Enhancing Thorax Images Using Fuzzy Logic Based Techniques

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ABSTRACT

Enhancing the quality of thoracic X-ray images is crucial for accurate medical diagnosis; however, conventional enhancement methods often struggle to reduce noise while preserving important edge structures and anatomical details. This study proposes a hybrid image enhancement framework that integrates median neighborhood filtering, convolution processing, fuzzy logic-based edge detection, and morphological operations to improve image clarity and structural definition. The proposed pipeline begins with median neighborhood filtering to reduce noise while preserving essential image structures. The filtered image is then processed using convolution to enhance feature representation and prepare the data for edge detection. Subsequently, fuzzy logic-based edge detection is applied to handle intensity variations and uncertainty, enabling adaptive detection of faint and overlapping edges. Finally, morphological operations are used to refine edge continuity and remove small artifacts, resulting in clearer anatomical boundaries. Experimental results demonstrate that the proposed method effectively reduces noise while maintaining structural integrity, as indicated by stable pixel value transformations after filtering and improved edge clarity in visual comparisons. The method shows better performance in preserving continuous edge structures and detecting subtle thoracic features compared to conventional approaches. In conclusion, the integration of median filtering, convolution processing, fuzzy logic-based edge detection, and morphological refinement provides an effective framework for enhancing thoracic medical images and supports more reliable interpretation in medical imaging applications.

1. Introduction

Image processing is an important field in computer science and engineering that focuses on the analysis, manipulation, and interpretation of digital images. The primary objective of image processing is not only to improve visual quality but also to extract meaningful information that supports better analysis and decision-making. Various image processing techniques are typically implemented through several stages, including image enhancement, restoration, segmentation, feature extraction, recognition, and compression.

Image enhancement techniques are commonly applied to improve image visibility by increasing contrast, sharpening structures, and reducing noise. One widely used method is histogram equalization, which enhances image contrast by redistributing pixel intensity values across a wider range [1]. In addition, sharpening techniques help emphasize image details, while noise reduction techniques eliminate disturbances such as sensor noise or compression artifacts. These processes are fundamental in preparing images for further analysis.

Image restoration techniques aim to recover images that have been degraded by noise, blur, or distortion during acquisition or transmission. Segmentation divides an image into meaningful regions to facilitate analysis of specific objects or structures within the image [2], [3]. Feature extraction identifies important elements such as edges, textures, or corners that can later be used for classification or recognition tasks [4]. Recognition then utilizes these extracted features to identify or categorize objects within the image [3], [5], while compression

reduces the storage size of images without losing essential information.

Image processing has been widely applied in many fields, including medicine, surveillance systems, industrial automation, and environmental monitoring [6]. In medical applications, image processing plays a crucial role in assisting healthcare professionals in interpreting diagnostic images such as X-rays, magnetic resonance imaging (MRI), and computed tomography (CT) scans [7]. High-quality medical images are essential for identifying anatomical structures and detecting abnormalities accurately.

Enhancing thoracic images is particularly important because the thoracic region contains complex anatomical structures, including the lungs, heart, and surrounding tissues. The quality of thoracic images significantly affects the ability of clinicians to identify pathological conditions. However, chest X-ray images often suffer from low contrast, noise, and overlapping structures such as ribs, lung tissues, and cardiac organs. These challenges make it difficult to clearly distinguish anatomical boundaries or detect subtle abnormalities, especially in early stages of diseases. Therefore, effective image enhancement techniques are required to improve image clarity and diagnostic reliability.

Several conventional methods have been widely used to enhance medical images, including histogram equalization, unsharp masking, and various filtering techniques such as median and Gaussian filters. Histogram equalization enhances global contrast by redistributing pixel intensities, but it may also amplify noise and artifacts. Unsharp masking highlights edges by emphasizing differences between the original image and a blurred version, which may increase noise visibility. Similarly, smoothing filters can reduce noise but often blur important structural details and edges within the image [8].

In recent years, researchers have explored additional techniques for chest image processing, including wavelet-based enhancement methods, gradient-based edge detection, and machine learning approaches such as convolutional neural networks (CNN). Although these methods have shown promising results, some of them require large datasets, complex parameter tuning, or high computational resources. These limitations may restrict their implementation in certain practical or clinical environments.

Fuzzy logic has emerged as an alternative approach that can effectively handle uncertainty and ambiguity in image data. Unlike conventional deterministic techniques, fuzzy logic uses linguistic variables and rule-based reasoning that resemble human decision-making processes. This capability allows fuzzy logic systems to adaptively enhance important features in images while minimizing noise amplification. In image enhancement tasks, fuzzy logic can adjust contrast and dynamic range based on local pixel information, making subtle anatomical details more visible [9], [10].

