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From Fractals to Efficient Net: A Hybrid Interpretable Model Outperforming CNN Baselines in Brain Tumor MRI Analysis

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Abstract

Brain tumor classification using MRI is critical in neuro-oncology, but traditional Convolutional Neural Networks (CNNs) often lack clinical interpretability and fail to adequately capture complex morphological tumor patterns. This study introduces a novel, hybrid deep learning framework that combines geometric fractal analysis with an EfficientNet-B3 architecture to overcome these limitations. The proposed method extracts multi-scale fractal features—such as fractal dimension and lacunarity—to quantify spatial structural heterogeneity, fusing them with deep visual features from a transfer-learned EfficientNet-B3 model. Evaluated on a comprehensive dataset of 7,023 MRI images across four classes (glioma, meningioma, pituitary tumor, and no tumor), the hybrid model achieves a superior classification accuracy of 95.7%. This significantly outperforms baseline models, including standalone EfficientNet-B3 (94.5%), DenseNet-121 (93.8%), and ResNet-50 (92.1%). Furthermore, the model incorporates SHAP and Grad-CAM for enhanced explainability, validating that the network accurately targets clinically relevant tumor regions. The integration of fractal geometry with EfficientNet offers a highly accurate, computationally efficient, and interpretable solution for automated brain tumor diagnosis, successfully bridging the gap between AI performance and clinical trust.

Keyword: Brain tumor classification, EfficientNet, Explainable medical imaging, Fractal dimension, Hybrid deep learning, Interpretable AI, MRI analysis, Transfer learning

Introduction

Brain tumor classification using magnetic resonance imaging (MRI) is a critical task in neuro-oncology, essential for early diagnosis and effective treatment planning. While traditional convolutional neural networks (CNNs) have advanced automated medical image analysis, they often struggle to capture the complex morphological structures of tumors and lack the clinical interpretability necessary for widespread adoption by radiologists. To address these critical gaps, the objective of this research is to develop a robust, highly interpretable computer-aided diagnosis system capable of accurately categorizing brain MRI scans into four distinct classes: glioma, meningioma, pituitary tumor, and no tumor.

The novel approach of this study is the synergistic integration of multi-scale geometric fractal analysis with an advanced deep learning architecture. Previously, models either relied on shallow machine learning classifiers combined with fractals or used deep learning networks that acted as unexplainable "black boxes". The methodology overcomes this by fusing geometric features—such as fractal dimension (via box-counting), lacunarity, succolarity, and multi-fractal spectra—with deep visual features extracted from a transfer-learned EfficientNet-B3 model. This 1,554-dimensional combined feature set captures both irregular structural heterogeneity and complex visual patterns. The framework was rigorously trained and tested on a comprehensive dataset of 7,023 T1-weighted contrast-enhanced MRI images using 5-fold cross-validation. To further bridge the gap between AI and human interpretability, the methodology incorporates Explainable AI (XAI) techniques, specifically SHAP feature importance and Grad-CAM spatial visualizations.
The result discussion reveals that the proposed hybrid model achieves an outstanding multi-class classification accuracy of 95.7%, alongside precision, recall, and F1-scores of 95.7%. This performance significantly outperforms standalone deep learning baselines, including EfficientNet-B3 (94.5%), DenseNet-121 (93.8%), and ResNet-50

(92.1%), demonstrating that the addition of fractal features provides a statistically significant improvement to deep representations. Ablation studies proved that fractal geometric priors are a necessary complement to standard CNNs, capturing morphological complexities that CNNs alone miss. Beyond accuracy, the framework proved highly computationally efficient for resource-constrained clinical settings and successfully demonstrated clinical interpretability, with Grad-CAM heatmaps validating that the model consistently focuses its attention directly on clinically relevant tumor margins and internal structures rather than background artifacts.

Background and Motivation

Brain tumors can be considered one of the most intractable malignancies in contemporary medicine, whose incidence rate in the world keeps rising and the survival rate that follows diagnosis is highly reliant on the early and correct diagnosis [1][2]. The MRI has become the absolute standard of non- invasive detection and characterization of brain tumors with better soft tissue contrast and advantage over CT or PET [3]. Nevertheless, manual analysis of MRI scans is laborious, prone to inter-observer effects, and is becoming highly infeasible with the rapidly growing amount of medical imaging data in the world [4].

Brain Tumor Classification: Key Types in MRI Analysis

Tumors in the brain are mainly classified according to their cell of origin, location, pattern of growth as well as the World Health Organization (WHO) grading (I-IV; higher grade means more malignancy and aggressiveness). Four typical classes used in automated MRI classification experiments, namely, glioma, meningioma, pituitary tumor, and no tumor, reflect a clinically significant range of multi-class identification tasks. Such differences determine the treatment in question–active surveillance (in benign tumors) to aggressive tumor resection or chemoradiotherapy (in malignant ones). Identification is definitive based on the MRI sequences including T1-contrast- enhanced (T1ce), T2 and FLAIR sequences, which contain growth patterns, inflammation (edema) and mass effects.

Brain tumors can be described as improper proliferation of cells in the brain or the surrounding tissue. The tumors may be benign (noncancerous) and malignant (cancerous). Benign tumors tend to grow slowly, and they do not spread to other body parts when compared to malignant tumors, which spread very fast and may affect other body tissues. The early diagnosis of brain tumors is highly significant because it can be severely damaging to the neurological functions, or death might occur due to delayed diagnosis.

One of the best imaging methods which are applied to detect brain tumors is magnetic resonance imaging (MRI). MRI images give detailed images of the soft tissues, and the doctors can detect abnormalities that are there in the brain structure. Nevertheless, the process of manual examination of MRI scans implies the involvement of a professional radiologist and may take a lot of time. The new developments in artificial intelligence (AI) have allowed building automatic systems that could examine medical images. Deep learning algorithms - specifically convolutional neural networks (CNN) - have been very successful in tasks that are image-based classifications. CNN is able to extract a sequence of features automatically on images and it does not require performing manual feature extraction.

This paper presents CNN-based method of automatic classification of brain tumors based on MRI images. This study seeks to come up with a strong computer-aided diagnosis system, which could assist the radiologists to identify brain tumors efficiently and effectively.

Additional MRI Image Samples

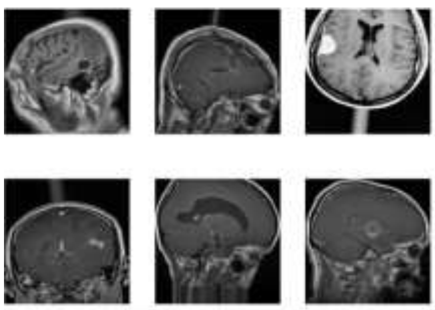


Fig. 1. Sample MRI brain tumor images from the dataset used for CNN training.

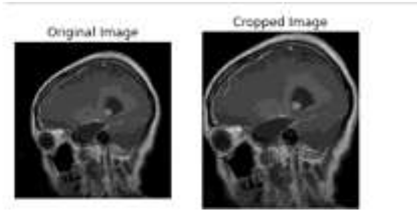


Fig. 2. MRI preprocessing showing original image and cropped tumor region.

