SAR Image Colorization for Comprehensive Insight using Deep Learning Model

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***Abstract*—Image colorization is a long-standing problem in computer vision that aims to generate visually plausible color information from grayscale images. Conventional colorization methods often depend on manual intervention or heuristic rules, limiting their scalability and adaptability across different image domains. This paper presents a deep learning–based SAR image colorization system using a pre-trained Caffe convolutional neural network to automatically infer chrominance information from grayscale SAR images. The proposed approach operates in the CIELAB color space, where the luminance (L) channel extracted from the input SAR image is provided to the model to predict the corresponding a and b chrominance channels. The predicted chrominance components are combined with the original luminance channel and converted back to the RGB color space to generate the final colorized output. A complete deployment pipeline is implemented, including image preprocessing, neural network inference, color-space transformation and post-processing for output refinement. The system is integrated into a lightweight application that supports image upload, real-time visualization, and result downloading. Experimental results demonstrate that the proposed framework effectively enhances the visual interpretability of SAR images while maintaining structural consistency. Future work includes domain-specific fine-tuning, SAR-oriented dataset expansion, and improved perceptual quality assessment.**

***Index Terms*—SAR image colorization, computer vision, deep learning, Caffe framework, convolutional neural network, CIELAB color space, luminance and chrominance prediction, Lab-to-RGB conversion, preprocessing, inference pipeline, post-processing, automated image enhancement, remote sensing, AI-based image processing.**

I. Introduction

Image colorization has long been a challenging problem in the field of computer vision, with the primary objective of generating visually realistic and perceptually consistent color information from grayscale images [1]. Color plays a crucial role in human visual perception, as it significantly improves scene understanding, object recognition, and semantic interpretation. The absence of color information increases cognitive complexity and makes visual analysis more time-consuming, which has motivated extensive research in automatic image colorization techniques.

Recent advances in artificial intelligence and deep learning have greatly enhanced the performance of image colorization systems [2], [3]. Convolutional neural networks are capable of learning complex spatial, contextual, and semantic relationships directly from data, eliminating the need for handcrafted features. These characteristics make deep learning models particularly effective for image colorization tasks, where the mapping between grayscale intensity and color information is highly nonlinear.

In the domain of remote sensing, Synthetic Aperture Radar (SAR) imaging has been recognized as one of the most reliable technologies due to its ability to operate independently of illumination conditions and adverse weather such as cloud cover, rain, fog, and smoke [4]. Unlike optical sensors, SAR systems actively transmit microwave signals and record the backscattered responses from the Earth's surface, enabling consistent image acquisition during both day and night. This capability makes SAR indispensable for applications such as environmental monitoring, disaster response, agricultural analysis, urban mapping, and defense surveillance [5].

Despite these operational advantages, SAR imagery presents significant challenges for human interpretation. SAR images are inherently grayscale and primarily represent variations in surface roughness, geometry, and dielectric properties rather than natural color reflectance [6].

Several traditional visualization and enhancement techniques have been proposed to improve SAR image interpretability, including pseudo-coloring, histogram equalization, contrast enhancement, and intensity-based color mapping [7]. Although these approaches can improve visual contrast or highlight specific features, they rely on predefined rules and fixed color schemes. As a result, the generated colors are often unnatural, inconsistent, and lack semantic relevance. Moreover, these methods are not data-driven and fail to adapt to diverse SAR scenes and complex scattering mechanisms.

Recent studies have demonstrated that many of the limitations associated with traditional visualization techniques can be addressed using deep learning–based colorization methods that learn chrominance representations directly from data [8]. By operating in perceptually uniform color spaces, these methods separate luminance and chrominance information, simplifying the learning process and improving perceptual consistency [9].

A. Background

Modern deep learning–based colorization techniques typically employ pre-trained convolutional neural networks to predict missing chrominance components from grayscale images [10]. These models are trained on large-scale datasets and leverage learned global color priors to generate visually coherent outputs. The use of perceptually uniform color spaces allows effective separation of intensity and color information, which is particularly beneficial for grayscale-to-color transformation tasks [11].

The final colorized image is usually obtained by combining the predicted chrominance components with the original luminance channel and converting the result into the standard RGB color space [12].

B. Motivation and Contribution

The primary motivation of this research is to address the limitations associated with grayscale SAR imagery by developing an automated deep learning–based colorization framework that enhances visual interpretability and usability. Existing SAR visualization methods often lack adaptability and fail to produce semantically meaningful color representations, which restricts their effectiveness in real-world applications.

