Al Furat Journal of Innovations in Engineering Applications (AJIEA)

Intelligent X-Ray Image Analysis using Fuzzy Inference Systems

Shaima Ibraheem Jabbar[1] , Ahmed M. Ali Ali[1] , Rana Ali Hussein[2] and Oras Khudhayer Obayes[1]

[1] Babylon Technical Institute, Al-Furat Al-Awsat Technical University, Babil, 51001, Iraq
[2]Al-Musaib Technical College, Al-Furat Al-Awsat Technical University, Babil, 51001, Iraq
E-mail: shaima.jabbar@atu.edu.iq

Abstract. *The cumulative experience of a physician or x-ray technician enables them to distinguish differences and changes in x-ray images, but they may not be completely accurate or automated for all images. Fuzzy inference system can be recruited to automate identify and quantify important characteristics of x- ray images (edges, textures, shapes, and intensity patterns. In this work, we proposed a novel technique for contrast x-ray image enhancement and feature extraction based on fuzzy logoc system. AI-driven feature extraction enhances the accuracy of medical diagnoses and reduce the need for manual preprocessing and speeds up analysis, making it useful in high-volume clinical settings. In this study, a novel method is proposed to enhance the content of X-ray images by improving contrast and facilitating the extraction of critical features that aid medical professionals in image interpretation and analysis. The enhancement technique was developed using fuzzy logic, a branch of artificial intelligence known for handling uncertainty and imprecision in image data. Experimental results validate the effectiveness of the proposed method, as evidenced by improvements in key quantitative metrics. In the future, it is possible to improve the performance of this technique by combining it with deep learning technology and applying it to other types of medical images.*

Keywords: *Artificial Intelligence (AI) tools;* X-ray image*;* image enhancement ; *Feature extraction,* F*uzzy* inference *system*

1. INTRODUCTION

X-ray imaging is an important and widely used method by specialists to monitor patients' conditions. Many medical imaging devices rely on X-rays, including computed tomography, mammography, and radiography. However, the technology used in X-ray imaging is the most widely used due to the ease, cost, and speed of image acquisition [1], [2]. In addition to the low radiation dose that penetrates the body compared to other medical devices, many diseases can be detected initially using X-ray imaging devices, including fractures, pneumonia, kidney stones, and others [3], [4]. Therefore, researchers have clearly shown interest in addressing the problems that plague X-ray images of any part of the body. The first of these problems is image clarity, noise, image analysis, and extracting parameters that describe the nature of the image [4], [5], [6]. Harnessing artificial intelligence tools to enhance image content and improve other steps in image processing has become a priority for several reasons. One of these reasons is the efficiency of AI methods in dealing with medical image content, in terms of all the image processing we may need to enhance or analyze the image. Another reason is the speed and accuracy of

AI compared to traditional methods. These reasons encourage researchers to focus on developing AI methods and achieve their goal of maximizing the use of X-ray image content in diagnosis and patient monitoring. Some studies have employed deep learning techniques to extract essential features from X-ray images, enabling automated classification and interpretation [7],[8]. Others have focused on cognitive analysis methods to establish fundamental fuzzy logic rules, which serve as the basis for implementing fuzzy inference techniques in medical image processing [9], [10]. Additionally, certain researchers have integrated traditional image processing methods with AI-based techniques to improve the robustness and precision of X-ray analysis [11], [12].

That means act as "black boxes," making it difficult for clinicians to trust AI-generated diagnoses. When extracting and analyzing features from X-ray images, Fuzzy Inference Systems (FIS) offer several advantages over deep learning methods, particularly in medical applications where interpretability, rule-based decision-making, and handling uncertainty are crucial. deep learning requires large, clean datasets for training and may struggle with ambiguous cases unless explicitly trained on them, while fuzzy inference techniques work with imprecise, vague, or noisy data (common in X-rays due to variations in imaging conditions, artifacts, or overlapping anatomies. Therefore, in this study, we propose a methodology that enhances X-ray images using an fuzzy inference system, optimizing them for subsequent parameter extraction. It operates on human-readable fuzzy rules (e.g., "IF the lung opacity is high AND the texture is irregular, THEN pneumonia likelihood is medium"). This makes it easier for doctors to understand and trust the decision-making process

The extracted parameters, which characterize the nature of the X-ray image, include edge detection, color contrast, entropy measurement, and color intensity analysis as pre-processing steps [13],[14], [15], this method aims to improve the reliability and accuracy of feature extraction, thereby facilitating more effective diagnostic applications.

