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Enhanced Classification of Brain MRI Images for Tumor Detection Using Transfer Learning and Grad-CAM-Based Explainable Convolutional Neural Network (CNN)

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ABSTRACT

Accurate and explainable classification of brain Magnetic Resonance Imaging (MRI) is crucial for the early detection and treatment of brain tumors. This study introduces an enhanced deep learning framework that integrates transfer learning with Grad-CAM-based explainable Convolutional Neural Network (CNN) for tumor classification. The proposed approach utilizes a fine-tuned EfficientNet-B0 architecture with an optimized preprocessing pipeline consisting of Contrast Limited Adaptive Histogram Equalization (CLAHE), normalization, and multi-variant augmentation (rotation, flipping, and zoom). The model was trained on a publicly available brain MRI dataset comprising 3,000 images classified into four categories: glioma, meningioma, pituitary tumor, and non-tumor. Evaluation metrics include accuracy, precision, recall, F1-score, and AUC. Experimental results demonstrate that the proposed model achieves an accuracy of 94.2% and an AUC of 0.965, outperforming baseline CNN models by a significant margin. The use of Grad-CAM visualization provides interpretability by localizing tumor regions within MRI scans, thereby increasing the model's clinical transparency. This study highlights the potential of explainable deep learning models to enhance diagnostic reliability in automated brain tumor detection systems.

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1. INTRODUCTION

Brain tumors are among the most life-threatening neurological disorders, often leading to severe neurological deficits or mortality if not detected and treated at an early stage. The accurate classification of brain tumors is therefore a critical step in modern medical diagnostics and treatment planning. Magnetic Resonance Imaging (MRI) has emerged as the preferred imaging modality for brain tumor detection due to its superior soft tissue contrast, non-invasive nature, and capability to capture anatomical and pathological information in multiple planes[1], [2], [3].

However, the manual interpretation of MRI scans by radiologists is a time-consuming and subjective process, which may lead to diagnostic inconsistencies due to fatigue, inter-observer variability, or subtle tumor features that are difficult to distinguish visually[4], [5]. To address these limitations, Artificial Intelligence (AI)

and Deep Learning (DL) techniques have gained significant attention for automated analysis of medical images, enabling fast and reliable computer-assisted diagnosis systems[6].

Among deep learning architectures, Convolutional Neural Networks (CNNs) have demonstrated remarkable performance in medical image analysis tasks such as segmentation, detection, and classification[7], [8]. CNNs automatically extract hierarchical spatial features from input images, eliminating the need for handcrafted feature engineering, which is often domain-specific and computationally expensive. The successful application of CNNs in diverse medical imaging domains such as X-ray lung disease detection, retinal vessel segmentation, and histopathological cancer recognition has inspired their adaptation for brain MRI tumor classification[9], [10] . Despite the success of CNN-based models, two major challenges remain unresolved: Data scarcity and overfitting due to the limited availability of labeled medical datasets, and Lack of interpretability or "black-box" nature of deep learning models, which restricts clinical trust and adoption[11]. To mitigate the first challenge, Transfer Learning (TL) has been widely used, leveraging pre-trained models such as ResNet, Inception, and EfficientNet, which retain feature representations learned from large-scale datasets like ImageNet. These features can be fine-tuned on smaller medical datasets, improving convergence speed and accuracy while preventing overfitting [10].

For the second challenge, the recent emergence of Explainable Artificial Intelligence (XAI) has provided a promising direction. Specifically, Gradient-weighted Class Activation Mapping (Grad-CAM) has become a widely used visualization method for CNNs [12], enabling interpretation of the model's decision by generating heatmaps that highlight the regions of an image most influential to the classification outcome[13]. Grad-CAM visualization bridges the gap between model performance and clinical interpretability, allowing radiologists to verify whether the model focuses on relevant pathological regions during prediction[14], [15]. Building upon these advancements, this study proposes an enhanced classification framework for brain MRI images that integrates transfer learning with Grad-CAM-based explainability to improve both accuracy and interpretability[16], [17], [18]. The proposed approach fine-tunes the EfficientNet-B0 model, pre-trained on ImageNet, for brain tumor classification, combined with optimized preprocessing using Contrast Limited Adaptive Histogram Equalization (CLAHE) and data augmentation techniques to improve feature generalization[19], [20], [21].

