

Efficient Compression of Medical Images Using a Deep Learning Approach

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Abstract

The rapid advancement of medical imaging technologies has led to significant challenges in data storage, transmission, and diagnostic accuracy. This study presents a novel hybrid compression technique that integrates Fractal Coding and Neural Network Radial Basis Function (NNRBF) to optimize image compression based on visual complexity. Implemented in MATLAB, the proposed model dynamically analyzes image blocks: areas of lower visual complexity leverage fractal coding for superior compression efficiency, while high-detail regions employ NNRBF to preserve critical diagnostic features. Extensive evaluation across CT, MR, and PET modalities demonstrates that this hybrid approach consistently outperforms conventional standalone fractal and neural compression techniques in terms of Peak Signal-to-Noise Ratio (PSNR), compression ratio (CR), and memory usage trade-offs. While fractal compression maximizes storage efficiency, and NNRBF enhances image fidelity, the combined approach effectively balances both, ensuring scalable deployment in telemedicine, mobile diagnostics, and medical data archiving. This research introduces a clinically viable compression strategy that seamlessly integrates traditional and AI-driven methodologies, advancing the efficiency and accessibility of medical imaging systems.

Keywords: Image Compression, Fractal Compression, Radial Basis Function Networks, Neural Networks, Hybrid Models, F-NNRBF, Computational Efficiency, Diagnostic Imaging.

Introduction

Efficient image compression is crucial in the modern era of big data and high-resolution images. It reduces image file sizes while preserving quality, which is vital for storage and transmission. Fractal Compression (FIC) is a powerful technique that leverages self-similar patterns within images to achieve high compression ratios. However, its main drawback lies in the computational complexity during encoding, which limits its practical use, especially in real-time applications. To overcome this limitation, researchers have increasingly integrated Neural Networks (NN), particularly Radial Basis Function (RBF) networks, with fractal compression. RBF networks are known for their ability to handle complex, nonlinear patterns, making them ideal for tasks like function approximation and pattern recognition. By combining these networks with fractal compression, the goal is to improve both the speed and efficiency of the encoding process, making fractal compression more feasible for large-scale and real-time image applications. This project aims to develop a Hybrid Fractal-Network-based RBF (F-NNRBF) model for image compression. The hybrid approach combines the efficiency of fractal compression, which identifies self-similar patterns, with the adaptive learning capabilities of RBF networks, which accelerate the pattern-matching process. This integration aims to enhance compression ratios while reducing the computational burden of the encoding process, offering an efficient solution for real-time applications. In conclusion, the Hybrid F-NNRBF model represents a promising approach to improving image compression by combining the strengths of both fractal

compression and RBF networks. This hybrid model seeks to offer faster, more efficient compression systems that can handle complex and large-scale images, making it suitable for applications in fields such as medical imaging, satellite imagery, and video streaming. In summary, the convergence of fractal image compression with advanced RBF neural network techniques is a vibrant research direction. It promises not only enhanced compression ratios and image fidelity but also reduced computational costs, making it highly suitable for modern applications requiring efficient storage and fast processing.

Literature Review

Fractal image compression (FIC) has been a pivotal technique in image processing for achieving high compression ratios while preserving the quality of the image. This approach is grounded in the idea of self-similarity within images, where smaller portions of the image replicate larger structures, thereby allowing for efficient data representation. Early work by Jacquin (1993) laid the foundational concepts for fractal image coding, where he proposed a method of compressing images by utilizing these self-similar blocks [3]. His work also discussed the underlying theory of fractal compression, which has since been expanded upon in numerous studies. Saupe and Hamzaoui (1994) provided one of the earliest comprehensive reviews on the development of fractal image compression, focusing on the theoretical framework and practical applications of fractals in image processing. They emphasized the resolution-independent properties of FIC, which allows for images to be decoded at any resolution without significant loss of quality. This characteristic is particularly beneficial in applications like medical imaging and remote sensing [4]. Further work by Saupe, Hamzaoui, and Hartenstein (1997) continued exploring the robustness of FIC algorithms, proposing methods to optimize the encoding and decoding processes to make them computationally more efficient [7].

