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RESEARCH ARTICLE

Fuzzy Image Processing for An Early Detection of Breast Tumours

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Abstract Breast tumour analysis via mammography remains challenging due to tumour appearances, poorly defined boundaries and low contrast differences. Fuzzy set theory, which can handle the ambiguity and intricacies of real-world applications, have shown promising results to overcome the constraints of the mammography imaging. This study incorporated a Fuzzy Intensification (INT) operator for the enhancement process and Fuzzy C-Mean (FCM) clustering for the segmentation process, implemented using MATLAB R2023a. The results of the fuzzy-based methods were compared with the traditional image processing techniques. The results yielded enhanced clarity and contrast of the mammography images, achieving higher Peak-to-Signal Ratio (PSNR) and lower Mean Squared Error (MSE) values. While the FCM-based clustering method successfully segmented tumour regions in some cases, it demonstrated over-segmentation in complex tumour characteristics. The results emphasised the potential for integrating fuzzy image processing techniques into clinical workflows to improve early detection of breast tumours. Future research directions are crucial to maximise the potential of fuzzy image processing in the field of medical imaging.

Keywords: Fuzzy set theory, Fuzzy Intensification operator, Fuzzy C-Mean clustering, breast cancer, early detection.

Introduction

Breast cancer is a highly prevalent and lethal form of cancer that affects people from all parts of the world. The diagnosis has made significant developments, for instance, mammography which has significantly reduced fatality rates by detecting breast cancer at its initial stages. However, the images may appear blurry or fuzzy, resulting in cases of missed diagnosis or unnecessary concern due to false alerts [1]. In the past few years, the application of fuzzy set theory with an image processing technique has yielded promising advances in resolving the uncertainties found in medical imaging. It is used in image enhancement to create rules and make decisions based on the degrees of membership of pixels in different categories or levels. It can also be used for image segmentation which corresponds to a significant portion of breast tumours. Fuzzy image processing involves mathematical equations relating to membership functions, fuzzy rules, fuzzy inference, and defuzzification [2].

The current issue is the need for more advanced and precise methods to quickly detect breast tumours. Medical images are often ambiguous and imprecise, making traditional image processing techniques, such as such as thresholding [3] and edge detection [4] ineffective. Thresholding is considered one of the simplest segmentation techniques. However, these methods were sensitive to noise and useful only when the intensity distribution of the foreground and background of an image is significantly distinct, as only one threshold setting for the entire image [5]. Furthermore, edge detection acts as an initial phase for image segmentation by locating and identifying sharp discontinuities in an image. However,

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derivatives used to calculate the gradients and curvatures of images, such as Sobel and Prewitt operators, typically only identify edges in horizontal and vertical directions, hence ignoring edge points in other directions [6].

Thus, fuzzy image processing must be explored to improve breast tumour detection and reduce diagnostic errors. Therefore, the main objective of the study is to utilise fuzzy enhancement and segmentation models for breast tumour imaging, examine how they may be incorporated into clinical workflows, and analyse their effectiveness in comparison with traditional methods. The study will apply Fuzzy Intensification (INT) Operator and Fuzzy C-Mean (FCM) clustering for the enhancement and segmentation processes, respectively.

The significance of this research lies in its potential for breast tumour detection and diagnosis. The finding of this study is useful to improve visual perception and accuracy of breast tumour imaging. Moreover, it is also useful to improve the chances of early detection, which is crucial for more effective treatment and higher survival rates. Furthermore, the scope of this study is strictly focused on the fundamental stages of image enhancement and segmentation to systemically assess the effectiveness of fuzzy-based methods in minimising uncertainty during the initial phases of mammography processing.

Therefore, the incorporation of fuzzy logic with image processing techniques opens the door to future studies into using fuzzy set theory to handle uncertainty in additional image processing tasks. The findings of the study have important implications for medical imaging, which relies on image qualities to make appropriate decision.

Related Studies

Mammography is one of the imaging techniques used to detect tumours in breasts. However, due to the diverse forms of breast tumours, relying just on it for the detection is insufficient. Mammography has certain limits which some may still be diagnosed with breast cancer that can only be detected through physical examination [7]. Furthermore, breast density has a significant role in the lack of tumour detection during screening mammography because of its “masking effect”, leading to misjudgement of the lesion [8]. Moreover, it is not accurate in detecting all types of cancer and the result is commonly referred to as a false-negative. In cases where a mammography shows abnormal characteristics but fails to show the presence of cancer, it is referred to as a false-positive [9]. In addition, there is a possibility that tumours located in the outermost region of the breast, beyond the captured field of view, may be missed [10]. Therefore, screening alone is not enough to detect the tumours.

Histogram Equalisation (HE) is one of the traditional image enhancement techniques. The traditional HE method demonstrated a higher Absolute Means Brightness Error (AMBE) score of 101.68 compared to the proposed Bi-level Histogram Modification-Adaptive Nonlinear Filter (BHM-ANF) with only 17.137 of AMBE score [11]. This suggests that the traditional HE lost many complex details in the enhanced mammography images. Furthermore, Iswardani and Hidayat [12] performed enhancement in mammography images for microcalcification detection using the HE method. The enhancing process is executed, however, only a few images show enhanced quality. This is influenced using thresholds, which play a crucial role in achieving better visualisation of complex mammographic images.

Sobel edge detection is one of the traditional segmentation techniques. Kekre and Gharge [13] proposed the extended Sobel operator for image segmentation. Based on the result, the extended Sobel provided better result compared to the traditional Sobel as it produces clear distinction of the tumour and sharp edges. This suggests that the traditional Sobel operator itself is not enough to exhibit more details on the edges. Moreover, a fuzzy automated edge detection is compared with the Sobel edge detection technique [14]. The proposed method exhibits 92.5% accuracy compared to the Sobel edge detection with only 84% of accuracy.