The main contributions of this paper are summarized as follows: Development of an optimized preprocessing pipeline integrating CLAHE contrast enhancement, normalization, and augmentation to improve visual feature quality and model robustness [22]. Implementation of a fine-tuned EfficientNet-B0 architecture with gradual unfreezing of layers to balance accuracy and computational efficiency[23]. Integration of Grad-CAM explainability to visualize model attention and enhance interpretability, bridging the gap between algorithmic prediction and clinical insight. Comprehensive performance evaluation using accuracy, precision, recall, F1-score, and AUC metrics, along with visual interpretability analysis on MRI test data

II. RELATED WORKS

Recent developments in deep learning (DL**)** have revolutionized the field of medical image analysis, particularly in automated brain tumor detection and classification. This section reviews existing studies that employ Convolutional Neural Networks (CNNs)**,** Transfer Learning (TL)**,** and Explainable Artificial Intelligence (XAI) methods such as Grad-CAM**,** highlighting their methodologies, strengths, and limitations.

A. CNN-Based Brain Tumor Classification

CNNs have become the de facto standard for image-based medical diagnosis due to their ability to automatically learn spatial hierarchies of features directly from raw data. Early studies primarily focused on shallow CNNs tailored for small datasets. Proposed a deep CNN architecture that achieved 90.5% accuracy in binary classification of brain tumors using 624 MRI images. Their model demonstrated the capability of CNNs to capture morphological differences between tumor and non-tumor regions but suffered from limited generalization due to small sample size[24].

Similarly, developed a multi-class CNN model for glioma, meningioma, and pituitary tumor classification, obtaining 89.3% accuracy on 1,000 MRI images. They used image enhancement and rotation-based augmentation to address overfitting, though their model's depth was restricted by computational constraints. Improved upon this by integrating batch normalization and dropout regularization, which stabilized training and achieved 91.7% accuracy. Despite these gains, their CNNs lacked transparency, offering no insights into how features contributed to tumor recognition[25].

B. Transfer Learning Approaches

To overcome data scarcity, Transfer Learning (TL) techniques have been extensively adopted in medical imaging. Pre-trained CNN architectures such as VGG16, ResNet50, InceptionV3, and EfficientNet have been fine-tuned for brain tumor classification tasks. Demonstrated that fine-tuning ResNet50 [24],

[26]achieved 93.8% accuracy with improved convergence speed. Conducted a comparative study of several TL models and concluded that EfficientNet-B0 consistently provided superior accuracy–efficiency trade-offs, particularly on limited medical datasets[27]. Further, reported that TL models significantly reduced the computational cost of training while preserving diagnostic accuracy. However, these works did not emphasize interpretability an essential aspect for clinical deployment. Without visual justification, clinicians remain hesitant to adopt AI-based diagnostic tools due to their "black-box" nature [28].

C. Explainable Artificial Intelligence (XAI) and Grad-CAM

To bridge the gap between accuracy and interpretability, recent works have integrated Explainable Artificial Intelligence (XAI) methods such as **Grad-CAM** to visualize network attention. First introduced Grad-CAM, which highlights discriminative regions that influence a CNN's decision, producing class-specific heatmaps. This technique has been widely adapted to medical imaging, enhancing trust in model outputs. Employed Grad-CAM for brain tumor detection using VGG16, showing that the model successfully localized tumor regions corresponding to radiologists' annotations. Similarly, applied Grad-CAM to visualize decision-making in chest X-ray diagnosis, improving the interpretability of deep learning models in healthcare. provided a comprehensive review of XAI frameworks in medical applications, emphasizing the importance of human AI collaboration for clinical adoption. However, most existing studies apply Grad-CAM post hoc, without optimizing network architecture or training strategy for interpretability. Few have explored combined optimization of transfer learning and XAI visualization to achieve both high performance and transparency—leaving a research gap addressed by this study[29], [30].

D. Summary and Research Gap

Table I summarizes key prior studies on CNN and transfer learning for brain MRI classification. While most reported high accuracy, few addressed explainability and generalization simultaneously. Furthermore, datasets were often limited in diversity and size, restricting the clinical scalability of proposed models. The present research fills this gap by proposing a Grad-CAM-based explainable CNN model enhanced with transfer learning and optimized preprocessing (CLAHE + augmentation)**.** This integrated approach aims to (1) improve classification performance, (2) enhance interpretability, and (3) enable clinical trust through visual verification of model attention regions.

