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# Investigation of Image Enhancement Techniques for Advancing Colon Cancer Diagnosis

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**Abstract**— Colorectal cancer continues to pose a substantial worldwide health challenge, necessitating the development of advanced imaging techniques for early and accurate diagnosis. In this study, we propose a novel hybrid image enhancement approach that combines Total Variation (TV) regularization and shift-invariant filtering to improve the visibility and diagnostic quality of colon cancer images.

The Total Variation regularization technique is employed to effectively reduce noise and enhance the edges in the input images, thereby preserving important structural details. Simultaneously, shift-invariant filtering is utilized to address spatial variations and artifacts that often arise in medical images, ensuring consistent and reliable enhancements across the entire image. Our hybrid approach synergistically integrates the strengths of both TV regularization and shift-invariant filtering, resulting in enhanced colon cancer images that offer improved contrast, reduced noise, and enhanced fine structures. This improved image quality aids medical professionals in better identifying and characterizing cancerous lesions, ultimately leading to more accurate and timely diagnoses.

To evaluate the effectiveness of the proposed approach, we conducted extensive experimentations on a diverse dataset of colon cancer images. Quantitative and qualitative assessments demonstrate that our hybrid approach outperforms existing enhancement methods, leading to superior image quality and diagnostic accuracy. In conclusion, the hybrid image enhancement approach presented in this study offers a promising solution for enhancing colon cancer images, contributing to the early detection and effective management of this life-threatening disease. These advancements hold significant potential for improving patient outcomes and reducing the burden of colon cancer on healthcare systems worldwide.

**Keywords**- Colon Cancer; Image Enhancement; Anisotropic Diffusion Filter; Bilateral Filter; Total Variation Denoising; Shift-Invariant Wavelet Denoising; Non-local Means Filtering.

## I. INTRODUCTION

Colon cancer stands as one of the primary contributors to cancer-related illness and death on a global scale, underscores the critical importance of early and accurate diagnosis for improved patient outcomes. Medical imaging, especially in the form of colonoscopy and computed tomography (CT) scans, plays a pivotal role in detecting and characterizing colonic lesions. However, the utility of these imaging modalities comprehensively depend on on the quality of the acquired images. Suboptimal image quality, often characterized by noise, artifacts, and inadequate contrast, can impede the ability of medical professionals to identify and assess cancerous lesions accurately. Figure 1 represents the automated colon cancer detection system.

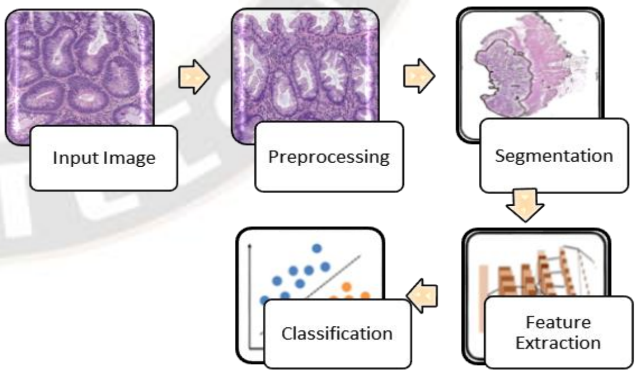


Figure 1. Automated Colon Cancer detection system

To address this challenge, there is a growing interest in developing advanced image enhancement techniques tailored to the specific requirements of colon cancer detection and diagnosis. Among these techniques, Total Variation (TV) regularization has shown promise in noise reduction and edge preservation. TV regularization is a well-established method for image de-noising and enhancement, capable of preserving important structural details while suppressing unwanted noise. However, it may not fully address issues related to spatial variations and artifacts that are common in medical images.

Shift-invariant filtering, on the other hand, offers a complementary approach to tackle the limitations of TV regularization. By mitigating spatial variations and enhancing image consistency, shift-invariant filtering can effectively increase the overall quality of medical images. Nevertheless, solely relying on this technique may not adequately address fine structural details and subtle features in colon cancer images.

