Traditional and Neural Network Approaches for Medical Image Compression: A Performance Evaluation

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Abstract

Medical imaging generates vast amounts of data, presenting challenges in storage, transmission, and quality retention. Efficient image processing techniques are essential to ensure diagnostic accuracy while addressing these constraints. This study evaluates Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT), Fractal Compression, Neural Network Back Propagation (NNBP), and Neural Network Radial Basis Function (NNRBF) as solutions to these challenges, implemented on Computed Tomography (CT), Magnetic Resonance (MR), and Positron Emission Tomography (PET) images using MATLAB. The results reveal that DCT offers high-quality retention with minimal computational overhead, while DWT balances compression and detailed texture preservation. Fractal Compression achieves superior compression ratios but demands significant computational resources. Neural methods, NNBP and NNRBF, exhibit adaptability and robustness in reconstruction, with promising potential for optimized diagnostic applications. This research highlights trade-offs among these methods, emphasizing the importance of application-specific selection. DCT and DWT are ideal for real-time applications, while neural methods, with further refinement, can advance adaptive medical image processing. These findings contribute to enhancing diagnostic workflows in healthcare, paving the way for efficient data management and improved clinical decision-making.

Keywords: Medical Image Processing; Compression Techniques; Neural Networks; Diagnostic Imaging; DCT; DWT; Fractal; NNBP; NNRBF;

Introduction

Medical imaging plays a critical role in modern healthcare, facilitating the diagnosis and monitoring of various medical conditions. However, the increasing resolution and complexity of medical images, such as those obtained from Computed Tomography (CT), Magnetic Resonance Imaging (MRI), and Positron Emission Tomography (PET), present significant challenges in terms of storage, transmission, and processing. Efficient medical image compression techniques are essential to address these challenges while ensuring high-quality image reconstruction for accurate diagnosis and clinical decision-making [1] [2].

Traditional image compression techniques, such as Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT), have been widely adopted due to their ability to reduce data size while preserving essential features. DCT is known for its computational efficiency and high Peak Signal-to-Noise Ratio (PSNR), making it suitable for real-time applications [6] [19]. On the other hand, DWT provides superior multi-resolution analysis, capturing intricate details in medical images, making it particularly useful for texture-rich images [6] [18] [24]. Fractal compression, another traditional technique, achieves high compression ratios but at the cost of increased computational complexity, which limits its applicability for real-time processing [6] [21] [12].

Recent advancements in artificial intelligence (AI) and neural networks have led to the development of more sophisticated medical image compression techniques. Neural Network Back Propagation (NNBP) and Neural Network Radial Basis Function (NNRBF) have demonstrated promising capabilities in adaptive image reconstruction, offering enhanced compression while maintaining diagnostic quality [6] [23] [3]. AI-driven techniques, such as those based on Variational Autoencoders

(VAE) and Gated Recurrent Convolutional Neural Networks (GRCNN), further push the boundaries of compression efficiency by leveraging deep learning for intelligent feature extraction and encoding [16] [11]. Hybrid approaches that combine traditional and AI-based methods are emerging as a viable solution to optimize compression efficiency while retaining image quality [5] [10].

Techniques such as Principal Component Analysis (PCA)-based compression and knowledge distillation for medical images have been proposed to enhance multi-data compression capabilities [5] [10] [7]. Additionally, region-of-interest (ROI)-based compression, where critical regions of an image are preserved at higher fidelity while background areas undergo aggressive compression, has gained traction for telemedicine applications [17] [22]. Other methods, such as vector quantization, wavelet difference reduction, and heuristic pixel segmentation, have shown significant advancements in balancing compression ratio and image quality [7] [9] [12].

This research paper evaluates the performance of traditional and neural network-based compression techniques applied to CT, MRI, and PET images. The study compares these methods based on key performance metrics, including Compression Ratio, PSNR, Memory Usage, and Execution Time [4] [8] [15]. By analysing the strengths and limitations of each approach, this study aims to provide insights into the optimal selection of compression techniques for medical imaging, ensuring a balance between efficiency and diagnostic accuracy [13] [14] [20] [25].

