Review of Computer Engineering Research
2026 Vol. 13, No. 2, pp. 22-36
ISSN(e): 2410-9142
ISSN(p): 2412-4281
DOI: 10.18488/76.v13i2.4929

Reference-based super-resolution for remote sensing images using a hybrid edge-aware loss function

Rajalaxmi Padhy[1]
Sanjit Kumar Dash[2]
Mohammed Altaf Ahmed[3+]
Sultan Alqahtani[4]

[1,2]*Odisha University of Technology and Research, Bhubaneswar, Odisha, India.*
[1]*Email: rpadhyit@outr.ac.in*
[2]*Email: skdash@outr.ac.in*
[3,4]*Department of Computer Engineering, College of Computer Engineering and Sciences, Prince Sattam bin Abdulaziz University, Al-Kharj, Saudi Arabia.*
[3]*Email: m.altaf@psau.edu.sa*
[4]*Email: su.alqahtani@psau.edu.sa*


(+ Corresponding author)

Article History
Received: 3 November 2025
Revised: 20 February 2026
Accepted: 13 March 2026
Published: 23 April 2026

Keywords
Domain adaptation module
Domain matching module
Feature aggregation
Hybrid loss function
Industry and Innovation
Remote sensing
SDG
Super-resolution image.

ABSTRACT

Acquiring high-resolution images is crucial for accurate remote sensing analysis; however, such data are often limited by sensor constraints, atmospheric conditions, and acquisition costs. Reference-based super-resolution (RefSR) addresses this limitation by using auxiliary high-resolution images, but the presence of domain mismatches due to changes in illumination, viewpoint, and sensor characteristics severely limits its performance, often resulting in blurred edges and structural distortions. To overcome these problems, this paper presents a reference-based super-resolution framework that integrates a hybrid edge-aware loss function into a domain-adaptive transfer super-resolution architecture. The proposed method first employs grayscale transformation for domain matching, followed by Whitening and Coloring Transform and Phase Replacement for efficient domain adaptation and texture alignment. To supervise the edges and overall structure more closely during image reconstruction, the authors have combined Sobel and Laplacian edge constraints in a new hybrid loss function. Experiments on the DIV2K dataset using a 4× scaling factor reveal that the method presented in this paper consistently generates better results than the baseline DATSR model, with substantial improvements in PSNR and SSIM metrics and visually sharper, more structurally coherent images. Furthermore, qualitative analyses verify that the images obtained from super-resolution preserve better edges with less boundary blurring. This approach serves as an efficient and computationally feasible solution for improving image quality in situations of domain mismatch, making it suitable for high-resolution remote sensing applications such as urban monitoring, environmental analysis, and industrial innovation in line with sustainable development goals.

Contribution/Originality: This article contributes to existing literature by addressing domain mismatches in reference-based super-resolution with a new hybrid Sobel–Laplacian edge-aware loss function. The primary contribution is that explicit edge supervision results in a significant improvement in structural fidelity and sharpness in remote sensing image reconstruction.

1. INTRODUCTION

Super-resolution (SR) images are reconstructed high-resolution images using low-resolution images. These SR images are used in various fields like remote sensing [1], medical imaging, urban planning [2], agriculture [3], disaster management [4], and more. Often, images captured by satellites are not high-resolution due to sensor capabilities, atmospheric conditions, and hardware constraints. Traditional Single Image Super-Resolution (SISR) methods use deep learning models to upscale low-resolution images but fail to recover high-frequency details when the original image lacks finer textures. To address these limitations, reference-based super-resolution (RefSR) models have been developed.

RefSR models use an additional high-resolution image as a reference image. However, despite their effectiveness, a major challenge persists: domain gaps between LR and HR images. These gaps arise from variations in color distributions, shooting angles, and lighting conditions, making it difficult for models to align features. When the reference image significantly differs from the LR input, the models fail, as transferred details introduce artifacts and do not blend naturally with the original content [5].

To address this issue, recent advancements introduced domain matching and domain adaptation techniques [6] to improve alignment between LR and HR reference images. By integrating these techniques, RefSR models significantly improved reconstruction quality while minimizing distortions. However, the SR image generated still has blurry edges and artifacts, and its quality can be improved for use in more detailed remote sensing tasks.

The primary objective of this research is to develop a super-resolution image to reveal finer details. The pair of LR and HR images is used as input to a domain matching technique involving grayscale transform. The domain adaptation methods include Whitening and Coloring Transform (WCT) and Phase Replacement (PR), which extract textures while preventing distortions during detail transfer. The features and textures extracted are then combined to generate the super-resolved image. However, the super-resolved image still exhibits blurry boundaries in the final output. The proposed method will incorporate a hybrid edge-aware loss function applied to the generated super-resolved image. This function effectively addresses blurry edges and enhances the sharpness of SR images by preserving edge continuity and fine structural details. By integrating this hybrid loss function, the visual quality of SR images is improved through better structural fidelity, making them more suitable for high-resolution remote sensing applications.

Even with recent improvements in super-resolution techniques and methods for adapting to different domains, many current approaches mainly focus on aligning features and transferring textures. Unfortunately, they often overlook the issue of edge degradation caused by differences in sensors, lighting variations, and mismatched resolutions. As a result, images produced through super-resolution can have fuzzy edges and lack structural coherence, reducing their effectiveness for precise applications in remote sensing.

The main contributions of this work are as follows:

- This study contributes to the existing literature by addressing domain gap issues in reference-based super-resolution for remote sensing imagery.
- This study uses a new estimation methodology based on a hybrid edge-aware loss that combines Sobel and Laplacian operators.
- This study is one of the few investigations into explicit edge continuity preservation under domain adaptation in RefSR frameworks.
- The paper's primary contribution is finding that edge-aware supervision significantly improves structural fidelity and sharpness in super-resolved images.

This paper is organized into several sections. In Section 2, we review existing literature on super-resolution, focusing on methods that rely on references. Section 3 introduces the framework we propose, along with a unique hybrid edge-aware loss function. In Section 4, we present the experimental results and discuss our findings. Finally, Section 5 concludes the paper and outlines future research directions.

