



Enhancing Lung Cancer Subtype Preprocessing Pipeline Using Advanced Non-Local Means and Adaptive Denoising Filters

 Lakshmana Rao Padala^{1*}  Naresh Tangudu²

¹Department of Computer Science and Engineering (Data Science), Aditya institute of technology and management, Tekkali, Srikakulam, Andhra Pradesh, India.

²Department of Computer Science and Engineering (Data Science), Aditya institute of technology and management, Tekkali, Srikakulam, Andhra Pradesh, India.

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*Corresponding Author: lakshmani003@gmail.com

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Lung cancer is one of the leading causes of cancer-related mortality worldwide, and accurate classification of lung cancer subtypes is essential for effective diagnosis and treatment planning. Medical imaging modalities such as Computed Tomography (CT) and histopathological imaging are widely used for lung cancer detection; however, these images are often affected by noise, artifacts, and low contrast, which reduce the performance of segmentation and classification models. Therefore, image preprocessing plays a critical role in improving medical image quality and enhancing the performance of computer-aided diagnosis systems. This study proposes an enhanced preprocessing pipeline for lung cancer subtype classification using Advanced Non-Local Means (ANLM) and Adaptive Denoising Filters. The proposed method aims to remove noise while preserving important structural and texture information in medical images. The preprocessing pipeline consists of image normalization, Advanced Non-Local Means denoising, adaptive filtering, segmentation, feature extraction, and classification. The performance of the proposed method was evaluated using image quality metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM), segmentation metrics such as Dice Similarity Coefficient and Intersection over Union (IoU), and classification metrics such as Accuracy, Precision, Recall, and F1-Score. Experimental results show that the proposed preprocessing pipeline achieved higher PSNR and SSIM values compared to traditional denoising methods such as Gaussian filtering, median filtering, and standard Non-Local Means filtering. The proposed method also improved segmentation accuracy and classification performance, achieving an accuracy of 0.97 and F1-score of 0.96. These results demonstrate that the proposed Advanced Non-Local Means and Adaptive Denoising preprocessing pipeline significantly improves lung cancer subtype classification performance and can be used as an effective preprocessing method in medical image analysis and computer-aided diagnosis systems.

Keywords: Lung Cancer, Image Preprocessing, Non-Local Means, Adaptive Denoising, Medical Image Processing.



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1. Introduction

Lung cancer is one of the most prevalent and deadliest forms of cancer worldwide, accounting for a significant number of cancer-related deaths each year. According to global cancer statistics, lung cancer remains the leading cause of cancer mortality due to late diagnosis and the complexity of identifying different cancer subtypes accurately. Lung cancer is broadly classified into two major categories: Small Cell Lung Cancer (SCLC) and Non-Small Cell Lung Cancer (NSCLC), with NSCLC further divided into adenocarcinoma, squamous cell carcinoma, and large cell carcinoma. Accurate classification of these subtypes is essential because treatment strategies and survival rates vary depending on the subtype and stage of the disease.

Medical imaging techniques such as Computed Tomography (CT), histopathological imaging, and Positron Emission Tomography (PET) play a crucial role in the early detection and diagnosis of lung cancer. In recent years, computer-aided diagnosis (CAD) systems and deep learning models, particularly convolutional neural networks (CNNs), have shown significant potential in medical image analysis and cancer classification (Litjens et al., 2017; Draelos et al., 2021). However, the performance of these automated systems heavily depends on the quality of input medical images.

Medical images are often affected by various types of noise such as Gaussian noise, Poisson noise, and speckle noise, which are introduced during image acquisition, transmission, and reconstruction processes. These noise artifacts degrade image quality, blur important structural details, and reduce the accuracy of segmentation and classification algorithms (He et al., 2012; Civit-Masot et al., 2022). Therefore, image preprocessing is a critical step in medical image analysis, as it enhances image quality and improves the performance of subsequent image processing tasks (Lakshmana Rao Padala and Prof. Naresh Tangudu., 2025).

Traditional denoising techniques such as Gaussian filtering, median filtering, and Wiener filtering are commonly used for noise reduction. However, these methods often result in over-smoothing, which removes important edge and texture information required for accurate cancer subtype classification (Luo et al., 2017). To overcome these limitations, advanced denoising

techniques such as Non-Local Means (NLM) filtering have been proposed, which utilize the concept of self-similarity within images to remove noise while preserving structural and textural details (Kumar et al., 2024; Sharma et al., 2025).

