# Neural Network-Based Medical Image Compression: A Comparative Analysis of NNRBF and NNBP Techniques

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**Abstract:**

Efficient medical image compression is crucial for enabling scalable storage, rapid transmission, and real-time processing in healthcare environments. This study presents a comparative analysis of two neural network-based techniques—Neural Network Radial Basis Function (NNRBF) and Neural Network Backpropagation (NNBP) applied to CT, MR, and PET images. Performance was measured through Compression Ratio (CR), Peak Signal-to-Noise Ratio (PSNR), memory consumption, and execution time. Results indicate that NNRBF offers faster compression and lower memory requirements, while NNBP excels in compression ratio and image quality preservation. These insights provide guidance for choosing optimal methods based on specific medical imaging applications. The findings support further exploration of hybrid and adaptive frameworks for enhancing digital health infrastructure.

**Keywords:** Medical image compression, Neural networks, NNBP, NNRBF, Compression Ratio, PSNR, Memory Usage, Execution time, Good Health and Well-Being

**Introduction:**

Medical imaging technologies, Computed Tomography (CT), Magnetic Resonance Imaging (MR), and Positron Emission Tomography (PET), have transformed clinical practice by generating high-resolution visual data for detailed anatomical analysis. Conventional algorithms such as JPEG and JPEG2000 may not suffice for medical images, as they risk degrading important details. As a result, neural network-based compression approaches have gained prominence for their ability to learn complex patterns and adapt to image-specific requirements. This research explores supervised learning algorithms specifically, error backpropagation learning for multi-layer feedforward networks for medical image compression, alongside unsupervised methods. By systematically analyzing NNRBF and NNBP approaches across CT, MR, and PET images, the study aims to determine the optimal strategy for efficient, high-quality medical image compression.

**Literature Survey:**

The rapid growth of medical imaging data from CT, MRI, and PET scans has driven research into efficient compression techniques that preserve diagnostic quality while addressing storage and transmission challenges. Traditional compression methods laid the groundwork for handling medical images. Chen et al. [3] explore classical techniques alongside region-of-interest (ROI) methods, which prioritize critical areas to maintain diagnostic fidelity, ideal for telemedicine where bandwidth is limited. Rojas-Hernández [5] proposes a lossless difference transform method, ensuring exact pixel retention but facing scalability issues with large datasets. Singh et al. [8] improve the SPIHT algorithm with block thresholding, enhancing compression ratios for MRI and CT images by adaptively managing wavelet coefficients, though processing speed remains a bottleneck. Hybrid approaches integrate transforms with adaptive techniques for better efficiency. Vikraman [2] combines DCT with learning-based thresholding, reducing redundancy while optimizing for low-bandwidth settings, showing strong results for storage-constrained environments. Monika and Suresh [4] develop a method with predictive coding to minimize artifacts, improving transmission efficiency. Gupta et al. [6] focus on telemedicine, blending transforms to balance speed and quality, validated on real-world datasets. Shi et al. [12] pair wavelet transforms with neural networks, leveraging multi-resolution analysis for higher PSNR in medical images. Roy and Saha [13] introduce a fast hybrid method using fractal and predictive coding, achieving quick encoding with minimal quality loss. Imane et al. [14] use quincunx wavelet and geometric active contours to compress complex regions, though parameter tuning is critical. Lim et al. [9] apply PCA for ROI compression, reducing dimensionality effectively, while Reddy and Rao [10] combine PCA with SPIHT for improved compression across modalities. Neural network-based methods have transformed medical image compression by learning complex patterns. Balasubramani [1] compares traditional and neural approaches, highlighting neural networks' flexibility in preserving quality. Sharma and Gandhi [7] utilize CNNs for lossy compression, learning hierarchical features to minimize perceptual degradation. Zhang [11] surveys deep learning methods, noting the promise of autoencoders but highlighting real-time challenges. For radial basis function networks (NNRBF), Zhang [15]

**Methodology:**

**NNRBF (Radial Basis Function Network):** An unsupervised network designed with a single hidden layer, where neurons use Gaussian radial basis functions as activation. The image is divided into blocks, with each block's feature vector fed into the network. Training involved computing centers and widths of the basis functions, followed by weight optimization using k-means clustering for center initialization. The model output provides reduced feature sets, which are quantized and encoded for final compression.