2. LITERATURE SURVEY

Various approaches have been developed to address issues such as cost-effective generation of HR images and the domain gap caused by changes in shooting angles, lighting, environmental, and acquisition conditions. These methods are broadly categorized into two types: SR and RefSR.

2.1. SR

The resolution of images can be improved through two techniques: MISR and SISR. MISR (Multi-Image Super-Resolution) techniques take multiple LR versions of the same scene into consideration, and rebuilding high spatial frequency details is the goal [7-11]. This method's drawback was considered in situations where several remotely sensed images of the same scene are either impossible or challenging [12]. SISR approaches are utilized to get around this problem. A SISR method based on the Residual Dense Back Projection Network (RDBPN) that employs residual learning in both global and local contexts was presented by Pan et al. [13]. After learning from a remotely sensed training model, deep learning based SISR approaches use that model to infer the missing information that lack in LR images Zhang et al. [4]. Dong et al. [14] developed a Super-Resolution Convolutional Neural Network (SRCNN) and employed a three-layer CNN to map LR and HR images. More advanced deep-learning architectures, including residual blocks [15], dense blocks [16], and recursive blocks [17], aim to minimize the Mean Absolute Error (MAE) between LR and HR images and enhance SISR's performance.

2.2. RefSR

The RefSR methods use an additional reference image which has high frequency details and is often taken from different viewpoints [18], video frames [19], online image searches [20], and so on. RefSR techniques are categorized into patch making and image aligning. Shim et al. [21] used the Similarity Search and Extraction Network (SSEN), which enhances reference-based super-resolution by efficiently extracting relevant features without heavy computation, improving robustness against irrelevant references. However, performance degrades when the reference image has little similarity to the input. A deep learning-based method for creating and synthesizing Ref and LR patches was presented by Zheng et al. [22]. Patch matching has the benefit of handling long-distance dependence, which strengthens the model in the event of a large misalignment between the Ref and LR pictures. It is time-consuming and computationally demanding, though. Additionally, it is unable to precisely handle nonrigid picture deformation, which frequently results in blocky artifacts [4], suggested CrossNet which employed optical flow to align Ref and LR images at various scales and U-Net was then used to execute multiscale feature fusion and synthesis utilizing the aligned Ref feature, Ronneberger et al. [23]. Dong et al. [5] proposed a method that excels in texture transfer but needs quality references, precise alignment, and high computation. However, it faced alignment issues and the performance is reduced in case of low-quality or poorly matched reference images. Lu et al. [1] proposed a MASA network that enhances reference-based image super-resolution through efficient detail matching and adaptive feature alignment for low-resolution images. However, its performance drops if the reference image lacks detail or differs from the LR image.

MISR requires multiple images of the same scene, which is often impractical. SISR methods, such as CNN- and transformer-based models, improve resolution using a single image but struggle with fine detail reconstruction and high computational costs. RefSR leverages high-resolution (HR) references for enhanced detail recovery but faces domain gap issues due to variations in illumination, viewpoint, and environmental conditions. Feature-matching and alignment techniques improve results but often suffer from misalignment, computational overhead, and texture inconsistency. To address these challenges, a hybrid edge-aware loss function has been proposed in this paper that enhances edge sharpness and structural details while mitigating the domain gap. This work addresses typical shortcomings seen in previous approaches, while also aligning with recent developments in generating super-resolved images, addressing domain gaps, and improving edge continuity and sharpness of the SR image.

2.3. Comparative Synthesis

Recent methods for reference-based super-resolution typically rely on pixel-wise reconstruction losses, such as L1 or L2 norms, combined with perceptual and adversarial losses to enhance overall visual quality and texture transfer [6]. When there is a mismatch between different image domains, techniques like feature alignment, including processes such as whitening and coloring transformation, patch-based matching, or deformable warping, are often employed [24]. However, these methods primarily emphasize matching textures and features but don't specifically address the need for continuous edges during the reconstruction process. As a result, images that have been super-resolved can often show soft, unclear boundaries and structural inconsistencies, especially when dealing with domain mismatches. In response to this, the new method proposes a hybrid loss function that focuses on both first-order (Sobel) and second-order (Laplacian) edge information. This approach not only enhances the compatibility of existing alignment techniques but also significantly improves the structural integrity of super-resolved images.

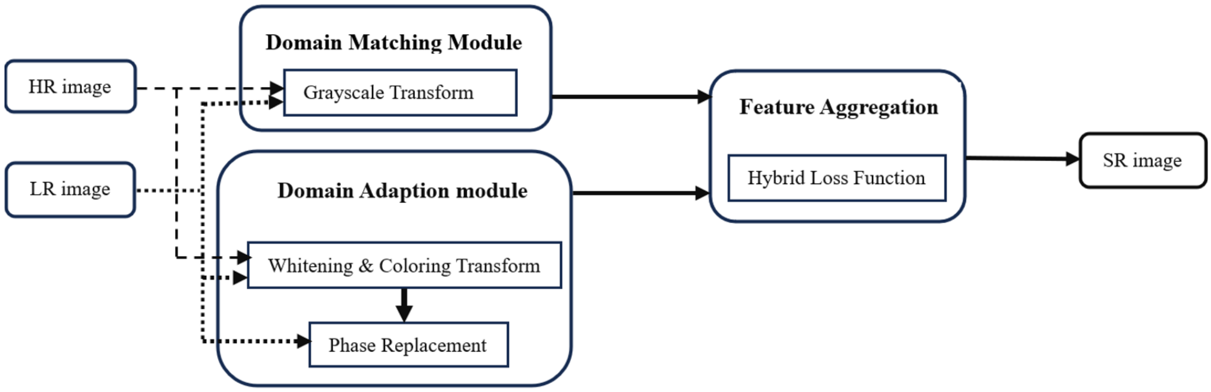

Figure 1. Proposed framework for generating SR images.

3. PROPOSED FRAMEWORK

Figure 1 shows the proposed deep learning framework for generating super resolution images. The proposed framework enhances LR images by using HR reference images while preserving structural and textural details. The process begins with a domain matching module, which includes grayscale transformation. Paired LR and HR images are converted to grayscale using an auto-encoder that extracts spatial features. These features are used in the next step, i.e., correspondence matching, to establish pixel-wise relationships between the two images. To ensure effective domain adaptation, Whitening and Coloring Transform (WCT) and Phase Replacement (PR) methods are applied. In the WCT method, textures are extracted, and the PR method aligns the reference features with the LR image while preserving structural details. A hybrid edge-aware loss function is applied during the feature aggregation and reconstruction phase. The extracted and adapted features are aggregated, then passed through the loss function and reconstruction module, generating an SR image with enhanced sharpness, structural consistency, and fine details.