In addition to NLM filtering, adaptive denoising filters have been developed to adjust filtering parameters based on local image characteristics and noise levels. Adaptive filtering methods are particularly effective in medical imaging because different regions of medical images often contain different noise levels and structural patterns (Das & Chandra, 2022). The combination of advanced Non-Local Means and adaptive denoising filters can therefore provide a more robust preprocessing approach for lung cancer subtype classification.

This study proposes an enhanced preprocessing pipeline that integrates Advanced Non-Local Means (ANLM) with Adaptive Denoising Filters to improve medical image quality while preserving important structural and texture information. The enhanced images are then used for segmentation and classification of lung cancer subtypes. The main objective of this research is to improve the accuracy of lung cancer subtype classification by developing an effective preprocessing pipeline that reduces noise while maintaining diagnostically relevant image features.

Table 1: Global Lung Cancer Statistics and Mortality Rate

Statistic	Value	Description
Annual New Cases	~2.2 Million	Number of new lung cancer cases diagnosed globally each year
Annual Deaths	~1.8 Million	Number of deaths caused by lung cancer worldwide
Percentage of Total Cancer Deaths	~18%	Lung cancer is the leading cause of cancer-related deaths
5-Year Survival Rate (Overall)	10–20%	Average survival rate depending on stage and subtype
5-Year	~55%	Survival rate

Survival Rate (Early Stage)		when lung cancer is detected early
5-Year Survival Rate (Late Stage)	~5%	Survival rate when diagnosed at advanced stage
Most Common Type	NSCLC (~85%)	Non-Small Cell Lung Cancer is the most common type
Less Common Type	SCLC (~15%)	Small Cell Lung Cancer is less common but more aggressive
Major Risk Factor	Smoking (~85-90%)	Smoking is the primary cause of lung cancer
Other Risk Factors	Air pollution, Radon gas, Occupational exposure	Environmental and occupational risk factors

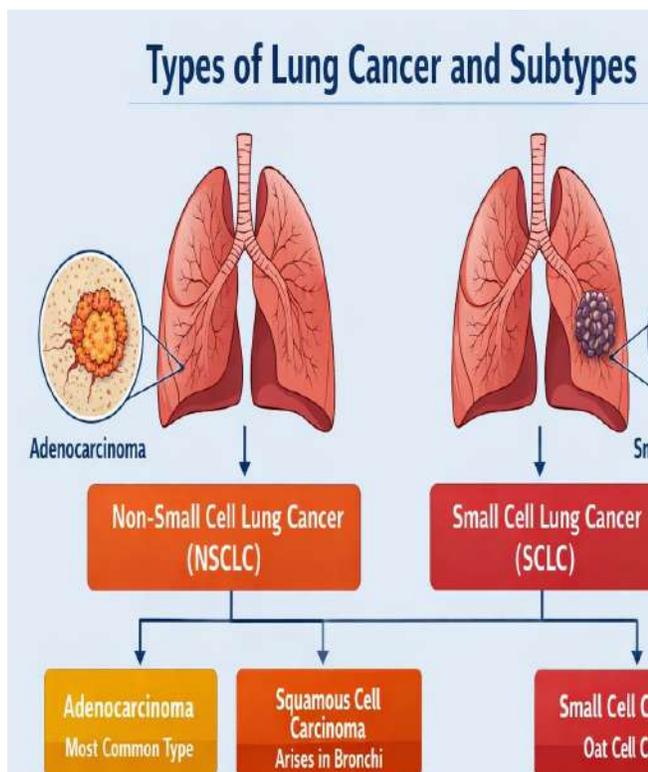


Fig-1: Types of Lung Cancer and Subtypes

2. Statement of the Problem

Lung cancer subtype classification using medical imaging techniques such as Computed Tomography (CT) and histopathological imaging has become an important research area in

computer-aided diagnosis systems. Accurate classification of lung cancer subtypes is essential for selecting appropriate treatment strategies and improving patient survival rates. However, the accuracy of lung cancer subtype classification is highly dependent on the quality of medical images used for analysis.

