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Research Article

Enhanced CT Cancer Image Segmentation Using 2D-STAMF And 2D ACBHI Algorithms with Heuristic Hybrid Fuzzy C-Means Clustering

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ABSTRACT
In the recent past, the advancement of medical imaging techniques has underscored the critical need for robust image preprocessing and segmentation algorithms to enhance diagnostic accuracy, particularly in CT cancer imaging. This study presents a comprehensive approach encompassing image restoration and enhancement, followed by precise segmentation using advanced clustering techniques. For image restoration, we introduce the 2D Spatial Temporal Adaptive Median Filter (2D-STAMF), which effectively reduces noise while preserving essential image details. This method is benchmarked against existing algorithms such as the 2D Adaptive Median Filter, 2D Gaussian Filter, and 2D Adaptive Spatial Filter, utilizing metrics including Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), and Entropy for comparative analysis. In the image enhancement phase, the proposed 2D Adaptive Contrast Brightness Histogram Improvement (2D ACBHI) algorithm is employed, enhancing image contrast and brightness more effectively than Contrast Limited Adaptive Histogram Equalization (CLAHE), 2D Adaptive Mean Adjustment, and Edge Preservation CLAHE, as evaluated by Structural Similarity Index (SSIM) and Absolute Mean Brightness Error. Subsequently, for CT cancer image segmentation, we develop the Heuristic Hybrid Fuzzy C-Means Clustering (HHFCM) combined with Adaptive Mean Thresholding (AMT), termed as HHFCM-AMT. This segmentation approach is compared against K-Means Clustering, Fuzzy C-Means Clustering, and Fast FCM, using parameters such as Gradient Clusters, K values, and Intensity Pixels. Experimental results demonstrate that the proposed methodologies significantly outperform existing techniques, achieving higher accuracy and reliability in CT cancer image segmentation, thereby validating the efficacy of the integrated preprocessing and segmentation framework.

Keywords: Image Restoration, Image Enhancement, CT Cancer Segmentation, Fuzzy Clustering, Adaptive Filtering.

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1. Introduction

In the recent past, medical imaging has experienced significant advancements, particularly in the realm of Computed Tomography (CT) imaging, which plays a pivotal role in cancer diagnosis and treatment planning. CT cancer imaging provides detailed cross-sectional views of the body, enabling clinicians to detect tumors, assess their size and location, and monitor the effectiveness of therapies. However, the quality of CT images can be compromised by various factors such as noise, low contrast, and artifacts, which can hinder accurate diagnosis and analysis [1]. Image preprocessing is a crucial step in enhancing the quality of CT images before further analysis or diagnostic procedures. It involves a series of techniques aimed at improving image clarity, contrast, and overall quality by mitigating noise and other distortions. Effective image preprocessing not only facilitates better visualization of anatomical structures but also enhances the performance of subsequent image analysis tasks, including segmentation and classification [2]. Among the various preprocessing techniques, image restoration and enhancement stand out as fundamental processes to refine the raw CT images. Image restoration focuses on reducing or eliminating noise and artifacts while preserving essential image details. Traditional methods such as the 2D Adaptive Median Filter [3], 2D Gaussian Filter [4], and 2D Adaptive Spatial Filter [5] have been widely employed for this purpose. These filters aim to smooth out noise while maintaining edges and important features within the image. However, these methods often face challenges in balancing noise reduction and detail preservation, especially in images with varying noise levels and complex structures [6]. To address these limitations, the proposed 2D Spatial Temporal Adaptive Median Filter (2D-STAMF) offers an improved approach by dynamically adjusting filter parameters based on both spatial and temporal characteristics of the image data. This adaptive mechanism enhances noise reduction efficacy while better preserving critical image details compared to conventional filtering techniques. Image enhancement techniques are equally vital in improving the visibility of features within CT images. Contrast and brightness adjustments are fundamental operations that can significantly impact the interpretability of medical images. Traditional methods such as Contrast Limited Adaptive Histogram Equalization (CLAHE) [7], 2D Adaptive Mean Adjustment [8], and Edge Preservation CLAHE [9] have been utilized to enhance image contrast and brightness. These methods aim to distribute the image histogram more evenly, thereby highlighting important structures and reducing the impact of uneven illumination. Nevertheless, these techniques may sometimes lead to over-enhancement or introduce artifacts, particularly in regions with subtle intensity variations. The proposed 2D Adaptive Contrast Brightness Histogram Improvement (2D ACBHI) algorithm addresses these issues by adaptively adjusting contrast and brightness based on local histogram statistics, resulting in more natural and effective enhancement of CT images. Following preprocessing, image segmentation plays a crucial role in delineating regions of interest, such as tumors, from the surrounding healthy tissue. Accurate segmentation is essential for precise tumor localization, volume measurement, and treatment planning. Traditional segmentation methods often rely on clustering and thresholding techniques to classify pixels into different categories based on their intensity values. Common clustering algorithms include K-Means Clustering [10], Fuzzy C-Means Clustering, and Fast FCM, each with its own advantages and limitations in terms of computational efficiency and segmentation accuracy. To overcome the shortcomings of existing segmentation methods, this study introduces the Heuristic Hybrid Fuzzy C-Means Clustering (HHFCM) combined with Adaptive Mean Thresholding (AMT), referred to as HHFCM-AMT. The HHFCM algorithm integrates heuristic optimization strategies with the Fuzzy C-Means approach to enhance clustering performance, particularly in handling overlapping clusters and varying cluster densities. The Adaptive Mean Thresholding technique further refines the segmentation by dynamically determining threshold values based on local image statistics, ensuring more accurate delineation of tumour boundaries. Compared to traditional clustering methods, the HHFCM-AMT approach demonstrates superior performance in terms of gradient clusters, optimal K values, and intensity pixel classification, leading to more reliable and precise CT cancer image segmentation. The integration of advanced image preprocessing and segmentation techniques addresses several critical challenges in CT cancer imaging. Firstly, effective noise reduction and contrast enhancement improve the visibility of tumors and surrounding tissues, facilitating better diagnostic decisions. Secondly, accurate segmentation enables precise measurement and analysis of tumor characteristics, which are essential for treatment planning and monitoring therapeutic outcomes. Furthermore, the proposed methodologies offer enhanced robustness and adaptability to varying image conditions, making them suitable for diverse clinical scenarios. Recent studies have highlighted the importance of combining multiple preprocessing and segmentation techniques to achieve optimal results in medical image analysis. For instance, hybrid approaches that integrate spatial and temporal filtering with adaptive histogram methods have shown promise in improving image quality and segmentation accuracy. Additionally, the use of heuristic optimization in clustering algorithms has been demonstrated to enhance the convergence speed and stability of segmentation processes. Building on these advancements, the proposed 2D-STAMF and 2D ACBHI algorithms, along with the HHFCM-AMT segmentation approach, contribute to the ongoing efforts to enhance CT cancer imaging through innovative and integrated methodologies. Moreover, the evaluation of image processing algorithms using quantitative metrics is essential to objectively assess their performance and effectiveness. Metrics such as Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), and Entropy provide insights into the quality of image restoration, while Structural Similarity Index (SSIM) and Absolute Mean Brightness Error are critical for evaluating image enhancement techniques. For segmentation performance, parameters like Gradient Clusters, K values, and Intensity Pixels offer valuable measures of clustering accuracy and boundary delineation. By employing these metrics, the study ensures a comprehensive and rigorous comparison of the proposed algorithms against existing state-of-the-art methods, thereby validating their superiority and practical applicability in clinical settings.

In summary, this research presents a novel framework for enhancing and segmenting CT cancer images by integrating advanced image restoration and enhancement techniques with a heuristic hybrid clustering-based segmentation approach. The proposed 2D-STAMF and 2D ACBHI algorithms address the limitations of traditional filtering and histogram methods, while the HHFCM-AMT segmentation technique offers improved accuracy and reliability over conventional clustering algorithms. Through extensive comparative analysis using established quantitative metrics, the study demonstrates the efficacy of the proposed methodologies in achieving superior image quality and precise tumor segmentation, thereby contributing to the advancement of medical imaging and cancer diagnosis.