There are several fuzzy image processing techniques used for breast tumour detection introduced by previous researchers. The intuitionistic fuzzy sets-based image enhancement technique was proposed by Deng et al. [15], which enhanced various mammography images with good performance and consistency, compared to other methods. Furthermore, Magudeeswaran and Balasubramanian [16] presented the fuzzy weighted histogram equalisation, which exhibits better contrast enhancement and brightness preservation of input mammogram images. In addition, the entropy-based intuitionistic fuzzy method was proposed by Dabass et al. [17], demonstrates enhanced visual quality and yields increased subjective and quantitative measures. Moreover, the fuzzy rule-based approach exhibits superior performance compared to other advanced enhancement techniques, resulting in enhanced visual representation of prominent features such as microcalcification [18]. Additionally, Dabass and Dabass

[19] presented that the intuitionistic fuzzy entropy function demonstrated proficiency in enhancing the contrast and effectively minimised the presence of uncertainty inside a specified region of tumours, while maintaining the overall shape and informational content of the mammography image. More recently, a five-stage framework, incorporating intuitionistic fuzzy entropy and neutrosophic sets (NSs) was proposed for enhancing digital mammography images [20]. This method achieved a high Contrast Improvement Index (CII), maintaining lower AMBE and optimal Absolute Mean Brightness Coefficient (AMBC), ensuring natural appearance and better quality of the images. Consequently, the method demonstrated strong performance across fatty, fatty-glandular, and dense-glandular breast tissues.

Image segmentation is a procedure of portioning an image into separate and well-defined areas. Zadeh et al. [21] utilised the fuzzy active contours for thermal image segmentation of breast malignant areas, which was effective compared to the traditional techniques. Furthermore, Huang et al. [22] presented an overview of the segmentation techniques is the utilisation of a unique extended fuzzy watershed method and a fully automatic system (neural network) which showed a high percentage of true positive accuracy with 81.7% and 92.8%, respectively. Moreover, Aswathy and Jagannath [23] discussed the fuzzy logic type I and II for the detection and segmentation are highly effective for the dentification and analysis of patterns, including the process of segmentation. In addition, Michael et al. [24] provided an analysis on fuzzy morphology and achieved a precision of 20.0%. Besides, Ansar and Raza [25] provided a thorough insight on fuzzy techniques for lesion detection in mammograms. An adaptive neuro-fuzzy inference system was used for feature extraction produces a high accuracy performance of 93.7%. The fuzzy c-mean method presents 94.12% of accuracy in detecting boundaries for various types of breast masses. Furthermore, Altameem et al. [26] presented a fuzzy ensemble technique, that provided fuzzy rankings to the component classifiers via a re-parameterised Gompertz function and employed it into deep learning models. This approach significantly outperformed individual transfer learning techniques and other advanced ensemble strategies, achieving accuracy rate of 96.79%, 97.67%, 98.35% and 99.32% in combination with ResNet-164, VGG11, DenseNet121 and InceptionV4, respectively.

Therefore, a significant gap remains in understanding the practical advantage and limitations of traditional image processing enhancement and segmentation techniques when applied to mammogram images with varied tumour characteristics. This study directly addresses this gap by evaluating the effectiveness of the fuzzy-based methods, including Fuzzy Intensification (INT) operator alongside Fuzzy C-Means (FCM) clustering method, analysing their performance across different tumour shapes and density conditions. This work provides domain-specific insights into the applicability, strengths, and limitations of fuzzy-based enhancement and segmentation approaches.

Materials and Methods

Image Enhancement using Fuzzy Intensification (INT) Operator

The INT operator is used to decrease fuzziness and hence enhance the contrast of the breast mammography images [27]. For an input image, I, let g_{ij} represents the grey level at position (i, j), and g_{max} and g_{min} represent the maximum and minimum grey level values. The membership function is precisely defined as

$$\mu_{ij} = \left[1 + \frac{g_{max} - g_{ij}}{F_d}\right]^{-F_e} \quad (1)$$

where F_d is the denominational fuzzifier and F_e is the exponential fuzzifier, which control the degree of ambiguity in greyscale. Numerically, as $\mu_{ij} \to 1$, when $g_{ij} \to g_{max}$, it indicates that the grey level approaches maximum brightness as the membership value trends towards 1, or the maximum. In other words, it indicates the degree to which the pixel exhibits an intense or light shade of grey. When the grey level approaches its maximum value, the maximum membership is 1. Therefore, maximum brightness is represented by $\mu_{ij} = 1$, while absolute darkness is represented by $\mu_{ij} = 0$.

Next, employing intensifier operators μ_{ij}, the membership values are transformed. The contrast between the membership values is increased by the intensity operator. For a better contrast in an image, it transforms membership values below 0.5 to much lower values and membership values over 0.5 (the standard value) to considerably higher values in a nonlinear manner. The modified INT operation is written as

$$\mu_{ij} = \begin{cases} 2(\mu_{ij})^2 & , \quad 0 \leq \mu_{ij} \leq 0.5 \\ 1 - 2(1 - \mu_{ij})^2 & , \quad 0.5 < \mu_{ij} \leq 1. \end{cases} \tag{2}$$

After the membership values have been modified, an inverse function, as defined by equation (3) is implemented to convert the modified grey values to the spatial domain

$$g'_{ij} = G^{-1}\left(\mu'_{ij}\right) = g_{max} - F_d\left[\left(\mu'_{ij}\right)^{-\frac{1}{F_e}} - 1\right] \tag{3}$$

where

$$\left(1 + \frac{g_{max}}{F_d}\right)^{-F_e} \leq \mu'_{ij} \leq 1. \tag{4}$$

such that g'_{ij}, G^{-1} and μ'_{ij} are the enhanced grey level intensity at position (i, j), inverse transformation function and enhanced membership value, respectively. Hence, the new pixel values will form a new image that has a higher contrast compared to the original image.

Image Segmentation using Fuzzy Clustering

For an input image *I*, let $imData$ represents the 1D array of intensity values obtained by reshaping the image. The Fuzzy C-Means (FCM) algorithm categorises each data point into one of c clusters according to its intensity rating. Let IDX denotes the cluster indices, and nn be the membership matrix with c columns, where each column j reflects the membership values of each data point to cluster j. The algorithm's purpose is to minimise the value of the objective function, J_m, which is calculated as the sum of the fuzzy distances between the data points and the cluster centroids [28]

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{c} {\mu_{ij}}^m \left\| imData_i - Centroid_j \right\|^2 \tag{5}$$

where N is the number of data points, c is the number of clusters, μ_{ij} is the membership function of data point i to cluster j and m is the fuzziness parameter. The clustered 1D array image is then reshaped into four 2D arrays, where each represents the membership values of data points in one cluster.

Traditional Image Processing Techniques

The effectiveness of the proposed method will be compared with traditional techniques. HE is a technique used to increase the contrast of the mammography images. The purpose of HE is to evenly distribute the intensity values of the images across the whole range of possible values. The HE works by first, computing the histogram of the images which displays the frequency of each intensity level. Then, the Cumulative Distribution Function (CDF) of the histogram values is calculated and scaled to cover the range of intensity values of 0 to 255 for 8-bit images. The intensity values of the images are transformed using the normalised CDF as a mapping function. At last, the enhanced image will be displayed after applying the mapping function to each pixel.

