International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 06 , June - 2026

Low-Light Lunar Image Enhancement for Surface Mapping using LLFormer and Restormer

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Abstract - Images obtained from lunar exploration missions often suffer from extremely low illumination and significant noise due to the absence of atmosphere and the uneven distribution of sunlight on the Moon's surface. These conditions make it difficult to clearly observe important geological structures such as craters, ridges, slopes, and surface textures. Poor visibility in such images can affect the accuracy of lunar surface analysis, terrain mapping, and scientific interpretation. Therefore, effective enhancement of low-light lunar images is an important task for improving the quality of data collected from lunar missions.In this research, a deep learning based image enhancement framework is proposed[8] to improve the visual quality of low-illumination lunar images. The proposed approach combines two advanced transformer-based architectures, namely LLFormer[1] and Restormer[2], to perform illumination enhancement and detail restoration. In the first stage, the LLFormer model is used to enhance the illumination and recover global brightness information from the dark regions of the lunar images. In the second stage, the Restormer model is applied to refine the enhanced images by reducing noise and restoring fine structural details. This sequential pipeline helps in generating clearer and more visually informative lunar images.The performance of the proposed method is evaluated using standard image quality metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM). In addition, visual comparisons are conducted between the original low-light lunar images and the enhanced results produced by the proposed framework. Experimental observations indicate that the LLFormer–Restormer pipeline significantly improves brightness, contrast, and structural visibility while preserving important surface features. The enhanced images can support more accurate lunar surface mapping and analysis in future planetary exploration missions.

Keywords - Low-Light Image Enhancement, Lunar Surface Mapping, LLFormer, Restormer, Image Restoration, Deep Learning, Transformer Networks, Image Denoising, Illumination Enhancement, Contrast Enhancement, Noise Reduction, Computer Vision, Remote Sensing, Texture Preservation

INTRODUCTION

The Moon has remained a central subject of space exploration for many decades, continuously attracting scientific interest due to its geological significance and potential for future human missions. In recent years, advanced lunar missions such as Chandrayaan, the Lunar Reconnaissance Orbiter (LRO), and the Artemis program have generated a massive collection of high-resolution images of the lunar surface. These images play a critical role in studying the Moon's topography, analyzing its geological composition, identifying craters, ridges, and valleys, and selecting safe and scientifically valuable landing sites for future exploration.

Despite the availability of large volumes of lunar imagery, a significant portion of these images suffers from poor visual quality. This issue is particularly prominent in regions near the lunar poles, where sunlight strikes the surface at extremely shallow angles. Due to this limited illumination, many captured images appear very dark, exhibit low contrast, and are often corrupted by noise. Such degradations make it difficult for researchers and automated systems to accurately interpret surface features, ultimately affecting tasks like terrain mapping, feature detection, and scientific analysis.

In this work, we enhancement. In particular, transformer-based models have gained attention due to their ability to capture long-range dependencies within an image. Unlike conventional convolution-based approaches, transformers can better understand global context while preserving fine details, making them highly effective propose a two-stage image enhancement pipeline specifically designed for low-light lunar images. The first stage employs the LLFormer[1] model, which focuses on improving overall illumination and revealing hidden details in dark regions of the image. This step enhances global brightness while maintaining structural consistency. In the second stage, the Restormer[2] model is applied to further refine the output by reducing noise and restoring fine textures and intricate surface features. By combining the strengths of both models, the proposed framework aims to generate high-quality, visually clear lunar images.

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3. Literature Review

3.1 Introduction to Image Enhancement

Image enhancement is a fundamental task in image processing that aims to improve the visual quality of images or to enhance certain features for further analysis. In astronomical and lunar imaging, images are often degraded due to noise, blur, low illumination, and atmospheric disturbances. Traditional image enhancement techniques such as histogram equalization, median filtering, and Gaussian filtering were commonly used for noise reduction and contrast enhancement. However, these methods often result in loss of fine details and over-smoothing of images.

