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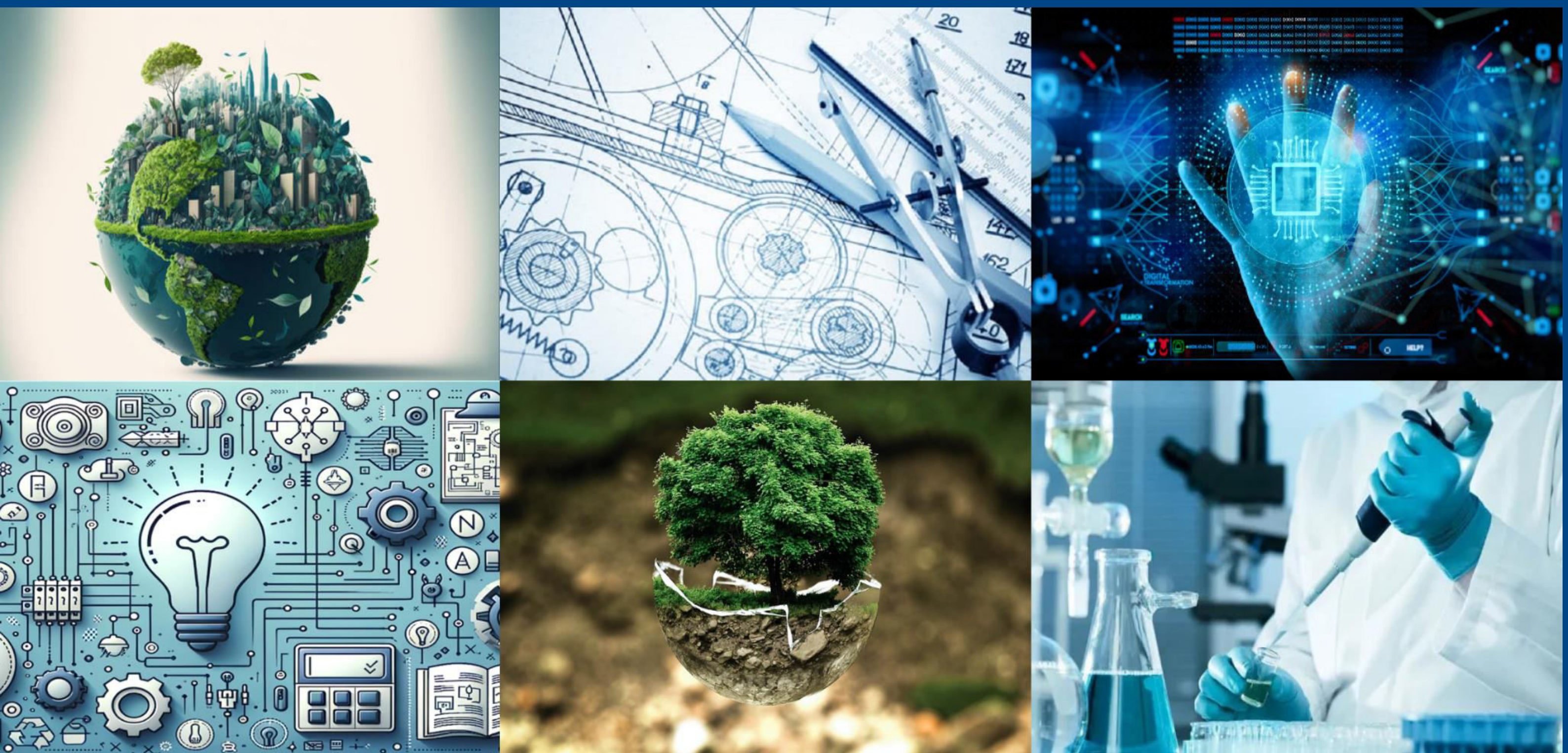

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Medical Image Enhancement using LWT and $Type_2$ Fuzzy Set

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ABSTRACT: Image enhancement plays a significant role in many areas, including medical imaging, satellite imagery, and others. It significantly enhances the quality of blurred images caused by machine limitations or environmental conditions. In this study, a hybrid scheme using the combination of the lifting wavelet transform with $type_2$ fuzzy sets is presented to enhance the medical images that are blurred to understand the visual information. A 2-level lifting wavelet transform is used to decompose the original image into four sub-bands. The LL sub-band is used for fuzzification using an interval $type_2$ fuzzy set. Finally, we apply the inverse transform to the original LH, HL, HH, and updated LL sub-bands to obtain the enhanced image. We assess a range of metrics to gauge the effectiveness of the proposed scheme, taking various factors into account. The comparison with state-of-the-art schemes confirms the efficacy and usefulness of the proposed scheme.

KEYWORDS: Medical image; Contrast enhancement; LWT; $Type_2$ fuzzy sets; AMBE; SSIM

I. INTRODUCTION

Image enhancement methods have introduced new dynamics to the medical field, significantly improving the observation capabilities of medical data. These enhancements have greatly assisted radiologists in making accurate disease diagnoses. Various medical imaging techniques including MRI, X-rays, CT scans, and mammograms have been developed to identify internal issues within the human body, contributing to ongoing advancements in medical analysis. Each modality produces distinct images of affected organs, highlighting detailed features that enable medical experts to plan treatment effectively. This enhances treatment success rates and reduces the risks and errors associated with the diagnostic process.

Medical images often encounter challenges during the acquisition, which can introduce issues such as noise, image artifacts, blurred background details, and inconsistent or uneven contrast. These problems frequently arise in the medical field due to the constraints of imaging modalities and the complexity of human internal organs. For example, X-ray images can be affected by scattering, which introduces noise into the data, while MRI images may incur artifacts due to surrounding magnetic fields and sudden patient movements [11]. These difficulties make it more demanding to interpret and analyze medical images. To address these challenges, image enhancement techniques are essential. Thus, there is a growing need to develop methods that minimize noise and improve the quality and clarity of medical images.