Key Contributions

1. Comparative study of image compression techniques on CT, MR, and PET images.
2. Introduction of neural networks (NNBP and NNRBF) for medical image processing.
3. Analysis of Compression Ratio, PSNR, Memory Usage, and Execution Time as performance metrics.
4. MATLAB-based experimental implementation and tabulated results showcasing insights across different imaging modalities.

Methodology

This study explores how different techniques can process medical images from CT, MR, and PET scans. We tested five methods using MATLAB, known for its powerful image processing and neural network tools.

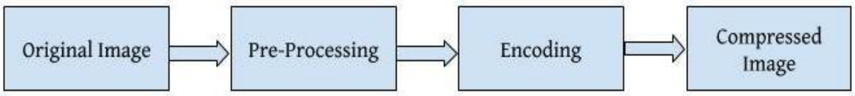

Fig.1 Basic Block Diagram of Image Compression

Compression Techniques Explored

1. **Discrete Cosine Transform (DCT):** DCT transforms images from the spatial domain to the frequency domain, highlighting different parts of the image based on their importance. This helps in removing less crucial parts, making the image smaller in size without losing much quality. DCT is fast and often used in situations where bandwidth is limited.

$$F(u,v) = \frac{2}{M} C(u) C(v) \sum_{X=0}^{M-1} \sum_{Y=0}^{M-1} f(x,y) \cos\left[\frac{\pi(2x+1)u}{2M}\right] \cos\left[\frac{\pi(2x+1)v}{2M}\right] \quad (1)$$

for $u=0,\ldots,M-1$ and $v=0,\ldots,M-1$ (2)

Where $M=8$ and $C(k) = \begin{cases} 1/\sqrt{2} & \text{for } k=0 \\ 1 & \text{otherwise} \end{cases}$

2. **Discrete Wavelet Transform (DWT):** DWT breaks down an image into wavelets, analysing it at multiple scales and resolutions. This method is great for images with lots of textures, as it captures both detail and frequency, preserving important diagnostic features.

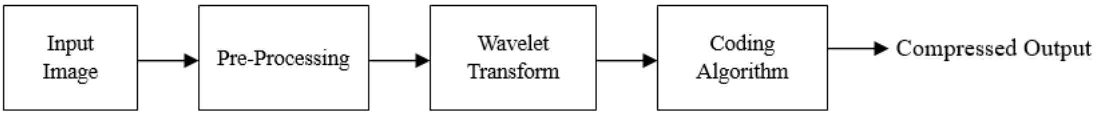

Fig.2 Block Diagram of Discrete Wavelet Transform

3. **Fractal Compression:** Fractal compression uses patterns that naturally repeat in images to represent them more compactly. It achieves high compression but is quite intensive computationally, meaning it takes longer to process and is better for offline analysis.

4. **Neural Network Back Propagation (NNBP):** NNBP is a supervised learning technique that uses gradient descent to reduce errors during image compression and decompression. It fine-tunes the network by adjusting weights to improve accuracy. We tested NNBP on various image types to see how well it retains important features.

5. **Neural Network Radial Basis Function (NNRBF):** NNRBF uses radial basis functions to compress images by mapping them into a higher-dimensional space. This method can handle complex details well but is also demanding in terms of computational resources.

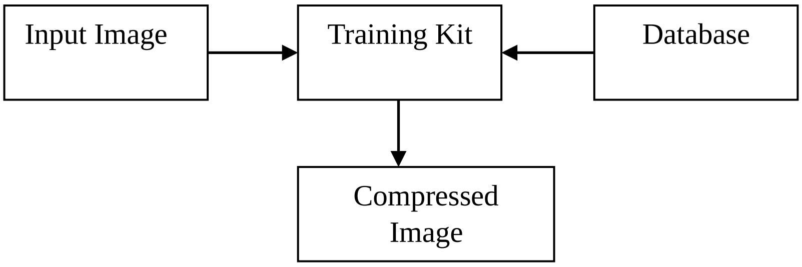

Fig.3 Basic Block Diagram of Neural Network

Implementation Process

1. **Preprocessing:** CT, MR, and PET images are standardized in size and intensity for uniformity.