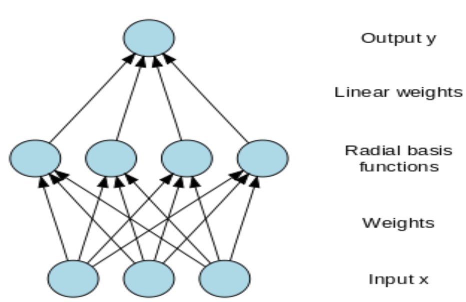


**Fig.3 General Structure of NNRBF Algorithm**

**NNBP (Backpropagation Network):** A supervised, feed-forward neural network with one input, one hidden, and one output layer. The input image is segmented into blocks, and block vectors are fed into the network. Training utilizes the standard gradient descent backpropagation algorithm, optimizing weights to minimize reconstruction error. Network hyperparameters, such as number of hidden neurons and learning rates, were tuned empirically to balance convergence speed and image fidelity. Both techniques operated in block-wise compression mode to better capture local anatomical details and heterogeneity, critical in medical images. The database (Figure 2) provided reference training sets and parameter initialization, while the training kit executed network optimization and compression encoding.

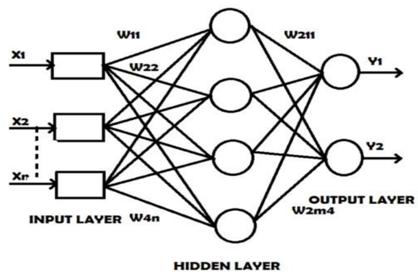


**Fig.4 General Structure of NNBP Algorithm**

**Performance Metrics**

Compression quality and resource efficiency were evaluated using four main parameters:

**Compression Ratio (CR):** Ratio of original image size to compressed output, indicating data reduction efficiency.

$$\textbf{CR} = \left(\frac{\text{Uncompressed file size}}{\text{Compressed file size}}\right)$$

**Peak Signal-to-Noise Ratio (PSNR):** Measures the ratio between the maximum possible image signal and the distortion introduced by compression; higher values represent superior fidelity.

**Memory Usage:** Monitored RAM consumption during training, compression, and decompression phases to simulate real-world operational constraints.

**Execution Time:** Recorded the elapsed time for network training (when applicable), encoding/compression, and final decoding. Measurements were taken on a standardized computing environment representative of clinical deployment hardware.

**Results & Discussion:**

A dataset of 24 medical images, including CT, MR, and PET modalities. The performance of NNRBF and NNBP techniques was rigorously compared using widely-accepted evaluation metrics—Compression Ratio (CR), Peak Signal-to-Noise Ratio (PSNR), memory usage, and execution time—providing a comprehensive benchmark against traditional and previously reported methods.