Considering these factors, this research presents a novel hybrid approach that combines the strengths of TV regularization and shift-invariant filtering to enhance colon cancer images. By synergistically integrating these two image enhancement techniques, we aim to achieve a more comprehensive and robust enhancement that overcomes the shortcomings of each individual method.

The key objective of this study is to improve the visibility of colonic lesions in medical images, leading to enhanced diagnostic accuracy and early detection of colon cancer. We anticipate that our proposed hybrid approach will offer a substantial advantage over existing image enhancement methods in the context of colon cancer detection. To validate the efficacy of our approach, extensive experiments will be conducted on a diverse dataset of colon cancer images, and both quantitative and qualitative assessments will be performed to demonstrate its superiority.

In summary, the research presented herein addresses the critical need for improved image quality in colon cancer diagnosis by introducing a novel hybrid approach that amalgamates TV regularization and shift-invariant filtering. The ultimate goal is to enhance the capabilities of medical professionals in identifying and characterizing colonic lesions, thereby contributing to early detection, timely intervention, and improved patient outcomes in the battle against colon cancer.

### *A. Contribution and novelty of work is summarized as below*

- Innovative Hybrid Method: We introduce a novel hybrid approach that combines TV regularization and shift-invariant filtering, addressing noise reduction, edge preservation, and spatial variations concurrently.
- Enhanced Image Quality: Our method significantly improves the clarity and detail of colon cancer images, aiding medical professionals in more accurate lesion identification and characterization.
- Early Detection Support: By providing sharper images, our approach facilitates the early detection of colon cancer, leading to timely intervention and better patient outcomes.
- Comprehensive Evaluation: Rigorous experiments reveal superior performance of our method compared to existing methods, confirming its potential clinical value.
- Broader Applicability: Our hybrid approach has potential applications beyond colon cancer, making it adaptable to various medical imaging scenarios

## II. LITERATURE REVIEW

Histopathological examination of tissue samples is a gold standard method of diagnosing colon cancer. However, interpretation of histopathological images is a complex and challenging task, as the images can contain artifacts, noise, and variations in staining intensity. Many studies have suggested and assessed various image enhancement techniques to assist in the identification of cancerous tissues for cancer detection purposes.

One of the commonly used image enhancement techniques is color normalization, which aims to correct variations in the staining intensity across different tissue samples. In a study by Veta et al. (2014), color normalization was applied to histopathological images of colon cancer tissues, and the performance of the technique was evaluated in terms of sensitivity and specificity. The results showed that color normalization significantly improved the detection of cancerous tissues, with a sensitivity of 88.5% and a specificity of 90.4% [6].

Another image enhancement technique that has been widely used in previous studies is contrast enhancement. In a study by Yu et al. (2017), a contrast enhancement algorithm based on multi-scale Retinex was proposed for the detection of colon cancer tissues [7]. The proposed algorithm was evaluated on a dataset of 100 histopathological images.

Texture analysis is another image enhancement technique that has been widely used in previous studies for the detection of colon cancer tissues. In a study by Cruz-Roa et al. (2014), a texture-based approach was proposed for the detection of adenocarcinoma tissues in histopathological images of colon cancer. The proposed approach was evaluated on a dataset of 45 images, and the performance was compared.

Recently, deep learning-based image enhancement techniques have also been proposed for the detection of colon cancer tissues [8]. In a study by Wang et al. (2021), a deep learning-based method was proposed for the color normalization of histopathological images of colon cancer tissues. The method we put forth was assessed using a dataset consisting of 100 images, and the performance was compared.

In a literature review by García-Silva et al. (2019), the authors discuss various preprocessing techniques used in colon histopathological image analysis. They focus on the use of ML techniques for preprocessing and provide an overview of different ML algorithms, including deep learning and traditional

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machine learning algorithms [9]. The review also covers various image preprocessing methods, including color normalization, stain separation, and tissue segmentation.