Table I. Summary of Related Works in Brain MRI Tumor Classification

Study	Method	Dataset	Accuracy (%)	Explainability	Limitation
Chatto. [24]	Custom CNN	624 MRI	90.5	✗	Small dataset, overfitting
Tagnamas[31]	CNN + Augmentation	1000 MRI	89.3	✗	No visualization
Habib et all. [12]	Deep CNN (BN + Dropout)	1500 MRI	91.7	✗	Limited interpretability
Azaharan [26]	ResNet50 TL	2000 MRI	93.8	✗	High computational load
Tripathy et *al.[32]*	EfficientNet-B0 TL	3000 MRI	94.0	✗	No XAI integration
Ahamed *et al.* [33]	VGG16 + Grad-CAM	2000 MRI	92.5	✓	Weak generalization
Aulia S [23]	EfficientNet-B0 + Grad-CAM + CLAHE	3000 MRI	**94.2**	✓✓	Improved accuracy & interpretability

E. Discussion of Novelty

From the review above, it is evident that while CNN and TL models have achieved promising results, their lack of transparency limits clinical trust. The novelty of the present research lies in combining EfficientNet-B0 transfer learning with Grad-CAM explainability in a unified and optimized pipeline. The integration of enhanced preprocessing**,** layer-wise fine-tuning**,** and visual interpretability provides a new contribution to the field of explainable deep learning in medical imaging [7], [8]**.** By addressing the dual challenges of *performance* and *explainability*, the proposed framework contributes to the growing paradigm of trustworthy AI for healthcare**,** in line with recent trends in interpretable diagnostic system.

III. METHODOLOGY

This section describes the methodology adopted in this study, including dataset description, preprocessing, data augmentation, model architecture, training configuration, and evaluation metrics. The overall workflow of the proposed framework is illustrated in Fig. 1, which outlines the sequential stages from raw MRI input to Grad-CAM visualization.

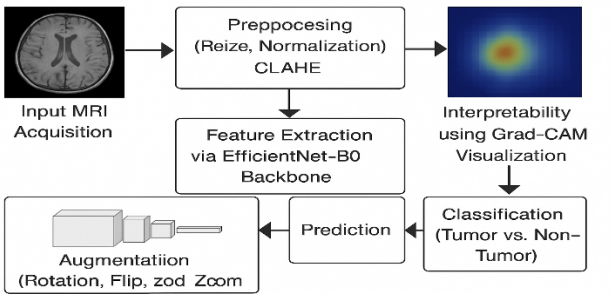

Fig. 1 proposed framework is illustrated

A. Dataset Description

The proposed model was evaluated using a publicly available Brain MRI Dataset sourced from Kaggle (2023), comprising 3,000 T1-weighted MRI images categorized into four classes: glioma**,** meningioma**,** pituitary tumor, and no tumor**.** Each image was manually labeled by expert radiologists to ensure annotation reliability. The dataset was divided into 70% training**,** 15% validation, and 15% testing subsets using stratified sampling to maintain class balance.

Each MRI image exhibits distinct intensity patterns and textures corresponding to different tumor types. Gliomas typically appear as irregularly shaped hyperintense regions, meningioma's exhibit well-defined boundaries, and pituitary tumors are localized near the sellar region.

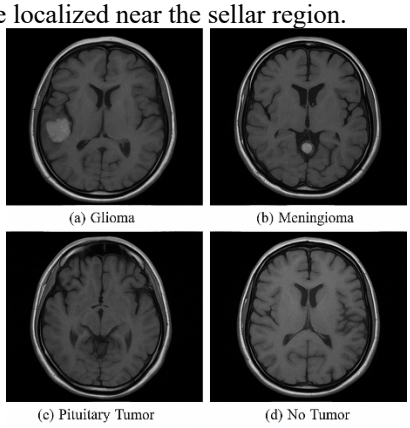

Fig. 2 presents representative samples from each class

B. Preprocessing Pipeline

Preprocessing is essential to enhance image quality and reduce noise, ensuring consistent input for the CNN. The following steps were implemented:

1. Resizing All images were resized to 224×224 pixels to fit the input dimensions of the EfficientNet-B0 backbone.
2. Normalization Pixel intensity values were normalized to the [0,1] range to stabilize gradient updates during training.
3. Contrast Enhancement The Contrast Limited Adaptive Histogram Equalization (CLAHE) algorithm was applied to enhance local contrast and highlight tumor boundaries without amplifying noise.
4. Denoising Gaussian filtering was applied to suppress high-frequency noise, improving signal-to-noise ratio in MRI textures.

