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SAR Image and Video Colorization Using Deep Learning for Defence Surveillance

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Abstract: Synthetic Aperture Radar (SAR) is widely used in defence and surveillance applications due to its capability to capture high-resolution imagery independent of weather conditions and illumination. However, the inherent grayscale representation and presence of speckle noise often limit intuitive visual interpretation and downstream analysis. To address this challenge, this paper proposes a deep learning–based approach for SAR image and video colorization that converts single-channel SAR data into visually enhanced, optical-like representations. The proposed framework integrates a hybrid architecture combining Generative Adversarial Networks (GANs) with transformer-based modules, along with speckle-aware preprocessing, perceptual loss optimization, and temporal consistency mechanisms for video sequences. Experimental results obtained on benchmark datasets, including MSTAR and Sentinel-1, indicate that the colorized outputs improve scene interpretability, object discrimination, and terrain perception compared to conventional grayscale SAR images. The incorporation of SAR image and video colorization into defence systems has the potential to support enhanced situational awareness, faster decision-making, and more effective intelligence analysis.
Keywords— SAR, Image Colorization, Deep Learning, GANs, Defence Surveillance.

I. INTRODUCTION

Synthetic Aperture Radar (SAR) has emerged as an indispensable remote sensing technology in contemporary defence and surveillance systems because of its ability to generate high-resolution imagery independent of lighting conditions and adverse weather. Operating in the microwave frequency range, SAR sensors can effectively image the Earth's surface through clouds, fog, smoke, and light vegetation, making them highly reliable for applications such as military reconnaissance, surveillance, target monitoring, and terrain analysis. However, SAR imagery is typically represented in grayscale and is affected by speckle noise, which reduces visual clarity and poses challenges for human interpretation as well as automated analysis.

In recent years, image and video colorization techniques have gained attention as a means to improve the interpretability and semantic richness of SAR data. Advances in deep learning, particularly through Generative Adversarial Networks (GANs) and transformer-based models, have enabled the transformation of single-channel SAR images into visually enhanced, colorized, or optical-like representations. Such representations can better convey structural details, spatial context, and object boundaries. For SAR video sequences, incorporating temporal consistency constraints is essential to maintain coherent color transitions across frames, thereby supporting stable and real-time visual analysis.

Motivated by these developments, this work presents a unified deep learning framework for SAR image and video colorization with a focus on defence applications. The proposed approach combines speckle-aware preprocessing with perceptual and adversarial learning strategies, along with temporal regularization for video data. The resulting colorized outputs improve visual perception and semantic understanding, assisting analysts and enhancing the performance of automated tasks such as target recognition and terrain classification. Overall, the proposed framework contributes toward more intelligent, interpretable, and effective defence surveillance systems.

II. MOTIVATION AND PROBLEM STATEMENT

Synthetic Aperture Radar (SAR) enables dependable imaging in all-weather and day–night environments, making it a vital component of defence surveillance and reconnaissance systems. However, the single-channel grayscale representation and speckle noise in SAR imagery restrict effective human interpretation and hinder automated analytical processes. Converting SAR images and videos into colorized representations can improve visual comprehension, situational awareness, and operational decision-making in defence applications.

Despite progress in deep learning and image-to-image translation techniques, SAR colorization faces challenges due to complex radar backscatter, limited availability of optical references, and noise-induced distortions. To address these issues, this work introduces a deep learning–based framework for SAR image and video colorization that emphasizes realistic color assignment, structural feature preservation, and temporal consistency, thereby enhancing the usability of SAR data in defence intelligence and surveillance systems.

III. LITERATURE REVIEW

Synthetic Aperture Radar (SAR) imagery is extensively employed in remote sensing applications because of its ability to acquire data independent of illumination and weather conditions. However, SAR images are inherently monochromatic and corrupted by speckle noise, which reduces visual clarity and makes interpretation more difficult than optical imagery. To address this limitation, research efforts have increasingly focused on SAR colorization and SAR-to-optical image translation as means to improve visual understanding and semantic information extraction.

Shen et al. [1] introduced a comprehensive benchmark for SAR colorization methods, comparing traditional regression-based techniques with recent deep learning approaches. Their evaluation demonstrated that deep neural networks are more effective in modeling the nonlinear relationship between SAR backscatter signals and corresponding optical color information. The study also emphasized the importance of standardized datasets and evaluation metrics for fair comparison of SAR colorization techniques.

