Enhanced Compression Time Efficiency of Brain MRI Fractal Image Compression Using CNN-Guided and KD-Tree Optimized Encoding

Tristan D. Anyayahan#1, Cassius Wayne N. Reyes#2, Princess May R. Tomongha#3

College of Informatics and Computing Sciences, Batangas State University - The National Engineering University, Golden Country Homes, Alangilan Batangas City, Batangas, Philippines 4200

[1]tristanyayahan.17@gmail.com

[2]suissacseyer@gmail.com

[3]maytomongha@gmail.com

***Abstract*— Medical imaging plays a salient role in healthcare, especially in the early detection and diagnosis of diseases such as brain cancer. Gliomas and pituitary tumors have shown a significant rise in global mortality rates, highlighting the urgent need for early and accurate diagnostic methods. Magnetic Resonance Imaging (MRI) is widely used in neurological diagnostics, providing detailed visualization of brain structures essential for identifying abnormalities. However, as MRI resolution improves, the resulting increase in image data volume poses challenges in storage, transmission, and processing. To overcome these limitations, this research proposed a hybrid image compression approach that improves upon conventional fractal compression by incorporating a Convolutional Neural Network (CNN) to guide the process. The approach aimed to reduce compression time while preserving the image quality necessary for clinical interpretation. A K-Dimensional Tree (KD-tree) search algorithm was employed alongside a CNN-based autoencoder to accelerate the self-similarity search phase, typically the most time-consuming part of fractal compression. The KD-tree + CNN compression method was evaluated using brain MRI datasets of glioma and pituitary tumor cases. Key performance metrics included compression time, Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index (SSIM). Results showed that the KD-tree + CNN approach achieved up to a 40% reduction in encoding time while maintaining diagnostic image quality. The compressed images consistently achieved PSNR values between 25 and 40 dB and SSIM scores ranging from 0.80 to 0.95, indicating a high level of visual quality and structural similarity. This hybrid approach improved compression efficiency and supported faster data handling, enhanced medical workflows, and strengthened telemedicine capabilities, making it a practical solution for modern healthcare systems.**

***Keywords*— Fractal Image Compression, K-dimensional Tree, Convolutional Neural Network, Peak Signal-to-Noise Ratio, Structural Similarity Index**

I. INTRODUCTION

Image compression is the method of minimizing the size of images in bytes without sacrificing the image's dominance or accuracy to an unacceptable amount [17]. Reducing file sizes without compromising critical image quality enables faster diagnoses and more effective telemedicine applications.

Fractal Image Compression (FIC) is presently utilized for image compression, texture segmentation, feature extraction, picture signatures, and image watermarking, among other things. The most important advantages of this technique are fast decompression and resolution independence. The fundamental principle of fractal compression was based on Mandelbrot sets, which take advantage of self-similarity, scaling dependency, and statistical features of nature [21].

It is based on Iterated Function System (IFS), omitting the image content, and only retaining self-similarity parameters of the local image content to complete data compression, which made it advantageous for high compression ratios, reconstruction at any scale, and fast decoding [11]. It ensures minimal data loss while preserving critical details in complex medical images like those used to study cognitive decline [16]. This method leverages the self-similar patterns inherent in medical images, allowing for significant data reduction while maintaining high image quality. Unlike FIC techniques like Joint Photographic Experts Group (JPEG), fractal compression preserves detail even when images are enlarged, reducing pixelation and enhancing clarity. Additionally, its ability to capture the intricate structures of biological tissues makes it particularly valuable for analyzing complex anatomical features, ultimately facilitating better diagnostic accuracy and efficiency in medical imaging practices [13].

Although the FIC algorithm offers advantages, it suffers from a significant drawback: prolonged compression time, which hinders its practical application, particularly in large medical images like brain MRI scans. This study aimed to address this limitation by enhancing the compression efficiency of the fractal algorithm. Specifically, it integrated a CNN to streamline the process, where the CNN assisted in quickly identifying similar regions in MRI images, ultimately reducing the overall time needed for effective compression. In addition, a K-Dimensional Tree (KD-tree) structure was employed to accelerate the self-similarity search by efficiently organizing image blocks for rapid nearest-neighbor retrieval, further improving the encoding speed without compromising image quality.

Medical imaging is essential in healthcare, facilitating the early detection of diseases, and tracking patient progress. Significant advancements in technology and methodology improved the capacity to diagnose and monitor diseases with enhanced precision [18]. Medical imaging technologies are vital for measuring illnesses, managing, treating, and preventing diseases. They are essential tools for identifying significant medical conditions. Medical imaging played a crucial role in diagnosis, which involved assessing patients' disease and symptoms through their medical history and physical examinations. This process provided essential information necessary for effective treatment [10].

Recent developments in information technology and medical imaging have considerably enhanced MRI's diagnostic potential. Accurate diagnosis depends on methods like segmentation and classification to separate healthy brain tissue from the tumor-affected area. While segmentation techniques like thresholding and morphological analysis separate the tumor region, preprocessing techniques like improved grayscale conversion and noise reduction enhance the quality of pictures. These advanced machine learning algorithms properly categorize benign, malignant, and non-tumorous conditions by using Support Vector Machines, among other techniques, to classify characteristics with extremely high accuracy. These developments demonstrate the significant role that MRI played in enhancing precision and task efficiency in the identification and categorization of tumorous states in the human brain.

