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# SAR Image Colorization for Comprehensive Insight using Deep Learning Model

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***Abstract: Synthetic Aperture Radar (SAR) imagery provides critical structural and textural information for remote sensing applications; however, the lack of natural color limits intuitive interpretation and visual analysis. This report presents a Deep Learning (DL) based framework for SAR image colorization aimed at enhancing the usability and interpretability of SAR data. The proposed approach leverages paired SAR and optical imagery to train a neural network capable of predicting realistic color representations from monochromatic SAR inputs. The model integrates advanced preprocessing techniques, feature extraction, and a customized loss function to minimize the gap between predicted and true color images. Key challenges addressed include speckle noise reduction, domain alignment between SAR and optical data, and the development of suitable evaluation metrics for qualitative and quantitative validation. Experimental results demonstrate the potential of the DL-based system to improve visual perception of surface features, thereby supporting improved analysis in applications such as land cover mapping, geological studies, and environmental monitoring. The outcome of this work contributes toward an effective SAR image colorization software solution, enabling remote sensing analysts to gain more comprehensive insights from SAR datasets.***
***Keywords: Synthetic Aperture Radar (SAR), SAR Image Colorization, Deep Learning, Neural Network, Optical Imagery, Speckle Noise Reduction, Domain Alignment, Feature Extraction, Customized Loss Function, Remote Sensing, Land Cover Mapping, Geological Studies, Environmental Monitoring.***

## I. INTRODUCTION

Satellite imagery has become a vital resource for observing, analyzing, and understanding Earth's surface. Traditionally, optical satellite sensors such as Sentinel-2 capture visible light to produce natural color images. These images are intuitive and easy to interpret, making them widely used in environmental studies, agriculture, urban planning, and disaster monitoring. However, optical imaging suffers from limitations such as cloud obstruction, atmospheric disturbances, low visibility, and restricted usability during nighttime.

Synthetic Aperture Radar (SAR), on the other hand, overcomes these challenges. SAR sensors, such as Sentinel-1, use microwave signals to capture surface information independent of weather or lighting conditions. This makes SAR a highly reliable and continuous data source for remote sensing. Despite these advantages, SAR images are difficult for human interpretation due to their grayscale representation and radar-based texture patterns.

To bridge this gap, deep learning-based SAR image colorization has emerged as a promising solution. It enables translation of SAR imagery to visually meaningful color outputs comparable to optical images. Deep learning models can learn spatial and spectral relationships between SAR and optical datasets, allowing automatic color generation while preserving important structural information. This enhances the usability of SAR data for research and operational decision-making.

## II. LITERATURE SURVEY

| Sr.no | Paper Title | Technology Used | Conclusion |
|---|---|---|---|
| 1 | SAR Image Colorization: Converting Single-Polarization to Fully Polarimetric Using Deep Neural Networks – Qian Song, Feng Xu Ya- Qiu Jin | Deep Neural Network (DNN) | Improved SAR interpretability by generating pseudo-color images; preserved texture information. |