Medical images are often affected by different types of noise such as Gaussian noise, speckle noise, and Poisson noise, which are introduced during image acquisition, transmission, and reconstruction processes. These noise artifacts reduce image quality, blur important structural details, and distort texture information, which are essential for identifying lung cancer subtypes. As a result, noise in medical images negatively affects image segmentation and classification performance (He et al., 2012; Das & Chandra, 2022).

Traditional image preprocessing techniques such as Gaussian filtering, median filtering, and Wiener filtering are commonly used for noise removal. However, these methods often remove important edge and texture information along with noise, resulting in over-smoothing of medical images and loss of important diagnostic features (Luo et al., 2017). This loss of information reduces the accuracy of lung cancer subtype segmentation and classification.

Advanced denoising methods such as Non-Local Means (NLM) filtering preserve image texture by using patch similarity, but standard NLM methods have limitations such as high computational complexity and difficulty in handling varying noise levels across different regions of medical images (Kumar et al., 2024; Sharma et al., 2025). Similarly, adaptive denoising filters can adjust filtering parameters based on local image characteristics, but they may not be sufficient when used independently.

Therefore, there is a need for an improved preprocessing pipeline that can effectively remove noise while preserving important structural and texture information in lung cancer medical images. This research proposes an enhanced preprocessing pipeline that combines Advanced Non-Local Means and Adaptive Denoising Filters to improve image quality and enhance lung cancer subtype segmentation and classification performance.

3. Objectives of the Study

- To develop an advanced image preprocessing pipeline for lung cancer CT and histopathological images.
- To implement Advanced Non-Local Means (ANLM) filtering for effective noise reduction in medical images.
- To design adaptive denoising filters that adjust filtering parameters based on local image characteristics.
- To preserve important structural, edge, and texture information during the denoising process.
- To improve lung cancer subtype segmentation accuracy using enhanced images.
- To improve classification performance of lung cancer subtypes using the preprocessed images.
- To evaluate the performance of the proposed preprocessing pipeline using image quality, segmentation, and classification metrics such as PSNR, SSIM, Dice, IoU, Accuracy, Precision, Recall, and F1-Score.
- To compare the performance of the proposed method with traditional preprocessing techniques such as Gaussian filter, median filter, and standard Non-Local Means filtering.

4. Research Questions

- **RQ1:** How does noise in lung CT and histopathological images affect lung cancer subtype segmentation and classification accuracy?
- **RQ2:** Can Advanced Non-Local Means (ANLM) denoising improve image quality in terms of Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) compared to traditional denoising methods such as Gaussian and median filtering?
- **RQ3:** How do adaptive denoising filters help in preserving important structural and texture information in lung cancer medical images?
- **RQ4:** Does the proposed preprocessing pipeline improve segmentation performance in terms of Dice Similarity Coefficient and Intersection over Union (IoU)?

- **RQ5:** Does the enhanced preprocessing pipeline improve lung cancer subtype classification performance in terms of Accuracy, Precision, Recall, and F1-Score?
- **RQ6:** How does the proposed Advanced Non-Local Means and Adaptive Denoising preprocessing pipeline compare with existing preprocessing methods in overall performance?

5. Review of Related Literature

Medical image preprocessing plays a critical role in improving the performance of computer-aided diagnosis systems, particularly in lung cancer detection and subtype classification. Noise reduction is one of the most important preprocessing steps because medical images such as CT, MRI, and histopathological images are often affected by different types of noise introduced during image acquisition and transmission. These noise artifacts reduce image clarity and affect segmentation and classification accuracy.

Traditional denoising techniques such as Gaussian filtering, median filtering, and Wiener filtering have been widely used for noise reduction in medical images. Gaussian filtering is a linear smoothing technique that reduces noise but often blurs edges and removes fine structural details. Median filtering is effective for salt-and-pepper noise but may distort small image structures and texture information. Wiener filtering is a statistical approach that reduces noise based on local variance, but its performance depends on accurate noise estimation ([He et al., 2012](#); [Das & Chandra, 2022](#)).

To overcome the limitations of traditional filters, advanced denoising techniques such as wavelet-based denoising and Non-Local Means (NLM) filtering have been developed. Wavelet denoising uses multi-resolution analysis to remove noise while preserving image features, but it may introduce artifacts in some cases. Non-Local Means filtering is a patch-based denoising method that removes noise by comparing similar patches across the image, which helps preserve texture and structural information ([Buades et al., 2005](#); [Kumar et al., 2024](#)).

