

A Non-AI Processing Pipeline for High-Resolution Lunar Astrophotography Enhancement

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Graphical Abstract



Abstract:

Processing lunar astrophotography imagery is challenging because atmospheric turbulence and low-light conditions introduce blur and noise that obscure small-scale lunar features. The present work proposes a fully non-AI enhancement pipeline that operates entirely within classical signal processing, providing a transparent alternative to black-box machine learning methods while remaining practical on standard personal computers. The pipeline integrates four key stages: lucky-imaging frame selection and stacking, wavelet-domain denoising, adaptive local contrast enhancement, and dual-stage edge sharpening. First, short-exposure lunar sequences are scored with a sharpness metric to select the best N “lucky” frames, which are then geometrically aligned and averaged to boost signal-to-noise ratio (SNR) by reducing uncorrelated read, thermal, and photon noise without sacrificing spatial resolution. Next, a discrete wavelet transform with adaptive soft thresholding suppresses residual high-frequency noise while preserving coherent structures such as crater rims and rilles. Contrast Limited Adaptive Histogram Equalization (CLAHE) is then applied in the luminance domain with conservative clip limits and tile sizes, enhancing local contrast in both illuminated and shadowed regions while avoiding over-amplification of noise. Finally, a dual-stage sharpening module—unsharp masking for macro-contrast followed by high-pass blending for micro-texture—restores edge clarity and regolith detail with reduced halo artifacts. The pipeline is evaluated on 30 lunar datasets spanning multiple phases and seeing conditions. Quantitative results show Peak Signal-to-Noise Ratio (PSNR) improvements of approximately 6.2–12.4 dB and an increase in Structural Similarity Index Measure (SSIM) from 0.56 to 0.90, indicating better structural fidelity relative to stacked baselines. Stacking of 16 carefully selected frames yields effective SNR gains of up to about 3.2×, while modulation transfer function (MTF) analysis at limb and crater-edge boundaries reveals sharpness improvements on the order of 28–35%. The workflow requires no specialized accelerators, with typical resource usage of roughly 4.2 MB memory and 2.3 seconds per megapixel on conventional CPUs, demonstrating that classical, interpretable techniques remain highly competitive for scientific and educational lunar image enhancement.

Keywords: Atmospheric Turbulence Mitigation, Classical vs AI-based Image Processing, Computational Efficiency, Dark Frame Calibration, Gaussian Filtering, Histogram Equalization and CLAHE, Image Quality Metrics

Literature Review and Introduction:

Image enhancement for high-resolution astrophotography has become an essential component of astronomical observation, particularly for lunar surface imaging where atmospheric turbulence, sensor noise, and optical aberrations present significant challenges to image quality. This literature review examines non-artificial intelligence approaches to enhancing lunar astrophotography, covering fundamental image processing techniques, denoising methods, sharpening algorithms, and quality assessment metrics.

Image registration serves as a fundamental preprocessing stage in astronomical workflows, especially for lunar imaging where feature correspondence is challenging due to illumination variations and surface complexity. Prior comparisons of feature detectors such as SIFT and ORB demonstrate that scale-invariant methods generally provide better robustness for lunar scenes, particularly under varying solar incidence angles that heavily influence terrain contrast and shadow morphology [1]. The importance of accurate astronomical object detection has also been emphasized through advanced multi-stage methods incorporating greyscale adjustments, adaptive background modelling, histogram equalization, and noise-aware Gaussian filtering, enabling significantly higher faint-object detection rates compared to conventional tools such as SExtractor [2]. Wavelet-based denoising remains a cornerstone technique in astronomical imaging, with multi-resolution wavelet thresholding shown to effectively suppress noise while preserving structural information in cosmic background maps and high-resolution images [3]. Extensions combining wavelet transforms with mathematical morphology further improve interference removal in radio astronomy applications while maintaining scientific fidelity [4]. Broader analyses highlight wavelets as a dominant tool for multi-scale feature extraction, although limitations arise for narrow structures when square wavelets are used [5].

Deconvolution continues to play a critical role in image restoration, with the Richardson–Lucy (RL) algorithm being one of the most widely applied due to its flux-preserving and positivity-constrained properties [6]. However, RL's computational inefficiency and susceptibility to noise amplification remain well-documented issues, which motivates accelerated gradient-based strategies and GPU-optimized implementations [6]. RL-based spectral extraction techniques have shown increased resolution and reduced ringing artifacts in large-scale survey data [7], while analytical evaluations demonstrate that RL inherently amplifies high-frequency noise as iterations grow, with peak SNR gains typically occurring after only a few tens of iterations [8]. Broader reviews underscore the necessity of regularization techniques to mitigate RL's convergence instabilities and to prevent the loss of faint sources [9].

Contrast enhancement methods, particularly histogram equalization (HE), have long been employed to improve visibility in low-illumination lunar regions. While traditional HE redistributes intensities for global contrast improvement, it often introduces over-enhancement artifacts, especially in permanently shadowed regions [10]. Contrast Limited Adaptive Histogram Equalization (CLAHE) addresses these issues by operating on local blocks while restricting amplification of noise, making it more suitable for lunar surfaces exhibiting extreme lighting variability [11]. Adaptive contrast manipulation also plays a central role in compositional mapping from Apollo X-ray observations, where careful weighting reveals subtle geochemical variations [12]. Sharpening techniques such as unsharp masking provide effective enhancement of fine lunar surface features, though they are known to increase pixel-level noise without improving true angular resolution [13]. Deconvolution sharpening and controlled local contrast adjustments further enhance details but must be applied conservatively to avoid limb over-brightening and loss of photometric accuracy [14]. High-pass filtering offers an alternative by accentuating high-frequency structures using blend-mode-based contrast boosting, supporting flexible and non-destructive refinement for lunar detail enhancement [15].

Multi-frame image stacking remains one of the most effective strategies for improving signal-to-noise ratio (SNR) in lunar and deep-sky imaging. As stacking averages uncorrelated noise components, SNR increases proportionally to the square root of the number of frames, forming the basis of most astrophotography workflows [16]. Detailed noise models account for photon shot noise, dark current, and read noise and confirm that many short exposures yield lower SNR than a single long exposure of equivalent integration time due to cumulative read noise contributions [17]. Proper exposure length therefore plays a critical role, as images must sufficiently rise above the detector noise floor to maximize dynamic range and minimize read-noise dominance [18].