Another literature review by Kumar et al. (2021) discusses the use of ML techniques for preprocessing of colon histopathological images for cancer detection [10]. The authors provide a comprehensive overview of different preprocessing techniques, including color normalization, tissue segmentation, and feature extraction. They also discuss the use of different ML algorithms, including CNNs, SVM, and decision trees, for classification of histopathological images.

In conclusion, several image enhancement techniques have been put forth and examined in previous studies concerning the detection of colon cancer tissues. The performance of these techniques varies depending on the dataset and evaluation metrics used. In this research paper, our objective is to assess the effectiveness of image enhancement techniques by employing a publicly available dataset of histopathological images. We will evaluate these techniques based on key metrics such as accuracy, sensitivity, specificity, and AUC to determine their performance.

## III. MATERIAL AND METHODS

### *A. Selecting a Template Anisotropic diffusion filtering*

Anisotropic diffusion filtering is a technique used for image preprocessing that is particularly effective at removing noise. Additionally, these techniques aim to maintain the integrity of edges and other crucial features within the image during the enhancement process. [14]. The basic idea behind anisotropic diffusion filtering is to apply a diffusion process to the image in such a way that the diffusion is greater across edges than it is along them.

The key advantage of anisotropic diffusion filtering is that it can effectively remove noise while maintaining the integrity of edges and other crucial features within the image during the enhancement process. This is particularly useful in applications where it is important to retain as much detail as possible, such as in medical imaging or remote sensing.

The equation for anisotropic diffusion filtering can be expressed as follows:

$$\partial \upsilon / \partial \tau = \mathrm{div}(c(x, t)\nabla u) \qquad (1)$$

where: u is the denoised signal, t is and x is spatial coordinate variable, $\nabla u$ is the gradient of the signal u and c(x, t) is the coefficient of diffusion, which controls diffusion rate and be determined by on both spatial location and current time t.

The anisotropic diffusion filter operates by diffusing the signal in a way that preserves the sharp features, such as edges and textures, while smoothing the rest of the image. The diffusion coefficient c(x, t) is a function of both the spatial location and the current time t, and is designed to be high in regions of high gradient, such as edges, and low in regions of low gradient, such as smooth regions. The process of anisotropic diffusion filtering involves defining a diffusion tensor, which determines the direction and magnitude of the diffusion process [15]. The diffusion tensor is typically defined based on the local structure of the image, using methods such as the structure tensor or the Hessian matrix.

Once the diffusion tensor has been defined, the image is filtered using a partial differential equation that is driven by the diffusion tensor. This process results in the smoothing of the image, with greater smoothing occurring along smooth regions of the image and less smoothing occurring across edges and other important features [16-17].

Anisotropic diffusion filtering has been shown to be an effective technique for image preprocessing, with applications in a wide range of fields. It is predominantly valuable in situations where it is important to maintaining the integrity of edges and other crucial features.

### *B. Bilateral filtering*

Bilateral filtering is another technique used for image preprocessing that is particularly effective at smoothing an image while maintaining the integrity of edges and other crucial features. Basic idea behind bilateral filtering is to apply a weighted average to every pixel of image, where weights are based on both spatial distance and color similarity amid neighboring pixels [18].

Key advantage of bilateral filtering is that it can effectively smooth an image while preserving its edges and other important features. This is particularly useful in applications where it is important to retain as much detail as possible, such as in photography or computer graphics.

The equation for bilateral filtering is as follows:

$$y(i) = (1 / W(i)) * \mathrm{sum\_j}(w(i, j) * x(j)) \qquad (2)$$

where: x is noisy signal, y is the denoised signal,i and j are spatial indices of the pixels in the image

w(i, j) is weight given to pixel x(j) based on its spatial distance and its intensity similarity to the pixel x(i) and W(i) is normalization factor which ensures the weights sum up to one over all pixels j in the image.