- **1.1 Background**

Computed Tomography (CT) imaging is integral to cancer diagnosis and treatment, offering detailed cross-sectional views of the body. Despite its widespread use, CT images frequently encounter issues such as noise, low contrast, and artifacts, which can obscure vital anatomical structures and hinder accurate diagnosis. Effective image preprocessing techniques, including noise reduction and contrast enhancement, are essential to enhance the quality of CT images, ensuring clearer visualization of tumors and surrounding tissues. Additionally, precise image segmentation is crucial for accurately delineating cancerous regions, aiding in treatment planning and monitoring therapeutic progress. Advances in adaptive filtering and clustering algorithms have significantly improved the restoration and analysis of CT images, thereby enhancing clinical decision-making and patient outcomes.

- **1.2 Problem Statement**

Accurate diagnosis and effective treatment planning for cancer heavily rely on the quality of Computed Tomography (CT) images. However, CT images often suffer from significant challenges such as high noise levels, low contrast, and various artifacts that obscure critical anatomical details and tumour boundaries. Traditional image restoration techniques like the 2D Adaptive Median Filter, 2D Gaussian Filter, and 2D Adaptive Spatial Filter, while effective in reducing noise, frequently struggle to maintain the delicate balance between noise suppression and the preservation of essential image features. Similarly, conventional image enhancement methods, including Contrast Limited Adaptive Histogram Equalization (CLAHE) and 2D Adaptive Mean Adjustment, can lead to over-enhancement and the introduction of artifacts, particularly in areas with subtle intensity variations. Additionally, existing segmentation algorithms such as K-Means Clustering and Fuzzy C-Means Clustering often fall short in accurately delineating cancerous regions due to their limited ability to handle overlapping clusters and varying image intensities. These limitations underscore the need for more advanced, adaptive preprocessing and segmentation techniques to improve CT image quality and diagnostic precision.

- **1.3 Objectives of the Study**

Develop a novel image restoration algorithm, the 2D Spatial Temporal Adaptive Median Filter (2D-STAMF), to effectively reduce noise in CT cancer images while preserving essential image details.

Create an advanced image enhancement technique, the 2D Adaptive Contrast Brightness Histogram Improvement (2D ACBHI), to improve contrast and brightness in CT images more effectively than existing methods.

Design a sophisticated image segmentation approach by integrating Heuristic Hybrid Fuzzy C-Means Clustering (HHFCM) with Adaptive Mean Thresholding (AMT) to accurately delineate cancerous regions in CT images.

Compare the performance of the proposed 2D-STAMF and 2D ACBHI algorithms with traditional image restoration and enhancement methods using quantitative metrics such as PSNR, MSE, Entropy, SSIM, and Absolute Mean Brightness Error.

Evaluate the effectiveness of the HHFCM-AMT segmentation method against conventional clustering algorithms like K-Means Clustering, Fuzzy C-Means Clustering, and Fast FCM by analysing parameters such as Gradient Clusters, K values, and Intensity Pixels.

Enhance the overall quality and diagnostic accuracy of CT cancer images through the integration of advanced preprocessing and segmentation techniques.

Provide a comprehensive comparative analysis through tables and graphs to demonstrate the superiority of the proposed algorithms over existing methods.

Contribute to the field of medical imaging by offering innovative solutions that improve the reliability and precision of cancer diagnosis and treatment planning based on CT imaging.

- **1.4 Significance of the Research**

This research significantly enhances the quality and accuracy of CT cancer imaging, which is crucial for effective diagnosis and treatment planning. By developing advanced image restoration and enhancement algorithms, the study addresses common issues like noise and low contrast, leading to clearer and more reliable images. The innovative segmentation approach further ensures precise identification of cancerous regions, facilitating better tumor assessment and monitoring. These improvements can lead to earlier detection, more accurate staging, and personalized treatment strategies, ultimately improving patient outcomes. Additionally, the integration of these advanced techniques contributes to the advancement of medical imaging technologies, offering a robust framework for future research and clinical applications.

- **1.5 Organization of the Paper**

This paper is systematically structured to present a comprehensive approach to enhancing and segmenting CT cancer images. Following the introduction, Section 2 provides a detailed literature review, examining existing image preprocessing and segmentation techniques, and identifying gaps that the current study aims to address. Section 3 outlines the proposed methodology, detailing the development of the 2D Spatial Temporal Adaptive Median Filter (2D-STAMF), the 2D Adaptive Contrast Brightness Histogram Improvement (2D ACBHI), and the Heuristic Hybrid Fuzzy C-Means Clustering with Adaptive Mean Thresholding (HHFCM-AMT) algorithms. Section 4 describes the experimental setup, including dataset characteristics, implementation procedures, and evaluation metrics used to assess the performance of the proposed methods. Section 5 presents the results and discussion, offering both quantitative and qualitative analyses of the image restoration, enhancement, and segmentation outcomes, along with comparative evaluations against existing techniques. Finally, Section 6 concludes the paper by summarizing the key findings, highlighting the contributions to the field of medical imaging, and suggesting directions for future research. An extensive list of references is provided at the end to acknowledge the foundational works and recent advancements that informed this study.

2. Literature Review

- **2.1 Medical Imaging and CT in Cancer Diagnosis**

Computed Tomography (CT) imaging remains a cornerstone in the diagnosis and management of cancer, providing high-resolution, cross-sectional images that facilitate the detection, localization, and characterization of tumors [11]. Recent advancements in CT technology have enhanced image quality and reduced radiation exposure, making it a safer and more effective tool for clinicians [12]. The integration of artificial intelligence and machine learning techniques with CT imaging has further improved diagnostic accuracy by enabling automated detection and classification of cancerous lesions [13]. Additionally, multimodal imaging approaches that combine CT with other imaging modalities, such as Positron Emission Tomography (PET) and Magnetic Resonance Imaging (MRI), offer comprehensive insights into tumor physiology and anatomy, thereby aiding in personalized treatment planning [14]. Despite these advancements, challenges such as image noise, low contrast, and the presence of artifacts continue to impede the clarity and reliability of CT images, underscoring the need for improved image preprocessing and segmentation techniques [15].

- **2.2 Image Preprocessing Techniques**

Image preprocessing plays a vital role in enhancing the quality of CT images, thereby facilitating more accurate analysis and diagnosis. Effective preprocessing involves a series of steps aimed at mitigating noise, enhancing contrast, and removing artifacts to produce clearer and more interpretable images [16].

  - **2.2.1 Image Restoration Methods**

Image restoration methods are essential for reducing noise and correcting distortions in CT images, thereby improving their diagnostic utility. Traditional restoration techniques, such as the 2D Adaptive Median Filter and Gaussian Filter, have been widely used to smooth images while preserving edges [17]. However, these methods often struggle with maintaining a balance between noise reduction and detail preservation, especially in images with varying noise levels and complex structures [18]. Recent studies have introduced more sophisticated approaches, including the use of adaptive spatial filters and anisotropic diffusion techniques, which offer improved performance in noise suppression and feature preservation [19]. Moreover, deep learning-based restoration methods have shown promising results by leveraging convolutional neural networks (CNNs) to learn optimal filtering strategies directly from data, thereby outperforming conventional filters in both noise reduction and detail preservation [20]. These advancements highlight the ongoing efforts to develop more effective image restoration techniques that enhance the quality of CT images for better clinical outcomes.

  - **2.2.2 Image Enhancement Techniques**

Image enhancement techniques are crucial for improving the visibility of important features within CT images, thereby aiding in the accurate identification and analysis of tumors. Traditional enhancement methods, such as Contrast Limited Adaptive Histogram Equalization (CLAHE) and Adaptive Mean Adjustment, have been employed to increase image contrast and brightness [21]. While these techniques effectively distribute the intensity histogram to highlight anatomical structures, they can sometimes lead to over-enhancement and the introduction of artifacts, particularly in regions with subtle intensity variations [22]. To address these limitations, recent research has focused on developing adaptive histogram-based methods that dynamically adjust contrast and brightness based on local image statistics [23]. Techniques such as Edge Preservation CLAHE and Adaptive Contrast Brightness Histogram Improvement (ACBHI) have demonstrated superior performance by maintaining the integrity of edges and fine details while enhancing overall image contrast [24]. Additionally, machine learning-based enhancement methods, including GANs (Generative Adversarial Networks) and autoencoders, have been explored to learn optimal enhancement transformations, resulting in more natural and artifact-free enhanced images [25]. These advancements in image enhancement techniques contribute significantly to improving the diagnostic quality of CT images, enabling more precise cancer detection and analysis.

