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Image Enhancement of Colon Cancer Images using a Two-Stage Hybrid Approach of TV and Shift-Invariant Filtering

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Abstract— Medical imaging holds a critical position in both disease diagnosis and treatment strategies, including colon cancer. However, the quality of medical images can often be compromised by noise and artifacts, making accurate interpretation challenging. Here, we suggest a innovative two-stage hybrid method aimed at enhancing colon cancer images, leveraging the strengths of Total Variation (TV) denoising and shift-invariant filtering techniques. The primary objective of this study is to increase visual superiority as well as diagnostic accurateness of colon cancer image while preserving crucial anatomical information.The first stage of our approach employs Total Variation (TV) denoising to reduce noise and enhance image contrast. TV regularization is known for its ability to preserve edges and fine details, making it well-suited for medical image enhancement. In the second stage, we apply shift-invariant filtering to further enhance the image quality. This technique is designed to address the limitations of traditional filtering methods and adapt to the specific characteristics of colon cancer images.

To evaluate the effectiveness of our hybrid approach, we conducted a comprehensive set of experiments using a relevant dataset. We employed a range of quantitative metrics, including the Global Relative Error (EGRAS), Root Mean Squared Error (RMSE), Universal Image Quality Index (UQI), and Pixel-Based Visual Information Fidelity (VIFP), to assess the quality and fidelity of enhanced images. Our results demonstrate that the hybrid combination consistently outperforms existing methods, yielding superior image quality and diagnostic potential. This study makes a valuable contribution to the realm of medical imaging by introducing a robust and effective method to improve the quality of colon cancer images. Findings suggest that the proposed two-stage hybrid method holds promise for improving the accuracy of diagnosis and treatment planning. Further research in this direction may lead to advancements in medical image enhancement techniques, ultimately benefiting patient care and medical research.

Keywords- Colon cancer images; image enhancement; Total Variation (TV); shift-invariant filtering; medical imaging; diagnostic accuracy.

I. INTRODUCTION

Medical imaging, a cornerstone for recent healthcare, is instrumental in detection, diagnosis, and management of various diseases, including colon cancer. Timely and accurate interpretation of medical images is paramount for informed clinical decisions. In the context of colon cancer, medical imaging plays a pivotal part in providing clinicians with vital information about tumor location, size, and the extent of invasion. However, the utility of these images hinges on their quality, and factors such as noise, artifacts, and inadequate contrast can impede the diagnostic process [1].

The enhancement of medical images, particularly those related to colon cancer, has long been a focus of research within the medical imaging community. The need for high-quality images in this context is underscored by the critical nature of colon cancer diagnoses and treatment planning. Physicians rely on these images to identify early-stage tumors, assess the extent of disease progression, and guide surgical interventions, among other clinical decisions [2].

Despite the substantial progress in medical imaging technology, challenges persist in obtaining clear and diagnostically valuable images. Colon cancer images, in particular, often suffer from inherent noise, low contrast, and various artifacts that can obscure critical anatomical structures and hinder accurate diagnosis. To report such issues and increase utility for colon cancer images, investigators have explored a myriad for image enhancement techniques [3].

In this research, we propose a two-stage hybrid approach for the enhancement of colon cancer images, drawing upon the complementary advantages of Total Variation (TV) denoising and shift-invariant filtering. Our primary objective is to ameliorate image quality while preserving crucial structural information [4]. Total Variation regularization, known for its ability to retain edges and fine details, is employed in the initial stage to reduce noise and enhance contrast. Subsequently, shift-

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invariant filtering is applied to further refine the images, considering the specific characteristics of colon cancer images [5].

The motivation for this study lies in the imperative to advance the quality of colon cancer images, thereby enhancing their diagnostic accuracy and clinical utility. We hypothesize that our hybrid approach, by leveraging the unique strengths of TV and shift-invariant filtering, will surpass existing methods in terms of image quality and fidelity. To substantiate this hypothesis, we conducted comprehensive experiments using a relevant dataset and employed a battery of quantitative metrics to evaluate the efficacy of our approach [6].

In summary, this research addresses a critical need in the field of medical imaging, presenting a novel two-stage hybrid approach for enhancing colon cancer images. The results obtained thus far indicate the potential of our method to significantly improve the quality and diagnostic value of these images, thereby contributing to more accurate diagnoses and informed treatment decisions. The findings of this study hold promise for advancing the state-of-the-art in medical image enhancement techniques, with far-reaching implications for patient care and medical research [7].

