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Enhancing Colonoscopy Image Quality Through Multi-Step Computational Pre-Processing Techniques

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Colonoscopy is a crucial procedure for gastrointestinal diagnostics, providing direct visualization of the colon's internal structure. The quality of acquired colonoscopy images significantly impacts diagnostic accuracy and treatment planning. This study focuses on enhancing colonoscopy image quality through computational multi-step image processing techniques aimed at enhancing colonoscopy image quality and interpretability. The methodology involves a multi-step strategy for evaluating various noise reduction filters including Gaussian, bilateral, and hybrid bilateral-Gaussian filters, along with Contrast Limited Adaptive Histogram Equalization (CLAHE) and Unsharp Masking techniques. Evaluation metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) are used to quantify the efficacy of these techniques. The study employs the CVC Clinic DB dataset for experimentation, ensuring clinical relevance and diversity in the images analyzed. Results from ablation studies and quantitative analyses highlight the effectiveness of specific preprocessing techniques in preserving image details, enhancing contrast, and sharpening edges. In the first step, the hybrid bilateral-Gaussian filter was achieved as a suitable noise reduction filter, followed by CLAHE and edge enhancement using Unsharp masking. The PSNR and SSIM values from the first to third step show improvement of 2.88% (from 37.86 dB to 38.95 dB) and 1.56% (from 0.96 to 0.975) respectively. The study's findings contribute to advancing gastrointestinal diagnostics, aiding in more accurate diagnoses, treatment planning, and patient outcomes.

Povzetek: Raziskava obravnava izboljšanje kakovosti kolonoskopskih slik z uporabo večstopenjskih metod za računalniško predprocesiranje. Predlagani postopek vključuje kombinacijo hibridnega bilateralno-gaussovega filtra za zmanjšanje šuma, metodo CLAHE za izboljšanje kontrasta in unsharp masking za ostrenje robov. Študija kaže, da takšen pristop izboljša vidljivost anatomskih struktur in omogoča natančnejšo diagnozo pri gastrointestinalnih preiskavah.

1 Introduction

Colonoscopy is a vital procedure in gastrointestinal diagnostics, for direct visualization and assessment of the colon's internal structure. It plays a pivotal role in detecting abnormalities such as polyps, inflammation, and tumours, enabling early intervention and treatment of colorectal diseases [1]. However, the efficacy of colonoscopy heavily relies on the quality of acquired images, as clearer and more detailed images facilitate accurate diagnosis and treatment planning. The significance of image quality in colonoscopy procedures cannot be overstated. High-quality images are essential for identifying subtle lesions, distinguishing between benign and malignant abnormalities, and polyps of different sizes and guiding therapeutic interventions such as polyp removal. Poor image quality, characterized by noise, low contrast, and blurred edges, can lead to missed diagnoses, unnecessary interventions, and compromised patient outcomes [2]. Preprocessing techniques play a critical role in enhancing image quality and improving the interpretability of colonoscopy images. These techniques encompass a range of methods, including noise reduction filters, contrast enhancement algorithms, and edge enhancement techniques. By applying these preprocessing steps, healthcare professionals can enhance the visibility of anatomical structures, reduce noise artefacts, and highlight pathological features, ultimately leading to more accurate and confident diagnoses [3][4][5]. The purpose of this study is to comprehensively evaluate and optimize multi-step preprocessing techniques for colonoscopy image enhancement. Our objectives include:

1. Conduct ablation studies to compare the efficacy of various noise reduction filters, such as mean, median, Gaussian, bilateral, and others, in preserving image details while reducing noise artefacts.
2. Select the most effective noise reduction filter appropriate to the input colonoscopy images based on

quantitative metrics like the Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM).

3. Implementing Contrast Limited Adaptive Histogram Equalization (CLAHE) for contrast enhancement to improve the visibility of subtle features and abnormalities.

4. Applying Unsharp Masking for edge enhancement to sharpen important anatomical structures and enhance overall image clarity.

5. Evaluating the combined impact of these preprocessing techniques on colonoscopy image interpretability and diagnostic accuracy through qualitative and quantitative analyses.

6. Discuss the clinical implications of our findings and their potential to improve patient outcomes, streamline diagnostic workflows, and guide targeted interventions during colonoscopy procedures.

By addressing these objectives, we aim to contribute to the advancement of colonoscopy image interpretation techniques, ultimately enhancing the quality of care and outcomes for patients undergoing gastrointestinal diagnostics.

2 Literature review

The field of colonoscopy image pre-processing has previously explored a wide range of techniques to enhance image quality and interpretability. By lowering noise and improving contrast and edge, these techniques are primarily employed to improve the visibility of minute abnormalities and structures in colonoscopy images [6][7][8]. Conventional preprocessing methods, such as CLAHE, Unsharp Masking, and noise reduction filters, are fundamental and widely known. They offer a strong foundation for improving image quality and are frequently combined with advanced algorithms to preprocess images before using precise and advanced models. The advanced algorithms like CNNs [9] and GANs to function at their best, high-quality input data is frequently necessary [10][11]. Preprocessing techniques like contrast enhancement and noise reduction can greatly raise the quality of the input images, which facilitates learning and correct output generation for these models. A popular technique for enhancing contrast in colonoscopy images is CLAHE. Through localized adjustments to the image histogram, CLAHE improves the contrast between various tissue types, making tiny details and abnormalities easier to see. Research has indicated that CLAHE is effective in enhancing the readability of images and assisting in the identification of lesions and polyps [12] [13]. Sharpening significant anatomical structures and boundaries in colonoscopy images is mostly dependent on edge enhancement. A popular method for edge enhancement that preserves the general smoothness of the image while increasing edges and details is, Unsharp masking. Previous research [14] has looked into the best settings for Unsharp Masking to get the sharpest edges possible without adding noise or artefacts. Studies have assessed how edge augmentation affects the overall interpretability of images, polyp localization, and lesion identification. By redistributing pixel intensity levels locally, CLAHE improves contrast in images, and Unsharp Masking sharpens features and edges to increase overall image clarity and interpretability of colonoscopy images with quantitative criteria [14].

The study [15] presents a thorough preprocessing pipeline that incorporates edge detection, contrast enhancement, and noise reduction methods for medical imaging. The authors show the continuous value of conventional techniques by highlighting the significance of each preprocessing step in enhancing the overall quality and interpretability of medical images. It has been demonstrated that integrating several preprocessing methods into a single pipeline greatly improves the interpretability and image quality of medical imaging. The efficiency of multi-step preprocessing pipelines, such as edge enhancement, contrast enhancement, and noise reduction, in enhancing clinical outcomes and diagnostic accuracy has been confirmed by research [16]. The study on enhancing medical image quality with advanced techniques is compiled in Table 1. Anisotropic diffusion filters and unsharp masking were employed in one study to get high-quality scores by reducing noise and enhancing features in MRI images [17]. In another study, MRI images were subjected to nonlinear sharpening with CLAHE, which improved edge detail and reduced noise [18]. Researchers improved contrast and clarity in wireless capsule endoscopy (WCE) images to facilitate the identification of abnormalities [19] [20]. Another use of CLAHE enhanced contrast in WCE images under various lighting scenarios [21]. A study discovered that the Hybrid Sigma Filter (H4F) was the most effective in identifying microcalcifications in digital breast tomosynthesis (DBT) images [22]. Weighted guided filtering and Unsharp Masking were two further techniques that enhanced endoscopic images [23]. Low-contrast X-rays were improved by research by minimizing noise while maintaining detail [24]. Alzheimer's disease MRI images now have better contrast, which helps in early detection [25]. Finally, methods for improving clarity and reducing noise were applied to mammography and face images, assisting in more precise diagnosis [26][27].