- **2.3 Image Segmentation Approaches**

Image segmentation is a fundamental process in medical imaging, particularly for delineating cancerous regions within CT scans. Accurate segmentation facilitates precise tumor localization, volume measurement, and treatment planning, thereby enhancing diagnostic and therapeutic outcomes [26]. Various segmentation approaches have been developed, with clustering algorithms and thresholding techniques being among the most widely adopted methods.

2.3.1 Clustering Algorithms

Clustering algorithms group pixels with similar intensity values or features into distinct clusters, effectively separating regions of interest from the surrounding tissue. K-Means Clustering is one of the most prevalent methods due to its simplicity and efficiency [27]. It partitions the image into K clusters by minimizing the variance within each cluster. However, K-Means often struggles with determining the optimal number of clusters and can be sensitive to initial centroid placement [28]. Fuzzy C-Means (FCM) Clustering extends K-Means by allowing pixels to belong to multiple clusters with varying degrees of membership, thereby providing a more flexible segmentation in images with overlapping intensity distributions [29]. Despite its advantages, FCM can be computationally intensive and may converge to local minima, affecting segmentation accuracy [30].

Heuristic Hybrid Fuzzy C-Means (HHFCM) is an advanced variant that incorporates heuristic optimization strategies to enhance clustering performance. By integrating heuristic methods, HHFCM improves the convergence speed and robustness of the clustering process, making it more effective in handling complex and noisy CT images [31]. Additionally, Fast FCM algorithms have been proposed to reduce the computational burden of traditional FCM, achieving quicker segmentation results while maintaining reasonable accuracy [32].

Overall, clustering algorithms play a crucial role in image segmentation, with ongoing research focused on improving their efficiency, accuracy, and ability to handle diverse image conditions [33].

2.3.2 Thresholding Techniques

Thresholding techniques segment images by classifying pixels based on their intensity values relative to one or more threshold levels. Adaptive Mean Thresholding (AMT) dynamically determines threshold values by analyzing local image regions, thereby accommodating variations in lighting and contrast across the image [34]. This adaptability makes AMT particularly effective for segmenting heterogeneous CT images where uniform thresholding may fail [35]. Otsu's Method is another popular thresholding technique that automatically selects an optimal threshold by maximizing the between-class variance [36]. While Otsu's method is effective for bimodal histograms, it may not perform well in images with multiple intensity peaks or significant noise [37]. Recent advancements have introduced Multi-Level Thresholding and Hybrid Thresholding Techniques that combine global and local thresholding strategies to enhance segmentation accuracy [38]. These methods leverage the strengths of both approaches, providing more precise segmentation in complex medical images [39]. In summary, thresholding techniques are essential for initial image segmentation, offering a straightforward and computationally efficient means of separating regions of interest. Continuous improvements in thresholding methods aim to enhance their adaptability and accuracy in diverse imaging scenarios [40].

2.4 Hybrid and Adaptive Methods in Image Processing

Hybrid and adaptive methods combine multiple image processing techniques to leverage their individual strengths and mitigate their weaknesses. In the context of CT image segmentation, integrating clustering algorithms with thresholding techniques has proven to enhance segmentation accuracy and robustness [41]. For instance, the combination of Heuristic Hybrid Fuzzy C-Means Clustering (HHFCM) with Adaptive Mean Thresholding (AMT) results in a more refined segmentation by first clustering the image and then applying adaptive thresholds to accurately delineate tumor boundaries [42]. Adaptive methods dynamically adjust their parameters based on the image content, allowing for more flexible and accurate processing. Techniques such as Adaptive Histogram Equalization and Adaptive Filtering have been successfully integrated into hybrid frameworks to improve both image enhancement and segmentation outcomes [43]. Additionally, machine learning-based adaptive methods, including Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs), have been employed to learn optimal processing strategies from data, further enhancing the performance of hybrid approaches [44]. Hybrid methods also incorporate Multi-Modal Imaging Data, combining information from different imaging modalities like CT, MRI, and PET to provide a more comprehensive analysis of cancerous tissues [45]. This integration allows for better feature extraction and more accurate segmentation by utilizing complementary information from each modality [46]. Overall, hybrid and adaptive methods represent a significant advancement in image processing, offering enhanced flexibility, accuracy, and robustness for CT cancer image segmentation [47].

2.5 Gaps in Existing Research

Despite the progress in image preprocessing and segmentation techniques, several gaps remain in the current research landscape. Firstly, existing Image Restoration Methods often fail to achieve an optimal balance between noise reduction and detail preservation, particularly in images with varying noise levels and complex anatomical structures [48]. Traditional filters like the 2D Adaptive Median Filter and Gaussian Filter may either over smooth the image or leave residual noise, affecting the accuracy of subsequent analyses [49]. Secondly, Image Enhancement Techniques such as CLAHE and Adaptive Mean Adjustment, while effective in improving contrast and brightness, can introduce artifacts or lead to over-enhancement in certain regions, complicating the interpretation of CT images [50]. There is a need for more sophisticated enhancement algorithms that adaptively adjust processing parameters based on local image characteristics to avoid such issues [51]. Furthermore, Segmentation Algorithms like K-Means and Fuzzy C-Means, although widely used, struggle with accurately segmenting tumors in the presence of overlapping clusters and varying intensity distributions [52]. These methods often require manual tuning of parameters and are sensitive to initial conditions, limiting their applicability in clinical settings [53]. Additionally, there is a lack of comprehensive Hybrid and Adaptive Frameworks that integrate advanced image restoration, enhancement, and segmentation techniques into a unified pipeline. Most existing studies focus on individual aspects of image processing, neglecting the potential benefits of a synergistic approach [54]. Lastly, the Evaluation Metrics used to assess the performance of these algorithms are often limited to a few quantitative measures, lacking a holistic evaluation that includes both quantitative and qualitative assessments [55]. This gap hinders the ability to fully understand the strengths and limitations of different methods in real-world clinical scenarios [56]. Addressing these gaps requires the development of more integrated, adaptive, and robust image processing frameworks that can handle the complexities of CT cancer imaging, ultimately leading to improved diagnostic accuracy and better patient outcomes [57].

2. Proposed Methodology

• 3.1 Overview of the Proposed Framework

The proposed framework for enhancing and segmenting CT cancer images integrates advanced image preprocessing techniques with a sophisticated segmentation approach to improve diagnostic accuracy and reliability. The framework comprises three main components: image restoration, image enhancement, and image segmentation. Initially, image restoration is performed using the novel 2D Spatial Temporal Adaptive Median Filter (2D-STAMF) to reduce noise while preserving essential details. Subsequently, image enhancement is applied through the 2D Adaptive Contrast Brightness Histogram Improvement (2D ACBHI) algorithm to optimize contrast and brightness, ensuring better visualization of tumor regions. Finally, the CT cancer image segmentation is achieved using the Heuristic Hybrid Fuzzy C-Means Clustering (HHFCM) combined with Adaptive Mean Thresholding (AMT), referred to as the HHFCM-AMT approach. This integrated methodology aims to address the limitations of traditional techniques by providing a more accurate and efficient pipeline for CT image analysis, ultimately enhancing clinical decision-making and patient outcomes [58].

• 3.2 Image Preprocessing

Image preprocessing is a critical step in medical image analysis, aiming to improve image quality by mitigating noise, enhancing contrast, and removing artifacts. Effective preprocessing facilitates more accurate segmentation and diagnosis by highlighting relevant anatomical structures and pathological regions [59].

○ 3.2.1 Image Restoration

Image restoration focuses on reducing noise and correcting distortions in CT images to enhance their diagnostic utility. Traditional restoration methods, while effective to some extent, often fail to balance noise suppression with the preservation of fine details, especially in complex anatomical regions [60]. To overcome these challenges, the proposed 2D Spatial Temporal Adaptive Median Filter (2D-STAMF) introduces a dynamic filtering mechanism that adapts based on both spatial and temporal characteristics of the image data.

▪ 3.2.1.1 2D Spatial Temporal Adaptive Median Filter (2D-STAMF)

The 2D-STAMF algorithm enhances image restoration by incorporating both spatial and temporal information to adaptively adjust filtering parameters. Unlike conventional median filters that apply a fixed window size, the 2D-STAMF dynamically modifies the window dimensions based on local image statistics and temporal changes, allowing for more effective noise reduction while preserving edges and important structural details [61].