**Compression Ratio:**

| Images | NNRBF | NNBP |
|---|---|---|
| CT Image 1 | 1.0537 | 1.0495 |
| CT Image 2 | 0.8386 | 1.0356 |
| CT Image 3 | 1.0632 | 1.0330 |
| CT Image 4 | 1.1561 | 1.0328 |
| MR Image 5 | 0.9678 | 1.0564 |
| MR Image 6 | 1.1854 | 1.0423 |
| MR Image 7 | 1.2092 | 1.0398 |
| MR Image 8 | 1.117 | 1.0442 |
| MR Image 9 | 1.1416 | 1.0208 |
| MR Image 10 | 1.0116 | 1.0591 |
| MR Image 11 | 0.9904 | 1.0605 |
| MR Image 12 | 0.956 | 1.0536 |
| MR Image 13 | 1.0728 | 1.0837 |
| MR Image 14 | 1.1096 | 1.0728 |
| MR Image 15 | 1.0365 | 1.0514 |
| MR Image 16 | 1.0499 | 1.0513 |
| MR Image 17 | 0.9978 | 1.0426 |
| MR Image 18 | 1.0365 | 1.0514 |
| MR Image 19 | 1.1379 | 0.9938 |
| MR Image 20 | 1.003 | 1.0398 |
| MR Image 21 | 1.0636 | 1.0591 |
| PET Image 22 | 1.0352 | 1.0530 |
| PET Image 23 | 0.7923 | 0.7662 |
| PET Image 24 | 1.0696 | 1.0709 |

**Table: 1 Comparison of Compression ratio of CT, MR, PET images using NNRBF, NNBP Techniques**

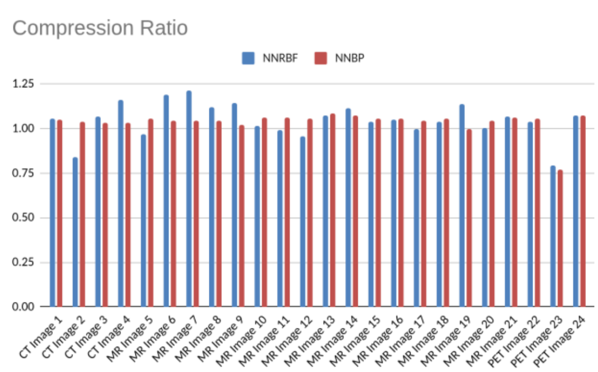


**Fig. 5 Comparison of Compression ratio of CT, MR, PET images using NNRBF, NNBP Techniques**

- **NNBP** generally gives better or equal compression ratios compared to NNRBF, leading to more compact storage of CT, MR, and PET images.
- Even though NNBP has the edge, the CR difference is usually modest—so **NNRBF** still performs well enough if you need both efficiency and some level of compression.

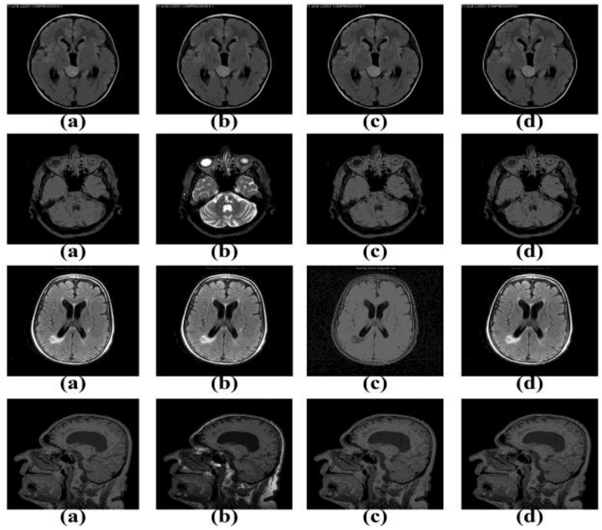


**Fig. 9 Results obtained for various medical images (a). Input Images (b). Neural Network Radial Basis Function (NNRBF) (c). Neural Network Back Propagation (NNBP)**

**Overall Observations:**

**High Quality and Compression:** NNBP is ideal where image quality and highest compression are critical, but at a much greater processing cost. **Fast and Efficient:** NNRBF is preferable for scenarios requiring rapid processing, lower memory, and practical speed, such as telemedicine or real-time streaming. **Clinical Impact: NNBP:** Best for storage of the diagnostic details **NNRBF:** Best for real-time diagnostics, mobile devices, and bandwidth-limited environments.