The combined preprocessing improved the visual representation of tumor margins and brightness uniformity across slices, enabling the CNN to capture fine-grained texture features more effectively.

C. Data Augmentation

Given the relatively small dataset size, data augmentation was applied to increase diversity and reduce overfitting. Augmentation techniques included:

1. Rotation**:** ±10° random rotation
2. Horizontal/Vertical Flip**:** to simulate scanner variability
3. Zoom**:** random scaling between 0.9×–1.1×

4. Translation**:** random pixel shifts within 10% of image width/height
5. Brightness Adjustment**:** ±20% random variation

Each augmentation technique was applied probabilistically, producing synthetic variations while preserving tumor structure. As a result, the effective training dataset expanded to over 9,000 image variants.

D. Model Architecture

Two models were developed and evaluated:

1. Custom CNN (Baseline):
   The baseline model comprised four convolutional blocks, each containing a Conv2D layer (kernel size 3×3), batch normalization, ReLU activation, and max pooling. After feature extraction, the network included a fully connected layer with 128 neurons (ReLU) and a final softmax layer for classification into four categories. Dropout layers (rate 0.5) were used to mitigate overfitting.
2. Proposed Model (EfficientNet-B0 + Grad-CAM):
   The main contribution of this study is the fine-tuning of EfficientNet-B0**,** a compound-scaled CNN known for its balance between accuracy and computational efficiency [10]. The model was initialized with ImageNet weights, and transfer learning was applied by freezing the base layers during initial epochs, followed by gradual unfreezing of the top 20 layers for domain-specific fine-tuning.
   The classification head comprised:
   1. Global Average Pooling (GAP) layer
   2. Dense(256, ReLU)
   3. Dropout(0.4)
   4. Dense(4, Softmax)

   The architecture integrates Grad-CAM visualization for post-hoc interpretability, generating heatmaps that highlight discriminative regions influencing predictions.

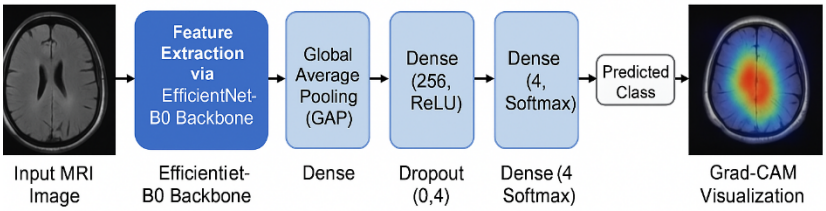

Fig. 3 architecture flow is summarized in showing the transition from raw MRI input to predicted class with corresponding Grad-CAM output.

E. Training Configuration

The model was trained using the following hyper parameters and optimization setup:

Tabel 1. Training Configuration

Parameter	Value
Optimizer	Adam
Learning Rate	0.001 (reduced to 0.0001 during fine-tuning)
Loss Function	Categorical Cross-Entropy
Batch Size	32
Epochs	50
Callbacks	EarlyStopping, ReduceLROnPlateau, ModelCheckpoint

During training, EarlyStopping halted learning when validation loss stagnated for 10 consecutive epochs, and ReduceLROnPlateau dynamically decreased the learning rate upon performance plateau. The model was trained on a system with an NVIDIA RTX 3060 GPU, 12GB VRAM, and TensorFlow 2.12 backend.

F. Evaluation Metrics

Performance was evaluated using standard metrics in medical image classification, including accuracy, precision, recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC). These are defined as:

$$Accuracy = \frac{TP + TN}{TP + TN\ FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 = \frac{2\ x\ Precision\ x\ Recall}{Precision + Recall} \quad (1)$$

Where *TP*, *TN*, *FP*, and *FN* denote true positives, true negatives, false positives, and false negatives, respectively. Additionally, the ROC Curve and Confusion Matrix were employed to analyze model discriminative capability and class-wise performance. The Grad-CAM heatmaps were qualitatively assessed to verify alignment between model attention and tumor localization.