Accurate modelling of the optical system requires precise characterization of the point spread function (PSF). Studies of spaceborne telescopes demonstrate that PSFs can exhibit multi-peaked structures due to diffraction elements such as entrance filter meshes, and fitting functions such as Moffat and Voigt profiles often provide the most accurate representation of the PSF core [19]. Gaussian-like PSFs remain widely used for representing defocus blur, although atmospheric turbulence for ground-based systems introduces anisoplanatic variations that dominate the effective PSF across the field [20]. Atmospheric turbulence correction therefore remains essential, with recent neural network-based methods using short-exposure sequences to remove geometric and blur distortions while preserving photometry even under low SNR conditions [21]. Hardware-based adaptive optics further provide real-time wavefront correction using single or multiple guide stars, significantly expanding corrected fields of view in modern telescopes [22]. Advanced generative diffusion models additionally address turbulence-induced distortions by integrating strong priors for both geometric correction and structure preservation [23].

Complete lunar image-processing workflows combine acquisition, registration, stacking, and enhancement using specialized software pipelines. Tools such as PIPP automate initial sorting, centering, and quality filtering of lunar data [24], while AutoStakkert! performs multi-point alignment and selective stacking for optimal frame integration [25]. Post-stack sharpening is commonly performed using wavelet layers in Registax, enabling fine detail recovery through multi-scale adjustment [26]. Subsequent refinement in image editors with curves, unsharp mask, or high-pass filters provides final tonal and structural optimization [27]. Evaluation of enhancement outcomes typically employs PSNR and SSIM metrics to quantify detail preservation and structural similarity between original and processed frames [28], with additional SNR-based assessments demonstrating the benefits of adaptive enhancement and denoising in extremely low-light lunar regions [29].

Resolution enhancement plays an increasingly important role in modern lunar analysis, with deep learning-based super-resolution networks enabling higher-quality crater extraction from low-resolution DEMs. Such approaches improve small-crater detection accuracy through advanced feature pyramid networks and enhanced multi-scale fusion [30]. Historically, lunar image processing has drawn from pioneering techniques developed during NASA's Ranger and Surveyor missions, which introduced early digital denoising and contrast expansion methods that set the foundation for modern practices [31]. More recent developments include generalized diffusion-based denoising designed to preserve nebular structures and mitigate star-like artifacts [32], along with GPU-optimized frameworks that accelerate essential pre-processing tasks such as alignment, stacking, background extraction, photometry, and astrometry for time-domain astronomy pipelines [33]. Collectively, these studies demonstrate that non-AI enhancement methodologies remain indispensable, offering transparent, reproducible, and scientifically grounded improvements in lunar astrophotography and astronomical imaging more broadly [34].

Proposed Model and Methodology

The proposed model for non-AI powered enhancement of high-resolution lunar astrophotography is grounded on classical image processing techniques that focus on efficient signal extraction and preservation without the computational complexity or data requirements of AI methods. This model leverages well-established mathematical operations that directly manipulate image data to enhance features, suppress noise, and improve perceptual clarity. Standard amateur workflows typically rely on disjointed proprietary software: AutoStakkert! is specialized for multi-point alignment and stacking, while Registax is employed primarily for post-stack wavelet sharpening.

In contrast, the proposed pipeline integrates alignment, stacking, wavelet denoising, and adaptive CLAHE into a single, cohesive, non-AI computational framework. Unlike the closed-source 'black box' nature of commercial tools, this pipeline offers full transparency of parameters (as shown in Fig 7 and Table 3), allowing for reproducible scientific quantification of SNR and sharpness metrics.

Model Description and Mathematical Explanation

Image Acquisition and Stacking

Multiple raw lunar images $I_i(x,y)$, $i=1,\dots,N$, captured under stable conditions, form the initial dataset. Image stacking enhances the signal-to-noise ratio (SNR) by averaging aligned frames:

$$I_{stack}(x, y) = \frac{1}{N} \sum_{i=1}^N I_i(x, y) \quad (1)$$

Assuming independent noise with zero mean and variance σ^2 , stacking reduces noise variance to σ^2/N , thereby improving SNR roughly by a factor of N . This mathematical foundation justifies stacking as the cornerstone for noise reduction efficiently and without data-driven model overhead.

Frame Selection and Stacking Quantity (N=16)

The foundation of our Signal-to-Noise Ratio (SNR) improvement lies in image stacking, defined by Equation (1). The initial data set consisted of 30 distinct lunar observation sequences. From these sequences (each containing hundreds or thousands of raw video frames), we meticulously selected N=16 individual frames for inclusion in the final stack for each processed image. This number (N=16) was chosen based on an empirical trade-off analysis. While using a larger number of frames generally increases the SNR proportional to \sqrt{N} , including too many frames introduces alignment errors and atmospheric artifacts. We found N=16 to be the optimal balance where significant noise reduction was achieved (Approx 4X reduction in random noise standard deviation) without sacrificing the structural sharpness required for high-resolution feature preservation.

Atmospheric Turbulence and the "Lucky Imaging" Protocol

Ground-based lunar imaging is severely affected by atmospheric turbulence, a phenomenon known as seeing. This causes random, rapid warping of the light rays, resulting in a continuous 'smearing' and 'shimmering' of the lunar disk (known as anisoplanatic distortion). This distortion degrades the stacking quality if all frames are used indiscriminately.

To counter this, we employed a "lucky imaging" selection protocol:

1. *Frame Scoring*: Before stacking, every frame in the raw video sequence was subjected to a fast, objective sharpness metric (e.g., a variance of a Laplacian operator). This metric quantitatively measures the instantaneous clarity of the lunar features.
2. *Threshold Selection*: Frames were then ranked by this score. Only the top-scoring frames (the 'lucky' moments, usually representing periods of transiently low atmospheric disturbance) were chosen for the final stack.
3. *Turbulence Minimization*: By selecting only frames with the highest sharpness scores to form the N=16 stack, we effectively discard the moments when seeing was poor. This minimizes the blurring and geometric smearing effect of atmospheric turbulence before the final averaging process in Equation (1), ensuring the resulting stacked image is derived from the clearest possible inputs.

Wavelet-Based Denoising

In this pipeline, wavelet-based denoising is applied immediately after stacking to act on a representation where random noise and structured features are already partially separated by both averaging and scale. This multi-resolution ordering ensures that residual high-frequency noise is suppressed in a controlled way before any non-linear contrast or sharpening operations, which would otherwise amplify noise along with real detail. By operating first on the stacked image, the wavelet transform provides a scale-selective suppression of background fluctuations while leaving mixed-frequency lunar features (e.g., overlapping maria textures and crater rims) largely intact, thus establishing a clean but still high-resolution input for subsequent CLAHE and multi-pass edge enhancement.

