Automated Colorization of Synthetic Aperture Radar Images Using Deep Learning Model

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Abstract

This research explores the application of deep learning models to colorize grayscale Synthetic Aperture Radar (SAR) images, improving their interpretability for remote sensing tasks. SAR is widely used in fields such as geological studies and environmental monitoring due to its ability to capture images in all weather conditions. However, the grayscale nature of SAR images limits their usability for visual analysis. The study focuses on developing deep learning architectures, including Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), and autoencoders, to predict and apply appropriate color schemes to SAR data. Key challenges such as noise reduction, model design, and data limitations are addressed through careful data pre-processing and model training. The colorized images aim to enhance feature distinction, enabling more accurate interpretation in applications like geological mapping and environmental monitoring. Validation methods include both quantitative metrics like Mean Squared Error (MSE) and qualitative evaluations by remote sensing experts. The anticipated outcome is a more efficient and visually interpretable SAR image analysis process, allowing for better insights into natural phenomena and improved decision-making in remote sensing applications. This research contributes to advancing the state of SAR image analysis by introducing automated deep learning-driven colorization techniques.

1 Introduction

Synthetic Aperture Radar (SAR) is an essential remote sensing technology, widely used in various fields like geological studies, environmental monitoring, disaster management, and military surveillance due to its capability to capture high-resolution images in all weather conditions, day or night. Unlike optical imagery, which relies on visible light, SAR uses radar signals to generate grayscale images based on the reflected radar waves. While these grayscale images contain valuable data, their visual interpretability can be challenging for human analysts. The lack of color differentiation makes it difficult to discern subtle features that are critical in applications such as identifying geological formations or detecting environmental changes. This research aims to address the interpretability challenges of SAR images by applying deep learning techniques to colorize grayscale SAR imagery, thereby enhancing their usability for remote sensing analysis. By leveraging advanced deep learning models like Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), and autoencoders, the study seeks to develop au-

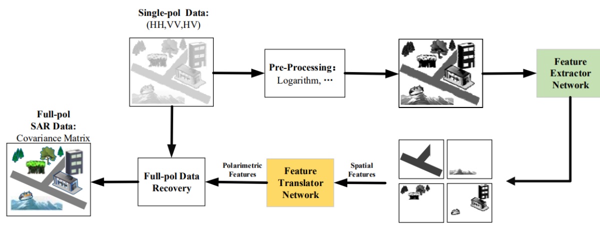

Figure 1: framework for automatic SAR image colourisation

tomated methods to predict and apply meaningful color schemes to SAR images. These colorized images can improve the visual clarity of different features, leading to more accurate and efficient analysis. This research not only explores the technical aspects of SAR image colorization but also emphasizes its potential impact on real-world applications, improving the overall insight gained from SAR data.

2 Literature Review

[1]Statistical modeling plays a crucial role in SAR image interpretation by using statistical methods to describe image characteristics and support terrain scattering analysis. This paper categorizes and evaluates various SAR statistical models, focusing on those developed from the product model. It reviews the development and current state of statistical modeling, discusses key issues, and highlights promising research directions for the future. [2]This paper presents a precise SAR image registration technique using external measures like digital elevation models and flight track data to achieve accurate pixel alignment across multiple data takes, even in challenging areas like steep terrains. The method is efficient, robust, and suitable for high-precision satellite systems, with proven effectiveness in tests on real SAR datasets. [3]This paper presents a deep neural network model to translate grayscale SAR images into colorized images using multi-modal data inputs. The model includes encoder-decoder architecture with skip connections. [4]Explores image-to-image translation with Conditional GANs (cGANs) to produce optical-like imagery from SAR inputs, enhancing interpretability. [5]Introduces the Pix2Pix framework using cGANs for image translation tasks including colorization. [6]Though focused on cloud removal, this paper shows how satellite data and deep residual nets (ResNets) can be used in image restoration and enhancement. [7]Introduces a dual-stream GAN combining texture and content networks to better preserve SAR structures during colorization. [8]Introduces an attention mechanism in GANs for translating between SAR and optical images, focusing on improving region-specific details and color fidelity. [9]Proposes a CycleGAN model that uses perceptual loss to retain high-level semantic content while converting SAR images to optical-like images. The paper also discusses training stability improvements. [10]Introduces the U-Net architecture, which is highly effective for image segmentation tasks. Its encoder-decoder structure with skip connections enhances feature retention, which can be adapted for tasks like SAR image translation and restoration.