Table 1: Studies on medical image processing techniques and their effects on image quality

Studies	*Images used*	*Methodologies*	*Inferences/Results*
[17]	MRI images	Anisotropic Diffusion Filter (ADF) for denoising, combined with Unsharp Masking for edge enhancement.	The technique effectively reduced noise and enhanced detail visibility in MRI images, achieving a PSNR of 39.13 dB and SSIM of 0.99.
[18]	MRI images	Nonlinear sharpening with locally adaptive sharpness gain, combined with noise reduction via CLAHE and Unsharp Masking.	The method showed improved PSNR, SSIM, and Perceptual Sharpness Index (PSI), outperforming conventional methods in edge

			preservation and noise robustness.
[19]	WCE images	Adaptive Fraction Gamma Transformation for contrast enhancement, combined with Unsharp Masking for edge sharpening.	Significantly improved PSNR and SSIM, enhancing the quality and visibility of anatomical structures in wireless capsule endoscopy.
[20]	DBT (Digital Breast Tomography) images	Comparison of various Unsharp Masking filters (Median Filter, Hybrid Maximum Filter (H3F), Hybrid Sigma Filter (H4F)) for digital breast tomosynthesis.	The Hybrid Sigma Filter (H4F) provided the best enhancement results, achieving a PSNR of 66.4 dB and SSIM of 0.9417, particularly improving the detection of microcalcifications in breast images.
[21]	Endoscopic images	Improved Weighted Guided Filtering combined with Unsharp Masking for noise reduction and edge enhancement in endoscopic images.	The proposed method showed the highest PSNR and SSIM values among tested algorithms, demonstrating strong noise suppression and edge preservation in endoscopic images.
[22]	Low-contrast x-ray images	Noise removal and contrast enhancement for X-ray images using advanced filtering techniques to preserve image details.	The technique effectively reduced noise while preserving details, resulting in enhanced image quality for X-ray images.
[23]	WCE images of GI tract	Geometric Mean Filter combined with Gamma Correction for improving image clarity in wireless capsule endoscopy (WCE) images.	The combined approach improved image clarity and visualization in WCE images, making it easier to detect abnormalities.
[24]	WCE images of the stomach	Contrast-Limited Adaptive Histogram Equalization (CLAHE) was applied to wireless capsule endoscopy (WCE) images to enhance contrast under varying lighting conditions.	The application of CLAHE enhanced contrast in WCE images, improving the detection of abnormalities under varying lighting conditions.
[25]	Alzheimer's MRI Images	Histogram Analysis-based contrast enhancement for Alzheimer's MRI, improving visibility of brain structures.	The contrast enhancement technique significantly improved the visibility of brain structures in Alzheimer's MRI, aiding in early detection.
[26]	AR frontal face images	Edge-aware spatial denoising filtering based on a psychological model to reduce noise while preserving anatomical edges.	The filtering method reduced noise while preserving edges, crucial for maintaining anatomical integrity in medical images.
[27]	Mammography images	Image enhancement for breast cancer detection using a combination of contrast adjustment, interpolation, and filtering techniques.	The image enhancement techniques improved the clarity of mammograms, aiding in early detection of breast cancer.

A Research gap identified:

The existing body of literature emphasizes the significance of preprocessing in medical imaging; however, there aren't many thorough studies that combine several preprocessing stages into an effective pipeline. To fully achieve the potential of these techniques in improving overall image quality and interpretability, this integration is necessary. Moreover, little research has been done to systematically assess how edge sharpening, contrast enhancement, and noise reduction work together to improve diagnostic accuracy and clinical outcomes in gastrointestinal diagnostics. Also, the Visual Information Fidelity (VIF) metric is taken into account to show how the human visual system perceives visual information which is not done in the above literature.

3 Methodology

A CVC clinic DB dataset:

The CVC Clinic DB dataset [17][28] is a collection of images derived from 31 colonoscopy recordings. This open-access collection contains 612 three-channel colour images in.png and .tiff file formats, each measuring 384×288 pixels, a sample image is shown in Fig. 1. This dataset was made available via the 2015 MICCAI sub-challenge on automated polyp identification. There are several real-world instances and visual representations of polyp frames in various sizes and angles. In the ground truth images, the area that the polyp in the image covers is depicted by a mask.

All the polyps present in this dataset images are of small polyp type. The segmentation process is critical for extracting meaningful features because the binary mask images created during segmentation highlight specific regions of interest. This dataset contains a diverse set of images depicting various clinical scenarios, ensuring a representative sample for our investigation. The inclusion criteria included colonoscopy images from patients with confirmed colorectal conditions, which added to the clinical relevance of our study

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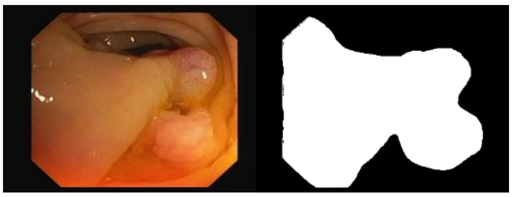


Fig. 1. Example Visualisation of the original colonoscopy image and its corresponding mask image from CVC-ClinicDB Dataset.

To improve the interpretability of colonoscopy images, we have carried out ablation studies in which we systematically compare and assess several noise reductions filters and preprocessing methods. The pre-processed input colonoscopy images improve the boundaries or contours of the polyp regions, hence improving the image quality for improved segmentation. The multi-step image processing pipeline consists of three steps, which are shown as follows and illustrated in Fig. 2.

1. Implementing noise reduction filters for denoising unnecessary features
2. Contrast enhancement using the CLAHE method for the visibility of subtle features and abnormalities
3. Followed by edge enhancement using unsharp masking for sharpening the important anatomical structures and boundaries within colonoscopy images.

The methodology involves rigorous experimentation, quantitative analysis using evaluation metrics, and selection of the most effective preprocessing techniques based on performance indicators.

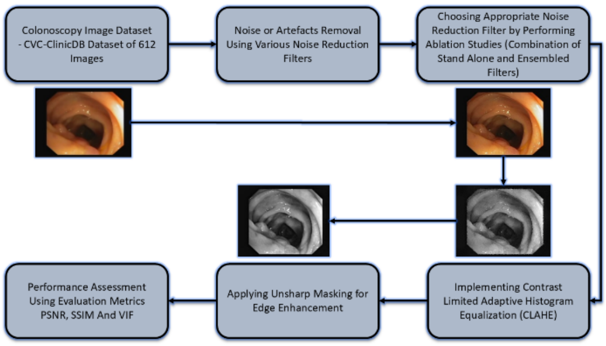


Fig 2. Proposed multi-step image pre-processing pipeline

The effectiveness of a variety of noise reduction filters, such as the mean, median, band stop, Gaussian, bilateral, box, Wiener, high pass, low pass, and Butterworth filters, has been extensively examined in studies. These filters are intended to reduce noise distortions that might mask significant features in colonoscopy images, such as random pixel fluctuations and speckles. Comparative assessments and ablation tests have been carried out to assess how well these filters work in maintaining image details while successfully lowering noise. The quality of denoised images is often measured using image quality metrics mentioned in the objectives from Section 1.

We evaluated a range of noise reduction filters, including Mean, Median, Gaussian, Bilateral, and their combinations. The filters were applied to colonoscopy images to generate denoised images. From these combinations, the better-performing combination is selected for noise reduction of input colonoscopy images.