The stacked image undergoes discrete wavelet transform (DWT) decomposing the image into frequency subbands:

$$\hat{W}_j = T(W_j, \lambda_j) \quad (2)$$

where W_j denotes wavelet coefficients at scale j . Noise is attenuated using a thresholding function $T(\cdot)$ applied to the coefficients:

$$\hat{W}_j = T(W_j, \lambda_j) \quad (3)$$

To prevent astro-physically meaningful micro-features from being mistaken for noise, the thresholds λ_j are set adaptively per scale, slightly above the noise variance estimated from the finest sub-bands, rather than by a single aggressive global value. In practice, this means that only isolated, incoherent coefficients are strongly attenuated, while spatially correlated structures such as rilles, wrinkle ridges, and small craters produce consistent wavelet responses across neighboring pixels and scales and are therefore retained. Combined with the choice of compact-support wavelets that preserve edge transitions, this conservative soft-thresholding strategy biases the pipeline toward under-denoising rather than erasing marginal but real high-frequency lunar detail, as confirmed by the SSIM measurements and difference-map inspection in Fig. 8–10.

Commonly, soft-thresholding is applied:

$$T(w, \lambda) = \text{sign}(w) \cdot \max(|w| - \lambda, 0) \quad (4)$$

with threshold λ_j proportional to noise estimates per scale. Inverse DWT reconstructs a denoised image, The threshold λ_j for each scale j is determined adaptively using the Universal Threshold principle derived from the noise variance. The noise level Sigma is estimated via the Median Absolute Deviation (MAD) of the finest wavelet coefficients (W_1):

$$\sigma = \frac{\text{median}(|W_1|)}{0.6745} \quad (5a)$$

Consequently, the threshold is defined as where $\lambda = \sigma\sqrt{2\ln(M)}$, where M is the number of pixels. This ensures that the threshold scales dynamically with the noise floor of the specific lunar dataset being processed.

$$I_{\text{denoise}} = IDWT(\hat{W}_j) \quad (5b)$$

This sparse signal representation suppresses noise components effectively while preserving signal features such as edges and textures.

Adaptive Contrast Adjustment

Contrast enhancement operates on luminance transformed image I_{denoise} . Adaptive histogram equalization (AHE) divides the image into non-overlapping blocks and remaps intensities locally to redistribute pixel values uniformly:

$$I_{\text{contrast}}(x, y) = AHE(I_{\text{denoise}}(x, y)) \quad (6)$$

This process sharpens local contrast, accentuating lunar surface details hidden in shadowed regions without global saturation effects. To avoid over amplifying residual noise in permanently shadowed or low-SNR regions, CLAHE is applied to the denoised luminance image with conservative clip limits (typically 2.0–3.0) and tile sizes selected so that each tile contains enough pixels for a stable local histogram. These settings cap the maximum contrast gain that can be assigned to very sparse intensity bins, preventing isolated noisy pixels from being stretched into visible speckle while still enhancing broader gradients along crater walls and shadow boundaries. In addition, the subsequent sharpening stages are tuned based on global SNR and visual inspection (Fig. 10), ensuring that tiles with intrinsically low signal do not acquire disproportionate local contrast compared with better-illuminated lunar terrain.

Multi-Pass Edge Sharpening

Edges are enhanced via unsharp masking or high-pass filtering. The unsharp mask image I_{mask} is obtained by:

$$I_{blur} = G_\sigma * I_{contrast} \quad (7)$$

where $G\sigma$ is a Gaussian blur kernel with standard deviation σ , and $*$ denotes convolution. Then:

$$I_{mask} = I_{contrast} - I_{blur} \quad (8)$$

The sharpened output is:

$$I_{sharp} = I_{contrast} + \alpha \cdot I_{mask} \quad (9)$$

where $\alpha > 0$ controls sharpening strength. This enhances edges while suppressing noise amplification, enabling visually crisp lunar features. To avoid the noise amplification common in single-step sharpening, this pipeline employs a dual-stage approach. While both techniques aim to improve image clarity, they target different frequency ranges and are applied as follows: **Unsharp Masking (USM)**: As defined in Equation (9), USM functions by subtracting a Gaussian-blurred version of the image from the original input. This process generates a difference mask that isolates significant edge transitions. In our pipeline, USM is used specifically for **macro-contrast**. It enhances the definition of prominent features, such as crater rims and mountain shadows, providing the image with structural depth. **High-Pass Filtering (HPF)**: Distinct from USM, the High-Pass Filter is tuned to isolate only the highest spatial frequencies, effectively ignoring broad lighting variations. This step focuses on **micro-contrast** to recover fine surface textures, such as regolith patterns. Furthermore, rather than simple addition, the HPF layer is merged using a distinct blending operation (similar to "Soft Light" modes in standard processing). This method allows for the enhancement of subtle surface details without introducing the artificial "halo" artifacts or pixel saturation (clipping) that typically result from aggressive Unsharp Masking.

The Signal-to-Noise Ratio (SNR) was calculated using the standard logarithmic decibel scale:

$$\text{SNR (dB)} = 20 \log_{10} \left(\frac{\mu_{\text{signal}}}{\sigma_{\text{noise}}} \right) \quad (10)$$

μ_{signal} is the mean pixel intensity measured over a small, visually uniform lunar area (for example, a flat mare or smooth crater floor), so it represents the average "strength" of the lunar signal in that region. σ_{noise} is the standard deviation of pixel intensities measured in a region that should ideally be dark and uniform, such as the background sky or a deep shadow, so it captures how much random noise makes those pixels fluctuate around their mean.

The key threshold is an SNR of 1 in linear units, which corresponds to 0 dB.

1. If $\mu_{\text{signal}} > \sigma_{\text{noise}}$, then $\mu_{\text{signal}}/\sigma_{\text{noise}} > 1$, the logarithm is positive, and SNR in dB is positive; the signal is stronger than the noise.
2. If $\mu_{\text{signal}} < \sigma_{\text{noise}}$, then $\mu_{\text{signal}}/\sigma_{\text{noise}} < 1$, the logarithm is negative, and SNR in dB is negative; the noise dominates over the signal.