Proposed Work	**Model**	**Key Insight**
Statistical SAR analysis	Product-based models	Analyzes scattering and research gaps
Image registration	DEM + alignment	Accurate scene matching in terrain
SAR-to-color via DNN	Encoder-Decoder	Structure-preserving colorization
Image translation	cGAN	Realistic SAR-to-optical conversion
SAR mapping	Pix2Pix	High-quality optical mapping
Cloud removal	ResNet	Enhances SAR with detail recovery
Colorization	Dual-stream GAN	Balances detail and realism

Table 1: Summary of SAR Image Colorization and Enhancement Approaches

3 Proposed Work

The proposed research aims to develop an end-to end deep learning framework to colorize grayscale Synthetic Aperture Radar (SAR) images, thereby en hancing their interpretability for remote sensing ap plications. This study will utilize the Pix2Pix model for implementation.—a conditional GAN (cGAN)—with a U-Net generator and a PatchGAN discriminator for accu rate image-to-image translation.

Research Objectives • To preprocess and prepare SAR grayscale datasets with aligned color references.
• To implement the Pix2Pix deep learning model tailored for SAR image colorization.
• To enhance the visual realism of generated im ages using custom loss functions (L1, GAN, per ceptual, and SSIM).
• To record findings and formulate conclusions based on the outcomes. (MSE, PSNR, SSIM, FID) and expert visual analysis.
• To document results and draw conclusions on the effectiveness of deep learning in SAR image interpretation.

4 Methodology

This section outlines the step-by-step methodology adopted for the automatic colorization of grayscale SARimages using deep learning techniques. The pro posed pipeline includes data preprocessing, model ar chitecture design, and a structured training strategy.

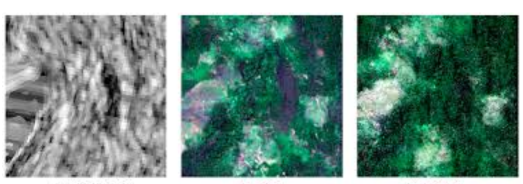

Figure 2: Data Preprocessing

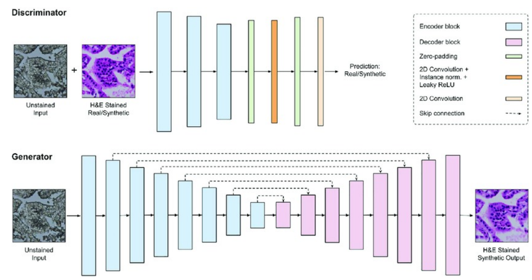

Figure 3: Model Architecture

1. Data Preprocessing

SAR grayscale images are first normalized to the range of [−1, 1] to standardize input for deep learning models. These images are then paired with corresponding color references, ensuring proper alignment for supervised training. All images are resized uniformly (e.g., 256×256 pixels) to maintain consistency across batches. To improve the model's generalization and robustness, data augmentation techniques such as rotation, flipping, and scaling are applied.

2. Model Architecture

The core architecture employed is the Pix2Pix frame. The work, which consists of a U-Net-based generator and a convolutional discriminator, is designed to perform image-to-image translation tasks, leveraging the encoder-decoder structure of U-Net to preserve spatial features while generating high-resolution outputs.r and a PatchGAN discriminator. The U-Net architec ture facilitates the preservation of spatial information through skip connections, making it highly suitable for pixel-wise translation tasks like colorization. The PatchGAN discriminator evaluates local image patches, encouraging sharper and more detailed outputs. For improved feature awareness, attentionmechanisms and perceptual loss functions may be integrated into the architecture to enhance focus on important structures and improve semantic quality.