Furthermore, as for the traditional segmentation process, Sobel operator is used to detect edges of each tumour. To compute the gradient magnitude at each pixel, it performs convolutional processes with a pair of 3x3 kernels (filters). The gradients show the rate of change in intensity, showing the locations where intensity changes dramatically, which correlate to edges. Two 3x3 kernels are used in this method, one for detecting horizontal edges (Gx) and one for vertical edges (Gy). Then, the gradient magnitude at each pixel is calculated using

$$Magnitude = \sqrt{Gx^2 + Gy^2} \tag{6}$$

Hence, this produces a binary image, highlighting the strongest edges. Note that, MATLAB also provides built-in functions to compute both traditional methods, which will be used directly in this study to simplify the comparison process.

Mean Square Error (MSE)

The MSE measures the average of the squared differences between the estimated values and the original values. The calculation involves obtaining the squared difference between the respective values in the estimated and original images, averaging these squared differences. A low MSE value signifies a high degree of similarity between the processed image and the input image, hence indicating a strong accuracy and little deformation. Therefore, the equation of the MSE used in this study is as follows

$$MSE = \left(\frac{1}{M \times N}\right) \times \sum_{i=0}^{M} \sum_{j=0}^{N} [I(i,j) - K(i,j)]^2 \quad (7)$$

In the above equation, $M \times N$ represents image dimensions, $I(i,j)$ and $K(i,j)$ denote as the pixel values at position (i,j) in the original image and enhanced image respectively.

Peak Signal-to-Noise Ratio (PSNR)

The quality evaluation of the processed image is conducted through a comparative analysis with the original image, which may be either uncompressed or unprocessed. The PSNR is determined by dividing the maximum potential power of the signal, often the original image, by the power of the distortion, which represents the difference between the original and processed images. A greater PSNR value indicates that the output image exhibits reduced levels of noise or distortion in comparison to the original input image. This ratio is expressed in decibels (dB). The numerical value serves as an indicator of the extent to which the processed image maintains the fidelity of the original. Therefore, the equation of the PSNR used in this study is as (8), where max is the maximum possible pixel values.

$$PSNR = 10 \times log_{10}\left(\frac{max^2}{MSE}\right) \quad (8)$$

Results and Discussion

The performance of the fuzzy image processing algorithm was evaluated using six distinct breast mammogram images [29], displaying varying tumour shapes and densities, all captured from the right craniocaudal (RCC) view. The images were selected to represent different tumour morphologies and breast density conditions, enabling the performance of the enhancement and segmentation methods to be assessed under diverse imaging characteristics. The input dataset was restricted to standard Joint Photographic Experts Group (JPEG) images to evaluate the effectiveness of the proposed fuzzy image processing techniques on conventional compressed digital mammograms. Although the number of images is limited, the selected cases provide representative examples of clinically relevant tumour characteristics for a comparative methodological evaluation. This study is intended as a proof-of-concept investigation rather than a large-scale clinical validation. Future studies should evaluate the proposed methods using larger publicly available mammography datasets to further assess their robustness and generalisability.

Enhancement Process

As this study is a proof-of-concept investigation with a pilot dataset of six mammogram images, formal inferential statistical analysis was not performed. Instead, the evaluation employed a detailed case-by-case comparative analysis using established image quality metrics: Mean Squared Error (MSE) and Peak Signal-to-Noise Ratio (PSNR). MSE provides direct quantitative evidence of pixel-level distortion, while PSNR indicates the fidelity of the enhanced images relative to the originals. These metrics are widely accepted in image processing research for evaluating enhancement performance [11, 27]. The six images were selected to represent distinct combinations of tumour morphology and breast density, enabling a case-by-case performance evaluation that demonstrates the consistency of the fuzzy-based methods across diverse imaging characteristics. Qualitative visual assessments of segmentation outputs were also conducted to evaluate tumour boundary delineation.

The performance of the image enhancement techniques was evaluated using MSE and PSNR across different structural shapes and density variations. The quantitative results demonstrated that the fuzzy method using Fuzzy INT operator uniformly surpassed traditional HE method across all images. This clear superiority is demonstrated by the significantly lower MSE values and substantially higher PSNR scores achieved by the fuzzy method. Table 1 shows the MSE and PSNR values of both traditional and fuzzy methods after going through the enhancement process.

In the shape-based evaluation, the fuzzy method demonstrated remarkable superiority over HE method. For oval-shaped image, fuzzy method drastically minimised MSE to 0.001458, whereas HE yielded a much higher score of 0.20357. This improvement was mirrored by the PSNR values, which increase from approximately 6-7 dB under HE to over 26 dB with fuzzy method, confirming a substantial leap in image quality. This strong performance pattern remained consistent for both round and irregular shapes, highlighting the versatility and strength of the Fuzzy INT operator across diverse tumour shapes and patterns.

Moreover, the fuzzy method maintained its clear advantage when evaluating density variations. Across different density images, it consistently outperformed HE by exhibiting lower MSE alongside higher PSNR scores. This capability was especially remarkable in low-density tumour, where the PSNR increase substantially from 6.7904 dB under HE to 27.984315 dB using Fuzzy INT operator.

Table 1. MSE and PSNR values of each mammogram image after enhancement process using HE and Fuzzy methods.

Image	HE		Fuzzy	
	MSE	PSNR (dB)	MSE	PSNR (dB)
Round-shaped	0.20154	6.9564	0.001607	27.940101
Oval-shaped	0.20357	6.9129	0.001458	28.361875
Irregular-shaped	0.18341	7.3658	0.002387	26.221320
High-density	0.19301	7.1442	0.001615	27.919436
Equal density	0.19209	7.1649	0.002011	26.966417
Low-density	0.20939	6.7904	0.001591	27.984315

These notable improvements using Fuzzy INT operator can be attributed to its ability to adaptively elevate contrast while preserving critical structural details. Consequently, traditional HE method relies on global contrast stretching, which frequently over-amplifies background noise and distorts overall intensity distribution. By integrating fuzzy logic to navigate uncertainties within pixel intensities, the fuzzy method ensures that the enhancement process is highly regulated, particularly in subtle and low-contrast intensity variations.