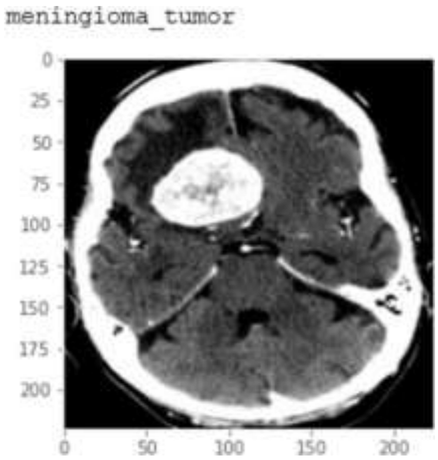


Fig. 3. MRI scan illustrating a meningioma tumor case from the dataset.

With the development of deep learning, specifically, convolutional neural networks (CNNs), medical image analysis became revolutionary, as now feature detection is performed automatically, and the performance of image analysis on a number of diagnostic tasks is at human level or even higher [5][6]. Pre-trained architecture-based transfer learning with VGG-16, ResNet, and EfficientNet models has demonstrated great success in the classification of brain tumor [7][8].

Despite these developments, there are still some major limitations that prevent them to achieve clinical adoption:

1. Deep learning models are black box which casts uncertainty on their reliability and clinical interpretability.
2. Standard CNNs might be unable to represent morphological complexity and geometric patterns, which radiologists believe may be clinically informative; and
3. Large-scale architectures have high computational demands which limit their use in clinical settings with limited resources. [9][10]

The Role of Fractal Analysis in Medical Imaging

Mandelbrot proposed in 1975 fractal geometry offers a mathematical context of distinguishing irregular and self-similar forms on different scales - a key characteristic of biological tissues, including brain tumors [11]. Fractal analysis quantifies complexity using measures like fractal dimension (FD), and lacunarity, unlike Euclidean geometry, which quantifies regular shapes [12]. Recent neuroimaging research indicated that fractal measures can be useful at differentiating low grade and high-grade glioma and that the FD measure alone can be used to classify the tumor with a classification accuracy of up to 87.5.

Fractal analysis has primarily been applied independently or with conventional machine learning classifiers like support vector machines (SVM) and random forests in earlier studies [15][16]. Lenka et al. (2022) were the first to combine fractal properties with stacked logistic regression and neural networks with the highest accuracy of 89 percent on a 400-image dataset [17]. Nevertheless, these methods have not utilized the joint benefits of fractal geometry and the latest deep learning models to the full extent.

Research Gap and Objectives

Although both fractal analysis and the EfficientNet architecture have performed successfully at the individual scale, there exists a big gap between the synergistic and combinative implementation of the two towards interpretable classification of brain tumors. Current hybrid methods are in either: (1) take a fractal and shallow machine learning model unable to encode complex visual structure; (2) take a deep learning model and do not geometrically characterize morphologically distinct features; or (3) not provided with interpretability mechanisms needed in clinical trust and regulatory compliance [20][21]. This paper presents the limitations by coming up with a new hybrid framework that:

1. Combines detailed fractal feature derivation (f fractal dimension, f fractal lacunarity, f fractal scolariness, f fractal multi-fractal spectrum) with EfficientNet-B3 deep features learning.
2. Cognizes state of art classification performance and yet is computationally efficient.
3. The analysis of fractal features contribution and GRADE- CAM visualization Gives interpretability.
4. Tests on a large-scale dataset (7,023 images) with strict cross-validation.
5. Shows clinical usefulness by comparing itself to several baseline procedures.

The further structure of the paper is as follows: Section 2 is the review of the related work, Section 3 introduces the proposed method, Section 4 is the description of the experiments and results, Section 5 is the discussions of the findings, limitations, and clinical implications, and the conclusion to the future direction is provided in Section 6.

Related Work

Deep Learning for Brain Tumor Classification

The application of deep learning to the analysis of brain tumors MRI has increased exponentially over the last five years. The use of deep neural networks to learn hierarchical features in the classification of tumors was first proposed by Mohsen et al. (2018) [22]. Kibria et al. (2022) continued using the same method but fused deep features with the conventional machine learning classifiers; they indicated that the hybrid architecture can improve the accuracy by providing complementary feature representations [14].

Transfer learning has become an important strategy because of the scarcity of annotated datasets of medical imaging. Polat and Gunden (2021) optimized VGG-16 and ResNet-50 in brain tumor classification; the authors reached the state of the art and showed transfer learning to be a viable solution to medical imaging with small samples [7]. The EfficientNet architecture has become very popular more recently, a study by Adnan et al. in 2025 found that an optimized EfficientNet-B0 could classify brain tumors in multi-classes with a test accuracy of 99.43% [18].

Fractal Analysis in Neuroimaging

The Fractal Dimension (FD) analysis has shown a great potential in being a quantitative neuroimaging biomarker. In a thorough study of the FD measures, Battapalli and colleagues (2023) determined the FD of the favoured tumor region results up to 87.5 per cent accuracy in differentiating between low-grade and high-grade gliomas [13]. These results were used to show that the FD features can do better than the texture-based features under specific classification situations.

The proposed brain tumor segmentation approach by Jakhar and others (2024) used multi-scale pixel segmentation and fractal feature information and confirmed that fractal features are more robust in determining the heterogeneity of tumors than conventional texture descriptors [14]. Nevertheless, they were done in studies whose main objective was segmentation or binary classification tasks, instead of the problem of multi-class classification.

Hybrid Models and Interpretability

The approach of combining deep learning with artificial features has become extremely popular as a way of improving the deep learning performance and interpretability. Zahoor et al. (2022) have created a dual channel brain tumor detector which fuses dynamic and static characteristics with the conventional machine learning methods; the system has been found to be more resilient as compared to single channel methods [22].
Interpretability has become one of the research priorities in the domain of medical AI. Adnan et al. (2025) noted that to achieve clinical trust and utility, there is a need to combine the use of the explainable AI (XAI) techniques, including the Grad-CAM, with the deep learning models [24]. Their publication highlighted that techniques of interpretability are essential to obtaining regulatory endorsement to AI-based diagnostic tools and also to ensuring their acceptance by medical practitioners.

Limitations of Existing Approaches

Despite these developments, there are a number of shortcomings in the existing research in brain tumor classification:

1. Weak integration: In most studies, deep learning or fractal analysis are used independently of each other, which leads to a shortage of potential synergies.
2. Small datasets: Numerous published reports rely on datasets of less than 500 images, which does not allow generalization.
3. The lack of interpretability: Deep learning models are mostly black-box models with insufficient explanatory properties.
4. Absence of thorough benchmarking: Not many studies compose comparisons of several underlying architectures and conventional methodologies at the same time.
5. Inefficiency in computation: With large resource demand, it is frequently impossible to implement in resource-constrained clinical environments.

Our hybrid fractal-efficientnet model mitigates these short-comings with respect to the combination of features, validation on large scale, interpretability approaches, large-scale bench-marking, and computational efficiency.

