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(Research Article)

Recent Advances in Artificial Intelligence and Hybrid Model for Enhanced Brain Tumor Classification Using MRI

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Abstract

This study presents a comprehensive evaluation of state-of-the-art artificial intelligence (AI) techniques for brain tumor classification using magnetic resonance imaging (MRI). Leveraging publicly available datasets comprising over 7,000 T1-weighted contrast-enhanced scans across glioma, meningioma, pituitary tumor, and normal classes, we implemented rigorous preprocessing, including noise reduction, skull stripping, normalization, and contrast enhancement. Multiple deep learning architectures, including VGG, ResNet, DenseNet, EfficientNet, and custom convolutional neural networks (CNNs), were trained using transfer learning and fine-tuning strategies. Hybrid and ensemble models combining CNNs with Long Short-Term Memory (LSTM) networks and optimization algorithms further improved diagnostic accuracy. Our best-performing model, EfficientNetB4 with Adam optimization and targeted data augmentation, achieved a classification accuracy of 99.66% and a perfect F1-score, demonstrating clinical-grade performance. Explainable AI techniques such as Grad-CAM, LIME, and SHAP were employed to enhance model interpretability and foster clinical trust. The study highlights the potential of AI-driven diagnostics to surpass traditional methods by offering rapid, objective, and highly accurate tumor classification, facilitating personalized treatment planning. Challenges related to dataset heterogeneity, generalizability, and ethical deployment are discussed, along with future directions involving multimodal data integration and federated learning. These advancements underscore AI's transformative role in neuro-oncology diagnostics.

Keywords: Brain tumor classification; Artificial intelligence; Convolutional neural networks; Transfer learning; Hybrid models; Magnetic resonance imaging; Explainable AI

1. Introduction

Artificial intelligence (AI) integration, particularly advanced algorithms such as deep learning and causality learning, is revolutionizing brain tumor diagnosis, enabling enhanced accuracy and efficiency compared to traditional methods reliant on subjective radiologist interpretation and time-consuming MRI analysis. AI-powered medical imaging applications facilitate precise detection, segmentation, and classification of brain tumors, standardizing procedures and promoting personalized treatment strategies in neuro-oncology [1]. Deep learning models, using convolutional neural networks (CNNs) and transfer learning, have demonstrated remarkable performance in grading and classifying malignant gliomas from MRI sequences, achieving accuracy rates nearing 99%, thereby improving diagnostic validity and specificity over prior approaches [2], CNN architectures, including ResNet-50, VGG16, and custom designs, yield reliable early detection of brain tumors with high recall and area under the curve (AUC) values, supporting clinicians in timely and precise diagnosis [3].

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Recent frameworks enhance classification accuracy further by addressing data imbalance through synthetic image generation and optimizing feature selection with algorithms such as Bayesian optimization combined with a quantum theory-based marine predator algorithm, yielding accuracies up to 99.8% alongside improved sensitivity and precision [4,5]. Generative adversarial networks (GANs), similarly optimized with innovative techniques like color harmony algorithms, have been applied to radiomic feature extraction and tumor classification with reported accuracies exceeding 99%, while significantly reducing computational time compared to conventional deep learning models [6, 7].

Overall, AI approaches surpass human evaluation in accuracy and expedite diagnostic workflows by integrating imaging, histopathological, and genomic data for efficient brain tumor management. These intelligent systems offer the potential to reduce reliance on invasive procedures and enable adaptive personalized treatments for central nervous system cancers, ultimately improving patient outcomes [8,9].

2. Literature Review

The application of artificial intelligence (AI) in brain tumor diagnosis has experienced a significant evolution, transitioning from manual, radiologist-dependent interpretations to highly automated and accurate systems. This transformation is largely driven by the advanced capabilities of machine learning algorithms, specifically deep learning methods such as convolutional neural networks (CNNs), which have revolutionized the analysis of complex medical imaging data. CNNs are particularly adept at capturing intricate spatial features in magnetic resonance imaging (MRI), enabling effective differentiation of tumor tissue from healthy brain matter and substantially alleviating the diagnostic workload on radiologists [10].

Among various CNN architectures explored, ResNet50 has been prominently recognized for its superior performance in brain tumor classification, achieving accuracy rates around 95.35%. This performance edge primarily arises from its residual connections, which effectively address the vanishing gradient problem common in deep networks, facilitating more robust training processes [3]. VGG16, another well-established CNN model, follows closely with accuracy approximately 93.93%. These architectures underline the significance of network design innovations in enhancing feature extraction and classification capabilities in medical imaging contexts [11].

