CONTRIBUTIONS:**

These days, it is more important than ever to have access to a large collection of satellite photos in order to analyse the many elements that influence the Earth's surface. Furthermore, research to remove radiometric inaccuracies like banding is crucial given the increasing frequency of Earth observation nanosatellite launches, which have a favourable cost-relation. These mistakes greatly limit the quantity and quality of images that can be obtained, which presents a chance to further novel initiatives and research in remote sensing jobs that use non-traditional techniques. A possible way to take use of these developments and enhance remote sensing is via the application of deep learning algorithms for image processing, as documented in recent papers.

The contributions of this work are summarized as follows:

A GAN-based technique for fixing banding issues. According to the findings of the evaluations based on experimental data, the suggested approach and the traditional method perform statistically similarly (accuracy of 91.15% and 93.64%, respectively).

the process of creating a banding error-filled satellite image data collection. There are 7607 images in this data collection, each measuring 256 by 256 pixels. Other methods in the same application may be assessed using this data set as a benchmark.

using the structural similarity index measure (SSIM) as a metric to assess the improvement in banding error correction that results from the use of GAN. This statistic quantifies the degree to which the processing of generative algorithms degrades a image.

This is how the current manuscript is organised: Section I with the introduction, Section II with related work, Section III with Methodology, Section IV with

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Experiments and the results, section V with conclusion and section VI with References.

**PROBLEM DESCRIPTION**

In order to rectify inaccuracies resulting from interferences, which have the ability to alter the information contained in satellite photos, certain approaches must be applied. These mistakes might be caused by air interferences, malfunctioning sensors, satellite movement interruptions, or image capturing processes. These mistakes cause the satellite image to become warped since they consistently change the values of the pixels. For instance, there are two sorts of incorrect pixels in radiometric corrections: one that needs filter applications and upgrades, and the other that has to do with pixel loss, or banding [1].

FIGURE 1. Adapted from [3]. Examples of areas having banding problems in Landsat-7 images.

Correcting these mistakes is essential, since maintaining the terrain's right visualisation would require restoring information lost in the photos. While traditional methods, including the use of Geographic Information Systems (GIS), may be able to solve these problems, their implementation calls for a substantial time commitment and previous technical expertise. In order to provide results that are comparable to those produced using GIS tools, this work intends to construct generative models to allow the automated correction of pixel line drop errors (banding).

**2 RELATED WORK**

By transforming images from a source domain to a target domain, image-to-image (I2I) processing has addressed a number of image processing problems and produced acceptable outcomes for semantic image synthesis [21], image segmentation [22], style transfer [23], and image/video colorization [24]. Image inpainting is one of the techniques included in the literature study; it is comparable to banding correction. In order to fill in the blank spots in a image, Pathak et al. [25] developed an unsupervised learning system for image inpainting that uses context-based pixel prediction (Figure 2). The feature of a context encoder, a convolutional neural network trained to produce the contents of any given visual area conditioned on its surroundings, powers the method.

Additionally, certain GAN use cases have shown how very promising they are for analysing aerial and satellite images. Among many other works that have been implemented to generate completely new satellite images, as presented in [31] and [32], is one such well-known case that involves automatically converting satellite images to maps and vice versa (Figure 3). This conversion has been explored and presented in numerous research studies and projects, including [26], [27], [28], and [29]. More specifically, in [32], they trained a PGGAN network model to produce artificial satellite photos of rivers that looked realistic.

## 3 METHODOLOGY

Any satellite may have banding, a mistake that manifests as the loss of successive pixel rows and columns (Figure 1). Banding is the result of an optical sensor malfunction. Some Landsat-7 satellite photos provide a good illustration of this inaccuracy. The Scan Line Corrector (SLC), a part that corrects for the satellite's forward motion, malfunctioned in May 2003, causing a contingency that led to this issue [2]. The United States Geological Survey (USGS) offered instruments for its correction using rectification techniques when this happened. Using GIS-style application tools is another common way to rectify banding. By using the image's front and back lines to designate an average value between the missing lines, these tools allow for modifications to be made.