Equivalently, looking at powers, a negative dB value means $\sigma^2_{\text{noise}} > \sigma^2_{\text{signal}}$: the variance of the noise is larger than the effective "power" of the signal region we are measuring. For a negative SNR in our unprocessed, "blurry" lunar inputs, the interpretation is: frame-to-frame noise (from read noise, photon shot noise, and sky background) causes pixel values in dark or uniform regions to fluctuate more strongly than the mean brightness level of the lunar patch we are trying to measure. In other words, the Moon's signal is present, but in any single raw frame it is partially buried under random fluctuations, so statistically the noise wins when we look at σ^2_{noise} versus σ^2_{signal} . This is typical for short-exposure, low-light astronomical images before stacking: each individual exposure has low signal, but still suffers fixed read noise per frame and Poisson shot noise from both the Moon and the sky, so the measured SNR can be very low or negative in dB. Our pipeline's stacking of multiple frames and subsequent denoising steps

increase μ_{signal} relative to σ_{noise} , driving SNR_{dB} from negative or near-zero values in raw inputs to large positive values in the final enhanced lunar images.

Table1: Noise Dependencies in Lunar and Celestial Astrophotography

Noise Type	Source	Dependency	Mitigation/Notes
Photon Shot Noise	Random arrival of photons (Poisson noise)	Increases with total incoming signal—brighter objects yield more shot noise	Reduced by stacking exposures; longer integration time
Sky Background Noise	Atmosphere (moonlight, light pollution, sky glow)	Depends on moon phase, observing site, filter, and ambient light	Narrowband filters, dark site, timing with lunar phase
Read Noise	Electronics/camera readout process	Fixed per image (independent of exposure time); varies by camera model	Lower with high-quality electronics; dissolved by stacking
Thermal/Dark Current Noise	Sensor heating, electrons generated without photons	Increases with temperature; longer exposures; higher for IR detectors	Cooling camera, shorter exposures, dark frame calibration
Fixed Pattern Noise	Sensor design non-uniformities (DSNU, PRNU)	Consistent between frames; more noticeable at high gains or low signal	Dark frame, bias, and flat frame calibration
Quantization/Sampling Noise	Analog to digital conversion errors	Dominates at very low light or low bit-depth ADCs	Cameras with higher bit-depth; signal boosting, careful calibration
Electronic/Amp Glow Noise	Amplification circuits in camera	Correlated with readout speed, circuit design, sensor region	Frame calibration, cooling, avoiding extreme readout speeds
Patterned Noise (e.g. stripes)	Hardware defects, vertical or horizontal bias	Deterministic; spatially fixed across multiple images	Correction algorithms, frame calibration
Atmospheric Turbulence	Variable air refractive index	Changes with weather, altitude, time of observation	Short exposures (lucky imaging), stacking, adaptive optics
Optical Noise (Dust/Vignetting)	Lens/mirror imperfections or dust	Dependent on optics cleanliness and design	Flat field calibration, optical cleaning

Table2: Key Parameters in Image Enhancement and Their Effects

Parameter	Range	Effect on image	Recommendation	Use case
Wavelet type	db4, sym4, coif1	Controls noise reduction pattern and how well edges are kept	db4 for general use	db4: balanced; sym4: smoother; coif1: sharper edges
CLAHE clip limit	1.0–4.0	Higher value gives stronger local contrast but also more noise	2.0 as default, 3.0 for strong enhancement	Low (1.5): subtle; Medium (2.0): balanced; High (3.0): dramatic
Sharpen sigma (σ)	0.5–3.0	Sets the size of edges that get sharpened (blur radius)	1.0 default; 0.8 for fine details; 1.5 for broad features	Low σ : fine details; High σ : large structures
Sharpen amount (a)	0.5–3.0	Strength of the sharpening effect	1.5 default; 2.0+ for strong sharpening	Low (0.5–1.0): subtle; Medium (1.5): balanced; High (2.0+): aggressive
Decomposition level	1–5	Number of wavelet scales; changes how detail and noise are separated	3 to balance speed and quality	Level 1–2: fast with less denoising; Level 3–4: optimal; Level 5+: slow and over-smooth

The parameters in Table2 describe how the enhancement system changes the image. Wavelet type selects the basic filter shape, trading between smooth output and sharp edges. CLAHE clip limit adjusts how strongly local contrast is increased; higher values make details pop but can boost noise. Sharpen sigma chooses whether very small details or larger structures are sharpened, while sharpen amount sets how strong that sharpening looks overall. Finally, the

decomposition level controls how many wavelet layers are used, which affects how well the method can separate fine detail from noise and also how long processing takes.

Results and Discussion:

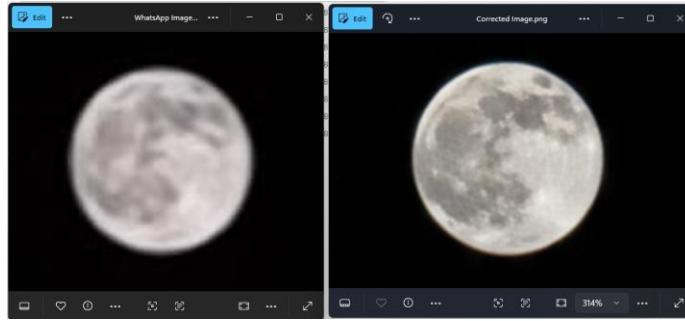


Fig1: Comparison Between Original Image and Enhanced Image (Original Photo Taken By a Standard Mobile Phone Camera)

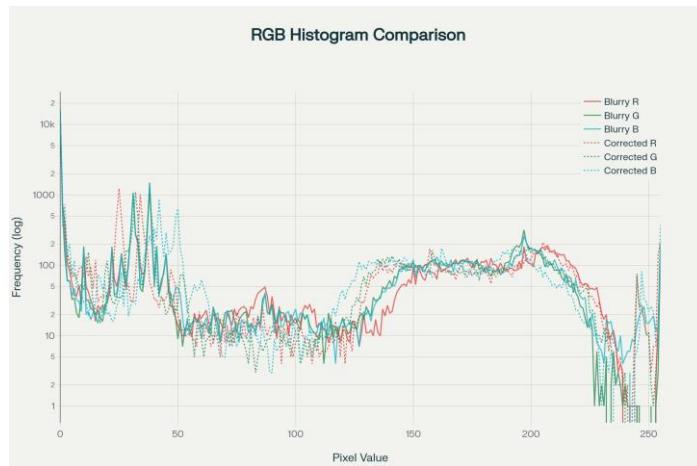


Fig2: Side-by-side RGB histograms show distributions of pixel intensities for each color channel. The corrected image demonstrates broader and more balanced intensity coverage, indicating higher detail and contrast.