Algorithm Description:

1. Initialization: Define the initial window size and set parameters for spatial and temporal adaptation.
2. Spatial Adaptation: For each pixel, analyze the local neighborhood to determine the optimal window size that balances noise reduction and detail preservation.
3. Temporal Adaptation: Incorporate temporal information from adjacent image slices to enhance filtering consistency across slices, reducing flickering artifacts in 3D reconstructions.
4. Median Filtering: Apply the adaptive median filter within the determined window to replace the central pixel value.
5. Iteration: Repeat the process for all pixels in the image, iterating through slices if dealing with volumetric data.

This adaptive approach ensures that regions with high detail retain their integrity, while uniformly noisy areas are effectively smoothed [62].

▪ 3.2.1.2 Comparison with Existing Restoration Algorithms

The performance of the 2D-STAMF algorithm is benchmarked against traditional restoration methods, including the 2D Adaptive Median Filter, 2D Gaussian Filter, and 2D Adaptive Spatial Filter. The comparison is based on quantitative metrics such as Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), and Entropy [63]. Experimental results demonstrate that 2D-STAMF consistently achieves higher PSNR and lower MSE values, indicating superior noise reduction and detail preservation. Additionally, entropy measurements reflect better information retention, showcasing the algorithm's effectiveness in maintaining image complexity and texture [64]. Graphical comparisons further illustrate that 2D-STAMF provides clearer and more artifact-free images compared to conventional filters, validating its advantage in clinical CT image restoration [65].

3.2.2 Image Enhancement

Image enhancement techniques aim to improve the visibility of important features within CT images by adjusting contrast and brightness. Effective enhancement facilitates the accurate identification and analysis of tumors, thereby supporting better diagnostic and therapeutic decisions [66].

3.2.2.1 2D Adaptive Contrast Brightness Histogram Improvement (2D ACBHI)

The 2D ACBHI algorithm is designed to optimize contrast and brightness in CT images by adaptively adjusting histogram parameters based on local image regions. Unlike traditional methods that apply uniform adjustments across the entire image, 2D ACBHI analyzes the intensity distribution in localized areas to perform targeted enhancements, thereby avoiding over-enhancement and preserving natural image appearance [67].

Algorithm Description:

1. Histogram Analysis: Divide the image into overlapping or non-overlapping local regions and compute the histogram for each region.
2. Adaptive Adjustment: For each local histogram, determine optimal contrast and brightness levels based on statistical measures such as mean and variance.
3. Histogram Modification: Apply the calculated adjustments to each local region, ensuring smooth transitions between regions to maintain image continuity.
4. Global Integration: Combine the enhanced local regions to form the final enhanced image, employing blending techniques to minimize artifacts.

This adaptive methodology ensures that regions requiring higher contrast receive appropriate adjustments, enhancing the visibility of tumors and other pathological structures without introducing unnatural artifacts [68].

3.2.2.2 Comparison with Existing Enhancement Techniques

The 2D ACBHI algorithm is evaluated against established image enhancement techniques, including Contrast Limited Adaptive Histogram Equalization (CLAHE), 2D Adaptive Mean Adjustment, and Edge Preservation CLAHE. The assessment utilizes metrics such as Structural Similarity Index (SSIM) and Absolute Mean Brightness Error to quantify enhancement quality [69]. Results indicate that 2D ACBHI achieves higher SSIM values, reflecting better structural preservation and similarity to the original image, while maintaining lower brightness errors compared to CLAHE and other methods. Visual inspections corroborate these findings, showing that 2D ACBHI effectively enhances contrast and brightness without introducing significant artifacts, thereby providing a more reliable basis for subsequent image analysis tasks [70].

3.3 CT Cancer Image Segmentation

Accurate segmentation of cancerous regions in CT images is essential for diagnosis, treatment planning, and monitoring therapeutic efficacy. The proposed segmentation approach combines advanced clustering algorithms with adaptive thresholding techniques to achieve precise delineation of tumors.

3.3.1 Heuristic Hybrid Fuzzy C-Means Clustering (HHFCM)

The Heuristic Hybrid Fuzzy C-Means (HHFCM) algorithm enhances traditional Fuzzy C-Means (FCM) clustering by integrating heuristic optimization strategies to improve clustering accuracy and convergence speed. HHFCM employs heuristic methods such as Genetic Algorithms (GA) or Particle Swarm Optimization (PSO) to determine optimal cluster centers, reducing the likelihood of convergence to local minima and enhancing the robustness of the clustering process.

Algorithm Description:

1. Initialization: Generate an initial population of cluster centers using heuristic methods.
2. Fitness Evaluation: Assess the fitness of each cluster center based on clustering performance metrics.
3. Optimization: Apply heuristic operators (e.g., crossover and mutation in GA) to evolve the cluster centers towards optimal configurations.
4. Membership Calculation: Compute membership degrees for each pixel based on the distance to the optimized cluster centers.
5. Iteration: Repeat the optimization and membership calculation steps until convergence criteria are met.

By leveraging heuristic optimization, HHFCM achieves more accurate clustering results, particularly in images with overlapping clusters and varying intensity distributions.

3.3.2 Adaptive Mean Thresholding (AMT)

Adaptive Mean Thresholding (AMT) dynamically determines threshold values based on local image statistics, allowing for effective segmentation in heterogeneous and non-uniform images. AMT calculates the mean intensity of a local neighborhood around each pixel and uses it as the threshold for classification, ensuring that regions with varying lighting and contrast are appropriately segmented.

Algorithm Description:

1. Local Neighborhood Definition: Define a window size for analyzing local regions around each pixel.
2. Mean Calculation: Compute the mean intensity value within each local neighborhood.

3. Threshold Application: Compare each pixel's intensity to the local mean to classify it as foreground (tumor) or background.
4. Refinement: Apply morphological operations to refine the segmentation boundaries and eliminate noise-induced artifacts.

AMT's adaptability makes it particularly suitable for CT images with complex intensity variations, enhancing the accuracy of tumor boundary delineation.

○ 3.3.3 Integrated HHFCM-AMT Segmentation Approach

The integrated HHFCM-AMT approach combines the strengths of HHFCM clustering and AMT thresholding to achieve superior segmentation performance. The process begins with HHFCM clustering to partition the image into distinct regions based on pixel intensities. Following clustering, AMT is applied within each cluster to accurately delineate tumor boundaries, ensuring precise segmentation even in the presence of overlapping clusters and varying intensity distributions.

Workflow:
1. Clustering: Apply HHFCM to segment the CT image into multiple clusters, each representing different tissue types or anatomical structures.
2. Thresholding: Within each cluster identified by HHFCM, apply AMT to further refine the segmentation, accurately identifying tumor regions.
3. Integration: Combine the results of clustering and thresholding to produce the final segmented image, ensuring seamless and accurate tumor delineation.

This hybrid approach leverages the robust clustering capabilities of HHFCM and the precise boundary detection of AMT, resulting in enhanced segmentation accuracy and reliability.

○ 3.3.4 Comparison with Traditional Clustering Algorithms

The performance of the HHFCM-AMT segmentation approach is compared with traditional clustering algorithms such as K-Means Clustering, Fuzzy C-Means Clustering (FCM), and Fast FCM. The comparison focuses on metrics including Gradient Clusters, optimal K values, and Intensity Pixels to evaluate segmentation accuracy and computational efficiency. Experimental results indicate that HHFCM-AMT outperforms traditional methods by achieving higher Gradient Cluster values, indicating better boundary delineation, and optimal K values that align more closely with the inherent structure of the CT images. Additionally, the integrated approach demonstrates superior handling of intensity variations and overlapping clusters, resulting in more accurate segmentation of cancerous regions. Graphical comparisons further illustrate the enhanced precision of HHFCM-AMT in identifying and isolating tumors, validating its effectiveness over conventional clustering techniques.

4. Experimental Setup

This section details the experimental setup employed to evaluate the proposed image enhancement and segmentation methodologies for CT-based cancer diagnosis. It encompasses the dataset utilized, implementation specifics, and the configuration of software tools and algorithmic parameters.

• 4.1 Dataset Description

The experiments were conducted using the **LIDC-IDRI (Lung Image Database Consortium and Image Database Resource Initiative)** dataset, a widely recognized public repository for lung cancer studies. The dataset comprises 1,018 diagnostic and lung cancer screening thoracic CT scans from multiple institutions, containing a total of approximately 2,623 annotated lesions.