Domain gaps exist between low-resolution and high-resolution images captured from different satellites. To address this, a domain matching and domain adaptation module have been introduced. The domain matching module is responsible for grayscale transformation, while the domain adaptation module handles whitening, coloring transformations, and phase replacement.

3.1. Model Overview

The proposed model is based on a reference-based super-resolution (RefSR) framework that uses a high-resolution reference image to help reconstruct low-resolution images. Unlike typical RefSR methods that mainly concentrate on transferring textures and aligning features, this new approach specifically addresses the issue of edge deterioration that arises when there's a mismatch between the input and reference images. The model incorporates a domain matching module, which utilizes grayscale transformation, followed by domain adaptation through techniques like Whitening and Coloring Transform (WCT) and Phase Replacement (PR). While previous research has employed similar alignment techniques, they have generally relied on pixel-level, perceptual, or adversarial losses during the reconstruction process. In contrast, this new approach features a hybrid edge-aware loss that directly focuses on supervising edge structures, resulting in better continuity at the boundaries and enhanced structural integrity in the super-resolved images.

3.2. Domain Matching Module for Grayscale Transform

The grayscale transformation removes colour discrepancies and focuses solely on structural information, enhancing feature similarity and texture transfer. It is implemented using an autoencoder model to convert high-resolution (HR) and low-resolution (LR) images into grayscale images. The autoencoder architecture, shown in Figure 2, consists of an encoder and decoder. The input includes paired LR and HR images. The encoder extracts key spatial features, while the decoder reconstructs them into grayscale images. To optimize the transformation, Mean Square Error (MSE) is calculated, ensuring the reconstructed grayscale image closely matches the original in pixel intensity and structural details.

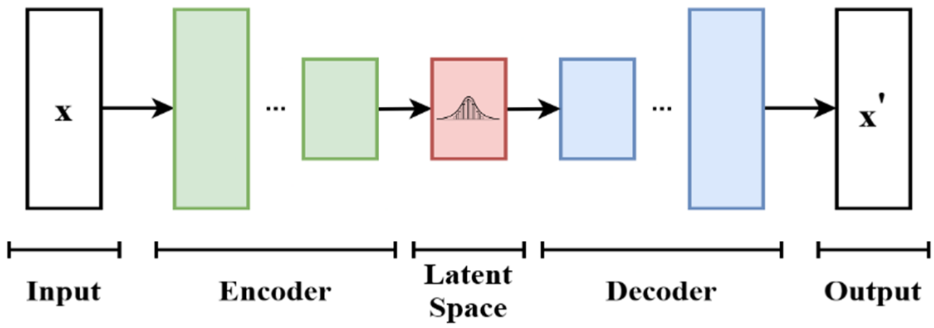

Figure 2. Architecture of autoencoder.

3.3. Domain Adaptation using WCT and PR

3.3.1. Whitening and Coloring Transform

The Whitening and Coloring Transform (WCT) is useful for domain alignment between LR and HR images, ensuring that essential features from HR images are transferred to LR images. The input images include paired LR and HR images, which are first pre-processed by resizing them to a uniform dimension of 224×224 pixels, normalizing pixel values to [0,1], and converting them to a channel-first format (C, H, W) for compatibility with matrix operations. In this process, the LR image is referred to as the content image, and the HR image is referred to as the style image.

In WCT, the whitening step removes unnecessary patterns from the LR image, and the coloring step applies important details from the HR image. This transformation uses Singular Value Decomposition (SVD), which helps transfer texture and structural details from HR to LR images. A blending factor, $\alpha = 0.6$, controls how much of the HR details are added to the LR image.

$$F_{out} = \alpha F_{cs}' + (1 - \alpha) F_c \qquad (1)$$

F_c is the feature map of the input content image, F_{cs}' is the adapted feature map after applying Whitening and Coloring Transform (WCT), and F_{out} is the final fused feature used for super-resolution reconstruction.

Finally, the transformed image is reshaped, adjusted for correct brightness, and saved in the output folder.

3.3.2. Phase Replacement

The Phase Replacement (PR) method is used to enhance the structure and details of an image by preserving the phase information of the Low-Resolution (LR) image while incorporating the transformed details from the Whitening and Coloring Transform (WCT) output. The input images for this process include the LR image and the transformed image, which is the stylized image output from the WCT process. These are processed in the frequency domain using the Fast Fourier Transform (FFT). The PR method extracts the magnitude (intensity) from the transformed image and the phase (structural details) from the LR image. The phase of the LR image is then combined with the magnitude of the transformed image to reconstruct a new image using the Inverse FFT (IFFT). This ensures that the final output retains the fine structural details from the LR image while benefiting from the enhanced texture of the transformed image. After reconstruction, the image is normalized to a pixel range of [0, 255] to ensure proper visualization.

3.4. Feature Aggregation using Hybrid Edge Aware Loss Function

The features and textures extracted from both LR and HR images are fused to generate an SR image while preserving the original structure of the LR image. To produce the SR image, a hybrid edge-aware loss function is introduced in the proposed framework, combining Sobel and Laplacian edge-aware loss functions. This loss function addresses the shortcomings of reference-based SR models by effectively reducing blurry edges and enhancing edge sharpness and structural details in super-resolved images. The features and textures obtained through grayscale transformation, WCT, and PR methods are combined and processed through a super-resolution model that employs the hybrid edge-aware loss function.

The gradients of the SR image edges are computed and compared against the corresponding high-resolution reference, enforcing consistency in edge structures. In the first step, the SR image is processed to extract its edge information using Sobel and Laplacian operators. In the second step, the same edge extraction process is applied to the HR reference image to extract the information for sharp edges. The extracted edge maps from both images are compared, and the difference is computed as the edge-aware loss. This loss is then backpropagated to optimize the model, ensuring that the generated SR image maintains fine structures and sharp contours similar to the HR reference.