### 3.1 Image-to-image translation

The process of image-to-image translation, or I2I, has received a lot of attention lately. Furthermore, significant advancements have been made in application development concerning the resolution of computer vision and image processing problems, including posture estimation, image synthesis, segmentation, style transfer, and restoration. The goal of the image-to-image (I2I) process is to transfer images, both supervised and unsupervised, from a source domain to a destination domain while maintaining content representations [4].

The I2I method, in general, transfers the destination extrinsic style and preserves the intrinsic content of the source domain "A" while converting an input image to the target domain "B" [5]. A well-known example of this may be seen in [6], where a image of a horse from the source domain gets "translated" into a zebra.

### 3.2 Generative adversarial network

Image-to-Image (I2I) tasks are based on the Generative Adversarial Network (GAN), a neural network architecture specialised in image production. The GAN model was first presented by Goodfellow et al. in 2014 [7] in order to produce images computationally that seem realistic to human perception. Using an adversarial method, this architecture offers a unique framework for generative model estimation. A generator network ("G") records the distribution of data, while a discriminator network ("D") calculates the probability that a sample comes from training data rather than generator network "G." These two networks are trained simultaneously in this procedure. The process of "G"'s training maximises the likelihood that "D" will make a mistake. In [8], for example, human faces are produced by a GAN model given a random input data distribution (noise).

### 3.3 Pix2Pix

Using paired training data, Pix2pix is an image-to-image (I2I) supervised training network. As a result, pre-converted photos from one domain to another via other methods must be accessible in order to build a dataset during model training [9]. A conditional Generative Adversarial Network (cGAN) framework is the source of this methodology [10]. The discriminator and generator artificial neural networks are trained as part of the Pix2pix architecture. "U-Net" is the name of the convolutional autoencoder type used in the generator architecture. According to references [11] and [12], autoencoders are neural networks made up of an encoder and a decoder. While the decoder recreates the compressed information as precisely as feasible from the encoder's latent space, the encoder reduces the amount of information in the input data by compressing it.

Specialised versions of autoencoders known as Convolutional Autoencoders (CAE) [13] employ deconvolutional layers in order to reconstruct image information from the compressed latent area representation after using convolutional layers to extract feature maps from input images via map compression.

Like autoencoders, the U-Net [14] makes use of the ideas of map compression and latent space representation. Furthermore, it creates skip connections between the layers of the encoder and decoder, which aid in resolving a number of challenges related to input-to-output (I2I) since inputs and outputs exchange a large quantity of low-level information. Transferring them straight via the network is beneficial.

The discriminator in pix2pix training [15] is a binary classifier that is fed both the generated image and an example of the desired image's appearance. The discriminator then determines whether these images are "true" or "false." After that, an error is computed and input into the autoencoder to enhance the produced images and modify weights in order to overcome the discriminator.

**3.4 Cyclegan**

Zhu et al. (2017) introduced CycleGAN, a deep learning technique for unsupervised image-to-image (I2I) translation [16]. In contrast to Pix2pix, CycleGAN needs several image samples from each domain rather than paired training data. For instance, in [17], images of horses were converted into images of zebras, with images of horses in domain (A) and images of zebras in domain (B). Images of horses may optionally be manually converted to zebras.

Two discriminators and two generators make up the CycleGAN architecture. The generators are comparable to Pix2pix's autoencoders. In contrast, discriminators use the PatchGAN approach. The PatchGAN architecture is simply a convolutional neural network that maps the image to a N × N-sized matrix output, as described in [18], [19], and [20]. Every value in the matrix corresponds to the image patches' "true" or "false" values. Loss functions are computed to optimise and update the generators throughout the CycleGAN training process using the generators and discriminators. These losses correlate to two opponent losses, as explained in [16]: an identity loss for each generator and a cycle consistency loss.

## 4 METHODOLOGY

### 4.1 Dataset creation to train generative adversarial networks models

We looked through the United States Geological Survey's (USGS) EarthExplorer programme to get a training dataset for the pix2pix and CycleGAN networks. Initially, we extracted photos from the Landsat-7 satellite that had banding problems and compared them to those that didn't. Eight distinct spectral bands and full information were included in each of the 105 photos that we received (Figure 3 shows a image that has two of the bands in TIFF format). After that, we merged the RGB bands to create natural-colored photos, which we then exported in JPEG and PNG formats (Figure 5).