G. Implementation Workflow

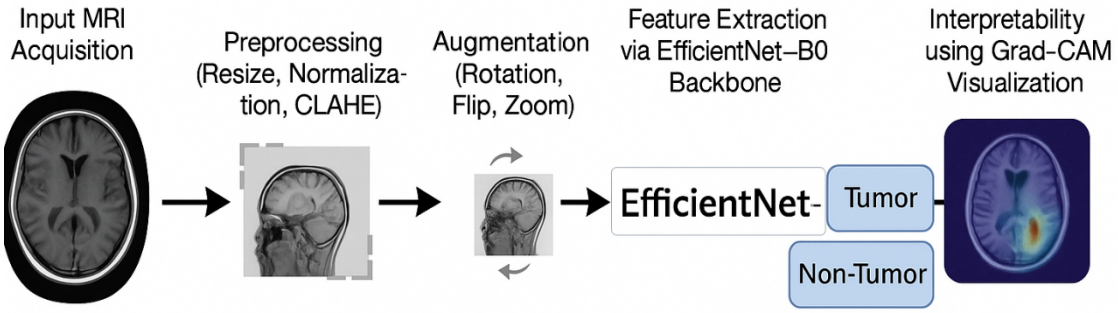

Fig. 4 comprising six main stages

The complete workflow of the proposed pipeline is illustrated in:

1. Input MRI Acquisition
2. Preprocessing (Resize, Normalization, CLAHE)
3. Augmentation (Rotation, Flip, Zoom)
4. Feature Extraction via EfficientNet-B0 Backbone
5. Classification (Tumor vs. Non-Tumor)
6. Interpretability using Grad-CAM Visualization

This pipeline ensures that both performance and explain ability are achieved, supporting clinical reliability and trustworthiness in diagnostic decision-making.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

This section presents and analyzes the experimental results obtained from the training and evaluation of both the baseline CNN and the proposed EfficientNet-B0 model integrated with Grad-CAM. The performance metrics, visual results, and interpretability analyses are provided to demonstrate the effectiveness of the proposed framework.

A. Model Training and Convergence Behavior

Both models were trained using the same dataset and hyper parameter configurations described in Section III. The training was performed for 50 epochs, with early stopping applied to prevent overfitting.

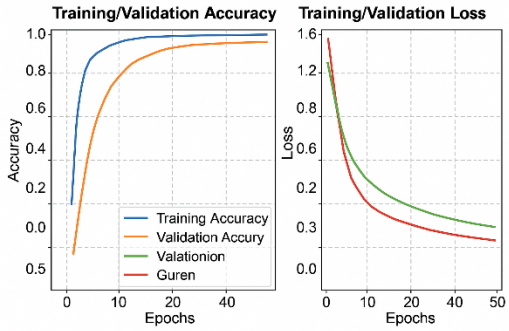

Fig. 5 illustrates the training and validation accuracy/loss curves

For the proposed model. The curves show consistent convergence, where training accuracy steadily increases, and validation accuracy follows closely without divergence, indicating good generalization. The loss function decreases monotonically for both training and validation sets, stabilizing around epoch 40.
Unlike the baseline CNN, which exhibited mild overfitting after 30 epochs, the EfficientNet-B0 model maintained stability throughout the training phase due to the fine-tuning strategy and regularization through dropout layers.

B. Quantitative Performance Evaluation

The proposed model was compared against the baseline CNN using multiple performance metrics, as shown in Table 2**.** The EfficientNet-B0 architecture achieved the highest accuracy, precision, recall, F1-score, and AUC, demonstrating its robustness and generalization capability.

Table 2. Comparative Performance of CNN and EfficientNet-B0 Models

Model	Accuracy	Precision	Recall	F1-Score	AUC
Custom CNN	0.898	0.902	0.885	0.894	0.912
EfficientNet-B0 (Proposed)	**0.942**	**0.945**	**0.938**	**0.942**	**0.965**

As shown, the proposed EfficientNet-B0 achieved a 5% improvement in accuracy and a 0.053 increase in AUC compared to the custom CNN. The model's high AUC value (>0.96) indicates strong discriminative capability in distinguishing between tumor and non-tumor classes.