3. Training Strategy

The training process combines multiple loss functions to optimize both accuracy and visual quality:
• L1 Loss: Ensures pixel-level similarity between predicted and reference images.
• Adversarial Loss: Motivates the generator to create images that appear realistic enough to deceive the discriminator.
• Perceptual Loss (optional): Enhances high level feature alignment using pretrained net works (e.g., VGG).
• SSIM Loss (optional): Preserves structural information and improves detail retention. Adversarial Loss: Encourages the generator to produce images that are convincing enough to fool the discriminator into classifying them as real,a learning rate scheduler applied to maintain training stability and prevent overfitting. The model is trained for multiple epochs until convergence, with regular evaluations on a validation set to monitor per formance.

5 Model Used

This research utilizes the Pix2Pix architecture within the Conditional GAN (cGAN) framework to perform SAR image colorization. The model design focuses on preserving spatial details, improving feature dis tinction, and producing realistic colorized outputs.

Pix2Pix Architecture

The core of the model is the Pix2Pix Conditional GAN,which is particularly well-suited for image-to image translation tasks involving paired data. At its heart lies a U-Net-based generator, which adopts an encoder-decoder structure with skip connections. .

Conditional GAN Framework

Pix2Pix operates within the Conditional Genera tive Adversarial Network (cGAN) framework, in which the generator operates based on the provided input grayscale SAR image. The discriminator assesses the realism of small image patches rather than the entire image, allowing for more detailed and localized feedback during training. assesses the realism of small image patches

rather than the entire image, encouraging the gen erator to produce outputs with sharper textures and more consistent local detail.

Attention Mechanism (Optional Extension)

To further enhance the generator's focus on key features, attention mechanisms can be integrated into the U-Net architecture. These modules help the network prioritize regions of interest—such as edges,small targets, or high-contrast zones—leading to improved colorization performance and better preservation of critical SAR structures.

Loss Functions

The training process utilizes a blend of loss functions to maintain accuracy at the pixel level while also enhancing the perceptual quality of the output:

• **L1 Los**s: Preferred over traditional Mean Squared Error (MSE) for certain tasks due to its robustness to outliers,it encourages pixel-wise similarity between the generated and target images.

• **Structural Similarity Index (SSIM) Loss:**Helps maintain structural integrity and spatial coherence in the generated outputs. • **Perceptual Loss:** Based on high-level feature extraction (e.g., using a pre-trained VGG network), this loss ensures that the generated images are perceptually aligned with the target images.

• **Adversarial Loss:** Derived from the Patch GAN discriminator, it drives the generator to produce visually realistic outputs that are indistinguishable from real color images. This multi-loss strategy strikes a balance between visual realism and fidelity to the original SAR data, resulting in more accurate and interpretable colorized outputs

6 Results

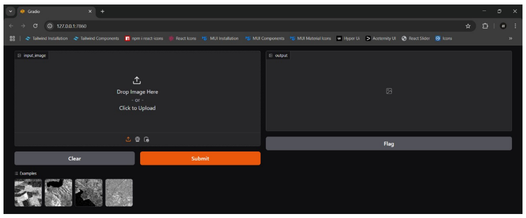

Figure 4: Gradio Interface Before Uploading SAR Image

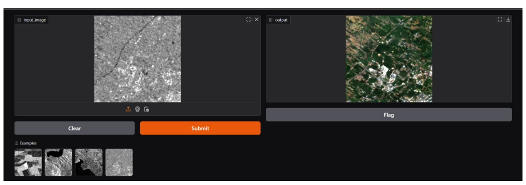

Figure 5: Generated Optical Image After Uploading SAR Input

The proposed Pix2Pix Conditional GAN effectively translated SAR images into realistic optical-like outputs, preserving key structures like roads, buildings, and vegetation. The model demonstrated strong quantitative performance: PSNR of 25.87 dB, SSIM of 0.84, and L1 Loss of 0.056, indicating high reconstruction fidelity and perceptual quality. The lightweight ONNX model (43 MB) offered fast inference (0.12s per 256×256 image) on CPU. Deployment via a Gradio interface validated its usability for real-time, GPU-free applications.