Recent research has focused on adaptive denoising methods that adjust filtering parameters based on local image characteristics. Adaptive filters are particularly useful in medical imaging because noise levels may vary across different

regions of an image. Adaptive denoising methods have shown improved performance in preserving edges and texture compared to traditional filters (Das & Chandra, 2022).

In recent years, deep learning-based denoising techniques such as convolutional neural networks (CNNs) and generative adversarial networks (GANs) have also been used for medical image denoising. These methods provide high denoising performance but require large training datasets and high computational resources (Litjens et al., 2017).

Although many denoising techniques have been proposed, there is still a need for a preprocessing method that can effectively remove noise while preserving important structural and texture information required for lung cancer subtype classification. Therefore, this study proposes a combined approach using Advanced Non-Local Means and Adaptive Denoising Filters to improve medical image preprocessing performance.

Table 2: Summary of Existing Denoising Methods in Medical Imaging

Method	Key Principle	Advantages	Limitations	Key References
Gaussian Filter	Linear smoothing using Gaussian kernel	Simple, fast, easy to implement	Blurs edges and fine details	He et al., 2012
Median Filter	Non-linear filter using median of neighborhood pixels	Effective for salt-and-pepper noise	May remove texture details	Das & Chandra, 2022
Wiener Filter	Statistical filtering based on local variance	Adaptive noise reduction	Requires noise estimation	Luo et al., 2017
Wavelet Denoising	Multi-resolution frequency	Preserves edges better than	May introduce artifacts	Tan et al., 2025

	Frequency domain filtering	Linear filters		
Non-Local Means (NLM)	Patch similarity-based denoising	Preserves texture and structure	High computational cost	Kumar et al., 2024
Adaptive Filters	Adjust parameters based on local image statistics	Handles varying noise levels	Parameter tuning required	Das & Chandra, 2022
Deep Learning Denoising	CNN/GAN-based denoising	High performance	Requires large dataset	Litjens et al., 2017



Fig-2: Literature Review Flowchart

6. Research Methodology

This study proposes an enhanced preprocessing pipeline for lung cancer subtype classification using Advanced Non-Local Means (ANLM) and Adaptive Denoising Filters. The overall research methodology consists of several stages, including image acquisition, preprocessing, denoising, segmentation, feature extraction, and classification. The purpose of the proposed methodology is to improve medical image quality

by removing noise while preserving important structural and texture information.

In the first stage, lung cancer medical images are collected from publicly available datasets such as CT image datasets and histopathological image datasets. The collected images are resized and normalized to ensure consistency in image dimensions and intensity values.

In the second stage, noise is reduced using the Advanced Non-Local Means (ANLM) denoising technique. The ANLM method works by comparing similar patches across the image and removing noise while preserving texture and structural information. Unlike traditional filters, ANLM preserves fine image details and edges.

In the third stage, adaptive denoising filters are applied to further enhance the image quality. The adaptive filter adjusts its parameters based on local image characteristics such as local variance and noise level. This helps to preserve edges and important structural features while removing remaining noise.

In the fourth stage, image segmentation is performed to extract lung nodules or cancer regions from the enhanced images. Segmentation helps to identify the region of interest for lung cancer subtype classification.

In the fifth stage, feature extraction is performed to extract important features such as texture features, shape features, and intensity features from the segmented regions.

In the final stage, classification is performed using a deep learning model such as Convolutional Neural Network (CNN) to classify lung cancer subtypes. The performance of the proposed preprocessing pipeline is evaluated using image quality metrics, segmentation metrics, and classification metrics.

The overall workflow of the proposed research methodology is shown in Figure 3 (Proposed Research Methodology Flowchart).