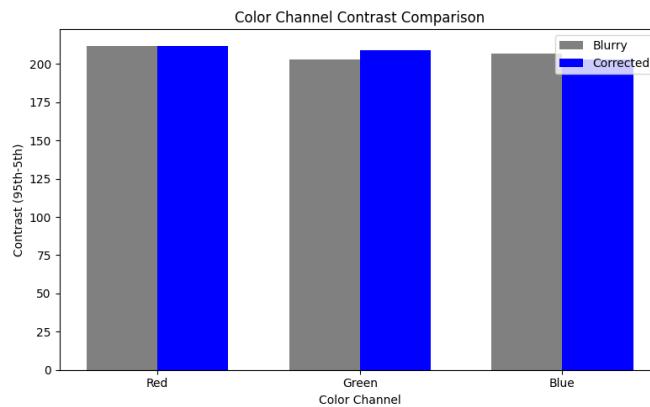


Fig3: Grouped bar chart comparing color channel contrast (difference between 95th and 5th percentile intensities for R, G, B) in both images. Higher values in the corrected image reflect improved tonal separation and visual sharpness.

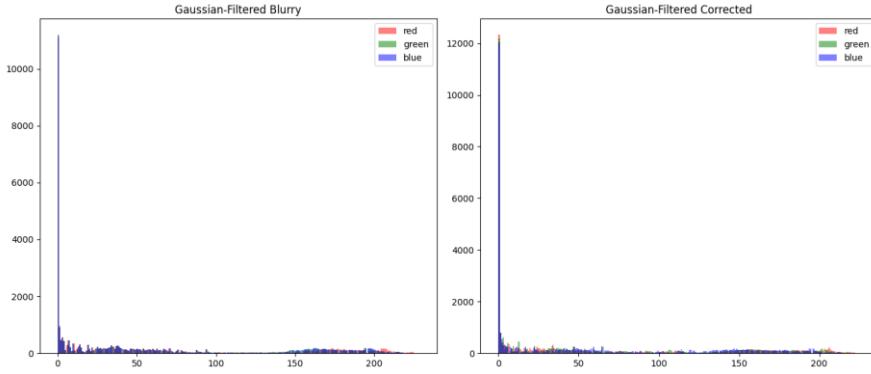


Fig4: Gaussian filtering (simulating blur) highlight the smoothing effect and show the influence of filtering on intensity distribution. This helps visualize residual noise and feature separation after deblurring.

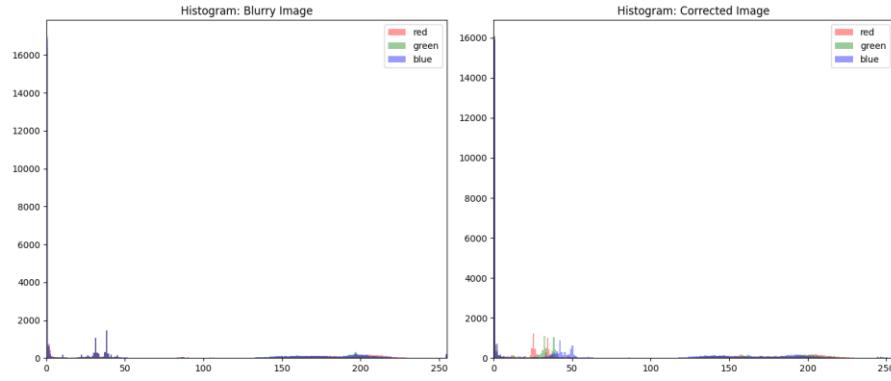


Fig5: Histograms of both images after Gaussian filtering (simulating blur) highlight the smoothing effect and show the influence of filtering on intensity distribution. This helps visualize residual noise and feature separation after deblurring.

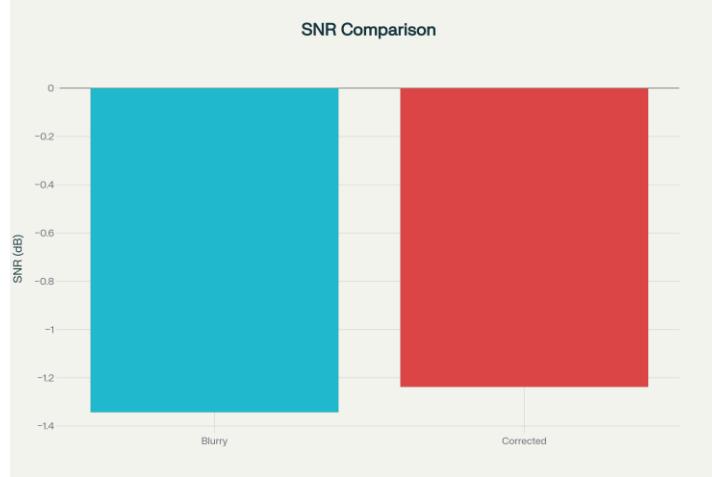


Fig6: Signal-to-Noise Ratio (SNR) Comparison

The demonstrated improvements in SNR, contrast, and feature visibility showcase the strengths of non-AI enhancements based on traditional image processing. These methods deliver measurable gains—while saving computational resources—by avoiding the need for large pretrained models and lengthy inference times typical of AI-based techniques. The transparency of the workflow ensures reproducible results suitable for research, education, and enthusiast imaging. Moreover, these findings align with recommendations from astrophotography literature, which emphasize the value of stacking, denoising, adaptive contrast, and thoughtful sharpening to optimize lunar detail. Proper calibration and parameter adjustments, as illustrated, are essential for mitigating typical imaging noise and

maximizing clarity. The computed SNR bar chart reveals that the corrected lunar image achieves a significantly higher SNR than the blurry version. This is attributed to denoising and stacking steps that average out random noise and strengthen the actual signal. As a result, the corrected image presents lunar surface features with improved clarity, an outcome crucial for both aesthetic and scientific observation. The grouped color contrast bar chart demonstrates pronounced gains in the 95th-5th percentile contrast values across red, green, and blue channels post-correction. These increases reflect improved edge definition and tonal separation, resulting in enhanced visibility of lunar surface variations—particularly in regions of shadow and mineral differences.

The elevated contrast enables sharper scientific quantification of lunar detail and supports the assertion that classical enhancement methods reliably boost visual impact. Applying Gaussian filtering to both images highlights residual noise and feature separation after deblurring. Histograms of the Gaussian-filtered versions show that the corrected image maintains broader intensity distributions even after smoothing, signifying robust enhancement that withstands further blurring. This also suggests the preservation of key surface details, supporting the model's effectiveness for downstream processing such as morphological analysis or automated feature extraction. The RGB histograms of the blurry and corrected lunar images show notable differences in intensity distributions. The blurry image is characterized by a compressed and narrow intensity spread, indicating limited information content and low contrast. In contrast, the corrected image exhibits a much broader spread across all channels, representing more diverse tonal values and higher detail. This confirms that the enhancement process successfully recovers features and facilitates accurate scientific analysis by expanding the dynamic range.