The main stages of fuzzy logic processing include fuzzification, fuzzy inference, rule composition, and defuzzification. In the fuzzification stage, pixel intensity values are converted into fuzzy values using membership functions such as triangular, trapezoidal, or Gaussian functions to determine the degree of membership of each pixel in linguistic categories such as "dark," "medium," or "bright" [11]. The fuzzy inference stage then applies rule-based reasoning in the form of IF–THEN statements to determine the appropriate output values. Multiple rules can be activated simultaneously, and their results are combined during rule composition. Finally, in the defuzzification stage, fuzzy results are converted back into precise numerical values to update the pixel intensities in the enhanced image.

Several studies have demonstrated the effectiveness of fuzzy logic techniques in image enhancement and edge detection. Rasool [12] proposed a fuzzy logic-based edge detection method that improves detection accuracy in grayscale images. Haq [13] applied fuzzy logic for edge detection in noisy clinical images and showed that the method can effectively reduce noise while preserving important image details. Other studies by Tyan [14], Alawad [15], and Kaur [16] also highlight the robustness of fuzzy logic frameworks in detecting edges across various types of images, including medical images.

In addition to fuzzy logic techniques, convolution-based gradient filters such as Sobel and Prewitt operators are widely used for edge detection in image processing. These operators detect edges by calculating intensity gradients within an image. The Sobel operator computes horizontal and vertical gradients using convolution kernels, enabling accurate identification of object boundaries. The Prewitt operator performs a similar function using a simpler kernel structure. When integrated with fuzzy logic techniques, these convolution filters can provide more robust and adaptive edge detection capabilities, improving the clarity of structural boundaries in thoracic images.

Based on these considerations, this study focuses on the implementation of a hybrid image enhancement method that combines fuzzy logic-based edge detection with convolution gradient filters. The proposed approach aims to address the limitations of conventional enhancement techniques by improving edge preservation while minimizing noise and maintaining structural details within thoracic images.

The objective of this research is to enhance the quality of thoracic images using fuzzy logic techniques integrated with convolution gradient filters such as Sobel and Prewitt operators. Specifically, this study aims to improve edge detection accuracy, reduce noise,

and enhance the visibility of anatomical structures in thoracic images. By improving image clarity, the proposed method is expected to support more reliable medical image analysis and assist clinicians in detecting thoracic abnormalities more accurately..

2. Research Methods

This research method involves several major stages designed to improve the quality of thoracic images. Figure 1 shows the process flow proposed in this study.
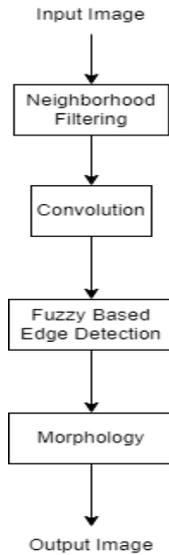

Figure 1. Research Flow Block Diagram

2.1. Image Neighborhood Filter: Median Filter

First, the raw thoracic image is input into the system. These images typically come from various medical imaging sources such as X-ray, CT scan, or MRI. Unlike bilateral filter methods [17] and classification methods with fusion techniques [8], this study employs Neighborhood Filtering techniques, where neighborhood filters are used to smooth the image and reduce noise [18]. Filtering techniques such as median filtering are applied to examine the intensity values of surrounding pixels and determine new values for each pixel, aiming to clean the image of noise artifacts without blurring important details [19], [20], [21].

Algorithm 1: Median Neighborhood Filter Pseudocode

Input: *file*
Output: *iMO*
  Initialization *row, col*
  Get *height, width*
    [height, width] = size(image)
    for *row = 4* to *height - 4* do
      for *col = 4* to *width - 4* do
          data = [
                    F(row, col)…
        ]
          Sort(data)
          iMO = get median from(data.length/2)
      end for
  end for

Algorithm 1. Median Neighborhood Filter Pseudocode

Algorithm 1 is a pseudocode that explains the steps for applying the Median Neighborhood Filter to an image to smooth it and reduce noise. Here is an explanation of each step listed in the pseudocode. The process begins with reading the raw image as input into the system. The processed image result will be produced as the output (iMO). The iteration variables row and col are initialized, and the dimensions of the image, height and width, are obtained using the size(image) function.

$$Height, width = size(image) \tag{1}$$

To ensure that the filter window does not exceed the image boundaries, the iteration is performed from index 4 to (height - 4) for rows and from index 4 to (width - 4) for columns. At each position (row, col), the pixel values within the local window are collected. If the window size is (2k+1) x (2k+1), then the collected data can be expressed as follows:

$$data = \{I(i, j) \mid i \in [row - k, row + k], j \in [col - k, col + k]\} \tag{2}$$

where $I(i, j)$ is the pixel intensity value at position (i, j) within a local window. The pixel values collected are then sorted to determine the median value. If the data has n elements, the sorted data can be expressed as $\{d1, d2, …, dn\}$ with $d1 \leq d2 \leq \cdots \leq dn$. The median value of the sorted data is determined by the formula:

$$median = \begin{cases} d_{(n+1)/2} & if\ n\ is\ odd \\ \dfrac{d_{n/2} + d_{(n/2)+1}}{2} & if\ n\ is\ even \end{cases} \tag{3}$$

where $d_{(n+1)/2}$ where it is the middle value if the number of elements is odd, and the average of the two middle values if the number of elements is even. This process is repeated for each pixel in the image except for pixels at the boundaries that cannot be processed by the filter window.