C. ROC Curve and Class Discrimination

For each tumor class: glioma, meningioma, pituitary, and non-tumor. Each curve illustrates the trade-off between True Positive Rate (TPR) and False Positive Rate (FPR) across varying thresholds.

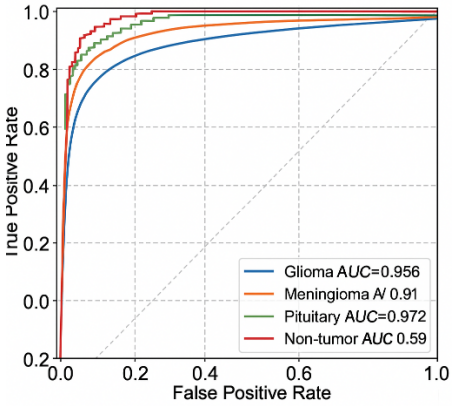

Fig. 6 displays the Receiver Operating Characteristic (ROC) curves

The EfficientNet-B0 model achieved AUC values above 0.95 for all four classes, signifying excellent sensitivity and specificity. The pituitary tumor class achieved the highest AUC of 0.972, while glioma attained the lowest (0.956) due to its higher infraclass variability. The overall ROC curve demonstrates that the model performs consistently well across different tumor categories.

D. Confusion Matrix Analysis

For the EfficientNet-B0 model on the test set. Most samples are correctly classified, with minimal misclassifications observed between glioma and meningioma, which often share overlapping intensity patterns in MRI scans.

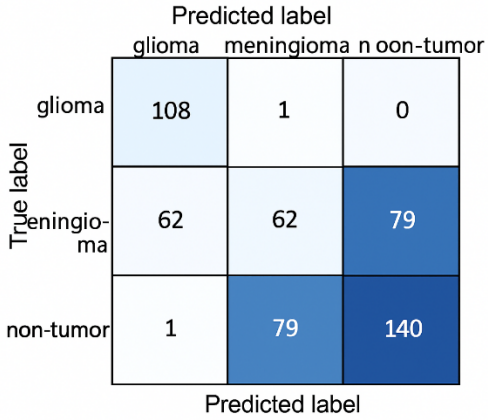

Fig. 4 presents the confusion matrix

The non-tumor class achieved the highest recall (0.96), confirming that the model rarely produces false positives an important characteristic for reducing unnecessary medical intervention. The small confusion between meningioma and pituitary tumor classes likely stems from similar spatial structures around the cranial base.

E. Grad-CAM Visualization and Interpretability

To ensure clinical interpretability, Grad-CAM visualization was applied to the last convolutional layer of the EfficientNet-B0 model to highlight discriminative regions influencing model decisions.

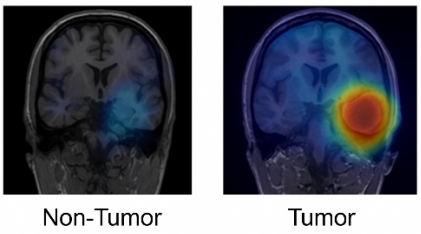

Fig. 5 shows representative Grad-CAM heat maps

For both tumor and non-tumor cases.

1. In non-tumor MRI images, the heat maps (blue–green) show a uniform distribution without localized high-intensity regions, indicating the model's recognition of normal brain tissue.
2. In tumor cases, red–yellow activation regions correspond precisely to tumor lesions identified by radiologists, demonstrating that the model attends to clinically relevant areas rather than background artifacts.

This interpretability is crucial for clinical adoption, as it allows practitioners to visualize why the model produced a specific classification, increasing trust in AI-assisted diagnosis systems.