In Figures (1-6), the enhancement of round-shaped, oval-shaped, irregular-shaped, high- density, equal density and low-density tumours are illustrated respectively using HE and Fuzzy method. Generally, in all cases, the HE method achieves higher MSE values which implies less accurate enhancement from the original images in Figure 1(a) to Figure 6(a). On the other hand, the fuzzy method produces significantly lower MSE values compared to HE method, indicating that the enhanced images produced are much closer and similar to the original images. In terms of the PSNR values, fuzzy method consistently outperforms the HE method which demonstrates that it produces images with better clarity and less noise. Based on the output of the images in Figure 1(c) to Figure 6(c), the proposed method has given more detail to the fine lines around the targeted tumours compared to the traditional method as shown in Figure 1(b) to Figure 6(b). Therefore, the fuzzy method used is more effective in enhancing the mammography images.

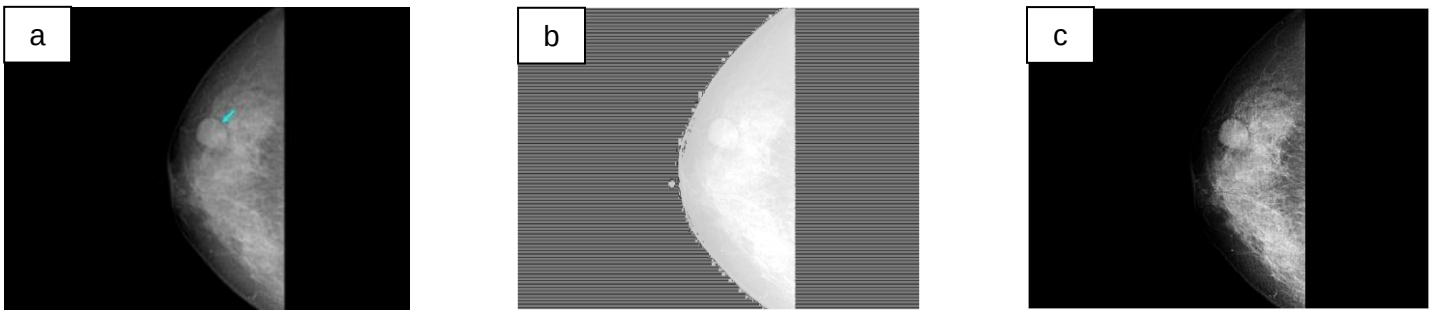


Figure 1. Enhancement of round-shaped tumour; (a) Original input images, (b) HE method, (c) Fuzzy method

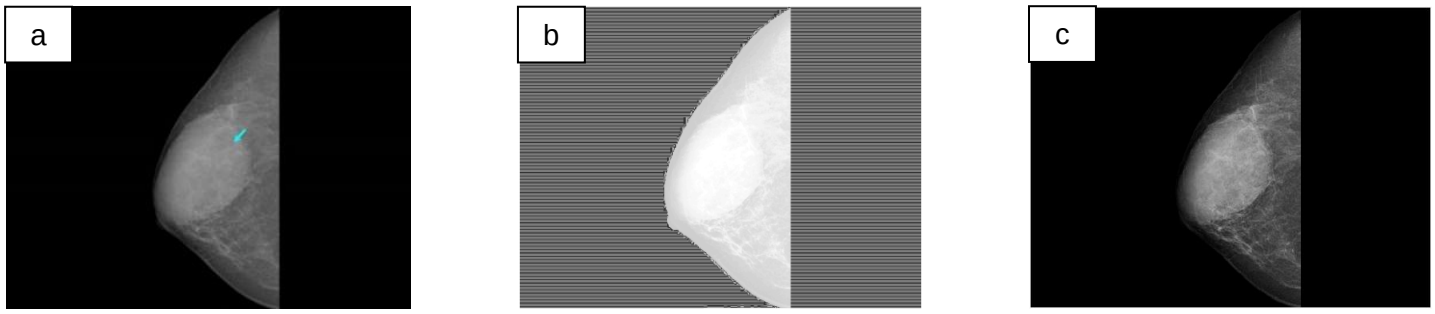


Figure 2. Enhancement of oval-shaped tumour; (a) Original input images, (b) HE method, (c) Fuzzy method

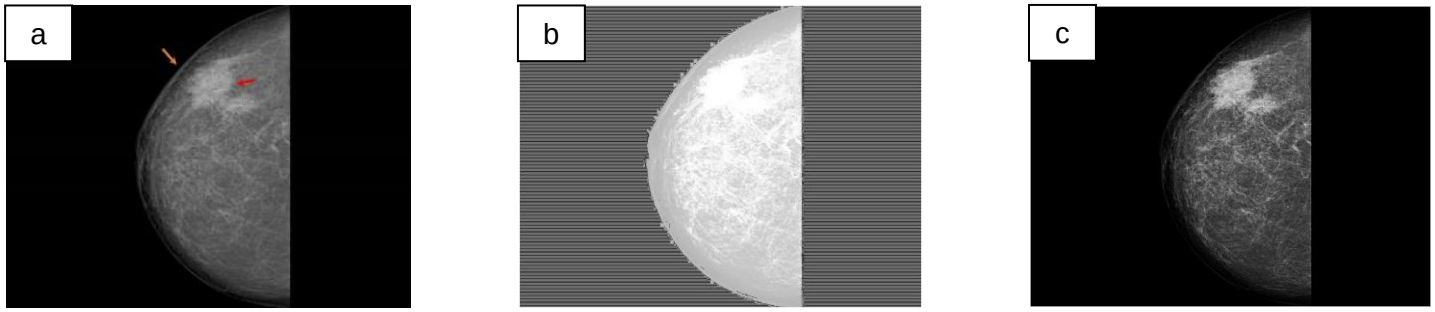


Figure 3. Enhancement of irregular-shaped tumour; (a) Original input images, (b) HE method, (c) Fuzzy method