The rest of paper illustrate the next section presents methodology which includes how can extract x-ray image properties and assess the results quamtitivly. Results and discussion in the next section , finally conclusions and future work

2. MATERIALS AND METHODS

Extraction image parameters of x- ray images and analysis presents supportive task for diagnosis sereral diseases. Enhancement the apperance of the imsge aiming to improve the visual appearance of an image or to facilitate subsequent image analysis. Traditional contrast enhancement techniques often rely on histogram equalization or edge detection algorithms; however, these methods may not always yield optimal results. Fuzzy linference system, , a subset of artificial intelligence, offers a more flexible approach by handling uncertainty and imprecision in image data. This study explores the application of fuzzy linference for image enhancement and parameter extraction, providing a structured methodology for improving contrast and extracting essential image features. The proposed fuzzy logic-based image enhancement technique involves three primary stages: fuzzification, membership function definition, and defuzzification. Each of these stages contributes to the overall enhancement process The proposed methodology is illustrated in the accompanying diagram in the figure (1).

ATU- AJIEA, Volume: 1, Issue: 1, June, 16, 2025,

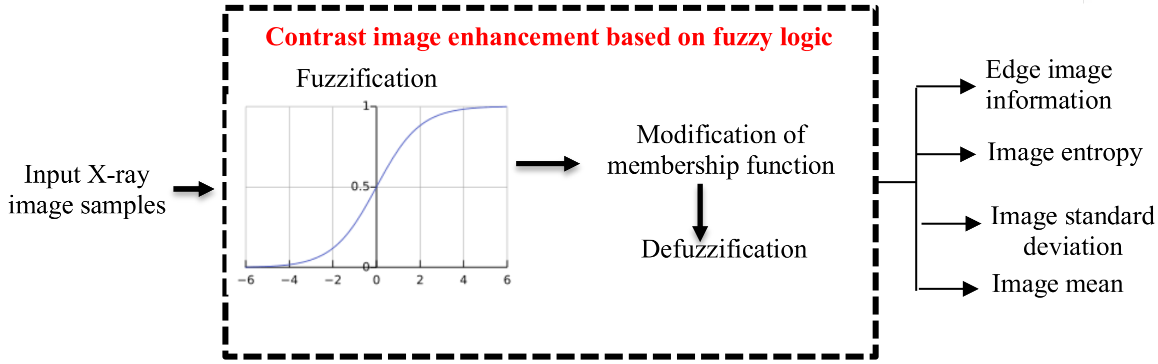


Figure (1), illustrates the pipline of proposed technique

In this project, Thirty X-ray image samples of the lung area has been utilized a dataset sourced from [10]. These images were used to develop and evaluate a AImodel for diagnosing lung diseases. The X-ray images provided valuable information for extraction knowledge to activetate fuzzy logic modele for performing contratast enhancement model, enabling it to learn patterns and features associated with different lung conditions. By leveraging this dataset, we aimed to improve the accuracy and reliability of lung disease diagnosis, ultimately contributing to better patient outcomes.

The process of image enhancement using fuzzy inference system begins with the transformation of grayscale image data into a normalized form where pixel values range from zero to one. This initial stage, referred to as fuzzification, facilitates subsequent processing. The first step in completing the image enhancement process using fuzzy logic is defining the membership function for the image content. An important aspect of this approach is defining the membership function, which governs the enhancement process. The membership function is specifically designed to adjust pixel intensity values near the midrange, increasing the contrast between color gradations and improving the overall image quality. This transformation is performed using the proposed equation in (1) and equation (2), which will be detailed in the subsequent discussion [16].

