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Evaluation Of Brain Tumor Models Using Optimal Deep Learning Approaches

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Abstract - Brain tumor classification using Magnetic Resonance Imaging (MRI) is a pretty important task in medical image analysis, especially for helping early diagnosis and deciding treatment plans. Usually, doctors and radiologists do it by hand, manual interpretation, but that takes time and the results can vary a bit, sometimes quite a lot. In this paper, we introduce an explainable deep learning setup, built on the ConvNeXt-Tiny architecture, and we use transfer learning plus phased fine-tuning, for multiclass brain tumor classification. The method groups MRI scans into four broad labels: glioma, meningioma, pituitary tumor, and no-tumor. Before training, we do image preprocessing and use data augmentation to make the model more robust, and also to improve generalization. That includes normalization, rotation, flipping, zooming, and brightness adjustment. To make the whole system feel more transparent and dependable, Gradient-weighted Class Activation Mapping (Grad-CAM) is added, so we can see which tumor areas are actually driving the prediction, kind of like a visual clue. In the experiments, the proposed framework reaches 93.48% accuracy, 94.20% precision, 92.86% recall, 93.53% F1-score, and a 99.22% ROC-AUC score. Overall, the framework gives accurate results while staying interpretable, so it could fit well into intelligent clinical decision-support tools, where automated brain tumor diagnosis is expected to be both fast and understandable.

Keywords - Brain Tumor MRI, Deep Learning, ConvNeXt, Explainable AI, Grad-CAM.

1. Introduction

Brain tumors represent one of the most severe neurological diseases because they lead to complete brain function loss and death of affected patients. The two main tumor types exist as benign tumors which grow slowly and malignant tumors which develop rapidly and result in greater death rates. The diagnosis needs to be both precise and timely because it directly affects how doctors create treatment strategies and what medical results they will achieve [1]–[3]. The medical field uses Magnetic Resonance Imaging (MRI) as a standard tool to detect brain tumors because it produces high-resolution images that show detailed brain tissue structural information [4], [5].

In recent years, artificial intelligence (AI), especially deep learning (DL), has achieved exceptional advancements for medical image analysis. The brain tumor classification task shows the strong ability of Convolutional Neural Networks (CNNs) and transfer learning models which include VGG, ResNet, DenseNet, and ConvNeXt to extract hierarchical features from MRI images without human input according to research [7]–[9]. The models decrease the need for human assessment while they enhance diagnosis precision according to research [10], [11].

The current state of deep learning systems remains restricted because most models function as black-box systems which create challenges for users who need to understand their operations. The ability to comprehend model prediction methods constitutes a fundamental requirement for implementing healthcare applications. Explainable Artificial Intelligence XAI serves as the primary research domain which aims to enhance both transparency and system understandability of artificial intelligence systems [12], [13].

XAI techniques such as Gradient-weighted Class Activation Mapping (Grad-CAM), Local Interpretable Model-Agnostic Explanations (LIME), and Shapley Additive Explanations (SHAP) provide visual explanations by highlighting important regions in MRI images that influence model predictions [14] [16]. The methods help doctors to confirm the model decisions which leads to stronger trust in diagnostic systems that use artificial intelligence.

Recent studies have focused on integrating deep learning with explainable AI to improve both system performance and system reliability. The combination of hybrid models with ensemble approaches and attention-based architectures has achieved better classification performance while maintaining system stability, according to research studies [6], [17], [18]. The research investigates federated learning together with multi-dataset techniques to enhance general system performance while protecting user privacy [1], [19]–[21]. The research system faces multiple obstacles which include restricted dataset diversity and excessive computational needs and inability to generalize results across different datasets and absence of proper clinical testing. The majority of current research studies focus on enhancing performance but they show only basic results when it comes to demonstrating interpretability and practical usage in the real world [3], [22], [23].

The paper introduces a deep learning framework which uses explainable AI methods to perform brain tumor classification. The system aims to reach accurate classification results while delivering visual explanations which will enhance transparency and reliability and clinical applications of AI diagnostic systems.