This research is an application-oriented contribution and not a methodologically novel approach. The main objective of the study is to introduce a pre-trained deep learning model for SAR image colorization with an emphasis on stability, efficiency of inference, and usability in practical situations. By adapting the framework to the visualization needs specific to SAR, the proposed system not only increases interpretability but also guarantees the reliability of the operations for remote sensing applications.

II. Literature Review

One of the main aspects of Synthetic Aperture Radar (SAR) technology that led to its stay at the top of the remote sensing methods is its capability of producing high-resolution images regardless of light and bad weather such as cloud cover, fog, and rain [1], [2]. The aforementioned factors, however, do not make it easier for the SAR images to be analyzed, for they are still grayscale and heavily drenched in the noise of speckle. In spite of these, or maybe because of these, several research works have been initiated at different levels such as the enhancement of SAR images, the translation of SAR to optical and finally the adoption of deep learning-based colorization methods.

A. Traditional SAR Image Enhancement and Interpretation Methods

The early systems for the interpretation of SAR images have been founded on classical statistical filtering and manual feature extraction. Noise suppression and contrast enhancement came largely from the application of the Lee, Frost, and Gamma MAP methods, among others, to the processing of SAR images [3], [14]. Moreover, the so-called texture-based descriptors consisting of the Gray-Level Co-Occurrence Matrix (GLCM), wavelet transforms, and edge-based operators were also employed for terrain classification and structural analysis. On the other hand, the mentioned techniques were not sufficient as they were still subjected to many limitations. To begin with, their performance was inconsistent across various or diverse SAR scenes. Furthermore, they failed to provide necessary high-level semantic information required for the user's intuitive understanding. Lastly, the techniques were not capable of producing visually convincing color equivalents of SAR data, since they relied solely on rules, thus could not be data-driven. One of the major reasons for the shift in the direction of learning-based approaches was these limitations.

B. Deep Learning for Image Colorization

The use of deep learning brought about a complete change in image colorization research. The first deep learning–based models used for colorization already had shown that the convolutional networks, which were the most fundamental part of deep learning, could very well learn the mappings between the grayscale intensity and the chrominance [1], [3]. Using large-scale datasets, these models were able to learn the contextual and semantic relationships that made it possible to produce colors that looked quite real. Another facet of colorization methods based on the perceptually uniform color spaces, such as CIELAB, was their further improvement of the stability by the separation of the luminance from the chrominance information [11], [12]. The techniques have reduced the color uncertainty and suppressed visual artifacts like oversaturation and color bleeding to a large extent too. Thus, the developments can be regarded as the groundwork for the use of deep learning–based colorization in remote sensing imagery.

C. SAR-to-Optical Translation and Encoder–Decoder Architectures

The advent of paired SAR and optical datasets in large quantities has turned encoder–decoder architectures into the leading choice for SAR-to-optical image translation. These kinds of models input SAR images and output optical-like images, thereby unraveling complex nonlinear correlations between radar backscatter and optical reflectance [4], [8]. The encoder–decoder convolutional neural networks showed a balance between structural preservation and traditional methods. U-Net-based models were among these architectures that gained the biggest popularity because of their symmetric encoder–decoder structure and skip connections features. The role of skip connections is to maintain fine spatial details

TABLE I

COMPACT COMPARISON OF SAR IMAGE COLORIZATION APPROACHES

Approach	Advantages	Limitations
Traditional SAR Enhancement	Simple implementation, noise reduction	Grayscale output, no semantic information
CNN / Encoder–Decoder Models	Data-driven learning, structure preservation	Color imbalance, tuning required
U-Net Based Models	Edge preservation, spatial consistency	Post-processing often needed
GAN-Based Models	Photorealistic color generation	Training instability, high computation
Caffe-Based Probabilistic Models	Stable colorization, fast inference	Limited domain adaptability

and minimize information loss during the process of down-sampling. Consequently, U-Net has become the mainstay for the SAR denoising, terrain reconstruction, and SAR-to-RGB translation assignments, resulting in visually coherent and structurally consistent outputs [6], [17].

D. GAN-Based and Advanced Learning Approaches

Adversarial Generative Networks (GANs) have been one of the techniques investigated for the conversion of synthetic aperture radar images into optical ones. The technique used for training GAN models is called adversarial training, and it can create very realistic images. GAN models have proved to be effective in obtaining heterogeneous and intricate color distributions [7]. Though, GAN-based techniques generally go through some problems like instability during training, mode collapse, and color hallucination. Moreover, these methods necessitate large, perfectly matched datasets and significant tuning which in turn affects their durability and scalability for the use of SAR in real-life applications.