2. **Application:** Each technique is applied to the images, and we reconstruct the compressed versions to evaluate quality.

3. **Evaluation Metrics:** We measure performance using Compression Ratio, Peak Signal-to-Noise Ratio (PSNR), Memory Usage, and Execution Time.

4. **Consistent Evaluation:** MATLAB scripts ensure that the evaluation is uniform across all techniques.

This approach helps us thoroughly evaluate each method's strengths and weaknesses, ensuring we understand how well they process medical images for diagnostic purposes.

Results & Discussion

Compression Ratio

Images	DCT	DWT	Fractal	NNBP	NNRBF
CT Image 1	1.4088	1.0002	6.6507	1.0495	1.0537
CT Image 2	1.3442	1.0011	6.6622	1.0356	0.8386
CT Image 3	1.4679	1.0015	13.2030	1.0330	1.0632
CT Image 4	1.3443	1.0020	5.0707	1.0328	1.1561
MR Image 5	1.4402	1.0005	6.5164	1.0564	0.9678
MR Image 6	1.6127	1.0048	10.9643	1.0423	1.1854
MR Image 7	1.3586	1.0229	4.4960	1.0398	1.2092
MR Image 8	1.5927	1.0265	7.5873	1.0442	1.117
MR Image 9	1.5900	1.0144	5.1806	1.0208	1.1416
MR Image 10	1.2792	1.0001	6.9771	1.0591	1.0116
MR Image 11	1.3006	0.9999	6.5397	1.0605	0.9904
MR Image 12	1.4355	1.0073	3.4217	1.0536	0.956
MR Image 13	1.4994	1.0013	1.8435	1.0837	1.0728
MR Image 14	1.3451	1.0006	2.3289	1.0728	1.1096
MR Image 15	1.6541	1.0001	3.0478	1.0514	1.0365
MR Image 16	1.5732	1.0023	3.4444	1.0513	1.0499
MR Image 17	1.4197	1.0001	4.8070	1.0426	0.9978
MR Image 18	1.6541	1.0001	3.0478	1.0514	1.0365
MR Image 19	1.7575	1.0152	3.4270	0.9938	1.1379
MR Image 20	1.0884	1.0015	4.1237	1.0398	1.003
MR Image 21	1.2792	1.0001	6.2566	1.0591	1.0636
PET Image 22	1.5891	1.0069	5.5154	1.0530	1.0352
PET Image 23	1.4908	1.0006	1.4721	0.7662	0.7923
PET Image 24	1.5791	1.0048	1.1946	1.0709	1.0696

Table: 1 Comparison of Compression ratio of CT, MR, PET images using different Techniques