In a recent study, scholars implemented a deep learning model based on the YOLOv7 architecture, which was fine-tuned through transfer learning to enhance its ability to detect various brain tumor types, including gliomas and meningiomas. This model achieved remarkable accuracy, reaching a detection rate of 99.5%, significantly surpassing FIC methods. The study highlighted the necessity of using a large dataset of MRI images for effective model training and employed a three-stage image preparation strategy to enhance low-resolution images. By addressing issues like overfitting through data augmentation techniques, the researchers aimed to reduce false detections and improve the overall reliability of brain tumor diagnostics. This innovative approach illustrated the significant progress in MRI technology that supported more accurate and timely diagnoses in the battle against brain cancer [1].

With the continuous advancement of medical imaging technology, especially the resolution of imaging devices, the amount of medical image data continues to grow. Existing bandwidth conditions make it difficult to meet the real-time transmission requirements of large data volumes. To achieve effective storage and transmission of medical images, it is not only necessary to expand storage space and transmission bandwidth, but also to study how to efficiently compress medical data. Therefore, it is necessary to implement effective compression of various medical images using an image compression algorithm [11].

This study focuses on gliomas and pituitary tumors not only because MRI is highly effective in evaluating them, but also because datasets for these two conditions are more widely available and well-documented compared to other brain pathologies. This accessibility allowed for more robust training and testing of the proposed KD-tree + CNN compression method, ensuring better validation and practical relevance.

This research supports Sustainable Development Goal (SDG) 3: Good Health and Well-being by improving the efficiency of brain MRI image compression using KD-tree for the self-similarity search and through the integration of a CNN into the fractal encoding process. By reducing compression time while preserving diagnostic image quality, the study promotes faster, more accessible, and reliable medical imaging, contributing to better healthcare outcomes and timely diagnosis.

A. Objectives of the Study

The main objective of this study is to improve fractal-based compression techniques for brain MRI images by integrating a CNN model and a KD-tree search algorithm into the encoding process, thereby enhancing compression efficiency while preserving diagnostic image quality.

Specifically, the study aimed to:

1. Train a CNN-based autoencoder using augmented brain MRI images for effective feature extraction, enabling improved representation learning and analysis.
2. Validate the generalizability of the proposed KD-tree + CNN autoencoder compression technique across two medical conditions, glioma and pituitary, by evaluating compression time and image quality to confirm its effectiveness in maintaining performance across diverse medical imaging scenarios.
3. Compare the performance of the proposed KD-tree + CNN autoencoder compression technique with:
    - 3.1. FIC, focusing on key metrics, and evaluating whether it achieved a 40% reduction in encoding time.
    - 3.2. KD-tree method without CNN integration to determine whether the CNN inference overhead in the KD-tree + CNN compression method negates the speed advantage gained from KD-tree search by comparing the breakdown of KD-tree search time versus CNN inference time.

II. RELATED WORKS

A. Fractal Image Compression (FIC)

FIC is a lossy technique that encodes images by dividing them into non-overlapping range blocks and overlapping domain blocks, then finding the best affine transformations—such as rotations and reflections—to match self-similar patterns between them [7], [19]. The encoded image is stored as a set of transformation rules, which are iteratively applied during decoding to reconstruct an approximation of the original image [3], [14]. FIC excels in compressing images with repetitive structures, like brain MRIs, and offers high compression ratios with minimal quality loss by exploiting self-similarity [2], [21]. Although encoding is computationally intensive, recent improvements such as quadtree partitioning and deep learning-assisted prediction of transformations have made it more efficient.

B. Self-Similarity Search

Self-similarity is a mathematical property where structures appear similar at different scales, making it valuable in areas like fluid dynamics and fractal image compression [15]. In fractals, this principle manifests as repeating patterns—often statistical rather than exact—that defy traditional Euclidean geometry and exhibit non-integer dimensions. These intricate, scale-invariant structures enable FIC to represent complex image regions using simpler, recursive transformations, significantly reducing data storage without major loss of detail. While traditional FIC relies on exhaustive pattern searches, methods like KD-tree combined with CNNs optimize and accelerate the identification of self-similar regions, particularly benefiting medical imaging tasks such as brain MRI compression.

C. Convolutional Neural Network (CNN)

CNNs excel at identifying patterns and structures in images, enabling efficient compression by automatically extracting essential features and discarding redundant data [23], [4]. CNNs enhance compression through adaptive rate control, improved block partitioning, and faster encoding/decoding processes. In medical imaging, they preserve critical details in complex regions, making them ideal for MRI compression [20]. Hybrid approaches combining CNNs with fractal methods or Transformers further improve adaptability and accuracy in various applications, from medical image analysis to energy forecasting and geospatial risk prediction [9], [22]. Deep autoencoders, leveraging loss functions like reconstruction and residual loss, have also demonstrated high compression efficiency and image quality, suggesting a promising direction for future advancements.