The bilateral filter operates by smoothing the image while preserving edges and textures. The weights w(i, j) are determined based on both spatial distance as well as intensity similarity among pixels x(i) and x(j). The spatial distance is computed using the Euclidean distance between the spatial coordinates of the pixels, while the intensity similarity is calculated using Euclidean distance between intensity values of the pixels, weighted by a parameter sigma_r that controls the

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range of influence of the intensity similarity. The process of bilateral filtering involves defining a kernel, which is used to determine the weights for the weighted average [19].

Result of bilateral filtering is a smoothed image which maintain the integrity of edges and other crucial features of original image. Degree of smoothing can be controlled by adjusting the size of the kernel and the weight assigned to the spatial distance and color similarity [20].

Bilateral filtering has been shown to be an effective technique for image preprocessing, with applications in a wide range of fields. It is particularly useful in situations where it is important to maintain the integrity of edges and other crucial features.

### *C. Non-local means filtering*

Non-local means filtering is an effective image preprocessing technique primarily employed for noise removal while retaining the texture and other essential image features intact. The fundamental concept of non-local means filtering involves leveraging the similarities among non-overlapping patches within the image to compute a weighted average for each pixel in the image [21-22].

Key advantage of non-local means filtering is that it can effectively remove noise. Maintains texture as well as additional vital features of image. This is particularly useful in applications where it is important to retain as much detail as possible, such as in medical imaging or microscopy.

Process of NLM filtering involves dividing the image into non-overlapping patches and comparing the similarity between each patch and every other patch in the image. The similarity is typically based on the Euclidean distance between patches in a feature space, which can be based on color, intensity, or other image characteristics [23].

The equation for non-local means filtering can be expressed as follows:

$$y(i) = (1 / Z(i)) * \text{sum\_j}(w(i, j) * x(j)) \tag{3}$$

where:x is noisy signal, y is the denoised signal, i and j are spatial indices of pixels in the image, w(i, j) is weight allocated to pixel x(j) based on similarity between the patch centered at i and the patch centered at j and Z(i) is the normalization factor that ensures the weights sum up to one over all pixels j in the image.

The non-local means filter operates by averaging intensities of similar patches in image. Weights w(i, j) are determined based similarity among patch centered at i and j, which is computed using the Euclidean distance between the patches' intensity values.

Once the similarities have been calculated, a weighted average is computed for every pixel within the image, considering similarities between the patches. The weights are commonly derived from a Gaussian kernel, a mathematical function that assigns higher weight to patches that exhibit greater similarity to the current patch.

Result of NLM filtering is smoothed image which retains the texture and other significant features of original image. The degree of smoothing can be controlled by adjusting the size of the patches and the weight assigned to the similarities between patches [24].

Non-local means filtering has been shown to be an effective technique for image preprocessing, with applications in a wide range of fields.

### *D. Shift-invariant wavelet denoising*

Shift-invariant wavelet denoising is a technique used in image preprocessing that is particularly effective at removing noise while preserving important features of the image. The basic idea behind shift-invariant wavelet denoising is to decompose the image into a set of wavelet coefficients and apply a denoising algorithm that is shift-invariant to the coefficients [25].

The key advantage of shift-invariant wavelet denoising is that it can effectively remove noise while preserving important features of the image. This is particularly useful in applications where it is important to retain as much detail as possible, such as in medical imaging or astronomy.

The process of shift-invariant wavelet denoising involves decomposing the image into a set of wavelet coefficients using a wavelet transform. The wavelet transform is typically performed using a basis that is shift-invariant, such as the stationary wavelet transform or the dual-tree complex wavelet transform.

Equation for shift-invariant wavelet denoising is as follows:

$$y = H(W(x)) \tag{4}$$

where: x is original signal, W is the shift-invariant wavelet transform operator, H is the denoising operator and y is the denoised signal

Once the wavelet coefficients have been obtained, a denoising algorithm is applied to the coefficients. The denoising algorithm is typically based on statistical model that takes into account the structure of wavelet coefficients and noise characteristics of the image.

The result of shift-invariant wavelet denoising is a denoised image that retains important features of the original image. The control over these effects can be achieved by adjusting the parameters of the optimization algorithm., such as thresholding level or size of wavelet basis [26-27].