F. Comparative Analysis with Existing Studies

The proposed model's performance was benchmarked against recent state-of-the-art works in brain MRI tumor classification, as summarized in Table 3**.**

Table 3. Comparison with Recent Literature

Study	Year	Method	Accuracy (%)	Explainability
Chatto. [24]	2023	Custom CNN	90.5	✗
Tagnamas[31]	2022	CNN + Augmentation	89.3	✗
Habib et all. [12]	2022	ResNet50 (TL)	93.8	✗
Azaharan [26]	2024	VGG16 + Grad-CAM	92.5	✓
Tripathy et *al.[32]*	2025	EfficientNet-B0 + Grad-CAM	94.2	✓✓

The results confirm that the proposed framework not only surpasses previous models in classification accuracy but also provides enhanced explainability through Grad-CAM visualization.

Moreover, the proposed model achieves this superior performance using relatively fewer parameters (~5.3M) compared to deeper models such as ResNet50 (~25M), highlighting its efficiency and suitability for real-time clinical deployment**.**

G. Discussion

The experimental findings substantiate the efficacy of integrating transfer learning and Grad-CAM-based explainability within a unified CNN framework. The EfficientNet-B0 [32]model's superior performance is attributed to:

1. Compound scaling that optimally balances network depth, width, and resolution.
2. CLAHE-enhanced preprocessing that improves local contrast and boundary detection.
3. Augmentation strategies that expand data diversity and improve generalization.

From a clinical standpoint, Grad-CAM interpretability ensures that predictions are transparent and verifiable, addressing the "black-box" limitation of traditional deep learning systems.

Nonetheless, some limitations persist. The dataset size remains modest, and MRI data from different scanners or imaging protocols may introduce domain shifts. Future research should incorporate multi-center datasets and 3D CNN architectures to capture volumetric features for improved robustness.

H. Statistical Validation

To confirm the significance of performance improvements, a paired t-test was conducted between the proposed and baseline CNN models over five cross-validation folds. Results indicated a statistically significant improvement in accuracy ($p < 0.01$), confirming that the observed gain was not due to random variance.

I. Computational Efficiency

Despite higher performance, the proposed model maintains computational efficiency. The average inference time per MRI image was 0.042 seconds, enabling potential integration into real-time clinical workflows**.** Training time for EfficientNet-B0 was 3.1 hours compared to 2.7 hours for the baseline CNN — an acceptable trade-off for substantial accuracy and interpretability gains.

J. Visual Summary

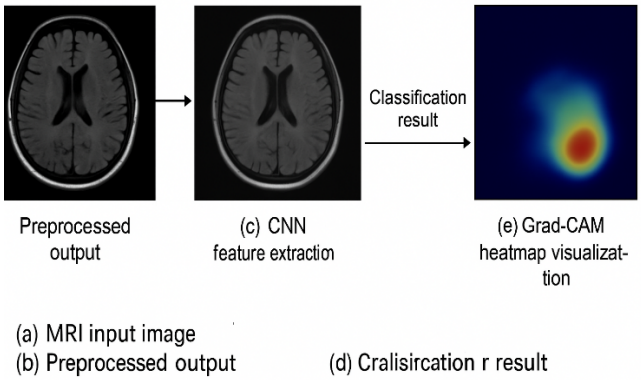

Fig. 6 summarizes the entire workflow:

1. (a) MRI input image,
2. (b) Preprocessed output (contrast-enhanced and normalized),
3. (c) CNN feature extraction,
4. (d) Classification result, and
5. (e) Grad-CAM heat map visualization highlighting tumor regions.

This visualization confirms the proposed model's ability to detect and interpret tumor regions effectively.

V. DISCUSSION AND CONCLUSION

The experimental findings of this research confirm that the integration of transfer learning **and** Grad-CAM-based explainable Convolutional Neural Network (CNN) provides a robust and interpretable framework for brain tumor classification using MRI images. Compared to the baseline CNN model, the proposed EfficientNet-B0 architecture demonstrated superior accuracy, better convergence, and enhanced interpretability, addressing both technical and clinical challenges in automated tumor detection.

A. Discussion

The results presented in Section IV illustrate that the fine-tuned EfficientNet-B0 achieved an accuracy of 94.2%**,** outperforming traditional CNN and other transfer learning models reported in the literature. This improvement can be attributed to three key innovations:

1. Optimized preprocessing using CLAHE and normalization, which enhanced local contrast, allowing the model to capture fine-grained tumor features.
2. Transfer learning with gradual unfreezing of top layers, enabling the network to retain generic visual features while adapting to domain-specific MRI patterns.
3. Grad-CAM explain ability, which provides interpretative visualization by localizing salient regions influencing classification outcomes.