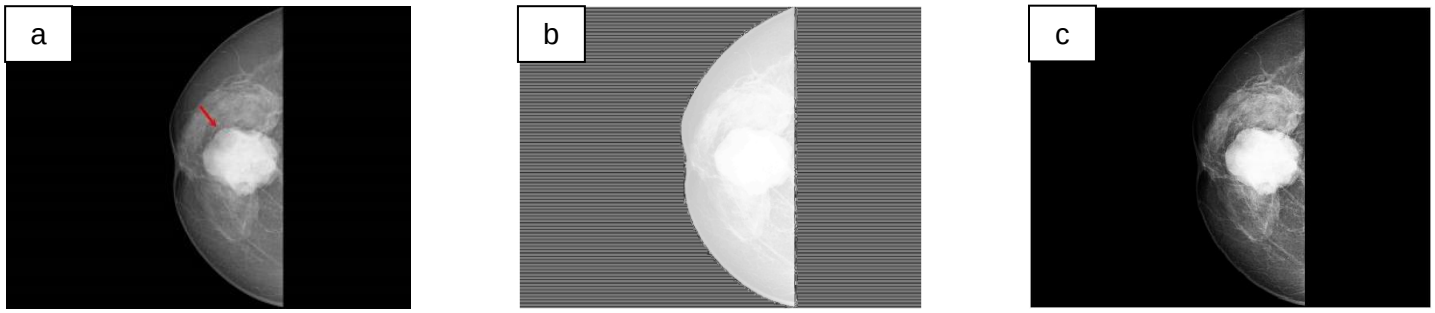


Figure 4. Enhancement of high-density tumour; (a) Original input images, (b) HE method, (c) Fuzzy method

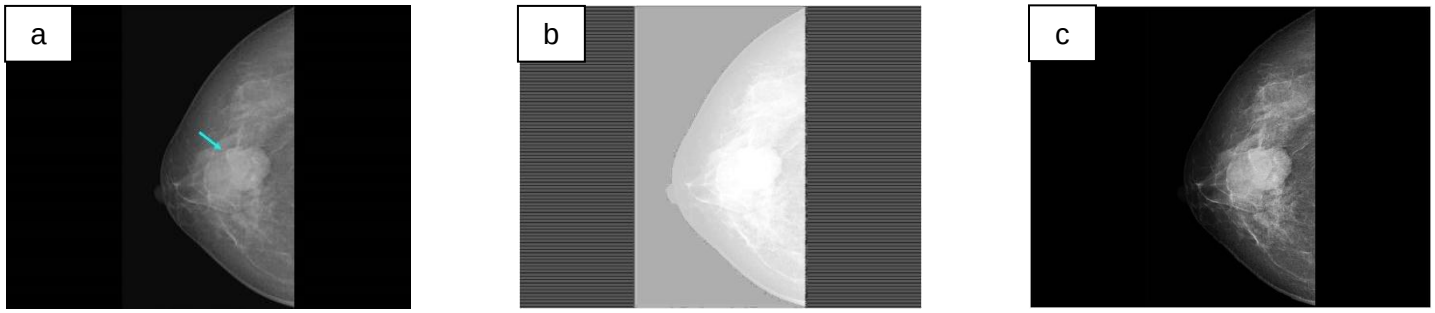


Figure 5. Enhancement of equal density tumour; (a) Original input images, (b) HE method, (c) Fuzzy method

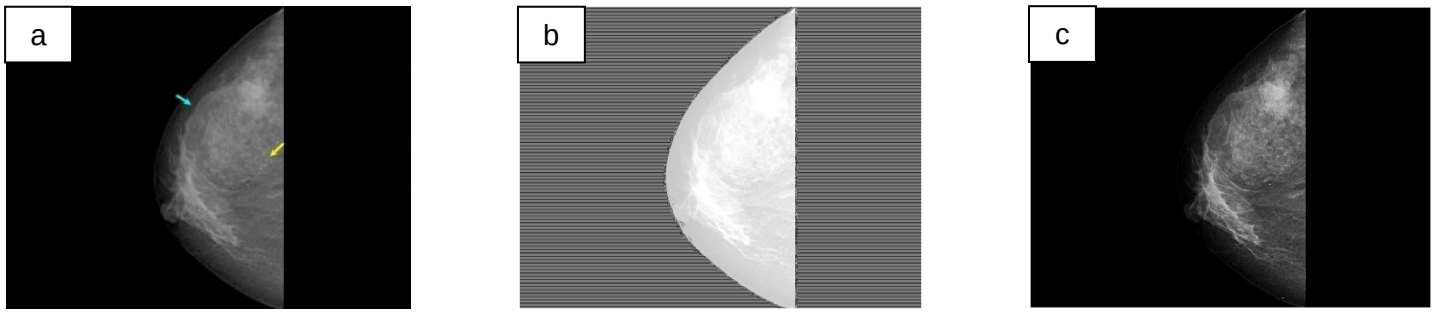


Figure 6. Enhancement of low-density tumour; (a) Original input images, (b) HE method, (c) Fuzzy method

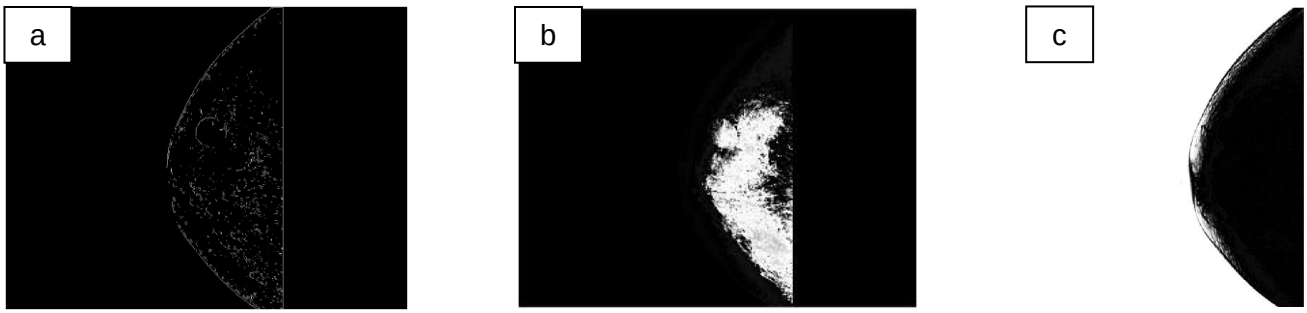
Segmentation Process

Following the enhancement process, the results of the segmentation task for round-shaped, oval-shaped, irregular-shaped, high-density, equal density and low-density tumours are evaluated in Figures (7-12), respectively.

While the gradient-based nature of Sobel edge detection method allowed it to capture fine structural edges, its high sensitivity to noise and intensity variations introduced notable limitations. Specifically, it struggled to cleanly isolate the tumour boundaries in round-shaped, oval-shaped and high-density tumours, as seen in Figures 7(a), 8(a) and 10(a), respectively. This limitation became more pronounced in complex tumours, such as the irregular-shaped, equal density and low-density tumours, as presented in Figures 9(a), 11(a) and 12(a), respectively. These outputs showed that faint or poorly defined boundaries resulted in incomplete and inaccurate segmentations. Moreover, the Sobel operator frequently misidentified surrounding healthy tissues as part of the tumour, hindering the clear distinction between tumour and non-tumour regions.