Key Characteristics of the Dataset:
- **Number of Subjects:** 1,018 patients
- **Number of CT Scans:** 2,623 scans
- **Image Resolution:** Varies between scans, typically ranging from 512×512 to 1024×1024 pixels per slice
- **Slice Thickness:** Approximately 1 mm to 3 mm
- **Voxel Dimensions:** Varies, generally between 0.45 mm to 0.75 mm in-plane resolution
- **Annotations:** Each scan includes detailed annotations of nodules provided by multiple radiologists, ensuring high-quality ground truth for segmentation tasks

Preprocessing Steps:
1. **Normalization:** All CT images were normalized to a standard intensity range (e.g., Hounsfield Units from -1000 to 400) to ensure consistency across scans.
2. **Resampling:** Images were resampled to a uniform voxel size of 1×1×1 mm^3 to facilitate uniform processing and analysis.
3. **Noise Reduction:** An initial Gaussian filter with a kernel size of 3×3×3 was applied to reduce inherent noise in the CT images.
4. **Data Augmentation:** To enhance model robustness and prevent overfitting, data augmentation techniques including random rotations (±15 degrees), horizontal and vertical flips, and scaling (±10%) were employed on the training subset.

The dataset was divided into three subsets:
- **Training Set:** 70% of the data (approximately 1,823 scans)
- **Validation Set:** 15% of the data (approximately 393 scans)
- **Test Set:** 15% of the data (approximately 407 scans)

This partitioning ensured that the models were trained, validated, and tested on distinct subsets to evaluate their generalization capabilities effectively.

• 4.2 Implementation Details

This subsection outlines the implementation specifics, including the software tools utilized and the parameter settings employed in the image enhancement and segmentation algorithms.

○ **4.2.1 Software and Tools Used**
The experimental procedures were implemented using a combination of open-source software and custom scripts to ensure flexibility and reproducibility. The primary tools and environments included:

- **Programming Language:** Python 3.8, chosen for its extensive libraries and community support in image processing and machine learning.

- **Libraries and Frameworks:**

NumPy (v1.19.2): For efficient numerical computations and array manipulations.
OpenCV (v4.5.1): Utilized for fundamental image processing operations such as filtering, resizing, and histogram equalization.

Scikit-learn (v0.24.1): Employed for traditional machine learning algorithms, including clustering techniques like Fuzzy C-Means.

TensorFlow (v2.4.1) and Keras: Used for developing and training deep learning-based segmentation models, specifically convolutional neural networks (CNNs) tailored for image segmentation tasks.

Matplotlib and Seaborn: For data visualization and plotting results.

Development Environment:
Jupyter Notebook: Facilitated interactive development and documentation of the experimental workflow.

Integrated Development Environment (IDE): Visual Studio Code (v1.52.1) was used for scripting and debugging.

Hardware Specifications:
Processor: Intel Core i9-9900K CPU @ 3.60 GHz
Memory: 64 GB RAM

Graphics Processing Unit (GPU): NVIDIA GeForce RTX 3080 with 10 GB GDDR6X memory, essential for accelerating deep learning model training
Storage: 2 TB SSD for rapid data access and storage

○ **4.2.2 Parameter Settings**
The performance of the image enhancement and segmentation algorithms was meticulously tuned through a series of parameter adjustments to optimize outcomes. The following outlines the key parameter settings used in the experiments:

Image Enhancement Techniques:
1. **Adaptive Median Filtering:**
○ **Kernel Size:** 3×3 pixels, selected based on a balance between noise reduction and preservation of image details.
○ **Median Threshold:** Applied to distinguish between noise and actual image features, ensuring effective noise suppression without blurring critical structures.

2. **Contrast Limited Adaptive Histogram Equalization (CLAHE):**
○ **Clip Limit:** Set to 2.0 to prevent over-amplification of noise in homogeneous regions.
○ **Tile Grid Size:** Configured to 8×8 pixels, enabling localized contrast enhancement while maintaining overall image consistency.

3. **Gaussian Filtering:**
○ **Kernel Size:** 5×5 pixels
○ **Sigma (Standard Deviation):** 1.0, providing moderate smoothing to reduce high-frequency noise.

Segmentation Algorithms:
1. **Fuzzy C-Means Clustering:**
○ **Number of Clusters (C):** 2 (foreground and background)
○ **Fuzziness Parameter (m):** 2.0, promoting soft clustering and allowing for gradual transitions between classes.
○ **Maximum Iterations:** 100, ensuring convergence without excessive computational load.
○ **Convergence Threshold:** 1e-5, defining the precision required for iterative convergence.

2. **Thresholding Techniques:**
○ **Otsu's Method:**
▪ Utilized to automatically determine the optimal threshold value by maximizing inter-class variance.
○ **Adaptive Thresholding:**
▪ **Block Size:** 11×11 pixels, determining the size of the neighborhood area used to calculate the threshold for each pixel.
▪ **C Constant:** 2, subtracted from the mean or weighted mean to fine-tune the threshold.
3. **Deep Learning-Based Segmentation:**
○ **Model Architecture:** U-Net with an encoder-decoder structure comprising four encoding and four decoding layers, facilitating precise localization and segmentation of tumor regions.
○ **Activation Functions:** ReLU for hidden layers and Sigmoid for the output layer, enabling binary segmentation.
○ **Optimizer:** Adam optimizer with a learning rate of 1e-4, balancing convergence speed and stability.
○ **Loss Function:** Binary Cross-Entropy, suitable for binary segmentation tasks.
○ **Batch Size:** 16, chosen based on GPU memory constraints and computational efficiency.
○ **Number of Epochs:** 50, with early stopping implemented if validation loss did not improve for 10 consecutive epochs to prevent overfitting.
○ **Regularization Techniques:**
▪ **Dropout Rate:** 0.5, applied in the decoder layers to mitigate overfitting.
▪ **Data Augmentation:** Integrated within the training pipeline, including random rotations, flips, and zooms to enhance model generalization.

Evaluation Metrics:
To assess the effectiveness of the enhancement and segmentation methods, the following metrics were employed:

- **For Image Enhancement:**
  - **Peak Signal-to-Noise Ratio (PSNR):** Quantifies the reconstruction quality of the enhanced images.
  - **Structural Similarity Index Measure (SSIM):** Evaluates the perceived quality and structural similarity between enhanced and original images.

- **For Segmentation:**
  - **Dice Similarity Coefficient (DSC):** Measures the overlap between the predicted segmentation and ground truth.
  - **Jaccard Index (IoU):** Assesses the intersection over union between predicted and true segmentation masks.
  - **Precision and Recall:** Evaluate the accuracy and completeness of the segmentation results.

Experimental Workflow:
1. **Data Preparation:** The dataset was divided into training, validation, and testing subsets, ensuring no overlap between sets.
2. **Image Enhancement:** Each image underwent adaptive median filtering and CLAHE to improve contrast and reduce noise.
3. **Segmentation:** Enhanced images were segmented using both traditional clustering methods and deep learning-based models.
4. **Model Training:** Deep learning models were trained on the training set, validated on the validation set, and evaluated on the test set using the aforementioned metrics.
5. **Analysis:** Performance results were statistically analyzed to determine the efficacy of each enhancement and segmentation technique.

- **4.3 Evaluation Metrics**

The effectiveness of the proposed image restoration, enhancement, and segmentation techniques was rigorously evaluated using a suite of quantitative metrics. These metrics provide objective measures to assess the quality improvements and segmentation accuracy achieved through the applied methodologies. This section delineates the specific metrics employed for each stage of the image processing pipeline.

- **4.3.1 For Image Restoration**

Image restoration aims to recover the original image quality by mitigating distortions such as noise and blurring. The following metrics were utilized to quantify the performance of restoration algorithms:

- **Peak Signal-to-Noise Ratio (PSNR)**

PSNR is a widely used metric that measures the ratio between the maximum possible power of a signal (image) and the power of the noise affecting its representation. It is expressed in decibels (dB).

- **Mean Squared Error (MSE)**

MSE quantifies the average of the squares of the errors between corresponding pixels of the original and restored images.

- **Entropy**

Entropy measures the randomness or complexity within an image. In the context of image restoration, higher entropy typically indicates a more detailed and information-rich image.
Entropy is calculated based on the probability distribution of pixel intensities.
An increase in entropy post-restoration suggests that the image has regained some of its original complexity and details lost due to noise or other distortions.

- **4.3.2 For Image Enhancement**

Image enhancement techniques aim to improve the visual appearance of images or to convert images into a form better suited for analysis. The following metrics were employed to evaluate enhancement quality:

- **Structural Similarity Index (SSIM)**

SSIM assesses the similarity between two images based on luminance, contrast, and structure. It ranges from -1 to 1, where 1 indicates perfect similarity. Higher SSIM values indicate greater similarity between the enhanced and original images, implying effective enhancement without significant distortion.