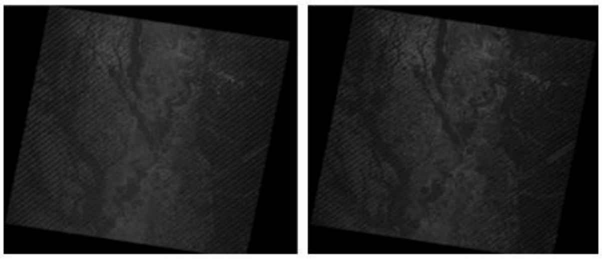

FIGURE 2. Adapted from [3]. Landsat-7 obtained this two-band image. Left: the satellite's blue band (B). Green bar (G) on the right.

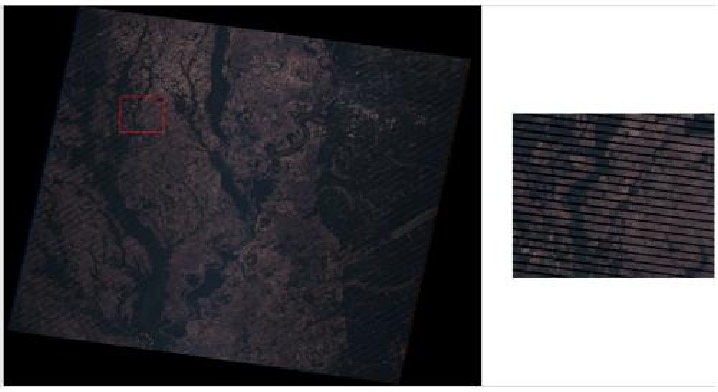

FIGURE 3. Band combination for banded real image colour. Left: the whole image. Right: banded image magnification in a specific location.

Upon closer inspection, banding was seen in each image band, resulting in pixel loss shown as continuous black lines (refer to Figure 4). Moreover, the presence of black lines in every band made this problem visible in the combined RGB image.
The first studies concentrated on using the Landsat Toolbox tool in ArcGIS Pro, which has a dedicated method for repairing flaws in Landsat-7 images, to correct radiometric banding. The three bands are then blended into an RGB image following this adjustment, which has to be done independently for each band. Obtaining reference is the main goal of this ArcGIS Pro adjustment.

FIGURE 4. Taken from [3]. Evidence of banding in one of the spectral bands.

FIGURE 5. Composite of band-corrected, band-free images for true colour. Left: the whole image. Right: a section of the image that has been enlarged without any banding.

Images for every original image, removing banding, and use these images as training data for the I2I dataset training procedure. An example of the final composite image produced by ArcGIS Pro image correction is shown in Figure 5. Experiments were carried out on many photos by using a comparable technique with the ArcGIS tool, combining Landsat-7's band 4—which corresponds to the NIR process—with bands 3 and 2 to provide valuable infrared images for vegetation study. In order to find possible model adaption in multispectral image processing and take into account their uses in future projects, these photos were included in the research. An illustration of the outcomes achieved using the NIR band is shown in Figure 5.

TABLE 1. Data set structure.

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| Set | Type of image | Number of samples |
|---|---|---|
| Training | With banding (inputs) | 6086 |
| | Without banding (ground truth) | 6086 |
| Validation | With banding (inputs) | 1141 |
| | Without banding (ground truth) | 1141 |
| Testing | With banding (inputs) | 380 |
| | Without banding (ground truth) | 380 |

The dataset was reexamined, removing the mentioned examples, in order to resolve this problem. In the end, 7,607 images—both with and without banding—for every class were acquired. Table 1 illustrates how these photos were split into three sets: training (80%), validation (15%), and testing (5%).

**4.2 Training of pix2pix and cyclegan models**

The generated dataset used as training data for a pix2pix model network. The training was conducted on a workstation equipped with an NVIDIA Quadro P5000-16 GB graphics/video card, an Ubuntu 18.04 operating system, a GPU, and 32 GB of RAM. Because of their network topology and the large number of trainable parameters they generate—more than 54 million in this instance—GANs demand a significant amount of memory. This, together with the computational weight of the photos, caused the GPU RAM to fill up to capacity, which in turn caused a CUDA error [34] that stopped programme execution. In order to get around this problem, the training method included a preprocessing phase that reduced the size of the images to 256 × 256 pixels when they were loaded. Because this method uses less memory, the code may run smoothly and without any errors. Partial validations were recorded for every epoch throughout the neural network training process, which showed that the generator outcomes would change with each training cycle until an equilibrium was achieved. As a result, the generator can rectify banding in different satellite photos, whether the colours are real or infrared.