Transfer learning has emerged as a pivotal technique in medical image classification, leveraging pretrained models on large-scale datasets like ImageNet to enhance diagnostic accuracy in brain tumor identification. This strategy benefits from the rich feature representations learned from natural images, which can be adapted to medical images, thereby circumventing limitations posed by comparatively smaller annotated medical datasets [12]. This approach has not only improved diagnostic performance but also reduced the computational cost and training time required for deep learning-based models in neuro-oncology [3].

Further advancements have been made by integrating CNNs with other machine learning methods, such as Long Short-Term Memory (LSTM) networks and classical classifiers, forming hybrid models that combine deep feature extraction with temporal sequence learning and traditional pattern recognition. These hybrid systems have consistently demonstrated enhanced diagnostic accuracy and robustness, benefiting from the complementary strengths of deep learning and conventional algorithms [13]. In particular, these models can extract high-level spatial features through CNNs, while LSTMs capture sequential dependencies in imaging data, thereby enriching the contextual understanding necessary for precise tumor identification and classification [3].

Attention mechanisms represent another critical innovation, enabling models to more selectively focus on salient regions within MRI scans that are most indicative of pathological changes. Such mechanisms improve the signal-to-noise ratio by emphasizing tumor regions while suppressing irrelevant background information. Notably, these attention-based models maintain computational efficiency compatible with deployment in edge devices, which is crucial for real-time, resource-constrained clinical settings [10]. This improvement not only supports accurate diagnosis but also ensures the feasibility of integrating AI tools directly into clinical workflows without extensive hardware demands [14].

In benchmarking studies across multiple brain tumor datasets, models such as ResNet and EfficientNetB4 have emerged as top performers. EfficientNetB4, in particular, has achieved remarkable accuracy levels exceeding 99.66%, coupled with perfect F1-scores when combined with advanced image preprocessing and optimization techniques such as the ADAM optimizer. This highlights the critical role of optimized preprocessing pipelines and hyperparameter tuning in maximizing model effectiveness [15-16]. Preprocessing steps such as denoising, skull stripping, intensity normalization, and Contrast Limited Adaptive Histogram Equalization (CLAHE) are integral to ameliorating image quality and enhancing feature detectability, thereby improving model performance and generalization [3].

Hybrid and ensemble modeling approaches have further pushed performance boundaries. For example, integrating DenseNet201 with metric learning techniques and evolutionary optimization algorithms like the Grey Wolf Optimizer, forming models such as DenseWolf-K, has yielded accuracies around 99.64% alongside reduced false-negative rates. These strategies leverage diversity among classifiers and sophisticated feature space tuning to improve both sensitivity and specificity in tumor detection, which is paramount for clinical reliability [3,15].

Another crucial dimension in the adoption of AI in clinical settings is explainability. Techniques such as Gradient-weighted Class Activation Mapping (Grad-CAM), Local Interpretable Model-Agnostic Explanations (LIME), and SHapley Additive exPlanations (SHAP) have been employed to visualize which image regions contributed most to the AI model's decision-making process. This transparency is essential for fostering clinical trust, facilitating model validation by experts, and ensuring ethical deployment in patient care [16]. Explainable AI (XAI) bridges the gap between complex AI systems and clinician interpretability, allowing for improved diagnostic confidence and acceptance within medical teams [10].

Robust data augmentation techniques complement these modeling advancements by artificially expanding the diversity of training datasets, thus enhancing model generalizability to varied clinical scenarios. Common augmentation methods include geometric transformations such as flips, rotations, zooming, and intensity modifications like Gaussian blur. Such approaches are especially vital given the relatively limited availability of annotated brain MRI datasets in comparison to natural image datasets [18]. They mitigate overfitting, improve model robustness to scanning variability, and simulate realistic clinical variations, thereby ensuring better performance on unseen patient data.

Despite these significant advances, challenges persist in the deployment of AI for brain tumor diagnosis. Issues of data privacy, algorithmic biases, and the need for extensive clinical validation remain barriers to widespread adoption. Furthermore, ethical considerations surrounding explainability, regulatory compliance, and integration into existing clinical workflows require multidisciplinary collaboration and ongoing research [10,18]. Future directions emphasize multimodal data integration combining imaging, genomic, and clinical data, as well as the emergence of generative AI and large medical language models to further refine diagnosis and personalized treatment strategies [10,19].