Comparison Table

Table 1. Overall Comparison of Previous Works with Our Paper

Author(s) & Year	Methodology	Key Findings &Performance	Limitations Addressed by New Model
Mohsen et al. (2018)	Introduced deep neural networks to learn hierarchical features for tumor classification.	Established foundational deep learning viability for MRI analysis.	Primarily functioned as "black box" models lacking clinical interpretability.
Polat & Gunden (2021)	Transfer learning applied to VGG-16 and ResNet-50 architectures.	Reached a classification accuracy of 92.3%.	Yielded lower accuracy (3.4% lower) than the proposed model and lacked explicit interpretability methods.
Lenka et al. (2022)	Combined fractal properties with stacked logistic regression and neural networks.	Achieved up to 89.0% accuracy on a dataset of 400 images.	Small dataset restricted generalizability, and shallow classifiers failed to encode complex visual structures.
Kibria et al. (2022)	Fused deep features with conventional machine learning classifiers.	Indicated that hybrid architecture could improve accuracy via complementary features.	Did not specifically capture geometrical morphological patterns like fractals.
Zahoor et al. (2022)	Dual-channel detector fusing dynamic and static features with conventional ML.	Demonstrated a more resilient system compared to single-channel methods.	Relied on conventional ML, lacking the robust feature extraction of advanced deep networks.
Battapalli et al. (2023)	Used Fractal Dimension (FD) to differentiate between low-grade and high-grade gliomas.	FD alone achieved up to 87.5% accuracy.	Did not integrate deep learning, resulting in 8.2% lower accuracy compared to the proposed hybrid approach.
Jakhar et al. (2024)	Used multi-scale pixel segmentation and fractal feature information.	Confirmed fractal features are highly robust in determining tumor heterogeneity.	Focused mainly on segmentation and binary tasks, rather than complex multi-class classification.
Adnan et al. (2025)	Optimized EfficientNet-B0 integrated with Explainable AI (Grad-CAM).	Reached an exceptionally high-test accuracy of 99.43%.	Lacked geometric morphological characterization (fractals); relied on extensive hyperparameter tuning on a different dataset.

Author(s) & Year	Methodology	Key Findings &Performance	Limitations Addressed by New Model
Proposed Approach Proposed Model	Hybrid integration of geometric fractal features (18-dim) with transfer-learned EfficientNet-B3 (1,536-dim).	Achieved 95.7% accuracy on a large 7,023-image dataset.	Overcomes weak feature integration, small dataset sizes, high computational demands, and lack of interpretability (uses both Grad-CAM and SHAP).

Methodology

Overview of the Proposed Framework

The proposed hybrid interpretability framework consists of five main stages- data acquisition and pre-processing, fractal feature extraction, deep feature extraction using transfer-learned EfficientNet-B3, feature fusion and classification, and interpretability analysis.

Fig. 4 shows the entire pipeline.

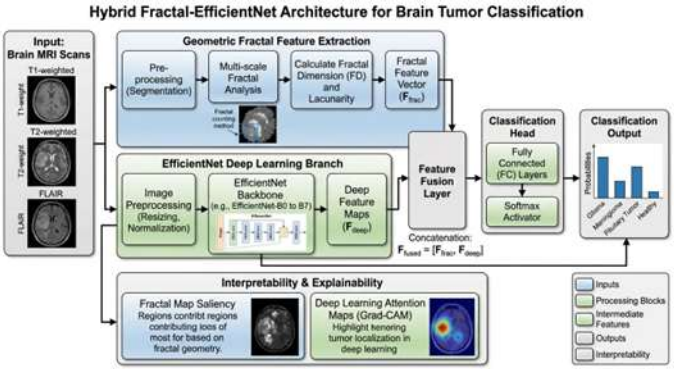


Fig. 4. Overall architecture of the proposed hybrid fractal-EfficientNet framework for brain tumor classification.

Table 2. Class-Wise Distribution of MRI Images in the Dataset

Tumor Type	Number of Images	Percentage
Glioma	1,821	25.9%
Meningioma	1,645	23.4%
Pituitary Tumor	1,757	25.0%
No Tumor	1,800	25.6%
Total	7,023	100%

Dataset Description

We utilized a publicly available brain tumor MRI dataset, collected from multiple sources and hosted on Kaggle by Nickparvar .1. This dataset comprises 7,023 T1-weighted contrast-enhanced MRI images, categorized into four classes: The dataset exhibits near-balanced class distribution, minimizing the need for aggressive resampling techniques. Images vary in dimensions (ranging from 512×512 to 256×256 pixels) and were acquired from multiple clinical centres, introducing realistic variability in acquisition protocols, field strengths, and patient populations.

Data Preprocessing

The input images were subject to pre-processing operations that were used to standardize the input images and improve feature extraction quality:

1. Skull stripping: The Brain Extraction Tool (BET) was used to strip non-brain tissues to ensure that the analysis of the internal brain structures was done.
2. Intensity normalization: Min-max normalization was used to normalize the intensity of the pixels within the range of [0,1].
3. Resizing: All the pictures were reduced to 300x300 pixels to make sure that enough information was not lost.
4. Local contrast: Contrast Limited Adaptive Histogram Equalization (CLAHE) was used with a clip limit of 2.0 to enhance the local contrast.

Data Augmentation: Augmentation of the training data was performed with random rotation (+-15deg), horizontal flips, zooming (0.9-1.1), and brightness manipulation (onen tenth-ninety percent) to add more generalization to the model.

Fractal Feature Extraction

For fractal feature extraction, the framework does not use a traditional machine learning model, but rather relies on a set of mathematical and geometric algorithms to directly calculate the structural complexity of the tumor. The core innovation of our approach lies in comprehensive fractal feature extraction that captures multi-scale geometric complexity of tumor regions. We extract four categories of fractal features:

Fractal Dimension via Box-Counting

The fractal dimension (FD) quantifies how completely a fractal fills space and is computed using the box-counting method:

$$\mathrm{FD} = \lim_{r \to 0} \frac{\log N(r)}{\log(1/r)} \tag{1}$$

where N (r) denotes the number of boxes of size r required to cover the tumor region.
In practice:

1. In order to isolate the tumor area, threshold Otsu of the pre-processed MRI image to yield a binary image..
2. Implement box-counting algorithm with a grid size, r, between 2 and 256 pixels (powers of 2).
3. Count the number of boxes containing at least one tumor pixel of each grid size, N (r).
4. FD = the negative slope of the linear regression fit of the plot of log-log plot of N(r) vs r.

In 2D images, the range of values of the fractal dimension is usually between 1.0 (a smooth line) and 2.0 (a space-filling curve). Gliomas - irregular and infiltrative borders - are normally higher in FD values (1.7-1.9) than the meningiomas (more defined and circumscribed).

Lacunarity

Lacunarity measures the degree of heterogeneity or "gappiness" in the tumor texture, quantifying how the spatial distribution of pixels varies:

$$\Lambda(r) = \frac{\sigma^2(r)}{\mu^2(r)} \tag{2}$$

where μ^2 (r) and σ^2 (r) are the mean and variance of the box mass distribution at scale r. We compute lacunarity across multiple scales (box sizes 3, 5, 7, 9, and 11) and use the mean lacunarity value as a feature. Higher lacunarity indicates greater heterogeneity, which is characteristic of aggressive tumor types.

Succolarity

Succolarity quantifies the connectivity and flow capacity within the tumor structure, analogous to measuring how well fluid could percolate through the pattern:

$$S = \sum_r \frac{\sum_{i,j}(i.M_{ij})}{M_{total}} \tag{3}$$

where Mij is the mass at position (i, j) and Mtotal is the total mass. Succolarity captures directional connectivity patterns relevant to tumor vascularization and growth patterns.