Numerous image enhancement methods have been developed and studied by researchers, ranging from traditional techniques to more advanced hybrid approaches. One commonly used standard technique for contrast enhancement is histogram equalization (HE) [16], which redistributes pixel values across the dynamic range of the image. However, in histogram-equalized images, artifacts and noise amplification can be quite noticeable. Additionally, HE can lead to excessive brightness, prompting the development of hybrid or upgraded versions such as BBHE [19], AGCHE [20], and CLAHE [12]. Although these techniques can produce clearer images with more detail, they sometimes create image artifacts or result in over-enhancement. Gandhamal et al. [4] developed the local grey level S-curve transformation, a contrast enhancement algorithm designed to improve image contrast and address issues associated with histogram equalization (HE)-based methods.

To streamline the enhancement process across various datasets, researchers utilized wavelet transforms, which enhance the algorithm's speed and computational efficiency. Wavelets have a wide range of applications, including image enhancement, tumor detection [14], data compression [9], noise reduction, and image reconstruction [13]. These transforms are effective for enhancing images as they can reduce the size of original data while preserving structural features. In [17], the authors proposed a lifting scheme combined with an adaptive median filter to remove salt-and-

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pepper noise from images, considering window sizes of 3 × 3 and 5 × 5 for filtering corrupted pixel values. Hussain [6] implemented a fast dyadic wavelet transform (FDyWT) based on lifted spline to enhance the quality of mammograms. This method employed Tsallis entropy to suppress noise and modified the coefficients of high-frequency sub-bands using a power law transformation. However, the method's performance is affected by the choice of wavelets. Several studies have emphasized the role of wavelet transforms in improving image quality and preserving edge details [15]. Furthermore, images can be acquired using an inverse transform without losing crucial features.

To further improve the clarity and quality of medical images while reducing uncertainties, fuzzy set-based approaches are being explored and refined. $Type_2$ fuzzy sets are beneficial in scenarios where accurately defining membership values is challenging. Chaira [1] introduced a method using $type_2$ fuzzy set to improve medical image contrast. She created a modified $type_2$ membership function for each pixel, utilizing the Hamacher tconorm as an aggregation operator to generate the output image. The authors [2] proposed an interval-based fuzzy enhancement algorithm that enhances image contrast by incorporating the parameter α and Dombi operator to combine the upper and lower bounds of $type_2$ fuzzy membership values, resulting in an improved quality in the image with the new membership function. The authors [22] have utilized the intensifier operator in conjunction with fuzzy sets to enhance the quality of images. The operator is computed using the OTSU method and applied multiple times before being subsequently applied to the fuzzy method to obtain the enhanced image. But the method has a high computational time, resulting from applying the intensifier operator multiple times on a test image.

In a recent study by Selvam et al. [23], an intuitionistic fuzzy generator combined with the CLAHE method was developed to enhance low-contrast images. The process began by fuzzifying the image, followed by the application of Intuitionistic Fuzzy Sets (IFS), and then the CLAHE method was applied. Finally, a defuzzification process was executed to produce the improved image. For calculating the non-fuzzy membership value in the IFS, the authors introduced a parameter, k, whose optimal value is determined using the entropy of the image.

The fuzzy set framework has proven effective in addressing the lack of clear boundaries in medical images, offering the potential for better performance. The present work aims to address challenges observed in medical images (such as artifacts removal, contrast improvement) by integrating features of LWT and a $type_2$ fuzzy-based hybrid method to improve the visual quality of medical images.

The paper is structured as follows: Section 2 discusses the motivation and contributions for conducting this research. Section 3 covers the fundamental concepts related to the proposed work. Section 4 outlines the developed methodology, including the algorithmic steps. Section 5 provides information about the dataset. Section 6 presents the experimental results through both quantitative and subjective analysis. Lastly, Section 7 includes the concluding remarks.

II. RESEARCH INSPIRATION AND CONTRIBUTION

In low-light imaging environments, enhancing image resolution becomes a crucial requirement due to significant degradation in image quality. This enhancement mechanism is essential for various applications, including medical imaging, remote sensing, face recognition, and astronomy. Improving contrast is key to utilizing these high-resolution images effectively across different fields. This work aims to develop and implement image-processing techniques that enhance the quality of medical images.

The primary contribution of this research is to provide better contrast enhancement for medical images obtained through various modalities. So, radiologists can more clearly identify anomalies, leading to more accurate diagnoses. To address the limitations of intensity-based transformation methods, this approach integrates LWT and $type_2$ fuzzy sets to improve the clarity and quality of medical images while preserving their structural features. Some of the key highlights are outlined below:

1. We present an enhancement method that exploits the features of LWT and $type_2$ fuzzy sets to improve the quality and contrast of medical images. The LWT is employed to prevent any loss of information in an image while effectively decomposing both the approximated and detailed components, enhancing efficiency.
2. $Type_2$ logic is applied to the approximated subband to reduce image blurriness. This involves the introduction of a fuzziness-controlling parameter, η, which is set to 0.1, along with the Dombi t-conorm operator.

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3. A comparative analysis is regulated to assess the proposed methodology qualitatively and subjectively against standard techniques and several existing methods.
4. Implementation of the proposed method on medical datasets, including MRI, X-ray, and ultrasound images, demonstrates its effectiveness and versatility across diverse imaging modalities.
5. Additionally, quantitative evaluation is performed by calculating the average values of various assessment metrics (like AMBE, PSNR, SSIM, and entropy) along with their corresponding standard deviations across different categories of medical images.