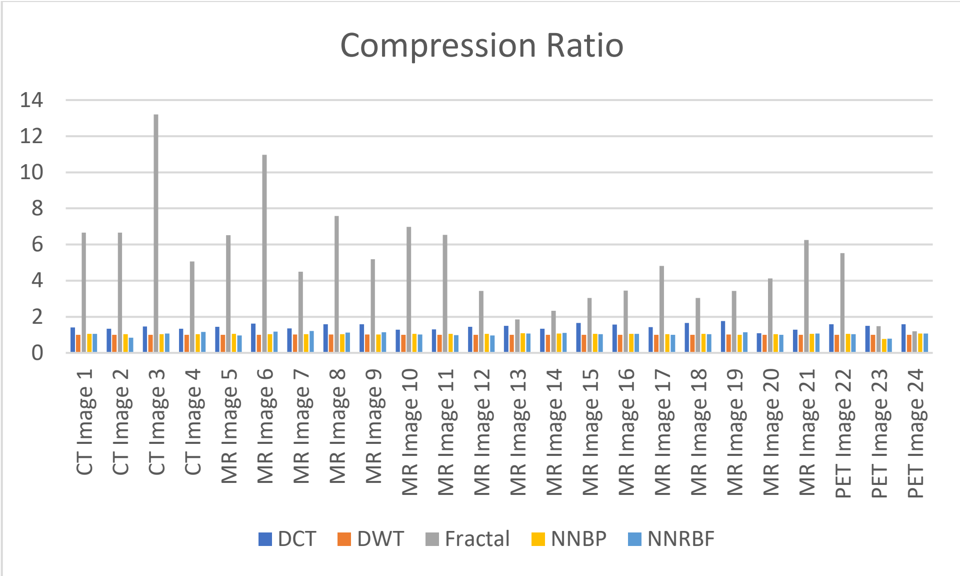

Fig.4 Compression Ratio of Images in Different Techniques

- DCT and Fractal Compression exhibit significantly higher compression ratios for CT and MR images, with Fractal achieving the highest across modalities.
- Neural networks (NNBP, NNRBF) offer moderate compression, maintaining balance with reconstruction quality.

Peak Signal-to-Noise Ratio (PSNR):

Images	DCT	DWT	Fractal	NNBP	NNRBF
CT Image 1	88.8087	71.7728	38.2519	69.6090	39.1906
CT Image 2	88.3888	71.3010	38.7416	42.3719	29.9663
CT Image 3	85.8091	55.7033	35.8632	62.5396	30.6855
CT Image 4	92.4192	67.3440	38.9335	40.2157	19.5331
MR Image 5	90.5865	67.7753	43.6002	62.0237	32.7573
MR Image 6	91.8776	63.8786	41.7960	46.7436	22.9515
MR Image 7	92.2370	62.7552	39.0490	44.7684	22.3658
MR Image 8	97.7195	60.1968	42.3063	48.5713	29.9071
MR Image 9	101.4771	64.2066	43.6769	45.7868	24.6009
MR Image 10	90.5101	67.8580	43.3527	73.0390	44.3570
MR Image 11	90.6810	68.4217	43.0880	68.0856	44.2258
MR Image 12	99.6740	67.9670	40.7357	54.1458	29.3755
MR Image 13	114.2706	72.8183	43.4892	66.8312	50.9330
MR Image 14	97.6726	72.5798	41.3458	47.6965	35.7803

MR Image 15	98.4225	64.5986	39.6035	72.3725	46.2050
MR Image 16	95.1357	65.2455	39.9027	57.2598	32.9302
MR Image 17	96.8298	61.9274	39.0449	84.0402	37.5945
MR Image 18	98.4225	64.5986	3.0478	72.3725	1.0365
MR Image 19	90.0821	54.2999	3.4270	36.2982	1.1379
MR Image 20	91.1779	60.5071	34.1952	69.1297	38.2271
MR Image 21	90.5101	67.8580	43.3019	73.0390	32.7369
PET Image 22	97.2405	66.0979	43.3578	50.2760	33.4930
PET Image 23	112.8808	78.9087	43.9157	42.7221	24.4163
PET Image 24	112.1955	70.6387	39.3448	84.0081	52.1345