Sobel edge-aware loss calculates the similarity between the gradient magnitudes of the SR image and the HR image, thus maintaining smooth edges and gradients, preventing blurry transitions. The equation is given as:

$$L_{Sobel} = ||\nabla_x I_{SR} - \nabla_x I_{HR}||_1 + ||\nabla_y I_{SR} - \nabla_y I_{HR}||_1 \quad (2)$$

$\nabla_x I_{SR}$ and $\nabla_y I_{SR}$ is the gradient magnitude of SR image in X direction and Y direction $\nabla_x I_{HR}$ and $\nabla_y I_{HR}$ is the gradient magnitude of HR image in X direction and Y direction.

The Laplacian loss minimizes the difference between the Laplacian maps of the SR image and the HR image, with the equation provided as follows.

$$L_{Laplacian} = ||\nabla^2 I_{SR} - \nabla^2 I_{HR}||_1 \quad (3)$$

$\nabla^2 I_{SR}$ is the gradient magnitude of SR image and $\nabla^2 I_{HR}$ is the gradient magnitude of HR image.

The hybrid edge-aware loss equation is given as:

$$L_{Hybrid} = \alpha(||\nabla_x I_{SR} - \nabla_x I_{HR}||_1 + ||\nabla_y I_{SR} - \nabla_y I_{HR}||_1) + \beta(||\nabla^2 I_{SR} - \nabla^2 I_{HR}||_1) \quad (4)$$

The final hybrid loss is formulated as:

$$L_{Hybrid} = \alpha L_{Sobel} + \beta L_{Laplacian} \quad (5)$$

Where α and β are hyperparameters controlling the balance between Sobel loss and Laplacian loss. For a balanced approach, the values are $\alpha=0.5$ and $\beta=0.5$. Lower loss function values indicate higher reconstruction quality.

The step-by-step procedure for generating SR images is provided below.

Algorithm 1: Algorithm for generating SR image

Input
- -Low Resolution image
- -High Resolution image

Procedure
- 2.1 Domain Matching Module
  - 2.1.1 Apply grayscale transform and calculate Mean Square Error (MSE)
- 2.2 Domain Adaptation Module
  - 2.2.1 Whitening and Coloring Transform

2.2.1.1 Preprocess the image by resizing them to uniform dimension of 224×224 pixels
2.2.1.2 Apply Whitening step to remove domain-specific variations
2.2.1.3 Apply Coloring step to transfer rich details
2.2.2 Phase Replacement
2.2.2.1 Apply PR to avoid distortions while transferring features
2.3 Feature Aggregation and Hybrid Loss Function
2.3.1 Feature Aggregation- Features and textures are aggregated
2.3.2 Hybrid Loss Function- Compute Hybrid edge aware loss function, combination of Sobel and Laplacian loss
2.4 Generate SR image
2.4.1 Utilize refined features and loss feedback to reconstruct Super Resolution image
Output
-Super Resolution image

Figure 3. Algorithm for generating SR image.

Figure 3 illustrates the step-by-step algorithmic procedure for generating the super-resolution image, detailing the process flow from the domain matching and adaptation modules to the final feature aggregation using the hybrid edge-aware loss function.

4. EXPERIMENTS

4.1. Experimental Setup

Experiments were conducted in Google Colab, an Integrated Development Environment (IDE). We used various deep-learning frameworks like TensorFlow 2.5+ and PyTorch 1.9+ for implementing and training the RefSR model, including T4 GPU and 16GB RAM, with Python 3.7+. The grayscale transform, whitening and coloring transforms, and phase replacement were carried out, and the multi-level self-encoder was executed using libraries such as OpenCV and SciPy. Necessary dependencies, including Matplotlib, TensorFlow, NumPy, and PyTorch, were installed to facilitate image visualization. Additionally, Google Drive was integrated for dataset and result storage at intermediate levels, ensuring an efficient and scalable workflow.

4.2. Dataset and Pre-Processing

The proposed approach is evaluated on the DIV2K dataset, a widely used benchmark in super-resolution research. This dataset contains high-quality natural images and is commonly used to assess reference-based super-resolution methods. Low-resolution images are generated from their high-resolution counterparts via bicubic down-sampling with a fixed scaling factor of ×4. This degradation process is applied consistently across all experiments to maintain uniformity and ensure reliable comparisons.

The experiments follow the official DIV2K data (https://www.kaggle.com/datasets/oshanyalegama/div2k-dataset) split, comprising 800 images for training, 100 for validation, and 100 for testing. Prior to training and evaluation, all images are normalized to the range [0, 1]. Although the framework is mainly designed for remote sensing applications, no remote sensing–specific dataset is used due to the limited availability of paired satellite imagery. Instead, DIV2K is employed to ensure fair comparison with existing RefSR methods and to validate the effectiveness of the proposed approach.

4.3. Sensitivity Analysis of Hybrid Loss Weights

The hybrid edge-aware loss combines Sobel and Laplacian components, regulated by parameters α and β. A sensitivity analysis tested various combinations (0.3, 0.7), (0.5, 0.5), and (0.7, 0.3) as shown in Table 1.

Table 1. Sensitivity analysis of hybrid edge-aware loss weights (α, β) using PSNR and SSIM.

α	β	PSNR (dB)	SSIM
0.3	0.7	26.51	0.823
0.5	0.5	27.08	0.836
0.7	0.3	26.63	0.829

The results in Table 1 indicate that assigning equal weights ($\alpha = 0.5$, $\beta = 0.5$) provides the best balance between edge sharpness and structural preservation. Increasing the Sobel weight ($\alpha = 0.7$) results in excessive edge enhancement and artifacts, while a higher Laplacian weight ($\beta = 0.7$) causes over-smoothing. Therefore, equal weighting is used in all experiments.

4.4. Ablation Study

We conducted an ablation study to assess the contribution of each component of our proposed framework to its overall effectiveness. This included examining the grayscale transformation, the Whitening and Coloring Transform (WCT), phase replacement, and the hybrid edge-aware loss.

Table 2. Ablation analysis of the proposed framework using PSNR and SSIM metric.