III. PRELIMINARIES

This section outlines the related concepts necessary to proceed with this work.

3.1 Lifting Wavelet Transform

Wavelets are mathematical function of finite length and is oscillatory nature. In this, a mother wavelet translation and dilation properties are utilized to manipulate the image data in spatial or frequency domain. This transform was developed by Sweldens in 1994 [18] to separate data using the wavelet function into a simpler set of steps. This method is applicable to image data as it is simpler and more effective than its counterparts and requires less memory computationally. This method was developed to create newer wavelets and is hence also termed second-generation wavelets [10]. This transform is applied to image data in three steps as shown in figure 1. We have used Haar wavelet for the processing of sub bands in this study.

- **Split:** Initially, the image is split into even and odd components when the lifting scheme is applied across the horizontal direction, creating even $i_e(p)$ and odd values $i_o(p)$; p number of samples.

$$i_e(p) = i(2p), i_o(p) = i(2p+1) \tag{1}$$

- **Predict:** in this an even set is used to predict an odd set if even and odd samples are correlated.

$$d(p) = i_o(p) - P(i_e(p)) \tag{2}$$

$d(p)$ is the difference between the original sample and its predicted value

- **Update:** with the help of detailed coefficients, even samples are updated.

$$I_e(p) = i_e(p) + U(d(p)) \tag{3}$$

here, $I_e(p)$ is the updated even values and $U(.)$ is the update operator.

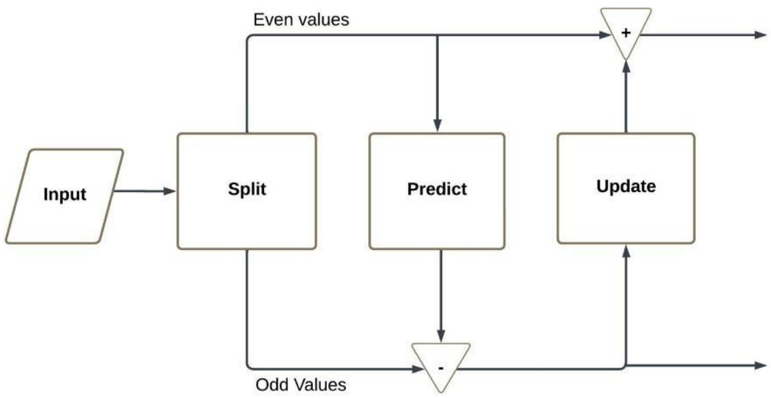

Fig. 1. Block diagram of LWT.

3.2 Fuzzy sets

A fuzzy set ($\tilde{X}$) introduced by Zadeh [21] in a finite set $X = \{x_1, x_2, x_3, \ldots, x_n\}$ may be represented mathematically as:

$$\tilde{X}_{type_1} = \{(x, \mu_{\tilde{X}}(x) \mid x \in X\} \tag{4}$$

where the function $\mu_{\tilde{X}}(x)$ is the membership values corresponding to each element of the set.

$Type_2$ fuzzy sets are an extension of $type_2$ fuzzy sets, which allows for the modelling of higher-order uncertainties in membership function.

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$$\tilde{X}_{type_2} = \{((x,u), \mu_{\tilde{X}}(x,u)) \mid \forall x \in X\} \tag{5}$$

where $\mu_{\tilde{X}}(x,u)$ is the $type_2$ fuzzy membership function. The upper (UMF) and lower (LMF) membership degrees, $\mu_u(x)$ and $\mu_l(x)$, of the initial membership function $\mu(x)$, which defines the boundary values of interval $type_2$ fuzzy sets.

$$\mu_{type_2}(x) = \left[\mu_u(x)^{\eta}, \mu_l(x)^{\frac{1}{\eta}}\right] \tag{6}$$

where parameter $\eta \in [0, \infty)$.

IV. PROPOSED METHODOLOGY

This section presents an overview of the proposed method, which aims to enhance medical images. This hybrid approach combines the computational efficiency of LWT with $type_2$ fuzzy sets to reduce the fuzziness present in images, as illustrated in the block diagram shown in the figure 2. The following steps are used to implement the method for obtaining the enhanced output image:

- Consider an image (I_o) of size 512×512 for experiment.
- First, we implement LWT on medical image to create four sub bands to make the further processing more convenient.
- The sub bands are termed as LL, LH, HL and HH, where LL represents approximated and LH, HL, HH depicts the detailed components of the image.
- Then on the decomposed LL sub band, we apply $type_1$ fuzzy membership function computed using eq. 7 to convert the pixel values from spatial to fuzzy domain.

$$\mu(i_{mn}) = \frac{i_{mn} - I_{\min}}{1 - I_{\min} + I_{\max}}; \ \forall\, i_{mn} \in I_o \tag{7}$$

where $I_{\max}$ and $I_{\min}$ represents the maximum and minimum intensity values of image I_o.

- Define upper and lower $type_2$ fuzzy membership functions corresponding to each pixel using the parameter (η) as in equations 8 and 9.

$$\mu_u(i_{mn}) = [\mu(i_{mn})]^{1-\eta^2} \tag{8}$$

$$\mu_l(i_{mn}) = [\mu(i_{mn})]^{\frac{1}{\eta^2}} \tag{9}$$

where μ_u and μ_l represent upper and lower membership functions for $type_2$ fuzzy set, respectively, and η is set to 0.1.

- Apply Dombi T-conorm operator to merge the upper and lower membership functions obtained in equations 8 and 9 to get modified $type_2$ LL sub band.

$$\mu_D(i_{mn}) = \frac{1}{\left(\left(\left(\frac{1}{\mu_u(i_{mn})}\right) - 1\right)^{-\tau} + \left(\left(\frac{1}{\mu_l(i_{mn})}\right) - 1\right)^{-\tau}\right)^{-\frac{1}{\tau}}} \tag{10}$$

here, τ represents the average value of the image (I_o).