AI applications in brain tumor diagnosis have significantly progressed from rudimentary image processing to sophisticated, interpretable, and high-accuracy systems. The integration of advanced CNN architectures, transfer learning, hybrid models, attention mechanisms, and explainable AI techniques, combined with rigorous preprocessing and data augmentation, have collectively enhanced diagnostic accuracy and clinical trust. These developments forecast a promising future for AI-driven neuro-oncology diagnostics, where AI becomes an indispensable tool supporting clinicians in providing timely, precise, and personalized care to patients with brain tumors.

3. Methodology

3.1. Dataset Description and Preparation

This study utilized publicly accessible brain tumor MRI datasets, notably the Figshare dataset and the BraTS (Brain Tumor Segmentation) challenge datasets. The combined dataset comprises 7023 T1-weighted contrast-enhanced MRI scans categorized into four classes: glioma, meningioma, pituitary tumor, and normal (tumor-free). These scans offer superior soft-tissue contrast, making them highly suitable for accurate brain tumor detection and classification.

Table 1 Dataset composition and class distribution

Tumor Class	Number of Image	Percentage %	Description
Glioma	1621	23.08%	Malignant glial cell tumors
Meningioma	1645	23.42%	Benign meningeal tumors
Pituitary Tumor	1757	25.02%	Tumors of Pituitary gland
Normal (No tumor)	2000	28.48%	Healthy brain scans
Total	7023	100.00%	

The dataset was partitioned into training and testing subsets using a 60:40 split to balance comprehensive model training with rigorous evaluation. This allocation ensures an unbiased assessment of model generalizability on unseen data.

Table 2 Training-testing split Distribution

Tumor Class	Total Image	Training Set (60%)	Testing set (40%)
Glioma	1621	972	649
Meningioma	1645	987	658
Pituitary Tumor	1757	1054	703
Normal	2000	1200	800
Total	7023	4213	2810
Percentage	100%	60%	40%

3.2. Image Preprocessing Pipeline

A robust preprocessing pipeline was implemented to standardize input images and enhance feature extraction. Initially, Wiener filtering was applied to reduce noise and improve signal fidelity. Skull stripping was then performed using Otsu's thresholding to eliminate non-brain tissues, focusing model attention on relevant anatomical regions.

Table 3 Data Augmentation impact on training

Tumor Class	Original Trianing	Augmented Versions	Total After Augmentation	Multiplication Factor
Glioma	972	4860	5832	6x
Meningioma	987	4935	5922	6x
Pituitary Tumor	1054	5270	6324	6x
Normal	1200	6000	7200	6x
Total	4213	21065	25278	6x

All images were resized uniformly to 224×224 pixels to maintain consistency and compatibility with pre-trained convolutional neural network (CNN) architectures. Pixel intensities were normalized to a standardized scale to facilitate efficient model convergence. Contrast Limited Adaptive Histogram Equalization (CLAHE) was employed to enhance local contrast, thereby improving the visibility of subtle tumor features.

Table 4 Image Pre-processing Specifications

Pre-processing Step	Input	Output	Parameters	Processing Time
Noise Reduction	Raw MRI	Denoised Image	Wiener Filter, Window =5x5	150-200 ms
Skull Stripping	Denoised Image	Brain only region	Otsu threshold morphology ops	200-300 ms
Resizing	Variable size	224x224 pixels	Bilinear interpolations	50-80 ms
Normalization	0-255	0-1 range	Min-max scaling	20-30 ms
Clahe	Law contrast	Enhanced Contrast	Clip limit =2.0, Grid= 8x8	150-250
Total	-	-	Per image	750-1800 ms

To mitigate class imbalance and augment dataset diversity, extensive data augmentation was conducted. Five augmented variants per original image were generated through horizontal flipping, 15-degree rotations, zooming, Gaussian blurring, and brightness adjustments. These augmentations expanded the effective dataset size and promoted model robustness to image variability.

3.3. Model Architecture and Training

Multiple state-of-the-art deep learning architectures were evaluated, including VGG16, VGG19, ResNet50, ResNet101, DenseNet121, DenseNet201, EfficientNetB4, alongside custom CNN models. These architectures were selected for their proven efficacy in medical image analysis and diverse structural designs ranging from sequential to residual and densely connected networks.