RELATED WORK

Recent advancements in brain tumor detection have been significantly driven by deep learning and explainable artificial intelligence (XAI) techniques. Traditional machine learning approaches depended on manual feature creation and basic classification systems which failed to deliver reliable performance across different situations. Deep learning models demonstrate better performance than traditional shallow learning methods because they use Convolutional Neural Networks (CNNs) to automatically extract multiple levels of features from MRI images [4], [7].

Deep Learning-Based Approaches

Deep learning has become the dominant approach for brain tumor classification. CNN-based architectures such as VGG, ResNet, DenseNet, and ConvNeXt have achieved high ac curacy in medical image analysis tasks [7]–[9]. Rasheed et al. [7] and Agarwal et al. [4] demonstrated the effectiveness of CNNs in automated tumor classification, achieving strong performance across multiple datasets.

Recent works have also explored advanced architectures and feature extraction techniques. Pant et al. [8] proposed a ConvNeXt-based framework that improves generalization and classification accuracy, while Mehmood and Bajwa [9] further validated the effectiveness of ConvNeXt for tumor grading tasks. Additionally, multi-scale and attention-based models such as the one proposed by Ke et al. [32] enhance feature representation by focusing on important tumor regions, leading to improved classification performance.

Hybrid and Ensemble Models

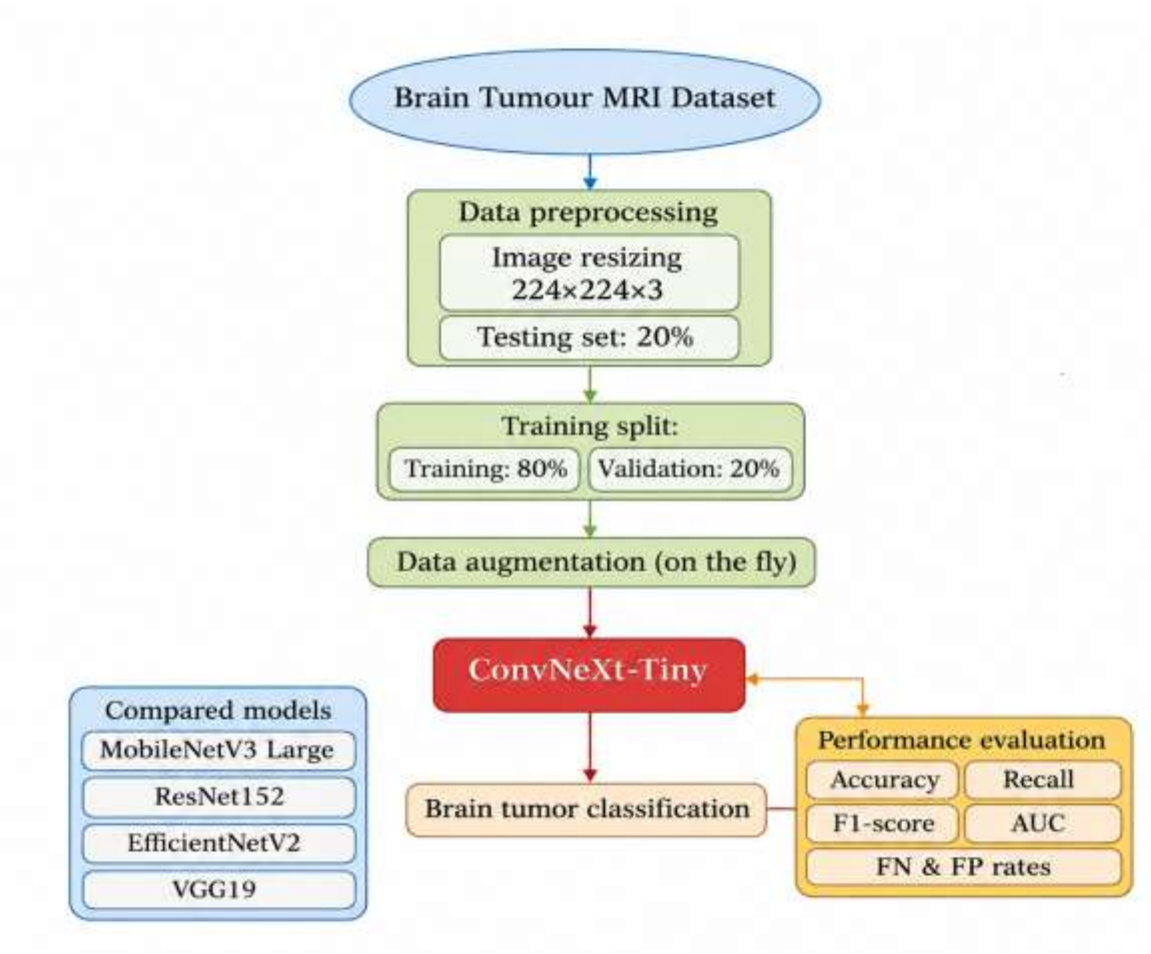
Hybrid models that combine deep learning with traditional machine learning methods have shown effective results because they increase both classification accuracy and system stability. Gundogan [17] developed a hybrid CNN-based model which uses explainable AI to achieve high performance in multi-class classification tasks. Sánchez-Moreno et al. [6] created an ensemble-based CNN framework which combines multiple architectural designs to enhance both accuracy and interpretability of their system.