The relevance of SAR colorization has been particularly evident in disaster management and flood monitoring scenarios. Al-Saad et al. [2] developed a SAR-based change detection framework for flood analysis, highlighting the robustness of SAR data in emergency conditions. Extending this work, Aburaed et al. [3] analyzed the influence of SAR colorization on flood mapping performance and reported that appropriately colorized SAR images enhance visual interpretation and mapping accuracy.

Advances in deep learning have significantly contributed to SAR representation enhancement. Song et al. [4] proposed a neural network–driven approach to infer fully polarimetric information from single-polarization SAR images, demonstrating the ability of deep models to recover missing information beyond conventional physical models. This work provided early evidence of the effectiveness of learning-based SAR data enhancement.

Generative Adversarial Network (GAN)–based image translation frameworks have been widely adopted for SAR-to-optical conversion tasks. CycleGAN, introduced by Zhu et al. [5], enables unpaired image translation through cycle-consistency constraints and has proven effective in remote sensing applications where paired SAR–optical datasets are unavailable. In contrast, Pix2Pix, proposed by Isola et al. [6], performs supervised image translation using paired data and produces visually realistic results when aligned SAR–optical images are available.

Several studies have customized GAN architecture specifically for SAR applications. Wang et al. [7] proposed a supervised cycle-consistent adversarial network that improves structural fidelity and spectral consistency in SAR-to-optical translation. Similarly, Hwang et al. [8] enhanced CycleGAN-based models by incorporating Structural Similarity Index Measure (SSIM) and perceptual loss functions, resulting in sharper and more coherent translated images.

Research focusing on GAN training stability has also influenced SAR colorization. Mao et al. [9] introduced the Least Squares GAN (LSGAN) framework to mitigate training instability and mode collapse, issues that are particularly pronounced when handling noisy SAR data. Such improvements have enabled more stable and reliable SAR image translation models.

Beyond direct image translation, SAR colorization has been explored in combination with multi-modal data fusion. Drakonakis et al. [10] presented OmbriaNet, a supervised convolutional neural network that integrates multi-temporal Sentinel-1 SAR and Sentinel-2 optical data for flood mapping, demonstrating improved classification performance through combined representations. Additionally, Shokr and Dabboor [11] reviewed the use of polarimetric SAR in sea ice monitoring, underscoring the value of enhanced SAR representations for complex surface characterization.

Deep learning–based segmentation methods further complement SAR colorization research. Liao et al. [12] showed that deep feature extraction significantly improves segmentation accuracy, suggesting that visually enhanced or colorized SAR images can provide more discriminative features for downstream tasks such as land cover mapping and disaster assessment.

In summary, existing studies indicate that deep learning–based SAR colorization and SAR-to-optical translation, particularly using CNNs and GANs, substantially enhance visual interpretability and application performance. Nevertheless, challenges remain in maintaining physical consistency and achieving robust generalization across different terrains and sensor configurations. These limitations motivate the development of robust deep learning frameworks trained on paired SAR–optical datasets for reliable and application-oriented SAR image and video colorization.

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IV. PROPOSED SYSTEM

A. Architecture Overview

The proposed system presents a deep learning–driven framework for SAR image and video colorization aimed at improving the visual interpretability of radar imagery in defence applications. The overall architecture is based on a Generator–Discriminator paradigm derived from conditional Generative Adversarial Networks (cGANs).

The Generator (G) is designed to transform speckle-suppressed SAR inputs into visually enhanced, colorized outputs by learning spatial structures and texture-related features. The Discriminator (D) evaluates the generated outputs against real optical images, enabling the generator to progressively refine its predictions and produce visually realistic representations.

To handle SAR video sequences, a Temporal Consistency Module (TCM) is incorporated to maintain coherence across consecutive frames and minimize temporal artifacts such as flickering. The training process employs a composite loss function that includes adversarial, pixel-wise, perceptual, and temporal components to ensure structural fidelity and smooth color transitions.

Overall, the proposed framework improves SAR data interpretability, facilitates object recognition and terrain assessment, and provides defence analysts with enhanced, color-enriched visual information to support faster and more informed decision-making.

B. Workflow Diagram

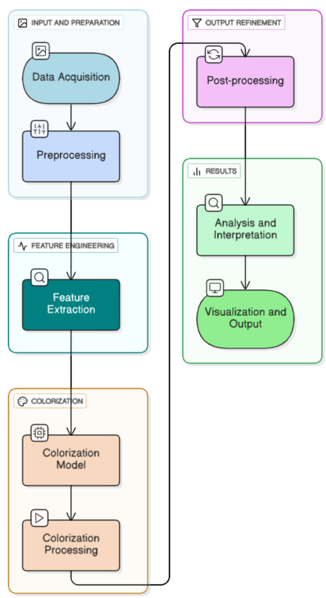

Fig. 1. Workflow diagram of the proposed system.