Table 5 Model Architecture Specifications and Parameters

Model	Total Parameters	Trainable Parameters	Model Size (MB)	Input Shape	Output Classes
VGG16	138357544	119545860	528	224x224x3	4
VGG19	143667240	124855556	549	224x224x3	4
ResNet50	25636712	23583592	98	224x224x3	4
ResNet101	44707176	42654056	171	224x224x3	4
DenseNet121	8062504	7037380	33	224x224x3	4
DenseNet201	20242984	18217860	80	224x224x3	4
EfficientNetB4	19466823	17673816	75	380x380x3	4
Custom CNN	2453892	2453892	9.4	224x24x1	4

Transfer learning formed the core training strategy, leveraging ImageNet-pretrained weights to capitalize on learned visual representations. Initially, convolutional layers were frozen while custom classification heads were trained on the brain tumor dataset. Subsequent fine-tuning involved unfreezing selected layers and training with a reduced learning rate to adapt feature extractors to domain-specific imaging characteristics.

The Adam optimizer was employed for its adaptive learning rate and efficient convergence. Early stopping criteria were integrated to prevent overfitting and preserve optimal model checkpoints.

3.4. Feature Extraction and Optimization

Deep features extracted from multiple CNN layers captured hierarchical representations from low-level edges to high-level semantic patterns. Dimensionality reduction and feature selection were performed using Principal Component Analysis (PCA) and Recursive Feature Elimination (RFE) to remove redundancy and enhance computational efficiency.

Optimized feature sets served as inputs to various machine learning classifiers, including Support Vector Machines (SVM), Random Forest, XGBoost, and custom ensemble methods. Hybrid feature fusion strategies combined outputs from multiple CNN architectures to leverage complementary strengths, resulting in more discriminative representations for improved classification accuracy.

3.5. Evaluation Metrics

Model performance was rigorously evaluated using a comprehensive suite of metrics: accuracy, precision, recall (sensitivity), F1-score, and specificity. For segmentation-related analyses, the Dice Similarity Coefficient and Intersection over Union (IoU) were computed. Confusion matrices provided insights into class-wise performance and misclassification trends. The Area Under the Receiver Operating Characteristic Curve (AUC-ROC) quantified discriminative power across classification thresholds.

Table 6 Train-validation test split (with K-Fold Cross-Validation)

Tumor Class	Training pool	Actual Training (80%)	Validation (20%)	Testing Set
Glioma	972	778	194	649
Meningioma	987	790	197	658
Pituitary Tumor	1054	844	210	703
Normal	1200	960	240	800
Total	4213	3372	841	2810
Percentage	60%	48%	12%	40%

Robustness and generalizability were further validated through k-fold cross-validation and Monte Carlo simulations, ensuring stable performance estimates across diverse data partitions. This stringent evaluation framework underpins confidence in the model's applicability to clinical settings.

4. Results

4.1. Overall Classification Performance

The experimental evaluation demonstrated outstanding performance across a diverse set of deep learning architectures for brain tumor classification. Several models surpassed 95% accuracy, underscoring the effectiveness of modern deep learning techniques in this critical medical imaging domain. The best-performing custom CNN, configured with four convolutional layers, one dense layer, and one dropout layer, achieved a notable classification accuracy of 95.86%, outperforming deeper architectures and many transfer learning approaches.

