International Journal of Scientific Research & Engineering Trends
Volume 10, Issue 6, Nov-Dec-2024, ISSN (Online): 2395-566X

Colourization of SAR Image Using Generative Adversarial Network

Dr. D. Suresh, P. Rakshitha, V. Manasa Aparna, V. Chaitanya Sai Kumar, S. Vamsi Krishna
Electronics and Communication Engineering
GMR Institute of Technology, Rajam.

Abstract- Employing generative adversarial networks, specifically with regard to cycle consistency loss and mask vectors, mainly concentrates on the colorization of Synthetic Aperture Radar (SAR). Most SAR imagery is devoid of chromatic information. Contemporary deep learning techniques are the predominant approach for SAR colorization. The methodology proposed herein employs a multidomain cycle-consistency generative adversarial network (MC-GAN). It enhances performance through the integration of a mask vector and cycle-consistency loss. The approach does not necessitate the availability of paired SAR-optical imagery. The multidomain classification loss contributes to the precision of the color output. The methodology has been evaluated using the SEN1-2 dataset for urban and terrain areas.

Index Terms- Deep Learning, Deep Neural Network, Generative Adversarial Network, Multidomain Cycle-Consistency Generative Adversarial Network, Mean Square Error, Peak Signal-to-Noise Ratio, Red-Green-Blue, Synthetic Aperture Radar, Structural Similarity Index Measure, Pix2Pix.

I. INTRODUCTION

Synthetic Aperture Radar (SAR) is a radar technology that generates high-resolution images of landscapes, surfaces, and structures from aerial or space-based platforms. SAR systems transmit radio waves and measure the temporal delay of the reflected signals upon encountering an object, thereby producing detailed imagery. In contrast to optical imaging systems, SAR possesses the capability to operate under diverse meteorological conditions, irrespective of diurnal cycles, rendering it particularly advantageous for remote sensing applications in domains such as environmental monitoring, topographical analysis, and military reconnaissance. Colourization of synthetic aperture radar (SAR) images is crucial for enhanced interpretation, as these images are typically monochromatic and lack colour information. Colourization refers to the process of adding colour to black-and-white images, such as photographs or films. This technique helps make historical images more relatable or refreshes old movies and shows for modern viewers. Colour plays a very crucial role in the process of human cognition of the world, and rich colours. There are different types of input to be colourized, and the methods to colourize can be divided into two broad categories, one is the colourization of grayscale images and black-and-white videos which are ordinary photos without colour, and the other is colourization of monochrome art forms. These activities span a wide range of sectors, including environmental management, agriculture, urban planning, and disaster management. For example, in agriculture, fully polarimetric SAR can improve crop classification and soil moisture estimation, while in disaster management it can enable detection and analysis of major flood or seismic areas it has been done. There are various techniques used for the colorization of SAR images likewise Image Segmentation, RGB Compositing, Pseudo color Mapping, Fusion with Optical Data, and Deep Learning-Based Colorization. In RGB compositing, if there are multi-frequency SAR data (e.g. X-band, C-Band, and L-Band) the pixels of these bands can be transformed into 3 RGB channels, and for the Polarimetric SAR, polarimetric channels (HH, HV, VH, VV) are assigned to RGB channels. For example, HH might be assigned to the red channel, HV to green, and VV to blue. In Pseudo-colour mapping there are three different types of mappings exist which are: Intensity-Based Mapping, Histogram Equalization, and Gradient-Based Mapping. In Intensity Based Mapping a single-channel SAR image is colourized by assigning colours based on their pixel intensity values, as like grayscale to heatmap conversion. In Histogram Equalization the histogram of the image is equalized or it is stretched and then the colour mapping is applied to the image to enhance, before colorization of the image.

