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TRANSFORMING LUNG CANCER DIAGNOSIS: TDYWT FILTERING FOR ENHANCED HISTOPATHOLOGICAL IMAGING

R. Soundharya Devi 1, S. Nirmala Sugirtha Rajini 2

1. Research Scholar 2. Professor

Department of Computer Applications,

Dr.MGR. Educational and Research Institute, Maduravoyal, Chennai -95, India

rsoundharya92devi@gmail.com nirmalasugirtharajini.mca@drmgrdu.ac.in

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ABSTRACT

Lung cancer has become one of the leading causes of mortality worldwide, and early and precise detection techniques become increasingly important. The goal of this work is to improve the identification and segmentation of lung cancer by using advanced image-processing methods on histopathology pictures. The preprocessing steps in the suggested technique include MedianFiltering(MF), Finite Impulse Responsefiltering(FIR), and Dyadic Wavelet Transform(DyWT). To improve the precision of lung cancer detection and segmentation, a novel method is presented that uses the Transverse Dyadic Wavelet Transform(TDyWT) as a filtering mechanism. The efficiency of different filters is determined by analyzing metrics like Mean Squared Error(MSE), Structural Similarity Index(SSIM), and Peak Singal-to Noise Ratio(PSNR). Research shows that the transverse dyadic wavelet transform (TDyWT) consistently performs better than the alternative filters, with improved results for all evaluated parameters. By ensuring that important characteristics are better preserved throughout the image processing pipeline, the implementation of TDyWT results in noticeable increases in picture quality. This improved performance is ascribed to the filter's skill at effectively gathering both horizontal and vertical data, which is essential for the precise detection and classification of lung cancer. The results highlight TDyWT's potential as a useful tool to enhance histopathological imaging's diagnostic capacity for lung cancer diagnosis.

Keywords:- Lung cancer, Transverse Dyadic Wavelet Transform, Peak Singal-to Noise Ratio, MedianFiltering, Mean Squared Error, Finite Impulse Responsefiltering, Dyadic Wavelet Transform

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I INTRODUCTION

Lung cancer is a major global health concern, and early detection and accurate diagnosis are crucial for effective treatment. Lung cancer is detected and diagnosed with the use of histopathology. It includes identifying and characterizing aberrant alterations linked to the malignancy through microscopic analysis of tissue samples taken from the lungs. First, a tiny tissue sample from a suspected tumor or abnormal region in the lungs is collected as part of the biopsy collection process. Following fixation, the tissue is embedded in paraffin wax and sectioned into thin slices in a laboratory setting. To highlight cellular features, the slices are further stained with histological stains like haematoxylin and eosin (H&E). To find aberrant cellular characteristics such as uneven cell shape, increased cellularity, and aberrant mitotic figures, pathologists use a microscope to analyse the stained tissue sections. Histopathological features are used to categorize lung malignancies into several kinds, such as small cell lung carcinoma (SCLC) and non-small cell lung carcinoma (NSCLC). To find particular genetic mutations or variations that might inform therapy choices, molecular testing is frequently done on the tissue. Treatment planning and prognosis are aided by staging, which establishes the amount of cancer dissemination. In order to identify tumor markers and pinpoint the origin of the tumor, immunohistochemistry employs antibodies to recognize certain proteins in the tissue. Evaluation of the tumor microenvironment, which includes immune cell presence, sheds light on the relationship between the immune system and the tumor and can help determine if immunotherapy is potentially beneficial.

Understanding the influence of preprocessing techniques on image quality and interpretability—such as Median Filter, FIR Filter, and DyWT—on histopathology images is critical. Each methodology, such as edge sharpness, feature improvement, and noise reduction, is evaluated using a systematic method. By analyzing noise reduction and structure preservation objectively, the Median Filter seeks to improve picture quality and minimize noise. Through the measurement of edge sharpness and the emphasis on pertinent characteristics, the FIR Filter improves feature extraction and interpretability. By examining resolution levels and frequency information, the DyWT seeks to provide multi-resolution representation for better analysis. Examining pre-processed photos visually to look for artifacts, blurring, or loss of important information is part of the whole evaluation process. The quality of the pictures following preprocessing may be quantitatively assessed using measures such as PSNR, MSE, and Structural Similarity Index (SSIM). Transverse dyadic wavelet transform (TDyWT) is a method that dissects pictures into their parts and reveals intricacies, much like looking at patterns under a microscope. It excels in identifying patterns from various perspectives, making it easier to spot edges or textures in images like histopathological images.The work focuses on the application of preprocessing methods to evaluatematrices such as PSNR, MSE, and Structural Similarity Index (SSIM).Previously compared three algorithms for the best method of lung cancer detection that can highlight deep learning's role in lung cancer detection, comparing segmentation methods like DB U-Net+ LLIE, U-Net, and DenseNet & dilation block with U-Net. DenseNet & dilation block with U-Net shows superior accuracy (95.05%) and sensitivity (90.52%), emphasizing its importance in precise segmentation for effective diagnosis and treatment planning.