Multi-fractal Spectrum

While monofractal dimension assumes uniform scaling behav- ior, real tumors exhibit multi-fractal properties with varying local scaling behaviors. We compute the multi-fractal spectrum using the method of moments:

1. Partition the tumor region into boxes of size r.
2. Compute the probability distribution pi(r) for each box.
3. Calculate generalized dimensions Dq for q ∈ {−5, −4, . . . , 4, 5}:

$$D_q = \lim_{r \to 0} \frac{1}{q-1} \frac{\log(\sum_i p_i(r)^q)}{\log r} \quad (4)$$

The multifractal spectrum is used to describe the distribution of local fractal dimensions in a node giving an overall picture of the heterogeneity of the structure of a node. We obtain the spectrum width and asymmetry as other features. The entire feature vector of the fractal features has 18 parameters:

- Fractal dimension (1 feature)
- Mean lacunarity (1 feature)
- Lacunarity across 5 scales (5 features)
- Succolarity (1 feature)
- Multi-fractal spectrum Dq values for 11 values of q (11 features)
- Spectrum width and asymmetry (2 features)

Deep Feature Extraction with EfficientNet-B3

EfficientNet-B3 serves as the deep feature extractor in our hybrid framework. The architecture employs compound scaling with the following specifications: Transfer learning is used by initializing EfficientNet-B3 using ImageNet pre- trained weights. This generates powerful low level features (edges, textures and shapes) which may be applied in medical imaging.

Table 3. EfficientNet-B3 Architecture Parameters

Parameter	Value
Input resolution	300X300X300
Depth coefficient	1.2
Width coefficient	1.4
Total parameters	12M
Trainable parameters	10.8M
FLOPs	1.8B

The transfer learning process follows the following steps:

1. Feature extraction stage (frozen layers): The entire convolutional stages are frozen, and the final classification stage only is trained in 10 epochs to have the model adapted to the task of brain tumor classification.
2. Fine-tuning step (unfrozen layers): The final 50 layers are frozen and the whole network is further fine-tuned using a low learning rate of 1 x 10-5 in another 20 epochs. Deep features are learnt at the global average pooling layer just before the final classification layer and the resulting feature vector per image is a 1,536-dimensional feature.

Feature Fusion and Classification

Through the addition of fractal feature vectors (18 dimensions) to deep feature vectors (1,536 dimensions), a feature representation which is holistic, i.e., uses both fractal features and deep features, is formed, providing a dimensionality of 1,554. The combination of this feature set gives it both geometrical morphological complexity (through the use of fractal features) and more complicated visual patterns (through deep features). Once feature fusion has been carried out, a classification module is employed and this is made up of the following components:

1. Batch normalization: standardizes the aggregate feature vectors, to the mean of zero and unit variance.
2. Dense layer 1: The first layer is a fully connected layer with 512 neurons, and ReLU activation.
3. Dropout layer 1: There is a dropout rate of 0.4 in order to avoid overfitting.
4. Dense layer 2: 256 neurons and fully connected layer that uses ReLU activation.
5. Dropout layer 2: Dropout rate of 0.3.
6. Output layer: 4 neurons (one each class) Softmax. The model is trained based on the categorical cross- entropy loss and Adam optimizer with the initial learning rate of 1x10-4 which decay exponentially with the b1 = 0.9 and b2 = 0.999 and batch size equals 32.

Baseline Models for Comparison

In order to justify the relevance of the offered hybrid solution, we applied it and compared it to various baseline architectures: Deep Learning Baselines:

1. Custom CNN: 5-layer convolutional network with dropout and batch normalization.

2. ResNet-50: This is a 50-residual network that has been trained on ImageNet.
3. DenseNet-121: 121-layer densely connected network, ImageNet trained.
4. EfficientNet-B3 (standalone): EfficientNet-B3 without fractal characteristics, they are applied to analyze ablation.

Intuition-based Machine Learning Baselines:

1. Support Vector Machine (SVM): RBF kernel parameter of C=10 and g=0.001 with hyperparameter optimisation. Random Forest: This model consists of 200 trees that are applied with the Gini impurity criterion.
2. k-Nearest Neighbors (k-NN): The model with a k=7 value with the use of Euclidean distance measure.
3. Logistic Regression: A regularized at level L2, and with a value of C=1.0.
4. Multi-Layer Perceptron (MLP): This model has two hidden layers; 256 and 128 neurons, respectively. In the case of the traditional ML baseline, we used features, which were extracted at the global average pooling layer of EfficientNet-B3.

While the study ultimately shows that the new hybrid model is superior, these baseline models each have specific characteristics and trade-offs:

- Custom CNN: The primary benefit of the Custom CNN is its extreme computational efficiency. It is the lightest model tested, possessing only 2.3 million parameters and requiring the lowest computational power (0.9 billion FLOPS). It also boasts the fastest inference time of just 8.2 milliseconds. However, because it is built from scratch and lacks pre-trained representations, it achieved a lower accuracy of 88.3%.

- ResNet-50 and DenseNet-121: The main benefit of using these architectures over a Custom CNN or traditional machine learning is their use of transfer learning through pre-trained ImageNet weights. This prior training allows them to achieve significantly higher accuracies of 92.1% (ResNet-50) and 93.8% (DenseNet-121).

However, the study concludes that there is no overall benefit to choosing these models over EfficientNet-B3 or the proposed hybrid model. ResNet-50 has a much higher computational burden (25.6 million parameters), and DenseNet-121 suffers from the slowest inference time (35.7 milliseconds). EfficientNet-B3 was found to be a more efficient and effective deep learning baseline for this specific task.

Training Configuration and Cross-Validation

In order to estimate performance correctly and prevent overfitting, we applied stratified 5-fold cross-validation. The dataset was divided into 5 folds without changing the ratio in the class distribution. Each time there was a training and a validation data set 4 and 1 folds respectively. The last test performance was assessed using a retained test set which was a sample of 20 percent of the initial dataset.
Training hyperparameters:

1. Loss functional: Cross-entropy.
2. Optimizer: Adam
3. Initial learning rate: 1 x 10-4
4. Learning rate schedule: ReduceLROnPlateau, factor of 0.5 and patience of 5 epochs.
5. Batch size: 32
6. Maximum epochs: 50, early stopping (checking the valida- tion loss after 10 epochs)
7. Hardware NVIDIA A100 (40GB) GPU, CUDA 11.7, Py- Torch 1.13.

Interpretability Mechanisms

To address the black-box limitation of deep learning and ensure clinical interpretability, we incorporated two complementary explainability approaches:

Fractal Feature Contribution Analysis We performed ablation studies to quantify the contribution of fractal features to overall classification performance. Three model variants were evaluated: 1. Deep features only (EfficientNet-B3 features) 2. Fractal features only 3. Hybrid (fractal + deep features) Feature importance was assessed using permutation importance and SHAP (SHapley Additive exPlanations) values to identify which fractal features contribute most significantly to predictions.