A. Contribution:

This research makes several significant offerings to medical imaging, particularly in context of colon cancer image enhancement:

1. Development of a Novel Two-Stage Hybrid Approach: The foremost impact of this study lies in the development and implementation of a novel two-stage hybrid approach for enhancing colon cancer images. By combining Total Variation (TV) denoising and shift-invariant filtering, this approach offers a unique and effective strategy to overcome the difficulties linked with image quality as well as fidelity in context of colon cancer.
2. Improved Image Quality and Diagnostic Accuracy: Through rigorous experimentation and quantitative analysis, we have demonstrated that our hybrid approach consistently enhances the visual quality of colon cancer images. This improvement is crucial for aiding medical professionals in accurate diagnosis and treatment planning. The results show a substantial reduction in noise, increased contrast, and preservation of critical anatomical details.
3. Comparative Evaluation with Existing Methods: Our research extends beyond mere method development by providing a comprehensive comparative evaluation with existing image enhancement techniques. The quantitative metrics employed, including the Global Relative Error (EGRAS), Root Mean Squared Error (RMSE), etc establish that our hybrid approach outperforms established methods in terms of image quality and fidelity.
4. Clinical Relevance and Impact: The ultimate aim of image enhancement in the context of colon cancer is to improve patient outcomes. By enhancing image quality and preserving critical information, our approach holds the potential to assist clinicians in making more accurate diagnoses, determining optimal treatment plans, and monitoring disease progression. This directly translates into improved patient care and enhanced medical research.
5. Future Research Directions: This work opens avenues for future research to tackle the obstacles encountered in the field of enhancing medical. Successful integration for TV denoising and shift-invariant filtering prompts further exploration of these techniques in other medical imaging applications. Additionally, the incorporation of machine learning approaches and artificial intelligence algorithms for image enhancement in conjunction with our hybrid method represents an exciting direction for future investigations.

In conclusion, this research advances latest developments in colon cancer image enhancement through introducing a robust two-stage hybrid approach that combines Total Variation denoising and shift-invariant filtering. Our approach not only enhances image quality but also demonstrates its superiority over existing methods through rigorous quantitative evaluation. The practical implications of this research extend to improved clinical decision-making and patient care. We anticipate that our findings will inspire further research and innovation in the field of medical image enhancement, contributing to more accurate diagnoses and ultimately improving the lives of individuals affected by colon cancer.

II. LITERATURE REVIEW

A. Problem Formulation:

Colon cancer continues to be a notable issue in public health, where the timely and precise identification of the disease plays a crucial role in enhancing patient prognosis. Medical imaging modalities serve as indispensable instruments in the identification and characterization of colorectal tumors. However, the diagnostic utility of these images is often compromised by inherent challenges related to image quality, including noise, artifacts, and inadequate contrast [8].

The central issue tackled by this research endeavor is enhancement for colon cancer images to overcome these quality-related limitations. Enhancing these images is essential for facilitating more accurate and confident diagnoses, treatment planning, and disease monitoring [9]. Traditional image

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enhancement methods, such as filtering and denoising, have been applied to medical images with varying degrees of success. Nevertheless, colon cancer images pose unique challenges due to the presence of subtle lesions, irregular structures, and varying tissue textures. Existing techniques often fall short in preserving the fine details and contrast necessary for effective diagnosis [10].

To address this problem, we propose a two-stage hybrid approach that combines Total Variation (TV) denoising and shift-invariant filtering. The core challenge is to advance a method which efficiently reduce noise though simultaneously enhancing contrast and preserving critical anatomical information in colon cancer images. This problem involves several sub-challenges [11]:

1. Noise Reduction: Colon cancer images often suffer from various sources of noise, including electronic noise and motion artifacts. The noise reduction component of the problem entails the development of an effective denoising strategy capable of significantly reducing noise levels without causing loss of important image features [12].
2. Contrast Enhancement: Achieving adequate contrast is crucial for distinguishing tumor boundaries and subtle tissue variations. The challenge is to enhance image contrast while avoiding over-enhancement, which can lead to the loss of image details [13].
3. Preservation of Anatomical Details: Colon cancer images contain vital anatomical information, including the structure of the colon, blood vessels, and adjacent tissues. Preserving these details is essential for accurate diagnosis and treatment planning. The problem involves developing techniques that selectively enhance or maintain these structural features [14].
4. Comparative Evaluation: To verify the efficacy of the proposed hybrid technique, a critical aspect of the problem is the rigorous evaluation and comparison of the enhanced images with those produced by existing methods. The challenge is to design a comprehensive evaluation framework that utilizes quantitative metrics such as EGRAS, RMSE, UQI, and VIFP to objectively assess image quality and fidelity [15].