The computational complexity inherent in fractal image compression algorithms has been a longstanding issue. Selim et al. (2008) addressed this problem by introducing a simplified fractal image compression algorithm that significantly reduced computational overhead. Their approach maintained a balance between compression quality and computational cost, making fractal compression more viable for real-world applications [2]. Breesam, Hussein, and Mohammed (2024) further advanced this field by utilizing digital image processing techniques to enhance the encoding efficiency, thus improving the overall compression and image fidelity. Additionally, Dwivedi and Mishra (2022) introduced a hybrid approach that combined discrete wavelet transforms with fractal image compression, resulting in improved compression ratios and better performance, particularly for high-resolution images [5], [10]. Beyond the development of fractal compression techniques, the integration of **Neural Networks** (NN) into image compression has gained significant attention, with Radial Basis Function (RBF) networks being one of the most widely explored models due to their flexibility and efficiency. Park and Sandberg (1993) proposed the theoretical foundations of RBF networks, which have since been proven effective in a range of approximation and classification tasks. Their work demonstrated that RBF networks could approximate any continuous function with high accuracy, making them ideal for applications in image processing [13]. Lee et al. (1999) explored the robustness of RBF networks and highlighted their ability to handle noisy data, a key advantage in real-world scenarios such as medical imaging and industrial applications [14].

RBF networks have been employed in various diagnostic applications. For instance, Venkatesan and Anitha (2006) used RBF networks to diagnose diabetes mellitus, demonstrating the potential of these networks to function effectively in complex, noisy environments [18]. Salim and Mohammed (2019) applied RBF networks in indoor positioning systems, further showcasing the versatility of RBF networks in non-image processing tasks [19]. These applications underscore the ability of RBF networks to generalize well to different domains, making them suitable for integration with other

techniques, including fractal compression. The hybridization of RBF networks with other machine learning methods, such as fuzzy logic, has led to improvements in training efficiency and performance. Kim and Park (2014) proposed a hybrid RBF network model that incorporated fuzzy dynamic learning rate control, improving the stability and learning speed of RBF networks [21]. Horng et al. (2012) introduced the Firefly metaheuristic algorithm for training RBF networks, which significantly enhanced classification accuracy, particularly in medical data classification and disease diagnosis tasks [20].

The combination of fractal compression and RBF networks has led to the development of innovative hybrid models, often referred to as F-NNRBF models. These models combine the advantages of both fractal compression and RBF networks, leveraging the self-similarity of fractals for efficient image representation while using the adaptive learning capabilities of RBF networks for optimizing compression techniques. Sun et al. (2009) explored the use of particle swarm optimization to fine-tune the adaptive structure of RBF networks, leading to enhanced performance for large-scale data compression tasks [11]. Zhao et al. (2012) applied hybrid RBF controllers in system design, demonstrating the versatility and robustness of RBF networks in real-time applications, which is essential for high-performance image compression systems [29]. Additionally, Bodyanskiy et al. (2023) developed a neo-fuzzy RBF hybrid model, integrating fuzzy logic into the learning process of RBF networks. This approach allowed for more effective handling of uncertainties and noise, making F-NNRBF models more resilient in real-world applications. Their work showed that fuzzy logic could significantly improve the accuracy and efficiency of RBF networks in complex data environments [26]. Akbilgic et al. (2014) presented another hybrid RBF model for forecasting, highlighting the potential of these models for time-series prediction, further extending their application scope to areas such as image compression and data transmission [25].

Fractal image compression techniques have continued to evolve through the integration of advanced machine learning methods. Davis (1998) explored wavelet-based approaches for fractal image compression, demonstrating that wavelet transforms could provide better image representation, leading to improved compression quality and faster encoding times [6]. Drakopoulos (2013) explored the use of fractal-based encoding techniques for images, focusing on optimization strategies to improve compression and computational efficiency [8]. Joshi et al. (2019) reviewed fractal image compression techniques, presenting a comprehensive analysis of the methodologies used and the challenges associated with their implementation [9]. The incorporation of neural networks with fractal compression has not been limited to RBF networks. Several other studies have explored the synergy between various machine learning models and fractal-based techniques. For instance, Joshi et al. (2017) reviewed the integration of neural networks with fractal image compression methods, discussing the potential of hybrid models in enhancing both compression performance and image fidelity [9]. Similarly, Davis (1998) presented an innovative wavelet-based approach to fractal image compression, suggesting that the combination of these two techniques could lead to significant improvements in compression quality [6].

