SCHOOL OF COMPUTER SCIENCE AND ENGINEERING

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On

SAR Image Colorization for Comprehensive Insight Using Deep Learning Model

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This is to certify that project entitled “SAR Image Colorization for Comprehensive Insight Using Deep Learning Model” is a bonafied work carried out by the student team Dhanush L Bellakki(01FE21BCS330) , Vinod S Badni(01FE21BCS305) , Suprit B(01FE21BCS292), Darshan Mudakavi(01FE21BCS326) in partial fulfillment of the completion of 7th semester B. E. course during the year 2024 – 2025. The project report has been approved as it satisfies the academic requirement with respect to the project work prescribed for the above said course.

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ABSTRACT

Synthetic Aperture Radar (SAR) images are a critical tool in remote sensing, renowned for their ability to capture high-resolution data regardless of weather conditions or lighting. By using microwave signals, SAR systems generate grayscale images that provide detailed information about terrain and objects, making them indispensable for applications like disaster monitoring, geological studies, and environmental analysis. Unlike optical images, SAR images can penetrate clouds, vegetation, and even ice, offering a unique advantage in uncovering hidden features. Moreover, SAR operates efficiently both day and night, ensuring continuous data acquisition. To enhance the interpretability of SAR images, recent advancements in deep learning have explored techniques like colorization, which maps grayscale radar data into colorized outputs. One such approach utilizes the Pix2Pix model, a generative adversarial network (GAN) designed for image-to-image translation tasks.Colorizing SAR images with deep learning offers several benefits. It enhances usability, allowing a broader range of users, including non-experts, to derive insights from the data. This is particularly useful in applications like urban planning and environmental monitoring, where visual clarity aids decision-making.In conclusion, while SAR images are a powerful resource for remote sensing, their grayscale nature limits accessibility and interpretability. Colorization using the Pix2Pix model addresses this limitation, transforming SAR images into visually enriched data that retain their structural fidelity. This innovation not only broadens the usability of SAR data but also demonstrates the potential of deep learning in overcoming complex challenges in remote sensing applications.

Keywords : *SAR, grayscale, GAN.*

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Chapter 1

INTRODUCTION

Synthetic Aperture Radar (SAR) is an advanced remote sensing technology that captures high-resolution images of the Earth's surface using radar signals. Unlike traditional optical imaging systems, SAR operates in the microwave portion of the electromagnetic spectrum, enabling it to function independently of sunlight and under all weather conditions, including rain, fog, and cloud cover. This unique capability makes SAR a vital tool for various applications in earth observation, environmental monitoring, disaster management, and defense.

The fundamental principle of SAR lies in its use of radar pulses to illuminate a target area and measure the reflected signals. These reflections provide information about the terrain, structures, and objects based on their geometry, material properties, and dielectric characteristics. A distinctive feature of SAR systems is their ability to achieve high-resolution imaging over a wide area by synthesizing a large virtual aperture from the radar's movement, either on a satellite or an aircraft. This process, known as aperture synthesis, enhances the spatial resolution far beyond what would be achievable with a physically small antenna.[1]

SAR images are represented in grayscale, where the intensity of each pixel corresponds to the strength of the radar backscatter from the corresponding ground area. High backscatter typically appears brighter and indicates surfaces with significant roughness or structures that strongly reflect radar signals. Conversely, low backscatter, appearing darker, is associated with smooth surfaces like water bodies or materials that absorb radar signals[2]. This grayscale representation, while rich in structural and textural details, lacks the visual intuitiveness of optical images, making interpretation challenging for non-specialists.

One of SAR's key advantages is its ability to penetrate through obstacles such as clouds, vegetation, and even shallow layers of soil or ice, depending on the radar wavelength used. This capability enables SAR to reveal features that are hidden in optical imagery, making it invaluable for applications like subsurface exploration, forestry, and agricultural monitoring. Additionally, SAR's day-night functionality ensures consistent data acquisition, making it indispensable for time-sensitive operations, such as disaster response during cyclones or floods.However, SAR images are not without challenges [3]. They are often affected by speckle noise, a granular interference that arises due to the coherent nature of radar signals. This noise can obscure fine details and complicate analysis. Furthermore, interpreting SAR data requires specialized expertise, as its grayscale representation differs significantly from the natural color imagery provided by optical sensors. Advanced algorithms and computational techniques are often necessary to process SAR data and extract meaningful insights.