TABLE 2. Comparison of the suggested techniques with the conventional approach in 12 assessments using the SSIM measure.

| Label | SSIM | | | |
|---|---|---|---|---|
| | Pix2pix | CycleGAN before Fine-Tuning | CycleGAN after Fine-Tuning | Traditional method (ArcGIS) |
| Image 1 | 0.6526 | 0.8838 | 0.8868 | **0.9016** |
| Image 2 | 0.6348 | 0.7686 | 0.8486 | **0.9583** |
| Image 3 | 0.7333 | 0.9454 | 0.9395 | **0.9511** |
| Image 4 | 0.8558 | 0.9284 | 0.9375 | **0.9975** |
| Image 5 | 0.7567 | 0.9178 | 0.9528 | **0.9893** |
| Image 6 | 0.7340 | 0.8107 | 0.8927 | **0.9733** |
| Image 7 | 0.7767 | 0.8372 | 0.9211 | **0.9990** |
| Image 8 | 0.6994 | 0.8185 | **0.8245** | 0.7784 |
| Image 9 | 0.6398 | 0.8321 | **0.8351** | 0.8338 |
| Image 10 | 0.8430 | **0.9234** | 0.9184 | 0.8518 |
| Image 11 | 0.8719 | 0.9004 | 0.9145 | **0.9614** |
| Image 12 | 0.6643 | 0.9057 | **0.9347** | 0.9216 |
| **Average** | **0.7385** | **0.8727** | **0.9005** | **0.9264** |

## 5 CONCLUSION AND FUTURE WORK

According to the assessment findings, CycleGAN performed better at repairing banding defects in photos that were not part of the training dataset than pix2pix. CycleGAN's exceptional performance is explained by its capacity to adjust to unanticipated events. Furthermore, both neural networks showed strong infrared image adaptation, suggesting that generative models might be used to interpret multispectral images taken by different optical sensor satellites. This discovery will be useful in further initiatives. The suggested approach, which uses artificial neural networks to analyse and rectify satellite images with banding, offers a number of benefits over the traditional approach, most notably a reduction in the amount of time needed for correction [38]. The traditional approach takes a long time and requires technical know-how to utilise GIS software functionalities appropriately. On the other hand, using CycleGAN to perform the suggested approach might process the composite image directly and automate this work without requiring any previous technical expertise (visible colour or with near-infrared compositing).

Additionally, putting the suggested strategy into practice would reduce the price of licencing GIS programmes like ArcGIS. Finally, the findings show that there are often no appreciable changes between the images generated by the two approaches, which implies that the GIS software may be replaced. There are several restrictions with the created GAN algorithm. One of them has to do with hardware and processing power since huge satellite images need significant memory capacity for deep neural network models to function. In order to improve error correction on bigger images, it was first required to adjust the dataset's data and fine-tune the network in order to get around memory constraints. Memory, however, places a restriction on the largest image size. The biggest image that could be processed on a 16 GB GPU without causing a CUDA error because of memory constraints was around 3500 × 3000 pixels. This size is still inadequate, however, since satellite photos with more than 10,000 pixels in both height and breadth may be found. As a result, the algorithm has to include a feature that enables the image to be divided into smaller parts for processing, with the ability to adjust each part independently and then reassemble the segments with the same brightness and contrast. This will enable immediate processing of big satellite photos.

Furthermore, this study was carried out in parallel with a project that used convolutional neural networks to identify patterns associated with unlawful mining. The goal of this study was to enhance photographs that were not in a good enough state to distinguish things in aerial or satellite photos. Starting with the banding correction, the use of GANs was investigated as a potential replacement for manual performance of these adjustments. Future study will look at using GANs for more image adjustments, such as adding filters and improvements, since they have shown the ability to handle satellite photos. These adjustments, which are also a component of the radiometric corrections, include atmospheric adjustments like clearing out dense clouds or reducing haze, as well as balancing histograms (pixel values).

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