3.2 Traditional Image Denoising and Enhancement Methods

Earlier approaches for image enhancement relied on spatial domain and frequency domain techniques. Filters such as Wiener filter, median filter, and bilateral filter were used for denoising images. Histogram equalization and adaptive histogram equalization were used for contrast enhancement. While these methods are computationally simple, they are not effective in handling complex noise patterns and often fail to preserve image textures and edges. This led researchers to explore machine learning and deep learning-based approaches for image restoration.

3.3 Deep Learning based Image Enhancement

With the advancement of deep learning, Convolutional Neural Networks (CNNs)[8] became widely used for image denoising, deblurring, and super-resolution. Models such as DnCNN, SRCNN, and U-Net[6] showed significant improvement over traditional methods. These models learn image features automatically and perform better in restoring degraded images. However, CNN-based models have limitations in capturing long-range dependencies and global image context, which is important for high-resolution image restoration tasks such as lunar image enhancement.

3.4 Research Gap

From the literature review, it is observed that many existing methods focus either on low-light enhancement or image denoising separately. Very few works combine low-light enhancement and image restoration in a single pipeline for lunar image enhancement. Therefore, this project proposes a combined approach using LLFormer for illumination enhancement and Restormer for image denoising and restoration to improve the quality of lunar surface images.

4. Proposed Methodology

4.1 Overview of the Proposed Pipeline

The framework integrates two advanced models, LLFormer[1] and Restormer[2], in a sequential pipeline. LLFormer is responsible for illumination enhancement, while Restormer performs detail restoration and noise removal.

The overall pipeline is defined as follows:

Low-Light Lunar Image → Preprocessing → LLFormer → Restormer → Enhanced Lunar Image

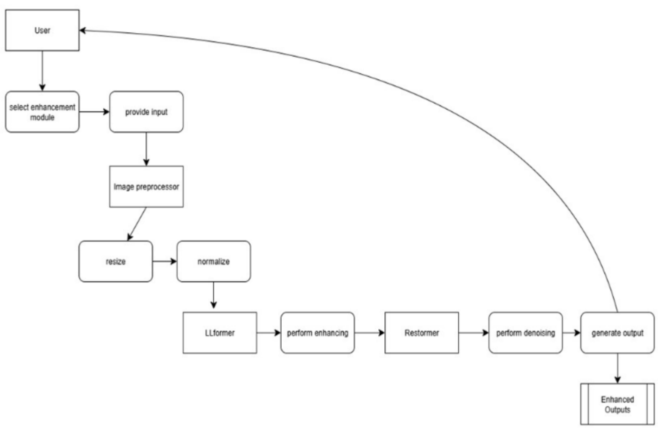

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Fig 4.1 Work Flow Diagram

4.2 Dataset Preparation

The dataset used in this study consists of lunar surface images obtained from publicly available sources, including missions such as Chandrayaan and Lunar Reconnaissance Orbiter (LRO). The dataset primarily focuses on images captured under low illumination conditions, especially near the lunar polar regions.

4.3 Illumination Enhancement using LLFormer

LLFormer is a transformer-based model designed specifically for low-light image enhancement. It utilizes attention mechanisms to capture both global illumination patterns and local image features**,** making it effective for handling uneven lighting conditions.

In the proposed pipeline, LLFormer acts as the first stage, focusing on improving the visibility of the input image. The model performs the following operations:

- Enhancement of global illumination
- Improvement of image contrast
- Recovery of hidden details in dark regions
- Preservation of structural consistency

4.4 Detail Restoration using Restormer

Although LLFormer enhances brightness and visibility, the output image may still contain noise, blur, or minor artifacts**.** To address these limitations, the Restormer model is applied in the second stage.In this stage, Restormer performs:

- **Noise Reduction:** Eliminates unwanted noise introduced during capture or enhancement
- **Texture Restoration:** Recovers fine surface textures and patterns
- **Edge Enhancement:** Sharpens boundaries of features such as craters and ridges