V. EQUATION ANALYSIS

Mathematical Formulation

SAR image intensity follows a multiplicative noise model:

$$I(x,y)=\sigma 0(x,y)\ n(x,y) \quad (1)$$

where $\sigma 0(x,y)$denotes the radar backscatter coefficient and $n(x,y)$represents speckle noise. Applying a logarithmic transformation converts this into an additive form:

$$L(x,y)=log I(x,y)=log \sigma 0(x,y)+log n(x,y) \quad (2)$$

The log-transformed SAR image $L(x,y)$is used as input to the colorization generator $G(\cdot)$, which maps SAR data to the optical color domain:

$$\hat{C}=G(L) \quad (3)$$

A conditional adversarial loss is employed to enforce realism:

$$\mathscr{L}GAN=\mathbb{E}(L,C)[logD(L,C)]+\mathbb{E}L[log(1-D(L,G(L)))] \quad (4)$$

The generator is optimized using a combination of pixel-wise, perceptual, and temporal consistency losses:

$$\mathscr{L}pix=\|G(L)-C\|1 \quad (5)$$

$$\mathscr{L}per=\Sigma\|l\phi l(G(L))-\phi l(C)\|22 \quad (6)$$

$$\mathscr{L}temp=\Sigma\|G(tLt)-Wt\leftarrow t-1(G(Lt-1))\|1 \quad (7)$$

The overall objective function is defined as:

$$\mathscr{L}total=\lambda 1\mathscr{L}GAN+\lambda 2\mathscr{L}pix+\lambda 3\mathscr{L}per+\lambda 4\mathscr{L}temp \quad (8)$$

Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) are used to assess model performance:

$$PSNR=10log\ 10(Lmax2MSE),SSIM\in[0,1] \quad (9)$$

VI. METHODOLGY

The proposed methodology for SAR image and video colorization begins with the collection of high-resolution SAR datasets, followed by preprocessing operations such as speckle noise suppression, data normalization, and region-of-interest extraction. These steps enhance input quality and improve learning stability. Spatial and textural features are then extracted using convolutional neural networks (CNNs), which are essential for generating visually consistent colorized outputs.

The core model adopts an encoder–decoder architecture with skip connections to effectively map grayscale SAR inputs to corresponding color representations. Training is guided by a combination of pixel-level reconstruction loss and perceptual loss, with an optional adversarial loss component to improve visual realism. For SAR video sequences, temporal coherence is preserved through optical flow–based propagation or recurrent architectures such as ConvLSTM, ensuring smooth color transitions across consecutive frames.

Post-processing includes edge-aware color refinement and histogram alignment with reference optical data to enhance visual consistency. The PyTorch framework is used to implement the model, and the Adam optimizer is used to optimize it. Data augmentation techniques, including rotations, flips, and intensity scaling, are applied during training to improve robustness and generalization.

VII. EXPECTED OUTCOME

The proposed deep learning–based SAR image and video colorization framework is expected to improve the interpretability of Synthetic Aperture Radar imagery by producing visually coherent and structurally consistent colorized outputs. By learning complex nonlinear relationships between SAR backscatter characteristics and optical color information, the model aims to reduce ambiguity in grayscale SAR images while retaining critical spatial and textural details.

The generated colorized images are anticipated to exhibit enhanced visual quality, including improved edge preservation, spatial continuity, and reduced speckle-induced artifacts when compared to conventional regression-based and shallow learning methods. These improvements are expected to support more efficient scene interpretation by both human analysts and automated systems.

From a quantitative perspective, the proposed approach is expected to achieve higher similarity scores and lower reconstruction errors, indicating realistic and physically consistent color representation. Enhanced SAR imagery is also expected to improve the performance of downstream remote sensing tasks such as flood mapping, change detection, land-cover classification, and image segmentation by providing more discriminative features.

Additionally, the framework is expected to generalize effectively across varying terrains, geographic regions, and acquisition conditions when trained on paired SAR–optical datasets. Overall, this work aims to deliver a scalable and application-oriented SAR colorization solution that bridges the interpretability gap between SAR and optical imagery, enabling more accurate analysis and reliable decision-making in real-world remote sensing applications.

