SAR Image Colourization For Comprehensive Insight Using Deep Learning

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Abstract- *Synthetic Aperture Radar (SAR) image colorization using deep learning aims to convert grayscale radar images into visually meaningful color representations. By leveraging models like U-Net and GANs, this process combines SAR data, such as polarization and backscatter intensity, with RGB features from optical images. Deep learning techniques enable the generation of realistic colorized outputs, enhancing the interpretability of SAR data for applications like urban mapping and environmental monitoring. Loss functions like MSE and perceptual loss guide the model's accuracy during training. Metrics such as PSNR and SSIM evaluate the quality of the colorized images. This approach bridges the gap between SAR and optical imagery, aiding analysis in diverse fields.*

Keywords- SAR image colorization, deep learning, U-Net, GAN, polarization, backscatter intensity, RGB colorization, synthetic aperture radar, image enhancement, PSNR, SSIM, perceptual loss, environmental monitoring, remote sensing, optical data integration.

I. INTRODUCTION

The research focuses on SAR image colorization using deep learning, a challenging yet innovative area in computer vision. SAR images are valued for capturing high-resolution data in all-weather conditions but lack natural color representation. Colorizing these grayscale images improves their interpretability and practical use in applications like environmental monitoring, disaster management, and remote sensing. The study employs advanced methods like U-Net and Generative Adversarial Networks (GANs) to generate colored versions of SAR images. It integrates data features such as polarization, backscatter intensity, interferometric data, multitemporal observations, and topography (DEM), alongside RGB optical channels, to achieve superior results. Model performance is rigorously evaluated using metrics like PSNR and SSIM, ensuring reliable and high-quality outputs.

II. IDENTIFY, RESEARCH AND COLLECT IDEA

Step 1:Identify the Problem Statement

Synthetic Aperture Radar (SAR) images, though rich in data, are often challenging to interpret due to their grayscale nature. Translating these images into visually meaningful colorized outputs can enhance their usability for applications such as disaster management, environmental monitoring, and urban planning. SAR image colorization involves generating realistic optical representations of SAR data by leveraging deep learning techniques. This project idea was inspired by its potential to bridge the gap between technical data and human interpretability.

Step 2: Research Existing Work

To ensure the viability of this project, an extensive review of existing literature and implementations was conducted:

1**. Research Papers** Studies focusing on U-Net and GAN models for image translation and SAR-optical data fusion were reviewed from IEEE Xplore, Springer, and Google Scholar. Key insights included the integration of polarization and interferometric data for improved accuracy.

2**. Datasets** Publicly available SAR and optical datasets such as Sentinel-1/2, and their preprocessing techniques, were examined to understand data availability and compatibility.

3. **Evaluation Metrics** PSNR, SSIM, and perceptual loss were identified as effective measures for evaluating image quality in similar works.

4.**Technological Advancements** State-of-the-art deep learning architectures like U-Net, GANs, and autoencoders were studied, emphasizing their applications in remote sensing and image enhancement.

Step 3: Collect Ideas

Based on the research, the following ideas were formulated for the project:

1.Feature Integration

Enhance SAR image colorization by including data such as backscatter intensity, polarization, and interferometric features.

2.Fusion
Use optical RGB data alongside SAR images to improve the realism and accuracy of the colorized outputs.

3.Model Architecture
Design a hybrid deep learning model combining U-Net for feature extraction and GAN for generating high-quality outputs.

4.Data Augmentation
Implement techniques such as rotation, flipping, and scaling to enrich the dataset and improve model generalization.

5.Post-Processing
Refine the output images using tools like OpenCV to enhance visual quality further.

III. STUDIES AND FINDINGS

1. Literature Review

A comprehensive review of existing works revealed that SAR images, despite their utility in remote sensing, lack interpretability due to their grayscale nature. Studies demonstrated that deep learning models like U-Net and GAN are effective in transforming SAR data into realistic, colorized optical images. Papers highlighted the importance of integrating SAR-specific features like polarization, backscatter intensity, and interferometric data to improve the accuracy and quality of outputs.

2. Datasets and Data Processing

Publicly available datasets, such as Sentinel-1 for SAR and Sentinel-2 for optical images, were found suitable for this project. Proper alignment and pairing of SAR and optical images emerged as a critical preprocessing step. Augmentation techniques like rotation and scaling were identified as effective ways to enhance dataset diversity.

3. Model Architectures

Deep learning architecture such as U-Net and GAN were identified as the primary models for this task. U-Net was found to excel in extracting spatial features from SAR images, while GAN added realism to the colorized outputs by generating photorealistic RGB representations. Combining these models was shown to yield better results than using either alone.