- Modified LL sub-band is computed using Eq. 11.

$$I_{LL} = \mu_D(i_{mn})(1 - I_{\min} + I_{\max}) + I_{\min} \tag{11}$$

- Merge the obtained modified LL (approximated) sub-band along with detailed sub-bands (LH, HL, HH) using inverse LWT.
- The output image (I_e) is contrast-enhanced.

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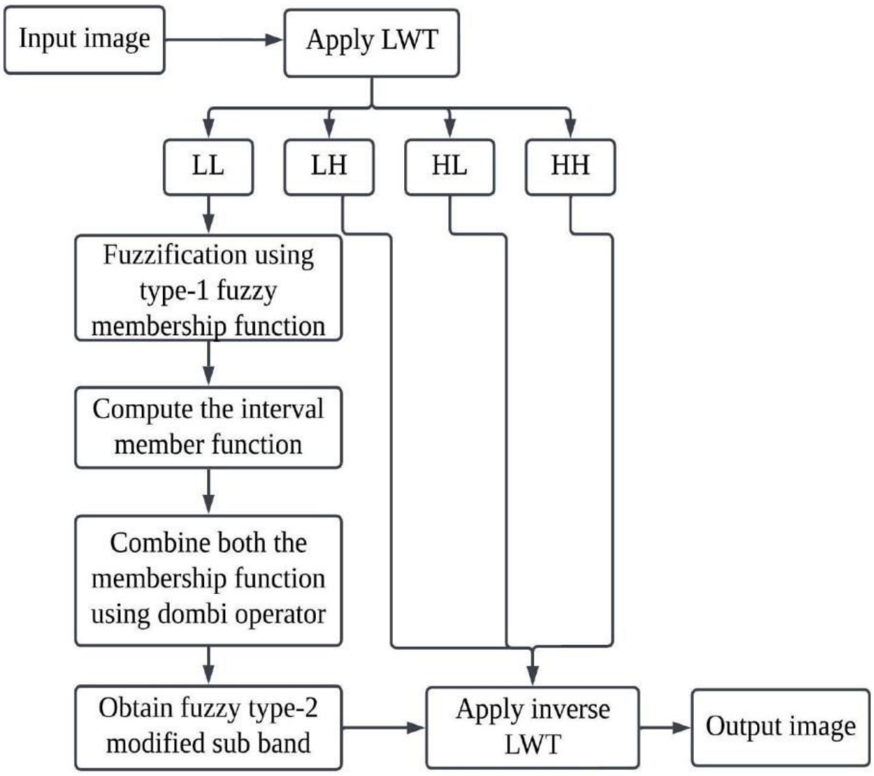

Fig. 2. Block diagram of proposed method.

Algorithm steps:

Step1: *Initially consider an input image* (I_o) *of size* 512×512.
Step2: *Then apply 2-level LWT to decompose the image into four sub bands, namely* LL, LH, HL *and* HH
Step3: *Apply* type_1 *fuzzy membership function on the LL sub band.*
Step4: *obtain the* type_1 *fuzzy image and compute* type_2 *fuzzy membership functions as in eqs. 8-9.*
Step5: *Combine upper and lower membership functions using Dombi operator given by eq. 10.*
Step6: *Obtain the modified* type_2 *fuzzy approximated image.*
Step7: *After step 6, merge sub bands using inverse* LWT.
Step8: *Finally, obtain the enhanced image* (I_e).
end algorithm

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V. DATASET

X-rays, ultrasounds, MRIs, and other imaging techniques provide valuable information about the affected tissues and the organs being examined, including their size and location [3]. For our experimental analysis and to evaluate the effectiveness of proposed method, we utilize a medical dataset [2] that includes various imaging modalities. In our assessment, we have 45 images, each sized 512×512 pixels, sourced from three distinct categories of imaging techniques: MRI, X-rays, and ultrasound scans. For subjective assessment and visualization, we select two images from each of the medical imaging modalities as depicted in figure 3.

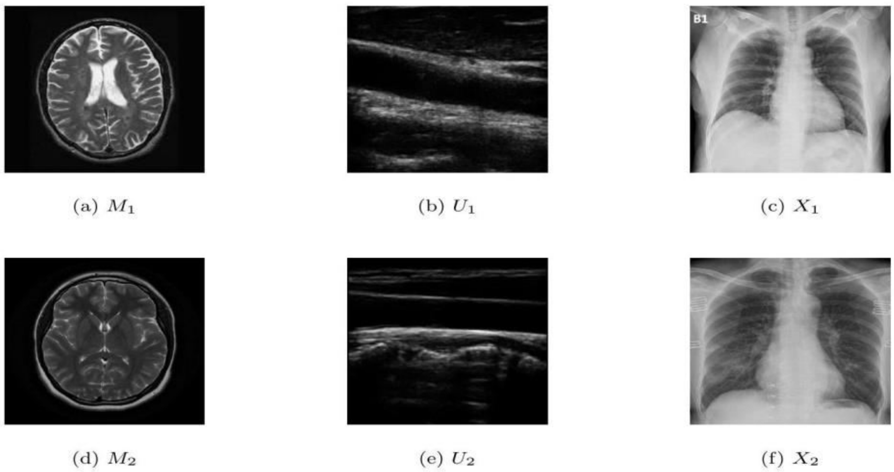

Fig. 3. Original MRI (M_1, M_2), ultrasound (U_1, U_2) and X-ray (X_1, X_2) images.