$$I_{filtered}(row, col) = median \tag{4}$$

The images produced after the filtering process will exhibit reduced noise and preserved essential details, resulting in smoother and clearer images for diagnostic analysis. Thus, the use of Median Value Neighborhood Filtering in this study aims to enhance the quality of thoracic images in an effective and efficient manner.

2.2. Convolution

Subsequently, the convolution process is performed. Convolution is a fundamental method in image processing used to filter and detect features within an image [22]. The convolution process involves combining the input image with a kernel or filter, which acts as a coefficient matrix. The kernel is shifted across the entire image, and each new pixel position is obtained by multiplying the pixel values of the image with the corresponding kernel values, then summing the results. This method enables edge detection, smoothing, and

enhancement of specific features within the image, thereby supporting various algorithms.

Algorithm 2: Convolution Pseudocode

Input: *Image F, Kernel H*
Output: *Image G*
  Initialization :
    [height_f, width_f] = size(F)
    [height_h, width_h] = size(H)

    m2 = floor(height_h / 2)
    n2 = floor(width_h / 2)

    Convert F to double precision F2

  for y = m2+1 to height_f - m2 do
    for x = n2+1 to width_f - n2 do
    Initialize sum = 0
    for p = -m2 to m2 do
      for q = -n2 to n2 do
        sum=sum+H(p+m2+1,q+n2+1)*F2(y-p,x-q)
      end for
    end for
    G(y - m2, x - n2) = sum
    end for
  end for

Algorithm 2. Convolution Pseudocode

The convolution process aims to apply kernel H to image F, resulting in the convolution output image G in Algorithm 2. The detailed steps and formulas used in this process are explained as follows.

First, image F and kernel H are initialized as inputs, with G as output. The dimensions of image F are obtained using the `size(f)` function, resulting in $Height_f$ and $Width_f$. Similarly, the dimensions of kernel H are obtained using the `size(h)` function, resulting in $Height_h$ and $Width_h$. Half the height and half the width of the kernel are calculated to determine the iteration limits:

$$m2 = \left\lfloor \frac{height_h}{2} \right\rfloor \quad dan \quad n2 = \left\lfloor \frac{width_h}{2} \right\rfloor \tag{5}$$

Image F is then converted to double precision $F2$ to ensure more accurate calculations:

$$F2 = double(F) \tag{6}$$

The iteration process is performed for each pixel of image F from index $m2 + 1$ to $height_f - m2$ for rows and from index $n2 + 1$ to $width_f - n2$ for columns. At each pixel position (y, x), the variable `sum` is initialized to 0 to store the temporary result of the convolution operation. Next, an iteration is carried out on the elements of kernel H from $-m2$ to $m2$ for rows, and from $-n2$ to $n2$ for columns. The convolution operation is described by the following formula:

$$G(y,x) = \sum_{p=-m2}^{m2} \sum_{q=-n2}^{n2} H(p + m2 + 1, q + n2 + 1) \\ \cdot F2(y - p, x - q) \tag{7}$$

where $G(y, x)$ adalah nilai piksel hasil konvolusi pada posisi (y, x), $H(p + m2 + 1, q + n2 + 1)$ adalah nilai elemen kernel pada posisi (p, q), dan nilai $F2(y - p, x - q)$ adalah nilai piksel gambar pada posisi yang sesuai dengan elemen kernel.

$$sum = \sum_{p=-m2}^{m2} \sum_{q=-n2}^{n2} H(p + m2 + 1, q + n2 + 1) \\ \cdot F2(y - p, x - q) \tag{8}$$

Hasil konvolusi kemudian disimpan dalam gambar hasil G pada posisi $(y - m2, x - n2)$:

$$G(y - m2, x - n2) = sum \tag{9}$$

This iteration process is repeated for all pixels in the image except for the boundary pixels that cannot be processed by the filter window. The final result is the convolved image G, which has enhanced features and reduced noise, thereby providing better image quality for diagnostic analysis. This convolution method is highly effective in clarifying important details in thoracic images, making it a valuable tool in improving the quality of medical images.