II LITERATURE REVIEW

Shah, Vishal H, et al., 2024 introduced a two-stage self-adaptive cognitive neural network model (SACNN) for capturing precise medical images, outperforming state-of-the-art techniques, and achieving superior performance through statistical analyses [1].Zaini, Hatim, et al., 2023proposed modifications to average and median filters for high noise ratios, enhancing denoising capability and effectiveness in gray and color images [2].Aksoy, Levent, et al., 2023introduced a hybrid protection technique for digital FIR filters, combining hardware obfuscation and logic locking, demonstrating enhanced security, competitive hardware complexity, and resilience to attacks [3].Reddy, Y. Pavan Kumar, et al., 2023 used pulse-coupled neural networks (PCNN) and shearlet transformation to fuse MRI and PET scan images, enhancing diagnostic accuracy and anatomical understanding in cases where a single imaging modality may be insufficient [4].Rajasekhar, K., 2024 introduced a novel approach to designing 20th-order linear phase finite impulse response (FIR) filters using optimization algorithms like CSA and GOA. The filters show superior performance, reducing pass band ripples, increasing stopband attenuation, and minimizing execution time [5].Muraoka, Ken, et al., 2023 proposed a diagnostic support system for colorectal cancer diagnosis, focusing on blood vessels. It uses vascular enhancement and lifting dyadic wavelet transform, enhancing features. Classification experiments show superior performance [6].Tomita, Hikaru,et al., 2023 introduced a method for detecting asbestos-specific fiber shapes in microscopic images using dye staining methods and the two-dimensional dyadic wavelet packet transform (2D-DYWPT). The method extracts 36 features and classifies images, outperforming fine-tuned ResNet in performance [7].Jagadeesh, K., and A. Rajendran., 2023 presented an improved model for lung cancer segmentation and classification using genetic algorithms, enhancing early detection of lung cancer. The model uses CT scan images, Guaranteed Convergence Particle Swarm Optimization, and Probabilistic Neural Networks, providing accurate classification results [8].

III PROPOSED METHODOLOGY

The specialized image preprocessing scheme tailored for histopathological images is introduced.Figure 1 shows the block diagram ofthe image preprocessing scheme tailored for histopathological images. The initial phase involves noise reduction through the sequential application of a Median Filter, adept at pixel value smoothing, an FIR Filter for finite impulse response-based noise removal, and a Dyadic Wavelet Transform designed for comprehensive multi-resolution analysis. A novel addition to the process is the Proposed Transverse Dyadic Wavelet Transform (TDyWT), which contributes an innovative approach to noise removal. The subsequent Performance Evaluation stage employs metrics such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Mean Squared Error (MSE) to quantify the efficacy of each noise reduction method. The ultimate output encapsulates the collective impact of these preprocessing steps, highlighting the TDyWT's effectiveness in achieving proficient noise reduction while preserving crucial image features.

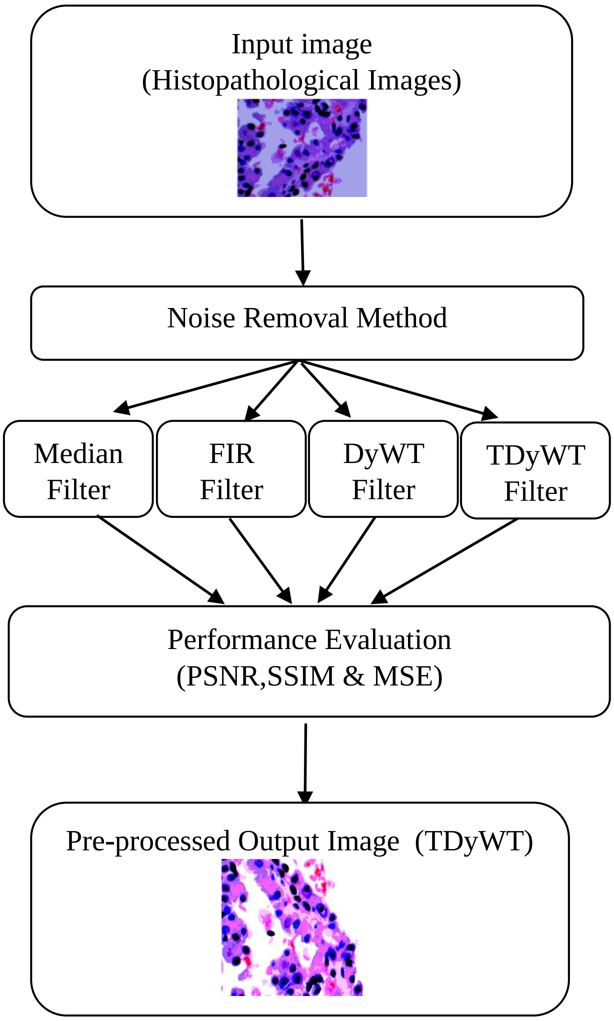


Figure.1. Block Diagram of Proposed Methodology

Median Filter

A nonlinear image processing method called the median filter is frequently used to reduce noise in images while maintaining edges and other significant characteristics. To reduce the effect of outliers or noisy pixels, it works by substituting the median value of each pixel for the value of its nearby pixels. Let I be the original filtered image of lung tissue. I_{filt}be the image after applying the median filter.

$$I_{filt}(x,y) = median\,\{I(i,j)|i = x - \frac{w}{2}, \dots, x + \frac{w}{2}; j = y - \frac{w}{2}, \dots, y + \frac{w}{2}\} \text{ - - -(1)}$$

- $I_{filt}(x,y)$ is the intensity of the pixel at coordinates (x,y) in the filtered image after applying the median filter
- $I(i,j)$ is the intensity value at position (i,j) in the original lung tissue image
- w is the size of the square window used for the median filter. The window dimensions are w x w.
- The median(…) function calculates the median value of the set of intensity values within the specified window

This formula describes the operation of the median filter applied to each pixel in the lung tissue image, resulting in the corresponding pixel intensity in the filtered image I_{filt}

FIR

Finite Impulse Response (FIR) filters are computer technologies used to enhance images before analysis in the context of lung cancer histopathology imaging. They are essential for activities including eliminating undesirable noise, emphasizing critical structures (such as cell boundaries), smoothing out anomalies, improving contrast, and customizing images to highlight certain details. In essence, FIR filters serve as picture enhancers, assisting medical practitioners in obtaining sharper and more insightful images for precise lung cancer detection and analysis. An FIR filter's output (y[n]) may be computed using the following formula:

$$y[n] = \sum_{i=0}^{N} b_i \,.\, x[n-i] \text{ - - - - (2)}$$

- $y[n]$ is the output signal at time n.
- b_i is the impulse response of the filter, representing the filter coefficients.
- $x[n-i]$ is the input signals delayed by i samples

The original picture's pixel values would be represented by x[n] in a lung cancer histopathology image pre-processing scenario, and the set of filter coefficients created based on the required filtering features (such as noise reduction and edge enhancement) would be represented by h[k]. The computation entails utilizing the relevant filter coefficients (h[k]) to get the weighted sum of previous input samples (x[n−k]). Every pixel in the picture undergoes this procedure, yielding a changed image output (y[n]).