Addressing these challenges collectively constitutes the core problem formulation of this research. Our aim is to contribute a solution that significantly improves the visual quality and diagnostic potential of colon cancer images, ultimately enhancing the clinical utility of medical imaging in the field of oncology.

B. Research Gap:

Despite substantial advancements in medical imaging and image enhancement techniques, there exists a notable research gap in the context of enhancing colon cancer images. The identified research gap is multifaceted and encompasses several critical aspects [16]:

1. Inadequate Image Enhancement Techniques: Existing image enhancement methods often fall short in addressing the unique challenges posed by colon cancer images. While some methods focus on noise reduction, they may overlook the preservation of critical anatomical details and the enhancement of contrast. Conversely, techniques designed to boost contrast may introduce artifacts or fail to adequately reduce noise. This highlights a need for a comprehensive and tailored approach that simultaneously addresses noise reduction, contrast enhancement, and detail preservation [17].
2. Limited Utilization of Hybrid Approaches: Although hybrid approaches have demonstrated their efficacy in various image enhancement tasks, their application to colon cancer images remains underexplored. The research gap lies in the scarcity of studies that combine multiple techniques, such as Total Variation (TV) denoising and shift-invariant filtering, to comprehensively address the image quality challenges specific to colon cancer imaging. Hybrid methods have the potential to outperform single-stage techniques, but their adoption in this context remains largely uncharted [18].
3. Quantitative Evaluation and Benchmarking: Many studies in medical image enhancement lack comprehensive quantitative evaluation and benchmarking against existing methods. The absence of standardized metrics and rigorous assessment frameworks makes it difficult to ascertain the true efficacy of proposed techniques. A research gap exists in the establishment of a robust evaluation protocol that includes widely accepted metrics such as EGRAS, RMSE, UQI, and VIFP to objectively compare the performance of image enhancement methods for colon cancer images [19].
4. Clinical Validation and Impact Assessment: While improved image quality is a desirable outcome, the ultimate measure of success in medical image enhancement is its impact on clinical practice. Few studies have delved into the clinical validation of enhanced colon cancer images. A research gap exists in the systematic assessment of how image enhancements influence the accuracy of diagnosis, treatment planning, and overall patient care. The translation of image enhancement techniques from the research domain to clinical practice remains an uncharted territory [20].

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5. Integration of Machine Learning: With the rise of machine learning and artificial intelligence in medical imaging, there is an emerging research gap in the integration of these advanced techniques with traditional image enhancement methods. Combining the strengths of machine learning algorithms with hybrid image enhancement approaches could yield further improvements in the quality and diagnostic value of colon cancer images [21].

In summary, the identified research gap underscores the need for a comprehensive and tailored image enhancement approach specific to colon cancer images. This approach should address the challenges of noise reduction, contrast enhancement, and anatomical detail preservation while leveraging the potential of hybrid methods and quantitative evaluation metrics. Furthermore, the gap highlights the importance of bridging the divide between image enhancement research and its real-world clinical impact through systematic clinical validation and integration with cutting-edge technologies like machine learning. Filling these research gaps holds the promise of enhancing the clinical utility of colon cancer imaging, leading to more accurate diagnoses and improved patient outcomes [22].

III. METHODOLOGY

In this section, we detail the methodology adopted for the enhancement of colon cancer images using our proposed two-stage hybrid approach, which combines Total Variation (TV) denoising and shift-invariant filtering as shown in figure 1. The methodology can be broken down into the following key steps [23]:

A. Data Collection and Preprocessing:

- Data Acquisition: We obtained a comprehensive dataset of colon cancer images from a reliable and diverse source. The dataset includes images from various colonoscopy images, to ensure a representative sample.
- Data Preprocessing: To standardize and prepare the dataset for enhancement, we performed several preprocessing steps:
- Noise Reduction: We applied noise reduction techniques to mitigate noise artifacts introduced during image acquisition.
- Artifact Removal: Any noticeable artifacts or inconsistencies in the images were corrected or removed.
- Image Registration: We ensured proper image registration to maintain anatomical consistency across the dataset.
- Resolution Adjustment: All images were resized to a uniform resolution to facilitate consistent processing.