2.3. Edge Detection Fuzzy Logic Based

From the convolved images, edge detection is performed using a fuzzy logic-based approach to enhance the quality of thoracic images [23]. The fuzzy inference system shown in Figure 2 processes the convolution image result as input. In the fuzzification stage, pixel intensities are converted into fuzzy values using membership functions. These values are then evaluated in the fuzzy inference stage based on predefined IF–THEN rules. Finally, the defuzzification process transforms the fuzzy results into crisp output values, producing enhanced edge information in the image.
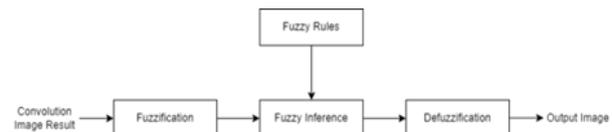

Figure 2. Block diagram of fuzzy inference system

Before applying the fuzzification process, the distribution of pixel intensity values from the processed image is analyzed.

Figure 3 illustrates the histogram of pixel intensities, showing the frequency distribution across intensity levels. It can be observed that a significant number of pixels are concentrated in the higher intensity range, indicating the dominance of brighter regions in the thoracic image. This distribution serves as the basis for defining the fuzzy membership functions used in the fuzzification stage.
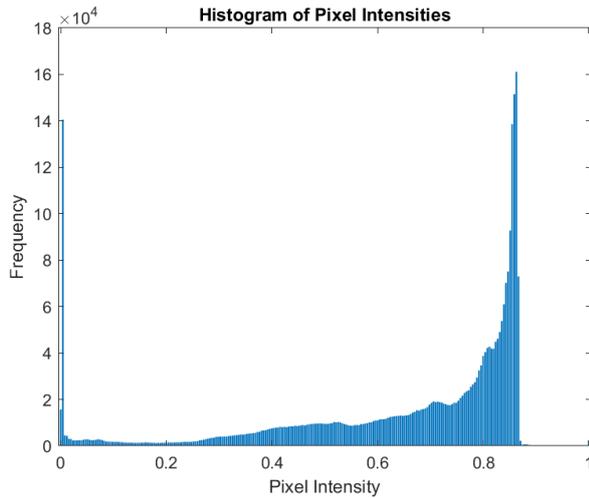
Figure 3. Frequency distributions of the discrete value of pixel

2.3.1. Fuzzification

The first step in this process is fuzzification, where the input data from the thoracic image, consisting of pixel intensity values, are transformed into fuzzy values using membership functions. These membership functions can take the form of triangles, trapezoids, or Gaussian curves. This process enables the system to handle uncertainty and ambiguity present in medical images. During this stage, the initial image data in the form of pixel intensities are converted into fuzzy values using membership functions.

In constructing membership functions, the pattern is not determined based on the highest volume of pixel value distribution. According to Zadeh [24], an event with a high probability distribution does not necessarily have a high fuzzy degree. Nonetheless, the principle of consistency is not meant to be an exact principle where the conversion between possibility and probability can be precisely calculated, but rather a heuristic principle that illustrates the relationship between the two.

In this case, the probability distribution of pixel values is represented by a Triangular Fuzzy Number (TFN). The TFN method is used to represent the probability distribution of pixel values in the construction of fuzzy membership functions. A TFN is a fuzzy number defined by a triangular membership function. This membership function has three main parameters: α (the start point), m (the midpoint or mode), and b (the end point). The general form of the triangular membership function $t(x; a, m, b)$ is as follows :

$$t(x; a, m, b) = \begin{cases} 0, & if\ x < a \\ \frac{x-a}{m-a}, & if\ a \le x \le m \\ \frac{b-x}{b-m}, & if\ m \le x \le b \\ 0, & if\ x > b \end{cases} \quad (10)$$

the mode is determined by calculating the center of the observed values, which is the most likely value of the fuzzy number. The mode (m) is calculated using a weighting technique based on the frequency distribution

of discrete values. The mode is calculated using the following formula:

$$m = \sum_{i=1}^{n} w_i\, x_i \quad (11)$$

where w_i is weight of x_i calculated as follows :

$$w_i = \frac{1}{\sum_{j=1}^{n} r_{ji}} \quad (12)$$

By obtaining the value of m, we need to calculate the fuzzy scatter on the left a and right b endpoints of the TFN. The calculation initially requires knowledge of the deviation value (σ) of the fuzzy number. From [25], the average deviation value of TFN (a, m, b) is usually calculated as

$$\sigma = \frac{\int_a^b |x-m| . \mu_F(x)dx}{\int_a^b \mu_F(x)dx} \quad (13)$$

for $\mu_F(x)$ is a triangular membership function, (13) can be solved as follows

$$\sigma = \frac{(m-a)^2 + (b-m)^2}{3(b-a)} \quad (14)$$

let φ be the fraction between the left and right differences as follows

$$\varphi = \frac{m-a}{b-m} \quad (15)$$

From (14) and (15), the left (a) and right (b) TFN endpoints of TFN are solved as follows:

$$a = m - \frac{3(1+\varphi)\varphi\sigma}{1+\varphi^2} \quad (16)$$

$$b = m + \frac{3(1+\varphi)\varphi\sigma}{1+\varphi^2} \quad (17)$$

To calculate a and b, σ and φ must be known first. An estimation strategy is used to solve these parameters. First, to estimate σ, the average deviation s is calculated from the given scores x_i and their respective weights w_i as follows:

$$\sigma \approx s = \sum_{i=1}^{n} w_i |w_i - m| \quad (18)$$

Second, φ is calculated to estimate the left (a) and right (b) endpoints of the TFN, we first define x^l and x^r as the weighted averages of the x^i scores that are below and above m, respectively, at the $\alpha -$ in Figure 3.