$$S(\mu_A(Ixy)) = -\mu(Ixy) \times \ln(\mu_A(Ixy) - \mu_A(Ixy) \times \ln\big(1-\mu_A(Ixy)\big) \quad (4)$$

$$H(\mu_A(Ixy)) = \frac{1}{s_1 * s_2 * \ln(2)} \times \Big(\sum_{y}^{Y}\sum_{x}^{X} S(\mu_A(Ixy))\Big) \quad (5)$$

$$\begin{aligned} \mu_A(Ixy)'' &= 2 \times (\mu_A(Ixy) & 0 \le \mu_A(Ixy) \le 1 \\ &= 1 - 2 \times (1 - (\mu_A(Ixy))^2 & 0.5 \le \mu_A(Ixy) \le 1 \end{aligned} \quad (6)$$

This final stage, known as defuzzification, After the contrast enhancement process, the final step involves converting the processed image data back into its original grayscale format. This step, known as defuzzification, ensures that the modified intensity values are mapped back to their appropriate grayscale range. By doing so, the image retains its structural integrity while benefiting from the contrast improvement introduced by the fuzzy inference approach.

2.1 AEESEEMENT QANTITATIVE METRICS

The proposed method need to quatitatiove assessment, in this work, several assessment are EME(Average Mean Error), AME (Average Mean Error) and SDME(Standard Deviation of Mean Error), see table (1)

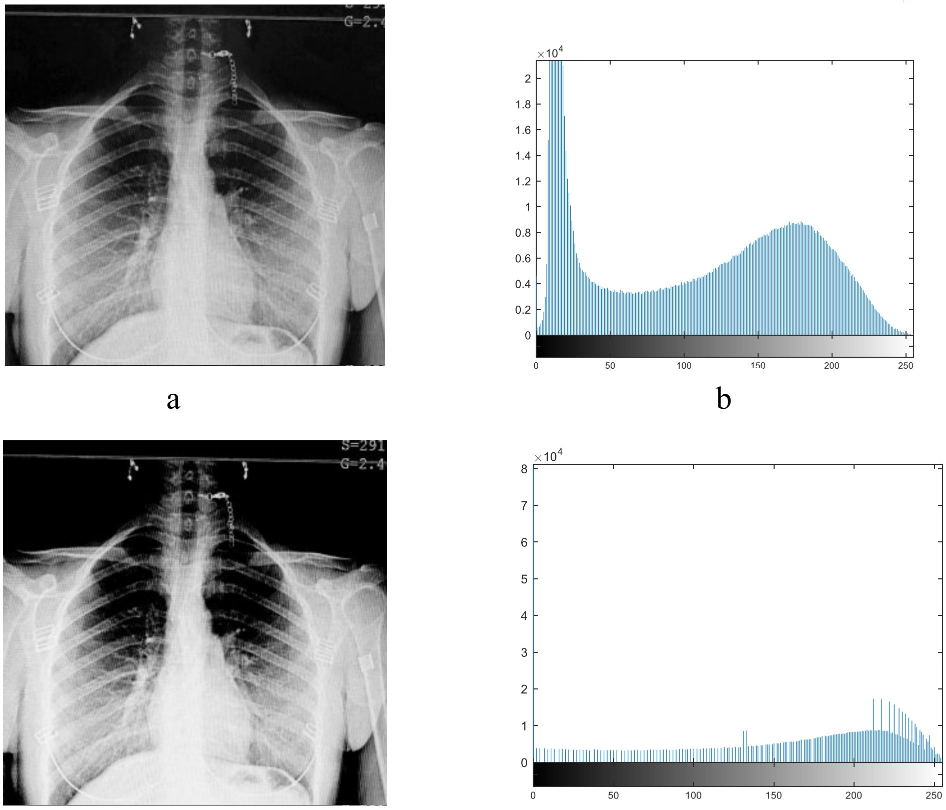
Table (1), Equations of three metrics (EME, AME and SDME).