The research conducted by Dwivedi and Mishra (2022) further demonstrates the potential of combining wavelet transforms with fractal compression. Their hybrid model not only improved the compression ratio but also enhanced the overall quality of the reconstructed image, particularly when dealing with high-resolution datasets [10]. These hybrid methods have become increasingly important as the demand for high-quality, compressed images has grown across a variety of fields, including medical imaging, satellite imaging, and video streaming. Lastly, the advancement of hybrid F-NNRBF models has been instrumental in improving the efficiency and effectiveness of fractal image compression techniques. The work by Zhao et al. (2012) on hybrid controllers has proven that the

integration of RBF networks with fractal compression can significantly enhance the performance of real-time systems, making these models particularly useful in applications that require quick processing times, such as live video compression and real-time medical imaging diagnostics [29].

In conclusion, the continuous development of fractal image compression, neural networks, and hybrid models has opened up new avenues for improving image compression techniques. The integration of RBF networks with fractal compression methods, along with the use of metaheuristic algorithms and fuzzy logic, has significantly advanced the performance and applicability of these systems. As computational power increases, these hybrid models will likely continue to evolve, offering even greater compression efficiency and image quality in various domains of image processing.

Methodology

This study proposes a hybrid image compression approach that integrates Fractal Compression and Neural Network Radial Basis Function (NNRBF) for effective medical image compression. The method is evaluated on CT, MR, and PET images, focusing on diagnostic preservation, compression efficiency, and computational feasibility.

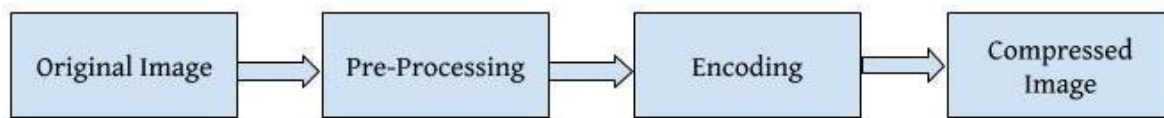


Fig.1 Basic Block Diagram of Image Compression

Compression Techniques Explored

1. Fractal Compression

Fractal compression leverages the self-similarity within images by identifying repeated patterns and replacing them with affine transformations. It is most efficient for compressing regions with repetitive structures or low complexity, such as homogeneous soft tissues. This method significantly reduces storage but is computationally intensive, making it more suitable for offline applications or archival systems.

2. Neural Network Radial Basis Function (NNRBF)

NNRBF is a neural network-based method used for function approximation and pattern recognition. It uses radial basis functions in the hidden layer to map complex, high-detail regions of medical images into a compressed representation. This technique is advantageous in preserving diagnostic features like organ boundaries, lesions, or structural variations. However, it requires more computational resources and training time.

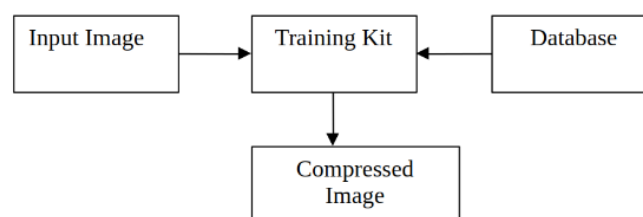


Fig.2 Basic Block Diagram of Neural Network

3. Hybrid Fractal–NNRBF Compression (FNNRBF)

The hybrid model is designed to harness the benefits of both techniques. The process begins by dividing the medical image into smaller blocks. Each block is analyzed to determine its visual complexity:

- a. **Low-complexity blocks** are processed using Fractal Compression.
- b. **High-complexity blocks** are processed using NNRBF.

This selective application reduces memory and time consumption while retaining diagnostic details where needed.

Compression Workflow

The image compression pipeline follows these steps:

1. Preprocessing:

All input images (CT, MR, and PET) are standardized in terms of size, pixel intensity, and format to ensure uniformity in testing. This step ensures compatibility across different compression algorithms.