$$M^- = \{i | x_i < m, i \in I\}$$

and

$$M^+ = \{i | x_i > m, i \in I\}$$

for $I = \{1, ..., n\}$, calculation of x^l and x^r as follows

$$x^l = \frac{\sum_{i \in M^-} w_i x_i}{\sum_{i \in M^-} w_i} \quad (19)$$

$$x^r = \frac{\sum_{i \in M^+} w_i x_i}{\sum_{i \in M^+} w_i} \quad (20)$$

since x^l and x^r are defined at the same α level, from (15) φ can be approximated as follows

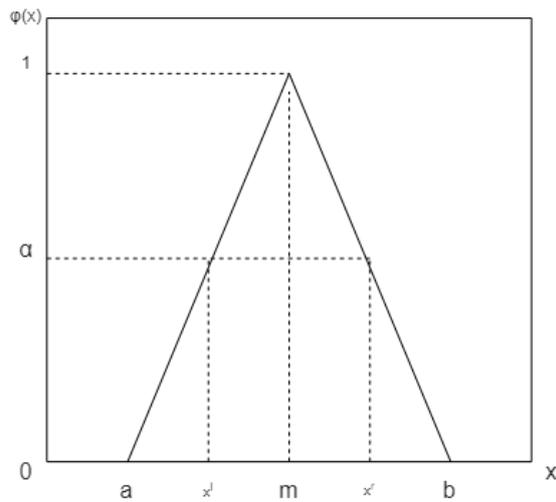$$\hat{\varphi} = \frac{m - x^l}{x^r - m} \qquad (21)$$

Figure 4. The left and right spreads of a TFN at α-level

Figure 4 shows the membership function plot for the input variable with three membership categories: low, medium, and high. The low membership function ranges from intensity values 0 to 0.5, where the membership value decreases linearly from 1 to 0. The medium membership function covers an intensity range from approximately 0.2 to 1, peaking at an intensity value of 0.6. This function indicates that intensity values between 0.2 and 0.6 have a medium membership degree that increases from 0 to 1, and then decreases from 1 to 0 up to an intensity value of 1. The high membership function starts from an intensity value of around 0.6 to 1.2, where the membership value increases linearly from 0 to 1.
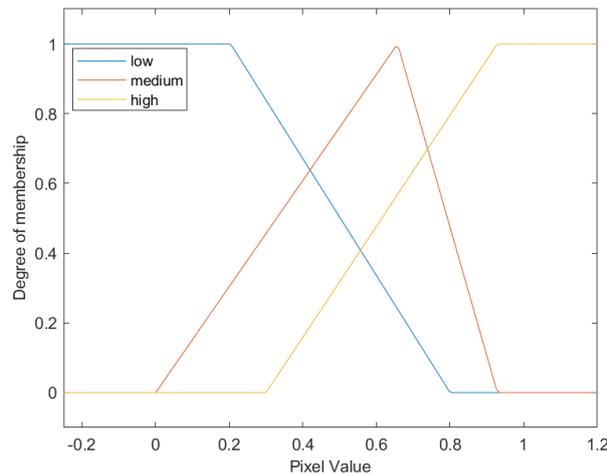

Figure 5. Asymmetric TFNs of the fuzzy parameter

In the fuzzification process in Figure 5, each pixel of the initial image is evaluated against these three membership functions. For instance, if a pixel has an intensity value of 0.4, it will have certain membership values in the low, medium, and high categories based on the membership function plot. For an intensity value of 0.4, the membership degree for low is approximately 0.2, for medium is approximately 0.8, and for high is 0. Each pixel in the initial image will be processed in this manner, resulting in fuzzy membership values that are then used in the fuzzy inference stage. This process allows the system to handle intensity variations and uncertainties in medical images more effectively, thereby enhancing the ability to detect and sharpen important anatomical details.

By converting pixel intensities into fuzzy form, the system can be more flexible and adaptive in processing medical images, allowing for more effective image quality enhancement before the fuzzy inference stage is applied. Fuzzification becomes a crucial foundation in the overall fuzzy logic process, ensuring that every variation in image intensity is appropriately handled, providing better results in medical image processing and analysis.