Metrics	Definition	
EME	$EME_{r_1 r_2} = \frac{1}{r_1 r_2}\sum_{e=1}^{r_1}\sum_{f=1}^{r_2}\left[20\log\left(\frac{g_{\max,e,f}}{g_{\min,e,f}}\right)\right]$	(1)
AME	$AME_{r_1 r_2} = -\frac{1}{r_1 r_2}\sum_{e=1}^{r_1}\sum_{f=1}^{r_2}\left[20\log(\frac{g_{\max,e,f} - g_{\min,e,f}}{g_{\max,e,f} + g_{\min,e,f}})\right]$	(2)
SDME	$SDME = -\frac{1}{r_1 r_2}\sum_{e=1}^{r_1}\sum_{f=1}^{r_2}20\log\left[\frac{g_{\max,e,f} - 2g_{center,e,f} + g_{\min,e,f}}{g_{\max,e,f} + 2g_{center,e,f} + g_{\min,e,f}}\right]$	(3)

The strength of using EME, AME and SDME is not having to use ground truth image in the applying of these metrics on the output image. However, using these metrics requires dividing output image into a set of blocks where the dimensions of these blocks are odd and square. Selection of the best dimensions of the blocks is challenging, particularly in the case of complex texture pattern such as musculoskeletal ultrasound images, However, this point was addressed in this thesis. The best dimensions of the block were selected based on the evaluation of the maximum entropy of selected block. Image entropy gives indication about distribution the image details, more details would record a higher level of entropy image is preperered after contrast image intensification to extract image parameters (edge detection informstion, image entropy, mean and standrad deviation). The step of image edge detction can be performed based on the evaluation of Canny operator. Canny operator represent

3. IMPLEMENTATION AND RESULTS

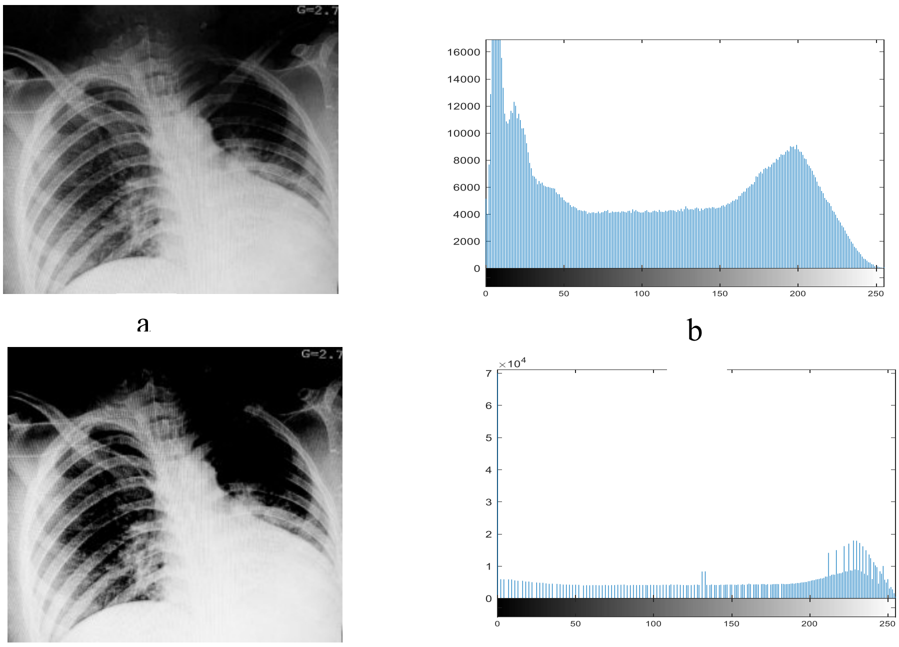
Contrast intesification method has been implemented based on using one of AI tools, it is based on fuzzy inference system. Output image after contrast enhancement has been assessed using non refrence metrics: EME (Edge Mean Enhancement)**,** generally increases after processing AME (Average Mean Error)**,** mostly decreases, indicating improved accuracy. Furthermore, using SDME (Standard Deviation of Mean Error)**,** often increases, possibly due to contrast enhancement. Figure (2), Figure (3) and Figure (4) illustrate some x-ray image with its histogram befer and after contrast enhancement.



a b

c d

Figure (2), illustrates x-ray image with its histogram after and before Fuzzy Contrast Enhancement (FCE) of (sample1), the first line (a,b) shows input image and second line (c, d) presents output image