The use of Deep Neural Networks is crucial in this process because it can able to take complex structures and relationships of data. There are 8 different types of networks are there in Deep Neural Networks. This process involves

Generative Adversarial Network (GAN). While GANs aren't always superior to other networks, they do particularly well at data generation and creative applications. They have an advantage in situations where these kinds of outputs are crucial since they can generate realistic, high-quality data with less oversight. They are most appropriate for situations where these benefits are crucial, nevertheless, because of their complexity and training challenges. Designed to execute image-to-image translation across several domains concurrently, the Multi-Domain Cycle Consistency GAN (MD-Cycle-GAN) is an expansion of the Cycle-GAN paradigm. Within a single framework, MD-Cycle-GAN facilitates transformations across multiple domains, in contrast to standard Cycle-Gans that concentrate on translating between two distinct domains. By preserving cycle consistency, it makes sure that the original image is preserved while converting an image from one domain to another. When numerous transformations are needed in a single system, such as in multi-style transfer and domain adaptation, this paradigm is especially helpful [1] in the MC-GAN colourization of SAR images for terrain-specific colouring. Overcomes cycle-consistency loss's restrictions on paired data. MC-GAN uses multidomain classification loss to improve the colouring of SAR images.

II. LITERATURE REVIEW / BACKGROUND

[1] In the study "SAR Image Colorization Using Multidomain Cycle-Consistency Generative Adversarial Network, the problem of colouring grayscale, complicated information-rich Synthetic Aperture Radar (SAR) images. Due to its capacity to provide high-resolution images in a variety of settings, SAR imaging is essential for remote sensing. However, conventional colorization techniques, which are frequently manual or heuristic, have had difficulty capturing context and features. Image processing has been transformed by recent developments in deep learning, especially the rise of generative adversarial networks (GANs). High-quality synthetic images can be produced using GANs, which are made up of a generator and a discriminator that work inside a game-theoretic framework. Since paired datasets for SAR pictures are frequently difficult to obtain, the Cycle GAN framework—which permits unpaired image-to-image translation while maintaining semantic meaning through cycle consistency. The substantial domain transfer presented by SAR images is still a problem, despite the fact that several neural network architectures, such as convolutional and fully convolutional networks, have been used for image colorization. Through multidomain translation using the Cycle GAN framework, the authors successfully present a unique method that demonstrates significant gains in the perceived quality of colorized SAR pictures [1]. This aimed at increasing training datasets and improving generalization in remote sensing applications by highlighting the potential of combining contemporary deep learning techniques with conventional image processing methods.

[2] In the paper "Radar Image Colorization: Converting Single-Polarization to Fully Polarimetric Using Deep Neural Networks," tackles the problem of improving radar imaging by using deep learning techniques to transform single-polarization radar images into fully polarimetric representations. By using several polarization states, polarimetric radar systems are able to acquire more specific information about targets, which improves radar data classification and interpretation. However, it can be expensive and logistically difficult to obtain fully polarimetric data; hence, it is crucial to create techniques that can deduce this information from single-polarization photos. The authors highlight how deep neural networks (DNNs) may capture complicated information that standard approaches might overlook by using them to learn the intricate correlations between single-pol and fully polarimetric images. The efficiency of earlier radar imaging studies in effectively modelling the high-dimensional relationships present in polarimetric data has been limited by their frequent reliance on statistical approaches or more basic machine learning techniques. The authors show notable improvements in the quality of the produced polarimetric images by using a deep learning methodology, exhibiting greater realism and detail compared to earlier methods [2]. In addition to demonstrating DNNs' ability to handle radar image enhancement tasks, this study paves the way for further research aimed at refining neural network architectures for particular radar applications and growing datasets to enhance model performance and generalization in a range of operational scenarios.