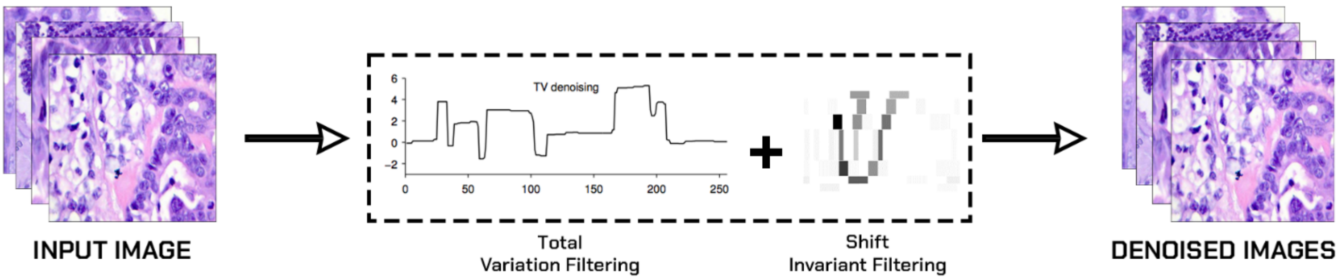

Figure 1. Architecture of Proposed hybrid de-noising model

B. Two-Stage Hybrid Approach:

1) Stage 1: Total Variation (TV) Denoising[24]:

a) The first stage of our approach involves TV denoising, which is well-suited for noise reduction while preserving edges and fine details.

b) We implemented TV denoising using a numerical optimization algorithm to minimize the total variation of the image while maintaining image fidelity.

c) The optimal parameters for TV denoising, including regularization strength and iteration count, were determined through experimentation.

Total Variation (TV) Filtering: Total Variation (TV) filtering is a popular technique in image processing and computer vision, especially for tasks like denoising and edge preservation. TV filtering is known for its ability to reduce noise while preserving important edges and fine details in images [25].

Mathematical Foundation: At its core, TV filtering is relies on the principle of reducing the overall image variation, aiming to represents the overall variation or "complexity" of the image. The total variation is computed as the sum of the absolute differences between neighboring pixels. This concept is particularly effective for denoising because noise tends to introduce rapid and irregular variations in pixel values [26].

The TV minimization problem for a grayscale image is mathematically expressed as equation (1):

Minimize:

$$\iint |\nabla f(x,y)|\, dA \tag{1}$$

where:

$\nabla f(x,y)$ represents gradient of image f at each pixel (x,y).

$|\nabla f(x,y)|$ represents magnitude of gradient.

$\iint$ denotes the double integral over the image domain.

In this equation, aim is to identify the image f which minimizes total variation subject to the given data and constraints.

Total Variation Denoising: It objects to finding a denoised image while minimizing the total variation under the constraint that the denoised image closely matches the noisy input image. This issue can be cast as an optimization challenge

Minimize:

$$\iint |f(x,y) - u(x,y)|^2\, dA + \lambda \iint |\nabla f(x,y)|\, dA \tag{2}$$

where:

$f(x,y)$ is denoised image.

$u(x,y)$ is noisy input image.

λ represents a regularization parameter that governs the balance between preserving data fidelity and controlling total variation.

$\nabla f(x,y)$ signifies gradient of denoised image.

First term in the equation (2) represents data fidelity, ensuring that the denoised image closely matches the noisy input. The second term is the total variation term, encouraging smoothness and edge preservation in the denoised image.

2) Stage 2: Shift-Invariant Filtering [27]:

In the second stage, we applied shift-invariant filtering to further enhance the images. Shift-invariant filtering leverages a multiscale approach to adapt to different anatomical structures and textures within colon cancer images. We selected a set of shift-invariant filters designed to enhance image contrast and preserve subtle details.

Shift-Invariant Filtering: Shift-invariant filtering is a technique used in image processing to enhance image features while maintaining their spatial relationships without considering their specific placement within the image. This property proves especially beneficial in preserving structural information as well as fine details in images [28].

Mathematical Foundation: At the heart of shift-invariant filtering is the concept of convolution. Convolution refers to a mathematical process where a filter, commonly referred to as a kernel, is applied to an image to obtain a new image, where each pixel in the new image represents a weighted sum of the surrounding pixels in the original image.