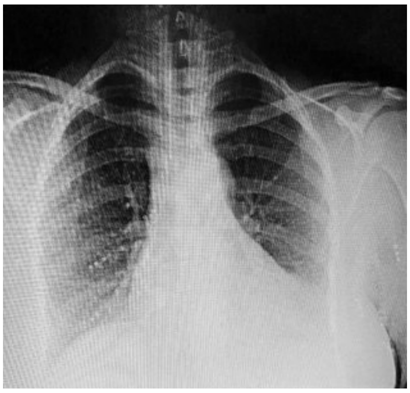


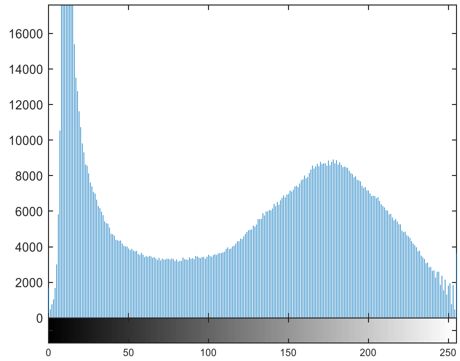
a b

c d

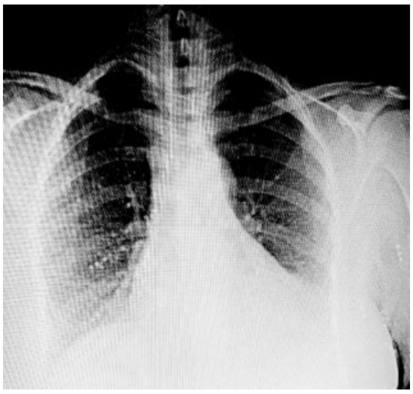
Figure (3), illustrates x-ray image with its histogram after and before Fuzzy Contrast Enhancement (FCE) of (sample5), the first line (a,b) shows input image and second line (c, d) presents output image

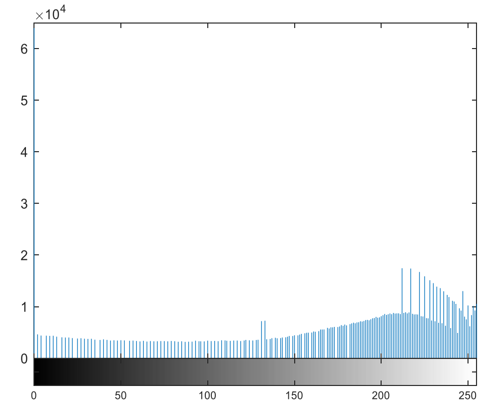
ATU- AJIEA, Volume: 1, Issue: 1, June, 16, 2025,