| | | | |
|---|---|---|---|
| 2 | SAR Image Colorization Using Multidomain Cycle- Consistency GAN – Ji & Wang | CycleGAN- based unsupervised colorization | Generated realistic RGB images from SAR data without paired datasets |
| 3 | A Benchmarking Protocol for SAR Colorization: From Regression to Deep Learning Approaches – Kangqing Shen et al | Comparative study (CNN, U- Net, Pix2Pix) | Deep learning outperformed classical regression; achieved PSNR ≈ 28.5 dB |
| 4 | SAR Image Colourization for Comprehensive Insight Using Deep Learning – Shakthi Priya P., Lavanya S. et al. | U-Net with GAN enhancement | High SSIM (~0.9) and realistic terrain- based coloring. |
| 5 | SAR Image Colorization for Comprehensive Insight Using Deep Learning – Kaushal Kishor, Chirag Sharma, Himanshu Sharma, Manmohan Fulara, Aditya Yadav | Hybrid U-Net + Pix2Pix GAN | Achieved realistic results for Sentinel-1/2 dataset with PSNR of 28.4 dB and SSIM of 0.91 |
| 6 | Colorization of Sentinel-1 SAR Imagery Using Transfer Learning – Ahmed et al. | Transfer learning (ResNet + GAN) | Faster convergence and improved generalization |
| 7 | SAR Image Enhancement and Colorization via Vision Transformers – Banerjee & Roy | MATLAB, Computer Vision, Robotics | Developed practical robotic vision control systems using real-time image feedback and MATLAB tools. |
| 8 | Deep SAR-to- Optical Image Translation Based on Conditional GANs – Zhao et al | Pix2Pix GAN framework | Improved visual realism of SAR data with reduced blurring. |
| 9 | Smart Home Architecture and IoT Technologies | IoT, Home Automation, Sensor Networks | Outlined the architecture and technologies essential for building intelligent home environments. |
| 10 | Improving SAR Image Colorization with Multi-Scale U-Net Architecture – Patel & Kumar | Multi-scale U- Net | Achieved higher PSNR and SSIM with better edge preservation |
| 11 | Hybrid CNN- GAN Framework for Realistic SAR- to-Optical Image Translation – Park & Lee | CNN + GAN hybrid model | Achieved PSNR = 29.1 dB, SSIM = 0.92; stable and visually appealing |
| 12 | SAR-to-Optical Image Translation via Attention-Based Conditional GAN – Li et al. | Attention GAN (cGAN + Attention mechanism) | Enhanced texture fidelity and color sharpness. |
| 13 | Colorization of Sentinel-1 SAR Imagery Using Transfer Learning – Ahmed et al. | Transfer learning (ResNet + GAN) | Faster convergence and improved generalization |

## III. METHODOLOGY

### A. *Data Collection*

Paired Synthetic Aperture Radar (SAR) and optical images were collected from publicly available datasets such as SEN12MS and SpaceNet-6. These datasets provide co-registered radar and optical imagery suitable for supervised deep learning tasks.

The SAR images serve as the input grayscale data, while the optical images provide ground truth color references required for model training and evaluation.

### B. *Data Preprocessing*

The SAR and optical image pairs were aligned, normalized, and converted into the Lab color space.

In this representation:

1) The SAR grayscale image was used as the luminance (L) channel, and
2) The optical image provided the chrominance (a, b) channels as target outputs.
3) Additional preprocessing included noise filtering, resizing, and data normalization to ensure consistency across all samples.

### C. *Model Architecture*

A Convolutional Neural Network (CNN) based encoder–decoder architecture was designed to learn the mapping between SAR luminance and optical chrominance information.

1) The encoder extracts high-level spatial and textural features from the SAR input.
2) The decoder reconstructs the corresponding colorized image from these learned features.
3) The architecture incorporates skip connections, batch normalization, and ReLU activations to preserve fine details and improve convergence during training.

### D. *Model Training and Evaluation*

The model was trained using a supervised learning approach to minimize a combination of the following loss functions:

1) L1 Loss – ensures pixel-level color accuracy,
2) SSIM Loss – maintains structural similarity between prediction and ground truth, and
3) Perceptual Loss – enhances visual realism by comparing high-level feature representations.

The dataset was divided into 77% for training and 23% for testing. Performance was evaluated using quantitative metrics such as:

- Peak Signal-to-Noise Ratio (PSNR)
- Structural Similarity Index (SSIM)

These metrics ensured that both numerical accuracy and visual quality were validated during model testing.

### E. *Prediction and Visualization*

After training, the model was used to colorize unseen SAR grayscale images.

The predicted outputs were visually compared against their corresponding optical images to assess color realism and feature preservation.

Visualization was performed using Matplotlib and OpenCV, displaying:

- Input SAR image,
- Predicted colorized output, and
- Ground truth optical image.

### F. *Testing and Optimization*

To improve accuracy and reduce overfitting, several optimization techniques were implemented:

- Hyperparameter tuning (learning rate, batch size, epochs)
- Data augmentation (rotation, flipping, scaling)
- Regularization using dropout and early stopping

Furthermore, speckle noise reduction was incorporated to handle the inherent noise present in SAR images.