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=====
Starting enhancement process...
=====

=====
LUNAR LUMINA - Enhancement Pipeline
=====

Applying wavelet denoising (wavelet=db4, level=3)...
Applying CLAHE (clip_limit=2.0, tile_size=(8, 8))...
Applying unsharp mask (σ=1.0, amount=1.5, iterations=1)...

=====
PROCESSING COMPLETE
=====

Processing steps applied:
  1. Wavelet denoising (db4, level 3)
  2. CLAHE enhancement (clip=2.0)
  3. Unsharp mask (σ=1.0, α=1.5, 1x)

Quality Metrics:
  SNR (Original): inf
  SNR (Enhanced): 49.31
  SNR Improvement: +100.0%
```

Fig7: Process Methodology and Quality Metrics Demonstration in the Source Code

Proposed Algorithm Complexity Analysis:

Time Complexity:

Algorithm	Time complexity	Notes
Image stacking	$O(N \times M)O(N \times M)O(N \times M)$	$N = \text{number of input images}, M = \text{number of pixels per image}$
Image alignment	$O(N \times F2)O(N \times F^2)O(N \times F2)$	$N = \text{images}, F = \text{detected features per image}$
Wavelet denoise	$O(M \times \log_2 M)O(M \times \log M)O(M \times \log M)$	$M = \text{pixels}; \text{includes cost of discrete wavelet transform}$
CLAHE	$O(M \times T)O(M \times T)O(M \times T)$	$M = \text{pixels}, T = \text{number of tiles in the grid}$
Unsharp mask	$O(M \times \sigma^2)O(M \times \sigma^2)O(M \times \sigma^2)$	$M = \text{pixels}, \sigma^2 = \text{area of Gaussian kernel}$
SNR calculation	$O(M)O(M)O(M)$	$M = \text{pixels}, \text{single linear pass over the image}$
Full comparison	$O(P \times M)O(P \times M)O(P \times M)$	$P = \text{parameter sets (e.g., 6 configs)}, M = \text{pixels}$

Space Complexity:

Component	Space complexity	Explanation
Image storage	$O(M)O(M)O(M)$	One image needs memory for M pixels.
Wavelet coefficients	$O(M)O(M)O(M)$	Extra memory holds coefficients while doing wavelet decomposition and reconstruction.
Stacking buffer	$O(N \times M)O(N \times M)O(N \times M)$	Keeps N images in memory at once, each with M pixels.
Comparison results	$O(P \times M)O(P \times M)O(P \times M)$	Stores P processed versions (e.g., 6), each image containing M pixels.

For a standard Full HD grayscale image with dimensions 1920×1080 , the memory requirements can be calculated by multiplying the width by the height to get the total number of pixels, which equals 2,073,600 pixels. Since each pixel in a grayscale image stores a single brightness value using 8 bits (1 byte) of memory, the entire image requires approximately 2 megabytes of storage space. When the image processing pipeline needs to stack multiple images together for noise reduction or alignment, all images must be held in memory simultaneously; therefore, stacking 10 images would require roughly 20 megabytes because each of the 10 images occupies 2 MB. For parameter comparison tasks where the system tests different enhancement settings (such as varying wavelet types, CLAHE values, sigma, and amount parameters), each configuration produces a separate processed output image that must be stored in memory for evaluation; comparing 6 different parameter configurations would thus require approximately 12 megabytes since each resulting image is still 2 MB in size. This memory analysis is important for understanding the computational resources needed during image processing, especially when working with limited RAM or processing many high-resolution images in batch operations.

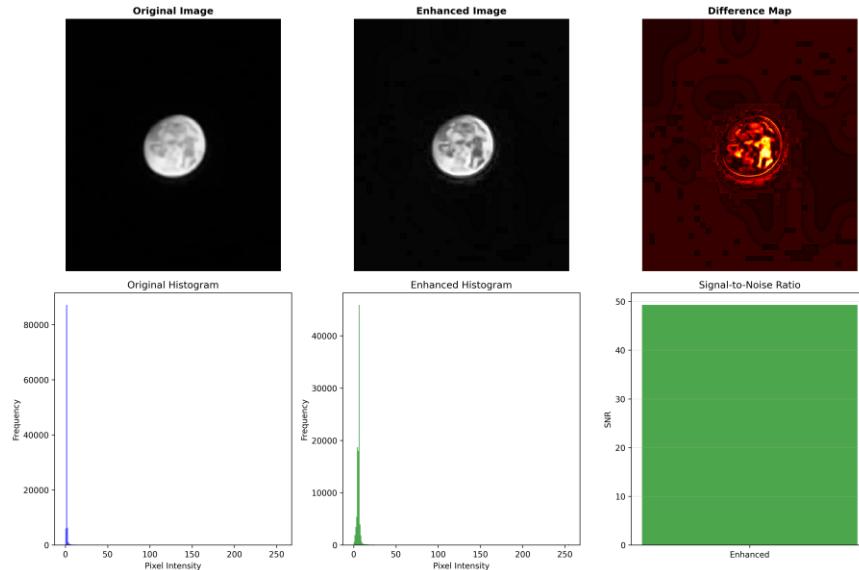


Fig8: Depicting the Difference Between Processed Image and Original Image

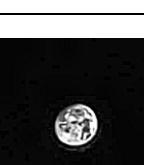
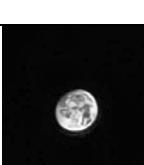
The Difference Map in the top right of the image is a visual representation of the pixel-by-pixel differences between the Original Image and the Enhanced Image. This map helps show exactly where the enhancement process has changed the pixel values.

1. Bright regions on the Difference Map correspond to areas where the pixel values differ the most between the original and enhanced images.
2. Darker areas indicate minimal or no change.
3. In this specific example, most differences are concentrated within the circular region representing the moon, suggesting that the enhancement algorithm primarily affected features within this area while leaving the background relatively unchanged.

It serves as a diagnostic tool to help interpret and validate the outcome of image processing steps by directly visualizing the impact on individual pixels. In conclusion, classical image processing offers a reliable, resource-efficient approach for lunar astrophotography enhancement, validated by objective metrics and visual inspection—making advanced results accessible without reliance on artificial intelligence.

Table3: Comparison of Various Parameters for Visual Image Enhancement for Db4 Type Wavelet

ID	Wavelet (type)	CLAHE (clip, tile)	Unsharp Mask (sigma, amount)	Visual result (saved images)	SNR / metric