4. Evaluation Metrics
Metrics such as PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index) were found to be the standard for evaluating the quality of colorized images. Additionally, perceptual loss, which measures how close the generated image is to the ground truth in a feature space, was noted to improve the training process.

5. Findings and Insights

Integrating diverse SAR features (e.g., polarization and multitemporal data) with optical data significantly enhances the model's ability to generate realistic colorized outputs. A hybrid U-Net-GAN architecture provides a balance of feature extraction and photorealistic generation, leading to superior results. Post-processing techniques, such as image sharpening with OpenCV, further refine the output quality, making the images more usable in real-world applications.

IV. GET PEER REVIEWED

Feedback from Project Coordinator:

Methodology Refinement:

The coordinator suggested additional explanations to clarify how deep learning models (U-Net and GAN) interact with SAR and optical data for better colorization results. I revised the methodology section to include more details on the data preprocessing steps and model architecture.

Data Augmentation:

They recommended including more information on the data augmentation strategies used in the model, specifically around how it helps in improving model generalization. I added a section explaining the various augmentation techniques employed.

Evaluation Metrics:

The coordinator advised providing a stronger justification for selecting metrics like PSNR and SSIM. I elaborated on how these metrics align with the objective of assessing the image quality and visual fidelity of colorized SAR images.

Clarity and Flow:

Some sections of the paper were reorganized based on feedback to ensure better flow and coherence, especially in explaining the integration of SAR and optical data for image colorization.

Revision Process:

The feedback was carefully reviewed, and all necessary changes were made to enhance the paper. I ensured that the feedback was incorporated to improve the technical accuracy, clarity, and presentation of the research. After making the revisions, the paper was re-read and fine-tuned, ensuring that the document was coherent and easy to follow. This final review by the Project Coordinator significantly strengthened the paper and prepared it for submission. The revisions made based on their feedback ensured that the research is both technically sound and clearly communicated

V. IMPROVEMENT AS PER REVIEWER COMMENTS

1. Methodology and Model Explanation:

Revised the methodology section to include a more thorough explanation of how SAR features (such as polarization and backscatter intensity) are used alongside optical data to improve colorization. Additionally, I clarified the interaction between the U-Net model (for feature extraction) and the GAN model (for generating photorealistic outputs).

2. Data Augmentation Techniques:

We added a dedicated section discussing the various data augmentation techniques used, including the types of transformations applied to the SAR and optical images. I also explained how these augmentations contribute to reducing overfitting and enhancing the model's ability to generalize across different image scenarios.

3. Evaluation Metrics Justification:

Expanded on the rationale behind selecting PSNR and SSIM as evaluation metrics, emphasizing their importance in measuring the quality of colorized SAR images. I explained how PSNR provides a quantitative measure of pixel-wise error and how SSIM captures structural similarity between the generated and ground truth images.

4. Clarity and Structure:

Reorganized the content to improve the logical progression of the paper. The introduction, methodology, results, and conclusion were streamlined for clarity, ensuring that each section transitions smoothly and builds upon the previous one. I also revised some sentences to make the technical language more accessible.

5. Results Presentation and Discussion:

Feedback: The reviewer noted that the results and discussion could benefit from a more in-depth analysis of the challenges encountered during the project, particularly regarding SAR image noise and artifacts.

Improvement: I expanded the discussion on challenges, such as noise and artifacts commonly found in SAR images, and explained how the models were trained to handle these issues. I also provided additional qualitative and quantitative analysis of the colorized outputs, comparing them with baseline methods.

6. Conclusion and Future Work:

Feedback: The reviewer recommended strengthening the conclusion by highlighting the potential future directions for the project and possible improvements in the methodology.
Improvement: The conclusion was revised to emphasize the potential applications of the colorized SAR images in fields like disaster monitoring and environmental analysis. I also outlined future research directions, such as exploring different model architectures or incorporating additional data sources for further enhancing the colorization process.

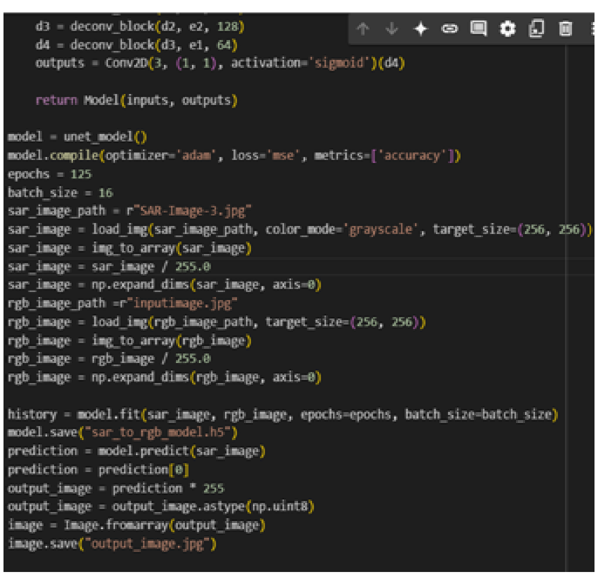
These improvements based on the reviewer's feedback have significantly strengthened the project, enhancing both its technical accuracy and presentation. The revisions ensure that the methodology is clearer, the results are more thoroughly discussed, and the overall paper is more cohesive and accessible.