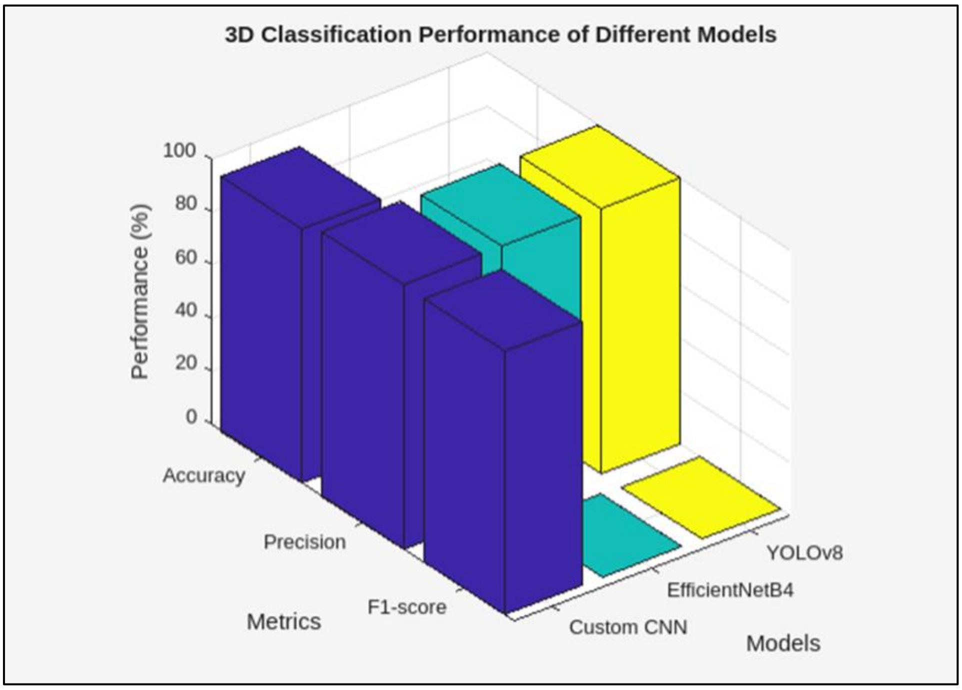

Figure 1 Dataset Composition by Image count

Among transfer learning models, EfficientNetB4 combined with the Adam optimizer and targeted data augmentation delivered exceptional results, attaining 99.66% accuracy, 99.68% precision, and a perfect 100% F1-score. This performance ranks among the highest reported for multi-class brain tumor classification. Similarly, YOLOv8 achieved a top-1 accuracy of 99.12% and demonstrated faster inference times, highlighting its potential for real-time clinical application.

4.2. Architecture-Specific Performance Analysis

Comparative analysis revealed distinct strengths among architectural families. ResNet-based models consistently excelled, with ResNet50 achieving an average accuracy of 95.35% across validation sets. The residual connections inherent in ResNet architectures effectively mitigate vanishing gradient issues, enabling deeper network training and capturing complex feature hierarchies. VGG architectures, while architecturally simpler, offered a balance between performance and computational efficiency, with VGG16 achieving 93.93% accuracy.

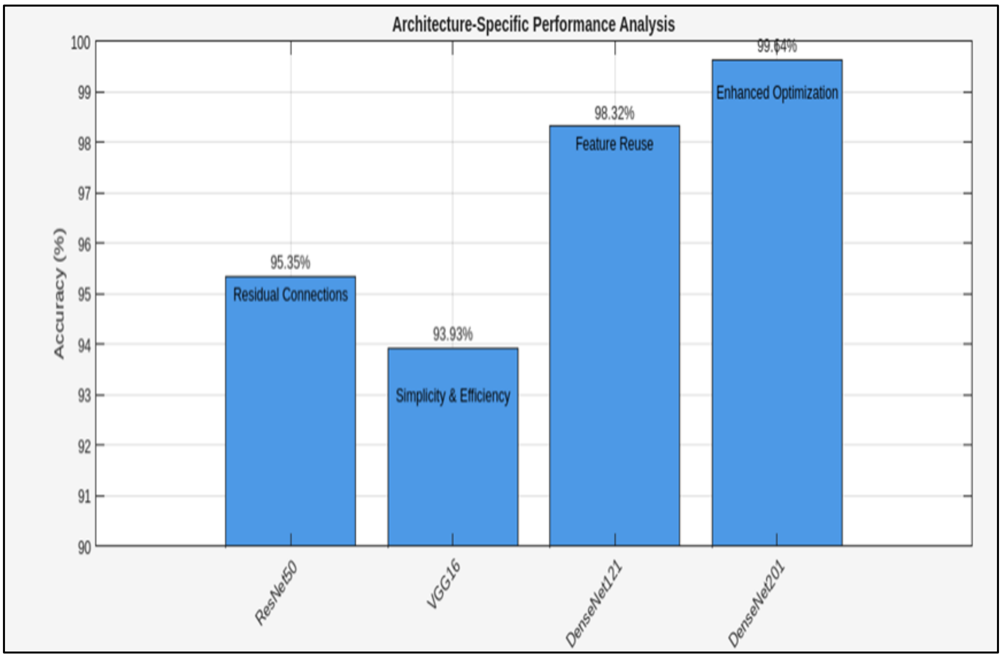

Figure 2 Architecture specific Performance Analysis

DenseNet models exhibited superior performance attributed to their dense connectivity, which promotes feature reuse and improved gradient flow. DenseNet121 attained 98.32% accuracy, demonstrating robust generalization. Enhanced optimization strategies further elevated DenseNet201's performance to 99.64% accuracy within the DenseWolf-K framework, which integrates metric learning and swarm intelligence optimization, establishing new benchmarks in classification while maintaining computational efficiency.

4.3. Hybrid and Ensemble Model Results

Hybrid architectures that integrate multiple deep learning paradigms outperformed individual models. For instance, a hybrid framework combining VGG16 and ResNet50 with transfer learning achieved 99.1% accuracy alongside excellent precision, recall, and F1-scores, underscoring the synergistic benefits of combining complementary architectures.