DyWT

The wavelet transform is an analytical technique to breaks down signals and images into components with different frequencies to study them at different scales. A power of two is referred to as "dyadic." Within the realm of wavelet transforms a dyadic wavelet transform denotes a split of the signal or image into two at each stage of the transformation. The dyadic wavelet transforms, to put it simply, splits a picture up into detail and approximation coefficients.

The low-frequency components are captured by the approximation coefficients, yielding a rough depiction of the picture. The high-frequency components are represented by the detail coefficients, which capture finer details. There are several filtering and down-sampling steps in the process. An approximate low-pass filter and a detailed high-pass filter are applied to the image at each level. A representation of the image at many resolutions is the result. The following procedures can be used to determine the DyWT.

Decomposition

- A low-pass and a high-pass filter are used to convolve the image.
- The estimated low-frequency components, and approximation coefficients (a_k) of the picture are extracted using the low-pass filter.

$$a_k = X * h_{low} \text{- - -(3)}$$

- The image's high-frequency, detailed components (d_k) are extracted by the high-pass filter.

$$d_k = X * h_{high} \text{- - - -(4)}$$

Let X be the input image, the lowpass, and high pass filters are represented by the h_{low} and h_{high}

Down-Sampling

- Down-sampling is done to minimize the size of the converted data after filtering.
- By retaining only every second sample, the resolution is essentially reduced in half.

$$a_k' = D(a_k) \text{ - - - (5)}$$

$$d_k' = D(d_k) \text{- - - - (6)}$$

a_k' and d_k' are down-sampled versions of a_k and d_k, respectivelythe down-sampling process is represented by D

Recursive Process

On the approximate coefficients acquired in the preceding phase, the aforementioned procedures are repeated.Until the required degree of breakdown is reached, this recursive procedure is carried out.

The dyadic wavelet transform is very helpful for multi-resolution analysis in image processing. It helps in image compression, denoising, and feature extraction by enabling the extraction of significant features at various scales. Benefits of DyWT a versatile and effective method for representing and analyzing signals or pictures with different degrees of detail is the dyadic wavelet transform. It is appropriate for a variety of applications as it aids in capturing both local and global properties.

TDyWT

A mathematics and signal processing method called the Transverse Dyadic Wavelet Transform (TDyWT) breaks down signals into different scales and frequency components. Transverse dyadic wavelet functions are used in this wavelet transform variant. When examining signals that have both temporal and frequency localization features, TDyWT is very helpful. By combining the input signal with a group of wavelet functions that are both dilated and translated in time, it decomposes the signal. TDyWT's usage of transverse dyadic wavelets, which have powers of 2, is its distinguishing characteristic. TDyWT has uses in image processing for the rapid detection of glaucoma and in image augmentation for accurate spatial measurement.For a continuous signal x(t), the general equation for the continuous TDyWT is as follows:

$$W(a,b) = \int_{-\infty}^{\infty} x(t) \cdot \Psi_{a,b}(t)dt \text{ - - - -(7)}$$

In this equation wavelet transform coefficient at scale and location a and b is W(a,b).The input signal is x(t).The transverse dyadic wavelet function at scale a and location b is denoted as a,b(t). These wavelet functions are translated and dilated forms of the mother wavelet, commonly abbreviated as (t), and are defined as:

$$\Psi a, b(t) = \frac{1}{\sqrt{a}} \Psi((t-b)/a) - -(8)$$

The scale parameter, denoted by the letter a, determines the wavelet's breadth in time. Smaller values of a result in narrower wavelets that catch high-frequency details, whereas greater values of a correlate to broader wavelets that collect low-frequency information. The wavelet's location along the time axis is determined by the translation parameter, represented as b.The input signal is commonly represented by a wavelet transform after the TDyWT has been calculated for various scales and places. Feature extraction, denoising, compression, and other signal-processing operations may all be carried out using this format.

$$I_{TDWT} = \text{TDyWT}(I_{\text{original}}) - -(9)$$

Where, The Original lung picture is known asI_{original}.The Transverse Dyadic Wavelet Transform, or TDyWT, is what was used to transform the original picture.

IV RESULTS AND DISCUSSION

Figure 2shows the unprocessed original lung image, serving as the reference for subsequent comparisons. Figure 3 illustrates the filtered images obtained after applying various preprocessing techniques. Subfigures (a), (b), (c), and (d) within Figure 3 depict the results of applying distinct filtering methods: Median Filter, FIR Filter, Dyadic Wavelet Transform (DyWT), and Transverse Dyadic Wavelet Transform (TDyWT), respectively. Each filtered image showcases the outcome of a specific denoising or enhancement technique applied to the original histopathological lung image, aiming to improve the quality and suitability for subsequent lung cancer detection and segmentation processes.the Transverse Dyadic Wavelet Transform (TDyWT) demonstrates superior performance compared to other filtering techniques, including Median Filter, FIR Filter, and Dyadic Wavelet Transform (DyWT). The TDyWT-filtered image exhibits enhanced clarity, sharper edges, and reduced noise artifacts, making it visually preferable for preprocessing in lung cancer detection and segmentation from histopathological images.Figure 4 illustrates the histogram of the Original Image, depicting the distribution of pixel intensities in the original histopathological image (Figure 2). This histogram offers valuable insights into the contrast and distribution of pixel values within the original image. In Figure 5, the Histogram of Filtered Images is presented, with subfigures (a), (b), (c), and (d) showcasing histograms corresponding to filtered images obtained through Median Filter, FIR Filter, Dyadic Wavelet Transform (DyWT), and Transverse Dyadic Wavelet Transform (TDyWT) methods, respectively. Each histogram visually represents the distribution of pixel intensities within its corresponding filtered image, aiding in the analysis of image preprocessing for lung cancer detection and segmentation.