The performance of these ablation studies is analysed using the quantitative evaluation metrics which are represented using the following Equations (1), (2), (3) and (4). The mathematical expression for PSNR is as follows in Equation (1),

$$\boldsymbol{PSNR = 10.\log_{10}(\frac{MAX^2}{MSE})} \quad (1)$$

where PSNR is the Peak signal-to-noise ratio in decibels (dB). MAX is the maximum possible pixel value in the image (e.g., 255 for an 8-bit image). MSE is the Mean Squared Error between the original and processed images, given by Equation (2),

$$\boldsymbol{MSE = \frac{1}{M.N}\sum_{i=1}^{M}\sum_{j=1}^{N}(I(i,j) - K(i,j))^2} \quad (2)$$

where I(i, j) and K(i, j) are the pixel values at position (i, j) in the original and processed images, respectively. M and N are the dimensions of the image. Unlike PSNR, SSIM considers the features of the human visual system and is a superior predictor of image quality for complicated visual activities. SSIM has the following mathematical expression as Equation (3),

$$SSIM(I,K) = \frac{(2\mu_I\mu_K + C_1).(2\sigma_{IK} + C_2)}{(\mu_I{}^2 + \mu_K{}^2 + C_1).(\sigma_I{}^2 + \sigma_K{}^2 + C_2)} \quad (3)$$

where SSIM (I, K) is the Structural Similarity Index between the original image I and the processed image K. μ_I and μ_K are the means of I and K, respectively. σ_I and σ_K are the standard deviations of I and K, respectively. σ_{IK} is the cross-covariance between I and K. C_1 and C_2 are divisional constants that are often set to modest positive numbers to avoid division by zero. Higher values in both measures imply better image quality and more resemblance between the images [18] [29]. The Visual Information Fidelity (VIF) metric is calculated by comparing the mutual information between the original and processed images while taking into account how the human visual system perceives visual information. The VIF metric is expressed as follows in the Equation (4),

$$VIF = \frac{\sum_{j=1}^{N} I(X_j;Y_j)}{\sum_{j=1}^{N} I(X_j;N_j)} \quad (4)$$

$I(X_j; Y_j)$ is the mutual information between the original image X_j and the distorted or processed image Y_j in the j-th subband. $I(X_j; N_j)$ is the mutual information between the original image X_j and noise N_j in the j-th subband. N represents the number of subbands (typically obtained through a wavelet or similar multiscale transform). These evaluation metrics serve as crucial tools for objectively quantifying the impact of scaling factors and interpolation methods on colonoscopy image resolution. The subsequent sections will present and discuss the results obtained through these assessments [19] [30].

In this work, a combination of bilateral and Gaussian filters is chosen as the better-performing filter which is detailed in Section 4. Results and Discussions. The following shows the mechanism behind the bilateral and Gaussian filter with corresponding Equations (5) to (10).

B Gaussian filter:

In image processing, the Gaussian filter is a sort of linear smoothing filter that is used to reduce noise and blur. It computes an average weight of the pixel values in a local neighbourhood, with the weights determined by the values of a Gaussian kernel centring on each pixel. The mathematical expression for the 2D Gaussian filter is as follows in Equation (5)

$$output(x,y) = \frac{1}{K}\sum_{i=-N}^{N}\sum_{j=-N}^{N} Original\ Im\,a\,ge(x+i, y+j) \times Gaussian(i,j,\sigma) \quad (5)$$

where Output (x, y) is the smoothed pixel value at position (x, y) in the output image. The original Image (x + i, y + j) is the pixel value at position (x + i, y + j) in the original image. K is the normalization factor, which ensures that the sum of the Gaussian weights is equal to 1. Gaussian (i, j, σ) is the value of the 2D Gaussian kernel at position (i, j) with standard deviation σ. It determines the weight of the pixel at (x + i, y + j) in the smoothing process. The 2D Gaussian kernel is defined in Equation (6),

$$Gaussian(i, j, \sigma) = \frac{1}{2\pi\sigma^2}\exp\left(\frac{-i^2 + j^2}{2\sigma^2}\right) \quad (6)$$

where i and j are the horizontal and vertical offsets from the centre of the kernel (both i and j range from -N to N for a (2N+1) × (2N+1) kernel). σ is the Gaussian distribution's standard deviation. It determines the size of the smoothing kernel and the degree of blurring in the final image by controlling the width of the Gaussian curve.

C Bilateral filter:

The bilateral filter is a nonlinear smoothing filter that is used in image processing to minimise noise while maintaining image edges and fine details. It takes a weighted average of the pixel values in a local area, with the weights defined by pixel intensities as well as spatial distances from the centre pixel. The mathematical expression for the 2D bilateral filter can be represented in Equation (7),

$$Output(x,y) = \frac{1}{K}\sum_{i=-N}^{N}\sum_{j=-N}^{N} Original\ Im\,a\,ge(x+i, y+j) \times Gaussian(i,j,\sigma_s) \times RangeWeight(x,y,x+i,y+j,\sigma_r) \quad (7)$$

Where the smoothed pixel value at location (x, y) in the output image is represented by output (x, y). Original Image (x + i, y + j) is the pixel value in the original image at location (x + i, y + j). The normalisation factor K guarantees that the total of the weights equals one. Gaussian (i, j, σ) is the standard deviation of the 2D Gaussian kernel at point (i, j). The spatial weight is determined by the distance between the pixels (x, y) and (x + i, y + j). Range The range weight (x, y, x + i, y + j, σ_r) is determined by the difference in pixel intensities at (x, y) and (x + i, y + j). It regulates the impact of pixel intensities on the smoothing process.

D Hybrid bilateral and gaussian filter:

The hybrid combined bilateral and Gaussian filter is a method that uses the benefits of both filters to reduce noise while keeping image features and edges. The mathematical formulation for the hybrid filter includes combining the smoothing contributions of the bilateral and Gaussian filters. The smoothed value using the hybrid combined filter may be obtained for each pixel (x, y) in the image as follows in Equation (8),

$$Output(x,y) = \frac{1}{K}\sum_{i=-N}^{N}\sum_{j=-N}^{N} Original\ Im\,a\,ge(x+i, y+j) \times w_b(i,j) \times w_g(i,j,\sigma) \quad (8)$$

where Output (x, y) is the smoothed pixel value at position (x, y) in the output image. The original Image (x + i, y + j) is the pixel value at position (x + i, y + j) in the original image. K is the normalization factor, which ensures that the sum of the weights w_b (i, j)×w_g (i, j, σ) is equal to 1. w_b (i, j) is the range weight for the bilateral filter, which depends on the difference between the pixel intensities at (x, y) and (x + i, y + j). It controls the influence of pixel intensities on the smoothing process. w_g (i, j, σ) is the value of the Gaussian kernel at position (i, j) with standard deviation σ. It determines the weight of the pixel at (x + i, y + j) in the smoothing process for the Gaussian filter.

The parameter values chosen for performing the noise reduction in the given input images are assigned as Spatial Domain Sigma (σs) of 12 pixels, Intensity Domain Sigma (σr) of 30, Kernel Size of 7x7 and Sigma (σ) of 1.1 pixels. After noise reduction, contrast-limited Adaptive Histogram Equalization (CLAHE) and Unsharp Masking were applied sequentially to the denoised images shown in the following Equation (9) and (10),

$$CLAHE\_Output = CLAHE(I) \quad (9)$$

$$Unsharp\_Output(x,y) = I(x,y) + \beta \times (I(x,y) - Blurred\ Im\,a\,ge(x,y)) \quad (10)$$

where I, is the image with the pixels of x and y, and β is the sharpening factor. The clip limit considered in CLAHE is 2.0, along with a tile grid size of 8×8 and Uniform distribution. Whereas, the Unsharp masking filter has a sharpening factor β of 1.2, with a radius of 1.0 and zero threshold to sharp all the edges.