Configuration	PSNR (dB)	SSIM
Baseline DATSR	25.05	0.801
+ Grayscale	25.89	0.815
+ Grayscale + WCT	26.31	0.824
+ Grayscale + WCT + PR	26.74	0.831
+ Hybrid Edge-Aware Loss	27.08	0.836

The results of this analysis are clearly summarized in Table 2. From our observations, each module contributes positively to the model's performance. Components aimed at domain adaptation mainly improve texture alignment between input and reference images. Notably, the hybrid edge-aware loss offers the greatest benefit by preserving edge continuity and structural integrity during image reconstruction.

4.5. Result and Discussion

The reference images for low-resolution (LR) and high-resolution (HR) are used as inputs in the proposed framework. Figure 4 displays four LR images, while Figure 5 shows the corresponding four HR images, which serve as references. These images are selected from a sample dataset and fed into an autoencoder to convert them into grayscale versions. Figure 6 presents these grayscale images, which are used in the subsequent feature extraction step to generate super-resolved images. Applying the grayscale transformation removes unnecessary color discrepancies, allowing focus on structural information such as shapes and edges. These features are then used in the next step of the correspondence matching process. The sample LR and HR images are processed through a Singular Value Decomposition (SVD) model, which transfers the textures from HR images to LR images. Figure 7 shows the images after applying the WCT method. These images, along with the LR images, are then input into the PR method. The PR method ensures that no distortion occurs during texture transfer. Figure 8 displays the resulting images after applying the PR method.

Figure 4. Four LR images taken from sample dataset.

Figure 5. Four HR images taken from sample dataset.

Figure 6. Grayscale images generated from sample LR images (Figure 4).

Figure 7. WCT transformed images generated using sample LR images in (Figure 4) and sample HR images (Figure 5).

Figure 8. PR transformed images generated using sample LR images (Figure 4) and result images of WCT method (Figure 7).

Figure 9. Super-Resolution images.

The features and textures extracted using the Grayscale transform, WCT, and PR methods are combined and processed through a super-resolution model. This model employs a hybrid edge-aware loss function, resulting in a super-resolution image with improved edge sharpness and structural details. Figure 9 shows the generated Super-resolution images.

4.6. Runtime and Computational Complexity

To evaluate the efficiency of the proposed framework, we conducted an analysis of runtime and complexity, comparing it with the baseline DATSR model. We measured inference time as the average processing duration per image during testing. Model complexity was assessed based on the number of parameters, floating-point operations (FLOPs), and memory requirements.

Table 3. Computational complexity and inference time comparison.

Model	Parameters (M)	FLOPs (G)	Inference Time (ms)	Memory (MB)
DATSR	18.6	92.1	84	620
Proposed	19.3	96.4	91	655

As shown in Table 3, our proposed method slightly increases computational cost compared to the baseline, mainly due to additional components for domain adaptation and edge-aware loss. Despite this, the increase in runtime and memory usage remains moderate and is justified by significant improvements in reconstruction quality and edge preservation.

4.7. Model Evaluation

To evaluate the effectiveness of the enhancement, qualitative analysis involves comparing HR images with super-resolution images. Quantitative analysis uses metrics such as PSNR, SSIM, NIQE, LPIPS, and Hybrid Edge-Aware Loss to assess the model's performance. PSNR (Peak Signal-to-Noise Ratio) estimates pixel-wise differences between the super-resolved and input HR images; higher PSNR values indicate lower distortion and better reconstruction quality. SSIM (Structural Similarity Index Measure) evaluates image quality by considering luminance, contrast, and structural information. NIQE (Natural Image Quality Evaluator) measures image realism without reference images; lower scores indicate more natural and higher-quality images. LPIPS (Learned Perceptual Image Patch Similarity) assesses perceptual quality, with lower values reflecting better perceptual similarity. The Hybrid Edge-Aware Loss combines Sobel and Laplacian edge losses to enhance edge sharpness in super-resolved images; lower loss values suggest improved edge preservation.

Table 4. Quantitative comparison of baseline and proposed SR models.

Models	PSNR ↑	SSIM ↑
Baseline DATSR model	25.055	0.801
Proposed model	27.082 **+2.026**	0.835 **+0.034**

Table 4 compares the reconstruction performance of the baseline DATSR model with the proposed framework. The new method achieves a PSNR of 27.08 dB, an increase of 2.02 dB over the baseline's 25.05 dB, indicating improved image clarity and noise reduction. The SSIM score also improves from 0.801 to 0.835 (+0.034), demonstrating enhanced structural consistency and texture preservation. These results suggest that integrating the hybrid edge-aware loss function effectively enhances structural consistency.

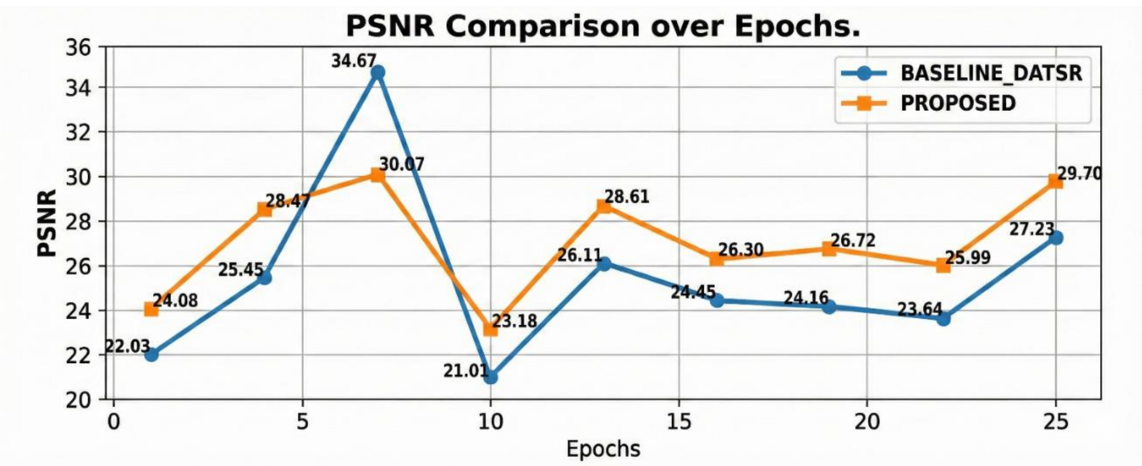

Figure 10. PSNR values of baseline DATSR model vs proposed model.