**Conclusion:**

This research explored the urgent challenge of storing and transmitting large medical images efficiently, which is increasingly critical in digital healthcare and telemedicine. By comparing two advanced neural network-based compression techniques NNRBF and NNBP our work focused on finding a practical balance between image quality, speed, and resource usage. The motivation was to enable reliable, fast, and cost-effective medical image management that doesn't compromise diagnostic detail and can adapt to both high-performance servers and resource-constrained devices.

**Future Work**

Needed to optimize neural networks for faster and lighter deployment, possibly through hardware acceleration, pruning, or quantization. Future models should adapt intelligently to different types of medical images, automatically balancing quality, compression ratio, and speed. Integrating AI-driven feature preservation and automated thresholding could further safeguard critical diagnostic content. Broad clinical validation, especially with emerging modalities and diverse patient data, will be essential for real-world acceptance and use.

**References:**


1. Perumal Balasubramani, Suriyakala ,Shakir Khan and Deny J "Traditional and Neural Network Approaches for Medical Image Compression: A Performance Evaluation," SGS - Engineering & Sciences, vol. 5, pp. 112–124, 2025.

2. B. P. Vikraman, “Effective image compression using hybrid DCT and learning-based adaptive thresholding for medical imaging,” Biomed. Signal Process. Control, vol. 97, 2024.
3. H. Chen, S. Kumar, and Y. Wang, “Image-Compression Techniques: Classical and ‘Region-of-Interest’ Approaches,” Front. Med., vol. 11, no. 1, pp. 24–35, Jan. 2024.
4. R. Monika and R. Suresh, “An Efficient Medical Image Compression Technique for Bandwidth and Storage Optimization,” Biomed. Signal Process. Contr., vol. 89, pp. 104523, 2023.
5. R. Rojas-Hernández, “Lossless Medical Image Compression by Using Difference Transform,” J. Healthc. Eng., vol. 2022, pp. 1–10, Jul. 2022.
6. S. Gupta, A. Mishra, and B. Singh, “Efficient Image Compression Techniques for Telemedicine,” Int. J. Imaging Syst. Technol., vol. 32, no. 4, pp. 1347–1361, Sep. 2022.
7. N. Sharma and K. Gandhi, “Compression of Medical Images by Convolutional Neural Networks,” IEEE Access, vol. 10, pp. 16410–16420, 2022.
8. A. Singh, R. Kumar, and P. Choudhary, “Medical Image Compression Using Improved SPIHT and Block Thresholding,” Elsevier, vol. 232, pp. 81–91, 2021.
9. D. Lim, K. Lee, and S. Yoon, “Principal Component Analysis for ROI Compression in Medical Imaging,” Comput. Med. Imaging Graph., vol. 90, pp. 23–30, 2021.
10. G. Reddy and T. Rao, “Hybrid PCA-SPIHT Method for Medical Image Compression,” Int. J. Adv. Comput. Sci. Appl., vol. 12, no. 6, pp. 103–109, 2021.
11. L. Zhang, “Deep Learning-Based Approaches to Medical Image Compression: A Survey,” arXiv preprint arXiv:2107.10615, 2021.
12. Y. Shi, M. Chen, and H. Xiao, “Wavelet and Neural Network Based Image Compression for Medical Applications,” Comput. Biol. Med., vol. 120, pp. 103768, 2019.
13. A. Roy and G. Saha, “A New Fast Medical Image Compression Technique using Hybrid Methods,” in Proc. Int. Conf. Computer Vision Systems, pp. 323–334, Springer LNCS, 2019.
14. H. Imane, M. Bouzid, B. Ahmed, “Hybrid Medical Image Compression Method Using Quincunx Wavelet and Geometric Active Contour,” Bull. Electr. Eng. Inform., vol. 9, no. 1, pp. 146–159, 2020.
15. Y. Zhang, “Region-Based and NNRBF Neural Network Lossless Image Compression,” Wiley Online Library, vol. 5, no. 2, pp. 230–244, 2019.