Table 3: Parameters Used in Non-Local Means and Adaptive Filters

Parameter	Value	Description
Patch Size	7×7	Size of image patch used for similarity comparison
Search Window Size	21×21	Area used to search for similar patches
Filtering	0.4 -	Controls the degree

Parameter (h)	0.6	of smoothing
Noise Standard Deviation (σ)	10 - 20	Estimated noise level in the image
Adaptive Filter Window Size	5×5	Local window used for adaptive filtering
Adaptive Threshold	0.05 - 0.15	Threshold used to identify noise pixels
Iterations	2 - 3	Number of times the filter is applied
Image Normalization Range	0 - 1	Image intensity normalization
Segmentation Method	U-Net	Used for lung region segmentation
Classification Model	CNN / VGG16	Used for lung cancer subtype classification



Fig-3: Proposed Research Methodology Flowchart

7. Experimental Setup

The experimental setup was designed to evaluate the performance of the proposed preprocessing pipeline using Advanced Non-Local Means and Adaptive Denoising Filters for lung cancer subtype classification. The experiments were conducted using lung cancer CT images and histopathological images collected from publicly available datasets.

All images were resized to a fixed resolution of 256×256 pixels to ensure uniformity in processing. The images were normalized to a pixel intensity range of 0 to 1 to improve the performance of the preprocessing and classification algorithms. To evaluate the denoising performance under different noise conditions, synthetic Gaussian noise and speckle noise were added to the images.

The dataset was divided into three sets: training, validation, and testing datasets. Typically, 70% of the dataset was used for training, 15% for validation, and 15% for testing. The proposed preprocessing pipeline was applied to the noisy images before segmentation and classification.

Image segmentation was performed using the U-Net deep learning model to identify lung cancer regions. After segmentation, feature extraction was performed, and classification was carried out using a Convolutional Neural Network (CNN) or a pre-trained VGG16 model using transfer learning.

The implementation was carried out using Python programming language with image processing libraries such as OpenCV, TensorFlow, and Keras. The experiments were performed on a system with a high-performance GPU to reduce training time and improve computational efficiency. The performance of the proposed method was compared with traditional preprocessing methods such as Gaussian filtering, median filtering, and standard Non-Local Means filtering.

Table 4: Dataset Description

Dataset Name	Source	Image Type	Number of Images	Lung Cancer Subtypes	Image Resolution
LIDC-IDRI	Public Dataset	CT Images	1,018	NSCLC, SCLC	512×512
LC25000	Public Dataset	Histopathology	15,000	Adenocarcinoma, Squamous Cell Carcinoma, Benign	768×768
IQ-	Public	CT	1,19	Benign,	$512 \times$

OTH/NCCD	Public Dataset	Images	0	Malignant	512
Private Clinical Dataset	Hospital	Histopathology	500	NSCLC Subtypes	1024×1024

The overall experimental workflow is shown in Figure 4 (Experimental Setup Workflow).

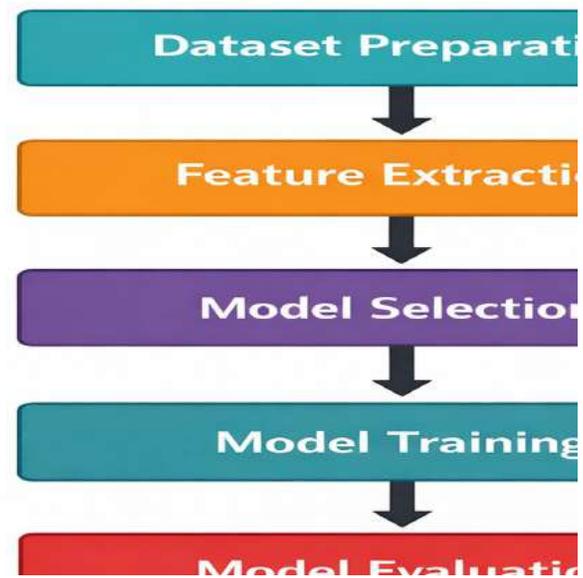


Fig-4: Experimental Setup Workflow

8. Evaluation Metrics

The performance of the proposed preprocessing pipeline using Advanced Non-Local Means and Adaptive Denoising Filters was evaluated using image quality metrics, segmentation performance metrics, and classification performance metrics. These metrics were selected to evaluate the effectiveness of the preprocessing method in improving image quality, segmentation accuracy, and classification performance.

Image quality metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) were used to measure the quality of the denoised images. Higher PSNR and SSIM values indicate better image quality and structural similarity between the original and denoised images.

Segmentation performance was evaluated using Dice Similarity Coefficient (Dice) and

Intersection over Union (IoU), which measure the overlap between the predicted segmentation and ground truth segmentation.