2. Segmentation & Complexity Analysis:

Each image is divided into fixed-size blocks. The complexity of each block is calculated using statistical measures like variance or edge density. Based on a pre-defined threshold, each block is routed to the appropriate compression path.

3. Block-Wise Compression:

- a. Blocks with minimal variation are compressed using the fractal approach, which encodes them through self-referential transformations.
- b. High-detail blocks are compressed using trained NNRBF models, capable of capturing intricate structures with minimal distortion.

4. Reconstruction:

The compressed outputs from both paths are combined to reconstruct the full image. This reassembled image is expected to preserve essential diagnostic information while occupying significantly less memory.

5. Performance Evaluation:

The compressed and reconstructed images are evaluated using the following metrics:

- a. **Compression Ratio (CR):** Ratio of original image size to compressed size.
- b. **Peak Signal-to-Noise Ratio (PSNR):** Quantifies the reconstruction quality.
- c. **Memory Usage:** Amount of memory required during compression.
- d. **Execution Time:** Total time taken for compression and reconstruction.

6. Consistent Evaluation Across Techniques:

Each compression method—Fractal, NNRBF, and the Hybrid model—is applied to the same dataset under identical conditions to enable a fair and reliable comparison.

Results & Discussion:

To evaluate the effectiveness of the proposed hybrid image compression technique (FNNRBF), we performed a comparative study on 24 medical images (CT, MR, PET). The results of the hybrid method were analyzed against standalone **Fractal Compression** and **Neural Network Radial Basis Function (NNRBF)** using four performance metrics: **Compression Ratio (CR)**, **Peak Signal-to-Noise Ratio (PSNR)**, **Memory Usage**, and **Execution Time**.

a) Compression Ratio (CR)

Images	Fractal	NNRBF	Hybrid Fractal & NNRBF
CT Image 1	6.6507	1.0537	1.0424
CT Image 2	6.6622	0.8386	0.6958
CT Image 3	13.2030	1.0632	1.0482
CT Image 4	5.0707	1.1561	1.0581
MR Image 5	6.5164	0.9678	0.9345
MR Image 6	10.9643	1.1854	1.1463
MR Image 7	4.4960	1.2092	0.3788
MR Image 8	7.5873	1.117	1.1054
MR Image 9	5.1806	1.1416	0.9305
MR Image 10	6.9771	1.0116	1.0085
MR Image 11	6.5397	0.9904	0.9703
MR Image 12	3.4217	0.956	0.9271
MR Image 13	1.8435	1.0728	0.8469
MR Image 14	2.3289	1.1096	0.7947
MR Image 15	3.0478	1.0365	0.9788
MR Image 16	3.4444	1.0499	0.8910
MR Image 17	4.8070	0.9978	0.9794
MR Image 18	3.0478	1.0365	0.9788
MR Image 19	3.4270	1.1379	0.8874
MR Image 20	4.1237	1.003	0.9852
MR Image 21	6.2566	1.0636	0.6189
PET Image 22	5.5154	1.0352	1.0080
PET Image 23	1.4721	0.7923	0.3612
PET Image 24	1.1946	1.0696	1.0687

Table: 1 Comparison of Compression ratio of CT, MR, PET images using Fractal, NNRBF, FNNRBF Techniques