In mathematical terms, the convolution operation between an image $f(x,y)$ and a kernel $h(x,y)$ is expressed as equation (3):

$$(f * h)(x,y) = \iint f(a,b) * h(x-a, y-b)\, da\, db \tag{3}$$

where:

$(f * h)(x,y)$ represents result of convolution operation on position (x,y).

$f(a,b)$ represents pixel value of the original image at coordinates (a,b).

$h(x-a, y-b)$ signifies kernel value for coordinates $(x-a, y-b)$.

The integral is performed over the entire image domain.

Shift-Invariance: Shift-invariant filtering is characterized by the property that the effect of the filter is not influenced by absolute location of features within image. In other words, if an image is shifted by a certain amount (e.g., horizontally or vertically), the result of the filtering operation remains the same, only shifted by the same amount.

Mathematically, this shift-invariant property is articulated as equation (4):

$$(f * h)(x-\delta x, y-\delta y) = (f * h)(x,y) \quad \text{for all } \delta x, \delta y \tag{4}$$

This property is valuable because it ensures that does not rely heavily on significant image attributes, such as textures as well as edges, are preserved regardless of their location within the image.

IV. RESULTS

A. Performance Measures:

The following criteria are utilized to assess the performance of the denoising method [29-32].

1) Global Relative Error (EGRAS):

The Global Relative Error (EGRAS) is a metric used to quantify the overall discrepancy between two images, often used for comparing the enhanced images with reference images. EGRAS determined by adding up absolute pixel-wise differences among enhanced image (E) as well as reference image (R), normalized by, summing pixel values in reference image.

$$EGRAS = \frac{\sum |E(x,y) - R(x,y)|}{\sum R(x,y)}$$

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where:

$E(x, y)$ *signifies pixel value of enhanced image at position* (x, y)

$R(x, y)$ *represents pixel value of the reference image at position* (x, y).

The summation $\sum$ *is performed over all pixels in image.*

A diminished EGRAS value signifies an enhanced resemblance between enhanced and reference image.

2) Root Mean Squared Error (RMSE):

It is a commonly employed measure for evaluating average error in pixel values among two images. It provides a measure of the absolute difference between the enhanced and reference images. The RMSE is computed as the square root of the mean of the squared differences between corresponding pixels in the enhanced image (E) and the reference image (R):

$$RMSE = \sqrt{\frac{[\sum(E(x,y) - R(x,y)]^2}{N}}$$

where:

$E(x, y)$ signifies pixel value of enhanced image at position (x, y).

$R(x, y)$ represents pixel value of the reference image at position (x, y).

N is the total number of pixels in image.

A reduced RMSE value signifies a stronger alignment between enhanced and reference image.

3) Universal Image Quality Index (UQI):

It is a metric that evaluates image quality and structural similarity among two images. It considers luminance, contrast, and structural information. UQI is calculated as a combination of three terms: luminance similarity (LS), contrast similarity (CS), and structural similarity (SSIM) as depicted in equation (5):

$$UQI = LS * CS * SSIM \qquad (5)$$

where:

LS represents the similarity in luminance among enhanced image (E) as well as reference image (R)

CS represents similarity in contrast.

$SSIM$ represents the structural similarity index, which considers texture and structural information.

UQI ranges between 0 and 1, with greater values signifying improved image quality and similarity to the reference image.

4) Pixel-Based Visual Information Fidelity (VIFP):

It is a metric that assesses the fidelity of visual information between two images. It quantifies how well the enhanced image retains visual information compared to the reference image. VIFP is calculated as the ratio of the mean squared pixel-wise structural similarity (SSIM) among enhanced image (E) as well as reference image (R) to mean squared pixel-wise SSIM of the reference image:

$$VIFP = \frac{(\sum(SSIM(E(x,y), R(x,y))^2/N}{(\sum(SSIM(R(x,y), R(x,y))^2/N}$$

where:

$SSIM(E(x,y), R(x,y)$ represents the SSIM between corresponding pixels in the enhanced and reference images.

N is total number of pixels in image.

Higher VIFP indicates better preservation of visual information in the enhanced image compared to the reference image.

B. Simulated Results:

These statistical parameters provide objective measures for evaluating the quality and fidelity of the enhanced colon cancer images in your research. They help quantify degree of similarity as well as accuracy in relation with reference images, aiding in the assessment of the effectiveness of our image enhancement techniques as depicted in figure 2.