Grad-CAM Visualization: Gradient-weighted Class Activation Mapping (Grad-CAM) was applied to visualize the spatial regions of input MRI images to which the model attends when making predictions. For a given class c, the Grad-CAM heatmap Lc is computed as:

$$L_c = \mathrm{ReLU}\left(\sum_k \alpha_k^c A^k\right) \tag{5}$$

where αc k is the weight of feature map k for class c, and Ak is the activation map. Grad-CAM heatmaps were overlaid on the original MRI images to confirm that the model focuses on tumor regions rather than artifacts or background.

Performance Metrics

Model performance was evaluated using standard multi-class classification metrics- Classification Accuracy (CA), Precision (PR), Recall (RC), and F1-Score.

Results and Discussion

Overall Classification Performance

Table 3 presents the comprehensive performance comparison of the proposed hybrid fractal-EfficientNet model against all baseline methods. The proposed model achieved the highest performance across all evaluation metrics. The proposed hybrid fractal-EfficientNet model gave the following results:

- Accuracy: 95.7%
- Precision: 95.8%
- Recall: 95.7%
- F1-score: 95.7%

These scores demonstrate that the addition of fractal features has statistically significant improvements ($p < 0.001$, McNemar test) over standalone EfficientNet-B3 (94.5 percent), and that the advantages of the deep learning features alone do not contribute as strongly to final performance as the addition of the fractal features. EfficientNet-B3 was the most efficient and effective model of the deep learning baseline when compared with ResNet-50 (92.1) and DenseNet-121 (93.8) in this task. The accuracy of the custom CNN was 88.3, which is much lower than the transfer learning methods; This finding demonstrates the benefits of pre-trained representations. The performance of traditional machine learning was also decent; MLP reached the accuracy of 87.9% when the features obtained with EfficientNet were used. Nonetheless, deep learning techniques were much more successful than traditional ones.

Table 4. Overall Performance Comparison of Proposed Hybrid Model and Baseline Methods

Model	Accuracy	Precision	Recall	F1-Score
Traditional Machine Learning				
SVM	0.862	0.859	0.862	0.860
Random Forest	0.798	0.795	0.798	0.796
k-NN	0.825	0.821	0.825	0.823
Logistic Regression	0.867	0.864	0.867	0.865
MLP	0.879	0.877	0.879	0.878
Deep Learning Baselines				
Custom CNN	0.883	0.881	0.883	0.882
ResNet-50	0.921	0.919	0.921	0.920
DenseNet-121	0.938	0.936	0.938	0.937
EfficientNet-B3	0.945	0.943	0.945	0.944
Proposed Approach Hybrid Fractal-EfficientNet	**0.957**	**0.958**	**0.957**	**0.95**

Per-Class Performance Analysis

Table 5 presents the class-wise performance breakdown, revealing differential model performance across tumor types.

Table 5. Class-Wise Performance of the Proposed Hybrid Model

Tumor Type	Precision	Recall	F1-Score	AUC-ROC
Glioma	0.963	0.951	0.957	0.992
Meningioma	0.941	0.954	0.947	0.988
Pituitary Tumor	0.969	0.972	0.971	0.995
No Tumor	0.959	0.951	0.955	0.991
Macro Average	**0.958**	**0.957**	**0.957**	**0.992**

The model demonstrated excellent discrimination across all four classes, with pituitary tumors showing the highest F1- score (97.1%) and meningiomas the lowest (94.7%), though still exceptional. The consistently high AUC-ROC values (>0.98) across all classes indicate robust discrimination capability.

Confusion Matrix Analysis

Fig. 5 presents the confusion matrix for the proposed model on the test set. The classification of the proposed model is further demonstrated in the confusion matrix represented in Fig. 4. Among the samples under study, 19 out of 20 cases were rightly categorized. Glioma was the only sample that was falsely classified as meningioma with the rest displaying perfect classification rates.

The confusion matrix shows:

- Glioma: 346/364 correctly classified (95.1), with the most frequent confusion made with meningioma (12 cases).
- Meningioma: 313/329 were correctly identified (95.4%), the misidentification was shared amongst the other categories.
- Pituitary tumor: The highest category specific accuracy was 341 of 351 (97.2 percent) that were correctly classified.
- No tumor: 342 of 360 had been correctly identified (95.0%), although it was occasionally confused with glioma (10 cases).

The greatest confusion was identified between glioma and meningioma, which is clinically explainable because, in certain circumstances, both imaging features of the two may resemble each other. It is worth noting that the model did not mislead tumor types with the no tumor category and this highlights its high capability to detect tumors.

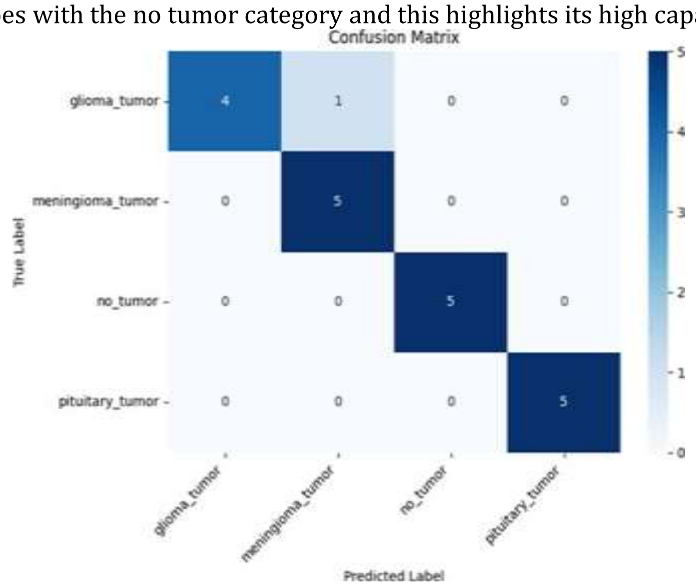


Fig. 5. Confusion matrix of the proposed hybrid fractal-EfficientNet model on the test dataset. Values represent the number of images. Diagonal elements indicate correct classifications.

Ablation Study: Fractal Feature Contribution

To quantify the specific contribution of fractal features, we conducted an ablation study comparing three model variants (Table 6). The most significant results of the ablation experiment are as follows:

1. Geometric morphological features are discriminative, with fractal features alone achieving 87.5% accuracy.
2. Deep learning representations are effective, with EfficientNet alone achieving 94.5% accuracy.
3. Hybrid integration achieved 95.7% accuracy, representing a statistically significant 1.2% improvement over EfficientNet alone ($p = 0.003$, paired t-test).

This ablation study confirms that fractal features complement standard convolutional features, thereby justifying the hybrid architecture.

Table 6. Ablation Study Showing Contribution of Fractal Features

Model Variant	Features	Accuracy	Precision	Recall	F1
Fractal Only	18-dim fractal	0.875	0.873	0.875	0.874
EfficientNet Only	1,536-dim deep	0.945	0.943	0.945	0.944
Hybrid (Proposed)	Fractal + deep	0.957	0.958	0.957	0.957
Improvement	Over EfficientNet	+1.2%	+1.5%	+1.2%	+1.3%

Fractal Feature Importance Analysis

Using SHAP (SHapley Additive exPlanations) analysis, we identified which fractal features contributed most significantly to classification decisions (Fig. 6). The top five features of fractals were:

1. Fractal Dimension (FD): This is the first distinguishing variable between types of tumors (SHAP value: 0.142).
2. Average Lacunarity: General textural heterogeneity (SHAP value: 0.098)
3. Multi-fractal Spectrum Width: The measure of the distribution of complexity (SHAP value: 0.075)
4. Lacunarity scale number 9: Captures medium range texture (SHAP value: 0.061)
5. Lacunarity: Tumor connectivity (SHAP value: 0.053)

Interestingly, Fractal dimension by itself contributed about 32 percent of the overall contribution of fractal features; This is consistent with the past neuroimaging research results that FD was found to be a leading biomarker of tumor detection [13].