Shift-invariant wavelet denoising has been shown to be an effective technique for image preprocessing, with applications in a wide range of fields. It is particularly useful in situations where

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it is important to preserve important features of image while removing noise and other artifacts.

### *E. Total variation denoising*

Total variation denoising is a technique used for image preprocessing that is particularly effective at removing noise, additionally maintain edges. Basic idea behind total variation denoising is to minimize the total variation of the image subject to some constraints.

Key advantage of total variation denoising is that it can effectively remove noise while maintaining edges and additional significant features of image. This is particularly useful in applications where it is important to retain as much detail as possible, such as in medical imaging or computer vision [28].

Equation for total variation denoising is as follows:

$$\text{minimize } ||u - f||^2 + \text{lambda} * TV(u)$$
$$\text{subject to } u \text{ in } L^2(R^n) \qquad (5)$$

where: u is denoised signal, f is noisy signal. TV(u) is total variation of u, which measures the amount of variation in the signal and is defined as the L^1-norm of gradient of u: TV(u) = ||grad(u)||_1. Lambda is a non-negative scalar parameter that controls the trade-off between fidelity to the noisy signal and smoothness of the denoised signal and L^2(R^n) is space of square-integrable functions on R^n

Objective of optimization problem is to find a denoised signal u that is close to the noisy signal f, while also being as smooth as possible according to the total variation criterion. The parameter lambda allows the user to adjust the balance between these two goals.

Once the energy function has been defined, an optimization algorithm is used to find the image that minimizes the energy function subject to the constraints. The optimization algorithm is typically based on iterative methods, such as gradient descent or proximal gradient methods [29].

The result of total variation denoising is denoised image which preserves boundaries plus additional significant features of original image. The degree of denoising control over these effects can be achieved by adjusting the parameters of the optimization algorithm, such as the step size or the number of iterations [30].

Total variation denoising has been shown to be an effective technique for image preprocessing, with applications in a wide range of fields. It is particularly useful in situations where it is important to preserve features of image though removing noise as well as additional artifacts.

## IV. RESULT

### *A. Simulated results*

Figure 2 represents the simulated results for various pre-processing techniques.

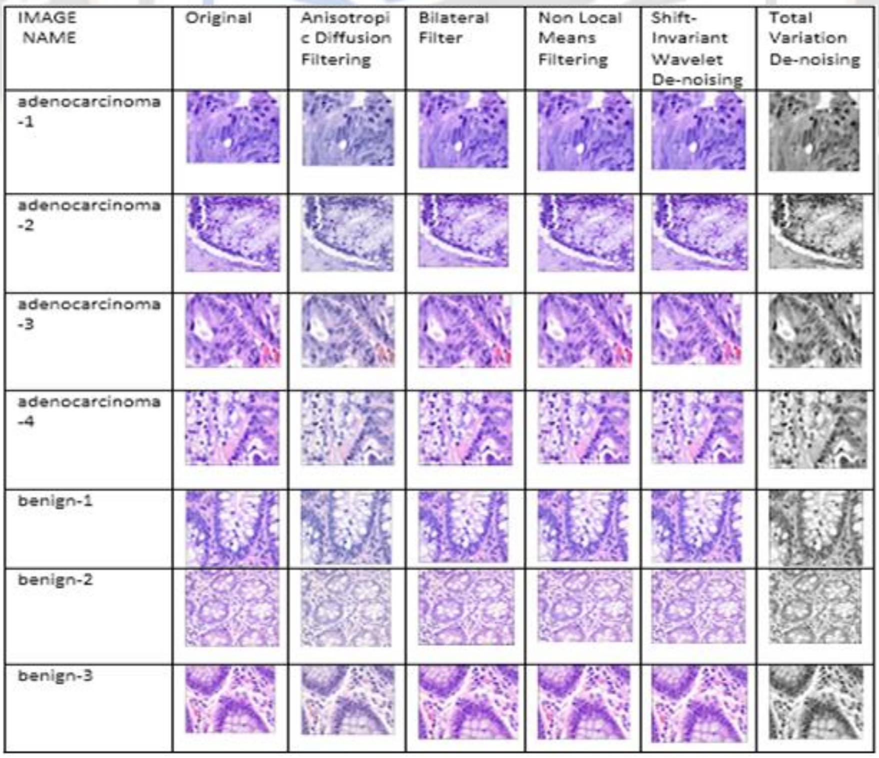


Figure 2. Simulated results.