In summary, SAR images represent a powerful and versatile resource for remote sensing, capable of providing critical information under conditions where optical imaging fails. Their ability to penetrate obstacles, capture fine details, and operate continuously makes them invaluable for scientific, commercial, and defense applications. However, their grayscale nature and susceptibility to speckle noise highlight the need for advanced processing techniques, such as colorization and noise reduction, to fully unlock their potential for diverse user groups[4].

1.1 Motivation

- The main reason for SAR image colorization is the need to enhance interpretability and usability in various fields that rely on remote sensing, such as environmental monitoring, urban planning, and disaster management.
- While SAR imagery offers unparalleled detail and the ability to capture images in all weather conditions and at any time of day, its inherent grayscale nature limits quick visual distinction of surface features.
- Colorized SAR images can complement optical data, improving data fusion techniques and leading to more comprehensive analyses in fields like remote sensing and geology.
- Colors can represent different radar backscatter intensities, textures, or material properties, helping to distinguish between various land types, water bodies, vegetation, and urban areas.
- SAR imagery provides detailed structural and textural data but lacks color, which is crucial for intuitive interpretation in applications like geological studies and environmental monitoring.

1.2 Literature Review / Survey

1] SAR Image Colorization Using Multidomain Cycle-Consistency Generative Adversarial Network [5].
Synthetic Aperture Radar (SAR) imaging is known for its robust all-weather, all-day imaging capabilities, which overcome limitations such as fog, night, or adverse weather conditions.Despite these advantages, SAR images are often grayscale and suffer from speckle noise, making their interpretation challenging for researchers.
MC-GAN The study introduces a Multidomain Cycle-Consistency Generative Adversarial

Network (MC-GAN) to overcome limitations in existing methods.Radar Polarimetry-Based Methods: These focus on reconstructing full-polarimetric SAR images from non-polarimetric data using scattering characteristics. While effective, these methods are limited to experts with domain knowledge of radar.
The MC-GAN demonstrates significant advancements in SAR image colorization, achieving comparable performance to pix2pix without requiring paired datasets. Its use of terrain-specific mask vectors and multidomain classification loss sets a new benchmark in SAR colorization research. This innovation paves the way for applications in remote sensing, disaster monitoring, and environmental studies, enhancing the usability of SAR imaging in real-world scenarios.

2] Radar Image Colorization Using Deep Neural Networks [6].
Synthetic Aperture Radar (SAR) imaging is crucial for remote sensing due to its robustness in adverse conditions. However, most SAR images are single-polarization (single-pol) grayscale, limiting their utility in polarimetric applications like terrain classification and target decomposition.Radar image colorization aims to reconstruct fully polarimetric (full-pol) SAR images from single-pol data using deep neural networks (DNNs), enabling the application of polarimetric techniques on otherwise limited data.
The study introduces a two-stage DNN-based framework: Feature Extractor Network: Leverages convolutional layers from VGG16 to extract spatial features from single-pol SAR images. Feature Translator Network: Maps extracted spatial features into polarimetric feature space, reconstructing the covariance matrix for full-pol SAR.The framework was tested on NASA/JPL UAVSAR L-band SAR images, demonstrating high visual and quantitative fidelity compared to true full-pol data. Applications in target decomposition and terrain classification showed the reconstructed data's usability for both qualitative and quantitative analyses.
This study provides a foundational framework for SAR colorization, bridging the gap between single-pol data and full-pol applications. Future advancements could refine the framework for operational use across diverse SAR systems and datasets.

3] Design of CycleGAN Model for SAR Image Colorization [7]
Recent advancements in deep learning have enabled significant progress in SAR image colorization, a process vital for improving the interpretability of grayscale SAR data. Traditional methods rely on radar polarimetry or DCNN-based approaches to generate fully polarimetric or pseudo-colorized images. However, these methods often require domain-specific expertise or paired datasets, limiting their broader applicability.
Generative Adversarial Networks (GANs), particularly CycleGANs, have emerged as a powerful alternative. Unlike paired-data-dependent models like Pix2Pix, CycleGAN operates on unpaired datasets, translating SAR imagery to colorized optical equivalents. By leveraging

adversarial and cycle-consistency losses, it ensures high fidelity in domain transformation. The architecture includes dual generators and discriminators, utilizing techniques like residual blocks and data augmentation to enhance performance.
Studies reveal that CycleGAN achieves superior results compared to other GAN variants, with metrics like PSNR, MSE, and SSIM underscoring its efficacy. For instance, it recorded the lowest MSE (639.4379) and highest PSNR (20.0728), indicating better accuracy and reduced noise. This makes CycleGAN an effective tool for generating colorized SAR images, potentially aiding applications in environmental monitoring and disaster management.
Future work includes improving CycleGAN's accuracy and expanding SAR datasets for more robust performance.