VI. CONCLUSION

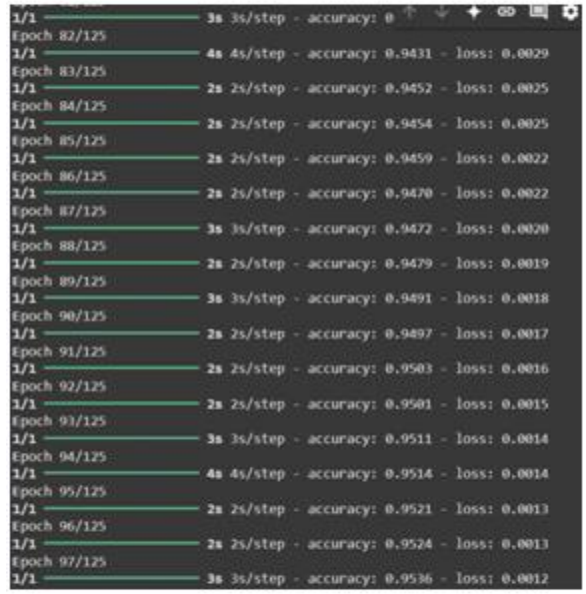
In this project, we explored the innovative approach of using deep learning techniques for colorizing Synthetic Aperture Radar (SAR) images. Through the integration of SAR data (including polarization, backscatter intensity, and interferometric data) with optical data (RGB), we developed a robust model leveraging a combination of U-Net and Generative Adversarial Networks (GANs) to produce realistic and visually enhanced colorized images. The model architecture was carefully designed to handle the unique challenges presented by SAR images, such as noise and lack of texture information, while preserving the structural integrity of the image.The project demonstrated the potential of deep learning in SAR image colorization, achieving notable improvements in image quality when evaluated using metrics like PSNR and SSIM. The data augmentation strategies employed further enhanced the model's generalization capabilities, ensuring it could adapt to various types of SAR and optical images.Despite the challenges of dealing with complex SAR data and image artifacts, the project's results indicate significant progress toward making SAR images more accessible and interpretable for practical applications, such as disaster monitoring, environmental monitoring, and agricultural analysis. The model successfully transformed SAR images into visually meaningful outputs, which could support more effective decision-making in these fields.

APPENDIX

```
import tensorflow as tf
from tensorflow.keras.layers import Conv2D, Conv2DTranspose, Input, Concatenate, Batch
from tensorflow.keras.models import Model
from tensorflow.keras.preprocessing.image import load_img, img_to_array
import numpy as np
from PIL import Image

def unet_model(input_shape=(256, 256, 1)):
    inputs = Input(shape=input_shape)

    def conv_block(x, filters, kernel_size=3, strides=2):
        x = Conv2D(filters, kernel_size, strides=strides, padding='same')(x)
        x = BatchNormalization()(x)
        return ReLU()(x)


    def deconv_block(x, skip_connection, filters, kernel_size=3, strides=2):
        x = Conv2DTranspose(filters, kernel_size, strides=strides, padding='same')(x)
        x = BatchNormalization()(x)
        x = ReLU()(x)

        # Resize skip_connection to match the shape of x before concatenation
        skip_connection = UpSampling2D(size=(2, 2), interpolation='nearest')(skip_conn

        x = Concatenate()([x, skip_connection])
        return x

    # Encoding
    e1 = conv_block(inputs, 64)
    e2 = conv_block(e1, 128)
```