VI. PERFORMANCE EVALUATION AND RESULTS

This section provides a brief discussion of the performance metrics selected to objectively evaluate the proposed technique. By quantitatively assessing various aspects of both the input and output images, these performance indicators measure the effectiveness of the algorithm. The factors considered include image quality, structural characteristics, blurriness, and other relevant aspects.

6.1 Qualitative Assessment

AMBE: This parameter assesses the overall difference in brightness preservation by averaging the input and output images [19].

$$AMBE = \left|\left(\mu_{I_o} - \mu_{I_e}\right)\right| \tag{12}$$

here, μ_{I_o} and μ_{I_e} are expected intensity values corresponding to the original (I_o) and enhanced (I_e) medical images.

The AMBE values for six medical images have been calculated and presented in the table 1. Images obtained using the Chaira [1] method exhibit the highest AMBE, indicating notable noise and excessive enhancement. In contrast, the CLAHE [12] method demonstrates better brightness preservation than images generated by the Gandhamal [4] method. Additionally, the AMBE value obtained with the proposed method is significantly better than all the other methods discussed, highlighting robustness of the proposed algorithm in maintaining brightness.

Table 1: AMBE values acquired using different enhancement methods.

Images	X_1	X_2	U_1	U_2	M_1	M_2
Proposed	**0.7285**	**0.6438**	0.3630	0.2472	**0.4254**	0.4463
CLAHE [12]	7.2017	7.4342	3.7281	3.9772	5.4272	5.9167
Chaira [1]	88.5340	81.2340	78.1570	102.1100	151.6100	111.8200

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Gandhamal [4]	16.5230	2.0585	9.3357	9.3314	18.3240	19.4740
T2FS [2]	0.7441	0.6882	**0.3614**	**0.2449**	0.4434	**0.4437**

PSNR: This metric assesses the difference in noise levels between the output and input images [8]. A higher PSNR value indicates lower distortion and better image quality.

$$PSNR = 10\log_{10}\left[\frac{(L-1)^2}{MSE}\right] \tag{13}$$

here, $MSE = \frac{1}{N}\sum_m \sum_n |I_o(m,n) - I_e(m,n)|^2$ and L represents dynamic range, while m and n is the intensity values in the image.

Table 2 demonstrates that the proposed method consistently achieves high PSNR values across all test images. This suggests that the proposed method effectively reduces noise, surpassing other techniques in terms of noise suppression and overall image quality.

Table 2: PSNR values computed for six medical images using various enhancement methods for comparative analysis.

Images	X_1	X_2	U_1	U_2	M_1	M_2
Proposed	**49.40**	**50.04**	52.53	**54.20**	**51.84**	51.64
CLAHE [12]	21.19	16.16	14.77	17.10	19.08	17.15
Chaira [1]	8.44	9.16	8.34	6.07	4.31	5.85
Gandhamal [4]	15.42	14.59	22.66	21.82	17.74	18.25
T2FS [2]	49.32	49.73	**52.55**	54.22	51.38	**51.66**

SSIM: The parameter measures the difference in loss of structural information between original and enhanced images [7], as described in the equation below. An SSIM value closer to 1 indicates better structural integrity.

$$SSIM = \frac{(2\mu_{I_o}\mu_{I_e} + a_1)(2\sigma_{I_oI_e} + a_2)}{({\mu_{I_o}}^2 + {\mu_{I_e}}^2 + a_1)({\sigma_{I_o}}^2 + {\sigma_{I_e}}^2 + a_2)} \tag{14}$$

where, μ_{I_o} and μ_{I_e} are the average of original and enhanced images, respectively, and $\sigma_{I_oI_e}$ represents the correlation between both the images; $\sigma_{I_o}^2$ and $\sigma_{I_e}^2$ is the corresponding variances; a_1 and a_2 are constants.

The results of the proposed method for this metric have been compared with other methods using the given dataset, as shown in the table 3. It is noted that the SSIM value approaches 1 for most of the test images, indicating that the proposed method effectively preserves the structural features in the output images.

Table 3: SSIM values recorded for six medical images obtained through different techniques.

Images	X_1	X_2	U_1	U_2	M_1	M_2
Proposed	0.9991	**0.9998**	**0.9997**	**0.9998**	**0.9999**	**0.9999**
CLAHE [12]	0.8224	0.7418	0.4853	0.4218	0.6942	0.5013
Chaira [1]	0.2341	0.2587	0.3102	0.3117	0.1795	0.3438
Gandhamal [4]	0.7996	0.6922	0.6119	0.5989	0.4740	0.5512
T2FS [2]	**0.9998**	0.9998	0.9997	0.9998	0.9998	0.9999

Entropy: This metric evaluates the information content of an image, as defined by Shannon. Higher entropy values indicate better pixel information and preservation of edges. [5].

$$Entropy = -\sum_k p(k)\log_2(p(k)) \tag{15}$$

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where $p(k)$ is the probability of occurrence of intensity values and is given by $p(k) = n(k)/M, k \in [0,255]$. The entropy for six medical images is calculated using the given equation and represented in the table 4. The resulting entropy values demonstrate that the proposed method leads to significantly less information loss and better retention of original pixel values in contrast to other existing methods. The higher value of the entropy as observed in case of CLAHE generated images is due to the over enhancement induced in the output images.

Table 4: Comparative analysis of medical image entropies generated by proposed and other enhancement methods.

Images	X_1	X_2	U_1	U_2	M_1	M_2
Original entropy	7.2830	7.2735	6.1745	4.7820	5.9177	5.4290
Proposed	7.3141	7.2844	5.9132	**5.4249**	6.1609	4.7730
CLAHE [12]	**7.4730**	**7.6843**	**7.2073**	5.3842	**6.9874**	**5.9467**
Chaira [1]	4.3366	4.3988	4.1335	4.4634	5.0096	4.7668
Gandhamal [4]	6.3358	6.8340	1.4297	1.8386	3.7767	3.1276
T2FS [2]	7.2843	7.2695	6.1603	4.7727	5.9113	5.4248

The table 5 displays the average performance metrics calculated for 45 medical images from various imaging modalities within the dataset. The results indicate that the proposed algorithm retains the most information while also enhancing contrast and reducing noise in the input images. This improvement is evident when compared to conventional methods and existing techniques, based on the defined metrics.