4] A Novel Approach of SAR Image Classification Using Color Space Clustering and Watersheds [8]
Synthetic Aperture Radar (SAR) image classification is essential for applications in military and scientific research. Traditional approaches for SAR image classification often relied on techniques like Maximum Likelihood Estimation, neural networks, and fuzzy methods, but their effectiveness heavily depends on feature quality and classifier design. Recent advancements introduced methods like wavelet-based texture features and deep neural networks to enhance classification accuracy.
The paper proposes a novel methodology that combines histogram thresholding with color space clustering and watershed classification for SAR image segmentation. Histogram thresholding identifies regions based on pixel intensity distribution, while color space clustering groups pixels by similarity in RGB histograms. The watershed algorithm enhances classification by simulating water flooding to separate regions based on image gradients.
Region merging techniques address over-classification, consolidating similar neighboring regions into cohesive segments. Experiments demonstrate improved classification performance compared to traditional histogram-based methods, showcasing the potential of combining clustering and gradient-based techniques for SAR imagery. This innovative approach provides a robust framework for SAR image classification, paving the way for more accurate analysis in diverse applications, including environmental monitoring and resource management.

1.3 Problem Statement

Develop a deep learning-based model to colorize grayscale SAR images by training on pairs of SAR and optical images, with a focus on enhancing interpretability and usability in remote sensing applications.

1.4 Objectives and Scope of the project

1.4.1 Objectives

- Configuring and modifying a DL model tailored to the colorization of SAR images using paired SAR and optical images.
- Enhance the visual appeal and interpretability of SAR images for better analysis of surface features.
- Optimize the loss function to accurately capture the difference between predicted colorized images and actual optical images.

1.4.2 Scope of the project

- Future advancements could focus on optimizing the model for real-time SAR image colorization, enabling its use in live monitoring systems for applications like disaster response or environmental monitoring.
- The colorization model can be adapted to different domains beyond remote sensing, such as medical imaging (e.g., ultrasound or MRI), geophysics, and archaeology, where grayscale data is commonly used.
- Colorizing SAR images could be integrated with multispectral or hyperspectral imaging systems to provide a more comprehensive view of the environment, combining radar and optical information for more robust analysis.

Chapter 2

REQUIREMENT ANALYSIS

2.1 Functional Requirements

- The system must be able to detect the SAR image.
- The system must be able to extract the maximum features out of the SAR image .
- The system should be able to colorize the SAR images by making use of the extracted features.

2.2 Non Functional Requirements

- The system should be easily accessed and available.(Accessibility and Reliability)
- The system should be easy to use.(Usability)

2.3 Hardware Requirements

- Memory - 16GB
- CPU- intel i5 11th generation
- Storage- minimum of 35GB
- GPU - CUDA

2.4 Software Requirements

- Operating System - Windows
- Machine Learning Libraries and Tools:

  Python: Programming language for developing Deep Learning models to extract features of SAR images. Scikit-learn: For implementing machine learning models. TensorFlow/PyTorch: For deep learning models. Pandas and NumPy: For data manipulation and processing.

Chapter 3

SYSTEM DESIGN

The Pix2Pix framework is a generative adversarial network (GAN) architecture designed for image-to-image translation tasks. It is used to convert input images into a desired output format, preserving the structure and appearance dictated by the input. The framework is widely utilized for tasks like image synthesis, style transfer, and domain adaptation.