Other studies used attention mechanisms together with ensemble learning methods to achieve better results in their studies. Nahiduzzaman et al. [10] and Aiya et al. [24] developed hybrid models that use attention mechanisms to boost classification performance while their systems remain strong across various testing conditions. The approaches show that using multiple models or techniques together leads to improved system performance and trustworthiness.

Explainable Artificial Intelligence (XAI)

Deep learning models achieve excellent performance results, yet their inability to provide interpretable results prevents their use in clinical settings. XAI techniques have become standard components in brain tumor classification systems to solve this problem. The methods of Grad-CAM, LIME and SHAP deliver visual explanations through their ability to identify MRI image areas which impact model prediction results [14] [16].

Chel and Poh [14] demonstrated Grad-CAM and LIME as effective tools for enhancing model transparency. Adnan et al. [25] developed an interpretable deep learning system which supports better clinical decision-making. Rahman et al. [26] used SHAP-based feature analysis to achieve better accuracy results and improved system interpretability. Recent studies have investigated new explainability systems through their recent academic studies. Gagliardi et al. [27] developed an MRI analysis system which combines two dis tinct explainable AI technologies. Mastoi et al. [19] created a federated learning system which uses XAI to provide secure data protection and system transparency. The two methods demonstrate that medical AI systems require transparent de sign to maintain their trustworthiness.



Advanced and Emerging Approaches

Fig. 1 Proposed methodology for multiclass brain tumor classification.

Recent research has focused on integrating advanced techniques such as transformers, federated learning, and multi modal analysis. Hosny and Mohammed [13] provided a com prehensive survey on vision transformers and explainable AI for brain tumor detection, highlighting their potential n improving model performance. The researchers achieved effective classification outcomes by developing a hybrid model that combined Vision Transformer (ViT) and GRU with XAI. Federated learning approaches have also been explored to address data privacy concerns. Mastoi et al. [19] and Gupta et al. [20] proposed privacy-preserving frameworks that enable collaborative learning across multiple institutions without shar ing sensitive data. The recent studies by Hussain et al. [28] and Kumar and Singh [29] developed hybrid systems that combine deep learning with machine learning and explainability to enhance accuracy and dependability.

Research Gaps

Although significant progress has been made, several challenges remain in brain tumor classification systems. Many studies focus primarily on improving classification accuracy while neglecting interpretability and clinical validation. Additionally, issues such as limited dataset diversity, high computational complexity, and poor generalization across datasets still persist [30], [31].

XAI methods display information through visual, their assessment process uses qualitative techniques because there is no established framework to evaluate their interpretative capabilities. The current research needs to create systems which achieve three goals: precise results, understand able results, and practical usage in field settings.