[3] In the paper "A Benchmarking Protocol for SAR Colorization: From Regression to Deep Learning Approaches," provides a thorough benchmarking framework designed to assess and contrast different approaches to colorizing SAR images. This effort is motivated by the growing interest in improving the visual quality and interpretability of SAR images, which are often displayed in grayscale. The authors thoroughly examine current colorization techniques, pointing out the advantages and disadvantages of each, ranging from sophisticated deep learning algorithms to conventional regression methods. Although recent deep learning models show promise in producing more realistic and contextually appropriate colorizations, previous methods frequently rely on simplistic models that may not be able to fully capture the complex relationships inherent in SAR data. By identifying successful tactics and directing future study, the report highlights the value of establishing uniform criteria to enable fair comparison among various approaches, which can promote developments in the field. The authors hope that by creating a uniform framework for assessing performance indicators, datasets, and procedures, this benchmarking process would encourage innovation and reproducibility in SAR colorization

research. This work lays the groundwork for future advancements in remote sensing applications, where better colorization of SAR images can greatly increase the ability to analyse and comprehend data.

[4] In this regard, the authors hope that by creating a uniform framework for assessing performance indicators, datasets, and procedures, this benchmarking process would encourage innovation and reproducibility in SAR colorization research. This work lays the groundwork for future advancements in remote sensing applications, where better colorization of SAR images can greatly increase the ability to analyse and comprehend data. paper [4] describes the "CFCA-SET: Coarse-to-Fine Context-Aware SAR-to-EO Translation with Auxiliary Learning of SAR-to-NIR Translation. The author presents a new method for converting SAR images to EO images by employing a coarse-to-fine framework that prioritizes context awareness. Remote sensing applications are significantly impacted by the conversion from SAR, which offers useful information in a variety of weather conditions but lacks visual features, to EO imaging, which is rich in colour and detail. By adding extra training for SAR-to-near-infrared (NIR) translation, the suggested approach makes use of auxiliary learning, enabling the model to use complementary spectral information to improve the quality of the translated EO images. This dual strategy preserves the contextual integrity of the radar data while simultaneously enhancing the resulting EO images' realism and visual accuracy.

[5] This paper describes the "CFCA-SET: Coarse-to-Fine Context-Aware SAR-to-EO Translation with Auxiliary Learning of SAR-to-NIR Translation. The author presents a new method for converting SAR images to EO images by employing a coarse-to-fine framework that prioritizes context awareness. Remote sensing applications are significantly impacted by the conversion from SAR, which offers useful information in a variety of weather conditions but lacks visual features, to EO imaging, which is rich in colour and detail. By adding extra training for SAR-to-near-infrared (NIR) translation, the suggested approach makes use of auxiliary learning, enabling the model to use complementary spectral information to improve the quality of the translated EO images. This dual strategy preserves the contextual integrity of the radar data while simultaneously enhancing the resulting EO images' realism and visual accuracy. The authors thoroughly compare their approach to other approaches and show that it performs better in terms of both quantitative and qualitative measures. This study advances the state of the art in SAR-to-EO translation approaches by tackling domain adaptation issues and utilizing contextual information.

[6] The paper introduces also suggests promising avenues for future research in the integration of multimodal remote sensing data. More efficient use of SAR imaging in a variety of applications, such as disaster management, urban planning, and environmental monitoring, is made possible by the CFCA-SET architecture. paper [5] presents a novel method for image-to-image translation in their paper, "Image-to-Image Translation with Conditional Adversarial Networks." This method makes use of conditional generative adversarial networks (c GANs) to facilitate flexible transformations between various image domains. Because it offers a unified model that can learn intricate mappings from input images to corresponding target images across a variety of tasks—like converting semantic segmentations into realistic images, translating sketches into photorealistic renders, or altering images with different styles—this work is crucial to the field of computer vision. In order to improve the relevance and coherence of the generated images, the authors stress the significance of using conditional inputs, which enable their generator to produce output images conditioned on a specific input [6].