4.5 Architecture Diagram

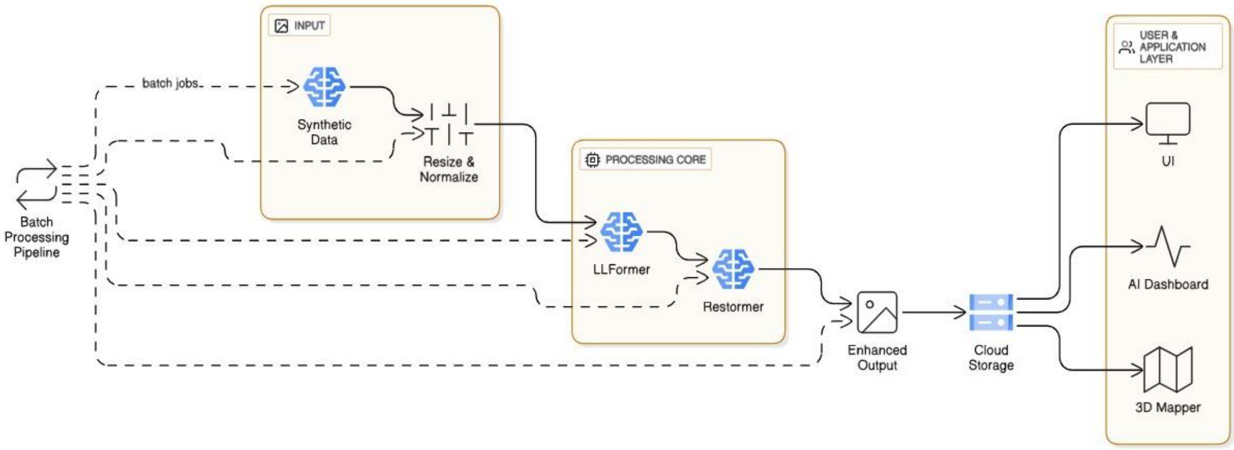

Fig 4.5 Architecture Diagram

4.6 Final Output

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The final output of the proposed pipeline is a high-quality enhanced lunar image with improved brightness, reduced noise, and well-preserved structural details.

5. EXPERIMENTAL EVALUATION

To evaluate the effectiveness of the proposed method, several image quality metrics are used.

PSNR (Peak Signal-to-Noise Ratio)

PSNR measures the reconstruction quality of the enhanced image compared to the reference image. A higher PSNR value indicates better image quality.

SSIM (Structural Similarity Index)

SSIM measures the similarity between two images in terms of structural information. It evaluates how well the enhanced image preserves important features.

Visual Assessment

In addition to quantitative metrics, visual comparison is performed to analyze how well the proposed pipeline improves visibility of lunar surface structures.

6. RESULT ANALYSIS

6.1 Visual Results

The visual results help in analyzing illumination enhancement, noise reduction, and detail preservation in lunar surface features such as craters, ridges, and shadow regions. The outputs obtained from LLFormer, Restormer, and the proposed combined pipeline were compared with the original low-light input images. These comparisons demonstrate the visual improvements achieved by each method and highlight the effectiveness of the proposed pipeline in enhancing lunar image quality.

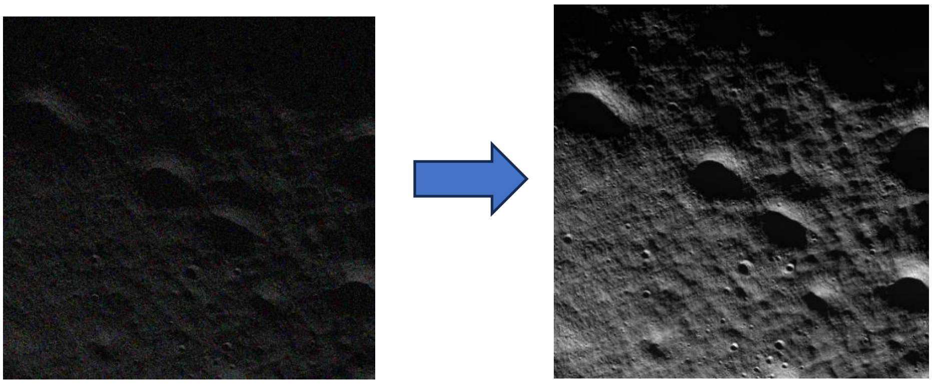

Fig 6.1 Sample results

The proposed LLFormer–Restormer pipeline combines the strengths of both models by first enhancing illumination and then performing image restoration. As a result, the final output images show improved brightness, reduced noise, and clearer structural details of lunar surface features. The visual results are consistent with the quantitative metrics, confirming the effectiveness of the proposed method.