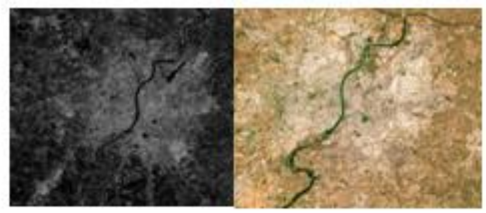


```
    d3 = deconv_block(d2, e2, 128)
    d4 = deconv_block(d3, e1, 64)
    outputs = Conv2D(3, (1, 1), activation='sigmoid')(d4)

    return Model(inputs, outputs)

model = unet_model()
model.compile(optimizer='adam', loss='mse', metrics=['accuracy'])
epochs = 125
batch_size = 16
sar_image_path = r"SAR-Image-3.jpg"
sar_image = load_img(sar_image_path, color_mode='grayscale', target_size=(256, 256))
sar_image = img_to_array(sar_image)
sar_image = sar_image / 255.0
sar_image = np.expand_dims(sar_image, axis=0)
rgb_image_path =r"inputimage.jpg"
rgb_image = load_img(rgb_image_path, target_size=(256, 256))
rgb_image = img_to_array(rgb_image)
rgb_image = rgb_image / 255.0
rgb_image = np.expand_dims(rgb_image, axis=0)

history = model.fit(sar_image, rgb_image, epochs=epochs, batch_size=batch_size)
model.save("sar_to_rgb_model.h5")
prediction = model.predict(sar_image)
prediction = prediction[0]
output_image = prediction * 255
output_image = output_image.astype(np.uint8)
image = Image.fromarray(output_image)
image.save("output_image.jpg")
```



```
1/1 ━━━━━━━━━━━━━━━━━━━━ 3s 3s/step - accuracy: 0
Epoch 82/125
1/1 ━━━━━━━━━━━━━━━━━━━━ 4s 4s/step - accuracy: 0.9431 - loss: 0.0029
Epoch 83/125
1/1 ━━━━━━━━━━━━━━━━━━━━ 2s 2s/step - accuracy: 0.9452 - loss: 0.0025
Epoch 84/125
1/1 ━━━━━━━━━━━━━━━━━━━━ 2s 2s/step - accuracy: 0.9454 - loss: 0.0025
Epoch 85/125
1/1 ━━━━━━━━━━━━━━━━━━━━ 2s 2s/step - accuracy: 0.9459 - loss: 0.0022
Epoch 86/125
1/1 ━━━━━━━━━━━━━━━━━━━━ 2s 2s/step - accuracy: 0.9470 - loss: 0.0022
Epoch 87/125
1/1 ━━━━━━━━━━━━━━━━━━━━ 3s 3s/step - accuracy: 0.9472 - loss: 0.0020
Epoch 88/125
1/1 ━━━━━━━━━━━━━━━━━━━━ 2s 2s/step - accuracy: 0.9479 - loss: 0.0019
Epoch 89/125
1/1 ━━━━━━━━━━━━━━━━━━━━ 3s 3s/step - accuracy: 0.9491 - loss: 0.0018
Epoch 90/125
1/1 ━━━━━━━━━━━━━━━━━━━━ 2s 2s/step - accuracy: 0.9497 - loss: 0.0017
Epoch 91/125
1/1 ━━━━━━━━━━━━━━━━━━━━ 2s 2s/step - accuracy: 0.9503 - loss: 0.0016
Epoch 92/125
1/1 ━━━━━━━━━━━━━━━━━━━━ 2s 2s/step - accuracy: 0.9501 - loss: 0.0015
Epoch 93/125
1/1 ━━━━━━━━━━━━━━━━━━━━ 3s 3s/step - accuracy: 0.9511 - loss: 0.0014
Epoch 94/125
1/1 ━━━━━━━━━━━━━━━━━━━━ 4s 4s/step - accuracy: 0.9514 - loss: 0.0014
Epoch 95/125
1/1 ━━━━━━━━━━━━━━━━━━━━ 2s 2s/step - accuracy: 0.9521 - loss: 0.0013
Epoch 96/125
1/1 ━━━━━━━━━━━━━━━━━━━━ 2s 2s/step - accuracy: 0.9524 - loss: 0.0013
Epoch 97/125
1/1 ━━━━━━━━━━━━━━━━━━━━ 3s 3s/step - accuracy: 0.9536 - loss: 0.0012
```

INPUT SAR IMAGE AND OUTPUT



VII. ACKNOWLEDGEMENT

We, the team members of theprojectSAR Image Colorization using Deep Learningwould like to extend our sincere gratitude to all those who contributed to the successful completion of this research.First and foremost, we express our heartfelt thanks to our Project Coordinator for their invaluable guidance, critical insights, and constant support throughout the course of this project. Their expertise and encouragement have been instrumental in driving our work forward and refining our approach. We also wish to acknowledge the unwavering support of our Institution, who provided the necessary resources, technical infrastructure, and a conducive environment for research and innovation. We are grateful to our faculty mentors and peers for their thoughtful suggestions and constructive feedback during the development and review phases of the project. Their contributions have greatly enhanced the

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