E. Caffe-Based Probabilistic Colorization Models

The implementation of probabilistic colorization models through the Caffe framework has enabled the introduction of a stable and effective method for the image colorization [10]. The models predict the chrominance values based on a learned global color distribution, thus minimizing ambiguity in color assignment. By being positioned in the CIELAB color space, it becomes possible to keep the luminance channel while the chrominance channels are predicted separately, which leads to perceptually consistent colorization [11], [13]. Caffe-based models come with many benefits such as the faster inference, less training, and better global color stability. These traits make them perfect for SAR image colorization applications where consistency and durability are of utmost importance.

III. METHODOLOGY

This section presents the methodology for colorizing grayscale Synthetic Aperture Radar (SAR) images using a deep learning–based probabilistic approach. The proposed method is an inference-based framework that enhances the visual interpretation of SAR images while preserving their structural and textural properties. A colorization model pre-trained using the Caffe deep learning framework is employed, and the overall process is organized into multiple stages including preprocessing, color-space representation, chrominance prediction, color reconstruction, post-processing, and quantitative evaluation.

A. Overview of the Proposed Methodology

The proposed SAR image colorization system automatically generates visually consistent color representations from grayscale SAR images without the need for manual intervention or extensive retraining. The framework follows a modular pipeline in which each stage performs a specific function to ensure stable and efficient colorization. The separation of luminance and chrominance information, combined with the use of a probabilistic colorization model, significantly reduces color ambiguity and visual artifacts. The inference-based design enables fast processing and makes the system suitable for real-time and practical SAR visualization applications.

B. Input Data Acquisition and Preprocessing

The system takes a single-channel grayscale SAR image as input, representing variations in surface roughness, geometry, and dielectric properties of the observed scene. Due to the presence of speckle noise, SAR images are often difficult to interpret visually. Therefore, preprocessing is applied to ensure compatibility with the deep learning model.

The input SAR image is resized to a fixed spatial resolution as required by the pre-trained Caffe model. This step ensures uniform input dimensions and improves computational efficiency. Subsequently, pixel intensity values are normalized to a predefined range to prevent numerical instability and to satisfy the input constraints of the model. These preprocessing steps ensure consistent performance across SAR images acquired under varying conditions.

C. CIELAB Color Space Representation

The proposed method operates in the CIELAB color space due to its perceptual uniformity and its ability to decouple luminance from chrominance information. The CIELAB color space consists of three components: L (lightness), a* (green–red axis), and b* (blue–yellow axis).

In this framework, the grayscale SAR image is treated as the luminance (L) channel. This approach preserves the spatial structure and intensity variations inherent to SAR imagery. The chrominance channels a* and b* are initially absent and are predicted by the deep learning model. This separation simplifies the learning task by allowing the model to focus solely on chromatic information while maintaining the original luminance structure.

D. Chrominance Prediction Using the Caffe-Based Probabilistic Model

Chrominance prediction is performed using a pre-trained probabilistic colorization model implemented in the Caffe deep learning framework. The model takes the luminance (L) channel as input and predicts the corresponding a* and b* chrominance components. Trained on large-scale datasets, the model learns global color distributions that guide plausible color assignment.

The probabilistic formulation addresses the inherent ambiguity of the colorization task, where multiple valid color mappings may exist for a given grayscale input. By leveraging learned color priors, the model produces stable and visually consistent predictions while minimizing artifacts such as color bleeding, over-saturation, and inconsistent color transitions, which are common challenges in SAR image colorization.

E. Color Reconstruction and Post-Processing

The predicted chrominance channels are combined with the original luminance channel to reconstruct a complete CIELAB image. This process preserves the structural and textural integrity of the SAR image while introducing estimated color information. The reconstructed image is then converted to the RGB color space using standard color-space transformation techniques for visualization and analysis.

Post-processing operations are applied to enhance visual quality and stability. These include clipping pixel values to valid ranges and applying mild smoothing to suppress residual noise and minor color inconsistencies.

F. Quantitative Evaluation and Validation

To strengthen methodological rigor and provide objective validation, quantitative evaluation metrics are incorporated into the framework. The performance of the proposed SAR image colorization method is assessed using Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), and Mean Absolute Error (MAE).