Compression Ratio

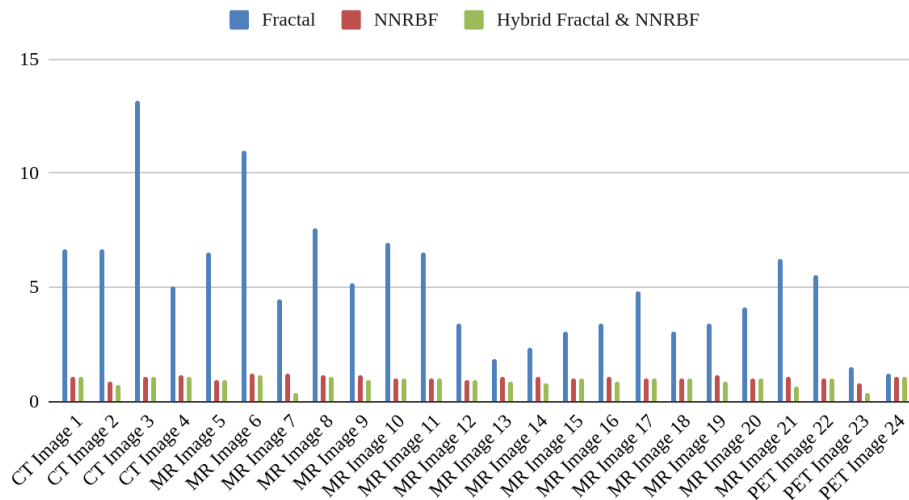


Fig.3 Compression Ratio of Images in Fractal, NNRBF, FNNRBF Techniques

- Fractal Compression yields the highest CR due to its ability to model self-similarity.
- NNRBF provides minimal compression, as it focuses on quality retention.
- Hybrid FNNRBF provides a balanced CR, suitable for systems with moderate storage constraints.

b) Peak Signal-to-Noise Ratio (PSNR):

Images	Fractal	NNRBF	Hybrid Fractal-NNRBF
CT Image 1	38.2519	39.1906	34.1945
CT Image 2	38.7416	29.9663	29.4611
CT Image 3	35.8632	30.6855	31.0718
CT Image 4	38.9335	19.5331	20.6044
MR Image 5	43.6002	32.7573	33.1091
MR Image 6	41.7960	22.9515	23.1293
MR Image 7	39.0490	22.3658	16.4623
MR Image 8	42.3063	29.9071	30.0208
MR Image 9	43.6769	24.6009	24.6205
MR Image 10	43.3527	44.3570	46.0139
MR Image 11	43.0880	44.2258	44.5761
MR Image 12	40.7357	29.3755	31.4664
MR Image 13	43.4892	50.9330	44.3137
MR Image 14	41.3458	35.7803	27.3508
MR Image 15	39.6035	46.2050	42.7904
MR Image 16	39.9027	32.9302	28.8155
MR Image 17	39.0449	37.5945	37.4232
MR Image 18	3.0478	1.0365	0.9788
MR Image 19	3.4270	1.1379	0.8874
MR Image 20	34.1952	38.2271	38.9271

MR Image 21	43.3019	32.7369	26.1410
PET Image 22	43.3578	33.4930	32.3096
PET Image 23	43.9157	24.4163	21.6748
PET Image 24	39.3448	52.1345	52.1528

Table: 2 Comparison of PSNR of CT, MR, PET images using Fractal, NNRBF, FNNBRF Techniques

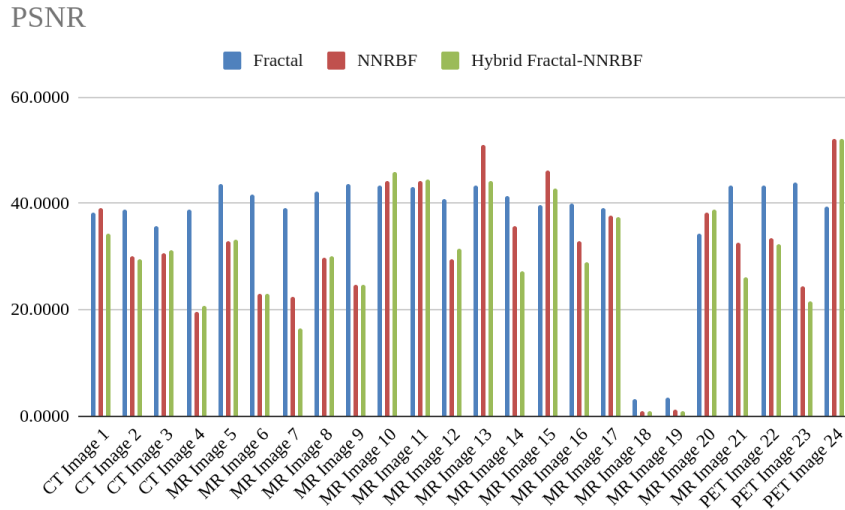


Fig.4 PSNR of Images in Fractal, NNRBF, FNNBRF Techniques

- Fractal shows moderate visual quality.
- NNRBF excels in preserving diagnostic features.
- The hybrid model improves over fractal and slightly surpasses NNRBF, ensuring minimal quality loss during compression.