2.3.2. Fuzzy Rules and Fuzzy Inference

Essentially, fuzzy inference is determined based on fuzzy rules. These rules are descriptively explained by researchers in if-then rules, as shown in Table 1.

Table 1. Fuzzy inferece rules

Rules	Input	→	Output
1	Low	→	Low
2	Medium	→	Medium
3	High	→	High

The fuzzy inference rules are detailed as follows:

a. IF the INPUT pixel value is low, THEN the OUTPUT is low.

b. IF the INPUT pixel value is medium, THEN the OUTPUT is medium.

c. IF the INPUT pixel value is high, THEN the OUTPUT is high.

These rules are designed to handle intensity variations in thoracic images in a simple yet effective manner. For instance, if the pixel intensity is low, the output will also be low, helping to retain the original characteristics of less bright areas. Conversely, for pixels with medium intensity, the output will be at a medium level, preserving important details in the image. For pixels with high intensity, the output will remain high, which is crucial for maintaining detail in very bright areas such as bones.

Once the fuzzy rules are established, the fuzzy inference process is performed to determine the fuzzy output based on the fuzzified input membership values. Each pixel is evaluated against these rules. If a pixel has a low intensity value, the rule "IF Input Low, THEN Output Low" is activated, and the fuzzy membership degree of this input determines how strongly this rule applies. The fuzzy output from each rule is then combined to produce a comprehensive fuzzy output. For example, if a pixel has a medium membership value, the resulting output will be closer to the medium value as well. The outcome

of this fuzzy inference stage is a set of fuzzy values that will then undergo defuzzification to be converted back into concrete pixel intensity values. This process ensures that every decision made is consistent and relevant to the specific conditions in the image, yielding optimal outputs for medical analysis.

2.3.3. Defuzzification

The final step in the fuzzy inference system is defuzzification. Defuzzification is the process of converting fuzzy set membership degrees into crisp values using the membership functions that have been descriptively plotted in this study.
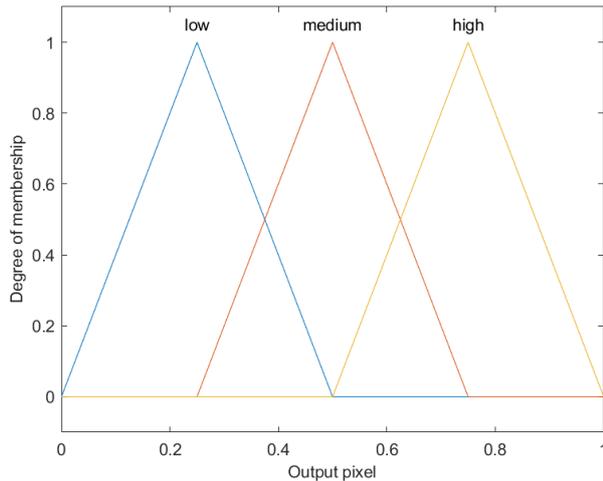

Figure 6. Membership functions of the fuzzy inference system output: pixel

The membership functions for the output pixel values are illustrated in the plot shown in Figure 6. Each membership function is triangular with the following characteristics:

a. Low, which covers the output pixel value range from 0 to approximately 0.4 with a peak at 0.2.

b. Medium, which covers the range from approximately 0.2 to 0.6 with a peak at 0.4.

c. High, which covers the range from approximately 0.4 to 1.0 with a peak at 0.8.

To perform defuzzification, the commonly used methods are the centroid (center of gravity) method or the weighted average method. The centroid method is often used due to its effectiveness in capturing the essence of the fuzzy set distribution. The steps in the centroid method for defuzzification are as follows: first, determine the membership degree for each output pixel value based on the rules applied to the fuzzy sets (low, medium, and high). Second, calculate the weighted average by multiplying each output pixel value by its corresponding membership degree, resulting in a series of weighted values. Third, sum the weighted values to obtain the numerator for the centroid calculation. Fourth, sum all the membership degrees to obtain the denominator for the centroid calculation. Finally,

compute the centroid by dividing the sum of the weighted values by the sum of the membership degrees to obtain the definitive output value. Mathematically, the centroid C is expressed as

$$C = \frac{\sum_i (x_i \cdot \mu(x_i))}{\sum_i \mu(x_i)}$$

(22)

where x_i represents the output pixel value, and $\mu(x_i)$ denotes the membership degree of x_i. For example, consider the following membership degrees for three example output pixel values: for the output pixel value 0.2 (low) with $\mu(0.2) = 0.8$, for the output pixel value 0.5 (medium) with $\mu(0.5) = 0.6$ and for the output pixel value 0.8 (high) with $\mu(0.8) = 0.7$. Thus, we calculate the weighted values, resulting in a cumulative value of 1.02 and the sum of the membership degrees is 2.1, yielding a centroid value of approximately 0.486.