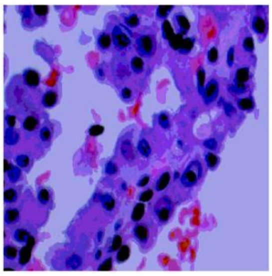
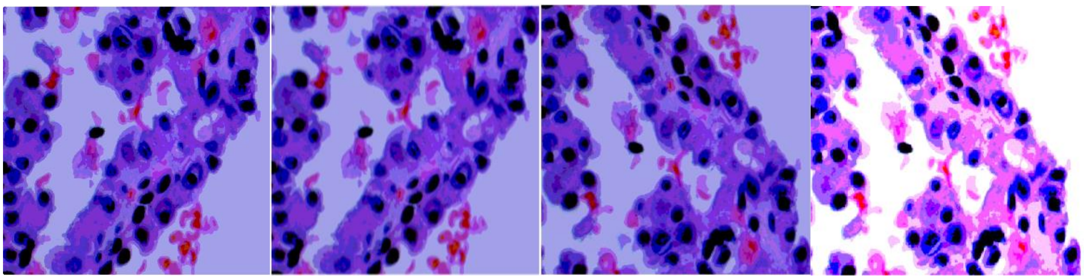


Figure.2. Original histopathological image of Lung Cancer



(a) **(b)** **(c)** **(d)**

Figure.3. Filtered Images (a) median filter (b) FIR filter (c) DyWT (d) TDyWT

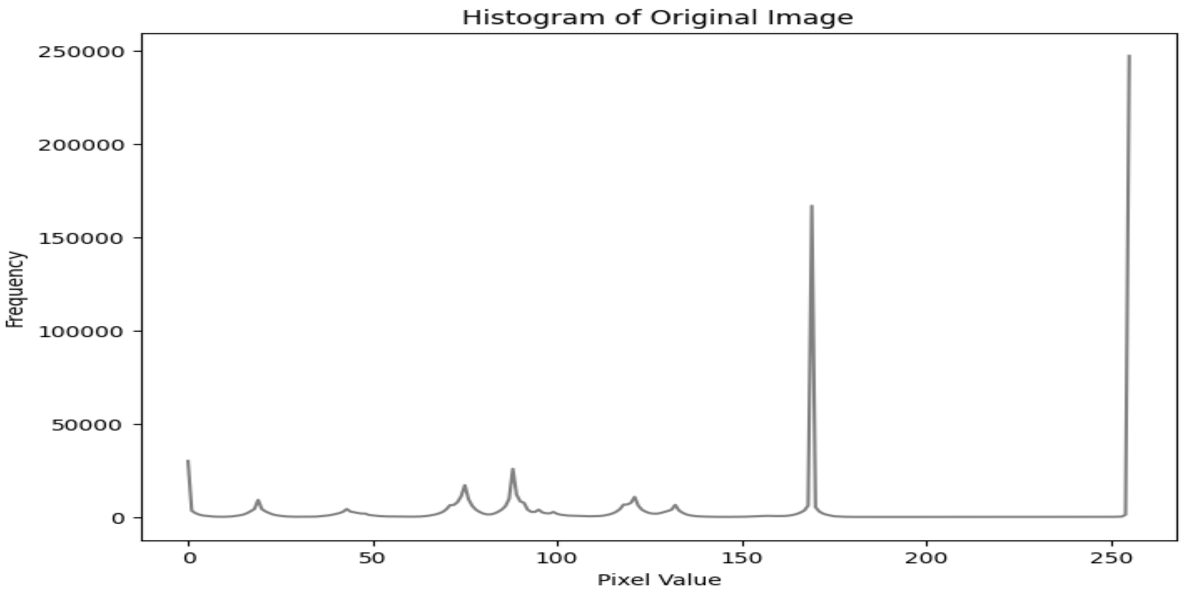
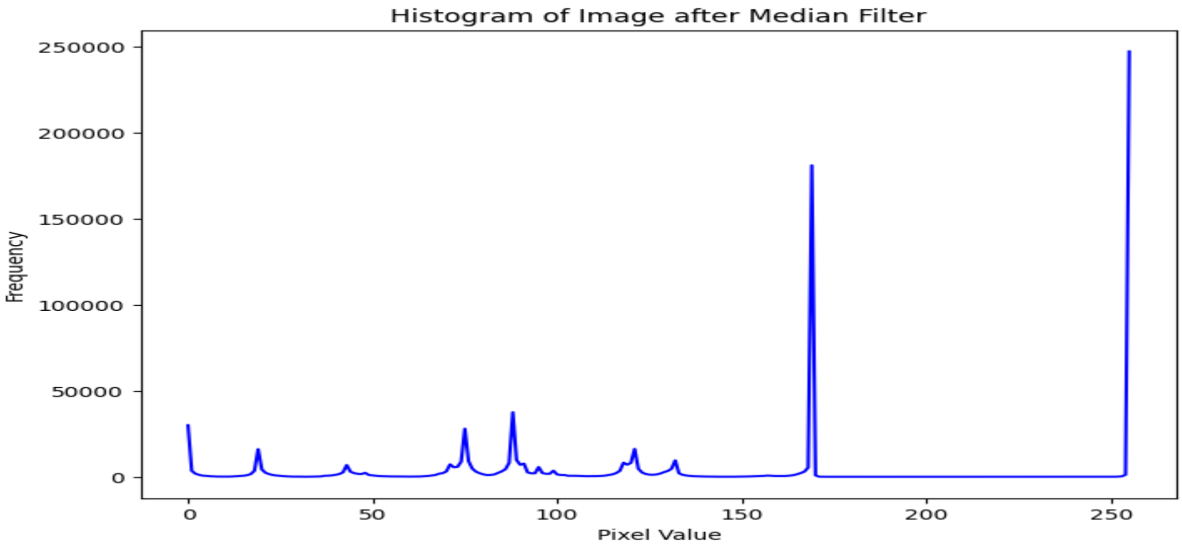
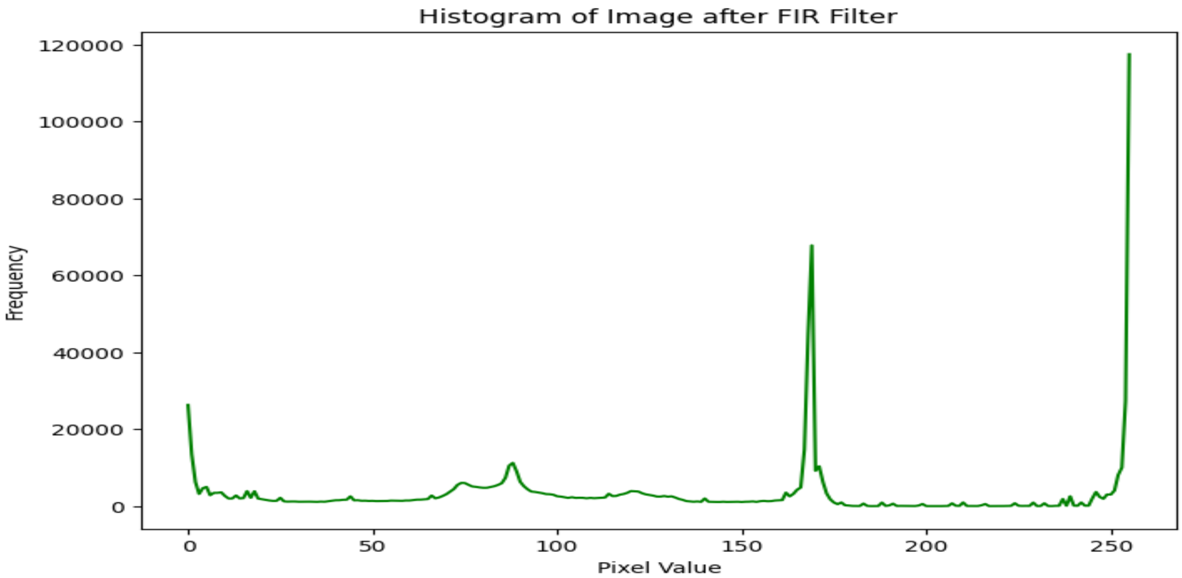