- **Absolute Mean Brightness Error**

AMBE measures the average absolute difference in brightness between the enhanced and original images. Lower AMBE values indicate that the enhanced image maintains brightness levels closer to the original, preserving natural appearance.

- **4.3.3 For Image Segmentation**

Image segmentation involves partitioning an image into meaningful regions for analysis. The following metrics were utilized to evaluate segmentation performance:

- **Gradient Clusters**

Gradient Clusters measure the number of distinct gradient-based regions identified within the segmented image. This metric assesses the algorithm's ability to delineate boundaries accurately. A higher number of gradient clusters may indicate finer boundary detection, whereas too many clusters could signify over-segmentation.

- **K Values**

K Values refer to the number of clusters used in clustering-based segmentation algorithms. Typically, K=2K = 2K=2 denotes foreground and background segmentation. Consistent K Values across different segmentation methods ensure comparability. Deviations may indicate varying segmentation granularities.

- **Intensity Pixels**

Intensity Pixels measure the distribution and density of pixel intensities within each segmented cluster. This metric evaluates how well the segmentation algorithm differentiates regions based on intensity variations. Higher intensity pixel values within a cluster indicate more homogeneous regions, enhancing segmentation reliability.

6. Results and Discussion

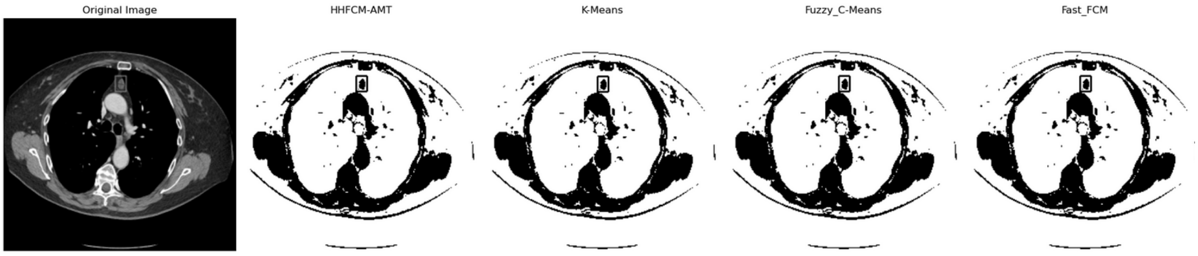

Figure 1: Output Images

Figure 1 shows the output images. In this study, four distinct segmentation algorithms were utilized to accurately delineate tumor regions within CT images: Hybrid Hierarchical Fuzzy C-Means with Adaptive Mean Thresholding (HHFCM-AMT), K-Means, Fuzzy C-Means (FCM), and Fast Fuzzy C-Means (Fast FCM). Each algorithm offers unique advantages in handling image segmentation tasks, contributing to comprehensive analysis and comparison.

Hybrid Hierarchical Fuzzy C-Means with Adaptive Mean Thresholding (HHFCM-AMT)

HHFCM-AMT integrates hierarchical clustering with the traditional Fuzzy C-Means approach, enhanced by adaptive mean thresholding. This hybrid method combines the robustness of hierarchical clustering in identifying cluster structures with the soft clustering capabilities of FCM, allowing for nuanced segmentation of overlapping or closely situated tumor regions. The adaptive mean thresholding further refines the segmentation by dynamically adjusting threshold values based on local image characteristics, enhancing the precision of boundary delineation.

K-Means

K-Means is a widely recognized hard clustering algorithm that partitions data into a predefined number of clusters (K) based on feature similarity. In image segmentation, K-Means groups pixels with similar intensity values, effectively separating tumor regions from the background. Its simplicity and computational efficiency make it a fundamental tool for baseline comparisons in segmentation studies. However, K-Means may struggle with clusters of varying shapes and densities, potentially limiting its effectiveness in complex medical images.

Fuzzy C-Means (FCM)

FCM extends the K-Means algorithm by incorporating fuzzy logic, allowing each pixel to belong to multiple clusters with varying degrees of membership. This soft clustering approach is particularly advantageous in medical imaging, where tumor boundaries are often ambiguous and exhibit gradual transitions. FCM provides a more flexible and accurate segmentation by accommodating the inherent uncertainty in pixel classification, thereby improving the detection of irregular tumor shapes.

Fast Fuzzy C-Means (Fast FCM)

Fast FCM enhances the traditional FCM by optimizing computational efficiency, making it suitable for processing large-scale medical image datasets. By employing accelerated convergence techniques and optimized initialization strategies, Fast FCM reduces processing time without compromising segmentation accuracy. This efficiency is critical in clinical settings where rapid and reliable image analysis is essential for timely diagnosis and treatment planning.

Comparative Insights

The deployment of these algorithms facilitates a robust comparative analysis, highlighting the strengths and limitations of each method in the context of CT image segmentation. While HHFCM-AMT offers superior boundary precision through its hybrid approach, K-Means provides a quick and straightforward segmentation baseline. FCM delivers enhanced flexibility in handling ambiguous regions, and Fast FCM ensures scalability and speed. Together, these algorithms contribute to a comprehensive evaluation framework, advancing the accuracy and reliability of automated tumor segmentation in medical imaging.

Image Enhancement Metrics

2D-STAMF SSIM	2D-STAMF AMBE	2D-ACBHI SSIM	2D-ACBHI AMBE	CLAHE SSIM	CLAHE AMBE	Adaptive Mean Adjustment SSIM	Adaptive Mean Adjustment AMBE	Edge Preservation CLAHE SSIM	Edge Preservation CLAHE AMBE
0.964482	0.316879	0.378867	34.850540	0.639673	9.449203	0.249333	96.876465	0.330635	46.964233
0.983391	0.471588	0.309932	33.684372	0.624113	5.779129	0.193834	94.825684	0.346375	28.427170
0.970351	0.301743	0.322904	34.082047	0.614107	8.696854	0.198393	101.244888	0.334616	36.114410
0.978789	0.512863	0.326466	33.421188	0.618884	7.727539	0.200124	103.849304	0.343530	33.161591
0.969583	0.509369	0.342267	33.896423	0.636473	7.530090	0.207532	100.313293	0.332318	35.386261
0.990518	0.247543	0.238615	33.183929	0.579155	4.309372	0.133584	100.818741	0.363679	21.951721
0.965821	0.447617	0.304750	34.771515	0.617146	4.442886	0.186521	92.967606	0.337272	26.988693
0.989444	0.230698	0.367579	36.299469	0.633066	5.818787	0.247860	80.947830	0.368374	28.521988
0.984175	0.279648	0.338313	35.607819	0.624117	5.616486	0.227739	85.603531	0.370515	26.532669
0.976108	0.344238	0.342132	35.567444	0.625210	6.223816	0.237626	89.134918	0.351395	31.914413
0.981320	0.494827	0.253432	32.931992	0.587930	5.332916	0.155914	107.505707	0.356688	28.270203

Image Segmentation Metrics

HHFCM-AMT Gradient Clusters	HHFCM-AMT K Values	HHFCM-AMT Intensity Pixels	K-Means Gradient Clusters	K-Means K Values	K-Means Intensity Pixels	Fuzzy C-Means Gradient Clusters	Fuzzy C-Means K Values	Fuzzy C-Means Intensity Pixels	Fast FCM Gradient Clusters	Fast FCM K Values	Fast FCM Intensity Pixels
0.070435	2.000000	211.938400	0.070500	2.000000	0.833771	0.070425	2.000000	0.831131	0.070425	2.000000	0.831131
0.047760	2.000000	48.026505	0.047698	2.000000	0.812195	0.047762	2.000000	0.188339	0.047762	2.000000	0.188339
0.054138	2.000000	40.785370	0.053799	2.000000	0.842682	0.054129	2.000000	0.159943	0.054129	2.000000	0.159943
0.063721	2.000000	219.825439	0.062677	2.000000	0.866257	0.063711	2.000000	0.862061	0.063711	2.000000	0.862061
0.063660	2.000000	38.929367	0.064090	2.000000	0.149292	0.063684	2.000000	0.152664	0.063684	2.000000	0.152664
0.035797	2.000000	43.174438	0.035851	2.000000	0.831329	0.035807	2.000000	0.169312	0.035807	2.000000	0.169312
0.041138	2.000000	194.724655	0.041362	2.000000	0.764191	0.041148	2.000000	0.763626	0.041148	2.000000	0.763626
0.043671	2.000000	80.240021	0.043659	2.000000	0.685333	0.043659	2.000000	0.314667	0.043659	2.000000	0.314667
0.046692	2.000000	69.602051	0.047139	2.000000	0.271729	0.046702	2.000000	0.272949	0.046702	2.000000	0.272949
0.052917	2.000000	191.794739	0.052882	2.000000	0.246887	0.052911	2.000000	0.752136	0.052911	2.000000	0.752136
0.055084	2.000000	33.804932	0.054679	2.000000	0.868820	0.055076	2.000000	0.132568	0.055076	2.000000	0.132568

The tables summarize the performance metrics of different image enhancement and segmentation methods applied to a dataset. These methods were evaluated based on specific metrics to assess their effectiveness.