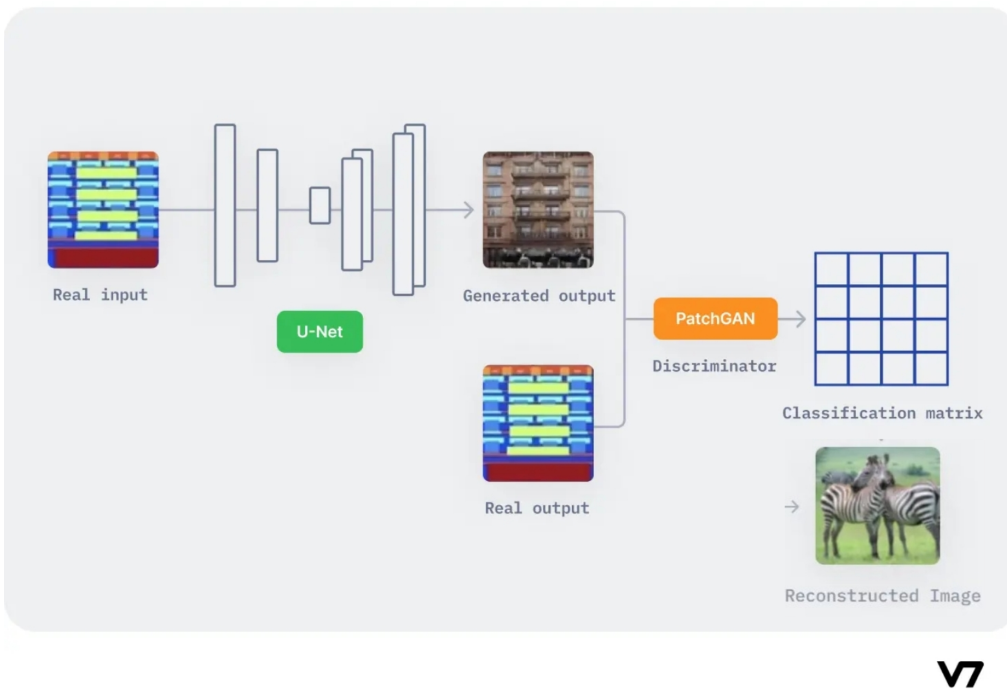

Figure 3.1: Pix2Pix Architecture Design Overview

3.1 Pix2Pix Architecture Design

The Pix2Pix framework combines two main components: a **Generator** (G) and a **Discriminator** (D). The generator is tasked with creating realistic images from input data, while the discriminator evaluates the quality of the generated images. This adversarial setup ensures the generator continuously improves to create more realistic results.

3.1.1 Generator Design

The generator in Pix2Pix uses a **U-Net architecture**, which includes:

- **Encoder-Decoder Structure**:
  - The encoder compresses the input image into a latent representation.
  - The decoder reconstructs the image in the desired output format.
- **Skip Connections**: Features from the encoder layers are directly passed to corresponding decoder layers. This allows the generator to preserve spatial details in the output image.

3.1.2 Discriminator Design

The discriminator employs a **PatchGAN architecture**, which:

- Divides the input image into smaller patches.
- Evaluates the realism of each patch, rather than the entire image, improving the focus on local features.
- Outputs a classification matrix indicating whether each patch is real or fake.

3.1.3 Training Mechanism

Pix2Pix uses the following steps for training:

1. The generator creates output images based on the input images.
2. The discriminator evaluates both real images and generated images, outputting a classification matrix.
3. A loss function is computed:
   - **Adversarial Loss**: Ensures the generator creates images that can fool the discriminator.
   - **L1 Loss**: Enforces similarity between the generated and target images.
4. The generator and discriminator are trained iteratively to minimize their respective losses.

3.1.4 Applications

Pix2Pix is highly versatile and finds applications in tasks like:

- Image colorization (e.g., grayscale to color images).
- Semantic segmentation (e.g., label maps to real-world images).
- Image super-resolution (e.g., low-resolution to high-resolution images).

This architecture, as illustrated in Figure 3.1, enables powerful image-to-image translation with high fidelity and structural integrity, making it a fundamental tool in deep learning for vision tasks.