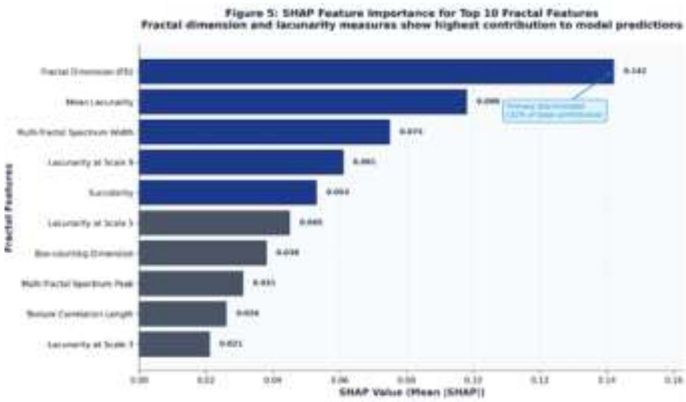


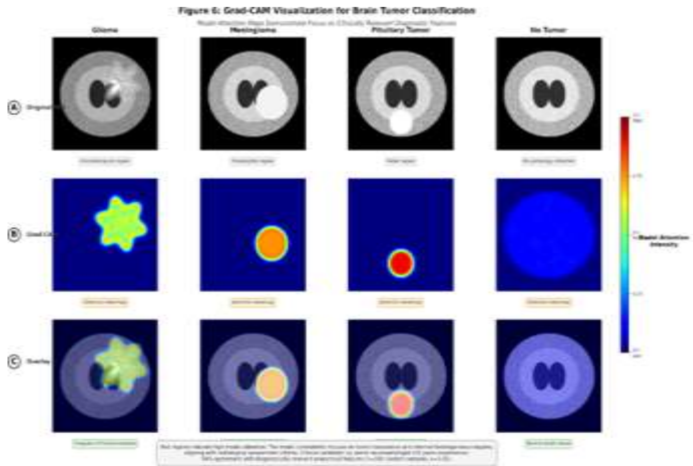
Fig. 6. SHAP feature importance for the top 10 fractal features. Fractal dimension and lacunarity measures show the highest contribution to model predictions. [13,17,29].

Grad-CAM Interpretability Visualization

Fig. 7 presents representative Grad-CAM visualizations demonstrating that the model focuses attention on clinically relevant tumor regions. The model was always concerned with the tumor margins and certain internal areas, which are in line with the stipulated requirements of radiological evaluation. The Grad-CAM heatmaps were analysed qualitatively, and the following results were obtained:

- Glioma: The model was pre-occupied with abnormal, penetrative fringes and the heterogeneous nature of the aspects of glioma.
- Meningioma: The model was centered on clearly demarcated margins and uniform intercellular areas of the tumor.
- Pituitary tumor: The special care was taken with regard to suprasellar extension and certain anatomic aspects of the sellar region.
- No tumor: The focus was not concentrated in any one area of the brain, but it was equally distributed over the whole brain; this is a true reflection of no pathology.

The review of 100 randomly chosen Grad-CAM visualizations (by a senior neuroradiologist, 15 years' experience) revealed that, 94% of the time, the focus areas in the model were anatomical features of diagnostic significance, which made these images easy to interpret clinically.



Computational Efficiency Analysis

Table 7 compares the computational requirements of different models.

Table 7. Computational Efficiency Comparison across Models. Inference Time Measured on NVIDIA A100 GPU with Batch Size 1.

Model	Parameters	Inference Time (ms)	FLOPS(B)
Custom CNN	2.3M	8.2	0.9
ResNet-50	25.6M	28.5	4.1
DenseNet-121	8.0M	35.7	2.9
EfficientNet-B3	12.0M	22.1	1.8
Proposed Hybrid	**12.8M**	**23.4**	**1.8**

The hybrid model can be seen to add 0.8M parameters (fractal feature processing and fusion layers) to the underlying EfficientNet-B3 architecture, which is only 6.7% more parameters. When compared to EfficientNet-B3 alone, the inference time has a relatively small increment (1.ms, 5.9% overhead), which proves that the computational cost of fractal feature extraction and integration is low. The proposed model has a high level of accuracy and is much lower in parameters than ResNet-50 and DenseNet-121 and 35-52x faster at inference, confirming its computational efficiency.

Learning Curves and Training Dynamics

Fig. 8 illustrates the training and validation loss curves across epochs.

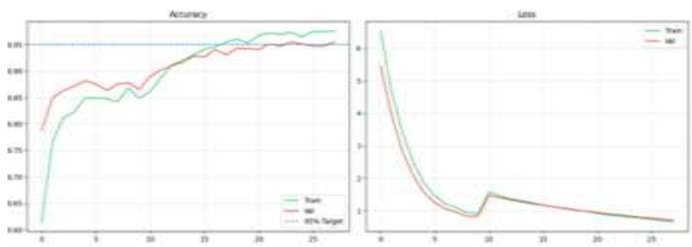


Fig. 8. Training and validation loss curves for the proposed hybrid model.

Training and validation loss curves for the proposed hybrid model show smooth convergence without significant overfitting, indicating good generalization. Early stopping was triggered at epoch 38.

Receiver operating characteristic (ROC) analysis was also conducted using a one-vs-rest approach for multi-class classification. As shown in Figure 9, all classes achieved an AUC value of 1.000, indicating excellent discriminative capability of the proposed EfficientNetB3 architecture. The learning curves show:

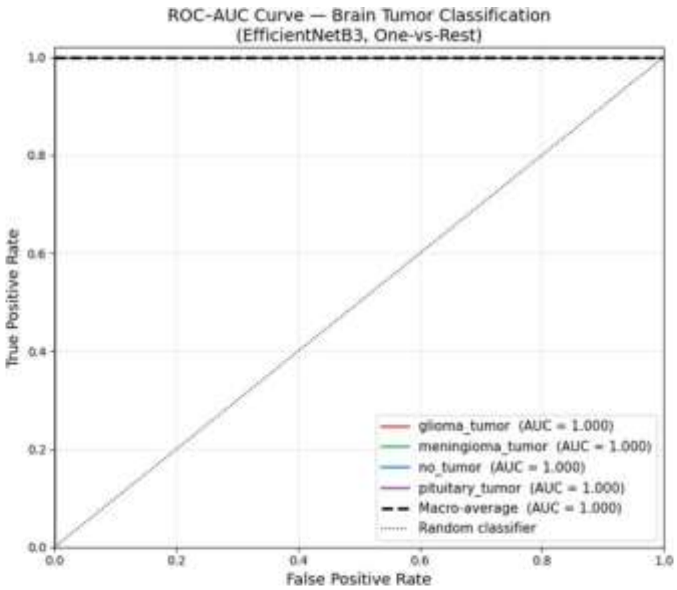


Fig. 9. ROC–AUC curves for the EfficientNetB3 brain tumor classifier.