D. K-Dimensional Tree (KD-tree)

A KD-Tree is a hierarchical binary search structure optimized for organizing and querying multi-dimensional data by recursively partitioning space using hyperplanes based on dimensions with the highest variance, often at median values to maintain balance [8], [5]. It supports efficient nearest neighbor and approximate searches, radius-based neighborhood queries, and k-nearest neighbor (k-NN) searches, which are crucial for tasks like image compression and clustering [6]. In this study, KD-Trees are applied to Euclidean clustering to segment SAR point clouds and group self-similar image regions, enhancing encoding precision and reducing redundancy—especially valuable for high-resolution medical images where spatial accuracy and compression fidelity are vital.

III. METHODOLOGY

This chapter details the methodological process undertaken to develop and evaluate a KD+CNN algorithm tailored for brain MRI image compression. The study employed a quantitative research design using glioma and pituitary tumor MRI datasets, as shown in Fig. 1.

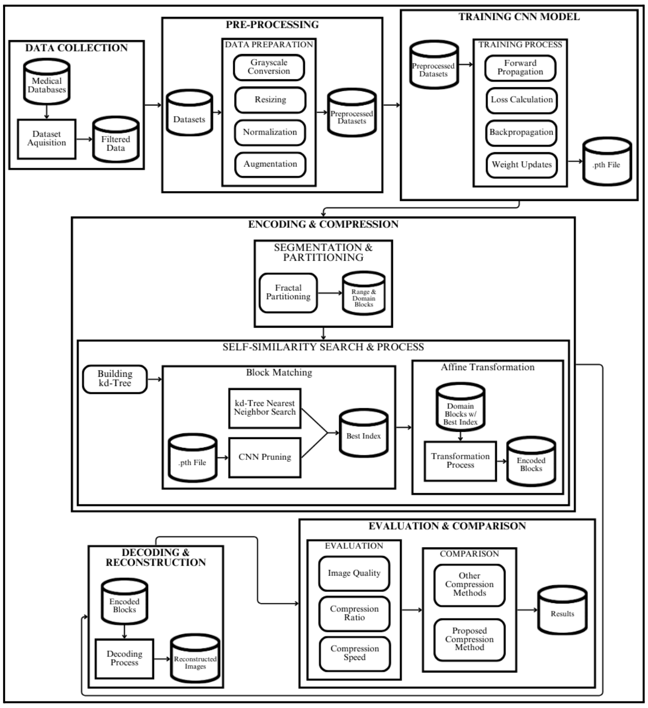

Fig. 1 Research Design

A. Dataset

This study utilized a total of 2,000 brain MRI images, evenly divided between glioma and pituitary tumor cases. The images were sourced from publicly available medical imaging repositories [12] and selected for their clinical relevance and variability in tumor presentation.

TABLE I
SAMPLE DATA FROM THE DATASET USED

Tumor Type	Resolution	Size (KB)
Glioma	512×512	870
Pituitary	256×256	420
Glioma	512×512	900
Pituitary	256×256	410

B. Data Preparation

Each image was preprocessed through grayscale conversion, resizing to uniform dimensions (e.g., 256×256 or 512×512 pixels), normalization, and noise reduction to standardize inputs and enhance image clarity. Data augmentation methods such as rotation and flipping were also applied to improve model generalization.

C. Model Architecture

To analyze the effectiveness of the KD-tree + CNN model for brain MRI images compression, the study focused on measuring the quality of the compressed images, the speed of the compression process, and the model's overall efficiency in handling large datasets.

1) Fractal Image Compression (FIC): FIC is a lossy image compression algorithm based on the principle of self-similarity. It divides the input image into two types of blocks : range and domain blocks.

2) CNN Autoencoder: A CNN-based Autoencoder was implemented to extract latent features from image patches. The encoder compresses high-dimensional input blocks into a smaller, meaningful representation, which captures the essential structural and textural features of MRI regions.

3) KD-tree-Based Nearest Neighbor Search: The KD-tree algorithm was employed to reduce the time complexity of the self-similarity search. After extracting feature vectors using the CNN encoder, all domain block features were organized into a balanced KD-tree data structure.
4) CNN-Guided and KD-tree Optimized FIC Pipeline: The proposed compression framework integrates FIC with a CNN encoder and a KD-tree structure to reduce encoding time while preserving image quality. The process begins by dividing the MRI image into range and domain blocks. Each domain block is processed through the CNN encoder to generate feature vectors, which are indexed in a KD-tree for efficient nearest-neighbor search. Range blocks are also encoded using the same CNN, and their features are used to query the KD-tree to find the most similar domain blocks.

D. Evaluation and Testing

Following training and compression, the proposed KD-tree + CNN-based fractal compression model was evaluated using standard metrics to assess its performance in both speed and image quality. Evaluation was conducted using a test set comprising MRI images of gliomas and pituitary tumors.