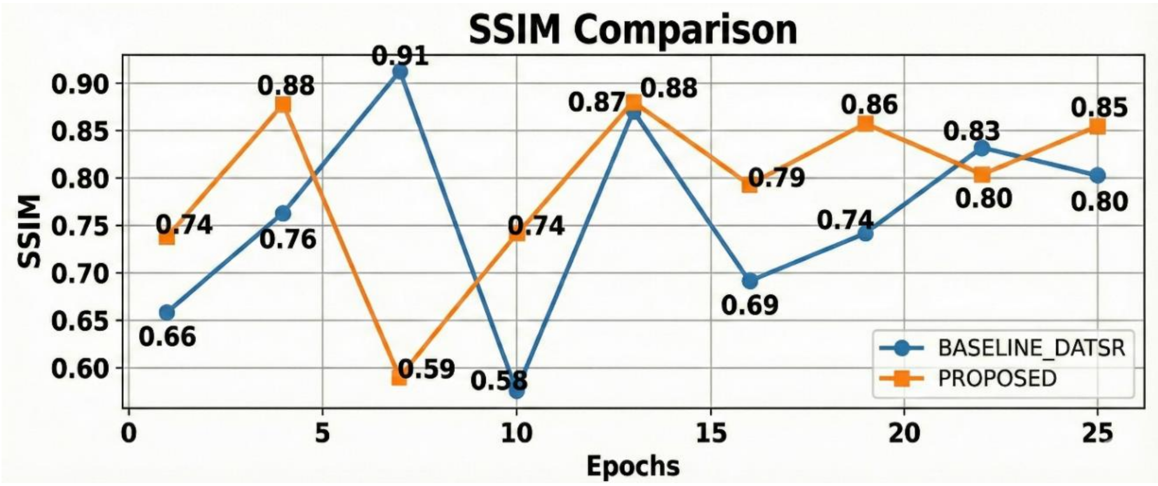

Figure 11. SSIM values of baseline DATSR model vs proposed model.

Figure 10 illustrates a graph comparing the PSNR values of the DATSR model with the proposed model, where the proposed model consistently achieves higher PSNR values, indicating better image quality and superior pixel fidelity. In Figure 11, the graph compares SSIM values between the two models, showing that the proposed model attains higher SSIM scores, which reflect improved texture and structure preservation.

Table 5. Quantitative Loss Metric Comparison for Baseline and Proposed SR Approaches.

Models	NIQE ↓	LPIPS ↓	Hybrid- edge-aware loss ↓
Baseline DATSR model	7.974584	0.333652	0.049723
Proposed model	7.185194 **-0.78939**	0.211708 **-0.124812**	0.042145 **-0.007578**

Table 5 compares the performance of the proposed super-resolution model with the baseline DATSR using NIQE, LPIPS, and Hybrid-edge aware loss metrics. The proposed model achieves a NIQE score of 7.18, showing an improvement of -0.79 over the baseline (7.97), indicating better perceptual quality. Likewise, the LPIPS score decreases from 0.334 to 0.212 (-0.125), and the Hybrid-edge aware loss reduces from 0.0497 to 0.0421 (-0.0076), demonstrating enhanced edge sharpness and perceptual similarity.

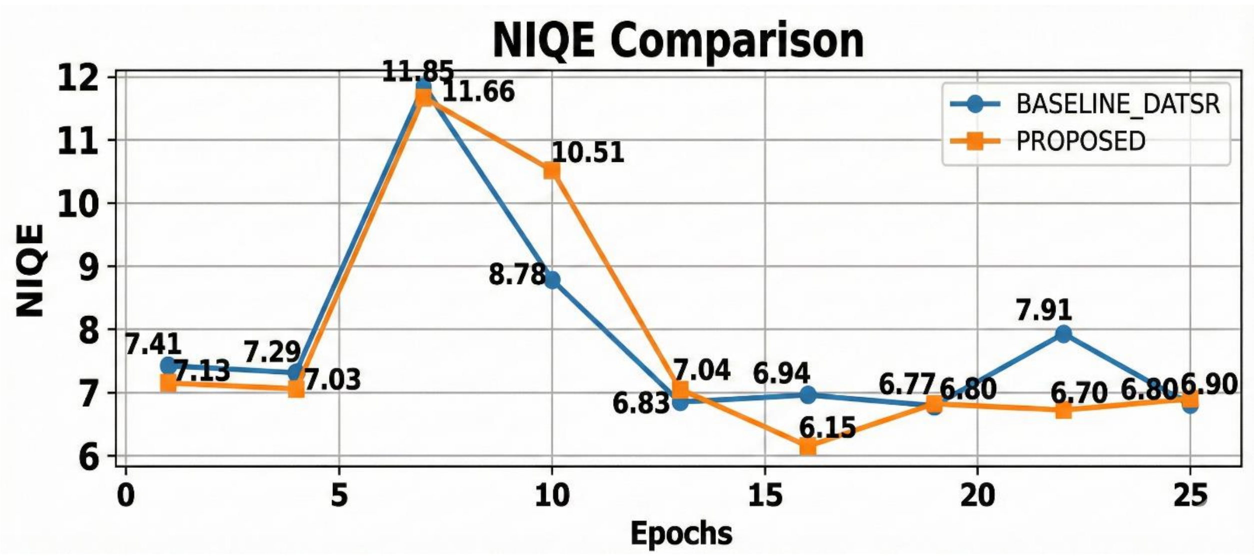

Figure 12. NIQE values of baseline DATSR model vs proposed model.