[7] The paper introduces a authors stress the significance of using conditional inputs, which enable their generator to produce output images conditioned on a specific input [6]. They successfully train the discriminator and generator by using adversarial training, which optimizes the generator to create realistic-looking images while preserving the semantic context of the input data. The effectiveness of the framework is demonstrated in the study using a variety of datasets, with remarkable outcomes in terms of preserving input fidelity and producing outputs of superior quality. By offering a solid methodology that has sparked numerous follow-up investigations and applications, this study dramatically advances the field of image translation and demonstrates the revolutionary potential of deep learning techniques in altering and producing visual content for a range of applications, including practical computer vision tasks, art, and design [7]. Overall, the work by Isola et al. marks a critical milestone in the evolution of adversarial networks, reinforcing their role as a fundamental tool in image synthesis and manipulation.

III. METHODOLOGY

the focus is on colorizing SAR images through deep learning models with special emphasis on GANs; such colorized images are easily interpretable than the usual monochromatic ones. Preprocessing of the SAR data is performed, then a GAN model that includes the Generator, which synthesizes colorized images and the Discriminator, which decides the realism of said images. The model is trained to make radar intensities correspond with natural color representations by using adversarial and perceptual loss functions. Once trained, the GAN can colorize new SAR images with preserving the features of terrain and structures. As this part of the task is computationally heavy, it is only done once after processing is complete; metrics such as PSNR and SSIM are used to

International Journal of Scientific Research & Engineering Trends
Volume 10, Issue 6, Nov-Dec-2024, ISSN (Online): 2395-566X

determine performance. These colorized images enhance the understandability of SAR data for application in areas such as environment, urban, and disaster management.

Following figure Fig.1 shows the colorization of SAR image using GAN:

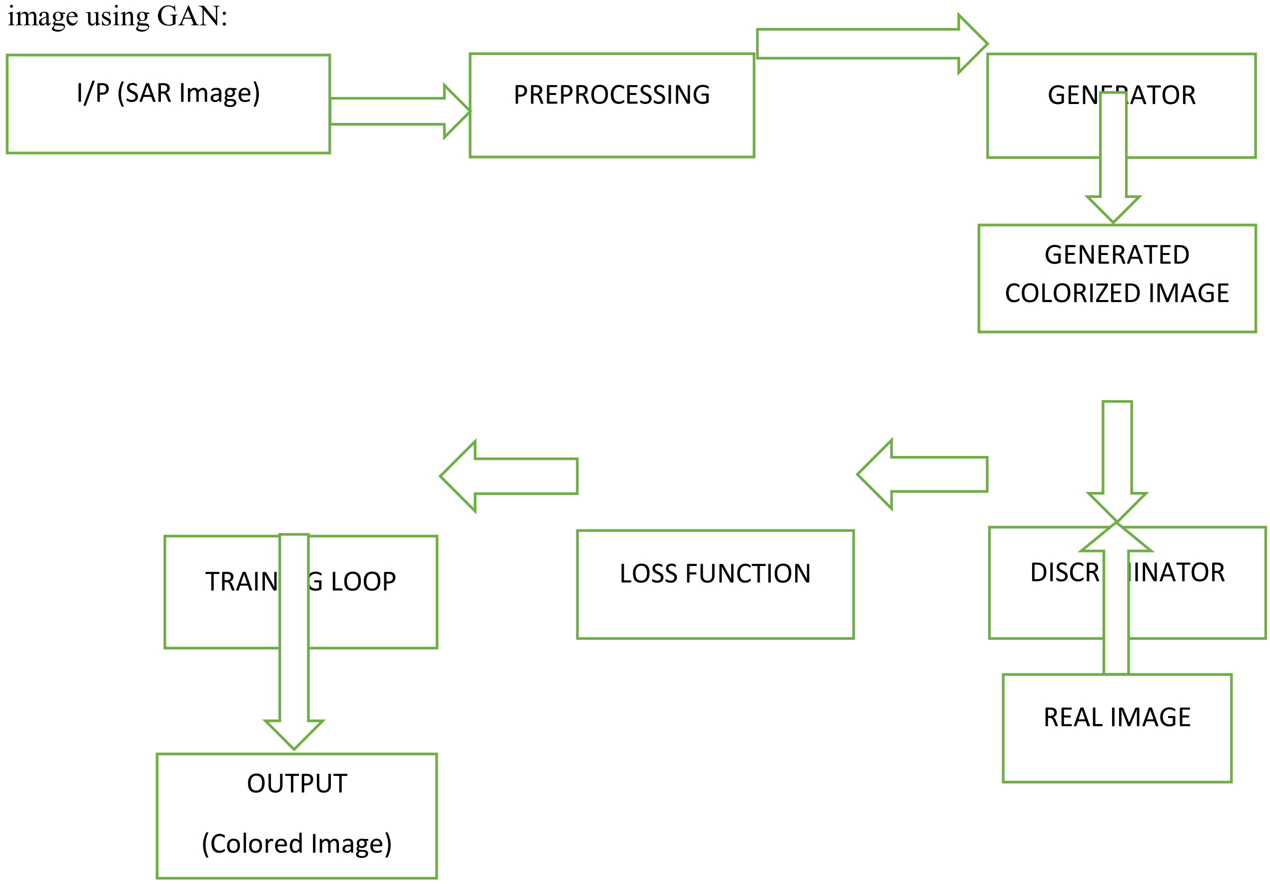

Fig.1: Implementation for the colorization of SAR Image using GAN

I. **Generative Adversarial Networks (GAN)**:

The two main parts of Generative Adversarial Networks (GANs) are:

Generator(G): Synthetic Aperture Radar (SAR) grayscale images are converted into coloured images in this instance via the generator (G). From the raw grayscale data, it creates realistic, high-resolution colour images using convolutional layers and up sampling algorithms.

Discriminator(D): Classifying images as "real" (authentic) or "fake" (produced by the generator) is the discriminator's (D) job. By giving the generator feedback on how well it is simulating real-world visuals, it serves as a critic, assisting the generator in producing better results.

The discriminator attempts to accurately distinguish between created and actual images, while the generator attempts to trick the discriminator into accepting generated images as real. The two networks cooperate. Over time, the generator becomes more effective at creating realistic, compelling images due to this adversarial process.

II. **Loss function:**

In a GAN, the loss function is crucial for training the discriminator and generator through optimization and backpropagation.

International Journal of Scientific Research & Engineering Trends
Volume 10, Issue 6, Nov-Dec-2024, ISSN (Online): 2395-566X

explanation of the loss function's operation is following:

Input Generation:
Both real photos from the dataset and fake ones produced by the generator are fed into the discriminator.

Discriminator Loss Calculation:

The discriminator's loss is determined by calculating how well it can identify created (false) images as fake and real images as authentic. Usually, binary cross-entropy is used by this loss function to measure classification accuracy. Poor performance in differentiating between actual and false images is indicated by a higher loss.

Generator Loss Calculation:

The degree to which the generator is able to fool the discriminator into considering its faked images to be authentic determines how much it loses. Over time, this loss motivates the generator to create increasingly realistic images.

Backpropagation:
Following the computation of the discriminator and generator losses, backpropagation modifies the network's weights according to their individual errors.

This enhances the discriminator's capacity to accurately classify pictures.
It improves the generator's capacity to create visuals that fool the discriminator.

III. Optimization:

To reduce both the discriminator and generator losses, an optimization technique is used, usually a random gradient descent (SGD) or a variation like Adam. While the discriminator minimizes its classification mistake, the generator minimizes the loss of fooling the discriminator.

Training Iteration:

Over a large number of steps (epochs), the process is repeated iteratively. With each iteration, both networks are improved, enabling the discriminator to distinguish between real and fake photos and the generator to create better, more realistic colorized images.

IV. Evaluation:

Two metrics for the evaluation of the generated image are been used, those are PSNR (Peak Signal-to-Noise) and SSIM (Structural Similarity Index Measure)

PSNR: A metric to evaluate the quality of a generated image by comparing it to the original image.