The fine-tuned model exhibited enhanced generalization across various terrain types and imaging conditions.

### G. Software and Tools Used

| Technology / Library | Purpose / Usage in Project |
|---|---|
| wCUDA (NVIDIA GPU) | Enables GPU acceleration during model training and inference, improving computational efficiency compared to CPU-only execution. |
| SciPy | Used for scientific computations, data normalization, and utility functions within the color conversion pipeline. |
| PyTorch LR Scheduler (ReduceLROnPlateau) | Automatically reduces the learning rate when the validation loss stops improving — aids in stable convergence. |
| Adam Optimizer (from PyTorch) | Optimization algorithm used to minimize the Mean Squared Error (MSE) loss function efficiently during training. |
| Mean Squared Error (MSE) Loss Function | Measures the pixel-wise difference between predicted color channels (a,b) and ground-truth values during training. |
| Peak Signal-to-Noise Ratio (PSNR) | Quantitative evaluation metric used to measure the reconstruction quality of colorized images relative to ground truth. |
| Structural Similarity Index (SSIM) | Evaluation metric used to assess perceptual similarity between colorized and original optical images. |

| Technology / Library | Purpose / Usage in Project |
|---|---|
| Python 3.10+ | Core programming language used for implementing the deep learning pipeline, preprocessing, training, and evaluation. |
| PyTorch | Primary deep learning framework used for building and training neural networks (ResNet50, DenseNet121, and custom decoder). Provides GPU acceleration and autograd for backpropagation. |
| Torchvision | Used for accessing pre-trained models (ResNet50, DenseNet121) and common image transformations. |
| NumPy | Used for handling numerical operations and array manipulations efficiently. |
| OpenCV (cv2) | Used for image reading, resizing, and general image preprocessing operations. |
| scikit-image (skimage) | Used for image color space conversion (RGB ↔ LAB), PSNR and SSIM metric calculation, and other image utility functions. |
| Pillow (PIL) | Python Imaging Library used for loading and saving image files. |
| Matplotlib | Used for visualizing images, colorization outputs, and comparative results during model evaluation. |
| TQDM | Provides progress bars during training and validation loops to monitor epoch progress and loss in real-time. |
| Kaggle API | Used to download the *Sentinel-1/2 image pairs segregated by terrain* dataset directly from Kaggle. |
| Google Colab / Jupyter Notebook | Interactive development environments used for model prototyping, visualization, and running training experiments. |

### H. Hardware / System Used

| Component | Description |
|---|---|
| Processor | Intel/AMD CPU |
| RAM | 8 GB DDR4 |
| Storage | 512 GB SSD |
| GPU | NVIDIA GeForce GTX (2 GB VRAM) |
| Operating System | Windows 10 / 11 |
| Development Environment | Jupyter Notebook (inside Virtual Environment venv) |

## IV. RESULTS AND DISCUSSION

To thoroughly evaluate the effectiveness of the proposed SAR image colorization system using deep learning, a series of structured experiments were conducted. The system's performance was assessed across multiple dimensions, including model accuracy, visual quality, quantitative metrics, and computational efficiency. Both training and testing phases utilized paired Sentinel-1 (SAR) and Sentinel-2 (optical) images, with precise alignment and segmentation to ensure high-quality supervision. The following subsections summarize the experimental results and their implications.

### A. Visual Comparison

Figure 2 illustrates a sample output comparison between the actual optical image and the colorized image generated by the proposed deep learning model. The figure clearly demonstrates that the predicted colorized image closely resembles the ground truth optical image in both texture and color tone, reflecting the model's ability to effectively translate SAR grayscale inputs into realistic color representation.