Chapter 4

IMPLEMENTATION

4.1 Pix2Pix Algorithm

Algorithm 1 Pix2Pix Model

Input: Paired datasets (X, Y), where X is the input image and Y is the target image.
Output: Trained Generator G and Discriminator D.
Initialize the Generator G and Discriminator D with random weights.
while training not converged **do**
    Step 1: Train Discriminator
    Sample a batch of input images x and corresponding target images y.
    Generate fake images $\hat{y}$ using the generator:

$$\hat{y} = G(x)$$

    Compute the discriminator loss:

$$L_D = -\mathbb{E}[\log D(x, y)] - \mathbb{E}[\log(1 - D(x, \hat{y}))]$$

    Update the discriminator weights by minimizing L_D.
    Step 2: Train Generator
    Generate fake images $\hat{y}$ using the generator:

$$\hat{y} = G(x)$$

    Compute the generator loss:

$$L_G = \mathbb{E}[\log(1 - D(x, \hat{y}))] + \lambda \cdot \mathbb{E}[\|y - \hat{y}\|_1]$$

Here, λ is a hyperparameter balancing the adversarial loss and L1 loss.
    Update the generator weights by minimizing L_G.
end while
return Trained Generator G and Discriminator D.

The Pix2Pix model is trained in an adversarial setting where the generator learns to produce realistic images and the discriminator assesses the quality of these images with minimal loss. The combination of adversarial loss and L1 loss ensures high-quality output that closely resembles the target images.

Chapter 5

RESULTS AND DISCUSSIONS

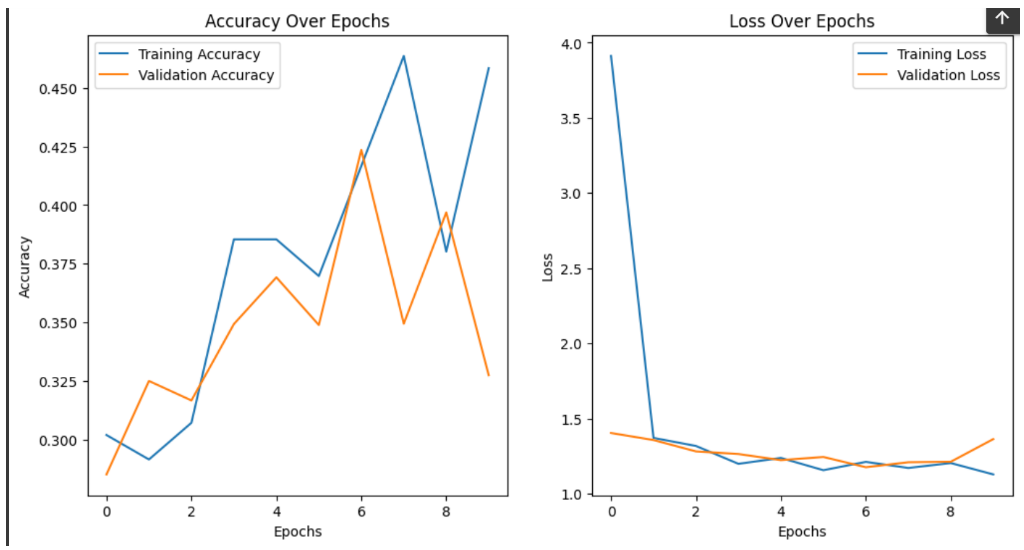

Figure 5.1: Accuracy and Loss over epochs

The above graphs represent accuracy over epochs. The first graph says that the training accuracy with respect to number of epochs the model is run by as well as validation accuracy that the model has validated .The training accuracy increases as the number epochs are increased ,but the validation accuracy exponentially increases and gradually decreases, but if the epochs are increased the validation accuracy also increases. The Loss over epochs for the training dataset is initially high and as the epochs are increased the loss decreases. It happens the same for validation dataset and initially it starts from less loss and remains almost constant as the epochs are increased .

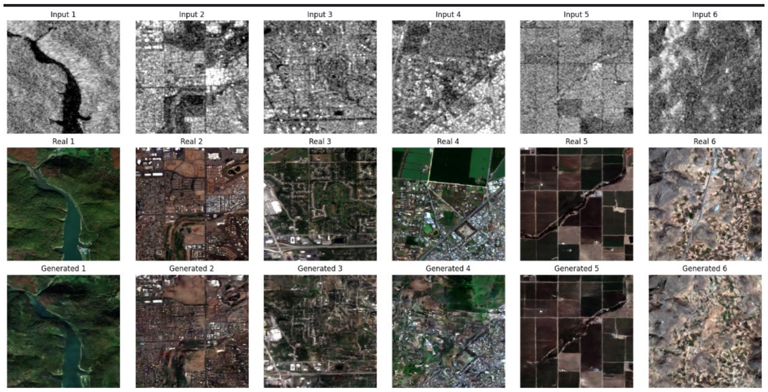

Figure 5.2: Generated Images

In this image we can see that the SAR greyscale image is being colorized by using of deep learning model (Pix2Pix) model.