Six key metrics were used to evaluate model performance: Compression Time, Compression Ratio, Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index (SSIM).

$$Total\,Time = End\,Time - Start\,Time \qquad (1)$$

To evaluate the computational efficiency of the compression algorithm, the Python *time* module was employed to accurately track the runtime performance of the compression process. The module recorded the timestamps for both the start and end of the image compression procedure.

$$CR = \frac{Original\ File\ Size}{Compressed\ File\ Size} \qquad (2)$$

A technique used for quality assurance was the compression ratio, the ratio of the original image size to the compressed image size. A higher compression ratio signifies greater data reduction, but it must be balanced against image quality loss.

$$PSNR = 10log_{10}(\frac{MAX^2}{MSE}) \qquad (3)$$

For quality assessment, PSNR was a common metric used to measure the quality of compressed images by comparing the original and decompressed images. A PSNR that is above 40 dB is considered excellent, while values between 30 and 40 dB indicate good quality with minimal noticeable distortion. PSNR values between 20 and 30 dB may still be acceptable but could show visible artifacts, and values below 20 dB often indicate significant degradation.

$$SSIM(X, Y) = \frac{(2\mu_X\mu_Y + C_1)(2\sigma_{XY} + C_2)}{(\mu_X^2 + \mu_Y^2 + C_1)(\sigma_X^2 + \sigma_Y^2 + C_2)} \quad (4)$$

SSIM was another metric that compared the structural similarity between the original and compressed images. It considered luminance, contrast, and structural information, offering a perceptually relevant assessment of quality. SSIM values range from -1 to 1, where 1 indicates perfect similarity between the original and compressed images. Generally, an SSIM score above 0.9 is considered high quality, while scores between 0.8 and 0.9 indicate good quality with slight perceptible differences. Scores below 0.8 may show noticeable distortions. This made SSIM a useful tool for evaluating how well the compression preserves the important features of the image.

IV. RESULTS AND DISCUSSION

The researchers of this study analyzed the training accuracy of the CNN model to evaluate its performance during the learning process. Fig. 2 shows the performance of the trained CNN autoencoder model over 10 epochs.

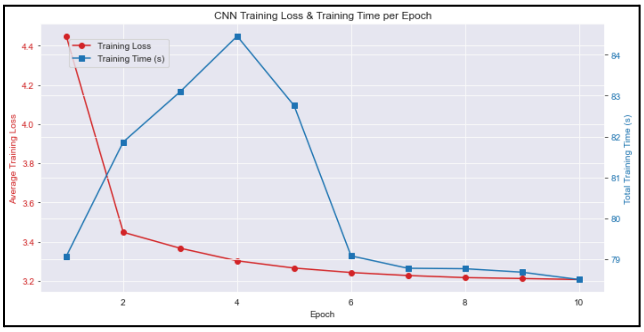

Fig. 2 CNN Autoencoder Model Training: Average Loss & Total Training Time per Epoch

The training process demonstrated effective and stable learning, with reconstruction loss decreasing consistently from 4.4484 at Epoch 1 to 3.2065 at Epoch 10. A sharp decline during the initial epochs indicated rapid pattern acquisition, while subsequent epochs showed a slower, steady reduction, suggesting fine-tuning and approaching convergence by Epoch 8. Training time per epoch ranged from 78.5 to 84.5 seconds, stabilizing around 78–79 seconds from Epoch 6 onward, indicating efficient computational performance. The consistent loss reduction without signs of overfitting, along with minimal gains in later epochs, suggests that further training would offer limited additional benefit.

The breakdown of encoding time in the proposed KD-tree + CNN method demonstrates its computational efficiency by analyzing KD-tree nearest neighbor search time and CNN inference time, key indicators of processing speed and performance. These metrics also support the comparative analysis of encoding time, decoding time, PSNR, and SSIM between glioma and pituitary brain MRI images, which served as the basis for the statistical evaluation presented in Table II.

TABLE II
INDEPENDENT T-TEST RESULTS COMPARING GLIOMA AND PITUITARY MRI COMPRESSION PERFORMANCE

Metric	T- Statistic	P- Value	Is it Significant?
Encoding Time (s)	-38.6704	0	Yes
Decoding Time (s)	-0.6209	0.5347	No
PSNR (dB)	35.8166	0	Yes
SSIM	42.2377	0	Yes

An independent t-test was conducted to assess the generalization capability of the proposed KD-tree + CNN compression model across glioma and pituitary brain MRI datasets. The analysis revealed statistically significant differences ($p < 0.05$) in encoding time, PSNR, and SSIM, indicating that the model's performance varied between the two tumor types. Specifically, encoding time was significantly faster for glioma images ($t = -38.6704$, $p < 0.0001$), likely due to differences in structural complexity, while PSNR ($t = 35.8166$, $p < 0.0001$) and SSIM ($t = 42.2377$, $p < 0.0001$) also favored one dataset, reflecting variations in reconstruction quality. Decoding time showed no significant difference ($t = -0.6209$, $p = 0.5347$), suggesting consistent decompression performance across conditions. These findings highlight the importance of evaluating compression methods across diverse medical imaging scenarios, as anatomical variability can significantly impact both efficiency and fidelity.