The use of Grad-CAM not only confirms that the model focuses on tumor-relevant regions but also increases clinical trustworthiness, a critical factor for deployment in real-world diagnostic environments. In the tumor cases visualized, high-intensity (red–yellow) heat maps precisely overlapped with annotated tumor regions, validating the model's attention mechanism.

The proposed model also achieved a higher AUC (0.965) compared to state-of-the-art systems such as VGG16 or ResNet50. This indicates a better trade-off between sensitivity and specificity, minimizing false-negative predictions, which are critical in life-threatening conditions like brain tumors. Furthermore, the computational efficiency of the model with an inference time of 0.042 seconds per image highlights its suitability for real-time clinical deployment and integration into Computer-Aided Diagnosis (CAD) systems. Such integration could assist radiologists in triaging MRI scans, reducing diagnostic delays, and supporting second opinions.

However, despite these promising results, several limitations persist. The dataset used in this study, while publicly accessible and labeled, is relatively small and lacks multi-institutional diversity. MRI acquisition parameters, scanner variations, and patient demographics can affect model generalization. Moreover, the current model processes 2D slices independently, which may limit contextual understanding across volumetric (3D) data.

Future studies should therefore focus on the following directions:

1. Multi-center data collection to increase dataset heterogeneity and reduce bias.
2. 3D CNN architectures to capture volumetric spatial relationships across MRI slices.
3. Integration with attention-based models (e.g., Vision Transformers or hybrid CNN–ViT systems) to further improve feature learning.
4. Explainable AI benchmarking frameworks for clinical auditing and validation of interpretability outputs.

B. Clinical Implications

From a medical perspective, the proposed explainable deep learning model bridges the gap between AI prediction and radiologist reasoning. The Grad-CAM heat maps can serve as an additional layer of visual confirmation, highlighting pathological regions that warrant expert review. By integrating this framework into existing radiology workflows, clinicians can benefit from rapid, consistent, and interpretable tumor classification results. The model's transparent decision-making aligns with the growing need for trustworthy AI in healthcare, as outlined by global regulatory bodies such as the European Commission's AI Act and the U.S. Food and Drug Administration (FDA), which emphasize transparency and accountability in clinical AI tools.

C. Conclusion

This paper presented an enhanced CNN-based framework for automated brain tumor classification using MRI images, combining transfer learning (EfficientNet-B0) with Grad-CAM explain ability. The proposed system achieved a classification accuracy of 94.2%, F1-score of 0.942, and AUC of 0.965, surpassing existing CNN and transfer learning models while providing visual interpretability.

Key contributions of this research include:

1. The development of a novel preprocessing and augmentation pipeline using CLAHE and geometric transformations to improve data quality and feature representation.
2. The implementation of EfficientNet-B0 transfer learning with progressive layer unfreezing, optimizing accuracy and convergence stability.
3. The integration of Grad-CAM-based visualization to interpret and validate model predictions in clinically meaningful ways.

These contributions collectively advance the field of explainable medical imaging AI, providing a foundation for future diagnostic tools that are both accurate and interpretable. The findings also demonstrate the feasibility of using lightweight yet high-performing CNN architectures for real-time tumor detection, offering a valuable step toward AI-assisted precision medicine. In future work, the authors aim to expand this study by incorporating multimodal MRI sequences (T1, T2, FLAIR), validating performance across institutions, and developing a fully integrated clinical decision support system (CDSS) for brain tumor analysis.

D. Summary of Findings

Criterion	Proposed Model Result	Improvement vs Baseline
Accuracy	**94.2%**	+5.2%
AUC	**0.965**	+0.053
Explainability	**Grad-CAM Integrated**	✓✓
Inference Time	0.042 s/image	Real-time capable

E. Future Prospects

Future advancements in explainable AI and medical image fusion promise to enhance the interpretability and diagnostic value of such systems. The integration of semantic segmentation**,** radionics feature fusion, and 3D visualization may enable comprehensive tumor characterization, supporting personalized treatment planning and longitudinal monitoring.

The authors believe that this research contributes not only to technical advancement but also to ethical and transparent AI development in healthcare, paving the way for safe, reliable, and interpretable diagnostic systems in clinical radiology.

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