Conversely, the FCM clustering method delivered superior segmentation performance by clustering based on intensity similarity rather than relying on edge gradients. By partitioning the enhanced images into different regions, this technique effectively distinguished the tumours from the background and the surrounding tissues, as illustrated in Figures 7(c) to 12(c), and Figures 7(e) to 12(e). This proved that the fuzzy clustering-based method is exceptionally advantageous for low-contrast images, where it successfully delineated ambiguous tumour regions that were otherwise difficult to detect.

However, the effectiveness of the FCM clustering method depends heavily on tumour characteristics. For lesions with pronounced intensity contrast, such as oval-shaped and high-density tumours (Figure 8(b) and Figure 10(b)), the method yielded highly promising segmentation results. However, with complex tumours, illustrated in Figure 7(b), Figure 9(b), Figure 11(b) and Figure 12(b), the method tended to over-segment by including the surrounding healthy tissues into the tumour cluster. This occurred due to the overlapping pixel intensity distributions between tumours and healthy tissues, which essentially compromised clustering accuracy and precision. Thus, while the FCM clustering method demonstrated strong capabilities in handling low-contrast and moderately structured tumours, its accuracy was affected by equal density and complex shapes tumours. Therefore, although it improved over traditional Sobel edge detection method, further enhancement is required for ensuring robustness across highly complex mammography images.



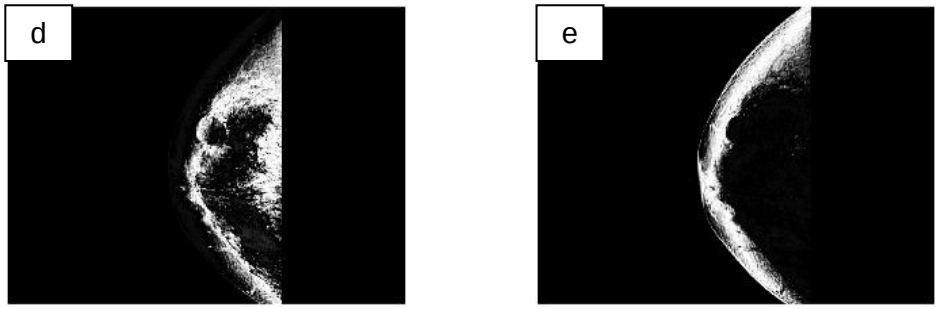


Figure 7. Segmentation results of round-shaped tumour; (a) Segmented tumour using Sobel edge detection method, (b) Segmented tumour using FCM clustering method, (c) Segmented breast area using FCM clustering method, (d) Segmented tissue using FCM clustering method, (e) Segmented background using FCM clustering method.

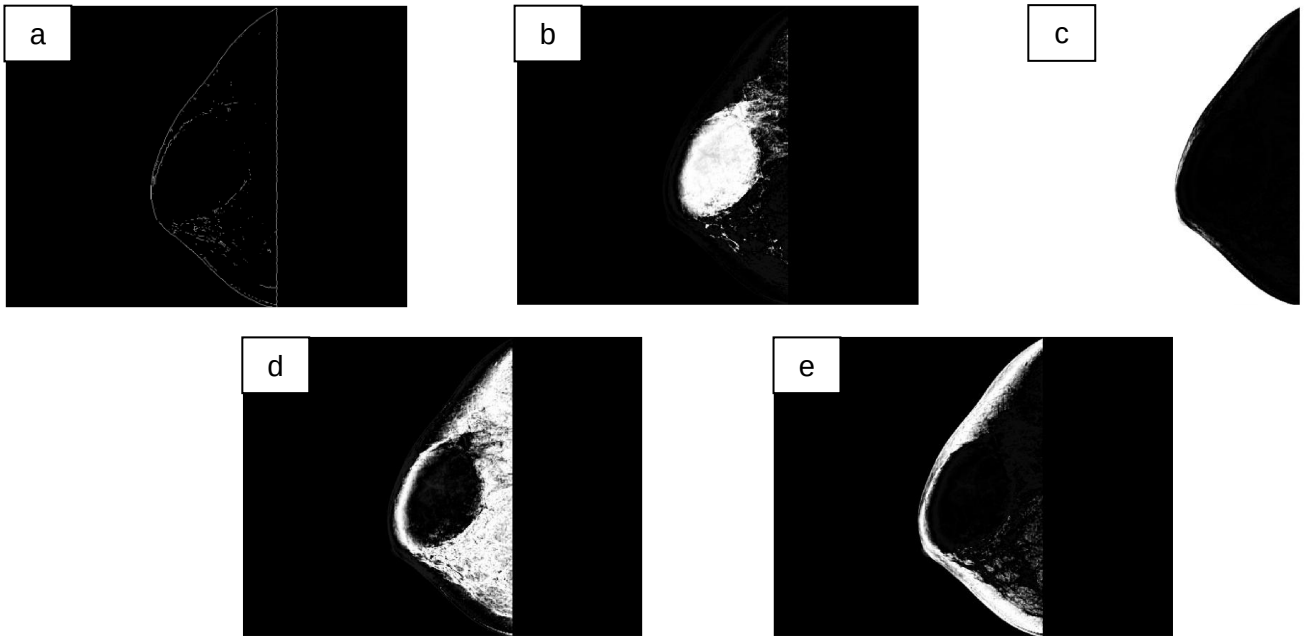
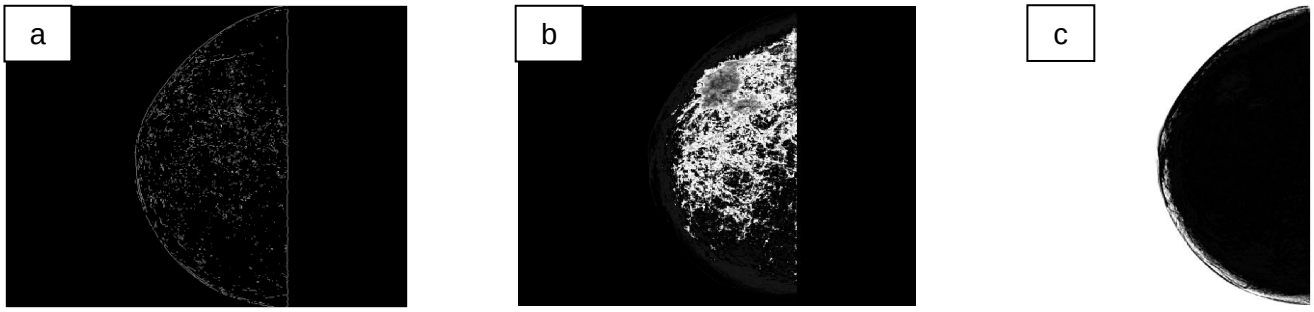


Figure 8. Segmentation results of oval-shaped tumour; (a) Segmented tumour using Sobel edge detection method, (b) Segmented tumour using FCM clustering method, (c) Segmented breast area using FCM clustering method, (d) Segmented tissue using FCM clustering method, (e) Segmented background using FCM clustering method.