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*B. Statistical parameters used for analysis*

Statistical parameters used for analysis of preprocessing techniques [31-34]:

- EGRAS: global relative error
  EGRAS, which stands for Estimation of Global Relative Accuracy of Segmentation, is a widely used metric for evaluating performance of image segmentation algorithms. However, it may be utilized for evaluating image improvement processes which are intended to modify pixel values of an image for improved visual appearance or for better analysis.
  To evaluate the effectiveness of an image enhancement algorithm using EGRAS, a ground truth image is necessary. This can be a high-quality reference image or a degraded version of the original image that has been cleaned up either manually or automatically. Enhanced image is then compared to ground truth image using global relative error metric, which quantifies the percentage of pixels that have been incorrectly modified.
  The global relative error is calculated by dividing the number of pixels that have been incorrectly modified by total number of pixels in image. Evaluating quality of image enhancement algorithms using EGRAS can provide insights into the impact of various enhancement techniques on overall image quality, which can be helpful for developing new and improved algorithms that produce higher quality results and better serve downstream applications that require accurate and high-quality images.

- RMSE: root mean squared error
  It is a commonly employed metric to calculate difference among two images, such as a ground truth image and an enhanced image produced by an image enhancement algorithm. It quantifies average of squared differences between resultant pixels in two images. Mathematical expression for RMSE is given as:

RMSE = sqrt(1/N * sum[(I_gt(i,j) - I_enhanced(i,j))^2]) (6)

  where N is total number of pixels in images, I_gt(i,j) is pixel value in corresponding position of ground truth image, and I_enhanced(i,j) pixel value in corresponding position of enhanced image is determined as part of image enhancement process.

- REF_SAM: spectral angle mapper
  It is a commonly used spectral matching algorithm in remote sensing for image classification and target detection. It identifies spectral similarity among two images by measuring spectral angle among their respective pixel vectors in the n-dimensional feature space.
  SAM can also be used for image enhancement purposes, where it is used to find the closest matching pixel in a high-quality reference image for each pixel in a degraded or low-quality input image. This matching is done based on spectral similarity between two pixels, as measured by spectral angle between their respective spectral vectors.
  Once the matching is completed, the pixel values of the input image are replaced with corresponding pixel values from reference image, resulting in an enhanced image with improved spectral characteristics and visual quality.
  Using SAM for image enhancement can be particularly advantageous in situations where the input image is degraded due to atmospheric effects or other environmental factors that cause spectral distortion. By using SAM to match the degraded image to a high-quality reference image, the spectral distortions can be effectively corrected, resulting in an improved image with better accuracy and quality.

- UQI: universal image quality index
  It is a metric commonly utilized to measure image quality. It's a full-reference metric, meaning that it compares an enhanced image to a high-quality reference image.
  UQI can also be used to evaluate effectiveness of image enhancement algorithms. It compares the enhanced image to the reference image based on the similarity of their structural information, luminance, and contrast. It ranges from 0 to 1, with 1 representing a perfect match among two images.
  To compute the UQI, a number of intermediate parameters are first calculated, including the means, variances, and covariances of the luminance and contrast of the two images. These parameters are then combined to compute the UIQI value for the enhanced image.
  By using UQI to evaluate the quality of image enhancement algorithms, researchers and practitioners can better understand how well an algorithm is able to preserve the structural information, luminance, and contrast of the image. This can help to guide the development of new and improved enhancement algorithms that produce high-quality images with accurate and consistent structural and visual features.