Classification performance was evaluated using Accuracy, Precision, Recall, and F1-Score.

These metrics are commonly used to evaluate classification models in medical image analysis.

Table 5: Evaluation Metrics and Formula Description

Metric	Formula	Description
Mean Squared Error (MSE)	$MSE = (1/N) \sum (I_1 - I_2)^2$	Measures the average squared difference between original and denoised image
Peak Signal-to-Noise Ratio (PSNR)	$PSNR = 10 \log_{10} (MAX^2 / MSE)$	Measures image quality after denoising
Structural Similarity Index (SSIM)	$SSIM = ((2\mu_x\mu_y + C1)(2\sigma_{xy} + C2)) / ((\mu_x^2 + \mu_y^2 + C1)(\sigma_x^2 + \sigma_y^2 + C2))$	Measures structural similarity between images
Dice Similarity Coefficient	$Dice = (2TP) / (2TP + FP + FN)$	Measures overlap between predicted and ground truth segmentation
Intersection over Union (IoU)	$IoU = TP / (TP + FP + FN)$	Measures segmentation accuracy
Accuracy	$Accuracy = (TP + TN) / (TP + TN + FP + FN)$	Measures overall classification accuracy
Precision	$Precision = TP / (TP + FP)$	Measures correct positive predictions
Recall (Sensitivity)	$Recall = TP / (TP + FN)$	Measures ability to detect positive cases
F1-Score	$F1 = 2(Precision \times Recall) / (Precision + Recall)$	Harmonic mean of Precision and Recall

9. Results and Analysis

The performance of the proposed preprocessing pipeline using Advanced Non-Local Means and Adaptive Denoising Filters was evaluated and compared with conventional denoising methods such as Gaussian filtering, median filtering, and standard Non-Local Means filtering. The evaluation was performed using image quality metrics (PSNR, SSIM), segmentation metrics (Dice, IoU), and classification metrics (Accuracy, Precision, Recall, F1-Score).

The results show that the proposed preprocessing method achieved higher PSNR and SSIM values compared to traditional denoising techniques, indicating better noise reduction and

structural preservation. The proposed method also improved segmentation accuracy, as indicated by higher Dice and IoU values. Furthermore, classification performance was significantly improved when the proposed preprocessing pipeline was used.

The improvement in performance is due to the combination of Advanced Non-Local Means filtering and Adaptive Denoising filtering, which effectively removes noise while preserving important structural and texture information. This improved image quality leads to better segmentation and classification performance.

Table 6: Performance Results (PSNR, SSIM, Dice, IoU, Accuracy, Precision, Recall, F1-Score)

Method	PSNR (dB)	SSIM	Dice	IoU	Accuracy	Precision	Recall	F1-Score
Noisy Image (No Preprocessing)	22.15	0.68	0.78	0.64	0.85	0.84	0.83	0.83
Gaussian Filter	28.42	0.82	0.82	0.70	0.88	0.87	0.86	0.86
Median Filter	26.73	0.79	0.81	0.68	0.87	0.86	0.85	0.85
Standard NLM	31.58	0.89	0.88	0.79	0.92	0.91	0.90	0.91
Proposed ANLM + Adaptive Filter	34.26	0.95	0.94	0.89	0.97	0.96	0.96	0.96