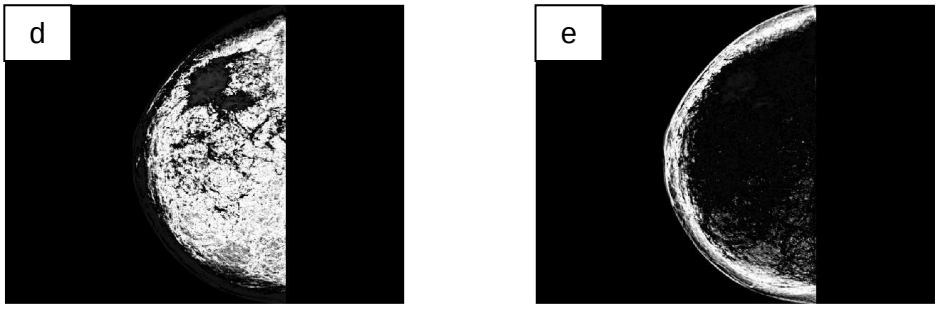


Figure 9. Segmentation results of irregular-shaped tumour; (a) Segmented tumour using Sobel edge detection method, (b) Segmented tumour using FCM clustering method, (c) Segmented breast area using FCM clustering method, (d) Segmented tissue using FCM clustering method, (e) Segmented background using FCM clustering method.

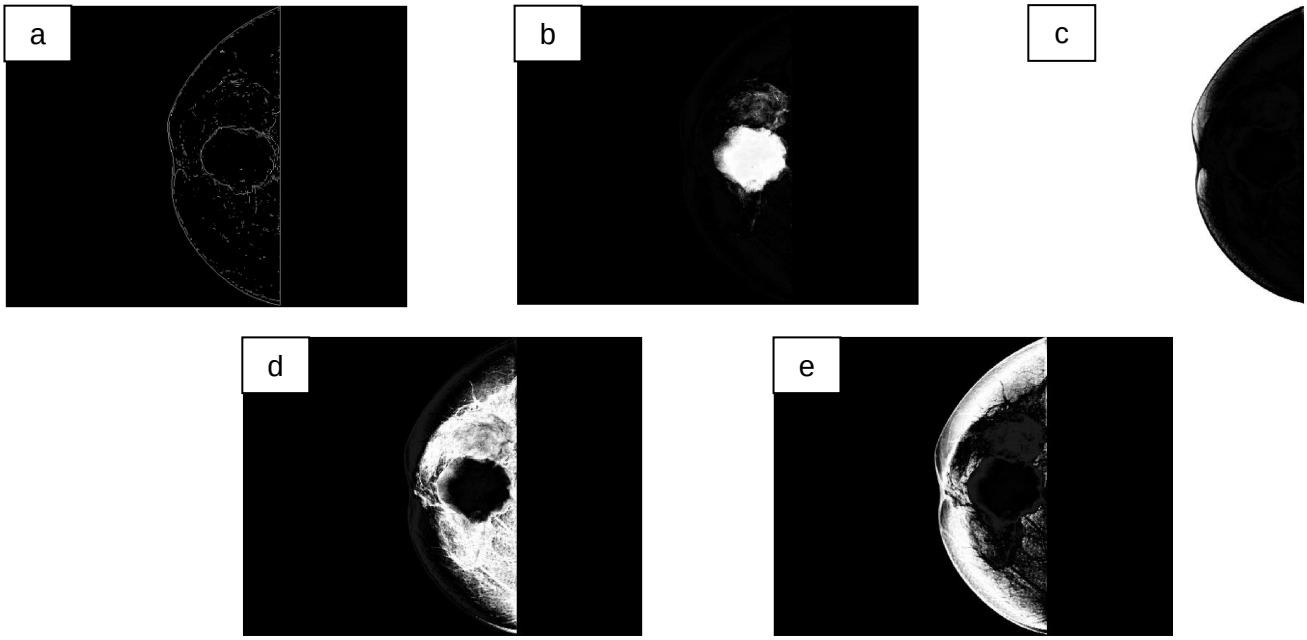
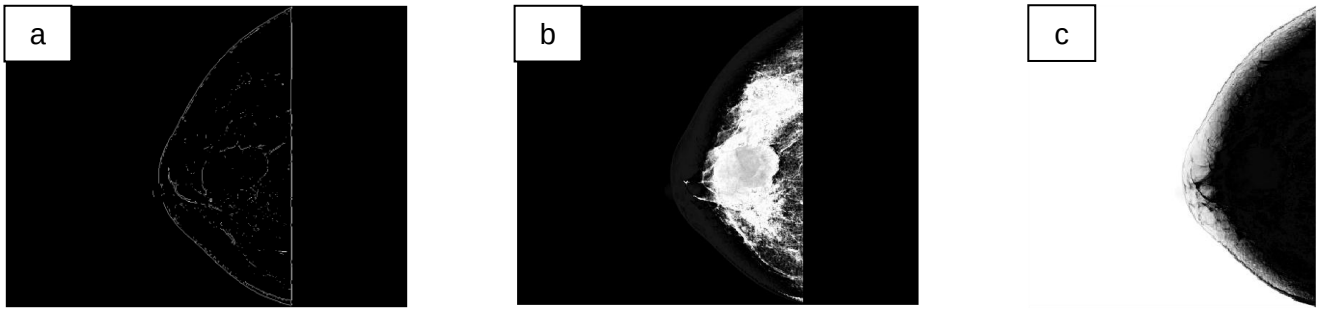


Figure 10. Segmentation results of high-density tumour; (a) Segmented tumour using Sobel edge detection method, (b) Segmented tumour using FCM clustering method, (c) Segmented breast area using FCM clustering method, (d) Segmented tissue using FCM clustering method, (e) Segmented background using FCM clustering method.