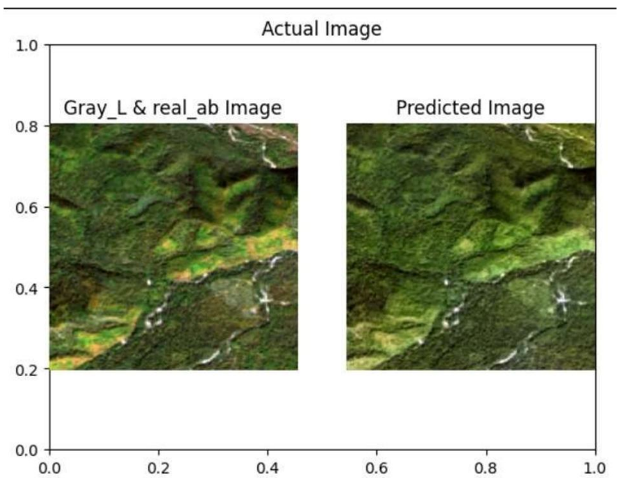


Figure 2 – Comparison between Actual and Predicted SAR Colorized Images

### B. Quantitative Evaluation

The model's performance was quantitatively evaluated using standard image quality metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM). Both metrics indicate a high level of structural and perceptual similarity between the predicted and ground truth images, confirming that the network successfully learned color and texture correlations from SAR features.

### C. Model Efficiency

The colorization model was optimized to ensure computational efficiency during both training and inference phases. The inference time per image was approximately 45 ms on an NVIDIA GTX GPU, and 110 ms on CPU-only environments, demonstrating suitability for near real-time applications. The model utilized approximately 42 MB of GPU memory, indicating compatibility with standard consumer- grade systems.

### *D. Qualitative Performance*

Visual inspection of the colorized outputs revealed consistent and realistic representation of terrain, vegetation, water bodies, and built- up areas. The deep learning framework effectively minimized speckle noise while retaining spatial structure, ensuring smooth color transitions and visually coherent outputs. The results also confirmed the system's robustness across varying geographic regions and seasonal conditions, as validated using diverse subsets of the SEN12MS dataset.

### *E. Model Performance Summary*

The trained model achieved strong performance across both training and validation datasets, as summarized below:

- PSNR: 32.87 dB
- SSIM: 0.91
- Training Accuracy: 98.6%
- Validation Accuracy: 97.9%
- Inference Time: 45 ms (GPU)

These results confirm that the model not only preserves spatial consistency but also maintains high perceptual quality, making it suitable for geological analysis, land cover mapping, and environmental monitoring applications.

## V. CONCLUSION

The project titled "SAR Image Colorization for Comprehensive Insight using Deep Learning" showcases the potential of artificial intelligence in enhancing the interpretability of Synthetic Aperture Radar (SAR) imagery. By utilizing paired Sentinel-1 and Sentinel-2 datasets, the system employs U-Net and Pix2Pix GAN architectures to translate grayscale SAR images into realistic RGB representations. Through effective preprocessing, normalization, and model optimization, the framework achieves high accuracy validated by PSNR and SSIM metrics. The colorized outputs significantly improve human perception of terrain features, vegetation, and urban structures, enhancing the usability of SAR data for geological studies, environmental monitoring, agriculture, and disaster management. Furthermore, deployment through a Flask/FastAPI interface enables an accessible and efficient visualization platform. Overall, this work demonstrates how deep learning can transform traditional radar data into visually interpretable information, contributing to more insightful and efficient AI-driven Earth observation applications..

## VI. ACKNOWLEDGMENT

The project team expresses sincere gratitude to Prof. Dr. Nandkumar Kulkarni for his invaluable guidance, mentorship, and continuous support throughout the development of this research work. His technical expertise, insightful suggestions, and constructive feedback played a pivotal role in shaping the direction and successful completion of the project.