To evaluate the effectiveness of the proposed method, a performance comparison is conducted against the traditional FIC algorithm. Fig. 3 demonstrates the comparison of the FIC algorithm with the proposed KD-tree + CNN method in terms of encoding time and compression ratio.

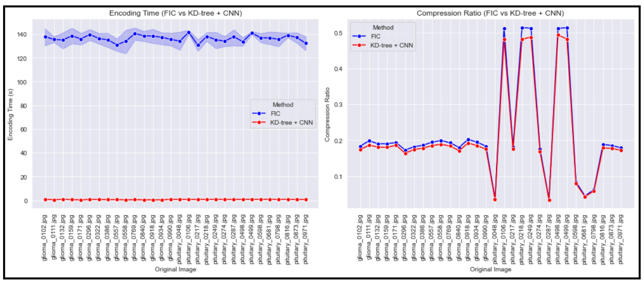

Fig. 3. Performance Comparison for Compression Time and Ratio Between FIC Algorithm and Proposed KD-tree + CNN Algorithm

The results demonstrate that the KD-tree + CNN method achieves a significant reduction in encoding time compared to the FIC method. Unlike FIC, which shows consistently slower performance, the KD-tree + CNN approach maintains a minimal and nearly constant encoding time across all tested images.

In terms of compression ratio, both methods perform at a similar level, showing only minor variations that do not significantly impact overall results. Taken together, the KD-tree + CNN algorithm offers a clear advantage by delivering much faster compression speeds while maintaining comparable effectiveness in preserving image quality.

To assess the performance of the proposed KD-tree + CNN algorithm on typical cases, five glioma MRI images with average file sizes are used for a comparative analysis against traditional FIC algorithm which is shown in Table III.

TABLE III
COMPRESSION TIME AND RATIO COMPARISON OF FIC VS. KD-TREE + CNN ON 5 AVERAGE GLIOMA IMAGES

Image Names	Self-Similarity Search (ms)		Encoding Time (s)		Compression Ratio	
	FIC	KD+ CNN	FIC	KD+ CNN	FIC	KD+ CNN
glioma_ 0159	138.55	0.58	138.56	0.67	0.19	0.18
glioma_ 0769	140.14	0.54	140.45	0.62	0.19	0.18
glioma_ 0386	135.17	0.58	135.18	0.67	0.19	0.18
glioma_ 0557	130.96	0.59	130.97	0.67	0.19	0.18
glioma_ 0840	138.64	0.45	138.65	0.53	0.18	0.17

The comparison underscores substantial improvements in encoding efficiency achieved by the proposed KD-tree + CNN method while maintaining compression effectiveness. Notably, the self-similarity search time is drastically reduced from 130.96–140.14 milliseconds using the traditional FIC algorithm to just 0.45–0.59 milliseconds with the KD-tree + CNN approach. Similarly, the overall encoding time drops significantly from 130.96–140.45 seconds to only 0.53–0.67 seconds, representing a major enhancement in processing speed.

Despite these performance gains, the compression ratios remain comparable between the two methods—ranging from 0.17 to 0.18 for KD-tree + CNN, and from 0.18 to 0.19 for FIC—indicating that the speed improvements do not come at the cost of compression effectiveness. To further validate these results, a focused comparison was conducted using five average-sized pituitary brain MRI images, with the results summarized in Table IV.

This comparison evaluated both algorithms across key metrics including search time, encoding time, image size before and after compression, and compression ratio. The findings confirm that the KD-tree + CNN algorithm delivers significantly faster processing while preserving image quality, making it a more suitable option for time-sensitive medical imaging applications.

TABLE IV
COMPRESSION TIME AND RATIO COMPARISON OF FIC VS. KD-TREE + CNN ON 5 AVERAGE PITUITARY IMAGES

Image Names	Self-Similarity Search (ms)		Encoding Time (s)		Compression Ratio	
	FIC	KD+ CNN	FIC	KD+ CNN	FIC	KD+ CNN
pituitary _0217	130.63	0.69	130.64	0.79	0.18	0.18
pituitary _0816	139.03	0.76	139.04	0.85	0.19	0.18
pituitary _0971	132.32	0.67	132.33	0.76	0.18	0.17
pituitary _0873	137.11	0.65	137.12	0.75	0.19	0.18
pituitary _0274	134.01	0.73	134.02	0.82	0.18	0.17

The KD-tree + CNN method significantly reduces self-similarity search time to 0.65–0.76 ms, compared to 130.63–139.03 ms with the FIC method. Encoding time is also greatly decreased, ranging from 0.75 to 0.85 seconds versus 130.64–139.04 seconds for FIC. Both methods achieve similar compression ratios around 0.17 to 0.19, with negligible differences in compressed image sizes—for example, pituitary_0217 compresses to 8.58 KB (KD-tree + CNN) versus 8.88 KB (FIC). Overall, the KD-tree + CNN method markedly improves processing speed while maintaining compression quality, demonstrating its efficiency for average-sized pituitary MRI images.