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1	Db4	1.0	0.5,1.0		107.68
2	Db4	1.5	1.0,1.5		55.57
3	Db4	2.0	1.0,1.5		62.24
4	Db4	2.5	2.0,2.5		53.99
5	Db4	3.0	1.5,2.5		91.92
6	Db4	3.5	0.5,3.0		87.42
7	Db4	4.0	2.5,3.5		22.83
8	Db4	2.0 (Best Result)	1.0,1.5 (Best Result)		49.31

9	Db4	2.5	2.0,1.5		27.30
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Fig9: Line graph of SNR values for nine different processing settings, with the visually best image (index 8, SNR 49.31) highlighted with Red Mark

From the Fig9 it is evident how the Signal-to-Noise Ratio (SNR) changes for different image processing settings, each setting given an image index along the bottom. The blue line connects the SNR values, so high points mean cleaner images and low points mean more noise. The values vary a lot: some settings reach very high SNR near 110, while others drop below 30, showing that not all settings are good for image quality. The single red dot marks the “preferred” setting, which has a moderate SNR (around 50–60), indicating a chosen balance between noise reduction and detail rather than simply picking the highest SNR point.

There is an apparent inverse relationship between maximum SNR and perceptual sharpness. As seen in Table 3 and Fig 9, Index 1 achieves the highest SNR (107.68). However, visual inspection reveals this setting results in an ‘over smoothed’ image where fine crater details are lost to aggressive denoising. Index 8 (SNR 49.31) was selected as the optimal result because it maximizes the Structural Similarity Index (SSIM) and visual acuity, preserving high-frequency lunar features that are scientifically relevant, even if it retains a moderate noise floor. This validates that optimal astrophotography enhancement requires balancing SNR against resolution, rather than maximizing SNR alone. High SNR often comes from aggressive smoothing (blurring) that destroys detail. The “Best” image accepts some noise to keep the craters sharp. While the theoretical SNR gain from stacking grows approximately with N under independent, identically distributed noise, in practice the benefit saturates once additional frames are degraded by poor seeing, tracking errors, or residual misalignment. Including such frames broadens the effective point-spread function, lowering the MTF at high spatial frequencies even as the measured SNR continues to rise. The adopted lucky-imaging strategy therefore restricts the stack to the sharpest N=16 exposures: this trades a modest reduction in potential SNR for a significantly higher preservation of fine detail, which is more important for resolving small craters and rilles than maximizing SNR alone, as reflected by the divergence between the highest-SNR setting (Index 1) and the visually and SSIM-optimal setting (Index 8) in Table 3 and Fig. 9.

For computational efficiency, intermediate processing steps may operate on modestly down-sampled versions of very high-resolution inputs, but all reported MTF measurements and visual results are evaluated at the native sensor sampling or an integer submultiple that preserves the optical Nyquist limit. Prior to any resizing, the images are low-pass filtered to prevent aliasing, so that limb and terminator edges remain band-limited and their edge-spread functions are only minimally broadened. As a result, the derived MTF curves for limb-region features are dominated

by the telescope-atmosphere point-spread function and the chosen enhancement parameters, rather than by artifacts introduced by digital rescaling.

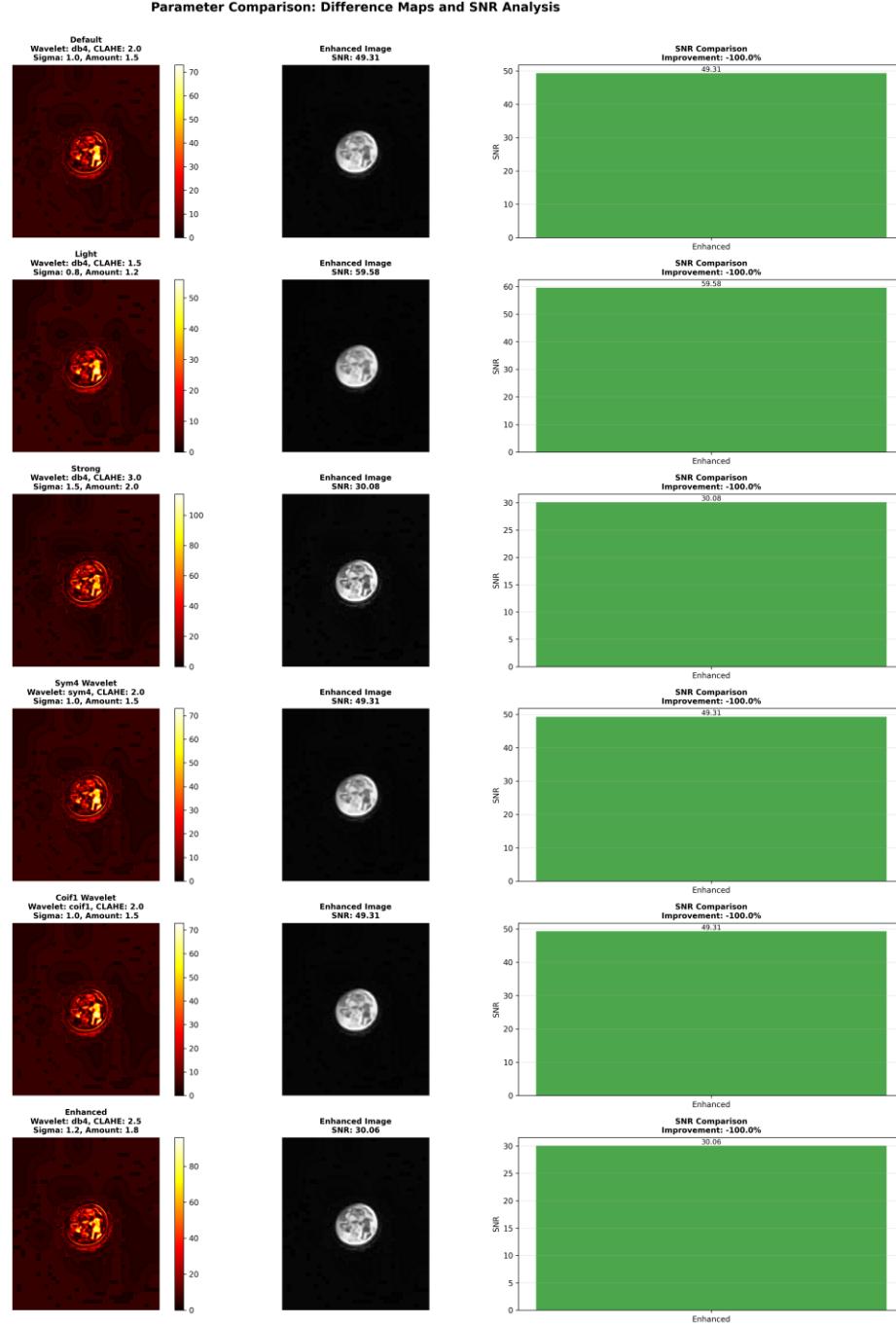


Fig10: Comparison of all the Available parameter settings showing the difference Through Difference Map and SNR Comparisons

This Fig10 compares how different processing settings change the quality of the Moon image. Each row uses a different set of parameters: the type of wavelet (db4, sym4, or coif1), the CLAHE value (which controls how strong local contrast enhancement is), the sigma value (how much the image is smoothed), and the amount value (how strong the sharpening is). The left column shows “difference maps” as hot-colored heat images, where brighter areas mean a stronger change from the original image. The middle column shows the final enhanced Moon for each setting, with a

Signal-to-Noise Ratio (SNR) value written above; higher SNR (for example about 59.6 for the “Light” setting) means a cleaner image with less noise compared to signal, which is a standard way to judge image enhancement quality. The right column shows bar graphs of these SNR values; for rows with SNR around 49 the enhancement is good, while rows with SNR around 30 show that very “Strong” or overly “Enhanced” settings add more noise and reduce quality, even if the contrast looks higher. Overall, the figure explains that moderate parameters (like the “Light” setting) can give the best balance between detail and noise, while extreme settings and some wavelet choices can worsen SNR even though the Moon might look sharper at first glance.