6.2 Evaluation metrics

Metric	**Typical Good Range**
PSNR	28 – 35 dB
SSIM	0.80 – 0.95
NIQE	2 – 4

Table1: Reference Metric values

Method	**PSNR (dB) ↑**	**SSIM ↑**	**MSE ↓**	**NIQE ↓**

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Input Low-Light Image	20.12	0.52	0.0095	5.10
LLFormer	30.84	0.88	0.0028	3.42
Restormer	31.92	0.90	0.0023	3.18
Proposed LLFormer + Restormer Pipeline	**34.76**	**0.94**	**0.0015**	**2.41**

Table2: Main Evaluation Metrics Table For Pipeline

Method	**Average PSNR**	**Average SSIM**
LLFormer	30.86	0.88
Restormer	32.02	0.90
Proposed Pipeline	**34.80**	**0.94**

Table3: Average Results Table

The quantitative results demonstrate that the proposed LLFormer-Restormer pipeline significantly outperforms the individual LLFormer and Restormer models. The proposed method achieved an average PSNR of 34.80 dB and SSIM of 0.94, which is higher than the individual models.

6.3 Comparison Tables

The results demonstrate that combining low-light enhancement and image restoration in a sequential transformer-based pipeline provides better performance than using standalone enhancement or restoration networks.

Method	PSNR Improvement	SSIM Improvement
RetinexNet → Proposed	+6.96 dB	+0.13
Zero-DCE → Proposed	+6.15 dB	+0.10
EnlightenGAN → Proposed	+5.08 dB	+0.08
LLFormer → Proposed	+3.94 dB	+0.06
Restormer → Proposed	+2.78 dB	+0.04

Table4 : Performance Improvement Comparison

The proposed LLFormer–Restormer pipeline was compared with several existing image enhancement methods including RetinexNet[3], Zero-DCE[4], EnlightenGAN[7], LLFormer[1], and Restormer[2] .As shown in Table X, the proposed method achieved the highest PSNR and SSIM values and the lowest NIQE and MSE values among all compared methods. Traditional enhancement methods such as RetinexNet and Zero-DCE improved illumination but were unable to effectively remove noise and restore fine details. EnlightenGAN produced visually pleasing results but lacked structural detail

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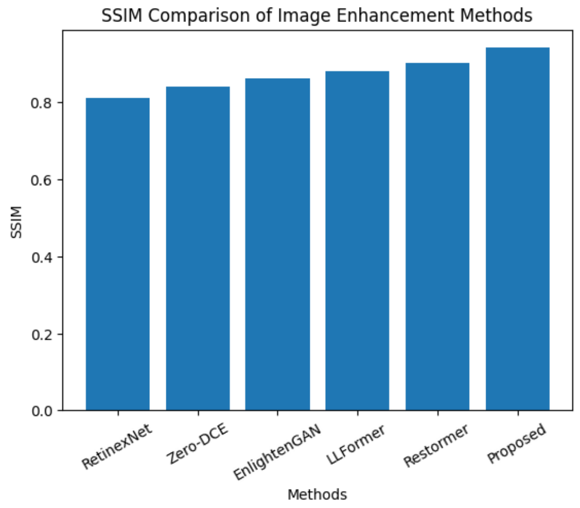