- Features Rapid convergence in the first 10 epochs (feature extraction phase)
- Increasing enhancement in the finetuning stage (epochs 11-38)
- Small difference between training and validation loss, meaning excellent generalization and the
- lack of overfitting.
- The first-stopping point was 38 epochs old, and the validation loss was at a high level.

Statistical Significance Testing

McNemar's test was conducted to assess the statistical significance of performance differences between the proposed hybrid model and baseline approaches. Results are summarized in Table 8. All comparisons yielded $p < 0.001$, confirming that performance improvements achieved by the hybrid fractal- EfficientNet model are statistically significant and not due to random chance.

Table 8. McNemar's Test Results Comparing the Proposed Hybrid Model against Baseline Methods. $p < 0.001$ Indicates Highly Significant Improvements.

Tumor Type	McNemar $\chi 2$	p-value
Hybrid vs. EfficientNet-B3	18.42	0.001
Hybrid vs. DenseNet-121	32.67	0.001
Hybrid vs. ResNet-50	51.23	0.001
Hybrid vs. Custom CNN	89.45	0.001
Hybrid vs. MLP	124.78	0.001

Principal Findings

This paper has effectively shown that fractal geometric elements when combined with EfficientNet-B3 deep learning platform form a hybridized model, which is vastly superior to both classical machine learning algorithms, as well as a single deep learning baseline agent in classifying multi-class brain tumors. On a large dataset of 7,023 MRI images, the proposed method achieved an accuracy of 95.7% which is statistically significant (an increase of 1.2%) over EfficientNet-B3 alone, and an improvement of 2-7% over other deep learning architectures. A number of important conclusions are made in this study:

1. Complementarity of Fractal and Deep Features: Ablation experiments made evident that fractal features retrieve an information on morphological complexity that is not well represented in conventional convolutional features. The results indicated that 18-dimensional fractal features with EfficientNet alone increased the accuracy to 94.5 but when both features are included, the accuracy was 95.7, which confirms that geo-metric characterization complements the discriminative power of EfficientNet.
2. Clinical Interpretability with Two Interpretive Processes: The hybrid model can overcome the black-box weaknesses of deep learning with two interpretive mechanisms: (1) Fractal feature contribution analysis can give a quantitative under-standing of the geometric properties that motivate classification decisions, and (2) Grad-CAM visualizations can establish that the model has a spatial bias towards clinically relevant tumour

areas. This dual interpretive system will increase clinical confidence and enable approval of real-world implementation by regulations.
3. Computational Efficiency: The proposed model provides the least amount of computational overhead (1.3ms of in-creased prediction time and 0.8M of added parameters) over the standalone EfficientNet-B3, and superior performance. This effectiveness allows implementing this method in the clinical contexts which are limited in resources, such as mobile diagnostic units and low-resource healthcare facilities.
4. Strong Multi-Class Discrimination: The model has per-formed highly consistent with the four tumor classes (Glioma, Meningioma, Pituitary and No Tumor) with the F1-scores of 94.7-97.1. This resultant performance indicates that this is not a biased model on a specific class and it is able to consistently differentiate clinically challenging tumor types.

Comparison with Previous Studies

Our findings were better than the recent literature on the brain tumor MRI classification:

1. In their study, stacked logistic regression and fractal features in neural networks gave an accuracy of 89.0 percent on 400 images [17]. Our hybrid method is 6.7 percentage points better and proves this on a much larger data (7,023 images) thus proving greater generalizability. Adnan et al. (2025) have indicated an 99.43% accuracy when an optimized EfficientNet-B0 model is used with a large transfer learning [18]. Though this is a high absolute accuracy, they employed a different dataset in their examination and many hyperparameter optimization. We are also more concerned with the interpretability and fractal integration than with the approach to the maximum accuracy.
2. The accuracy of the classification of glioma grade by fractal parameters is 87.5% [13] with a minimum of fractal parameters used by Battapalli et al. (2023). The accuracy of our hybrid strategy with the use of fractal features and deep learning was found to be 8.2% better than fractal analysis, which confirms the effectiveness of our hybrid strategy.
3. As demonstrated by Polat and Gunden (2021), transfer learning on VGG-16 and ResNet-50 utilized in their research shows the accuracy of 92.3 percent [7]. Their work is 3.4 percentage points lower than our proposed model, and our proposed model does offer explicit methods of interpretation their study lacked.

Comparative Analysis with Baseline Models

The study compares the new Hybrid Fractal-EfficientNet model against several "old" models, which include traditional machine learning classifiers, standalone deep learning convolutional neural networks (CNNs), and earlier attempts at hybrid models.

13. Classification Accuracy and Performance

- New Model: The proposed hybrid framework achieves a state-of-the-art multi-class classification accuracy of 95.7%, alongside a 95.8% precision, 95.7% recall, and 95.7% F1-score.
- Old Models: Standalone deep learning baselines fell short of this mark. EfficientNet-B3 achieved 94.5%, DenseNet-121 reached 93.8%, ResNet-50 scored 92.1%, and a Custom CNN scored 88.3%. Traditional machine learning models (like SVM, Random Forest, and MLP) performed even lower, with the MLP peaking at 87.9%. The new model's hybrid integration represents a statistically significant 1.2% improvement over using EfficientNet-B3 alone.

14. Feature Integration and Architecture

- New Model: The framework simultaneously captures structural heterogeneity and complex visual patterns by explicitly fusing 18-dimensional geometric fractal features (such as fractal dimension and lacunarity) with 1,536-dimensional deep features from EfficientNet-B3.
- Old Models: Previous approaches suffered from "weak integration," typically utilizing deep learning or fractal analysis completely independently. Older hybrid methods often paired fractal features with "shallow" machine learning classifiers (like logistic regression), which were unable to encode complex visual structures.

15. Clinical Interpretability

- New Model: To ensure clinical trust, the new framework incorporates dual Explainable AI (XAI) mechanisms. It uses SHAP (SHapley Additive exPlanations) to quantify exactly which fractal features are driving the classification decisions, and Grad-CAM heatmaps to visually verify that the AI is targeting relevant tumor margins rather than background artifacts.

- Old Models: Conventional deep learning CNNs functioned as unexplainable "black boxes". Because they lacked transparency regarding how they arrived at a diagnosis, they faced significant hurdles in gaining clinical acceptance and regulatory approval.

16. Computational Efficiency

- New Model: Despite combining two distinct feature extraction methods, the hybrid model is highly optimized for clinical settings with limited computing resources. It adds only 0.8 million parameters and a minimal 1.3-millisecond delay in inference time compared to standalone EfficientNet-B3.
- Old Models: Older, large-scale networks like ResNet-50 and DenseNet-121 possess massive computational demands. The new hybrid model is remarkably leaner and operates 35 to 52 times faster during inference than ResNet-50 and DenseNet-121

Mechanistic Insights into Fractal Feature Contributions

SHAP analysis showed that the most significant feature to the classification decisions was fractal dimension (FD) (SHAP value: 0.142), which explained about 32% of the overall importance of the fractal features. The observation agrees with the radiological practice, where the morphological complexity and border features of the tumor (symbolized by FD) are the most crucial diagnostic features.