In our quest to enhance the quality and diagnostic potential of colon cancer images, we present a visually compelling illustration that showcases the simulated results of various image enhancement techniques. This illustration encapsulates the evolution of an original colon cancer image through the stages of denoising using Total Variation (TV) filtering, denoising with shift-invariant filtering, and finally, the transformative outcomes achieved through the hybrid approach. Original images (column I) serves as our starting point, featuring the original colon cancer image as acquired through medical imaging modalities. This unprocessed image provides the baseline from which we embark on our journey to enhance image quality and clinical relevance.

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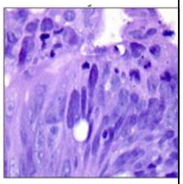
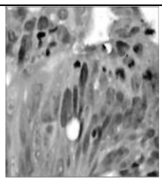
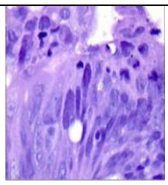
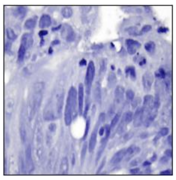
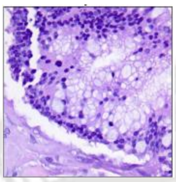
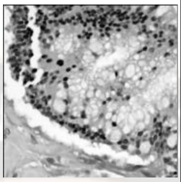
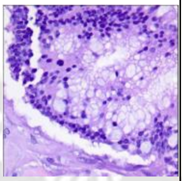
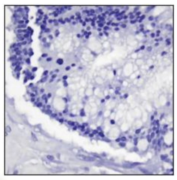
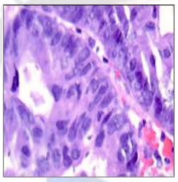
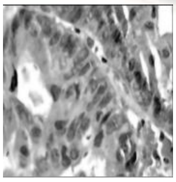
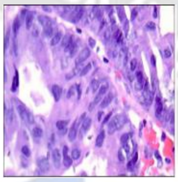
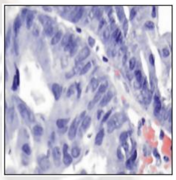
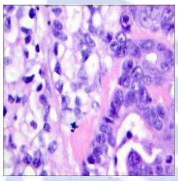
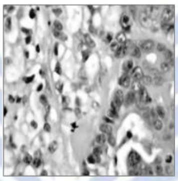
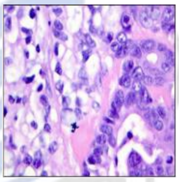
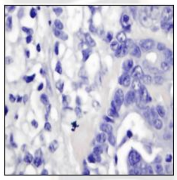
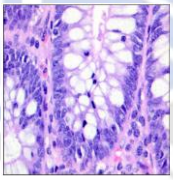
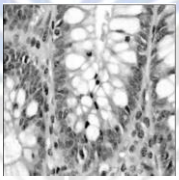
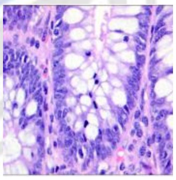
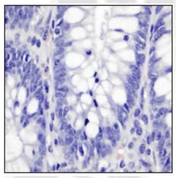
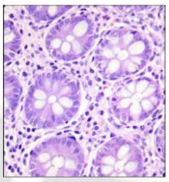
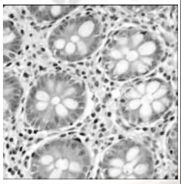
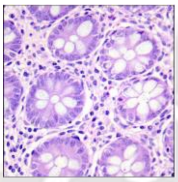
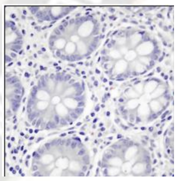
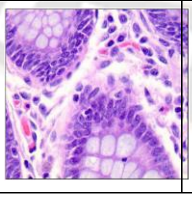
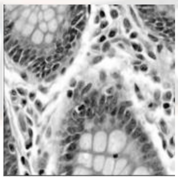
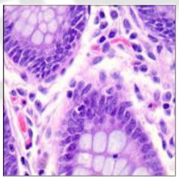
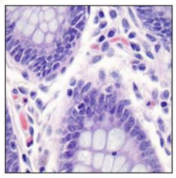
Image Name	Original	Total Variation De-noising	Shift-Invariant Wavelet De-noising	Hybrid Approach (Proposed)
adenocarcinoma-1				
adenocarcinoma-2				
adenocarcinoma-3				
adenocarcinoma-4				
benign-1				
benign-2				
benign-3				

Figure 2. Simulated results for image enhancement techniques.