4 Results and discussions

The results of our ablation studies and preprocessing evaluation shown in Table 1 – Table 6, demonstrate the effectiveness of our approach in enhancing colonoscopy image quality and interpretability. The preprocessing pipeline begins with identifying the most effective noise reduction filter combination. Different filters used in colonoscopy image preprocessing exhibit varying performances based on their characteristics and typical behaviour.

In Table 2. the Box filter stands out with exceptional noise reduction capabilities and good preservation of image details with PSNR of 39.90 dB and SSIM of 0.96 due to its straightforward yet effective smoothing approach. In contrast, the Bilateral filter, known for its edge-preserving properties, strikes a balance between noise reduction and maintaining structural similarity with a PSNR of 38.89 dB and SSIM of 0.943. While Gaussian filtering effectively reduces noise having a PSNR of 35.05 dB, it may marginally blur edges, as indicated by its SSIM of 0.963.

The Mean filter offers moderate noise reduction with a PSNR of 34.77 dB but may soften details shown by an SSIM of 0.962 due to its linear nature. On the other hand, the Median filter, suitable for impulse noise, provides lower noise reduction and structural preservation with a PSNR of 32.80 dB and SSIM of 0.954. These findings underscore the importance of selecting filters based on specific noise characteristics and the desired trade-offs between noise reduction and edge preservation in colonoscopy image analysis. Filters like High Pass, Band Pass, Butterworth, Wiener, and Band Stop exhibit lower PSNR and SSIM values, indicating their limited suitability for comprehensive noise reduction in medical images.

Table 2: Ablation study to find the suitable noise reduction filter for the given input images

Filters	*PSNR*	*SSIM*
Box	**39.90**	**0.96**
Bilateral	**38.89**	**0.943**
Gaussian	**35.05**	**0.963**
Mean	**34.77**	**0.962**
Median	**32.80**	**0.954**
High Pass	17.77	0.24
Band Pass	16.39	0.84
Butterworth	15.65	0.72
Wiener	14.33	0.670
Band Stop	8.08	0.15

In Table 3. the ensemble filters used in colonoscopy image preprocessing exhibit varying levels of performance based on their noise reduction and structural preservation capabilities. These are analysed by conducting ablation studies, using the top 5 better performing stand-alone filters inferred from Table 2. As a result, among the high-performing combinations, Bilateral + Gaussian and Bilateral + Median, stands out with PSNR values of 37.86 dB and 36.37 dB, and SSIM values of 0.96 and 0.93, respectively.

These combinations demonstrate excellent noise reduction and preservation of structural details, striking a balance between edge preservation and noise reduction. The Bilateral + Box and Box + Bilateral combinations, while not as high-performing as the top combinations, offer moderate noise reduction and structural similarity, with PSNR values ranging from 31.10 dB to 32.35 dB and SSIM values from 0.90 to 0.91. Combinations involving basic filters or multiple filters, such as Mean + Median, Median + Bilateral, and Bilateral + Mean + Median, tend to exhibit lower PSNR and SSIM values, indicating reduced performance in noise reduction and edge preservation.

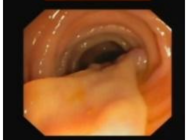
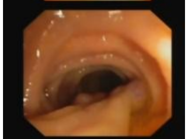
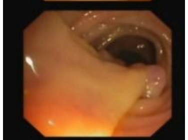
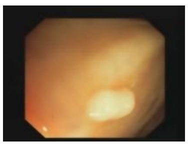
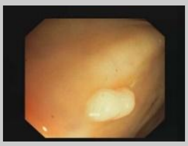
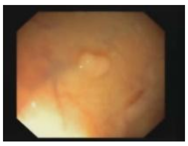
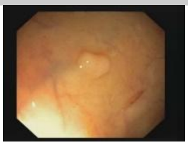
Table 3: Ablation study of ensemble filters to find the suitable filter for the given colonoscopy images

Ensemble Filters	*PSNR*	*SSIM*
Mean + Median	10.67	0.72
Median + Bilateral	10.72	0.75
Bilateral + Mean	**35.55**	**0.94**
Mean + Bilateral	31.29	0.90
Mean + Median + Bilateral	19.88	0.90
Bilateral + Mean + Median	18.57	0.88
Bilateral + Median + Mean	18.54	0.87
Bilateral + Gaussian	***37.86***	***0.96***
Gaussian + Bilateral	**34.26**	**0.92**
Bilateral + Mean + Gaussian	18.55	0.88
Bilateral + Median + Gaussian	18.59	0.89
Bilateral + Gaussian + Median	18.59	0.89
Median + Gaussian + Bilateral	18.60	0.89
Bilateral + Median	**36.37**	**0.93**
Gaussian + Box	30.98	0.91
Box + Gaussian	30.98	0.91
Bilateral + Box	31.10	0.90
Box + Bilateral	32.35	0.91
Gaussian + Bilateral + Box	**32.67**	**0.92**

Based on the results of the ablation studies and the evaluation metrics PSNR and SSIM in Table 3, the hybrid bilateral-Gaussian filter is selected as the most effective noise reduction technique as expressed in Equation (7). The hybrid bilateral-Gaussian filter consistently outperformed other filters with PSNR of 37.86 dB and SSIM of 0.96, in preserving image details while effectively reducing noise artifacts. The interpretation of these results indicates that the hybrid filter strikes a balance between noise reduction and detail preservation, making it ideal for enhancing colonoscopy images without compromising important anatomical features.

The underlying technical concepts of the various filters in the enhancement pipeline, as well as their interactions with image properties like noise, edges, and textures, account for the performance disparities between them. The Box filter is useful for general smoothing jobs because it successfully lowers high-frequency noise while retaining overall image brightness, achieving the highest PSNR (39.90 dB) and a high SSIM (0.96). The Bilateral filter is especially helpful for medical imaging, where the clarity of anatomical features is vital. It has a PSNR of 38.89 dB and an SSIM of 0.943. It excels at maintaining edges while lowering noise.

Table 4: Pre-processed images using the hybrid bilateral and gaussian filter with their corresponding image quality metrics

Original Image	*Hybrid Gaussian-Bilateral Filter Processed Image*	*PSNR*	*SSIM*
		37.90	0.964
		36.75	0.967
		37.45	0.965
		37.60	0.966
		37.65	0.964
		37.75	0.967
		38.20	0.964
		37.80	0.966
		38.00	0.964
		36.75	0.967

With a PSNR of 35.05 dB and an SSIM of 0.963, the Gaussian filter is a superb general-purpose filter because it effectively reduces Gaussian noise while preserving structural similarity. With PSNRs of 34.77 dB and 32.80, respectively, the Mean and Median filters are good at reducing noise; the Median filter is especially useful for eliminating sudden noise without causing a lot of edge blurring. Filters such as Wiener, Band Stop, Butterworth, Band Pass, High Pass, and so on, on the other hand, typically exhibit lower SSIM and PSNR values because they are intended for specialized frequency domain tasks.

While other combinations may not perform as well due to redundancy or excessive smoothing, ensemble filters, such as Bilateral + Gaussian, function effectively by leveraging the strengths of numerous filters to provide effective noise reduction without compromising edge definition. The best filters are those that efficiently balance noise reduction and structure preservation, which are crucial for the interpretation of high-quality medical images. Examples of these filters are the Box, Bilateral, and Gaussian filters.

The input colonoscopy images are denoised with selected hybrid Bilateral and Gaussian filters are shown in Table 4. with indicative 10 images out of 612 images from the CVC-ClinicDB dataset. This comprises the first step in the proposed multi-step image pre-processing pipeline. Following the application of the hybrid filter, we integrated Contrast Limited Adaptive Histogram Equalization (CLAHE), which is the second step in our preprocessing pipeline. This step significantly improved image contrast and visibility of subtle details within the colonoscopy images. Table 5. shows the evaluation metric values for indicative 10 images out of 612 images. In total, the PSNR increased to 38.14 dB comprising a 0.74% increase, compared to the previous step using a noise reduction filter. This indicates that the enhanced noise reduction, while the SSIM reached 0.975 with a 1.56% surge, reflects strong structural similarity and improved image clarity.