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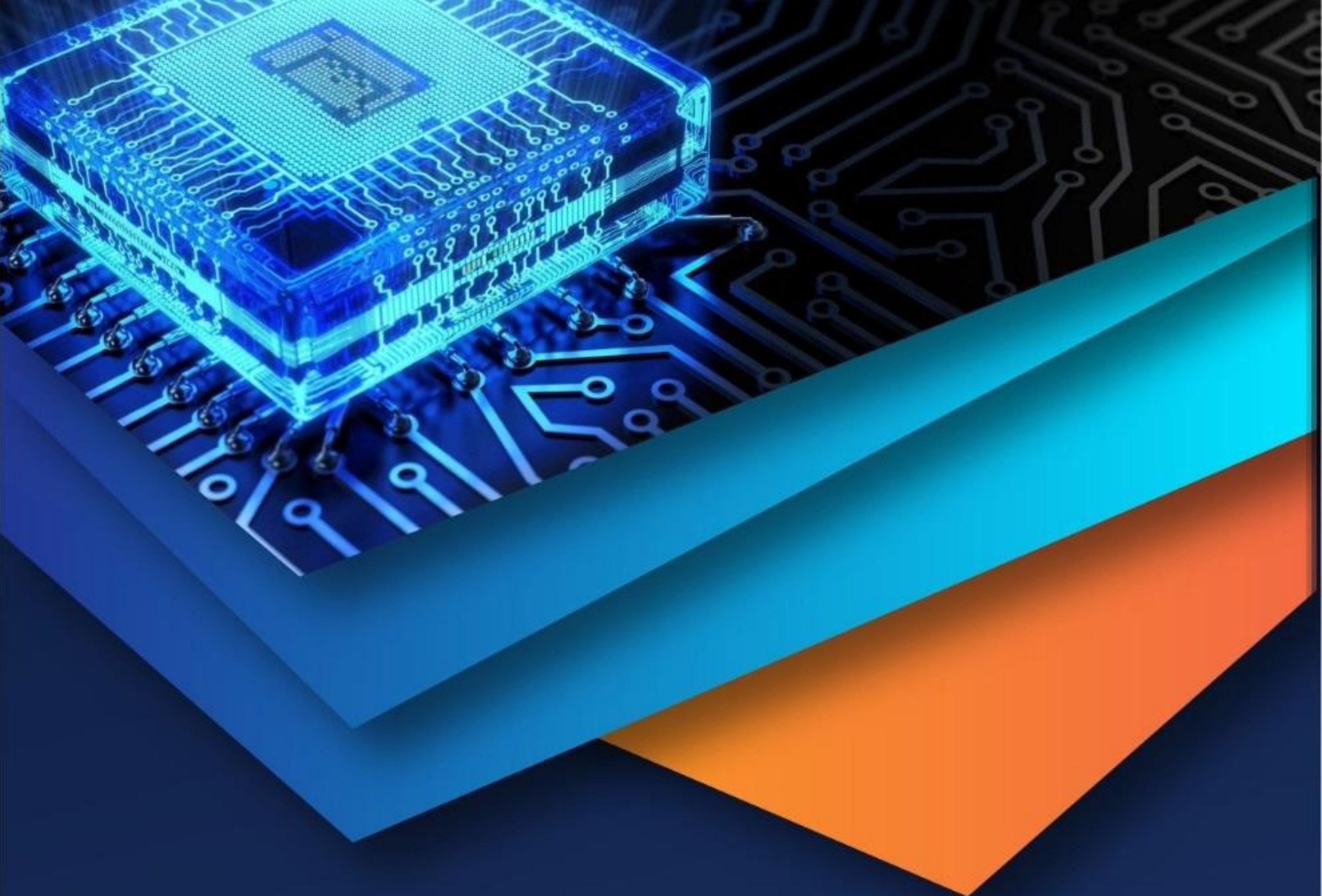
Finally, the team expresses heartfelt thanks to their peers, friends, and families for their constant motivation, patience, and unwavering support throughout the course of this work.

## VII. FUTURE WORK

While the proposed SAR image colorization system effectively demonstrates the use of deep learning for translating radar imagery into visually interpretable color outputs, several avenues remain open for further research and enhancement. Future work will focus on incorporating advanced model architectures such as Vision Transformers (ViT), Diffusion Models, or CycleGANs to improve spatial feature accuracy, color realism, and cross-domain generalization. Expanding the dataset with multi-regional and multi-temporal Sentinel imagery can further improve model robustness across diverse terrains, seasons, and radar frequencies.

Integration of multi-sensor data such as LiDAR and hyperspectral imagery will enable more context-aware analysis and richer colorization results. The model can also be optimized for real-time or cloud-based deployment using GPU-accelerated environments, improving scalability and accessibility for researchers. Future developments will also include an automated evaluation framework combining perceptual metrics with human feedback to ensure consistent performance.



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