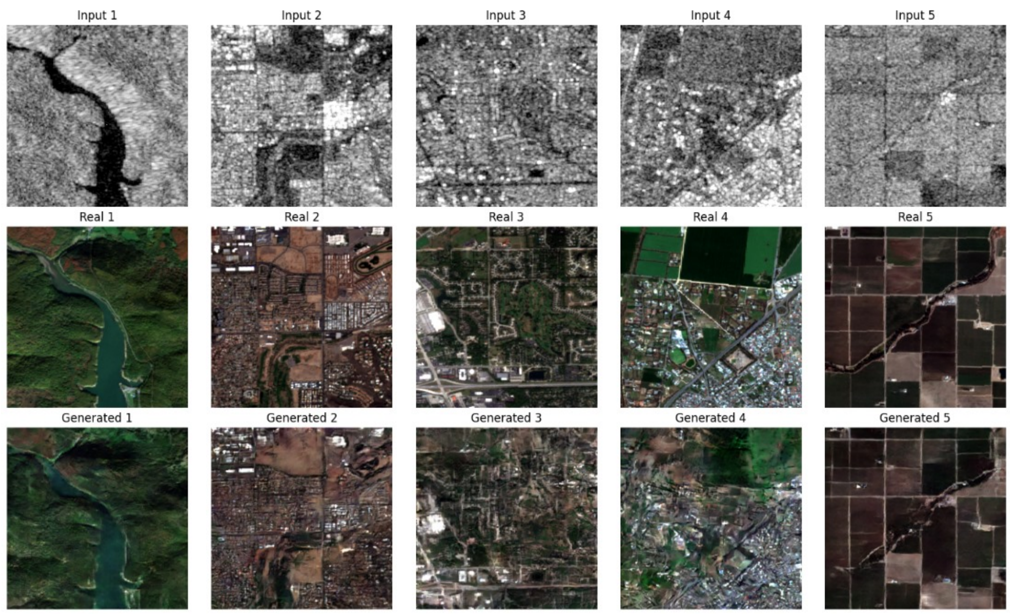

Figure 5.3: Generated Images compared with real images

We can see that the generated images are the colorized SAR images that are compared to the optical images which were taken by satellite for comparision of these images .