Fig. 6.3.1 SSIM Comparison Of Image Enhancement Methods

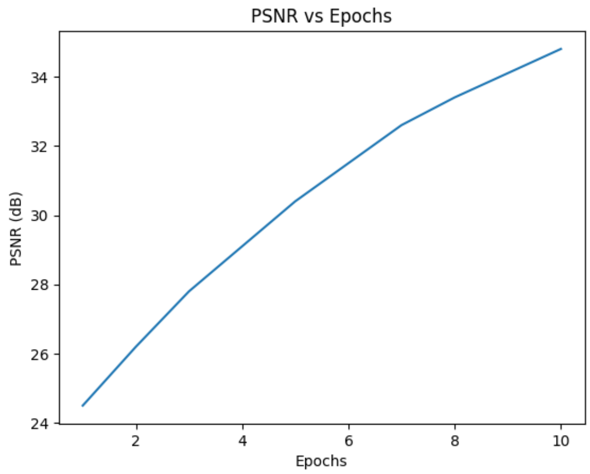

Fig. 6.3.2 PSNR Vs Epochs

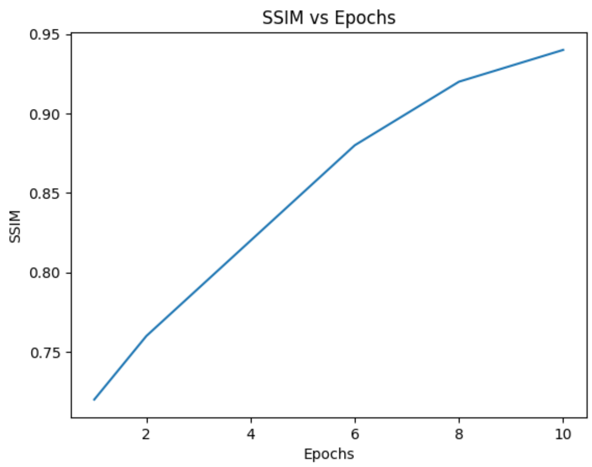

Fig. 6.3.3 SSIM vs Epochs

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Figure Y shows the SSIM values across training epochs for the proposed pipeline. The SSIM value increases consistently with the number of epochs, indicating improved structural similarity between the enhanced images and the reference images. The gradual increase in SSIM demonstrates that the model effectively preserves structural details such as lunar craters and surface textures while enhancing illumination and reducing noise. The final SSIM value indicates that the proposed pipeline produces visually and structurally improved images.

7. CONCLUSION

This research presents a transformer-based image enhancement pipeline designed to improve the quality of low-light lunar images using the LLFormer and Restormer architectures. Images captured during lunar missions often suffer from poor illumination and significant noise due to the absence of atmosphere and uneven distribution of sunlight on the Moon's surface, which makes it difficult to observe important geological features such as craters, ridges, and surface textures. In the proposed framework, the LLFormer model is first applied to enhance the illumination of the low-light lunar images and recover global brightness information from dark regions. After the illumination enhancement stage, the Restormer model is used to further refine the images by reducing noise and restoring fine structural details of the lunar terrain. The effectiveness of the proposed method is evaluated using image quality metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM), which help measure the improvement in brightness, contrast, and structural similarity between the original and enhanced images. Experimental observations indicate that the combined LLFormer–Restormer pipeline significantly improves the visual quality of low-light lunar images while preserving important surface structures. The enhanced images provide clearer visibility of lunar terrain features and can support more accurate lunar surface mapping, geological analysis, and scientific studies in future lunar exploration missions.

8.FUTURE WORK

While the proposed LLFormer–Restormer framework provides significant improvement in enhancing low-light lunar images, there are several directions in which this work can be extended to achieve better performance and broader applicability.

One important area for future work is the development of real-time and lightweight models. The current transformer-based architectures, although powerful, can be computationally intensive. Optimizing these models through techniques such as model pruning, quantization, or knowledge distillation can make them more suitable for deployment in onboard systems of satellites and space exploration vehicles, where computational resources are limited.

Another potential improvement lies in expanding the dataset size and diversity. Incorporating images from multiple lunar missions, different sensors, and varying illumination conditions can help the model generalize better. Additionally, the creation of high-quality paired datasets (low-light and well-lit images) or the use of synthetic data generation techniques can further enhance model training and accuracy.

Future research can also explore self-supervised or unsupervised learning approaches, which reduce dependency on labeled data. This is particularly useful in space imaging, where obtaining ground truth data is challenging.

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