Table: 2 Comparison of PSNR of CT, MR, PET images using different Techniques

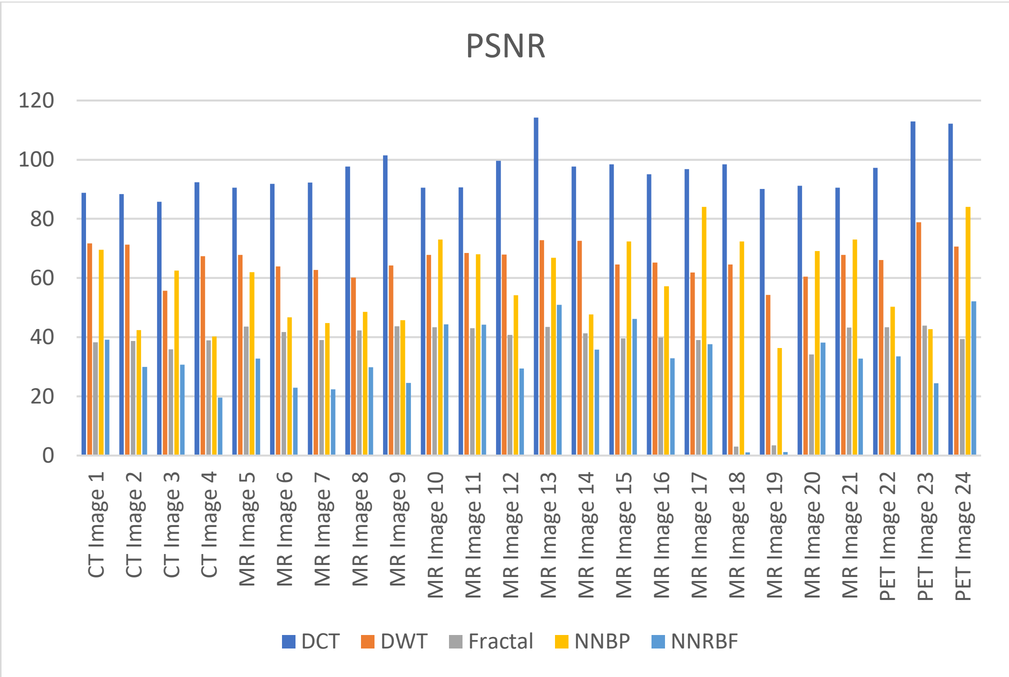

Fig.5 Peak Signal to Noise Ratio of Images in Different Techniques

- DCT consistently provides superior PSNR across all image types, demonstrating minimal quality degradation.
- Neural techniques perform well but are more sensitive to image modality. NNRBF slightly lags in certain MR images.

Memory Usage:

Images	DCT	DWT	Fractal	NNBP	NNRBF
CT Image 1	21.40	28.70	26.80	28.70	28.60
CT Image 2	23.20	29.80	28.40	30.10	37.20
CT Image 3	31.60	44.80	43.20	44.90	43.60
CT Image 4	21.10	26.90	25.00	27.40	24.50
MR Image 5	18.00	24.50	21.90	24.50	26.70
MR Image 6	18.90	28.90	26.40	29.20	25.70
MR Image 7	22.60	28.60	23.00	29.50	25.40
MR Image 8	19.20	28.40	25.10	29.30	27.40
MR Image 9	15.70	23.30	20.50	24.50	21.90
MR Image 10	20.50	24.80	23.70	24.80	25.90
MR Image 11	19.60	24.10	23.00	24.10	25.80
MR Image 12	17.50	23.70	22.30	23.90	26.30
MR Image 13	12.40	17.10	17.80	17.10	17.30
MR Image 14	14.40	18.00	15.90	18.10	71.50
MR Image 15	17.20	27.00	20.50	27.00	27.40
MR Image 16	18.20	27.20	22.70	27.30	27.30
MR Image 17	23.40	31.90	29.90	31.90	33.30
MR Image 18	17.20	27.00	20.50	27.00	27.40
MR Image 19	26.80	45.00	28.20	47.10	41.40
MR Image 20	27.40	39.10	32.70	39.20	40.60
MR Image 21	20.50	24.80	20.60	24.80	22.90
PET Image 22	14.80	21.90	19.20	22.40	22.80
PET Image 23	9.97	13.40	14.30	19.40	18.70
PET Image 24	13.20	19.40	18.80	19.50	19.60

Table: 3 Comparison of Memory Usage of CT, MR, PET images using different Techniques