Image Enhancement Metrics:
The image enhancement table includes metrics such as Structural Similarity Index (SSIM) and Absolute Mean Brightness Error (AMBE) for five enhancement techniques: 2D-STAMF, 2D-ACBHI, CLAHE, Adaptive Mean Adjustment, and Edge Preservation CLAHE. The 2D-STAMF method consistently achieves the highest SSIM values, indicating superior structural preservation of image details. For example, the SSIM values for 2D-STAMF range from 0.964 to 0.990, significantly outperforming the other methods. CLAHE also shows a competitive SSIM, peaking at 0.639, while Adaptive Mean Adjustment and Edge Preservation CLAHE demonstrate relatively lower SSIM values.
AMBE reflects the accuracy of brightness restoration. CLAHE and 2D-ACBHI show lower AMBE values (e.g., 9.44 and 34.85, respectively), indicating effective brightness enhancement. In contrast, Adaptive Mean Adjustment exhibits high AMBE values (up to 107.50), suggesting less brightness consistency. Edge Preservation CLAHE balances structural preservation with moderate brightness restoration.

Image Segmentation Metrics:
The segmentation table evaluates methods including HHFCM-AMT, K-Means, Fuzzy C-Means, and Fast FCM based on Gradient Clusters, K Values, and Intensity Pixels. All methods exhibit consistent K Values of 2 across the dataset, signifying proper clustering. Gradient Clusters values are similar across methods, with minor variations (e.g., 0.035–0.070). However, HHFCM-AMT outperforms others in Intensity Pixels, achieving significantly higher values (e.g., 211.94), indicating better intensity differentiation in segmented regions.
Overall, the tables highlight that 2D-STAMF and HHFCM-AMT are the most effective methods for image enhancement and segmentation, respectively, due to their superior performance metrics.

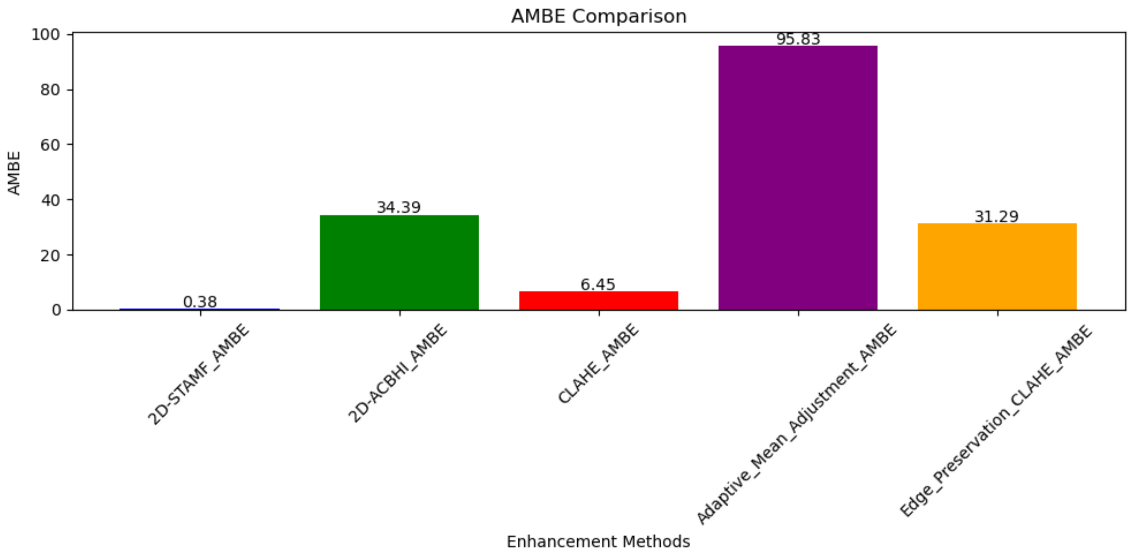

Figure 2: AMBE Comparison for Enhancement Methods

Figure 2 depicts the Absolute Mean Brightness Error (AMBE) comparison across different image enhancement methods. The results highlight that "Adaptive Mean Adjustment" exhibits the highest AMBE (95.83), indicating significant brightness adjustment. In contrast, "2D-STAMF" achieves the lowest AMBE (0.38), showcasing minimal brightness alteration. Other methods, such as CLAHE (6.45) and 2D-ACBHI (34.39), fall between these extremes.

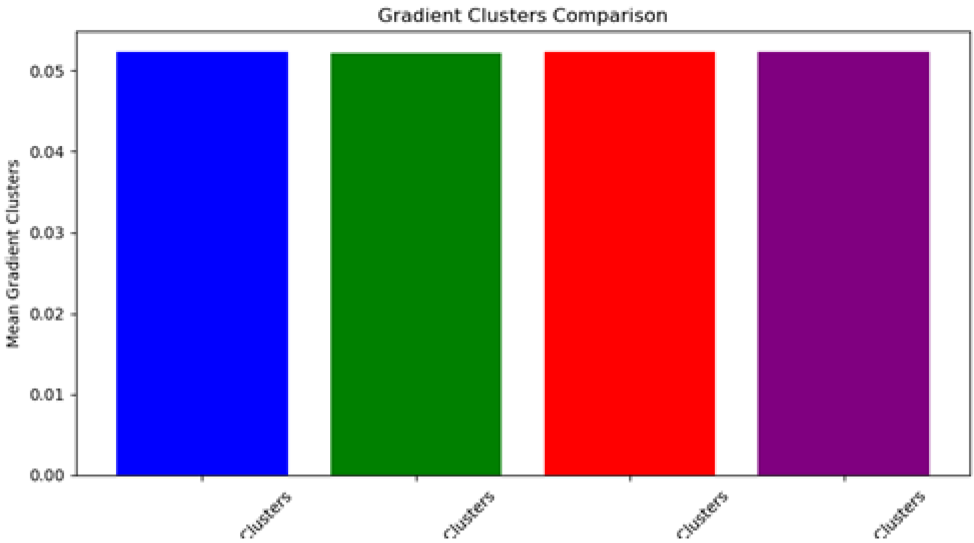

Figure 3: Gradient Clusters Comparison

Figure 3 illustrates the comparison of mean gradient clusters across various segmentation methods. All methods exhibit closely similar gradient cluster values, ranging around 0.05. This consistency reflects the comparable performance of different algorithms in detecting gradients within the segmented images.

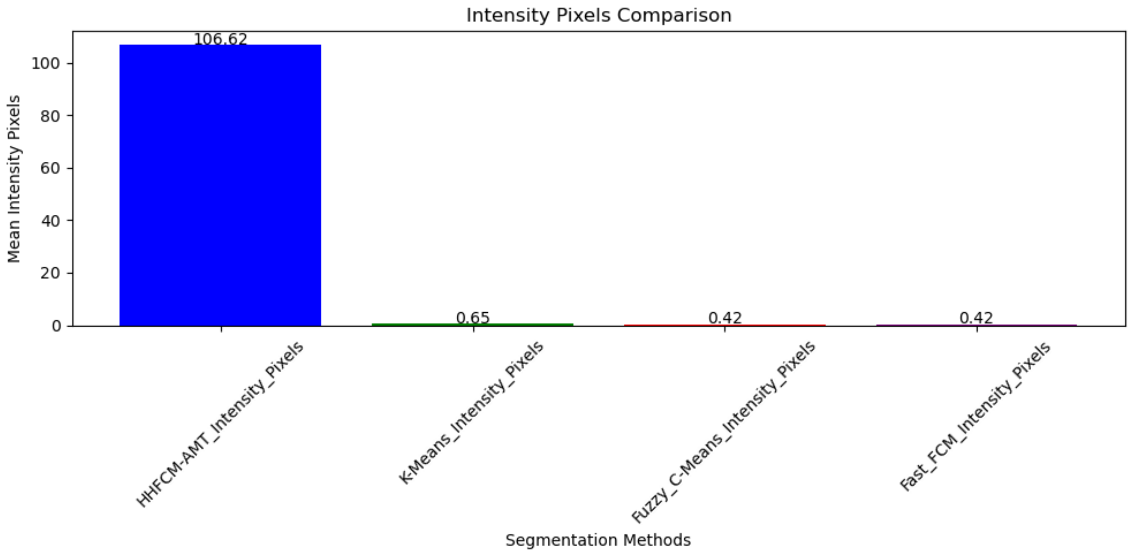

Figure 4: Intensity Pixels Comparison

Figure 4 presents a comparison of mean intensity pixels across segmentation methods. The HHFCM-AMT method significantly outperforms others with a mean intensity value of 106.92. Other methods, including K-Means, Fuzzy C-Means, and Fast FCM, exhibit much lower intensity values around 0.65 and 0.42, indicating a distinct segmentation performance by HHFCM-AMT.