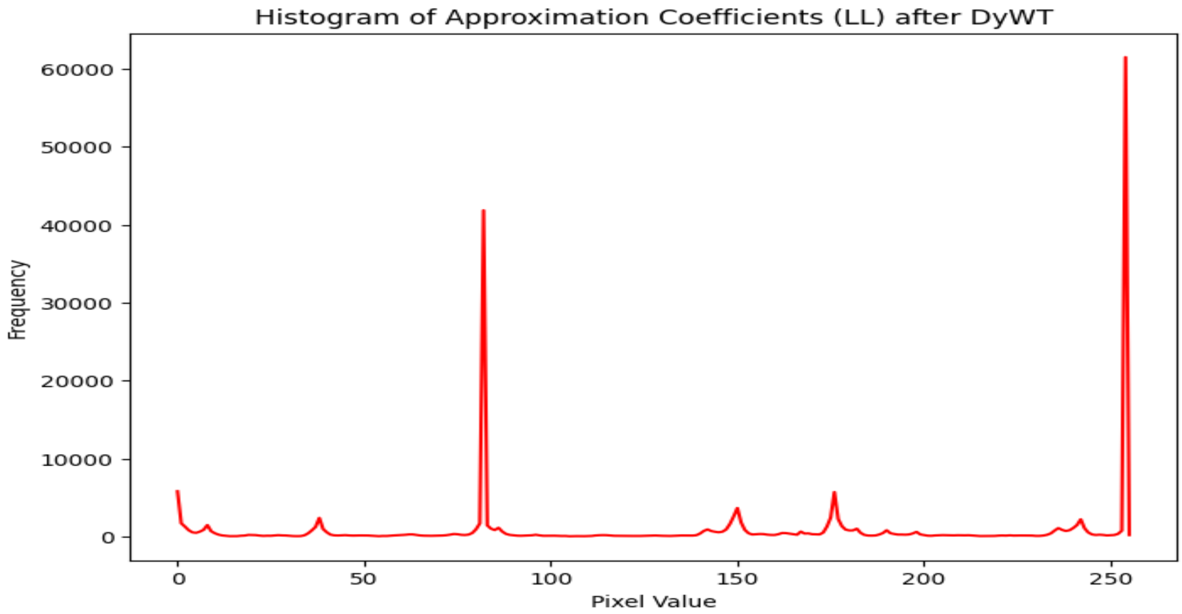
Figure.4. Histogram of the Original Image


Histogram of Image after Median Filter
Frequency
Pixel Value
250000
200000
150000
100000
50000
0
0
50
100
150
200
250