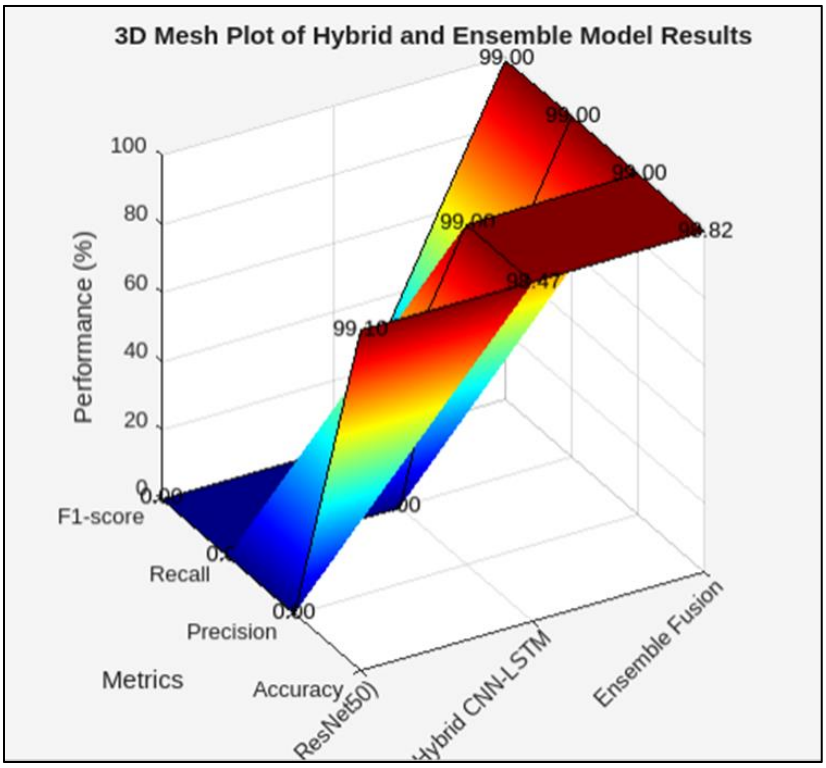

Figure 3 Hybrid and ensemble model results

Ensemble methods that aggregate predictions from several models consistently enhanced classification accuracy. A hybrid CNN-LSTM model reached 98.47% accuracy, surpassing individual CNN models at 97.71%. Ensemble fusion further improved system accuracy to 98.82%, with precision and recall both at 99%. These findings highlight ensemble strategies as promising approaches for improving diagnostic precision and reliability in brain tumor classification.