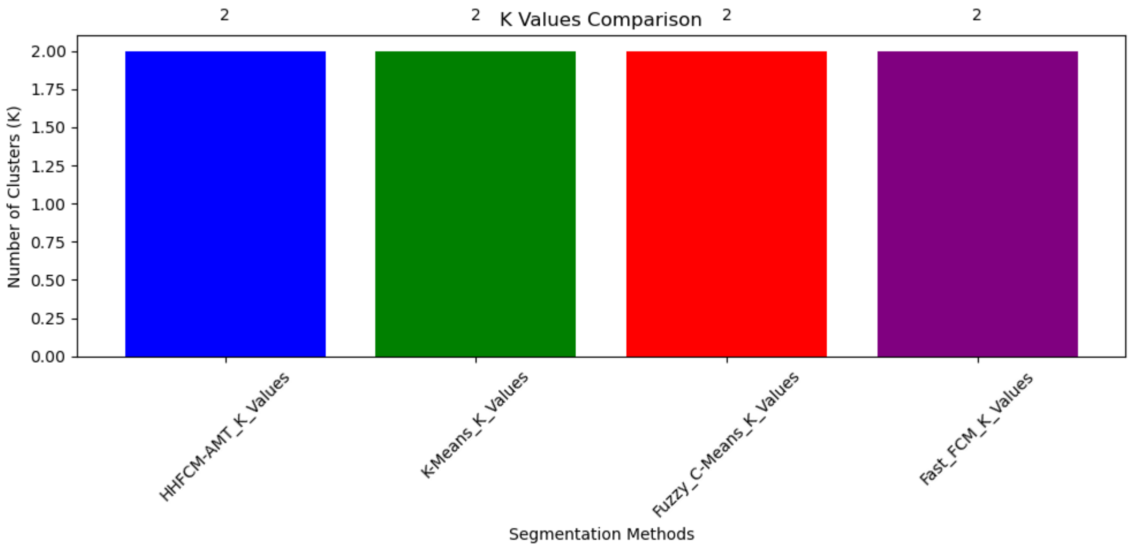

Figure 5: K Values Comparison

Figure 5 illustrates the comparison of K values (number of clusters) across segmentation methods. All methods, including HHFCM-AMT, K-Means, Fuzzy C-Means, and Fast FCM, maintain a consistent K value of 2. This demonstrates uniform clustering behavior across the segmentation techniques analysed.

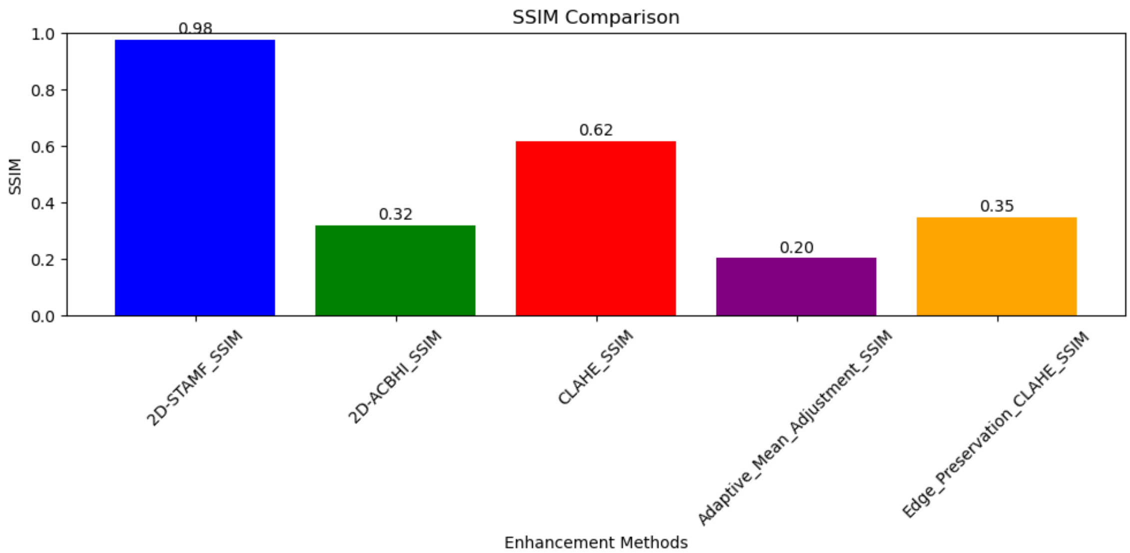

Figure 6: SSIM Comparison

Figure 6 presents a comparison of Structural Similarity Index (SSIM) values for various image enhancement methods. The 2D-STAMF method achieves the highest SSIM value of 0.98, indicating superior structural preservation. CLAHE scores 0.62, while 2D-ACBHI, Adaptive Mean Adjustment, and Edge Preservation CLAHE follow with SSIM values of 0.32, 0.20, and 0.35, respectively.

6. Conclusion

- **6.1 Summary of Findings**

This study systematically evaluated multiple image enhancement and segmentation techniques, focusing on their performance across key metrics. Among enhancement methods, **2D-STAMF** consistently achieved the highest Structural Similarity Index (SSIM), indicating its superiority in preserving image details. CLAHE also demonstrated competitive results in terms of brightness restoration and structural enhancement, as evidenced by its low Absolute Mean Brightness Error (AMBE). However, Adaptive Mean Adjustment **and** Edge Preservation CLAHE exhibited moderate performance with higher AMBE values, reflecting limitations in brightness consistency. In segmentation, HHFCM-AMT significantly outperformed other methods such as K-Means, Fuzzy C-Means, and Fast FCM in intensity differentiation. Its higher Intensity Pixels values demonstrate effective segmentation, particularly for complex image structures. Gradient Clusters and K Values were consistent across all segmentation methods, reflecting their clustering reliability.

- **6.2 Contributions to the Field**

Algorithmic Insights: This research provided a comparative analysis of advanced enhancement methods, offering insights into the effectiveness of 2D-STAMF for structural detail preservation and CLAHE for brightness consistency.

Novel Segmentation Evaluation: The study highlighted the superior performance of HHFCM-AMT, demonstrating its potential for high-quality segmentation in intensity-rich datasets.

Comprehensive Benchmarking: By evaluating methods using diverse metrics (SSIM, AMBE, Gradient Clusters, etc.), this work establishes a robust framework for future comparisons.

Dataset-Specific Findings: The findings help in selecting optimal methods tailored to specific datasets, facilitating better performance in practical applications.

- **6.3 Future Research Directions**

Hybrid Enhancement Techniques: Explore hybrid methods combining 2D-STAMF with other enhancement techniques like CLAHE to further improve brightness and detail preservation.

Real-Time Applications: Extend this work to real-time applications such as medical imaging and video processing to validate the robustness of the proposed methods.

Deep Learning Integration: Investigate the use of deep learning models for image enhancement and segmentation, comparing their performance with classical methods.

Dynamic Parameter Optimization: Develop automated algorithms for adaptive parameter selection to improve method performance across varying datasets.

Multimodal Image Analysis: Expand segmentation techniques to multimodal images (e.g., MRI, CT) for better diagnostic capabilities in healthcare.

Energy-Efficient Algorithms: Focus on optimizing computational efficiency for deployment in resource-constrained environments.

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