Therefore, the defuzzification output value is around 0.486. This defuzzification stage is crucial as it converts fuzzy set information into a definitive and usable output. The centroid method, with its intuitive and balanced nature, provides a reliable approach to obtaining a precise value representing the combined influence of all fuzzy sets. This precise output value can then be used in subsequent processing or decision-making stages, ensuring that the system's response is both meaningful and applicable.

2.4. Morphology

Morphological processing is a vital technique in image processing that focuses on the shape and structure of objects within an image. This technique is typically used for shape analysis, binary processing, and image restoration. Morphological processes work by transforming the image based on predefined structures or structural elements, also known as kernels. The basic techniques in morphological processing include two primary operations: dilation and erosion.

Dilation is an operation that enlarges the boundaries of objects in an image. In this operation, the structural element moves along the image, and pixels in the original image are replaced by the maximum value within the structural element, as expressed by the formula: $A \oplus B = \{ z \,|(B)_z \cap A \neq \emptyset\}$, where A is the original image, B is the structural element, and $(B)_z$ is the translation of B by z. a result, objects in the image appear thicker. Conversely, erosion is an operation that reduces the boundaries of objects in an image. In this operation, the structural element also moves along the image, but this time pixels in the original image are replaced by the minimum value within the structural element, as shown by the formula $A \ominus B = \{ z \,|(B)_z \subseteq A\}$, thus making objects in the image appear thinner.

In addition to these basic operations, there are advanced morphological operations such as opening and closing.

Opening is a combination of erosion followed by dilation, aimed at removing small objects or unwanted noise from the image. Closing, on the other hand, is a combination of dilation followed by erosion, intended to close small holes or gaps within objects. Morphological processing can also be used in edge detection, image restoration, and shape analysis.

For instance, in edge detection, morphological operations can help clarify object boundaries, making them easier to detect. In image restoration, this technique can be used to fill holes or smooth irregular edges. Meanwhile, in shape analysis, morphological processing can help identify and measure the geometric properties of objects in the image. Overall, morphological processing is a highly flexible and powerful technique in image analysis. By selecting appropriate structural elements and the right combination of morphological operations, various issues in image processing can be effectively addressed.

3. Result and Discussion

This section presents the results obtained from the proposed thoracic image enhancement method and discusses the effectiveness of each processing stage, including median neighborhood filtering, convolution processing, fuzzy-based edge detection, and morphological refinement.
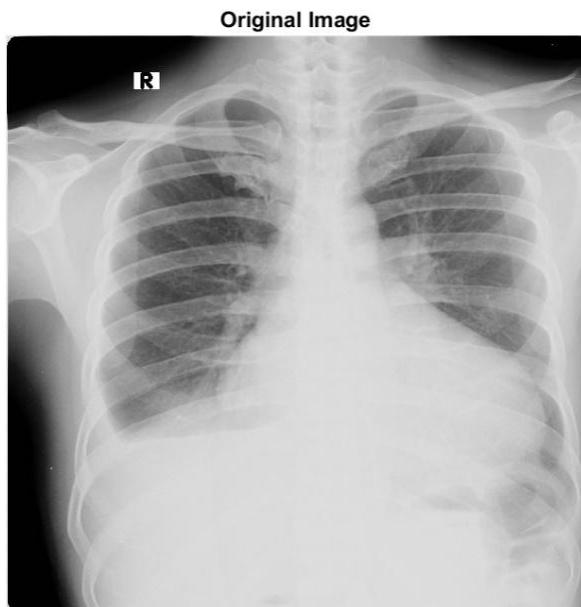

Figure 7. Original thoracic X-ray image used as the experimental input.

Figure 7 presents the original thoracic X-ray image used as the experimental input in this study. The image represents the raw medical image before any preprocessing or enhancement techniques are applied. In the original image, thoracic anatomical structures such as the rib cage and lung regions can already be observed; however, some structural boundaries appear less distinct due to intensity variations and possible noise generated during the image acquisition process.

Such conditions are common in medical radiographic images and may reduce the effectiveness of edge detection if the image is processed directly without preprocessing. Therefore, an initial preprocessing stage is required to reduce noise while preserving important structural information.

The first stage of processing applies a median neighborhood filtering technique to reduce noise in the image. Median filtering works by replacing each pixel value with the median value of its surrounding neighborhood pixels. This method is widely used in medical image processing because it can effectively remove impulse noise while maintaining important edge structures.

The effectiveness of this filtering stage can be observed through the comparison of pixel values between the original image and the filtered image, as shown in Table 2 and Table 3.