Materials and Methods

The proposed framework is designed for multiclass brain tumor classification using Magnetic Resonance Imaging (MRI) images. The methodology consists of dataset preparation, image preprocessing and augmentation, deep learning-based feature extraction, explainable classification, and performance evaluation. The overall workflow of the proposed system is illustrated in Figure 1.

a. Dataset Preparation

The research study uses publicly accessible brain tumor MRI datasets which contain multiple categories of brain tumors including glioma, meningioma, and pituitary tumor images together with no-tumor images. A total of 5600 images are used for training and validation, while 1600 images are reserved for testing. The dataset is balanced across all classes to reduce classification bias and improve model robustness [7], [8]. The dataset is divided into training, validation, and testing subsets to ensure proper model generalization and unbiased evaluation. Data diversity plays a critical role in improving model robustness and performance [4].

b. Image Preprocessing and Augmentation

Image preprocessing is performed to improve image quality and enhance model performance. First, all MRI scans are resized into 224×224 pixels, also they are normalized prior to being fed into the deep learning model. Then, in order to boost generalization and limit overfitting a bit, different data augmentation steps are used, like horizontal flipping, random rotation, zoom, translation, brightness adjustment, and contrast enhancement. On top of that, noise reduction procedures are applied to clear away irrelevant artifacts from the MRI images. In practice, these preprocessing moves help the model learn stronger features and they make it more robust for multiclass classification tasks.

c. Proposed Model Architecture

The proposed framework is based on the ConvNeXt-Tiny deep learning architecture because of its strong feature extraction capability and improved classification performance in medical image analysis tasks. The architecture consists of an input layer, convolutional feature extraction layers, pooling layers, fully connected layers, and a softmax output layer for multiclass classification. Transfer learning is employed using pretrained ImageNet weights to accelerate convergence and improve feature representation capability. The ConvNeXt-based framework effectively captures complex spatial features from MRI images and provides improved classification accuracy compared with traditional CNN models.

The SoftMax function is used in the output layer to calculate the probability distribution for multiclass classification and is represented in Equation (1).

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}}$$

where $P(y_i)$ represents the predicted probability of class i, z_i denotes the output logits, and n represents the total number of output classes.

d. Training Strategy

The model training process follows a phased transfer learning strategy. Initially, the backbone layers of the pretrained ConvNeXt-Tiny network are kept frozen, while just the classification layers get trained. Then in the second stage, some deeper blocks are selectively opened up for fine-tuning, and for better feature refinement. Adam optimizer does the work, with a learning rate set to 0.0001 and a categorical cross-entropy loss function, since this is for multiclass classification. The batch size is kept somewhere between 16 and 32, and training runs across a bunch of epochs, depending on how fast convergence looks. Early stopping is also used, plus learning rate scheduling, so it can avoid overfitting, and keep training more stable. The categorical cross-entropy loss function used during model training is expressed in Equation (2).

$$L = -\sum_{i=1}^{n} y_i \log \hat{y}_i$$

where y_i represents the actual class label, $\hat{y}_i$ denotes the predicted probability, and n is the total number of classes.

e. Explainable Artificial Intelligence Framework

The model performance needs Explainable AI (XAI) methods because they enhance its capacity to show how it operates. The MRI classification system uses Grad-CAM to create heatmaps which identify crucial areas that determine the classification outcome [14], [16]. The model uses LIME and SHAP to produce both local and global model prediction explanations which enhance transparency and trustworthiness for clinical applications [15].

f. Evaluation Metrics

The proposed model gets its performance assessment through standard classification metrics.

Table 1. EVALUATION METRICS

Metric	Formula	Description
Accuracy	$\frac{(TP + TN)}{(TP + FP + FN + TN)}$	Overall correctness
Precision	$\frac{TP}{(TP + FP)}$	Correct positive predictions
Recall	$\frac{TP}{(TP + FN)}$	Sensitivity
F1-Score	$2 \times \frac{Precision \times Recall}{Precision + Recall}$	Balance between precision and recall

Results and Discussion

The proposed ConvNeXt-Tiny based framework was evaluated using standard multiclass classification metrics, including accuracy, precision, recall, F1-score, and ROC-AUC.

Quantitative Performance Evaluation

The proposed ConvNeXt-Tiny based framework is evaluated using standard multiclass classification metrics, including accuracy, precision, recall, F1-score, and Receiver Operating Characteristic – Area Under Curve (ROC-AUC). The experimental results demonstrate strong classification performance across all tumor categories, indicating the effectiveness of the proposed deep learning framework for automated brain tumor diagnosis.