Table 5: Average of the evaluation metrics.

Images	AMBE	PSNR	SSIM	Original entropy	Enhanced entropy
Proposed	**0.42 ± 0.23**	**52.75 ± 2.91**	**1 ± 0**	5.74 ± 1.41	5.57 ± 1.36
CLAHE [12]	16.67 ± 9.65	18.4 ± 1.88	0.6 ± 0.18	5.74 ± 1.41	**6.29 ± 1.39**
Chaira [1]	96.22 ± 32.24	7.47 ± 2.01	0.51 ± 0.18	5.74 ± 1.41	4.44 ± 0.7
Gandhamal [4]	12.27 ± 7.5	5.74 ± 1.41	3.94 ± 2.09	5.74 ± 1.41	0.65 ± 0.13
T2FS [2]	0.5 ± 0.31	51.34 ± 4.67	1 ± 0	5.74 ± 1.41	5.7 ± 1.39

6.2 Subjective Evaluation

For the subjective evaluation, we applied the proposed methodology to a medical dataset consisting of 45 images, which includes various imaging modalities such as MRI, ultrasound, and X-rays. We provided six images from each modality for visualization purposes to assess the quality of enhanced images. Additionally, the results obtained using our proposed method were compared with images generated by several existing standard methods, including Chaira [1], Gandhamal [4], T2FS [2] and CLAHE [12].

Figures 4-6 display enhanced images generated using the following methods: $((a), (e))$ Chaira, $((b), (f))$ CLAHE $((c), (g))$ Gandhamal, and $((d), (h))$ proposed method. The proposed methodology focuses on enhancing contrast and preserving edges without compromising the structural features of the images.

MRI images enhanced by Chaira [1] exhibit a washed-out effect, which compromises structural integrity and leads to the loss of pixel information, overshadowing the affected regions. In contrast, CLAHE [12] generated images show significant enhancement in specific brain regions but suffer from over-amplification of higher grey levels, resulting in reduced visibility of soft tissues. Images acquired using T2FS [2] exhibit improved clarity and detail, providing enhancement that effectively matches the results obtained through the proposed methodology. Gandhamal [4] method decreases overall brightness, impacting the visibility of sensitive features and leading to loss of structural details in images. However, MRI images produced by the proposed method maintain superior image quality by preserving important features without compromising structural integrity. A similar pattern is observed with X-rays and ultrasound images, where other techniques lead to significant noise and excessive enhancement issues.

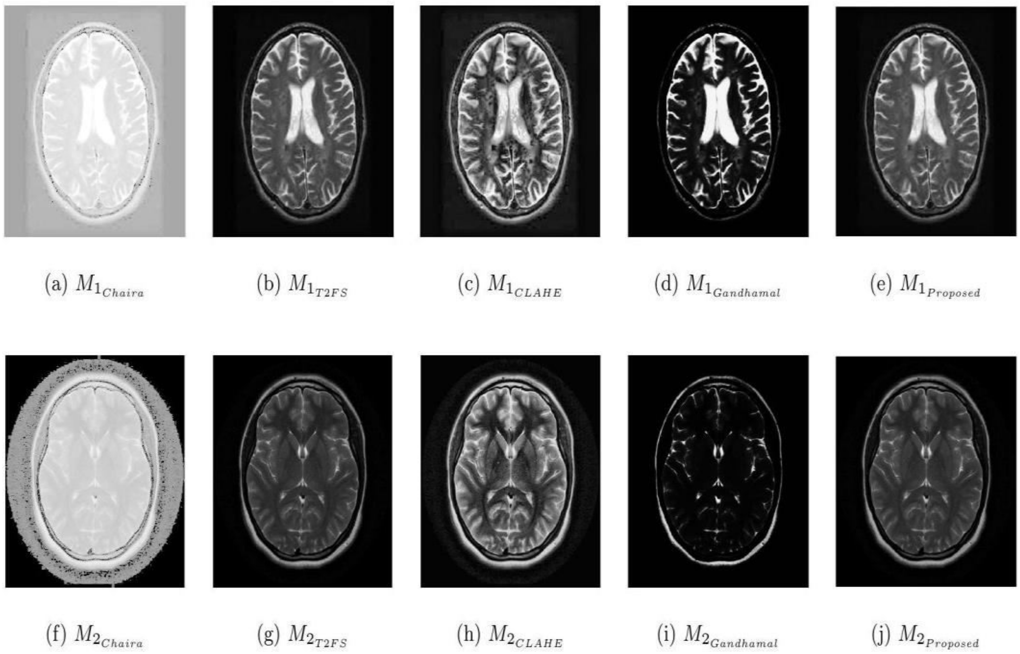

Fig. 4. Subjective analysis of MRI images acquired using various techniques.