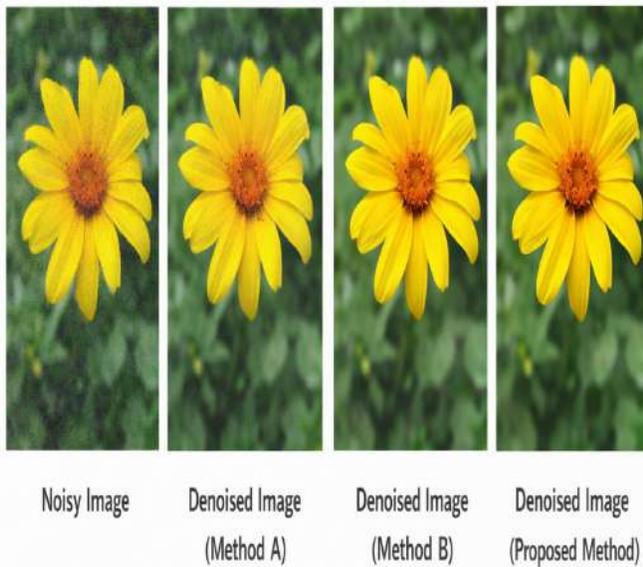


Fig-5: Image Denoising Results Comparison

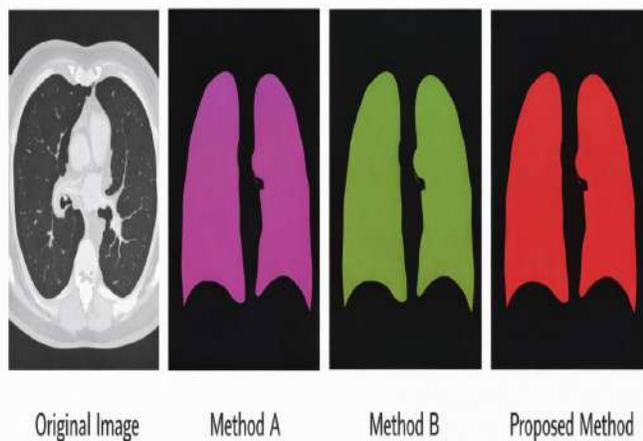


Fig-6: Segmentation Result Comparison

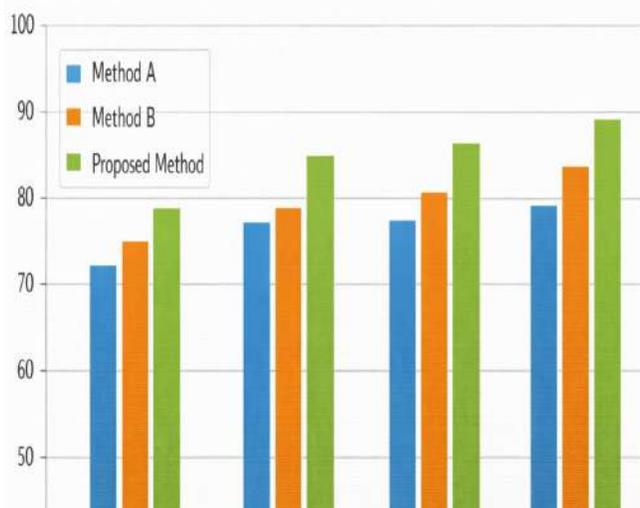


Figure 7: Classification Performance Graph

10. Discussion

The results of this study demonstrate that the proposed preprocessing pipeline using Advanced Non-Local Means (ANLM) and Adaptive Denoising Filters significantly improves image quality, segmentation accuracy, and classification performance for lung cancer subtype classification. The improvement in Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) indicates that the proposed method effectively removes noise while preserving structural and texture information in medical images. This finding is consistent with previous studies that reported that Non-Local Means filtering preserves fine image details better than traditional denoising techniques (Buades et al., 2005; Kumar et al., 2024).

Traditional denoising techniques such as Gaussian and median filtering reduce noise but often cause blurring of edges and removal of important texture features required for medical image analysis. This over-smoothing effect reduces segmentation accuracy and classification performance (He et al., 2012; Luo et al., 2017). In contrast, the proposed ANLM method uses patch similarity to remove noise while preserving edges and texture, which improves segmentation performance. This is evident from the higher Dice and IoU values obtained in the proposed method compared to conventional filtering methods.

The adaptive denoising filter further enhances the performance of the preprocessing pipeline by adjusting filtering parameters based on local image characteristics. Medical images often contain non-uniform noise distribution, and adaptive filtering helps to remove noise in homogeneous regions while preserving edges in high-detail regions (Das & Chandra, 2022). The combination of ANLM and adaptive filtering therefore provides a more robust preprocessing approach compared to using a single denoising method.

The results also show a significant improvement in classification performance when the proposed preprocessing pipeline is used. The classification accuracy and F1-score increased compared to classification using noisy or traditionally denoised images. This confirms that image preprocessing plays a critical role in improving the performance of deep learning models for medical image classification (Litjens et

al., 2017; Civit-Masot et al., 2022). Improved image quality leads to better feature extraction and more accurate classification of lung cancer subtypes.