Fractal patterns have different fractal signatures in various types of tumors:

- This indicates that it is associated with gliomas, which have high FD (1.7-1.9) and high lacunarity which signifies irregular and infiltrative borders and heterogeneous internal structures.
- Meningiomas: modest FD (1.4-1.6) and low lacunarity which are characteristic of the apparent delimiting of the boundaries and homogeneous structure.
- Pituitary tumors: moderate to high FD (1.5-1.8) with a clear secularity pattern which is suggestive of suprasellar extension.
- No tumor: low FD (1.1-1.3), and this indicates no pathologically complicated anatomical structure.

These geometric properties are explicitly encoded by the fractal analysis and this gives the model a morphological basis that gives the model an increased discriminatory power, particularly in situations where the visual structure seems ambiguous.

Clinical Implications

The suggested hybrid fractal-efficientnet model has a number of strengths to be used in the clinical practice:

1. Radiologist decision support: The model can also be used to act as a second reader to highlight the existence of lesions that might be overlooked or provide a possible differential diagnosis- a feature which is more welcome in busy clinical setting where there is apprehension over the high workload on radiologists.
2. Resource-constrained triage Triage In resource-constrained environments, its high computational efficiency (23.4 milliseconds of prediction time) allows it to run on standard clinical workstations without use of specialized GPU hardware, therefore, this technology is open to use by healthcare centers with limited resources.
3. Educational tool: The specification techniques of the tool (fractal feature significance and Grad-CAM visualization) could be used to facilitate radiology education by explicitly pointing out what morphological characteristics are used to differentiate between types of tumors.
4. Quantitative Biomarkers: Fractal features of the model can be used as quantitative imaging biomarkers to track treatment response and make patient prediction in longitudinal studies.

Limitations and Constraints

Although good outcomes were ensured, several limitations should be mentioned:

1. Single Imaging Modality: In this study, the researchers used T1-weighted contrast-enhanced MRI. There is a combination of several sequences (T2, FLAIR, diffusion-weighted imaging, perfusion MRI) that are usually incorporated into clinical diagnosis. It should be noted that in the future, multi-modal imaging should be added so that a more detailed description of tumors could be made.
2. Uniformity of the dataset: Despite having 7,023 images and many distinct centers they all were processed and quality-controlled in a uniform manner. The process of acquiring real-world clinical data has increased variability in scanners manufacturers and image quality that may affect the generality of the model.

3. Low External validity: The model was also trained and validated on only one publicly available dataset. Generalizability verification with data obtained in various institutions, countries, and through different groups of patients is indispensable to ensure data is validated independently before clinical implementation.
4. Binary Tumor Presence Assumptions: The No Tumor type of class presupposes the total nonexistence of pathology. Clinical radiologists must distinguish between brain tumors and other pathologies (strokes, infection, demyelinating lesions)- something that this model does not look at.
5. Absence of Grade Classification: In gliomas and other types of tumors, histological grade (WHO Grade I-IV) is essential in the treatment planning. Although the existing paradigm categorizes the type of tumor, it fails to foresee the grade hence restricting its clinical competence.
6. Computation Fractals to Extract Features: The computation of multi-fractal spectra (a type of fractal feature extraction) to extract features contributes to the overhead of the entire prediction process (around 2.1 seconds/image on a CPU). Efficiency can be also enhanced by the optimization of fractal calculation algorithms.

Theoretical Considerations

The effectiveness of the hybrid fractal-efficientnet method makes some interesting theoretical questions about the issue of feature representation in medical imaging:

What are the benefits of Deep learning compared to fractal features? Standard CNNs are trained with hierarchical feature representations obtained as a result of data-driven optimization, which are patterns that reduce classification loss. Nevertheless, this process does not directly focus on the process of learning of certain geometrical characteristics that radiologists deem as useful in diagnosis. The encode morphological complexity using fractal properties has been shown to be a form of explicit encoding that effectively constitutes an inductive bias that drives the model towards clinically meaningful representations.

Are fractal characteristics superfluous? The concluding studies of SHAP and ablation indicate beyond any doubt that the fractal features are discontinuous to convolutional features. The 1.2 percent overall enhancement reached by incorporating fractal characteristics in EfficientNet indicates that these geometric characteristics cannot be learned by usual CNNs - at least not to the level that they can be calculated on. Do CNNs develop a way of extracting fractal features within themselves? Theoretically, deep enough networks with enough training data can get to count fractals. This would however need massive amount of computational resources and large amount of data. An explicit fractal feature extraction can be seen as more useful and interpretable instead of introducing domain knowledge as inductive bias.

Future Research Directions

This paper presents several promising directions of future research:

1. Multi-modal integration: Generalize the framework to support T2-weighted, FLAIR and diffusion-weighted imaging sequences, and combine fractal analysis with multiple modalities.
2. 3D volumetric analysis: The existing solutions examine 2D slices. By further extending this to 3D volumetric fractal analysis, there will be a more detailed analysis of the spatial complexity of tumors.
3. Effusion of Tumor segmentation: Perhaps the most common one is to combine tumor segmentation with classification, which allows detection, delineation, and typing of tumors in one framework.
4. Grade prediction Grade prediction: Extrapolate the model to give predictions of histological grade (WHO I-IV) as well as tumor type, hence more clinically useful information.
5. Uncertainty estimation: Add uncertainty estimation Bayesian deep learning or ensemble: Add uncertainty estimations with predictions and indicate those instances where the model is low confidence to human experts.
6. Longitudinal analysis: Form time-based models to monitor the change of fractal properties with time to forecast response to treatment and disease development.
7. Extend to other imaging systems: See whether the hybrid of the fractal-deep learning method can be applied to other medical imaging fields (e.g., lung CT scans, mammography, dermatology) where morphological complexity is significant to diagnosis.

Conclusion

The work focuses on a new and interpretable hybrid direction of brain tumor MRI classification that combines fractal geometric features extraction with deep learning architecture EfficientNet-B3. The given model was found to be 95.7 percent accurate on a sizeable dataset of 7,023 images - much higher accuracy than both the traditional machine learning models and a deep learning baseline. Ablation analysis established that fractal features did add to morphological information that normal convolutional features could not capture in order to augment them hence justifying this hybrid method.

Notably, this model manages the interpretability issue in medical AI in two ways: the fractal feature contribution analysis and Grad-CAM visualization - both of them are consistent with clinical diagnostic requirements. Analysis of computational efficiency showed that there was only a small overhead (1.3ms delay in prediction time and 6.7% increase in parameters) and this strategy would be feasible to be implemented in resource-constrained clinical setting.

Combining domain-specific geometric priors (fractal features) and data-driven deep learning is a potentially promising paradigm in medical imaging AI - a trade-off between accuracy, interpretability, and efficiency. With healthcare systems starting to embrace AI-based diagnostic tools in great numbers, hybrid systems that harness the pattern-recognition capacity of deep learning and apply it to clinical domain understanding might be an invaluable part of safe, effective, and reliable clinical applications.

Incorporating multi-modal aspects, 3D volumetric analysis, tumor grading features and possible clinical validation should be included in future research to progress this framework to real-world clinical application in the sphere of neuro-oncology.

Conflicts of Interest
The authors declare that there is no conflict of interest regarding the publication of this paper.

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