PSNR Calculations:
MSE Calculation: Compute the Mean Squared Error (MSE) between the original and generated images.

$$MSE = \frac{1}{m * n}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2$$

where:

- I(i,j) is the pixel value at position (i, j) in the original image,
- K(i,j) is the pixel value at position (i, j) in the generated image,
- m*n is the total number of pixels.

PSNR Formula:

$$PSNR = 10\log_{10}\left(\frac{MAX^2}{MSE}\right)$$

where MAX is the maximum possible pixel value of the image(e.g.,255 for 8 bit images).

Interpreting **PSNR:**

High PSNR **(>30 dB):** The generated image is very close to the ground truth, with minimal distortion.
Low PSNR **(<20 dB):** The generated image has significant differences from the ground truth, indicating poor quality.

SSIM (Structural Similarity Index Measure):
Evaluates the structural similarity between two images.
Components:

Luminance: Compares brightness of the images

Contrast: Compares contrast levels of the images.

Structure: Measures local patterns like edges and textures.

Range:

- SSIM score ranges from **-1 to 1**.
- **1** = Perfect structural similarity.
- Lower values = Greater structural differences.

Usage: In SAR colorization, SSIM helps ensure the generated images maintain structural integrity compared to the original SAR images.

IV. EXPERIMENTATION AND RESULTS

The SAR Image of the terrain region has been taken as the input [Fig.2] and generated a coloured image by using Generative Adversarial network.

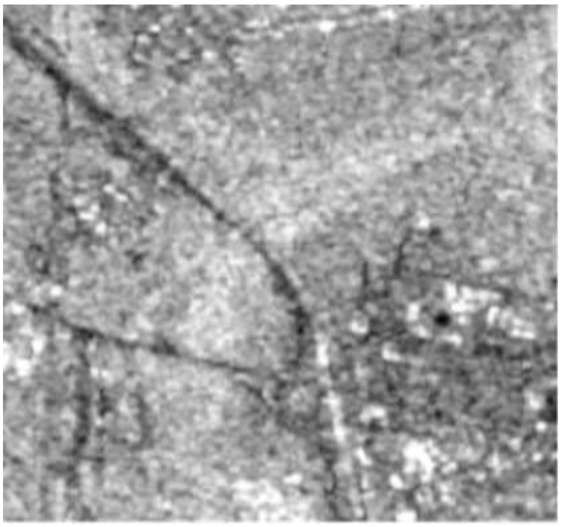

Fig.2. SAR Image of terrain landscape

The characteristics that stand out when a monochromatic image is colorized includes edging, shape and border segregation is easily discernible. This means that the color improves the sharpness or the acuteness of edges which are called also boundaries between the areas of different intensity of tone or colour while recreation objects in the image seem to be more prominent.

This transformation as used here aide in creating the dynamism and a well-structured image that is easy to interpret due to a clear focus on specific image aspects.

The generated coloured output image is as follows:

Fig.3. Generated Coloured image

From comparison between the result image [Fig.3] and input SAR image [Fig.2], we have extracted some detailing like borders, shape of the paths on the landscape. the circled shape in the following [Fig.4] gives the information about the vegetation at the area or zone and also it gives the information about the dark coloured region as the traces of water source.

As the input image that taken is a landscape of terrain it consists of plantation and barren or rocky land

So, colourization is also in green to enhance the visual perception of greenery on land