To assess the efficiency of our proposed KD-tree + CNN algorithm, comparison was conducted with the compression time and the resulting compression ratio against the KD-tree without CNN algorithm. Illustration of the comparison across the dataset of MRI images was evident in Fig. 4.

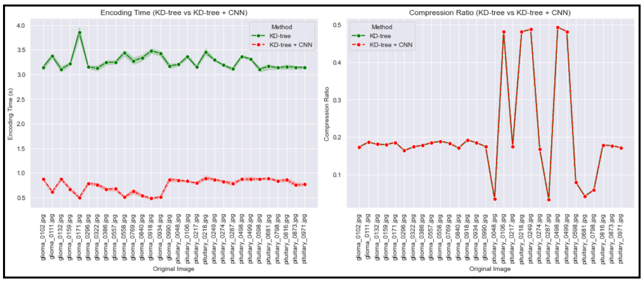

Fig. 4 Performance Comparison for Compression Time and Ratio Between KD-tree without CNN Algorithm and Proposed KD-tree + CNN Algorithm

The left graph shows that the KD-tree + CNN method significantly reduces encoding time compared to KD-tree only. The right graph indicates that both methods achieve similar compression ratios.

Comparison between the KD-tree without CNN and the proposed KD-tree + CNN algorithms using five glioma images with average sizes was conducted and was shown in Table V.

TABLE V
COMPRESSION TIME AND RATIO COMPARISON: KD-TREE VS. KD-TREE + CNN ON 5 AVERAGE GLIOMA IMAGES

Image Names	**Self-Similarity Search (ms)**		**Encoding Time (s)**		**Compression Ratio**	
	KD	**KD+ CNN**	**KD**	**KD+ CNN**	**KD**	**KD+ CNN**
glioma_ 0159	3.11	0.58	3.22	0.67	0.18	0.18
glioma_ 0769	3.16	0.54	3.27	0.62	0.18	0.18
glioma_ 0386	3.13	0.58	3.24	0.67	0.18	0.18
glioma_ 0557	3.13	0.59	3.24	0.67	0.18	0.18
glioma_ 0840	3.23	0.45	3.34	0.53	0.17	0.17

The integration of a (CNN with the KD-tree method results in a substantial improvement in self-similarity search performance. Specifically, the KD-tree + CNN approach reduces the search time to a range of 0.45–0.59 milliseconds, compared to the significantly slower 3.11–3.23 milliseconds observed when using the KD-tree alone. This represents a notable speedup, enhancing the efficiency of the search process, which is particularly valuable in applications requiring rapid data retrieval or real-time performance.

Despite the added complexity introduced by incorporating the CNN, the encoding times for both the KD-tree and KD-tree + CNN methods remain comparable. Both methods demonstrate encoding durations within a narrow range of 0.53 to 0.67 seconds, suggesting that the CNN's contribution does not add any significant overhead in terms of processing time during encoding. This balance is crucial for maintaining usability in time-sensitive scenarios.

Furthermore, the compression ratios achieved by both methods remain consistently between 0.17 and 0.18. This consistency indicates that the inclusion of the CNN does not compromise the compression efficiency. The compact representation of the data is preserved, which is important for reducing storage requirements and transmission bandwidth.

To further explore the impact of integrating a CNN into the KD-tree algorithm on compression efficiency, Table VI provides a comparison between the KD-tree without CNN and the proposed KD-tree + CNN algorithms using five pituitary images with average sizes.

TABLE VI
COMPRESSION TIME AND RATIO COMPARISON: KD-TREE VS. KD-TREE + CNN ON 5 AVERAGE PITUITARY IMAGES

Image Names	**Self-Similarity Search (ms)**		**Encoding Time (s)**		**Compression Ratio**	
	KD	**KD+ CNN**	**KD**	**KD+ CNN**	**KD**	**KD+ CNN**
pituitary _0217	3.05	0.69	3.15	0.79	0.18	0.18
pituitary _0816	3.05	0.76	3.15	0.85	0.18	0.18
pituitary _0971	3.03	0.67	3.14	0.76	0.17	0.17
pituitary _0873	3.04	0.65	3.15	0.75	0.18	0.18
pituitary _0274	3.07	0.73	3.18	0.82	0.17	0.17

The KD-tree + CNN method reduces self-similarity search time to 0.65–0.76 ms, compared to 3.03–3.07 ms for KD-tree alone, demonstrating a significant improvement in search efficiency due to CNN's ability to quickly filter and prioritize relevant features. This substantial reduction in search time is particularly valuable in large-scale image or video processing tasks, where real-time or near-real-time performance is critical.

Although encoding time is slightly higher with KD-tree + CNN—ranging from 0.75 to 0.85 seconds versus 0.65 to 0.79 seconds for KD-tree—the increase is relatively minor and can be considered an acceptable trade-off given the gain in search speed. Compression ratios are similar for both methods, mostly between 0.17

and 0.18, indicating that the integration of CNN does not adversely affect the overall compression performance. In summary, the KD-tree + CNN approach enhances search efficiency and maintains comparable compression quality, making it a compelling option for applications that demand both high-speed processing and effective data reduction.