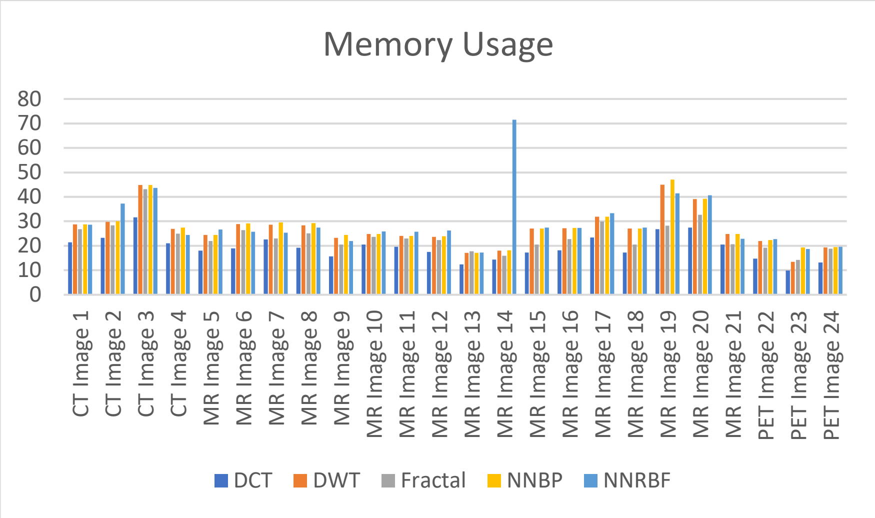

Fig.6 Memory Usage of Images in Different Techniques

- DCT demonstrates lower memory usage, making it suitable for storage-constrained environments.
- Fractal Compression, while achieving high compression, has moderate memory demands. Neural networks show variable memory requirements, with NNRBF occasionally consuming more.

Execution Time:

Images	DCT	DWT	Fractal	NNBP	NNRBF
CT Image 1	0.7572	1.0867	11.7500	850.4214	17.4231
CT Image 2	0.7645	1.0818	11.7969	278.7227	16.4425
CT Image 3	0.7522	2.3126	16.3281	542.2186	18.6835
CT Image 4	0.8272	1.6483	10.8594	935.6339	18.5866
MR Image 5	0.9514	1.1104	12.0000	387.0713	18.5779
MR Image 6	0.8773	1.1089	14.8125	667.3835	18.2230
MR Image 7	0.7620	1.2349	10.5625	658.0410	18.2627
MR Image 8	1.5385	1.0894	12.3906	1164.2615	18.7018
MR Image 9	0.7825	1.0646	10.9688	836.9937	18.3615
MR Image 10	1.1055	1.1229	12.1094	751.2015	18.6340
MR Image 11	0.8540	1.1197	11.9219	294.9351	18.7667
MR Image 12	0.7832	1.1865	9.8438	415.8369	17.8159
MR Image 13	0.7919	1.0898	9.0625	497.0650	17.9883
MR Image 14	1.4770	1.0197	9.0938	313.2422	17.2854
MR Image 15	0.7612	1.0705	9.4844	285.6100	17.7939

MR Image 16	0.8803	1.0782	10.0625	610.1797	18.7660
MR Image 17	1.0694	1.1614	10.7031	843.5427	26.7360
MR Image 18	0.9104	1.0800	9.5000	285.4747	27.1599
MR Image 19	1.0884	1.0605	10.1094	654.8289	17.9907
MR Image 20	1.2724	1.2132	10.5156	504.8591	18.1835
MR Image 21	0.7581	1.0645	11.5313	744.2455	18.5056
PET Image 22	0.8768	1.1157	11.2656	652.3676	18.8691
PET Image 23	0.7791	1.0681	8.5625	452.7775	16.5292
PET Image 24	1.0188	1.1340	8.8125	378.8078	16.7909

Table: 4 Comparison of Execution Time of CT, MR, PET images using different Techniques