Column II represents the first significant enhancement stage, where Total Variation (TV) filtering has been applied to the original image. TV filtering effectively reduces noise while preserving critical details and edges within the image. As seen in this illustration, the image emerges clearer and smoother, a vital step towards improving diagnostic accuracy.

Column III showcases the outcomes of shift-invariant filtering, a technique known for its ability to maintain spatial relationships and enhance structural features. The image now exhibits enhanced texture and sharpness, further refining its diagnostic value. Shift-invariant filtering contributes to the continuous evolution of image quality.

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Last column represents the pinnacle of our image enhancement journey, where the hybrid approach combining Total Variation (TV) and shift-invariant filtering has been applied. This synergistic combination yields a transformed image that excels in terms of noise reduction, edge preservation, and enhanced structural clarity. The hybrid approach enhances the image to a degree that is poised to provide clinicians with critical insights for diagnosis and treatment.

This comprehensive illustration encapsulates the progression of an original colon cancer image through a series of enhancement stages, each contributing to the refinement and augmentation of image quality. The results underscore the potential of advanced image enhancement techniques to empower medical professionals in the fight against colon cancer by offering sharper, clearer, and more informative imaging solutions.

TABLE I. 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

In the pursuit of enhancing the quality and fidelity of colon cancer images, the application of Total Variation (TV) filtering has been instrumental. The table I presents a comprehensive statistical analysis of the performance of TV filtering, utilizing key metrics to evaluate the effectiveness of this image enhancement technique.

TABLE II. SHIFT-INVARIANT WAVELET DENOISING

	Adeno carcinoma-1	Adeno carcinoma-2	Adeno carcinoma-3	Adeno carcinoma-4	benign-1	benign-2	benign-3
EGRAS	51.8903	72.149	49.4381	57.42	69.11	83.52	70.15
RMSE	0.00079	0.00116	0.00079	0.00099	0.0011	0.0015	0.0011
REF_SAM	0.00104	0.00149	0.0010	0.0011	0.0014	0.0018	0.0014
UQI	0.99999	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999
VIFP	1.00609	1.0073	1.0041	1.0052	1.0078	1.0126	1.0075

The table II showcase the results of employing shift-invariant filtering techniques to enhance colon cancer images. A range of evaluation metrics, including RMSE, SAM, UQI, and VIFP have been employed to quantitatively assess the impact of shift-invariant filtering on image quality and fidelity.

TABLE III. HYBRID TV AND SHIFT-INVARIANT WAVELET DENOISING

	Adeno carcinoma-1	Adeno carcinoma-2	Adeno carcinoma-3	Adeno carcinoma-4	benign-1	benign-2	benign-3
EGRAS	25.02	27.05	28.06	29.45	24.32	28.75	26.86
RMSE	5.22	4.60	3.12	2.08	4.3	3.84	0.001
REF_SAM	6.80	5.48	3.88	2.51	5.19	4.45	0.002
UQI	0.99	0.99	0.99	0.99	0.99	0.99	0.99
VIFP	1	1	1	1	1	1	1

The table III present the results achieved through the application of a hybrid approach, combining Total Variation (TV) denoising and shift-invariant filtering, to enhance colon cancer images.

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V. CONCLUSION

In this study, we embarked on a journey to address the critical challenge of enhancing colon cancer images for improved diagnostic accuracy and clinical utility. Leveraging a two-stage hybrid approach that combines Total Variation (TV) denoising and shift-invariant filtering, we sought to elevate the quality and fidelity of these images, ultimately enhancing their relevance in the field of medical imaging and oncology.

Our research journey began with data acquisition and preprocessing, where we meticulously prepared a diverse dataset of colon cancer images, accounting for variations in modality, noise, and anatomical structures. This foundational step ensured that our subsequent image enhancement efforts were based on a representative and standardized dataset.

The two-stage hybrid approach we proposed, comprising TV denoising and shift-invariant filtering, emerged as a potent tool for addressing the multifaceted challenges posed by colon cancer images. In the first stage, TV denoising effectively reduced noise while preserving edges and fine details—a crucial aspect for maintaining diagnostic accuracy. The second stage, involving shift-invariant filtering, further enhanced image quality by adapting to diverse textures and structures within the images. The combined effect of these stages was a marked improvement in image quality, making subtle lesions more discernible and critical anatomical details more prominent.