VIII. CONCLUSION

This work presents a unified deep learning framework for SAR image and video colorization designed to enhance situational awareness in defence applications. By integrating feature extraction, encoder–decoder–based colorization, and temporal consistency mechanisms, the proposed system generates visually coherent and realistic colorized outputs while preserving essential structural information. The enhanced representations improve human interpretability and support faster, more reliable decision-making.

Furthermore, this study establishes a foundation for future extensions involving multimodal data fusion and real-time operational deployment.

IX. ACKNOWLEDGEMENT

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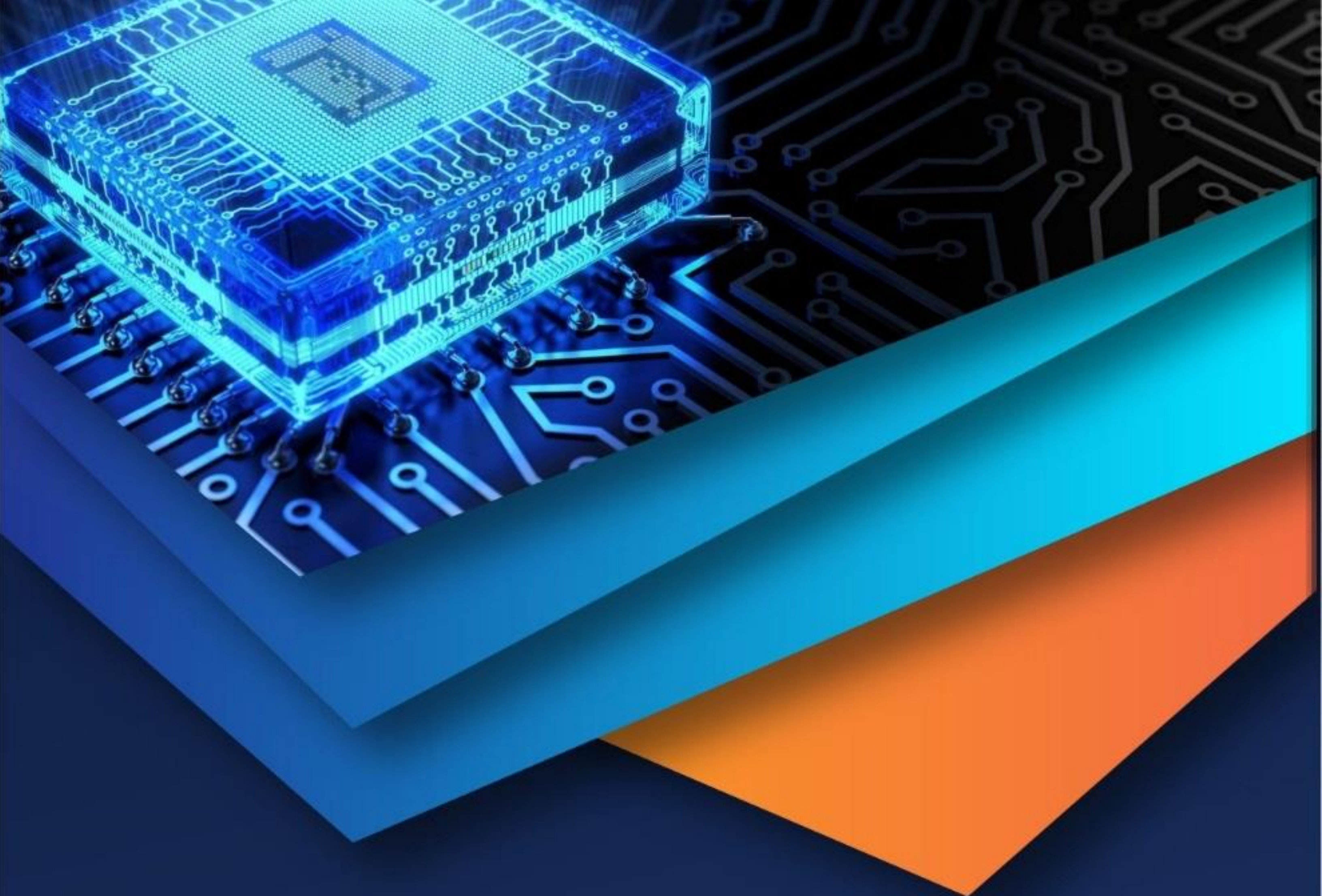

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