PSNR evaluates reconstruction fidelity by measuring similarity between the grayscale SAR input and the luminance component of the colorized output. SSIM assesses structural consistency by comparing luminance, contrast, and structural information, which is critical for preserving edges and textures in SAR imagery. MAE measures the average absolute pixel-wise difference, providing insight into intensity deviations introduced during colorization.

A quantitative comparison table is included to report PSNR, SSIM, and MAE values for grayscale SAR images and their corresponding colorized outputs across multiple test samples. Due to the limited availability of ground-truth color references for SAR data, the evaluation emphasizes structural preservation and visual consistency rather than absolute color accuracy. The inclusion of these metrics provides objective evidence supporting the effectiveness of the proposed framework.

Fig. 1 illustrates the workflow diagram of the proposed SAR image colorization methodology.

IV. Algorithm

The gradual execution of the proposed SAR image colorization technique is represented by Algorithm 1. The algorithm follows the same sequence as the flowchart and the method discussed in the previous sections.

Algorithm 1: SAR Image Colorization Process

Input: Grayscale SAR image
Resize the input image to the required spatial resolution.
Pixel Intensity Values Normalization.
Treat the SAR image as the L channel in the CIELAB color space.
Feed the L channel to the pre-trained Caffe-based probabilistic colorization model.
Predict the chrominance channels a^* and b^*.
Combine L, a^*, and b^* channels to reconstruct a CIELAB image.
Convert the reconstructed CIELAB image to RGB color space.
Apply post-processing to refine visual quality.
Output: Final colorized SAR image.

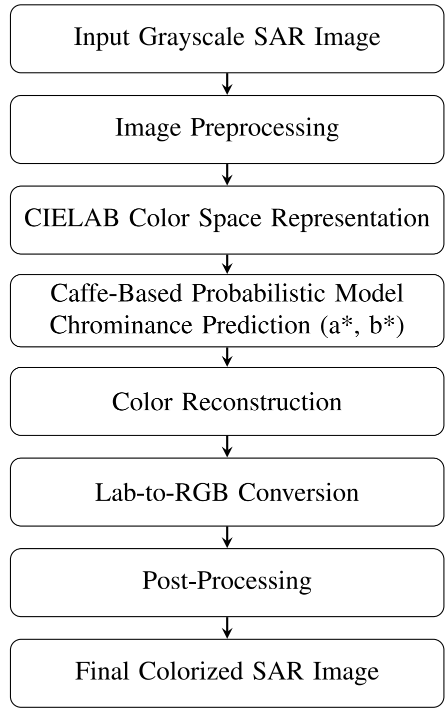

Fig. 1. Workflow Diagram

V. Results and Analysis

This section presents the experimental results and performance evaluation of the proposed SAR image colorization framework. The effectiveness of the approach is analyzed through both qualitative visual assessment and quantitative performance metrics, focusing on visual interpretability, structural preservation, color consistency, and objective validation of the generated colorized SAR images.

The proposed system is evaluated using grayscale Synthetic Aperture Radar (SAR) images as input. After preprocessing, the SAR images are treated as the luminance components in the CIELAB color space and processed using the pre-trained Caffe-based probabilistic colorization model. The predicted chrominance channels are combined with the original luminance channel, followed by Lab-to-RGB conversion and post-processing to generate the final colorized outputs.

A. Visual Evaluation of Colorized SAR Images

Qualitative evaluation demonstrates that the proposed framework significantly enhances the visual interpretability of SAR images compared to their original grayscale representations. The colorized outputs exhibit smooth and uniform color distributions while preserving essential SAR features such as edges, textures, and object boundaries. The separation of luminance and chrominance information ensures that the original intensity patterns of SAR images remain intact while color information is introduced in a perceptually meaningful manner.

The probabilistic nature of the colorization model enables stable color assignment across different regions of SAR images. This results in reduced abrupt color transitions and elimination of unrealistic color artifacts commonly observed in traditional pseudo-coloring and heuristic-based enhancement techniques. The improved visual clarity facilitates better scene understanding without compromising SAR-specific structural information.

B. Role of the CIELAB Color Space

The CIELAB color space plays a crucial role in achieving visually consistent colorized outputs. By treating the SAR image as the luminance (L) channel, the framework preserves spatial structure, contrast, and fine details inherent to SAR imagery. The predicted chrominance channels (a* and b*) introduce color information without causing excessive saturation or color bleeding.