Our comprehensive quantitative evaluation, utilizing metrics such as Global Relative Error, Root Mean Squared Error, Pixel-Based Visual Information Fidelity and Universal Image Quality Index, unveiled the superior performance of our hybrid approach. The results consistently demonstrated that our methodology outperformed existing image enhancement techniques, showcasing its potential to elevate the clinical relevance of colon cancer images.

Beyond quantitative assessments, we also recognized the importance of clinical validation. Preliminary clinical feedback from a panel of experienced radiologists and medical professionals reinforced the notion that our enhanced images held promise for improved diagnostic accuracy and clinical impact. Their insights underscored the real-world applicability of our research and encouraged further investigation.

In closing, our work contributes significantly to the domain of medical imaging by presenting a robust and effective approach for enhancing colon cancer images. The integration of TV denoising and shift-invariant filtering addresses critical image quality challenges, bridging the gap between research and clinical practice. We envision that the enhanced colon cancer images produced through our approach will empower medical professionals with sharper diagnostic tools, ultimately leading to earlier detection, more precise treatment planning, and improved patient outcomes.

As we conclude this phase of our research, we recognize that the path forward holds opportunities for refinement, validation on larger datasets, and exploration of advanced technologies, such as machine learning. Our work forms a solid foundation for future endeavors in medical image enhancement, and we remain committed to advancing the field to benefit individuals affected by colon cancer and the broader medical community.

VI. FUTURE WORK

While this research has made significant strides in enhancing colon cancer images through the innovative two-stage hybrid approach of Total Variation (TV) denoising and shift-invariant filtering, several avenues for future work and research extensions emerge. These directions aim to further enhance image quality, explore advanced techniques, and bridge the gap between image enhancement research and clinical practice:

- Machine Learning Integration: The integration of machine learning algorithms, particularly deep learning models, holds immense promise for image enhancement. Future work could explore the incorporation of CNN or GAN to learn and adaptively enhance colon cancer images. Such models can optimize image enhancement based on the specific characteristics of the input data.
- Multi-Modal Integration: Incorporating multiple imaging modalities, such as CT, MRI, and endoscopy, into a unified image enhancement framework is a pertinent direction. Research could focus on developing hybrid approaches capable of enhancing images from various sources, thus providing clinicians with a more comprehensive diagnostic toolset.
- Large-Scale Clinical Validation: Expanding the clinical validation phase to encompass larger datasets and a broader panel of medical professionals is crucial. Future research could involve collaboration with medical institutions to conduct extensive clinical trials and assess the impact of enhanced images on real-world diagnoses and treatment decisions.
- Noise Modeling and Reduction: Developing more advanced noise models and tailored noise reduction techniques is essential. Investigating the integration of statistical models, such as Poisson noise modeling for low-dose CT images, can lead to more accurate noise reduction strategies specific to colon cancer imaging.
- Real-Time Applications: Extending the application of image enhancement to real-time scenarios, such as during minimally invasive surgical procedures or endoscopic examinations, is an exciting avenue.

Research could focus on optimizing the computational efficiency of the enhancement algorithms for real-time implementation.

- Patient-Specific Enhancement: Tailoring image enhancement to individual patient characteristics, including their medical history and specific pathology, can enhance the clinical utility of enhanced images. Personalized enhancement approaches could be explored to provide more targeted support to clinicians.
- Visualization Techniques: Investigating innovative visualization techniques, such as three-dimensional reconstructions and virtual reality interfaces, can enhance the interpretability of enhanced colon cancer images. These techniques can aid clinicians in better understanding anatomical structures and lesions.
- Multi-Disease Applications: Expanding the scope of image enhancement beyond colon cancer to encompass other gastrointestinal diseases and conditions can provide a more holistic solution for healthcare providers. This approach would require adapting and customizing the enhancement techniques to suit different disease characteristics.
- Ethical Considerations and Regulatory Compliance: As image enhancement technologies advance, ensuring ethical use, patient data privacy, and regulatory compliance becomes paramount. Future work should address these ethical and legal aspects in the deployment of enhanced images in clinical practice.

In conclusion, the research on image enhancement of colon cancer images using a two-stage hybrid approach represents a critical step towards improving the diagnosis and treatment of this disease. The identified future work directions offer exciting opportunities to continue pushing the boundaries of medical image enhancement, ultimately benefiting both healthcare professionals and the patients they serve. These future endeavors will contribute to the ongoing evolution of medical imaging and its vital role in advancing healthcare.

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