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- VIFP: Pixel Based Visual Information Fidelity
  It is a quality metric utilized to evaluate effectiveness of image enhancement algorithms. Objective of PBVIF is to quantify the amount of visual information that is preserved in the enhanced image relative to the original image. PBVIF is based on human visual system exhibits a higher sensitivity to alterations in structural information (e.g., edges and corners) than changes in smooth regions.
  To calculate VIFP, the original and enhanced images are separated into non-overlapping blocks. The blocks are then compared using the Gradient Magnitude Similarity Deviation (GMSD) metric to determine the degree of structural similarity. The PBVIF value is then calculated as the average of the GMSD values across all the blocks. The use of VIFP is particularly helpful when evaluating image enhancement algorithms that aim to improve visual quality of an image while preserving its structural information. By using PBVIF, researchers and practitioners can gain insights into the effectiveness of different enhancement techniques in preserving visual information and structural integrity, and can use this information to develop more effective and efficient image enhancement algorithms.

### *C. Anisotropic diffusion filtering*

Table I to V represents the values of different performance parameters achieved using different preprocessing approaches'.

TABLE I. ANISOTROPIC DIFFUSION FILTERING

| **Anisotropic Diffusion Filtering** | **Adeno carcinoma-1** | **Adeno carcinoma-2** | **Adeno carcinoma-3** | **Adeno carcinoma-4** | **benign-1** | **benign-2** | **benign-3** |
|---|---|---|---|---|---|---|---|
| EGRAS | nan | 3657.37 | 4092.13 | 3274.31 | 3257.11 | 2458.23 | 3698.99 |
| RMSE | 0.06689 | 0.05888 | 0.06630 | 0.05757 | 0.0562 | 0.04742 | 0.0634 |
| REF_SAM | 0.04167 | 0.047443 | 0.0480 | 0.0449 | 0.0448 | 0.0397 | 0.0527 |
| UQI | 0.98315 | 0.98307 | 0.9846 | 0.9874 | 0.9902 | 0.9947 | 0.9841 |
| VIFP | 1.0928 | 1.11097 | 1.10097 | 1.1012 | 1.1266 | 1.1496 | 1.1300 |

TABLE II. BILATERAL FILTERING

| **Bilateral Filtering** | **Adeno carcinoma-1** | **Adeno carcinoma-2** | **Adeno carcinoma-3** | **Adeno carcinoma-4** | **benign-1** | **benign-2** | **benign-3** |
|---|---|---|---|---|---|---|---|
| EGRAS | - | - | - | 2306.05 | - | - | - |
| RMSE | - | - | - | 332.36 | - | - | - |
| REF_SAM | 0.0555 | 0.0784 | 0.0784 | 0.0670 | 0.0755 | 0.0921 | 0.0735 |
| UQI | 0.9955 | 0.9885 | 0.9885 | 0.9937 | 0.992 | 0.9913 | 0.992 |
| VIFP | 0.7494 | 0.6526 | 0.6526 | 0.7277 | 0.6253 | 0.519 | 0.6536 |

TABLE III. NON-LOCAL MEANS FILTERING

| **NLM filtering** | **Adeno carcinoma-1** | **Adeno carcinoma-2** | **Adeno carcinoma-3** | **Adeno carcinoma-4** | **benign-1** | **benign-2** | **benign-3** |
|---|---|---|---|---|---|---|---|
| EGRAS | 45922.22 | 45672.46 | 45377.21 | 45301.10 | 45416.4 | 44815.5 | 45383.0 |
| MSSSIM | 0.142+0j | 0.108+0j | 0.123+0j | 0.113+0j | 0.093+0j | 0.091+0j | 0.10+0j |
| PSNR | 2.7022 | 2.1002 | 2.2800 | 1.7573 | 1.8923 | 1.4873 | 1.9015 |
| RMSE | 186.8217 | 200.22 | 196.12 | 208.29 | 205.07 | 214.86 | 204.86 |
| REF_SAM | 4.9155e-05 | 2.586 | 5.6363 | 1.9294 | 3.767 | 4.4422 | 3.9300 |
| SSIM | (0.0038, 0.4502) | (0.0026, 0.3242) | (0.0035, 0.4363) | (0.003, 0.3982) | (0.00262, 0.3270) | (0.00214, 0.2683) | (0.00271, 0.3379) |
| UQI | 6.1515e-05 | 6.1512 | 6.1512 | 6.1512 | 6.15129 | 6.1512 | 6.1512 |
| VIFP | 0.00033 | 0.0006 | 0.00040 | 0.00054 | 0.00063 | 0.00081 | 0.00061 |