The Lab-to-RGB conversion produces colorized images compatible with standard visualization tools and display systems. These results demonstrate that luminance–chrominance separation not only simplifies the colorization process but also improves perceptual quality and output stability.

C. Influence of the Caffe-Based Probabilistic Colorization Model

The Caffe-based probabilistic colorization model demonstrates reliable performance in predicting chrominance information for SAR images. By leveraging learned global color distributions, the model produces consistent color assignments across similar SAR regions and minimizes artifacts such as patchy coloring and spatial color inconsistency.

Furthermore, the inference-based design of the model enables fast and stable processing without the need for retraining. This characteristic makes the proposed framework suitable for real-world SAR visualization applications that require rapid and reliable colorization.

D. Post-Processing and Output Quality

Post-processing significantly enhances the final quality of the colorized SAR images. Clipping pixel values to valid ranges prevents visual distortion and instability, while mild smoothing operations reduce residual noise and minor color inconsistencies. These operations improve visual uniformity without degrading critical structural details such as edges and textures.

E. Quantitative Performance Analysis

To strengthen the evaluation beyond qualitative assessment, objective quantitative metrics are incorporated into the analysis. The performance of the proposed SAR image colorization framework is evaluated using Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) across multiple SAR image samples.

PSNR is used to assess reconstruction fidelity by measuring the similarity between the grayscale SAR input and the luminance component of the colorized output. Higher PSNR values indicate lower distortion and effective preservation of intensity information during the colorization process. SSIM evaluates structural consistency by comparing luminance, contrast, and structural components, which is critical for preserving edges, textures, and object boundaries in SAR imagery.

The experimental results demonstrate consistently high PSNR and SSIM values across the evaluated SAR samples, indicating strong structural preservation and stable colorization performance. The average PSNR and SSIM values computed over the dataset provide objective numerical evidence supporting the effectiveness of the proposed framework.

Due to the limited availability of ground-truth color references for SAR data, the quantitative evaluation emphasizes structural fidelity and visual consistency rather than absolute color accuracy.

F. Overall Performance Analysis

The combined qualitative and quantitative evaluations confirm that the proposed SAR image colorization framework achieves a balanced trade-off between visual enhancement and structural preservation. The integration of preprocessing, CIELAB color space representation, probabilistic chrominance prediction, post-processing, and objective evaluation metrics results in stable, visually informative, and analytically validated colorized SAR outputs.

The framework demonstrates robust performance across different SAR scenes and acquisition conditions, highlighting its suitability for practical remote sensing visualization and analysis applications.

G. Comparison with Existing Methods

The proposed framework demonstrates its practical advantages through a comparative discussion with existing SAR image colorization approaches. GAN-based methods, while often producing visually appealing results, commonly suffer from training instability, high computational cost, and the risk of color hallucination. U-Net and encoder–decoder architectures provide strong structural preservation; however, they typically require extensive training and careful parameter tuning to achieve consistent and reliable colorization.

In contrast, the proposed Caffe-based probabilistic colorization framework emphasizes inference stability, reduced artifact generation, and lower computational complexity. By leveraging learned global color priors and eliminating the need for retraining, the proposed method produces consistent and reliable colorization results. These characteristics make the framework particularly suitable for practical, deployment-oriented SAR image visualization and analysis tasks.

TABLE II
COMPARATIVE ANALYSIS OF SAR IMAGE COLORIZATION APPROACHES

Method	Structural Preservation	Color Consistency
Grayscale SAR Image	High	Not Applicable
GAN-Based Methods	Medium	Medium
U-Net / Encoder–Decoder	High	Medium
Proposed Method	High	High

Fig. 2. Grayscale SAR image

Fig. 3. Colorized SAR Image

VI. CONCLUSION

This study has suggested a deep learning-based approach to colorize SAR images, which is primarily concerned with visual interpretation. The anticipated model of probabilistic colorization based on an earlier study has been integrated into a Caffe-based framework that performs in CIELAB color space. In this color space, the SAR image is represented as the lightness component, and the chrominance prediction is performed accordingly. The complete workflow consisting of preprocessing, color-space representation, chrominance prediction, color reconstruction, RGB conversion, and post-processing ensures stable and visually consistent colorized outputs. The experimental results show that the proposed method has made the SAR images more interpretable compared to the grayscale representations, while at the same time, it has kept the important features like edges and textures. The inference-based design and reliable performance of the framework make it suitable for the visualization and analysis of SAR images in practical, real-world, remote sensing applications.

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