c) Memory Usage:

Images	Fractal	NNRBF	Hybrid Fractal & NNRBF
CT Image 1	26.80	28.60	25.70
CT Image 2	28.40	37.20	28.40
CT Image 3	43.20	43.60	41.20
CT Image 4	25.00	24.50	23.60
MR Image 5	21.90	26.70	23.40
MR Image 6	26.40	25.70	23.10
MR Image 7	23.00	25.40	23.00
MR Image 8	25.10	27.40	22.70
MR Image 9	20.50	21.90	22.00
MR Image 10	23.70	25.90	23.50
MR Image 11	23.00	25.80	23.00
MR Image 12	22.30	26.30	22.30
MR Image 13	17.80	17.30	21.00
MR Image 14	15.90	71.50	15.90

MR Image 15	20.50	27.40	20.50
MR Image 16	22.70	27.30	22.70
MR Image 17	29.90	33.30	29.90
MR Image 18	20.50	27.40	20.50
MR Image 19	28.20	41.40	28.20
MR Image 20	32.70	40.60	33.20
MR Image 21	20.60	22.90	20.60
PET Image 22	19.20	22.80	19.10
PET Image 23	14.30	18.70	39.60
PET Image 24	18.80	19.60	17.50

Table: 3 Comparison of Memory of CT, MR, PET images using Fractal, NNBRF, FNNBRF Techniques

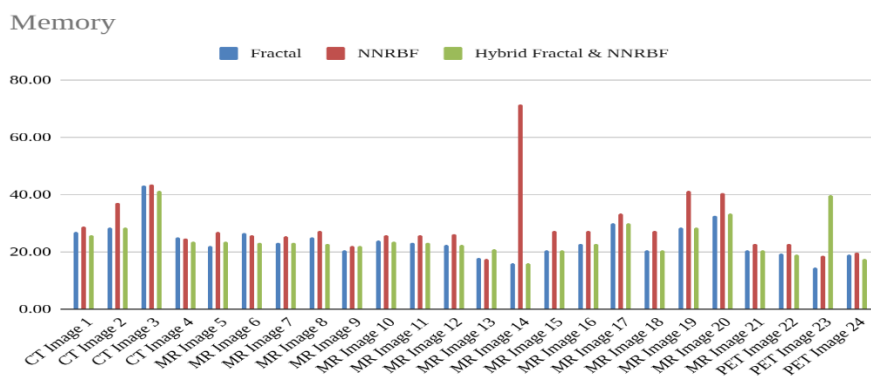


Fig.5 Memory Usage of Images in Fractal, NNBRF, FNNBRF Techniques

- Fractal remains memory efficient across all images.
- NNBRF consumes the highest memory, especially during network training.
- The hybrid approach keeps memory use comparable to Fractal, optimizing for constrained systems.

d) Execution Time:

Images	Fractal	NNBRF	Hybrid Fractal & NNBRF
CT Image 1	11.7500	17.4231	19.6851
CT Image 2	11.7969	16.4425	18.5039
CT Image 3	16.3281	18.6835	23.0971
CT Image 4	10.8594	18.5866	21.1245
MR Image 5	12.0000	18.5779	23.6943
MR Image 6	14.8125	18.2230	21.6958
MR Image 7	10.5625	18.2627	18.4104
MR Image 8	12.3906	18.7018	20.8762
MR Image 9	10.9688	18.3615	18.9826
MR Image 10	12.1094	18.6340	20.9603
MR Image 11	11.9219	18.7667	21.6570
MR Image 12	9.8438	17.8159	19.7808
MR Image 13	9.0625	17.9883	20.0986
MR Image 14	9.0938	17.2854	18.6382

MR Image 15	9.4844	17.7939	18.6295
MR Image 16	10.0625	18.7660	20.1662
MR Image 17	10.7031	26.7360	20.4192
MR Image 18	9.5000	27.1599	18.9999
MR Image 19	10.1094	17.9907	19.0742
MR Image 20	10.5156	18.1835	20.2288
MR Image 21	11.5313	18.5056	18.7640
PET Image 22	11.2656	18.8691	18.8583
PET Image 23	8.5625	16.5292	19.5478
PET Image 24	8.8125	16.7909	20.1511