Table 2. Performance Metrics of Proposed Model

Metric	Value(%)
Accuracy	93.48
Precision	94.20
Recall	92.86
F1-Score	93.53
ROC-AUC	99.22

The high ROC-AUC score demonstrates excellent discriminative capability between different tumor classes. The obtained results are comparable with recent ConvNeXt-based and hybrid deep learning approaches reported in the literature. The performance evaluation confirms that the proposed framework effectively extracts discriminative spatial features from MRI images and provides reliable classification performance.

Confusion Matrix Analysis

The confusion matrix provides detailed insight into class-wise classification performance. The model achieves high true positive rates across all categories, indicating strong classification capability for glioma, meningioma, pituitary tumor, and no-tumor classes. Minor misclassifications are observed between visually similar tumor categories, particularly between glioma and meningioma images.
Fig. 2. Confusion matrix for multiclass brain tumor classification.

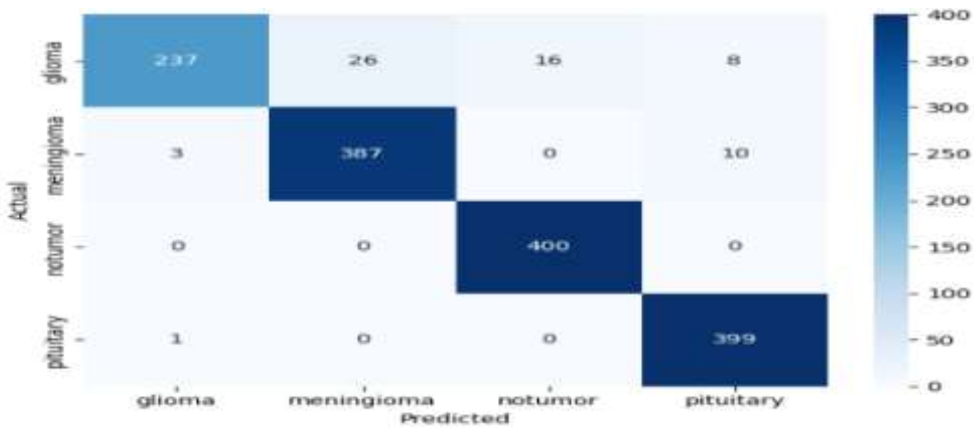


Fig. 2 Confusion matrix for multiclass brain tumor classification.

The confusion matrix analysis demonstrates that the proposed framework maintains consistent performance across different tumor classes while minimizing classification errors. The results validate the robustness and effectiveness of the proposed deep learning model for medical image classification tasks.

ROC-AUC Analysis

The Receiver Operating Characteristic (ROC) curve, mean is used to check how well the proposed framework can do classification, like its capability. In the end, the ROC-AUC score of 0.9922, and that suggests really strong discrimination between the tumor classes. Higher AUC values represent improved classification reliability and better sensitivity-specificity balance.

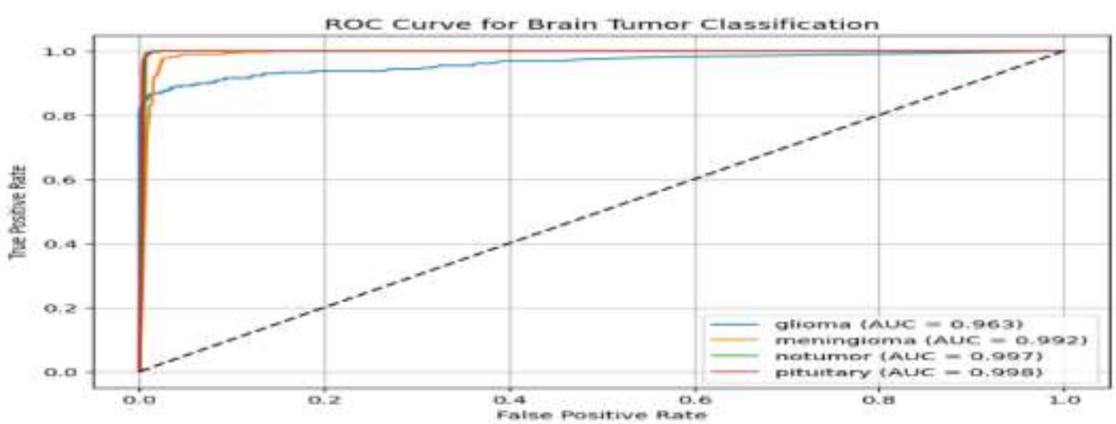


Fig. 3 ROC-AUC curve for the proposed brain tumor classification framework.