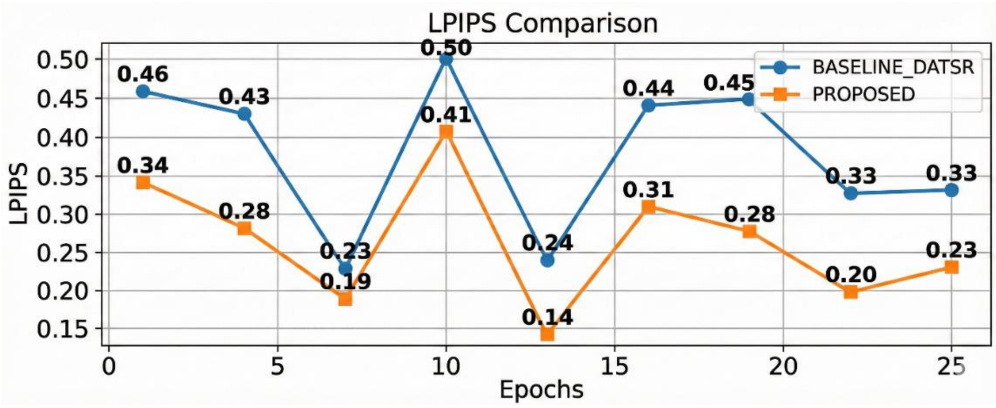

Figure 13. LPIPS values of baseline DATSR model vs proposed model.

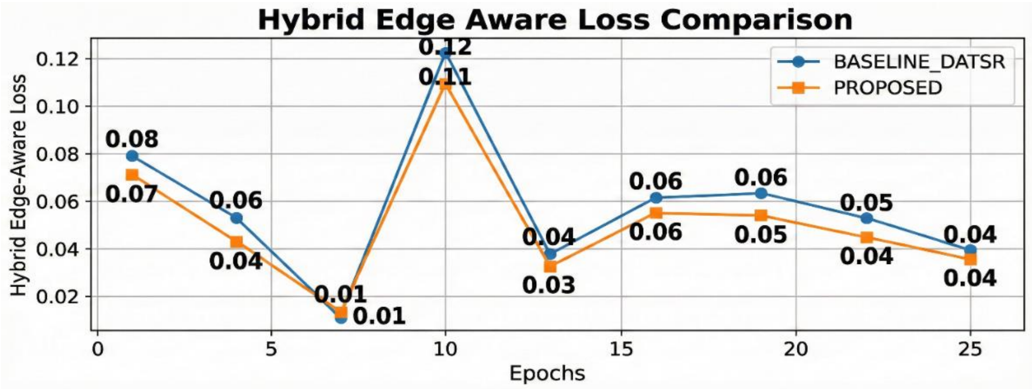

Figure 14. Hybrid Edge Aware Loss values of baseline DATSR model vs proposed model.

In Figure 12, the graph compares the NIQE values of the DATSR model with the proposed model. Initially, both models follow a similar trend, but after a few epochs, the proposed model maintains significantly lower NIQE values, indicating that the hybrid approach produces images with more realistic textures and fewer artifacts compared to the baseline model. The graph in Figure 13 compares the LPIPS values of the DATSR model with the proposed model, which consistently attain lower LPIPS values than the baseline DATSR, signifying improved perceptual similarity to real images. In Figure 14, the graph compares the hybrid edge-aware loss values of the baseline model with the proposed model. Both models exhibit a gradual reduction in edge-aware loss, but the proposed model achieves slightly lower loss values, confirming its effectiveness in preserving edges and reducing blurriness in the final outputs.

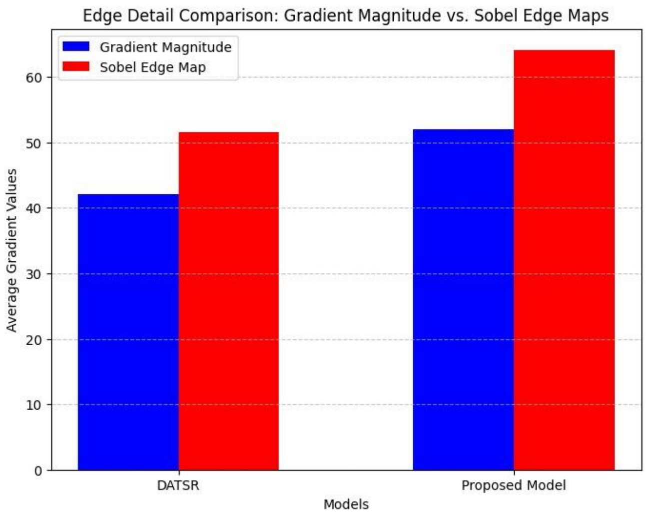

Figure 15. Comparison of edge details between DATSR model and proposed model based on gradient magnitude and Sobel edge maps.

Figure 15 compares the edge-preserving capabilities of both models using gradient magnitude and Sobel edge maps. The proposed model shows a notable increase in both gradient magnitude and Sobel edge responses compared to the baseline model. This suggests that the proposed hybrid model enhances edge structures more effectively, leading to sharper and more detailed super-resolved images. The higher gradient values indicate that the proposed approach successfully mitigates blurriness and preserves fine textures, optimizing it for high-fidelity image restoration tasks.

4.8. Discussion

The improvement in edge clarity and structural quality aligns with recent studies demonstrating the benefits of edge-aware supervision in super-resolution. Several recent RefSR and edge-based SR methods report that gradient-based losses help reduce blurry boundaries and enhance visual quality (Refs). However, some studies also note that strong edge constraints can cause over-sharpening or increase computational costs, especially for high-resolution or real-time applications. In comparison, the proposed hybrid edge-aware loss offers a good balance between image quality and computational efficiency, as confirmed by runtime analysis.

5. CONCLUSION

This paper introduces a reference-based super-resolution framework that incorporates a hybrid edge-aware loss to enhance edge clarity and preserve structural details despite domain mismatch. By integrating Sobel and Laplacian edge constraints with domain adaptation strategies, the method effectively reduces boundary blur and produces visually sharper super-resolved images. Experimental evaluation on the DIV2K dataset demonstrates that the approach consistently achieves higher PSNR and SSIM values than the baseline RefSR model, while maintaining practical computational costs.

Although the results are encouraging, some limitations remain. The evaluation is limited to the DIV2K dataset, which contains natural images and may not fully represent the complexity of real remote sensing imagery. Moreover, the framework relies on the availability of appropriate high-resolution reference images, which may not always be accessible in real-world applications. The use of a fixed bicubic degradation model is another constraint, as it may not accurately reflect the diverse degradation patterns present in satellite images.