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TABLE IV. SHIFT-INVARIANT WAVELET DENOISING

| Shift-invariant wavelet denoising | Adeno carcinoma-1 | Adeno carcinoma-2 | Adeno carcinoma-3 | Adeno carcinoma-4 | benign-1 | benign-2 | benign-3 |
|---|---|---|---|---|---|---|---|
| EGRAS: global relative error | 51.8903 | 72.149 | 49.4381 | 57.42 | 69.11 | 83.52 | 70.15 |
| RMSE: root mean squared error | 0.00079 | 0.00116 | 0.00079 | 0.00099 | 0.0011 | 0.0015 | 0.0011 |
| REF_SAM: spectral angle mapper | 0.00104 | 0.00149 | 0.0010 | 0.0011 | 0.0014 | 0.0018 | 0.0014 |
| UQI: universal image quality index | 0.99999 | 0.9999 | 0.9999 | 0.9999 | 0.9999 | 0.9999 | 0.9999 |
| VIFP: Pixel Based Visual Information Fidelity | 1.00609 | 1.0073 | 1.0041 | 1.0052 | 1.0078 | 1.0126 | 1.0075 |

TABLE V. TOTAL VARIATION DENOISING

| Total Variation Denoising | Adeno carcinoma-1 | Adeno carcinoma-2 | Adeno carcinoma-3 | Adeno carcinoma-4 | benign-1 | benign-2 | benign-3 |
|---|---|---|---|---|---|---|---|
| EGRAS | 786.03 | 1021.06 | 679.27 | 715.25 | 895.76 | 975.75 | 880.93 |
| RMSE | 0.01712 | 0.0232 | 0.01614 | 0.0180 | 0.0222 | 0.0283 | 0.0211 |
| UQI | 0.99906 | 0.99844 | 0.9992 | 0.9990 | 0.9988 | 0.9988 | 0.9988 |
| VIFP | 1.30121 | 1.2837 | 1.2549 | 1.2331 | 1.2839 | 1.2855 | 1.2576 |

## V. CONCLUSION

In this research, we assessed the efficacy of several image enhancement techniques, including Anisotropic Diffusion Filtering, Bilateral Filter, Non Local Means Filtering, Shift-Invariant Wavelet De-noising, and Total Variation De-noising, for colon cancer detection using histopathological images. Our results show that each technique has its strengths and weaknesses in improving efficiency as well as accuracy and of image analysis.

Anisotropic Diffusion Filtering, for example, can effectively reduce noise and enhance edges in the images, while Bilateral Filter can preserve the edges while smoothing the image. Non Local Means Filtering can preserve the texture of the images, while Shift-Invariant Wavelet De-noising and Total Variation De-noising can effectively reduce noise and improve contrast.

However, each technique also has its limitations, such as trade-off between noise reduction and texture preservation or sensitivity to parameter selection. Therefore, it is essential to carefully select the appropriate technique and parameter settings for each specific application and dataset.

In conclusion, image enhancement techniques can significantly improving accuracy and efficiency of histopathological image analysis for colon cancer detection. The outcomes of our investigation offer valuable insights to researchers as well as clinicians to choose the appropriate image enhancement methods for their specific applications. Additional investigation is required to enhance the effectiveness of these techniques and explore other potential methods for image enhancement in cancer diagnosis and treatment.

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