a b

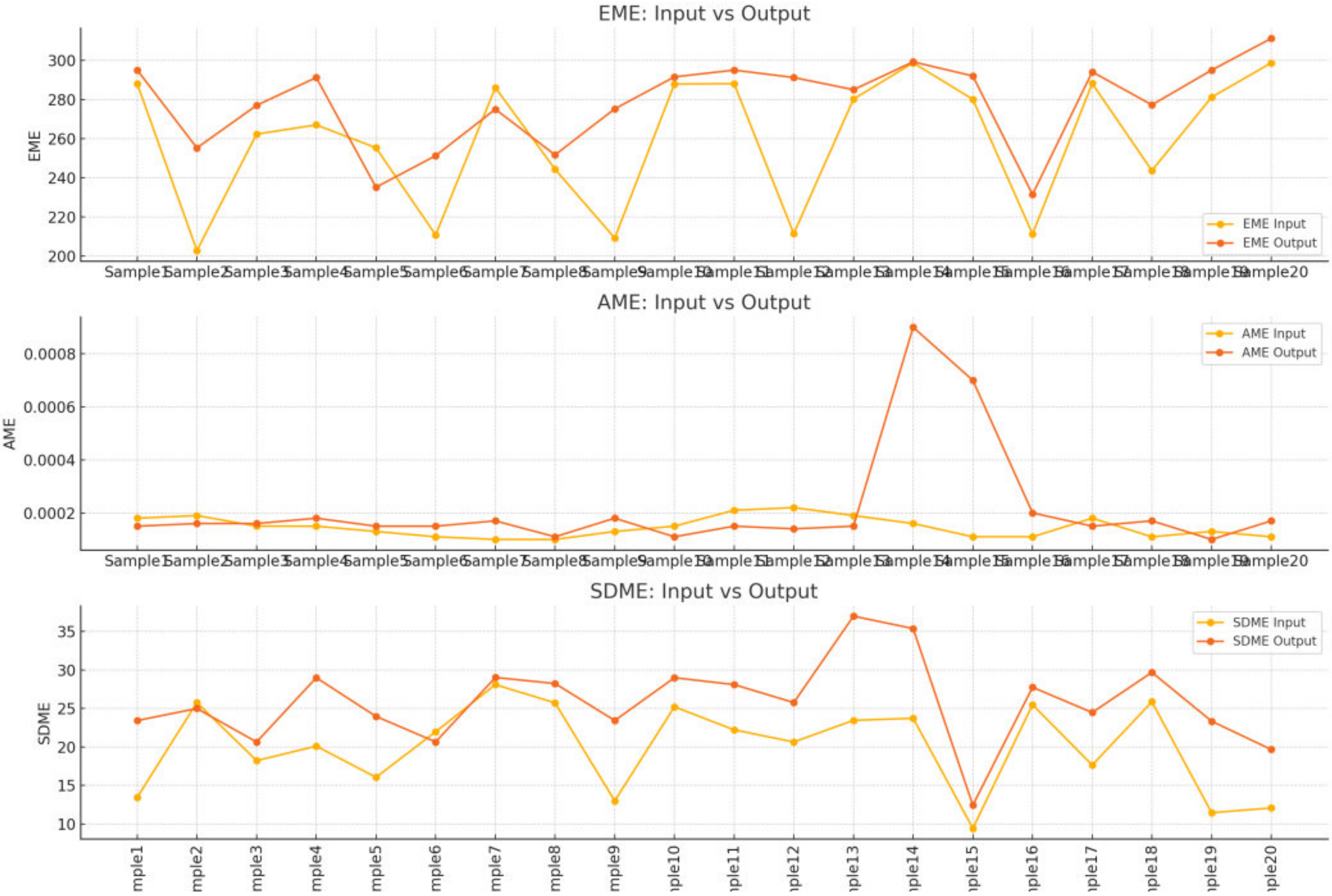




c d

Figure (4), illustrates illustrates x-ray image with its histogram after and before Fuzzy Contrast Enhancement (FCE) of (sample13), the first line (a,b) shows input image and second line (c, d) presents output image.

This suggests your enhancement algorithm successfully sharpened edges across most images, improving visibility of important structures. Quantitative assessment using **EME, AME and SDME** have been applied on the input and output image to present the performance of AI technique on the input x-ray images. Figure (5), demonstrates the comparison between input and output images based on the evaluation of these metrics



Figure(5), demonstrates the comparison between input and output images based on the evaluation of EME, AME and SDME

Contrast enhancement is a crucial preprocessing step that prepares medical images for the feature extraction stage. In this study, contrast enhancement was applied to X-ray image samples using the proposed Fuzzy Contrast Enhancement (FCE) technique and compared with conventional histogram equalization. Table 2 presents a summary of feature evaluations for selected samples based on these two methods.

The results demonstrate that the proposed FCE technique improves image detail, as evidenced by increased contrast and entropy values—indicators of richer image information. Additionally, a reduction in edge pixels was observed, suggesting that redundant pixels were effectively suppressed, leading to a clearer image representation. Compared to histogram equalization, the FCE method shows notable differences in output quality. These differences significantly influence the visual quality of X-ray images and may enhance diagnostic accuracy.