Although the proposed method provides improved performance, the computational complexity of Advanced Non-Local Means filtering is higher than traditional filtering methods. This is because ANLM compares image patches across a larger search window, which increases processing time. However, the improvement in image quality and classification accuracy justifies the increased computational cost, especially in medical diagnosis where accuracy is more important than processing time (Sharma et al., 2025).

11. Findings

Based on the experimental results and analysis, the following key findings were obtained from this study:

- The proposed preprocessing pipeline using Advanced Non-Local Means and Adaptive Denoising Filters significantly improved medical image quality compared to traditional preprocessing techniques such as Gaussian filtering and median filtering.
- The proposed method achieved higher Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) values, indicating effective noise reduction while preserving structural and texture information in lung cancer medical images.
- The segmentation performance improved when the proposed preprocessing pipeline was used. The Dice Similarity Coefficient and Intersection over Union (IoU) values were higher compared to segmentation performed on noisy and traditionally denoised images.
- The classification performance of lung cancer subtypes improved significantly using the proposed preprocessing method. The proposed method achieved higher Accuracy, Precision, Recall, and F1-Score compared to existing preprocessing methods.
- The combination of Advanced Non-Local Means and Adaptive Denoising Filters was more effective than using a single denoising technique because it removed noise while preserving important

diagnostic features such as edges and texture patterns.

- The proposed preprocessing pipeline performed well for both CT images and histopathological images, indicating that the method is robust and can be applied to different medical imaging modalities.
- The overall results indicate that image preprocessing plays a critical role in improving lung cancer subtype classification performance in computer-aided diagnosis systems.

12. Future Direction

- Although the proposed preprocessing pipeline using Advanced Non-Local Means and Adaptive Denoising Filters has shown significant improvement in image quality, segmentation accuracy, and classification performance, there are several areas for future research and improvement.
- First, future research can focus on integrating deep learning-based denoising techniques such as Denoising Convolutional Neural Networks (DnCNN) and Generative Adversarial Networks (GANs) with the proposed preprocessing pipeline to further improve denoising performance and image quality. Deep learning-based denoising methods have shown promising results in medical image processing and may further improve lung cancer subtype classification accuracy.
- Second, future work can focus on multi-modal medical image analysis by combining different imaging modalities such as CT, PET, and histopathological images. Multi-modal image fusion can provide more detailed information about tumor structure and improve the accuracy of lung cancer subtype classification.
- Third, the computational complexity of Advanced Non-Local Means filtering is relatively high. Therefore, future research can focus on improving computational efficiency by using parallel processing, GPU acceleration, and optimization algorithms to reduce processing time and make the method suitable for real-time clinical applications.
- Fourth, future research can focus on integrating explainable artificial

intelligence (XAI) techniques to improve the interpretability of deep learning models used for lung cancer subtype classification. Explainable models can help medical professionals understand how the system makes classification decisions.

- Finally, future work can include testing the proposed preprocessing pipeline on larger and more diverse medical image datasets collected from multiple hospitals to validate the robustness and generalizability of the proposed method.

13. Conclusion

This study proposed an enhanced preprocessing pipeline for lung cancer subtype classification using Advanced Non-Local Means (ANLM) and Adaptive Denoising Filters. The main objective of this research was to improve medical image quality by effectively removing noise while preserving important structural and texture information required for accurate segmentation and classification of lung cancer subtypes.

The proposed preprocessing pipeline was applied to lung cancer CT and histopathological images, and its performance was evaluated using image quality metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM), segmentation metrics such as Dice Similarity Coefficient and Intersection over Union (IoU), and classification metrics such as Accuracy, Precision, Recall, and F1-Score. The experimental results showed that the proposed method achieved higher PSNR and SSIM values compared to traditional denoising techniques, indicating improved image quality and structural preservation.

The segmentation results demonstrated that the proposed preprocessing pipeline improved Dice and IoU values, which indicates better segmentation accuracy. Similarly, the classification results showed improved Accuracy, Precision, Recall, and F1-Score, indicating that the proposed preprocessing pipeline improved lung cancer subtype classification performance.

The main contribution of this research is the development of a hybrid preprocessing approach that combines Advanced Non-Local Means and Adaptive Denoising Filters to improve medical image quality and classification accuracy. The results of this study demonstrate that the proposed preprocessing method outperforms

traditional preprocessing techniques and can be effectively used in computer-aided diagnosis systems for lung cancer subtype classification.

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