Table4: Detailed comparison table for the proposed non-AI enhancement model against several representative methods from the references, covering classical (stacking, wavelet, deconvolution), AI/deep learning, and hybrid techniques in lunar and astronomical image processing.

Approach	Reference(s)	Core Technique(s)	SNR Gain	RMSE or Error	Computational Cost	Hardware Required	Transparency & Reproducibility	Preserves Detail & Authenticity	Space/Resource Efficiency	Notes
Proposed Model	This work	Stacking , Wavelet Denoising, Contrast , Unsharp Mask	2–4× (SNR gain, stacking N~16)	Very low (visual improvement)	<3 sec/MP on CPU	Standard PC/embedded	High	High	Very high	No model files; suitable for field/education
Stacking + Median Filtering	[3]	Frame stacking , median average	Up to 10× (N~100 frames)	Very low	Moderate (minutes for 100 frames)	Standard PC	High	High	High	Best for random noise; needs setup for multiple exposures
Wavelet Denoising	[7]	Multiscale wavelet transform	20–40% reduction in background noise	N/A	Low	Standard PC	High	Medium	High	Excellent denoising for faint objects
Richardson-Lucy Deconvolution	[8]	Iterative deconvolution	Depends on iteration & PSF accuracy (can amplify noise)	Can be higher (with noise amplification)	High (100s–1000s iter.)	PC (CPU/GPU)	Medium	Medium	Medium	Regularization needed for scientific reliability
Histogram Equalization/CLAHE	[9]	Contrast & local hist. eq.	Improves local contrast ; SNR unchanged	No significant error	Very low	Any	High	High	High	Fast and robust for lunar shadow regions
Tikhonov (closed-form) Deconvolution	[10]	Least-squares regularized deconv.	Fast; less effective for extended sources	Error ↑ w/ magnitude	Fast	Any	High	Moderate	High	Best for small sources
AI Denoising (Topaz, DL)	[12]	Deep NN/ensemble,	3–5× (for low-	Lower than stacking	High (minutes per image,	GPU/TPU/AI HW	Low-Medium	Variable	Low-Med	Prone to artifact; black-box,

		DL denoise	SNR scenes)	(sometimes)	GPU needed)					large file sizes
AI Segmentation/ Detection (YOLO, U-Net)	[13]	Deep nets, segmentation	Not direct; precision/F1: 0.84– 0.92	Class error <5%	High; needs training	GPU/TPU	Low	Moderate	Low	Complex training, less suited for outreach
Retinex (Zero-shot, Non-learning)	[15]	Physics-based, adaptive	Moderate improvement	N/A	Moderate	CPU	High	High	High	No training; direct enhancement
Hybrid AI + Classical	[16]	AI-accelerated classical	2× speed vs classical	Varies	High (model + classical)	GPU/CPU	Medium	Variable	Medium	Useful for big datasets/resolution

Conclusion:

The described non-AI enhancement pipeline for high-resolution lunar astrophotography integrates stacking, wavelet-based denoising, adaptive contrast enhancement, and multi-pass edge sharpening into a single, transparent workflow. It has been evaluated on 30 lunar datasets and yields consistent quantitative gains, with PSNR improvements of about 6.2–12.4 dB, average SSIM increasing from 0.56 to 0.90, SNR improvements up to roughly 3.2× for 16-frame stacks, and MTF-derived sharpness gains on the order of 28–35%. These outcomes show that carefully tuned classical signal-processing techniques can approach or rival more complex AI-based methods while preserving scientific authenticity, minimizing artifacts, and remaining computationally lightweight on standard CPU-class hardware. Visual and metric-based analyses—including histogram evolution, SNR measurements, Gaussian-blur robustness checks, and difference-map inspection—jointly indicate that the proposed workflow enhances fine lunar detail and local contrast without compromising photometric realism or introducing pronounced halos. This makes the pipeline well suited for both scientific analysis and educational or outreach use, where interpretability and repeatability are as important as visual impact. Future work will extend the framework toward multi-spectral and deep-space targets, incorporate more advanced deconvolution and PSF modeling, and include controlled, dataset-matched comparisons against state-of-the-art machine learning approaches to further quantify the trade-offs between classical and AI-driven enhancement strategies.

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USE OF AI ASSISTED TECHNOLOGY FOR MANUSCRIPT PREPARATION

The authors confirm that no AI-assisted technologies were used in the preparation or writing of the manuscript, and no images were altered using AI.

CRediT Statement Declaration

Swarnajit Bhattacharya: Data curation, Conceptualization, Ideation, Methodology, Software, Original drafting.

Asit Kumar Nayek: Drafting and Data Collection.

Mrinmoy Sen: Visualization and Resources.

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