Future research will aim to overcome these limitations by validating the proposed approach on remote sensing-specific datasets, investigating adaptive strategies for selecting suitable reference images, and adopting more realistic degradation models. Further efforts will also focus on designing lightweight, efficient versions of the framework to support large-scale deployment and real-time remote sensing applications.

Funding: This research was supported by the Prince Sattam bin Abdulaziz University for funding this research under project number (PSAU/ 2025/01/32835).
Institutional Review Board Statement: Not applicable.
Transparency: The authors state that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.
Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.

REFERENCES

[1] L. Lu, W. Li, X. Tao, J. Lu, and J. Jia, "MASA-SR: Matching acceleration and spatial adaptation for reference-based image super-resolution," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2021, pp. 6368-6377.

[2] S. Yuan *et al.*, "Long time-series analysis of urban development based on effective building extraction," presented at the Geospatial Informatics X, SPIE, 2020.

[3] S. Zhang, Q. Yuan, J. Li, J. Sun, and X. Zhang, "Scene-adaptive remote sensing image super-resolution using a multiscale attention network," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 58, no. 7, pp. 4764-4779, 2020. https://doi.org/10.1109/TGRS.2020.2966805

[4] L. Zhang, D. Chen, J. Ma, and J. Zhang, "Remote-sensing image superresolution based on visual saliency analysis and unequal reconstruction networks," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 58, no. 6, pp. 4099-4115, 2020. https://doi.org/10.1109/TGRS.2019.2960781

[5] R. Dong, L. Zhang, and H. Fu, "RRSGAN: Reference-based super-resolution for remote sensing image," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 60, pp. 1-17, 2022. https://doi.org/10.1109/TGRS.2020.3046045

[6] J. Min, Y. Lee, D. Kim, and J. Yoo, "Bridging the domain gap: A simple domain matching method for reference-based image super-resolution in remote sensing," *IEEE Geoscience and Remote Sensing Letters*, vol. 21, pp. 1-5, 2024. https://doi.org/10.1109/LGRS.2023.3336680

[7] R. Y. Tsai and T. S. Huang, "Multiframe image restoration and registration," *Multiframe Image Restoration and Registration*, vol. 1, pp. 317-339, 1984.

[8] T. Akgun, Y. Altunbasak, and R. M. Mersereau, "Super-resolution reconstruction of hyperspectral images," *IEEE Transactions on Image Processing*, vol. 14, no. 11, pp. 1860-1875, 2005. https://doi.org/10.1109/TIP.2005.854479

[9] J. Ma, J. C.-W. Chan, and F. Canters, "An operational superresolution approach for multi-temporal and multi-angle remotely sensed imagery," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 5, no. 1, pp. 110-124, 2012. https://doi.org/10.1109/JSTARS.2011.2182505

[10] H. Shen, M. K. Ng, P. Li, and L. Zhang, "Super-resolution reconstruction algorithm to MODIS remote sensing images," *The Computer Journal*, vol. 52, no. 1, pp. 90-100, 2009. https://doi.org/10.1093/comjnl/bxm028

[11] F. Li, X. Jia, D. Fraser, and A. Lambert, "Super resolution for remote sensing images based on a universal hidden Markov tree model," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 48, no. 3, pp. 1270-1278, 2010. https://doi.org/10.1109/TGRS.2009.2031636

[12] R. Fernandez-Beltran, P. Latorre-Carmona, and F. Pla, "Single-frame super-resolution in remote sensing: A practical overview," *International Journal of Remote Sensing*, vol. 38, no. 1, pp. 314-354, 2017. https://doi.org/10.1080/01431161.2016.1264027

[13] Z. Pan, W. Ma, J. Guo, and B. Lei, "Super-resolution of single remote sensing image based on residual dense backprojection networks," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 57, no. 10, pp. 7918-7933, 2019. https://doi.org/10.1109/TGRS.2019.2917427

[14] C. Dong, C. C. Loy, K. He, and X. Tang, *Learning a deep convolutional network for image super-resolution. In European conference on computer vision.* Cham: Springer International Publishing, 2014.

[15] C. Dong, C. C. Loy, K. He, and X. Tang, "Image super-resolution using deep convolutional networks," *IEEE Transactions on Pattern Analysis and Machine Intelligence,* vol. 38, no. 2, pp. 295-307, 2016. https://doi.org/10.1109/TPAMI.2015.2439281

[16] J. Kim, J. K. Lee, and K. M. Lee, "Accurate image super-resolution using very deep convolutional networks," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2016, pp. 1646-1654.

[17] J. Kim, J. K. Lee, and K. M. Lee, "Deeply-recursive convolutional network for image super-resolution," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2016, pp. 1637-1645.

[18] H. Zheng, M. Ji, H. Wang, Y. Liu, and L. Fang, "CrossNet: An end-to-end reference-based super resolution network using cross-scale warping," in *Proceedings of the European Conference on Computer Vision (ECCV)*, 2018, pp. 88-104.

[19] J. Caballero *et al.*, "Real-time video super-resolution with spatio-temporal networks and motion compensation," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2017, pp. 4778-4787.

[20] Z. Zhang, Z. Wang, Z. Lin, and H. Qi, "Image super-resolution by neural texture transfer," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2019, pp. 7982–7991.

[21] G. Shim, J. Park, and I. S. Kweon, "Robust reference-based super-resolution with similarity-aware deformable convolution," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2020, pp. 8425-8434.

[22] H. Zheng *et al.*, "Learning cross-scale correspondence and patch-based synthesis for reference-based super-resolution. In T.-K. Kim, S. Zafeiriou, G. Brostow, & K. Mikolajczyk (Eds.)," in *Proceedings of the British Machine Vision Conference 2017 (BMVC). BMVA Press*, 2017, pp. 138.1–138.13.

[23] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional networks for biomedical image segmentation," presented at the International Conference on Medical Image Computing and Computer-Assisted Intervention, Springer, 2015.

[24] J. Cao *et al.*, *Reference-based image super-resolution with deformable attention transformer. In S. Avidan, G. Brostow, M. Cissé, G. M. Farinella, & T. Hassner (Eds.), Computer Vision – ECCV 2022 (Lecture Notes in Computer Science.* Cham, Switzerland: Springer, 2022.