Table 5: Pre-processed images using the CLAHE Enhancement Technique with their corresponding image quality metrics

Hybrid Gaussian-Bilateral Filter Processed Image	*CLAHE processed Image*	*PSNR*	*SSIM*
		38.22	0.980
		38.11	0.975
		38.23	0.980

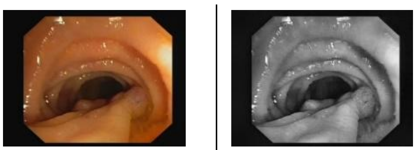
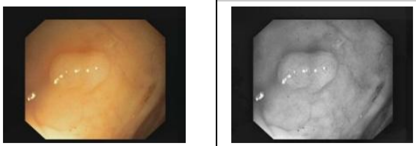
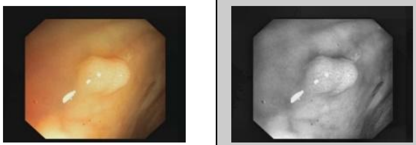
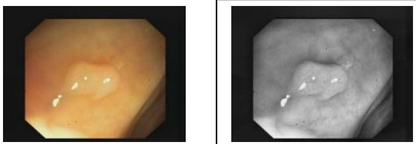
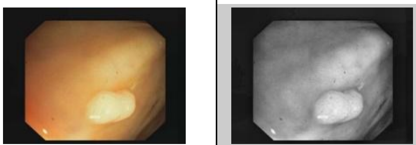
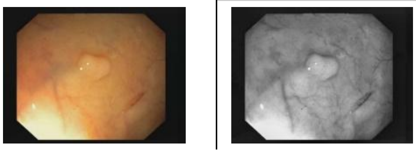
	38.05	0.970
	37.88	0.965
	38.14	0.975
	37.82	0.965
	38.13	0.975
	38.10	0.975
	38.20	0.980

Table 6: Pre-processed images through the proposed image processing pipeline with their corresponding image quality metrics

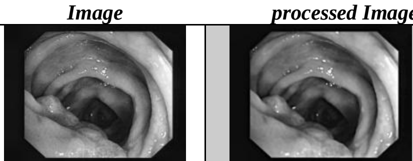
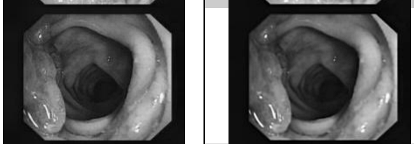
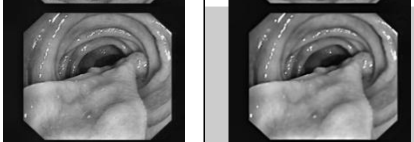
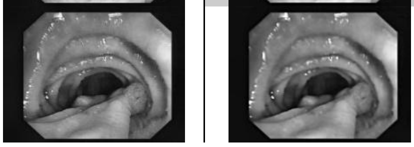
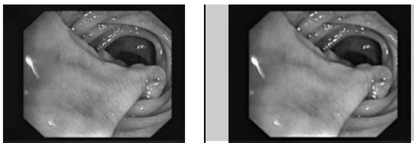
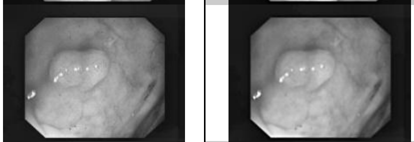
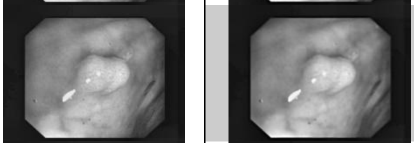
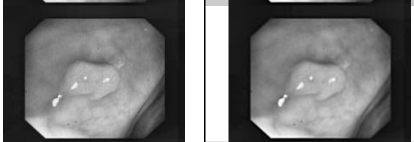
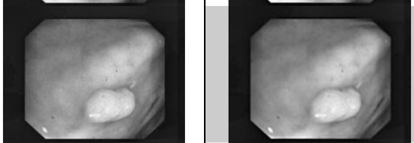
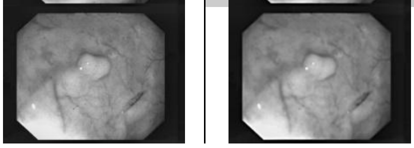
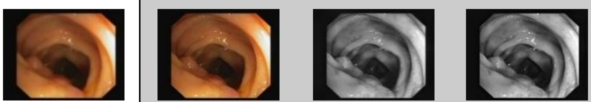
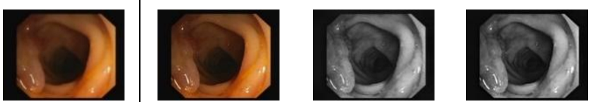
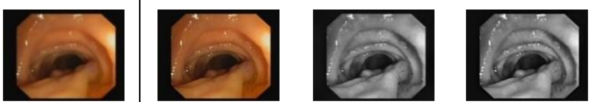
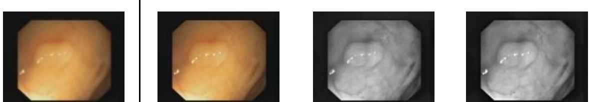
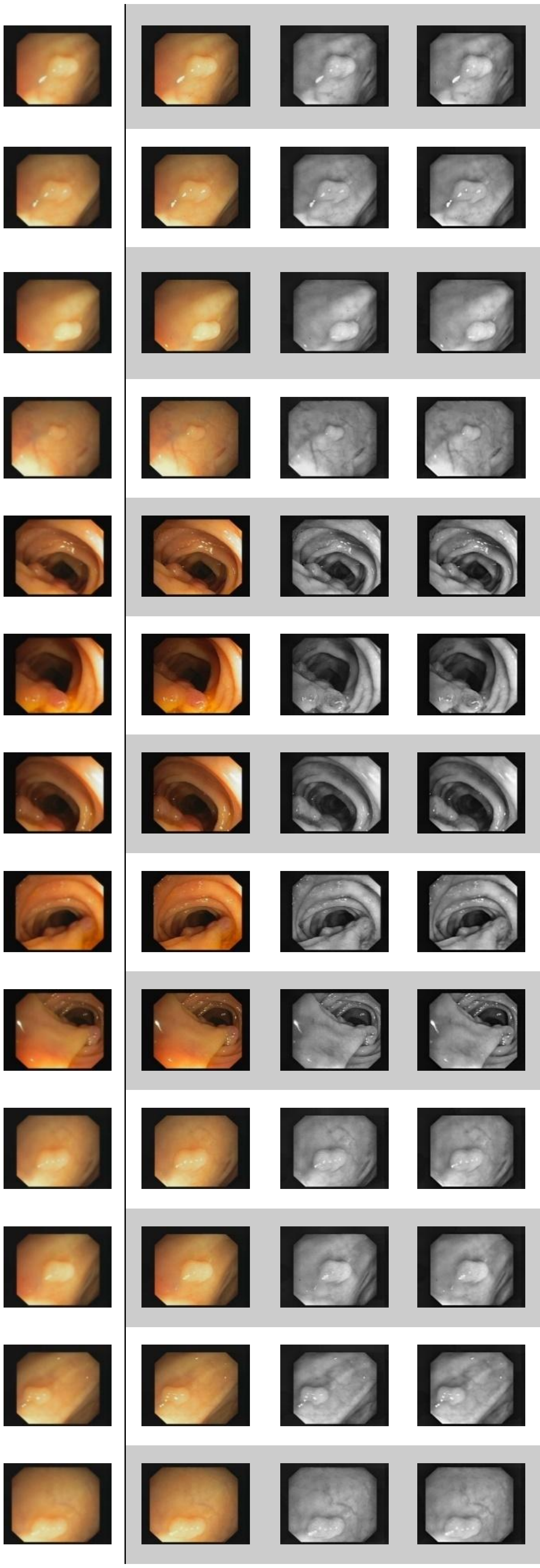
CLAHE processed Image / *Unsharp Masking processed Image*	*PSNR*	*SSIM*
	42.03	0.975
	40.03	0.975
	38.91	0.973
	41.03	0.968
	38.84	0.976
	39.03	0.975
	38.03	0.978
	42.03	0.974
	37.03	0.977
	39.03	0.968