Table (2),

Samples	Image	Contrast	Entropy	Standard deviation	Edges pixel
Sample1	Original image	253.9824	104.3014	73.5565	236607
	FCE	254.3080	115.4391	96.0058	196479
	Histrogram equilization	256	117.55	97.345	190541
Sample5	Original image	253.9816	106.3531	75.8035	176926
	FCE	254.2823	116.0460	97.4912	156426
	Histrogram equilization	254.123	116.003	96.98	167048
Sample13	Original image	253.9798	117.2795	75.9118	249170
	FCE	254.2479	129.7271	96.9034	195645
	Histrogram equilization	254.11	120.432	80.734	2054205

Contrast values increased slightly, indicating better distinction between light and dark regions. Entropy rose significantly, reflecting richer texture and higher information content in the images. The standard deviation also increased, suggesting a wider range of pixel intensities and more detailed image structures. Although edge pixel counts decreased, this likely indicates a reduction in noise or removal of weak edges, leading to cleaner visuals. Overall, the enhancement emphasized important features while suppressing irrelevant details. These changes suggest that the enhancement method was effective in improving diagnostic clarity. Therefore, the technique can be considered beneficial for medical image analysis applications.

4. DISCUSSIONS

The proposed AI-based image enhancement technique offers several advantages over traditional methods. First, the use of fuzzy inference allows for adaptive contrast enhancement, making it suitable for images with varying lighting conditions. Second, the methodology provides a more flexible approach to intensity modification, ensuring that details are preserved while enhancing visual clarity. Finally, the extraction of key parameters describing image behavior can be useful for further image analysis tasks, such as feature extraction and object recognition. In this work, we applied proposed technique on different samples of x ray image , some samples for healthy paticipants and others for unheealthy participants. We observerd, there is a noticible difference in the value of evaluated image paremeters (edge detection informstion, image entropy, mean and standrad deviation). EME measures edge clarity. Higher EME usually means better-defined image features. The mean EME increased from 259.76 **to** 278.50, indicating that the output images have generally enhanced edge clarity. The standard deviation decreased**,** meaning the output values are more consistently improved across the samples. AME reflects how far pixel intensities deviate on average. Lower values are better. Surprisingly, the mean AME slightly increased**,** from 0.000146 to 0.000218. A much higher standard deviation in the output suggests inconsistency, with a few samples showing a large error (e.g., one hitting 0.00090**).** While most outputs improved or stayed consistent, a few outliers **i**ncreased AME**,** impacting the average and spread. Enhancement was successful in boosting clarity while maintaining consistency. SDME captures intensity variation — a proxy for contrast. Higher values often mean richer, more contrasted images. A clear increase in the mean SDME from 19.99 to 25.81 shows contrast enhancement. Standard deviation remained similar, suggesting contrast enhancement was applied evenly across samples. Output images tend to be more vivid and detailed.

Enhancing image contrast is an essential preprocessing step in preparing medical images for effective feature extraction. In this research, contrast enhancement was applied to X-ray samples using the proposed Fuzzy Contrast Enhancement (FCE) method and compared against traditional histogram equalization. Table 2 provides a comparative summary of feature metrics for selected image samples processed by both techniques. Findings indicate that the FCE approach yields superior image clarity, as reflected in higher values of contrast and entropy—parameters associated with enhanced image information. Furthermore, a noticeable reduction in edge pixels suggests the method effectively minimizes redundant visual data, resulting in a more refined image. When compared to histogram equalization, the FCE method produces distinct improvements in image quality. These improvements have a meaningful impact on the visual presentation of X-ray images and hold potential to improve diagnostic outcomes.

5. CONCLUSIONS

In this research, we presented a method based on fuzzy logic, an artificial intelligence tool, to enhance x-ray images and improve their quality. This prepares them for sequential steps to extract basic parameters that can be useful to a specialist physician in describing the image. This can certainly aid in diagnosis and making sound decisions regarding patients. This method has proven its effectiveness compared to traditional methods based on numerical evaluation performed on both methods. This method can be developed further by combining it with other artificial intelligence tools, such as general learning, and it can also be applied to other medical images.