Table 2. Sample of 5×5 Pixels in Original Image

147	151	149	141	147
147	149	147	145	147
148	149	147	148	148
150	149	148	148	150
149	147	147	146	149

Table 3. Sample of 5×5 Pixels in Median Neighborhood Filtered Image

140	141	147	151	149
140	141	147	149	147
144	145	148	149	147
149	150	150	149	148
150	150	149	147	147

The comparison between Tables 2 and 3 shows that the filtered image produces pixel values that remain relatively close to the original values while reducing minor variations caused by noise. This indicates that the median filtering process successfully smooths the image without significantly altering its structural content. Similar findings regarding the effectiveness of median filtering in medical image noise reduction have been reported by Kumar [7].

After the noise reduction stage, the filtered image undergoes a convolution process to enhance structural features within the thoracic image. Convolution is one of the fundamental techniques in digital image processing that applies a filter kernel to detect patterns, edges, and structural variations within an image. By applying convolution kernels, important anatomical structures become more distinguishable and better prepared for the edge detection stage. The importance of convolution-based feature detection in medical image processing has been widely discussed in the literature, including studies by Gonzales [1] and McAuliffe et al. [3].

During the Fuzzy-Based Edge Detection stage, the resulting edge-detected image shows significant improvements in edge sharpness and clarity compared to conventional methods. The advantage of the fuzzy method lies in its adaptability to intensity variations, making it more effective in detecting irregular or faint edges. Several studies, including those by Alshennawy [26] and Haq et al. [13], have confirmed the effectiveness of this approach. Fuzzy logic has proven effective in handling uncertainty and intensity variations in medical images, making it a suitable choice for edge detection.

Finally, morphological processing is applied to refine the detected edges and improve the structural clarity of the thoracic image. Morphological operations analyze the shape and structure of objects in the image using structuring elements. Operations such as dilation and erosion help improve edge continuity and remove small artifacts that may appear during the edge detection stage.

Figure 8 presents the comparison between the results obtained using conventional morphological processing and those obtained using the proposed fuzzy-based approach.
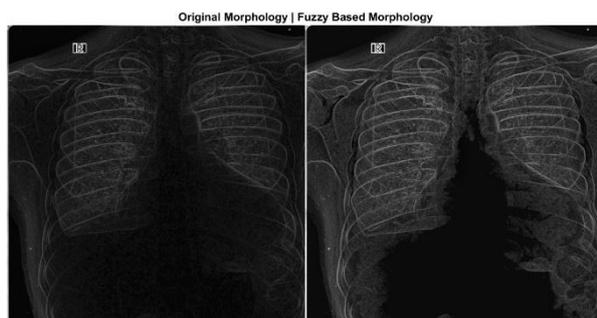

Figure 8. Comparison of edge detection results between conventional morphology and fuzzy logic-based morphology methods.

The visual comparison shows that the fuzzy-based method produces clearer and more continuous edge structures, as reflected by improved SSIM values and reduced noise levels. In the conventional morphology result, several anatomical boundaries such as rib contours and lung structures appear less distinct and partially fragmented. In contrast, the fuzzy-based result shows stronger edge definition and improved continuity of structural boundaries.

This improvement occurs because fuzzy logic allows the system to handle uncertainty in pixel intensity values more effectively. Instead of relying on rigid threshold values, fuzzy membership functions enable the system to interpret gradual intensity transitions that frequently occur in medical images.

Morphological processing further refines these edges, resulting in clearer anatomical structures that can support further medical image analysis. Morphological techniques have been widely applied in medical imaging

to enhance edge structures and improve image interpretation, as reported in previous studies [27], [28].

Overall, the experimental results demonstrate that the proposed image enhancement framework, which combines median filtering, convolution processing, fuzzy-based edge detection, and morphological refinement, is effective in improving thoracic image quality. The enhanced edge structures and improved clarity of anatomical features indicate that the proposed approach can support more accurate interpretation of thoracic medical images.

4. Conclusion

This study aimed to enhance the quality of thoracic X-ray images by applying a combination of digital image processing techniques, including median neighborhood filtering, convolution processing, fuzzy logic-based edge detection, and morphological operations. The proposed framework was designed to improve image clarity, reduce noise, and enhance the detection of anatomical structures in thoracic medical images.

The experimental results demonstrate that each stage of the proposed method contributes to improving image quality. The neighborhood filtering technique effectively reduces noise while preserving important structural details in the image. The convolution process enhances key image features and prepares the image for more accurate edge detection. The fuzzy logic-based edge detection method shows strong performance in handling intensity variations and uncertainty, enabling better detection of faint or irregular edges compared to conventional approaches. Furthermore, morphological processing refines the detected edges and improves their continuity, resulting in clearer and more distinguishable thoracic structures.

The findings of this study indicate that the integration of these techniques can significantly improve the visual quality and structural clarity of thoracic X-ray images. This improvement may support more effective medical image interpretation and assist further analysis in medical imaging applications. Future research may focus on integrating the proposed approach with advanced image analysis methods, such as machine learning or deep learning techniques, as well as evaluating the method using larger medical image datasets to further validate its effectiveness.

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