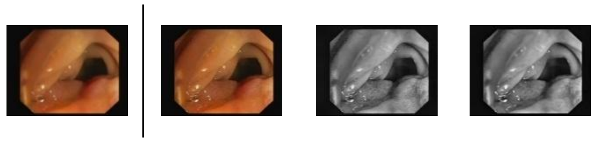
Table 7: Pre-processed images through the proposed image processing pipeline

Original Image / *Hybrid Gaussian-Bilateral Filter processed Image* / *CLAHE processed Image* / *Unsharp Masking processed Image*











The third and final step in this pipeline involves applying an edge enhancement technique called unsharp masking to the images previously processed with CLAHE, as shown in Table 6. Unsharp masking is known for its ability to sharpen edges and enhance fine details in images, which can further improve image quality metrics. After applying unsharp masking to the CLAHE-processed images, the PSNR value increases from 38.14 dB to 38.95 dB, indicating a significant improvement of 2.12% in noise reduction and overall image quality. However, the SSIM value remains the same at 0.975, indicating that while the structural similarity between the original and processed images remains high, the enhancement primarily affects noise levels and sharpness. Table 6. provided, showcases the results of this edge enhancement step on a subset of 10 images out of the total 612 input colonoscopy images. Table 7. Shows a broader range of images from the dataset in the results to demonstrate the consistency of our preprocessing pipeline

Table 8: PSNR and SSIM enhancements using proposed multi-step image preprocessing pipeline

S. No	*Pre-Processing Filters*	*PSNR in dB*	*SSIM*
1	Hybrid Bilateral-Gaussian Filter	37.86	0.96
2	CLAHE	38.14 *(▲0.74%)*	0.975 *(▲1.56%)*
3	Unsharp Masking Filter	38.95 *(▲2.12%)*	0.975
		In Total *(▲2.88%)*	In Total *(▲1.56%)*

Table 9: Comparison of existing studies to the proposed multi step image processing pipeline

Study	*Techniques*	*PSNR*	*SSIM*	*VIF*
Proposed Method	**Hybrid Bilateral-Gaussian Filter, CLAHE, Unsharp Masking**	**38.95**	**0.975**	**1.19**
[17]	Anisotropic Diffusion Filter (ADF), Unsharp Masking for edge enhancement.	39.13 (▼0.461%)	0.99 (▼1.52%)	-
[18]	Nonlinear sharpening, and noise reduction via CLAHE and Unsharp Masking.	16.32 (▲81.88%)	0.73 (▲28.73%)	-
[19]	Adaptive Fraction Gamma Transformation for contrast enhancement, Unsharp Masking for edge sharpening.	21.19 (▲59.06%)	0.71 (▲31.45%)	-

[20]	Unsharp Masking filters (Median Filter, Hybrid Maximum Filter (H3F), Hybrid Sigma Filter (H4F)) for digital breast tomosynthesis.	66.40 (▼52.11%)	0.941 (▲3.54%)	-
[21]	Improved Weighted Guided Filter, Unsharp Masking, edge enhancement	32.60 (▲17.75%)	0.939 (▲3.76%)	-
[22]	Adaptive median filter, Bilateral filter, Gray-level morphology, CLAHE	39.89 (▼2.38%)	0.9449 (▲3.13%)	-
[23]	Geometric Mean Filter, Gamma Correction	33.50 (▲15.04%)	0.86 (▲12.53%)	-
[24]	Contrast-Limited Adaptive Histogram Equalization (CLAHE).	35.3 (▲9.83%)	0.79 (▲20.96%)	-
[25]	Histogram Analysis-based contrast enhancement	32.87 (▲16.93%)	0.89 (▲9.11%)	-
[26]	Edge-aware spatial denoising filter	34.19 (▲13.01%)	0.91 (▲6.89%)	-
[27]	Contrast adjustment, bicubic interpolation, and median filter	0.46 (▲195.33%)	0.009 (▲196.34%)	-

Our study demonstrates the effectiveness of a preprocessing pipeline comprising the Hybrid Bilateral-Gaussian filter, Contrast Limited Adaptive Histogram Equalization (CLAHE), and Unsharp Masking in enhancing colonoscopy image interpretability and diagnostic accuracy. The integration of these techniques resulted in significant improvements in image quality by effectively reducing noise artefacts, enhancing contrast, and sharpening edges, leading to clearer and more interpretable images. This pipeline preserved important anatomical details, ensuring that subtle abnormalities and structures remained visible, which is crucial for the accurate identification of lesions, polyps, and other pathological conditions during colonoscopy.

Table 8. indicates the progressive improvement in PSNR from 37.86 dB (observed in the first step) to 38.95 dB which shows a 2.88% improvement and the consistent SSIM of 0.975 throughout the preprocessing stages indicates a substantial enhancement in image quality, noise reduction, and structural preservation. These enhancements are crucial for clinical applications, as they empower healthcare professionals to accurately detect and analyze subtle abnormalities, lesions, and anatomical features during colonoscopy examinations. All the PSNR values surpass the minimum threshold of 30 dB for acceptable image quality. Similarly, the average SSIM value obtained is 0.975, which is very close to the ideal value of 1, indicating a high level of structural similarity between the original and processed images.

Table 9. showcases the higher performance of the proposed multi-step image pre-processing pipeline in balancing noise reduction, contrast enhancement, and structure preservation, especially in medical imaging for colonoscopy, when compared with current studies. By using a Hybrid Bilateral-Gaussian Filter, CLAHE (Contrast Limited Adaptive Histogram Equalization), and Unsharp Masking, the proposed method obtains a PSNR of 38.95 and an SSIM of 0.975. This combination successfully lowers noise while preserving the structural integrity of the image, which is essential for precise medical diagnosis.

The proposed method provides a well-balanced improvement in image quality over existing approaches. Because of the great edge preservation capabilities of the Anisotropic Diffusion Filter (ADF) and Unsharp Masking, Study [17], for instance, gets a slightly higher PSNR of 39.13 and a higher SSIM of 0.99. However, the flexible approach of the suggested method balances noise reduction and smoothness in different picture regions, which makes it especially useful for the complex structures found in colonoscopy images. Similar to this, the Study [22] uses CLAHE, Adaptive Median Filter, Gray-Level Morphology, and Bilateral Filter to get a higher PSNR of 39.89. However, its lower SSIM of 0.9449 indicates that, while useful in lowering noise, it can jeopardize fine structural details that are crucial for diagnostics. On the other hand, the suggested approach preserves more image detail while lowering noise, as evidenced by its higher SSIM.