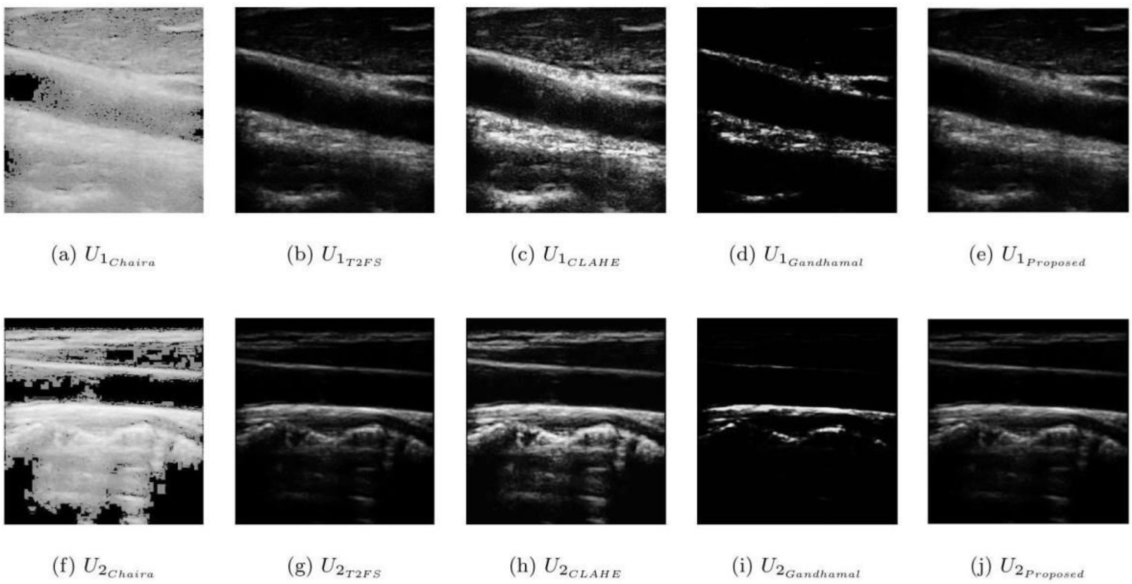

Fig. 5. Subjective analysis of ultrasound images acquired using various techniques.

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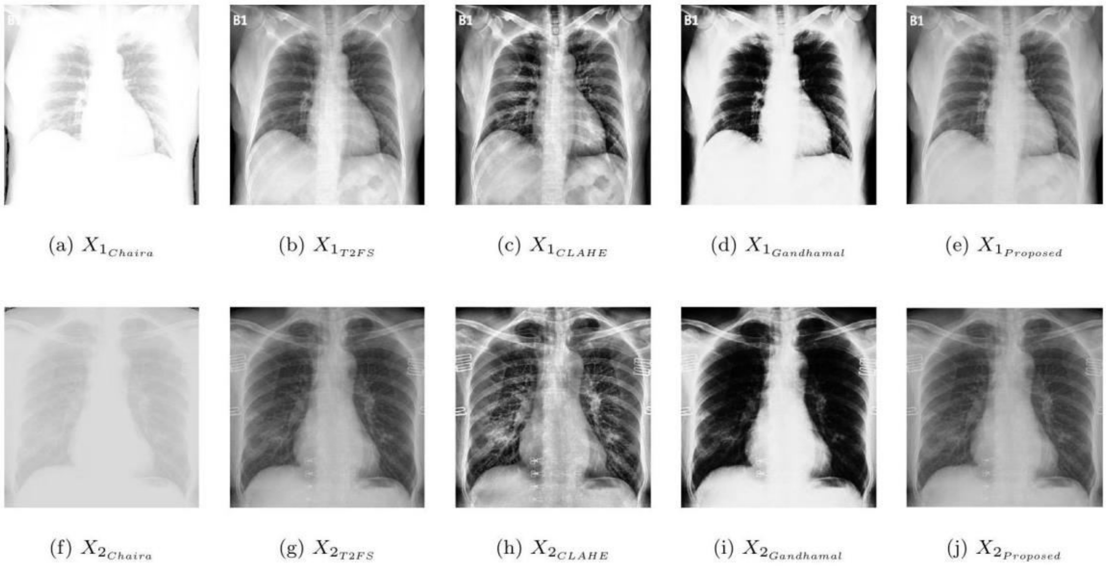

Fig. 6. Subjective analysis of chest X-ray images acquired using various techniques.

Compared to these methods, the enhanced images generated by the proposed method reduce noise and eliminate artifacts, providing better results for the medical dataset. This improvement assists medical professionals in preparing accurate diagnosis plans. The proposed method can be applied to other medical datasets to enhance efficiency. Additionally, it could be combined with other enhancement techniques to develop a hybrid approach that addresses limitations (as observed in the proposed method), such as selecting the optimal value for the alpha parameter to prevent excessive brightness in the resulting images.

VII. CONCLUSION

Medical image enhancement plays a vital role during the pre-processing step, to improve the visibility of anomalies in the internal organs of human body. This enhancement aids in the identification and treatment of diseases. This paper introduces a hybrid method for medical image enhancement that combines LWT and $type_2$ fuzzy sets. The proposed method is designed to resolve the uncertainties encountered in medical images and provides clear information, contributing to advancements in the field. Initially, LWT is applied to medical images to generate four sub-bands, including approximated and detailed components. We then implement a $type_2$ fuzzy set to the approximated portion of the image to enhance contrast and reduce blurriness, leading to better interpretability. To evaluate the effectiveness of proposed image enhancement method, we conduct both subjective assessments and numerical analyses using various metrics, including AMBE, PSNR, entropy, and SSIM. We test the method on a medical dataset containing diverse imaging modalities. The results show that the technique significantly improves the quality and contrast of medical images, achieving a PSNR of approximately 50 dB, a better AMBE (0.42), an SSIM value closer to 1, and increased entropy. These outcomes suggest that the proposed method effectively preserves structural details without introducing unwanted artifacts.