V. CONCLUSION AND RECOMMENDATION

In this paper, the researchers explored the enhancement of fractal-based compression techniques for brain MRI images by integrating a CNN and a KD-tree search algorithm into the encoding process. The primary objective was to improve compression efficiency while maintaining diagnostic image quality across different brain conditions.

A. Conclusion

The CNN-based autoencoder efficiently extracted features from augmented brain MRI images, as shown by steady learning improvement and no overfitting. However, additional training beyond later epochs provided little extra benefit.

The KD-tree + CNN compression model encoded glioma and pituitary MRI images significantly faster than traditional methods, a difference ultimately attributed to image size and anatomical complexity. Despite some variation in post-compression image quality between tumor types, decoding remained consistent and reliable across datasets.

The CNN-guided KD-tree technique reduced compression time by over 40% compared to FIC, thanks to more efficient block matching, while maintaining or even improving image quality. This demonstrates the method's speed and reliability for both glioma and pituitary MRI datasets.

Quantitative results showed that the KD-tree + CNN algorithm significantly improved self-similarity search time compared to the KD-tree method across glioma and pituitary datasets, with no loss in PSNR or SSIM. This enhancement enabled faster processing while maintaining image quality.

B. Recommendation

This study opens avenues for further enhancement of the proposed technique. Future research is recommended in the following areas to expand the method's utility and effectiveness:

Wavelet-CNN Hybridization: Incorporating wavelet transforms into the CNN-guided FIC framework may improve compression efficiency and better retain anatomical detail. Wavelets can enhance the ability to capture both spatial and frequency features.

Application to Other Modalities: Expanding the use of the proposed KD-tree + CNN method to other imaging formats, such as CT, PET, or ultrasound, would test its versatility and broader applicability in medical diagnostics.

3D/4D Data Compression: Future work can explore adaptation of the framework for volumetric (3D) and temporal (4D) imaging data. This would support efficient compression of complex datasets like dynamic CT or functional MRI while preserving spatial-temporal continuity.

ACKNOWLEDGMENTS

The researchers would like to express their profound gratitude to all those who contributed to the successful completion of this study. The time, effort, and skills contributed by each person were invaluable, and they are extremely grateful for this support.

First and foremost, to the Almighty God, for his love and guidance, which enlightened the researchers' minds during their darkest hours of frustration, hopelessness, and hardships while preparing this study.

To our thesis adviser, Mr. Erwin L. Enriquez, for his insightful feedback and continuous guidance throughout every stage of this research. His mentorship played a crucial role in shaping the direction and quality of this study.

Furthermore, the contributions of all the study authors and scholars were acknowledged, whose pioneering work laid the foundation for the study. Their insights and innovations in the field served as a source of inspiration and guidance for our research.

Lastly, the researchers extend their gratitude to their colleagues, friends, and family members for their unwavering support and encouragement throughout this journey. Their understanding and encouragement provided the motivation necessary to overcome challenges and achieve our research objectives.

Together, the collective efforts of all these individuals have made this study possible, and they are sincerely grateful for their support and collaboration.

REFERENCES

[1] Abdusalomov, A. B., Mukhiddinov, M., & Whangbo, T. K. (2023). Brain Tumor Detection Based on Deep Learning Approaches and Magnetic Resonance Imaging. Cancers, 15(16), 4172. https://doi.org/10.3390/cancers15164172

[2] Abood, B., Akkar, H., & Al-Safi, A. (2022). Acceleration of Video and Images Processing using Fractal Image Compression Based on FPGA. https://www.researchgate.net/publication/382061266_Acceleration_of_Video_and_Images_Processing_using_Fractal_Image_Compression_Based_on_FPGA/references

[3] Ali, A. H., Abbas, A. N., George, L. E., & Mokhtar, M. R. (2019). Image and audio fractal compression: Comprehensive review, enhancements and research directions. Indonesian Journal of

Electrical Engineering and Computer Science, 15(3), 1564. https://doi.org/10.11591/ijeecs.v15.i3.pp1564-1570

[4] Alzubaidi, L., Zhang, J., Humaidi, A. J., Al-Dujaili, A., Duan, Y., Al-Shamma, O., Santamaría, J., Fadhel, M. A., Al-Amidie, M., & Farhan, L. (2021). Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions. Journal of Big Data, 8(1), 53. https://doi.org/10.1186/s40537-021-00444-8

[5] Cao, J., & Wang, M. (2023). A Fast and Generalized Broad-Phase Collision Detection Method Based on KD-Tree Spatial Subdivision and Sweep-and-Prune. IEEE Access, 11, 44696–44710. https://doi.org/10.1109/ACCESS.2023.3274202

[6] Guo, Z., Liu, H., Shi, H., Li, F., Guo, X., & Cheng, B. (2023). KD-Tree-Based Euclidean Clustering for Tomographic SAR Point Cloud Extraction and Segmentation. IEEE Geoscience and Remote Sensing Letters, 20, 1–5. https://doi.org/10.1109/LGRS.2023.3234406