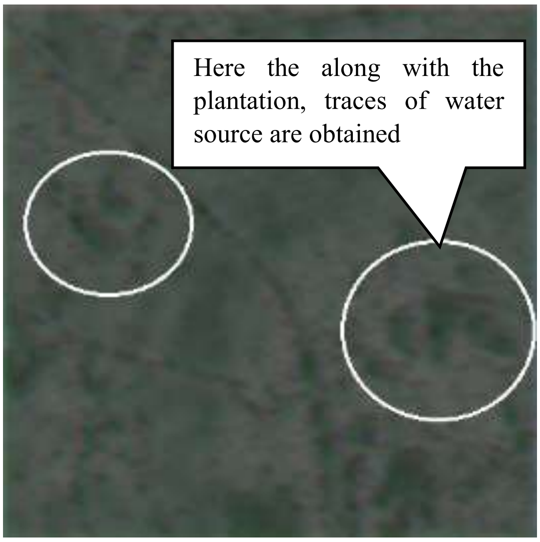

Fig.4. Marking Details of the generated image

International Journal of Scientific Research & Engineering Trends
Volume 10, Issue 6, Nov-Dec-2024, ISSN (Online): 2395-566X

Another two SAR images that are [Fig.5] &[Fig.7] of terrain landscape and the results of the respective generated coloured images [Fig.6] &[Fig.8] is seen as follows:

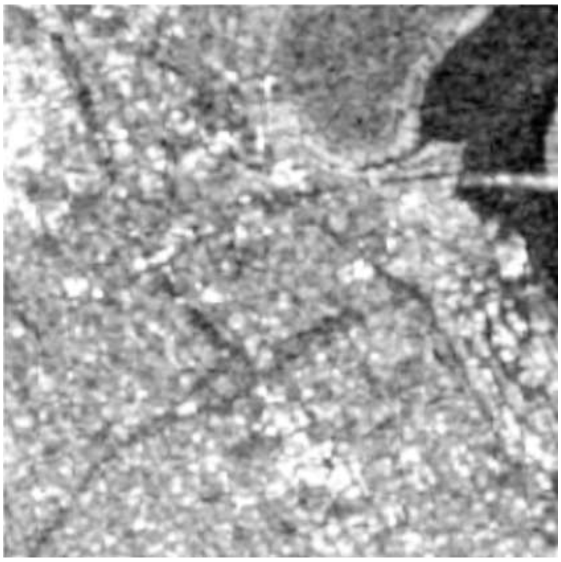

Fig.5. SAR Image of terrain landscape

Here, the green colour represents the plantation on the terrain area, where, as similar to the previous image output here the colourization is happened.

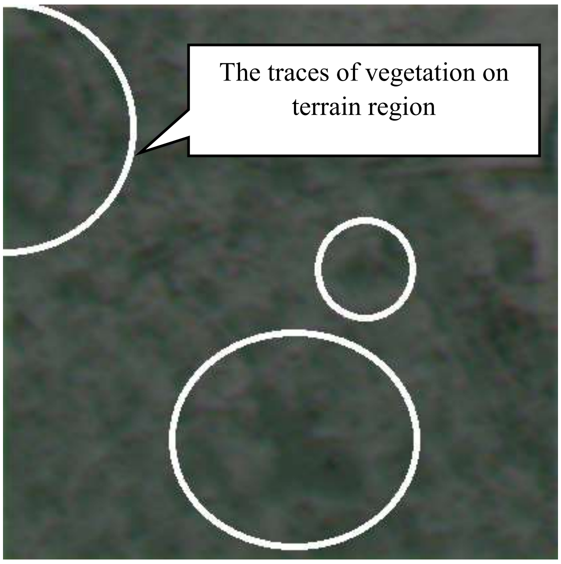

Fig.6. Coloured image of input2(terrain)