Table: 4 Comparison of Execution Time of CT, MR, PET images using Fractal, NNRBF, FNNBRF Techniques

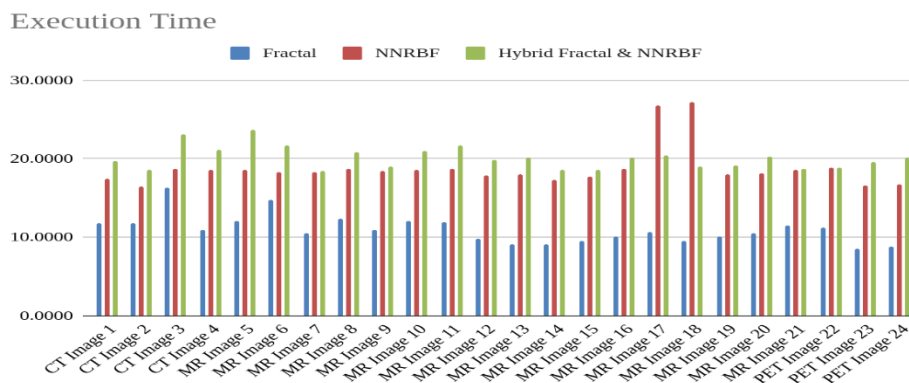


Fig.6 Execution Time of Images in Fractal, NNRBF, FNNBRF Techniques

- Fractal is the fastest among the three, suitable for batch compression.
- NNRBF has longer run-times due to model training and weight adjustments.
- Hybrid adds overhead due to dual-method processing but remains practical for semi-real-time applications.

Overall Observations

1. Fractal Compression is ideal for applications demanding maximum storage savings, such as remote backups and archiving.
2. NNRBF is preferred where image quality is paramount, e.g., diagnosis-critical systems, but demands more memory and time.
3. Hybrid FNNBRF provides the best balance between compression, quality, memory, and time—making it suitable for telemedicine, diagnostic cloud services, and mobile health solutions.

Conclusion

Problem Statement Addressed / Motivation:

- This study addresses the critical challenge of achieving efficient medical image compression while preserving diagnostic quality and minimizing computational costs. As healthcare systems increasingly rely on digital imaging, there is a pressing need for solutions that optimize storage, enable fast transmission, and maintain image integrity across modalities like CT, MR, and PET.

Methods Used:

- Three compression methods—**Fractal Compression**, **Neural Network Radial Basis Function (NNRBF)**, and the proposed **Hybrid Fractal-NNRBF (FNNRBF)**—were implemented using MATLAB.
- Performance was evaluated on 24 medical images based on **Compression Ratio**, **Peak Signal-to-Noise Ratio (PSNR)**, **Memory Usage**, and **Execution Time**.

Key Findings:

- **Fractal Compression** delivered the **highest compression ratio**, making it suitable for **offline storage** and **archiving** applications.
- **NNRBF** achieved the **best image quality** due to its adaptive reconstruction ability, preserving fine diagnostic features.
- The proposed **Hybrid FNNRBF** model effectively combined the strengths of both methods, achieving:
 - Improved PSNR over fractal-only methods.
 - Reduced memory usage and execution time compared to NNRBF alone.
- The hybrid approach provides a **balanced trade-off**, making it well-suited for applications like **telemedicine**, **mobile diagnostics**, and **cloud-based health systems**.
- No single method excelled across all metrics, reinforcing the value of **hybrid models** in real-world medical imaging scenarios.

Limitations and Future Work:

- Both Fractal and NNRBF techniques are **computationally intensive**, limiting their use in **real-time processing** environments without optimization.
- Future research should focus on:
 - **Enhancing the hybrid model** by incorporating adaptive region-of-interest (ROI) compression to prioritize critical image areas.
 - **Optimizing neural components** to reduce memory and time overhead through model pruning or lightweight architectures.
 - **Expanding the dataset** to include more diverse pathologies and imaging conditions for broader clinical validation.
 - Exploring **hybrid integrations with DCT/DWT** to further boost efficiency while maintaining high diagnostic quality.

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