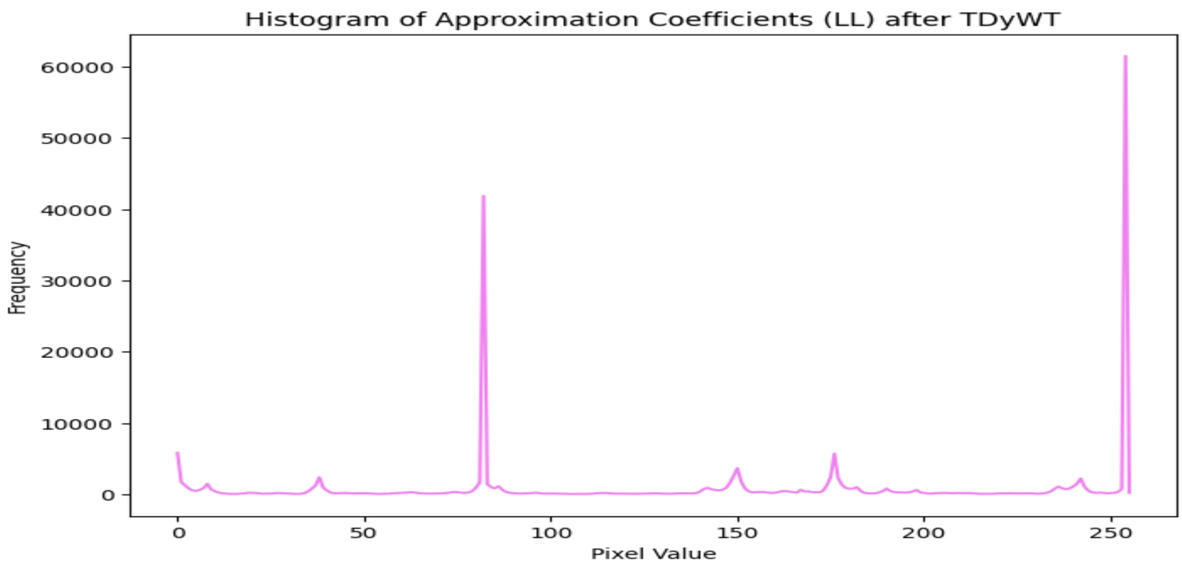
(a)


Histogram of Image after FIR Filter
Frequency
Pixel Value
120000
100000
80000
60000
40000
20000
0
0
50
100
150
200
250

(b)



(c)



(d)

Figure.5. Histogram of the Filtered Images
(a) Median filter (b) FIR filter (c) DyWT (d) TDyWT

Table 1 shows a comparative analysis of four filtering methods applied to histopathological images for lung cancer detection and segmentation, highlighting their performance metrics: Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Mean Squared Error (MSE).

Peak Signal-to-Noise Ratio (PSNR):PSNR is a measure of the quality of a reconstructed or filtered signal relative to the original signal, expressed in decibels (dB).

$$PSNR = 10X \log_{10}\left(\frac{MAX^2}{MSE}\right) - -(10)$$

- PSNR is the Peak Signal-to-Noise Ratio.
- MAX is the maximum possible pixel value of the image (usually 255 for 8-bit images).

- MSE is the Mean Squared Error between the original and reconstructed images.

Structural Similarity Index (SSIM):SSIM is a perceptual metric that measures the

similarity between two images, taking into account luminance, contrast, and structure.

$$SSIM(x,y) = \frac{(2\mu_x \mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} - -(11)$$

Mean Squared Error (MSE): measures the average squared difference between the original and filtered images, providing a quantitative measure of the level of distortion or error.

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} (I(i,j) - K(i,j))^2 \quad \text{- - (12)}$$

- I is the original image.
- K is the reconstructed (or filtered) image.
- m and n are the dimensions of the images.

These metrics are commonly used in image processing and provide valuable insights into the quality and fidelity of processed images compared to their originals.The median filter method, employing a median filter technique, achieves a PSNR of 37.5484 and SSIM of 0.98661, indicating effective noise reduction with an MSE of 11.4352. In contrast, FIR filter utilizing a Finite Impulse Response filter, exhibits lower PSNR (17.288) and SSIM (0.89491) values, implying less effective noise reduction and image quality preservation with a higher MSE of 23.1767. However, DyWT (Dyadic Wavelet Transform) demonstrates significantly higher PSNR (62.56) and SSIM (0.99489), indicating superior noise reduction and image quality preservation, accompanied by a lower MSE of 2.1527. Furthermore, TDyWT (Transverse Dyadic Wavelet Transform) exhibits the highest PSNR (96.3541) and perfect SSIM (1), signifying exceptional noise reduction and minimal distortion, with a minimal MSE of 1.00255. Finally, DyWT and TDyWT methods outperform Median Filter and FIR Filter in terms of noise reduction and image quality preservation for histopathological images in lung cancer detection and segmentation applications.Figure 6,7,8shows a comparison bar chart depicting the performance metrics of four distinct filtering methods utilized for image preprocessing in the context of lung cancer detection and segmentation in histopathological images. each filtering method is represented by a bar for three different metrics: Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Mean Squared Error (MSE). The height of each bar corresponds to the value of the respective metric. Among the methods, TDyWT exhibits the highest bar for PSNR, with a value of 96.3541, indicating superior noise reduction. Additionally, TDyWT achieves a perfect SSIM value of 1, which is represented by the highest bar for SSIM. Moreover, for MSE, TDyWT demonstrates the lowest value of 1.00255, indicating minimal distortion in the processed images. Therefore, in the comparison bar chart, the bars representing TDyWT stand out as the tallest for PSNR, SSIM, and the shortest for MSE, highlighting its superior performance compared to the other filtering methods.Figure 9. Shows the compares the image quality metrics (PSNR, SSIM, MSE) for four different image filtering methods (Median Filter, FIR Filter, DyWT, TDyWT). Each method is represented on the x-axis, and the y-axis displays the corresponding values for the three metrics. The chart uses distinct line styles and markers for PSNR, SSIM, and MSE, with a legend for clear identification. This visualization facilitates a quick assessment of how each filtering method performs across the selected metrics, aiding in the comparison of their overall effectiveness.