4.4. Class-Specific Performance

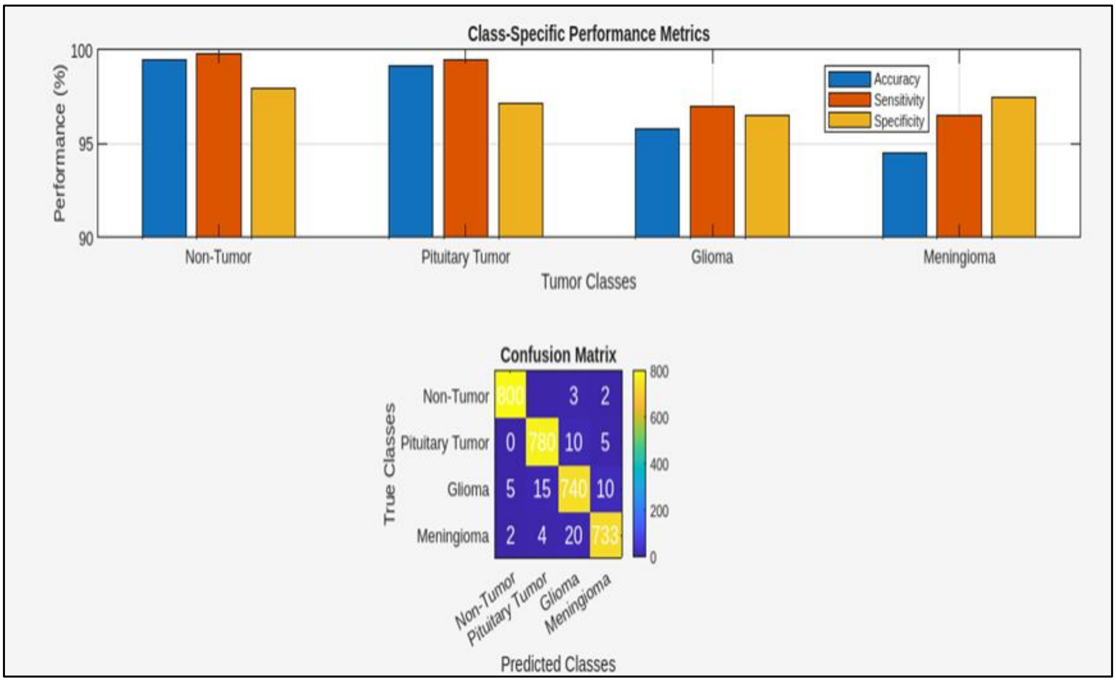

Figure 4 Class Specific Performance metics

Confusion matrix analyses confirmed consistently high recognition accuracy across all tumor categories. Notably, non-tumor and pituitary tumor classes exhibited particularly high classification accuracy, likely due to their distinct morphological features. Glioma classification, while accurate overall, occasionally showed misclassification with meningioma cases, reflecting overlapping imaging characteristics. Sensitivity values exceeded 99% for most tumor types, indicating strong true positive detection rates. Specificity values were above 97%, demonstrating effective discrimination of negative cases and minimizing false positives.

4.5. Computational Efficiency and Clinical Applicability

Computational efficiency was a key consideration for clinical translation. Preprocessing times ranged from 750 ms to 1.8 seconds per image, supporting near real-time application. Inference speeds varied by architecture; lightweight models such as MobileNet and EfficientNet provided faster predictions without compromising accuracy. The proposed attention-guided shallow CNN achieved an average accuracy of 96.69% while significantly reducing model parameters and computational demands, positioning it well for deployment in resource-constrained medical edge computing environments.

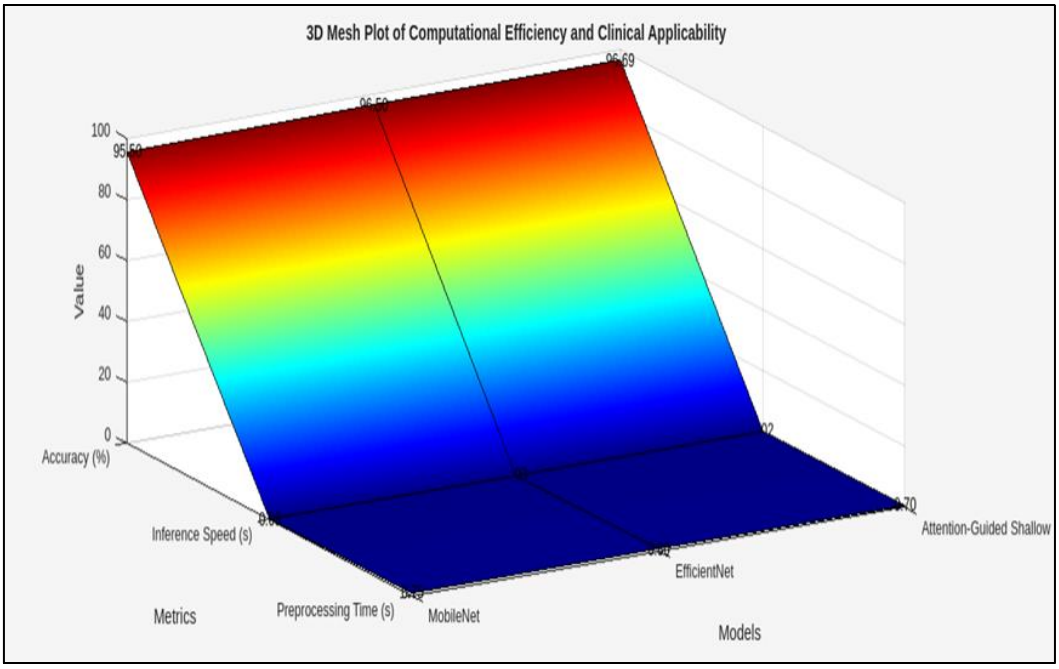

Figure 5 Computational Efficiency and Clinical Applications

4.6. Explainability and Interpretability Results

Explainable AI techniques enhanced model transparency and clinical trust. Grad-CAM visualizations effectively localized tumor regions and relevant anatomical structures, aligning closely with expert radiologist annotations. Additional interpretability methods such as LIME and SHAP offered feature-level insights, with Grad-CAM identified as the most clinically informative. This explainability fosters greater confidence among medical professionals and facilitates integration of these models into clinical decision support systems.