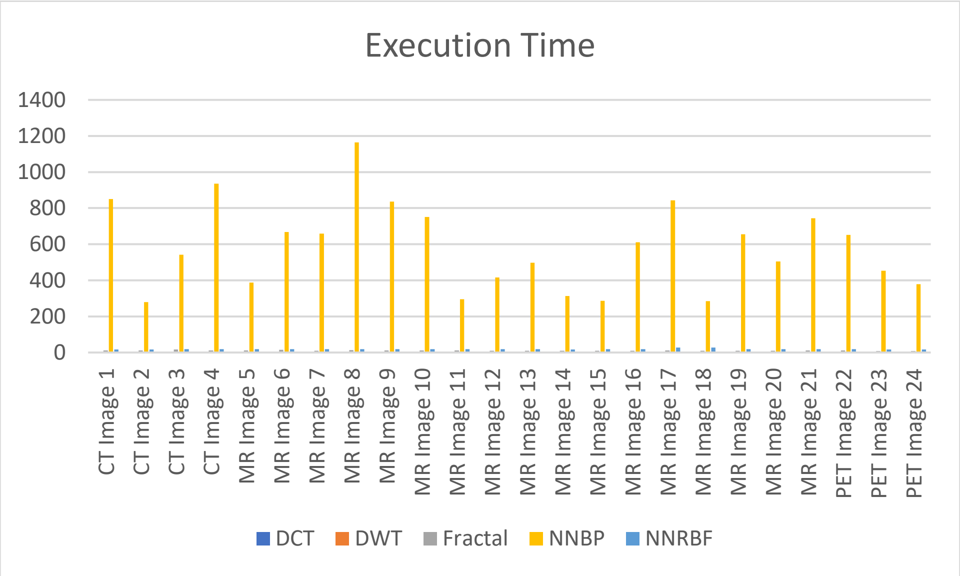

Fig.7 Execution Times of Images in Different Techniques

- DCT and DWT outperform other methods in speed, making them ideal for real-time applications.
- Fractal Compression and neural methods require significantly more time, highlighting the trade-off between computational complexity and performance.

Overall Observations:

1. DCT is optimal for scenarios prioritizing speed and PSNR.
2. Fractal Compression is ideal for high compression demands but is computationally expensive.
3. Neural methods show promise for adaptive processing but require optimization for real-time use.