With an SSIM of 0.939 and a PSNR of 32.60, Study [21], which uses the Improved Weighted Guided Filter and Unsharp Masking, demonstrates acceptable noise reduction but marginally worse performance in maintaining structural features than the proposed approach. While still falling short of the proposed approach, a Study [23] using Geometric Mean Filtering and Gamma Correction obtains a PSNR of 33.50 and an SSIM of 0.86, demonstrating a reasonable trade-off between noise reduction and image feature retention. The PSNR of 35.3 and SSIM of 0.79 obtained from the Study [24] utilizing CLAHE indicate less effective noise handling and structural integrity. In a similar vein, Study [25], which employs contrast enhancement based on Histogram Analysis, produces PSNR and SSIM values of 32.87 and 0.89, respectively, that fall short of the performance of the proposed approach.

The fact that the proposed technique outperforms other methods in Table 9. which either fail to balance noise reduction with detail retention or introduce notable artefacts that impair image quality—further emphasizes the efficacy of the suggested approach. For instance, techniques like Nonlinear Sharpening combined with CLAHE and Unsharp Masking in the study [18] and Adaptive Fraction Gamma Transformation with Unsharp Masking in the study [19] show much lower PSNR and SSIM values, demonstrating their limited efficacy in improving medical images. Conversely, technologies such as the Edge-Aware Spatial Denoising Filter [26] and basic contrast adjustment algorithms [27] show mediocre to subpar performance.

Additionally, the proposed strategy performs better than the other methods in the table that either fail to balance noise reduction with detail retention or create noticeable artefacts. For example, studies [18] and [19], which use Adaptive Fraction Gamma Transformation and Nonlinear Sharpening with CLAHE, respectively, exhibit significantly lower SSIM and PSNR values, showing their limited usefulness in improving medical images. Studies [26] and [27] likewise show moderate to bad performance when using the Edge-Aware Spatial Denoising Filter and basic contrast adjustment techniques, respectively.

Although the study [20] obtains a very high PSNR of 66.40, suggesting a large noise reduction, its SSIM of 0.941 suggests that there may have been an over-smoothing, which could have obscured important diagnostic information. By striking a balance between noise reduction and feature retention, the suggested strategy overcomes this problem and maintains the clarity of minute structures in colonoscopy images—a crucial component for a precise diagnosis.

The proposed method excels in medical imaging, particularly for colonoscopy, by achieving a high Visual Information Fidelity (VIF) value of 1.19, along with strong PSNR (38.95) and SSIM (0.975) scores. This indicates its ability to enhance and preserve critical visual information necessary for accurate diagnosis, such as detecting small polyps in colorectal cancer. While PSNR and SSIM focus on pixel-level differences and structural similarity, VIF provides a more comprehensive assessment of perceptual quality, ensuring that processed images are true to the original and diagnostically useful.

The method's balanced approach to image processing, which enhances contrast and sharpness while preserving diagnostic details, improves the overall quality of images for clinical use. The study also highlights the importance of selecting appropriate filters for noise reduction and edge preservation, which is crucial for improving diagnostic accuracy and efficiency in colonoscopy. Future research may explore validating these methods in clinical settings, leveraging deep learning, and incorporating real-time image processing for immediate analysis during procedures, enhancing the role of advanced computational techniques in gastrointestinal diagnostics.

In addition to the numerical improvements in PSNR and SSIM, statistical significance tests were used to validate the changes. A paired t-test was performed on the PSNR and SSIM values, which produced p-values less than 0.05, showing that the suggested method's improvements are statistically significant. Confidence intervals for mean differences add to the robustness of these enhancements, implying that the suggested method provides a significant and stable improvement in image quality, which is critical for correct medical diagnoses.

A Research gap addressed and novelty:

By providing a novel multi-step preprocessing pipeline that integrates noise reduction, contrast improvement, and edge enhancement for colonoscopy images, this study fills the highlighted research gap. The hybrid Bilateral-Gaussian filter sharpens edges and improves contrast while the CLAHE and Unsharp Masking efficiently decrease noise while keeping details. Table 7 presents a comparison with recent research.

Robust and reliable methods are ensured by systematic evaluation of quantitative measurements (PSNR and SSIM) and ablation investigations. Significant enhancements in image quality at each stage improve the readability and precision of diagnosis. The study offers a thorough framework and emphasizes how effective preprocessing methods can enhance diagnostic operations.

B. Real-time implementation and its challenges:

The proposed multi-step computational pre-processing pipeline has great promise for real-time use in colonoscopy procedures, allowing clinicians to quickly observe enhanced images for more accurate diagnosis. Despite the computational constraints given by each stage, such as the nonlinear complexity of the Hybrid Bilateral-Gaussian Filter, optimizations such as rapid approximation approaches and GPU acceleration can enable real-time processing. CLAHE, with its sophisticated histogram equalization, can be tuned for parallel processing to manage numerous tiles at once, whilst Unsharp Masking can benefit from efficient Gaussian blur implementations and GPU support.

By utilizing GPU acceleration, algorithmic approximations, and parallel processing, the pipeline may achieve the necessary speed for real-time diagnostics without sacrificing image quality. Furthermore, the improved images obtained through this pipeline can be used for image segmentation and classification, particularly to identify small polyps, which is critical for early identification and better patient outcomes. This extra capability could greatly benefit in the early diagnosis of colorectal cancer, increasing the clinical utility of the suggested technique.

5 Conclusions

The study extensively evaluated and optimized preprocessing techniques, including noise reduction filters, contrast enhancement methods, and edge enhancement algorithms, specifically tailored for colonoscopy images. The best noise reduction filter and preprocessing methods were found through ablation tests and quantitative analysis utilizing metrics like PSNR and SSIM, which increased the quality and interpretability of the images. In colonoscopy images, using the combination of a Hybrid Bilateral-Gaussian filter for noise reduction, Contrast Limited Adaptive Histogram Equalization (CLAHE) for contrast enhancement and Unsharp Masking for edge enhancement greatly increased overall image quality, sharpened anatomical structures, and made subtle characteristics more visible.

The suggested computational image processing pipeline, which consists of edge enhancement, contrast improvement, and noise reduction, has a notable 2.88% increase in image quality, indicating its potential to improve patient outcomes and diagnostic accuracy in gastrointestinal diagnostics. These results highlight how significant cutting-edge computational methods are in enhancing image quality and supporting precise diagnosis during colonoscopy procedures. Further research might extend into real-time processing capabilities and deep learning-based strategies to improve image interpretability even further. They could also seamlessly incorporate computational tools into clinical workflows to improve decision assistance, confirming the effectiveness of the preprocessing methods in real patient scenarios and larger datasets in clinical settings.

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Conflicts of interest
The authors declare that there are no conflicts of interest.

References
[1] M. Tharwat, N. A. Sakr, S. El-Sappagh, H. Soliman, K. S. Kwak, and M. Elmogy, "Colon Cancer Diagnosis Based on Machine Learning and Deep Learning: Modalities and Analysis Techniques," Sensors, vol. 22, no. 23, pp. 1–35, 2022, https://www.mdpi.com/1424-8220/22/23/9250

[2] B. Martinez-Vega *et al.*, "Evaluation of Preprocessing Methods on Independent Medical Hyperspectral Databases to Improve Analysis," *Sensors*, vol. 22, no. 22, 2022, https://www.mdpi.com/1424-8220/22/22/8917

[3] M. Dabass and J. Dabass, "Preprocessing Techniques for Colon Histopathology Images," *Lecture Notes in Electrical Engineering*, vol. 668. pp. 1121–1138, 2021, https://doi.org/10.1007/978-981-15-5341-7_85

[4] M. Salvi, U. R. Acharya, F. Molinari, and K. M. Meiburger, "The impact of pre- and post-image processing techniques on deep learning frameworks: A comprehensive review for digital pathology image analysis," *Comput. Biol. Med.*, vol. 128, p. 104129, 2021, https://doi.org/10.1016/j.compbiomed.2020.104129