Table.1. Comparative Analysis Of Four Filter Method Applied To Histopathological Image With The Metrices (PSNR,SSIM,MSE)

Method	PSNR	SSIM	MSE
Median Filter	37.5484	0.98661	11.4352
FIR Filter	17.288	0.89491	23.1767
DyWT	62.56	0.99489	2.1527
TDyWT	96.3541	1	1.00255

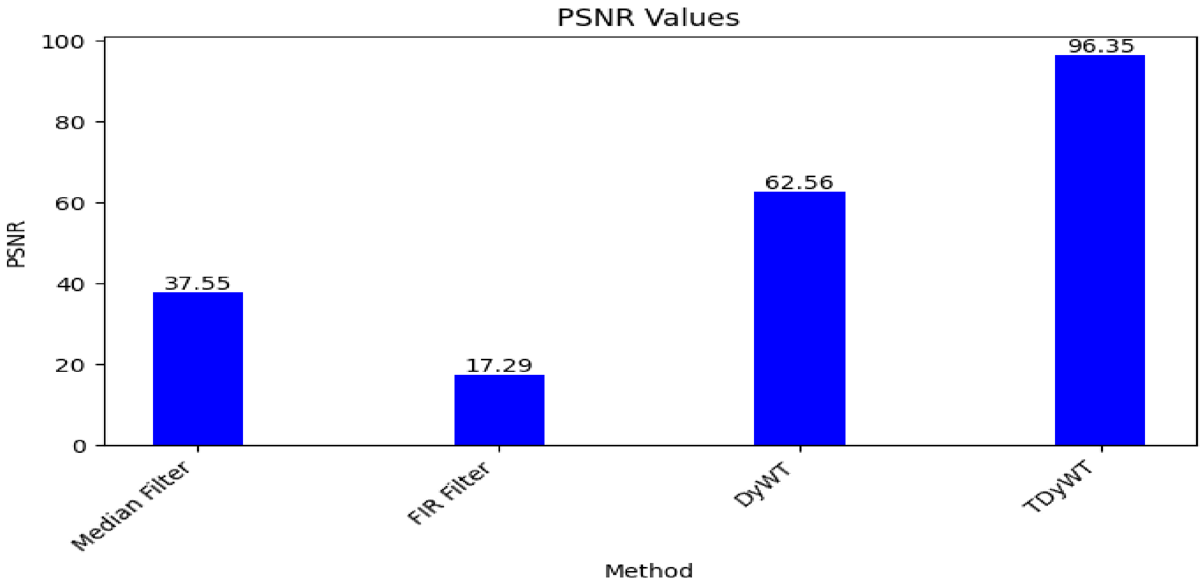


Figure.6. Comparison of PSNR value for Four Methods

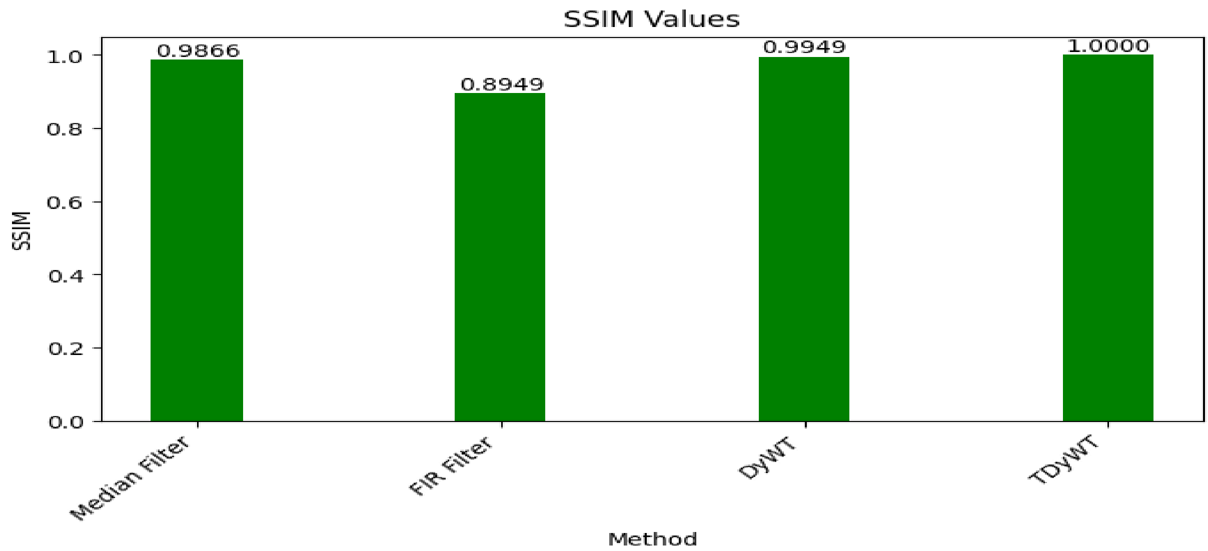


Figure.7. Comparison of SSIM value for Four Methods

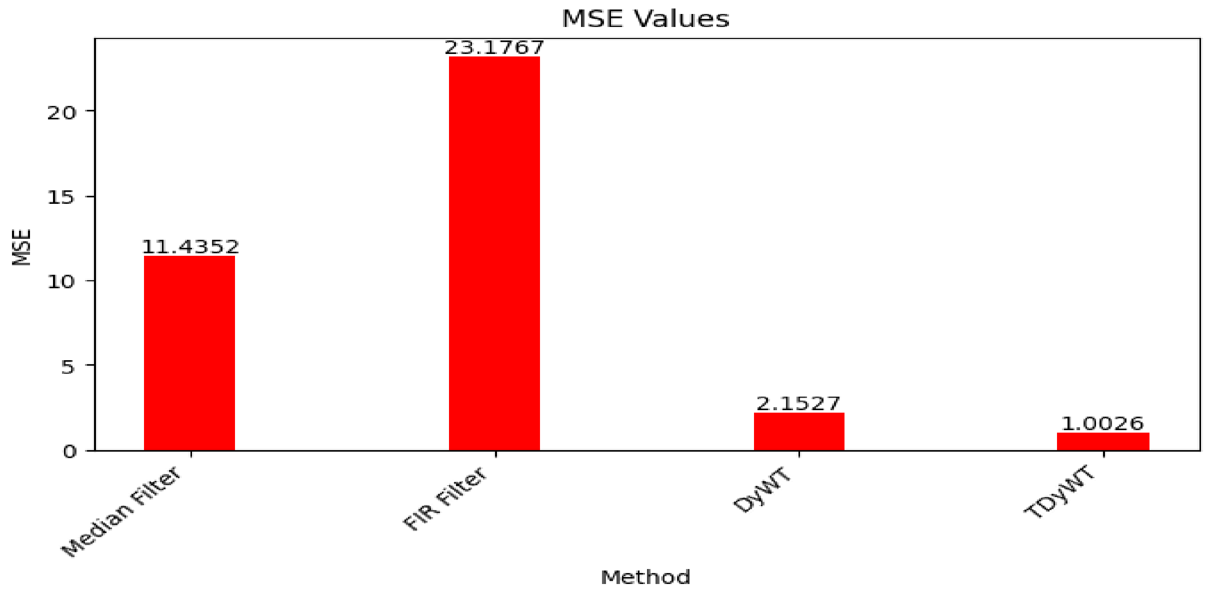


Figure.8. Comparison of MSE value for Four Methods

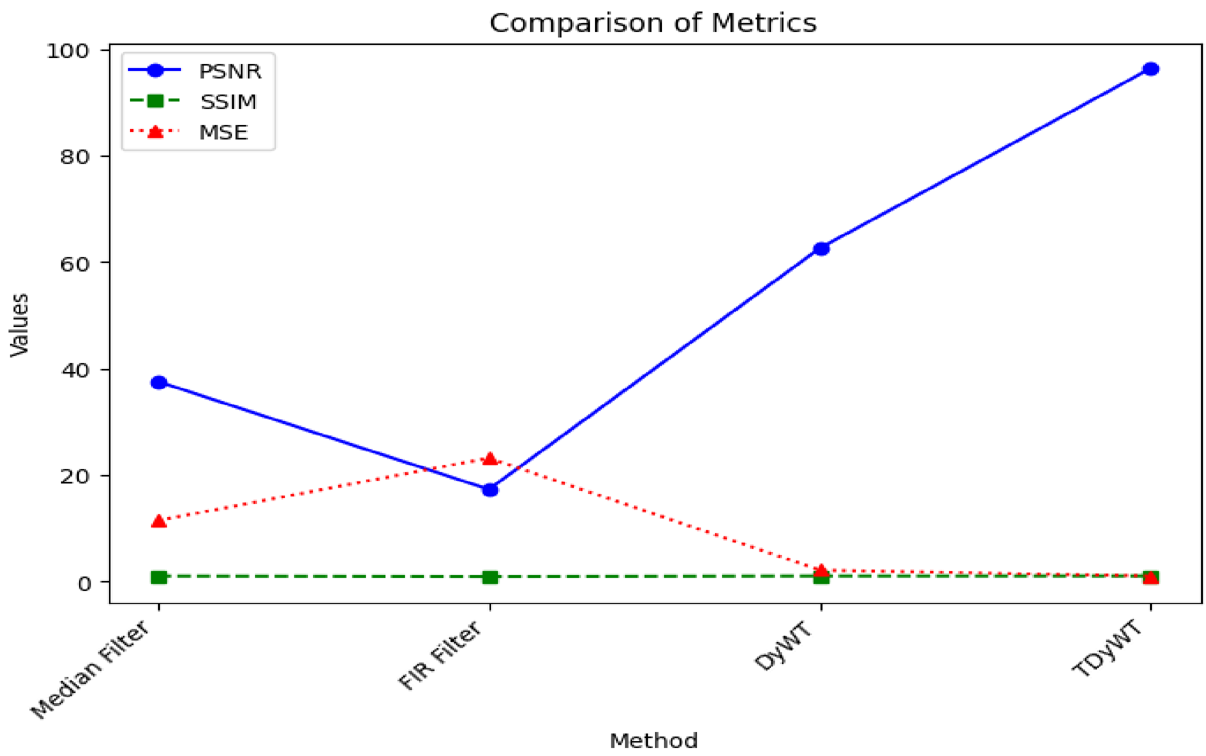


Figure.9. Comparison of MSE value for Four Methods

V CONCLUSION AND FUTURE WORK

In conclusion, this study assesses effectiveness of various filtering methods, including the Transverse Dyadic Wavelet Transform (TDyWT), for preprocessing histopathological lung images in the context of cancer detection and segmentation. Our findings highlight the superior performance of TDyWT in reducing noise and preserving image quality compared to other filtering techniques. Moving forward, our future work will focus on utilizing the TDyWT-filtered images as input for implementing and evaluating three different segmentation techniques for lung cancer classification and detection. By combining advanced image preprocessing with innovative segmentation algorithms, we aim to enhance the accuracy and efficiency of lung cancer diagnosis, contributing to advancements in medical imaging and patient care.

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