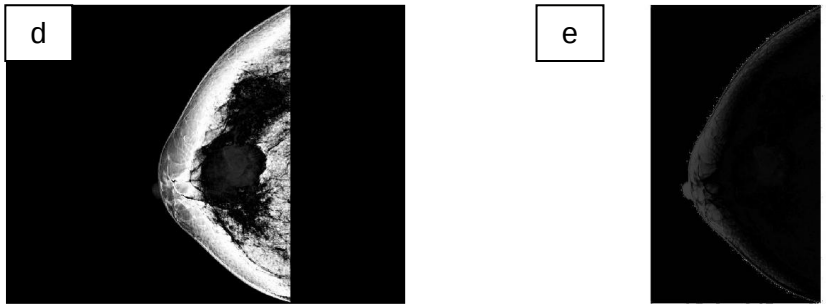


Figure 11. Segmentation results of equal density tumour; (a) Segmented tumour using Sobel edge detection method, (b) Segmented tumour using FCM clustering method, (c) Segmented breast area using FCM clustering method, (d) Segmented tissue using FCM clustering method, (e) Segmented background using FCM clustering method.

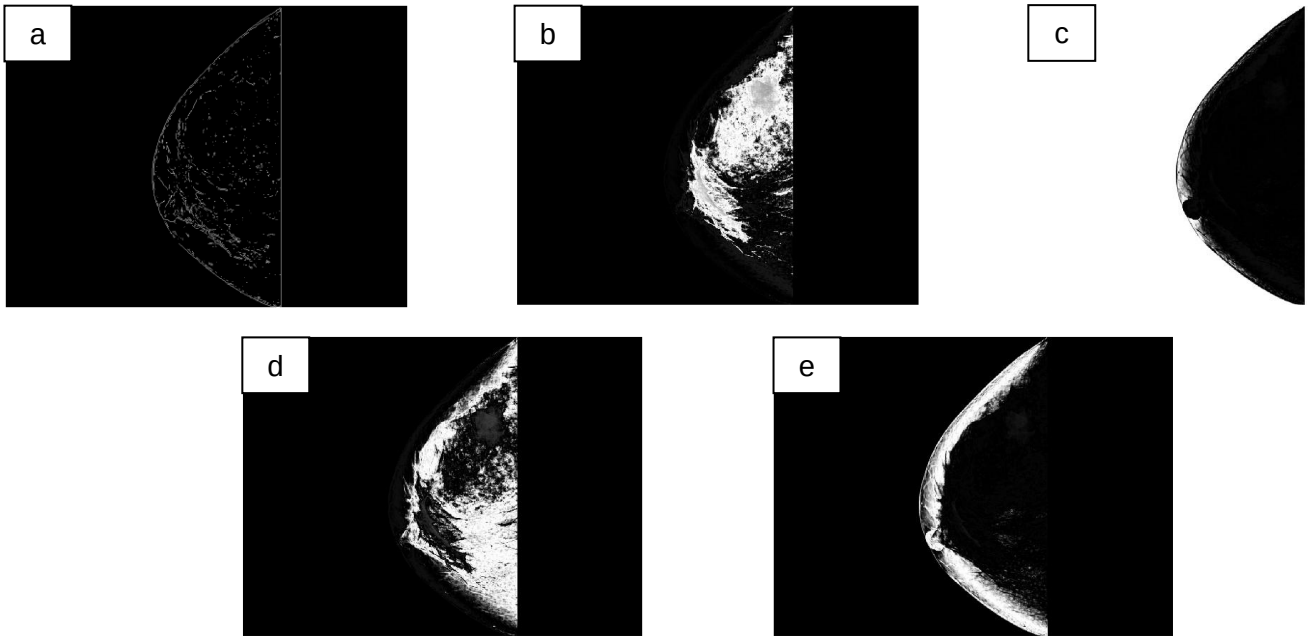


Figure 12. Segmentation results of low-density tumour; (a) Segmented tumour using Sobel edge detection method, (b) Segmented tumour using FCM clustering method, (c) Segmented breast area using FCM clustering method, (d) Segmented tissue using FCM clustering method, (e) Segmented background using FCM clustering method.

Conclusions

The analysis showcases the effectiveness and limitations of the fuzzy-based enhancement and segmentation methods in mammography images. The enhancement process using fuzzy INT operator demonstrates improved image quality across diverse tumour characteristics. This effectiveness is quantitatively supported by the lower MSE and higher PSNR values compared to the traditional HE method, proving its ability to minimise distortion. Ultimately, this enhanced image quality provides superior representation of the tumour regions, greatly assisting in the segmentation task. However, the segmentation task utilising FCM clustering method yielded mixed results, which heavily dependent on the tumour characteristics. In the cases with clear intensity difference, the FCM clustering method effectively clustered the tumours from surrounding breast tissues, highlighting its potential as a reliable unsupervised segmentation technique. However, in certain cases, especially those involving tumours with complex shapes and densities, it frequently over-segmented, by clustering surrounding healthy tissues with the tumour, and thereby reducing overall accuracy.

The primary limitation of this study is the absence of formal statistical validation. While the comparative results consistently favoured the fuzzy-based methods, future studies with larger datasets should employ

statistical analyses to confirm the significance of these improvements and establish generalisability. Moreover, the dependency of the FCM clustering method on pixel intensity distribution inherently restricts its precision in analysing complex tumours. Collectively, the findings establish the fuzzy INT operator as a highly promising enhancement method for optimising image quality. However, it is important to recognise that the challenges in this study, especially the segmentation task, highlight the need for further improvement and future study in order to fully take advantage of the potential of fuzzy image processing in medical imaging.

Recent developments in fuzzy concept, such as the q-Rung simplified neutrosophic set (q-RSN) emphasise the profound impact of advanced analytical approaches [30]. The framework, comprising of several fuzzy and neutrosophic fuzzy frameworks, provides a more adaptable and flexible representation of truth, falsity and uncertainty memberships. By synthesising the q-Rung orthopair fuzzy and neutrosophic sets, this approach effectively tackles more intricate Multi-Criteria Decision Making (MCDM) problems that existing models cannot handle. Thus, these advancements provide a compelling motivation for exploring hybrid uncertainty modelling approach, such as integrating neutrosophic fuzzy frameworks. Leveraging these models can significantly improve the robustness and accuracy of medical image processing tasks, extending the capabilities well beyond the traditional fuzzy approaches.

Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

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