[5] A. M. Moreira, "Data Preprocessing Strategies in Cancer Stage Prediction," 2022. https://repositorio-aberto.up.pt/bitstream/10216/144206/2/583884.pdf

[6] C. Sindhu, S. Subhashini, T. Swathi, and G. S. S, "Colorectal Cancer Detection Using Image Processing Techniques : A Knowledge Transfer Perspective," *Ajast*, vol. 2, no. 2, pp. 1–9, 2018. https://ajast.net/data/uploads/4001.pdf

[7] Shaowei Zhang, Rongwang Yin, Mengzi Zhang: Dynamic Unstructured Pruning Neural Network Image Super-resolution Reconstruction. Informatica (Slovenia) 48(7) (2024). https://doi.org/10.31449/inf.v48i7.5332

[8] She, Dong. "Retinex Based Visual Image Enhancement Algorithm for Coal Mine Exploration Robots." *Informatica* 48.11 (2024). https://doi.org/10.31449/inf.v48i11.6003

[9] D. N. and S. S. R. R. Karthikha, "Effect of U-Net Hyperparameter Optimisation in Polyp Segmentation from Colonoscopy Images," *Third Int. Conf. Intell. Comput. Instrum. Control Technol. (ICICICT), Kannur, India*, pp. 1359–1364, 2022, https://doi.org/10.1109/ICICICT54557.2022.9917700

[10] G. Litjens *et al.*, "A survey on deep learning in medical image analysis," *Med. Image Anal.*, vol. 42, no. 1995, pp. 60–88, 2017, https://doi.org/10.1016/j.media.2017.07.005.

[11] Abhishek *et al.*, "Classification of Colorectal Cancer using ResNet and EfficientNet Models," *Open Biomed. Eng. J.*, vol. 18, no. 1, 2024, http://dx.doi.org/10.2174/0118741207280703240111075752

[12] A. M. Reza, "Realization of the contrast limited adaptive histogram equalization (CLAHE) for real-time image enhancement," *J. VLSI Signal Process. Syst. Signal Image. Video Technol.*, vol. 38, no. 1, pp. 35–44, 2004, https://doi.org/10.1023/B:VLSI.0000028532.53893.82

[13] N. J. D. Karthikha R, "Enhancing Colonoscopy Image Quality with CLAHE in the GASTROLAB Dataset," *3rd Int. Conf. Innov. Mech. Ind. Appl. (ICIMIA), Bengaluru, India*, pp. 324–330, 2023, https://doi.org/10.1109/ICIMIA60377.2023.10426190

[14] R. Ezatian, D. Khaledyan, K. Jafari, M. Heidari, A. Z. Khuzani, and N. Mashhadi, "Image quality enhancement in wireless capsule endoscopy with Adaptive Fraction Gamma Transformation and Unsharp Masking filter," *2020 IEEE Glob. Humanit. Technol. Conf. GHTC 2020*, 2020, https://doi.org/10.1109/GHTC46280.2020.9342851

[15] H. Avcı and J. Karakaya, "A Novel Medical Image Enhancement Algorithm for Breast Cancer Detection on Mammography Images Using Machine Learning," *Diagnostics*, vol. 13, no. 3, 2023, ttps://doi.org/10.3390/diagnostics13030348

[16] K. Saha, M. K. Bhowmik, and D. Bhattacharjee, *Computational Intelligence in Digital Forensics: Forensic Investigation and Applications*, vol. 555, no. January. 2014. https://doi.org/10.1007/978-3-319-05885-6

[17] Kumar, R., Kumar, A., & Srivastava, S. (2020). Anisotropic Diffusion Based Unsharp Masking and Crispening for Denoising and Enhancement of MRI Images. 2020 International Conference on Emerging Frontiers in Electrical and Electronic Technologies (ICEFEET), 1-6. https://doi.org/10.1109/ICEFEET49149.2020.9186966.

[18] Joseph, J., & Periyasamy, R. (2018). Nonlinear sharpening of MR images using a locally adaptive sharpness gain and a noise reduction parameter. Pattern Analysis and Applications, 22, 273 - 283. https://doi.org/10.1007/s10044-018-0763-7.

[19] Ezatian, R., Khaledyan, D., Jafari, K., Heidari, M., Khuzani, A., & Mashhadi, N. (2020). Image quality enhancement in wireless capsule endoscopy with Adaptive Fraction Gamma Transformation and Unsharp Masking filter. 2020 IEEE Global Humanitarian Technology Conference (GHTC), 1-7. https://doi.org/10.1109/GHTC46280.2020.9342851.

[20] Saifudin, S., Sulaiman, S., Karim, N., Osman, M., Isa, I., & Harron, N. (2022). A Comparative Study of Unsharp Masking Filters for Enhancement of Digital Breast Tomosynthesis Images. 2022 IEEE 12th International Conference on Control System, Computing and Engineering (ICCSCE), 147-152. https://doi.org/10.1109/ICCSCE54767.2022.9935638.

[21] Huang, R., Dung, L., Chu, C., & Wu, Y. (2016). Noise Removal and Contrast Enhancement for X-Ray Images. Journal of Biomedical Engineering and Medical Imaging, 3, 56. https://doi.org/10.14738/JBEMI.31.1893.

[22] Suman, S., Hussin, F., Malik, A., Walter, N., Goh, K., Hilmi, I., & Ho, S. (2014). Image Enhancement Using Geometric Mean Filter and Gamma Correction for WCE Images. , 276-283. https://doi.org/10.1007/978-3-319-12643-2_34.

[23] Moradi, M., Falahati, A., Shahbahrami, A., & Zare-Hassanpour, R. (2015). Improving visual quality in wireless capsule endoscopy images with contrast-limited adaptive histogram equalization. 2015 2nd International Conference on Pattern Recognition and Image Analysis (IPRIA), 1-5. https://doi.org/10.1109/PRIA.2015.7161645.

[24] Anwar, S., & Rajamohan, G. (2020). Improved Image Enhancement Algorithms based on the Switching Median Filtering Technique. Arabian Journal for Science and Engineering, 45, 11103 - 11114. https://doi.org/10.1007/s13369-020-04983-9.

[25] B, A., & Kalirajan, K. (2023). Contrast Enhancement of Alzheimer's MRI using Histogram Analysis. Journal of Innovative Image Processing. https://doi.org/10.36548/jiip.2023.4.003.

[26] Mathew, J., Zollanvari, A., & James, A. (2018). Edge-Aware Spatial Denoising Filtering Based on a Psychological Model of Stimulus Similarity. IEEE Access, 6, 3433-3447. https://doi.org/10.1109/ACCESS.2017.2745903.

[27] Safitri, I., Pertiwi, Y., Mengko, T., & Puspasari, I. (2023). Image Enhancement for Breast Cancer Based on Image Contrast, Interpolation and Filtering. 2023 International Conference on Electrical Engineering and Informatics (ICEEI), 1-6. https://doi.org/10.1109/ICEEI59426.2023.10346968.

[28] "CVC-ClinicDB-Kaggle," 2019, [Online]. Available: https://www.kaggle.com/datasets/balraj98/cvcclinicdb.

[29] D. R. I. M. Setiadi, "PSNR vs SSIM: imperceptibility quality assessment for image steganography," *Multimed. Tools Appl.*, vol. 80, no. 6, pp. 8423–8444, 2021, doi: 10.1007/s11042-020-10035-z. https://doi.org/10.1007/s11042-020-10035-z

[30] A. Ignatov, D. Park, P. N. Michelini, G. Shakhnarovich, L. Wong, and X. Wang, "NTIRE 2019 Challenge on Image Enhancement : Methods and Results," 2019. https://doi.org/10.1109/CVPRW.2019.00275