The ROC analysis confirms that the proposed ConvNeXt-Tiny based framework achieves strong classification capability and outperforms several conventional machine learning approaches used for brain tumor diagnosis.

Explainability Analysis using Grad-CAM

To improve interpretability and transparency, Gradient-weighted Class Activation Mapping (Grad-CAM) is integrated into the proposed framework. Grad-CAM generates heatmaps highlighting the important tumor regions influencing model predictions. The generated visualizations assist in understanding model behaviour and increase clinical trustworthiness for automated diagnosis systems.

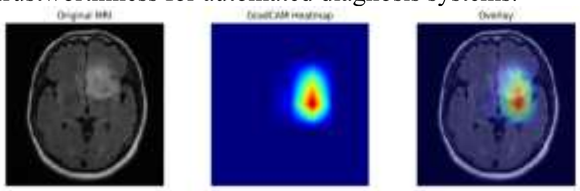


Fig. 4 Grad-CAM visualization showing the original MRI, corresponding heatmap, and overlay highlighting tumor region

Comparative Analysis

The performance of the proposed framework is compared with existing deep learning and hybrid classification approaches. The proposed ConvNeXt-Tiny based model achieves competitive classification accuracy while maintaining improved interpretability through explainable AI integration.

The comparative analysis demonstrates that the proposed framework provides a balanced trade-off between classification accuracy, computational efficiency, and interpretability. Unlike several black-box deep learning models, the proposed system offers explainable predictions through Grad-CAM visualization, making it more suitable for intelligent clinical decision-support applications.

Table 3. Comparison with Existing Methods

Model	Accuracy (%)
CNN (Baseline)	88–90
ResNet	91–93
Hybrid DL Models	94–99
Proposed Model	93.48

g. Discussion

The experimental results demonstrate that integrating deep learning with explainable artificial intelligence, boosts brain tumor classification performance and interpretability at the same time. The ConvNeXt-Tiny setup is pretty good at pulling out meaningful spatial cues from MRI images, and Grad-CAM plots make the model feel more transparent, plus more clinically reliable. Overall, the suggested framework delivers solid multiclass classification results, and it also gives interpretable predictions that can fit real world medical imaging use.

Despite the strong performance, several limitations remain. The classification quality might shift depending on dataset diversity, the image quality, and how similar the tumors look to each other. In some cases, visually alike tumor categories still lead to small mistakes, it happens. For future work, researchers could explore multimodal medical imaging integration, transformer-based architectures, federated learning pipelines, and more advanced explainable AI methods, to push diagnostic performance higher and make clinical deployment feel more practical

Conclusion

This paper presented an explainable deep learning framework for multiclass brain tumor classification using Magnetic Resonance Imaging (MRI) images. The proposed framework employed the ConvNeXt-Tiny architecture with transfer learning and phased fine-tuning to classify MRI scans into four categories: glioma, meningioma, pituitary tumor, and no-tumor. Image preprocessing and augmentation techniques were applied to improve model robustness and generalization capability. In addition, Gradient-weighted Class Activation Mapping (Grad-CAM) was integrated to enhance model interpretability and provide visual explanations for classification decisions.

The experimental evaluation demonstrated strong classification performance with an overall accuracy of 93.48%, precision of 94.20%, recall of 92.86%, F1-score of 93.53%, and ROC-AUC score of 99.22%. The generated Grad-CAM heatmaps successfully highlighted clinically relevant tumor regions, improving the transparency and reliability of the proposed diagnostic framework. The obtained results indicate that the proposed system can effectively support automated brain tumor diagnosis and assist radiologists in intelligent clinical decision-making processes. Although the proposed framework achieved promising performance, several challenges remain, including dataset diversity limitations, computational complexity, and classification difficulty among visually similar tumor categories. Future research may focus on multimodal medical image integration, transformer-based architectures, federated learning techniques, and advanced explainable artificial intelligence methods to further improve diagnostic accuracy, generalization capability, and real-time clinical applicability.

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