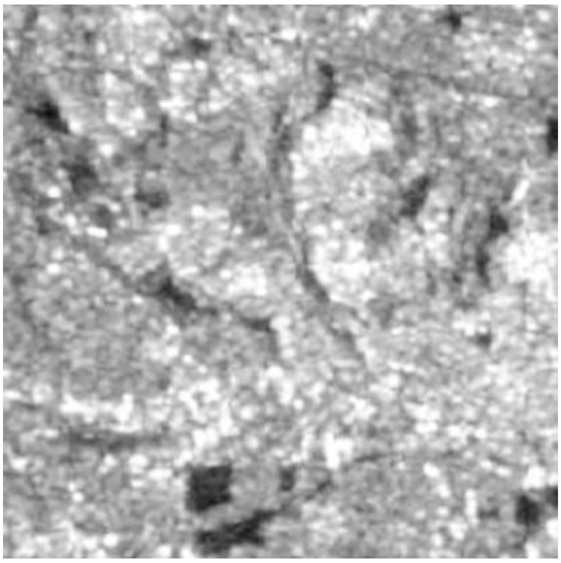

Fig.7. SAR Image of barren landscape

Here also, the vegetation area has been colorized by GAN, the result shows precise information about the greenery in the location it colorized the higher pixel value to the green based upon the intensity value of the pixel the level greenery is differentiated throughout coloured zone or area.

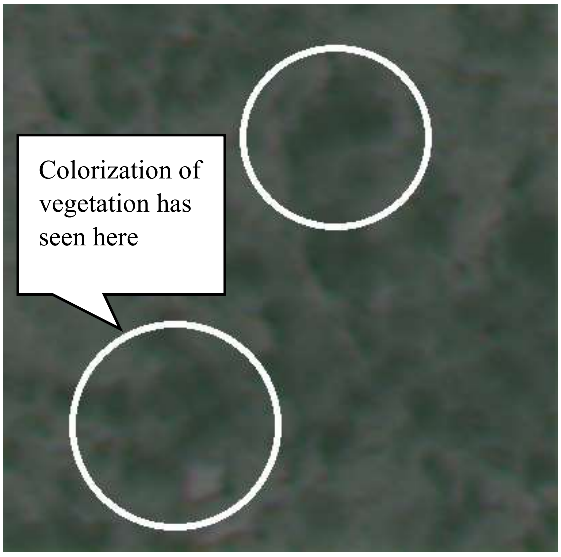

Fig.8. generated output image

V. CONCLUSION

In this paper, colorization of SAR Image is done using Generative Adversarial networks, where a coloured image is generated using networks along with methods such as cycle consistency and mask vector for better results. Thus, the extraction of specific feature of the images like their edges, density of plantation and its occupation in terrain areas as seen in results. Hence this could be useful in various fields such as, in agriculture, where we can perceive about the land data. Also useful at Urban Planning, disaster management and also in military reconnaissance for the information regarding the foe troops and their movements. Here, in the results it gives an idea about the traces of water source and also, vegetation in the remaining-coloured output images.

REFERENCES

1. Guang Ji, Zhaohui Wang, Lifan Zhou, "SAR Image Colorization Using Multidomain Cycle-Consistency Generative Adversarial Network" in Geoscience and remote sensing letters, vol. 18, no., 2021
2. Qian Song (Student Member, IEEE), Feng Xu (Senior Member, IEEE), and Ya-Qiu Jin, "Radar Image Colorization Converting Single-Polarization to Fully Polarimetric Using Deep Neural Networks" February 2018
3. Kangqing Shen, Gemine Vivone, Xiaoyuan Yanga, Simone Lolli, Michael Schmitt, "A Benchmarking Protocol for SAR Colorization: From Regression to Deep Learning Approaches" October 2021.
4. Qian Song, Student Member, IEEE, Feng Xu, Senior Member, IEEE, and Ya-Qiu Jin, Fellow, IEEE ," SAR Image Colorization: Converting Single-Polarization to Fully Polarimetric Using Deep Neural Networks.
5. Jaehyup Lee , Student Member, IEEE, Hyebin Cho, Doochun Seo Hyun-Ho Kim,Jaeheon Jeong," CFCA-SET: Coarse-to-Fine Context-Aware SAR-to-EO Translation With Auxiliary Learning of SAR-to-NIR Translation",2023.
6. M. Schmitt, L. H. Hughes, and X. X. Zhu, "The SEN1-2 dataset for deep learning in SAR-optical data fusion," 2018.
7. I. Goodfellow et al., "Generative adversarial nets," in Proc. Adv. Neural Inf. Process. Syst., 2014