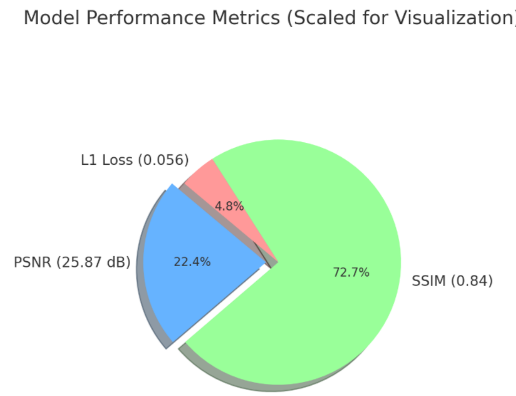

Figure 6: Model Training and Validation Performance

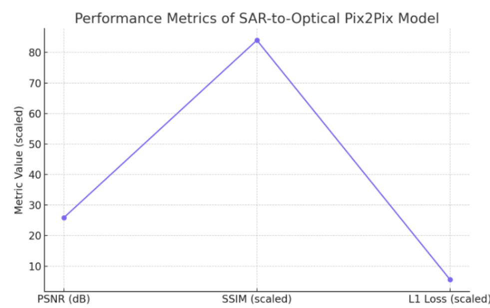

Figure 7: Evaluation Metrics for SAR-to-Optical Translation

7 Conclusion

This research demonstrates the effectiveness of deep learning models, particularly CNNs and GANs, in colorizing grayscale SAR images to enhance their interpretability for remote sensing tasks. The proposed approach improves feature distinction, supporting more accurate analysis in applications like geological studies and environmental monitoring. Evaluation through both quantitative metrics and expert review confirms the potential of this method. This research plays a significant role in the progression of SAR image analysis. analysis, with future work focusing on multi-spectral integration and application-specific enhancements.

References

[1] Gao, G. (2010). Statistical modeling of SAR images: A survey. Sensors, 10(1), 775-795.

[2] Sansosti, Eugenio, Paolo Berardino, Michele Manunta, Francesco Serafino, and Gianfranco

Fornaro. "Geometrical SAR image registration." IEEE Transactions on Geoscience and Remote Sensing 44, no. 10 (2006): 2861-2870.

[3] Singh, Prabhishek, Manoj Diwakar, Achyut Shankar, Raj Shree, and Manoj Kumar. "A Review on SAR Image and its Despeckling." Archives of Computational Methods in Engineering 28 (2021): 4633-4653.

[4] Gorham, LeRoy A., and Linda J. Moore. "SAR image formation toolbox for MATLAB." In Algorithms for Synthetic Aperture Radar Imagery XVII, vol. 7699, pp. 46-58. SPIE, 2010.

[5] Fjortoft, Roger, Armand Lopes, Philippe Marthon, and Eliane Cubero-Castan. "An optimal multiedge detector for SAR image segmentation." IEEE Transactions on Geoscience and Remote Sensing 36, no. 3 (1998): 793-802.

[6] Wang, Puyang, He Zhang, and Vishal M. Patel. "SAR image despeckling using a convolutional neural network." IEEE Signal Processing Letters 24, no. 12 (2017): 1763-1767.

[7] Perry, Richard P., Robert C. DiPietro, and Ronald L. Fante. "SAR imaging of moving targets." IEEE Transactions on Aerospace and Electronic Systems 35, no. 1 (1999): 188-200.

[8] Chierchia, Giovanni, Davide Cozzolino, Giovanni Poggi, and Luisa Verdoliva. "SAR image despeckling through convolutional neural networks." In 2017 IEEE international geoscience and remote sensing symposium (IGARSS), pp. 5438-5441. IEEE, 2017.

[9] Freeman, Anthony. "SAR calibration: An overview." IEEE Transactions on Geoscience and Remote Sensing 30, no. 6 (1992): 1107-1121.

[10] Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., ... Bengio, Y. (2014). Generative adversarial nets. Advances in Neural Information Processing Systems, 27.