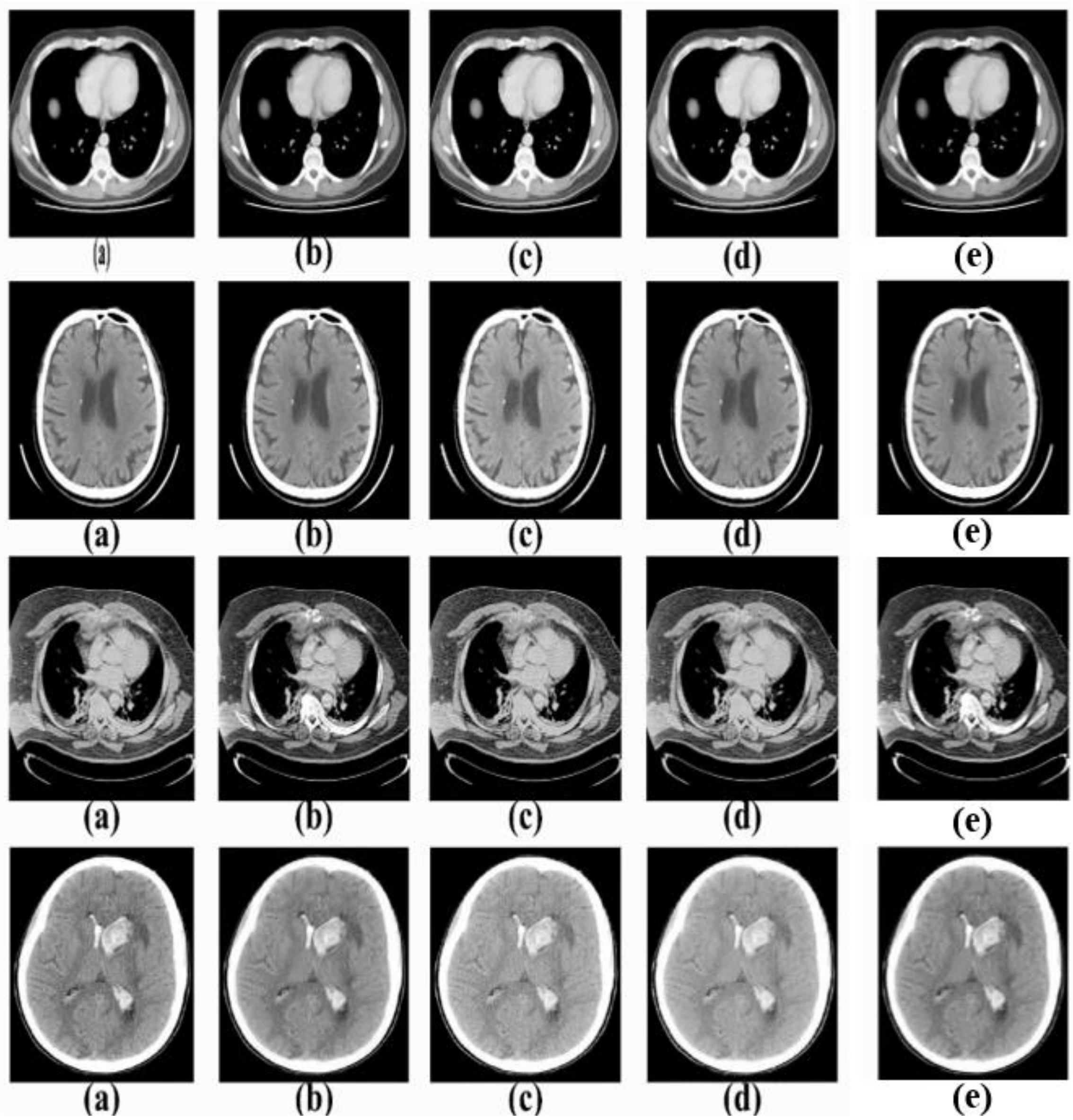

Fig.8 Results obtained for various medical images (a) Input Image (b) DCT (c) DWT (d)Fractal (e) Neural Network Techniques

The findings reveal that no single method dominates across all metrics, necessitating application-specific selections. Neural networks, although computationally intensive, exhibit potential for enhancing image quality with future optimization. Balancing these trade-offs is crucial for integrating these methods into clinical workflows.

Conclusion:

Problem Statement Addressed/Motivation:

- This study addresses the challenges of efficient storage, transmission, and quality retention in medical image processing, critical for modern diagnostic workflows. It highlights the need for techniques that balance compression efficiency, image quality, and computational speed.

Methods Used:

- Five techniques—Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT), Fractal Compression, Neural Network Back Propagation (NNBP), and Neural Network Radial Basis Function (NNRBF)—were implemented and evaluated on CT, MR, and PET images using MATLAB. Performance was assessed based on Compression Ratio, Peak Signal-to-Noise Ratio (PSNR), Memory Usage, and Execution Time.

Key Findings:

- DCT provides high-quality image retention with low computational demands, making it suitable for real-time applications.
- DWT captures intricate details through multi-resolution analysis, balancing compression and quality.
- Fractal Compression achieves the highest compression ratios but is computationally expensive, suitable for offline archival purposes.
- Neural methods (NNBP and NNRBF) show robust reconstruction capabilities and adaptability, with the potential for optimization to improve performance in real-time applications.
- No single method outperformed across all metrics, underscoring the need for application-specific technique selection.
- A hybrid approach combining any of techniques could potentially address the limitations of individual methods, satisfying the requirements of both real-time efficiency and quality retention.

Limitations and Future Work:

- Fractal Compression and neural methods require significant computational resources, limiting their suitability for real-time processing.
- Future work should focus on developing hybrid techniques that integrate the strengths of traditional methods (e.g., DCT/DWT) and neural networks, optimizing them for real-time performance while maintaining image quality.
- Future work should focus on optimizing neural techniques to reduce computational overhead while enhancing quality and efficiency.
- Expanding the dataset to include more diverse imaging modalities and developing hybrid approaches combining traditional and neural methods can further improve diagnostic accuracy and efficiency.

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