6. REFRENCES

[1] M. A. Rahman and M. R. Ahmed, "RepVGG-Based Deep Learning Model for the Automated Detection of Lung Diseases from Chest X-rays," *arXiv preprint arXiv:2211.08244*, 2022.: https://arxiv.org/abs/2211.08244

[2] J. H. Thrall et al., "Artificial Intelligence and Machine Learning in Radiology: Opportunities, Challenges, Pitfalls, and Criteria for Success," *Radiology*, vol. 294, no. 3, pp. 550–560, 2020.: https://pubmed.ncbi.nlm.nih.gov/32757950/

[3] D. Campbell, "NHS England to Use AI Tools for X-ray Fracture Detection," *The Guardian*, Oct. 2024. https://www.theguardian.com/society/2024/oct/22/nhs-ai-artificial-intelligence-tools-scans-broken-bones-fractures-x-rays

[4] S. Bennani and et al., " Using AI to Improve Radiologist Performance in Detection of Abnormalities on Chest Radiographs”, Radiology, 2023.

[5] X. Zhang, J. Liu, and H. Wang, "AI-Based Feature Extraction for Differentiating Benign and Malignant Pulmonary Nodules in CT Images," *Computational and Mathematical Methods in Medicine*, vol. 2022, Art. no. 5762623, 2022, https://onlinelibrary.wiley.com/doi/10.1155/2022/5762623

[6] G. Litjens, T. Kooi, B. Ehteshami Bejnordi, et al., "A survey on deep learning in medical image analysis," *Medical Image Analysis*, vol. 42, pp. 60–88, 2017.

[7] P. Rajpurkar, J. Irvin, K. Zhu, et al., "CheXNet: Radiologist-level pneumonia detection on chest X-rays with deep learning," *arXiv preprint arXiv:1711.05225*, 2017.

[8] V. Gulshan, L. Peng, M. Coram, et al., "Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs," *JAMA*, vol. 316, no. 22, pp. 2402–2410, 2016.

[9] S. I. Jabbar, H. S. Majdi, S. I. Hakeem, A. A. Altaee, M. H. Mohammmed and A. Q. Aladi, "Analysis of CT images of the COVID-19 patients," *2022 Muthanna International Conference on Engineering Science and Technology (MICEST)*, Samawah, Iraq, 2022, pp. 60-64, doi: 10.1109/MICEST54286.2022.9790201.

[10] S. I. Jabbar and A. Qahtan Omran Aladi, "Fuzzy inference system for detection CT and X-Ray image's edges," *2024 IEEE 18th International Conference on Application of Information and Communication Technologies (AICT)*, Turin, Italy, 2024, pp. 1-4, doi: 10.1109/AICT61888.2024.10740426.
[11] W. Pedrycz, S.-M. Chen, and J. E. Mendoza, "Fuzzy modeling and granular computing in medical image analysis," *IEEE Transactions on Fuzzy Systems*, vol. 27, no. 1, pp. 1–13, 2019.
[12] X. Wang, Y. Peng, L. Lu, et al., "ChestX-ray8: Hospital-scale chest X-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2017, pp. 2097–2106.
[13] J. Irvin, P. Rajpurkar, M. Ko, et al., "CheXpert: A large chest radiograph dataset with uncertainty labels and expert comparison," in *Proc. AAAI Conf. Artif. Intell.*, 2019, pp. 590–597.
[14] R. R. Selvaraju, M. Cogswell, A. Das, et al., "Grad-CAM: Visual explanations from deep networks via gradient-based localization," in *Proc. IEEE Int. Conf. Comput. Vis. (ICCV)*, 2017, pp. 618–626.
[15] R. Putha, S. Tadepalli, R. J. Sadineni, et al., "AI-driven diagnostics for rural healthcare: A case study on chest X-ray analysis," *IEEE Access*, vol. 6, pp. 40481–40488, 2018.
[16] S. I. Jabbar and A. Q. Aladi, "Automated Contrast Enhancement of the MRI Video Imaging," *2019 IEEE 13th International Conference on Application of Information and Communication Technologies (AICT)*, Baku, Azerbaijan, 2019, pp. 1-5, doi: 10.1109/AICT47866.2019.8981719.
[17] J. Canny, "A computational approach to edge detection" IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 8, 1986, pp. 679–698.