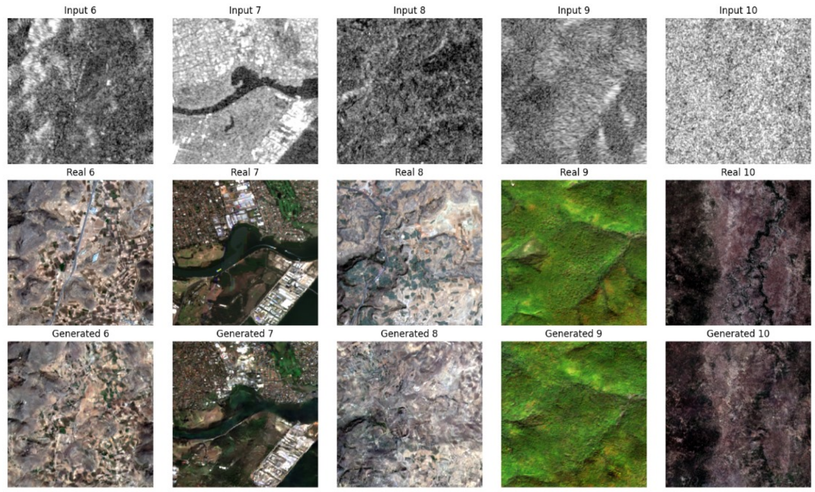

Figure 5.4: Generated image with less noise

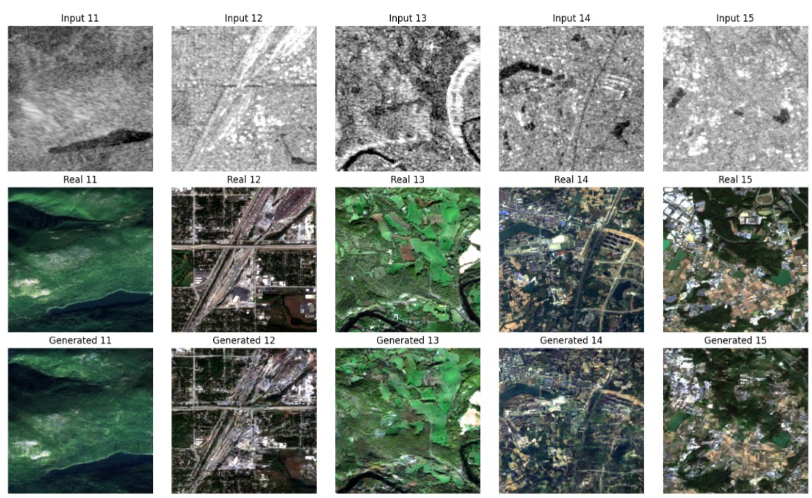

Figure 5.5: Generated image with less noise

Chapter 6

CONCLUSION AND FUTURE SCOPE

In conclusion, advancements in real-time SAR image colorization hold immense potential for various domains. By optimizing the existing model for real-time processing, it could be integrated into live monitoring systems for critical applications such as disaster response and environmental monitoring. These real-time capabilities could significantly enhance decision-making during emergencies, providing actionable insights to responders and authorities.

Furthermore, the colorization model's adaptability opens avenues for its application beyond remote sensing. It can be utilized in fields like medical imaging (e.g., ultrasound or MRI), geophysics, and archaeology, where grayscale data is prevalent. This cross-domain utility demonstrates the model's versatility in addressing diverse challenges.

Integration with multispectral or hyperspectral imaging systems represents another transformative advancement. Combining SAR data with optical information can deliver a comprehensive environmental perspective, improving the robustness and accuracy of analysis. These developments not only elevate SAR imaging's usability but also contribute to technological innovation across numerous scientific and industrial domains.

REFERENCES

[1] Lekun Zhu, Lipeng Fu, Xionghao Zhao, Xiaowei Huang, and Tianye Xie. Research on optical image and sar image fusion method. In *2023 4th China International SAR Symposium (CISS)*, pages 1–5. IEEE, 2023.

[2] Hongying Liu, Shuang Wang, Biao Hou, Shuyuan Yang, Junfei Shi, Tao Xiong, and Licheng Jiao. Unsupervised classification of polarimetric sar images integrating color features. In *2014 IEEE Geoscience and Remote Sensing Symposium*, pages 2762–2765. IEEE, 2014.

[3] Ning Yu, Ailong Ma, Yanfei Zhong, and Xiaodong Gong. Hfgan: a heterogeneous fusion generative adversarial network for sar-to-optical image translation. In *IGARSS 2022-2022 IEEE International Geoscience and Remote Sensing Symposium*, pages 2864–2867. IEEE, 2022.

[4] Xiaodong Zhou, Chunhua Zhang, and Song Li. A perceptive uniform pseudo-color coding method of sar images. In *2006 CIE International Conference on Radar*, pages 1–4. IEEE, 2006.

[5] Guang Ji, Zhaohui Wang, Lifan Zhou, Yu Xia, Shan Zhong, and Shengrong Gong. Sar image colorization using multidomain cycle-consistency generative adversarial network. *IEEE Geoscience and Remote Sensing Letters*, 18(2):296–300, 2020.

[6] Qian Song, Feng Xu, and Ya-Qiu Jin. Radar image colorization: Converting single-polarization to fully polarimetric using deep neural networks. *IEEE Access*, 6:1647–1661, 2017.

[7] Jung-Hoon Lee, Kyeongrok Kim, and Jae-Hyun Kim. Design of cyclegan model for sar image colorization. In *2021 IEEE VTS 17th Asia Pacific Wireless Communications Symposium (APWCS)*, pages 1–5. IEEE, 2021.

[8] Debabrata Samanta and Goutam Sanyal. A novel approach of sar image classification using color space clustering and watersheds. In *2012 Fourth International Conference on Computational Intelligence and Communication Networks*, pages 237–240. IEEE, 2012.

Appendix A