REFERENCES

1. Chaira, T., An improved medical image enhancement scheme using type II fuzzy set, Applied soft computing, vol. 25, pp. 293-308, 2014. https://doi.org/10.1016/j.asoc.2014.09.004.
2. Chandra, N., Bhardwaj, A., Medical image enhancement using modified type II fuzzy membership function generated by Hamacher t-conorm, Soft Computing vol. 28, pp. 6753-6774, 2024. https://doi.org/10.1007/s00500-023-09535-5.
3. D' Alterio, P., Garibaldi, J.M., John, R.I., Pour Abdollah, A., Constrained interval type-2 fuzzy sets, IEEE Transactions on Fuzzy Systems, vol. 29, pp. 12121225, 2020. doi: 10.1109/TFUZZ.2020.2970911.

4. Gandhamal, A., Talbar, S., Gajre, S., Hani, A.F.M., Kumar, D., Local gray level s-curve transformation-a generalized contrast enhancement technique for medical images, Computers in biology and medicine, vol. 83, pp. 120-133, 2017. 10.1016/j.compbiomed.2017.03.001.
5. Hanmandlu, M., Arora, S., Gupta, G., Singh, L., Underexposed and overexposed color image enhancement using information set theory, The Imaging Science Journal, vol. 64, issue 6, pp. 321-333, 2016. https://doi.org/10.1080/13682199.2016.1215063.
6. Hussain, M., Mammogram enhancement using lifting dyadic wavelet transform and normalized tsallis entropy, Journal of Computer Science and Technology, vol. 29, pp. 1048-1057, 2014. https://doi.org/10.1007/s11390-014-1489-7.
7. Joseph, J., Periyasamy, R., A fully customized enhancement scheme for controlling brightness error and contrast in magnetic resonance images, Biomedical Signal Processing and Control, vol. 39, pp. 271283, 2018. https://doi.org/10.1016/j.bspc.2017.08.003.
8. Kannan, K., Deepika, T., Analysis and comparison of different wavelet transform methods using benchmarks for image fusion, 2020. https://doi.org/10.48550/arXiv.2007.11488.
9. Li, X., Naman, A., Taubman, D., Exploration of learned lifting-based transform structures for fully scalable and accessible wavelet-like image compression, IEEE Transactions on Image Processing, 2024. https://doi.org/10.48550/arXiv.2402.18761.
10. Mehta, R., Rajpal, N., Vishwakarma, V.P., A robust and efficient image watermarking scheme based on lagrangian svr and lifting wavelet transform, International Journal of Machine Learning and Cybernetics, vol. 8, pp. 379-395, 2017. https://doi.org/10.1007/s11042-023-15144-z.
11. Nguyen-Tat, T.B., Hung, T.Q., Nam, P.T., Ngo, V.M., Evaluating pre-processing and deep learning methods in medical imaging: Combined effectiveness across multiple modalities, Alexandria Engineering Journal, vol. 119, pp. 558-586, 2025. https://doi.org/10.1016/j.aej.2025.01.090.
12. Priyadharsini, C., Jagadeesh K. R., Retinal image enhancement based on color dominance of image, Scientific Reports, vol.13, pp. 7172, 2023. https://doi.org/10.1038/s41598-023-34212-w.
13. Rao, B.J., Krishna, O.V., Lifting wavelet transform for super resolution image reconstruction using MATLAB, CVR Journal of Science and Technology, vol. 5, pp. 42-49, 2013. doi 10.32377/cvrjst0508.
14. Rao, T.P., Rao, D.B.R., Image fusion using lifting wavelet transform with neural networks for tumor detection, International Research Journal of Engineering and Technology, vol. 6, issue 9, 2019. doi: 10.1109/MI-STA54861.2022.9837655.
15. Singh, K.K., Pandey, R.K., Suman, S., Contrast enhancement using lifting wavelet transform, 2014 International Conference on Control, Instrumentation, Communication and Computational Technologies (ICCICCT), pp. 447-451. IEEE, 2014. doi: 10.1109/ICCICCT.2014.6993003.
16. Solomon, C., Breckon, T., Fundamentals of Digital Image Processing: A practical approach with examples in MATLAB, John Wiley & Sons, 2011.
17. Sree, P.S.J., Kumar, P., Siddavatam, R., Verma, R., Salt-and-pepper noise removal by adaptive median-based lifting filter using second-generation wavelets, Signal, Image and Video Processing, vol. 7, pp. 111-118, 2013. https://doi.org/10.1007/s11760-011-0210-3.
18. Sweldens, W., The lifting scheme: A construction of second-generation wavelets, SIAM journal on mathematical analysis, vol. 29, issue 2, pp. 511-546, 1998. https://doi.org/10.1137/S0036141095289051.
19. Tang, J.R., Isa, N.A.M., Bi-histogram equalization using modified histogram bins, Applied Soft Computing, vol. 55, pp. 31-43, 2017. https://doi.org/10.1016/j.asoc.2017.01.053.
20. Veluchamy, M., Subramani, B., Image contrast and color enhancement using adaptive gamma correction and histogram equalization, Optik, vol. 183, pp. 329337, 2019. https://doi.org/10.1016/j.ijleo.2019.02.054.
21. Zadeh, L.A., Fuzzy sets, Information and control, vol. 8, issue 3, pp. 338-353, 1965. http://dx.doi.org/10.1016/S0019-9958(65)90241-X.
22. Yang L., Zenian S., Zakaria R., "Fuzzy Image Enhancement Method based on a New Intensifier Operator", International Journal of Advanced Computer Science and Applications (IJACSA), vol. 13, 2022. http://dx.doi.org/10.14569/IJACSA.2022.0130903
23. Chithra Selvam, Reegan Jebadass Johnson Jebadass, Dhanasekar Sundaram, Lakshmanan Shanmugam, A novel intuitionistic fuzzy generator for low-contrast color image enhancement technique, Information Fusion, vol. 108, pp. 102365, 2024.https://doi.org/10.1016/j.inffus.2024.102365.

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