[7] Gupta, R., Mehrotra, D., & Tyagi, R. K. (2018). Comparative analysis of edge-based fractal image compression using nearest neighbor technique in various frequency domains. Alexandria Engineering Journal, 57(3), 1525–1533. https://doi.org/10.1016/j.aej.2017.03.038

[8] Gutiérrez, G., Torres-Avilés, R., & Caniupán, M. (2024). cKd-tree: A Compact Kd-tree. IEEE Access, 12, 28666–28676. https://doi.org/10.1109/ACCESS.2024.3365054

[9] Hu, H., Gong, S., & Taheri, B. (2024). Energy demand forecasting using convolutional neural network and modified war strategy optimization algorithm. Heliyon, 10(6), e27353. https://doi.org/10.1016/j.heliyon.2024.e27353

[10] Hussain, S., Mubeen, I., Ullah, N., Shah, S. S. U. D., Khan, B. A., Zahoor, M., Ullah, R., Khan, F. A., & Sultan, M. A. (2022). Modern Diagnostic Imaging Technique Applications and Risk Factors in the Medical Field: A Review. *BioMed Research International, 2022*, 1–19. https://doi.org/10.1155/2022/5164970

[11] Liu, S., Bai, W., Zeng, N., & Wang, S. (2019). A Fast Fractal Based Compression for MRI Images. *IEEE Access, 7*, 62412–62420. https://doi.org/10.1109/ACCESS.2019.2916934

[12] Mandal, R. (2024, September 16). Brain tumor (MRI scans) [Dataset]. Kaggle. https://www.kaggle.com/datasets/rm1000/brain-tumor-mri-scans

[13] Marzi, C., Giannelli, M., Tessa, C., Mascalchi, M., & Diciotti, S. (2021). Fractal Analysis of MRI Data at 7 T: How Much Complex Is the Cerebral Cortex? *IEEE Access, 9*, 69226–69234. https://doi.org/10.1109/ACCESS.2021.3077370

[14] Mellin, F. (2021). Introduction to Fractal Image Compression. Uppsala University. https://www.diva-portal.org/smash/get/diva2:1561273/FULLTEXT01.pdf

[15] Nigmatullin, R., & Chen, Y. (2023). Self-Similarity Principle and the General Theory of Fractal Elements: How to Fit a Random Curve with a Clearly Expressed Trend? Mathematics, 11, 2781. https://doi.org/10.3390/math11122781

[16] Pantoni, L., Marzi, C., Poggesi, A., Giorgio, A., De Stefano, N., Mascalchi, M., Inzitari, D., Salvadori, E., & Diciotti, S. (2019). Fractal dimension of cerebral white matter: A consistent feature for prediction of the cognitive performance in patients with small vessel disease and mild cognitive impairment. *NeuroImage: Clinical, 24*, 101990. https://doi.org/10.1016/j.nicl.2019.101990

[17] Puthentharayil Vikraman, B., & Afthab, J. (2024). Effective image compression using hybrid DCT and hybrid capsule auto encoder for brain MR images. *Journal of Visual Communication and Image Representation*, *104*, 104296. https://doi.org/10.1016/j.jvcir.2024.104296

[18] Rong, J., & Liu, Y. (2024). Advances in medical imaging techniques. *BMC Methods, 1*(1), 10, s44330-024-00010–00017. https://doi.org/10.1186/s44330-024-00010-7

[19] Saad, A.-M. H. Y., Abdullah, M. Z., Alduais, N. A. M., Abdul-Qawy, A. S. H., Nasser, A. B., Ghanem, W. A. H. M., & Sa'd, A. H. Y. (2022). Deep Pipeline Architecture for Fast Fractal Color Image Compression Utilizing Inter-Color Correlation. IEEE Access, 10, 110444–110458. https://doi.org/10.1109/ACCESS.2022.3213723

[20] Salehi, A. W., Khan, S., Gupta, G., Alabduallah, B. I., Almjally, A., Alsolai, H., Siddiqui, T., & Mellit, A. (2023). A Study of CNN and Transfer Learning in Medical Imaging: Advantages, Challenges, Future Scope. Sustainability, 15(7), 5930. https://doi.org/10.3390/su15075930

[21] Svynchuk, O., Barabash, O., Nikodem, J., Kochan, R., & Laptiev, O. (2021). Image Compression Using Fractal Functions. *Fractal and Fractional, 5*(2), 31. https://doi.org/10.3390/fractalfract5020031

[22] Zhang, S., Bai, L., Li, Y., Li, W., & Xie, M. (2022). Comparing Convolutional Neural Network and Machine Learning Models in Landslide Susceptibility Mapping: A Case Study in Wenchuan County. Frontiers in Environmental Science, 10. https://doi.org/10.3389/fenvs.2022.886841

[23] Zhang, Z., Esenlik, S., Wu, Y., Wang, M., Zhang, K., & Zhang, L. (2024). End-to-End Learning-Based Image Compression With a Decoupled Framework. IEEE Transactions on Circuits and Systems for Video Technology, 34(5), 3067–3081. https://doi.org/10.1109/TCSVT.2023.3313974