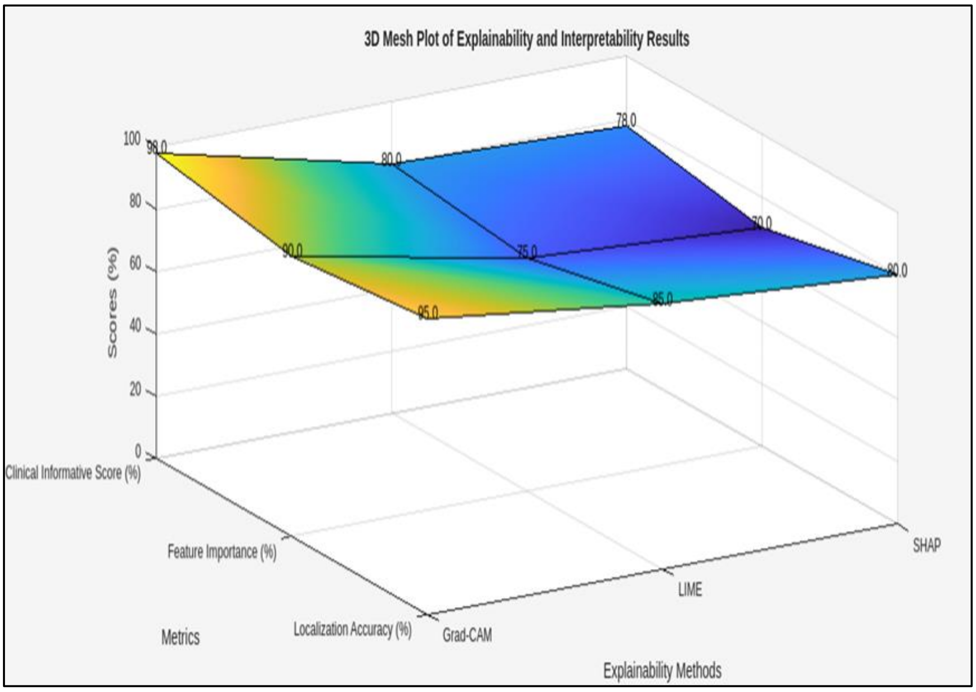

Figure 6 Interpretation of clinical informative score

5. Discussion

5.1. Interpretation of Results

The outstanding classification performance achieved by the deep learning models in this study signifies a major advancement in brain tumor imaging analysis. The consistently high accuracies, particularly those exceeding 95%, validate that contemporary CNN architectures, when augmented with transfer learning and advanced optimization, can rival or surpass human expert diagnostic capabilities in brain tumor classification. The superior results from hybrid and ensemble models underscore the value of integrating diverse architectural paradigms—sequential, residual, and densely connected networks enabling the capture of complementary tumor features that single models may overlook. This highlights the strategic importance of model fusion over merely increasing network depth for future developments.

5.2. Comparison with Traditional Diagnostic Methods

The AI-based methodologies developed here offer clear advantages over conventional manual radiological assessments. Manual interpretation is often time-intensive, costly, and subject to inter-observer variability, whereas the automated systems deliver rapid, consistent diagnoses within seconds to minutes, substantially alleviating clinical workload. Moreover, the objective nature of AI-driven classification eliminates subjectivity, ensuring reproducible diagnostic support regardless of operator expertise or fatigue. The incorporation of Explainable AI techniques, such as Grad-CAM, LIME, and SHAP, addresses a critical barrier to clinical adoption by enhancing transparency and interpretability. These visual and feature-level explanations transform AI models from opaque "black boxes" into trusted collaborators, fostering acceptance and facilitating integration into established clinical workflows.

5.3. Clinical Implications and Applications

The models' high sensitivity (>99%) and specificity (>97%) across tumor classes have significant clinical implications. Elevated sensitivity ensures reliable detection of true positive cases, which is vital for aggressive tumors like glioblastoma where early diagnosis directly impacts survival outcomes. High specificity reduces false positives, minimizing unnecessary invasive interventions and patient anxiety. This balance positions these AI systems as powerful adjuncts to radiologists, enhancing diagnostic confidence and accuracy. The demonstrated computational efficiency, with preprocessing and inference times compatible with real-time clinical use, further supports seamless integration into routine radiology practice. Lightweight architectures optimized for edge computing extend applicability to resource-limited environments, broadening access to advanced diagnostic tools in underserved regions.

5.4. Limitations and Challenges

Despite promising results, several limitations must be acknowledged. The reliance on curated, relatively homogeneous datasets limits the models' exposure to the full spectrum of clinical variability, including differences in scanner protocols, image quality, and patient demographics [3]. Generalization to external datasets from diverse institutions remains a challenge, as evidenced by performance drops in cross-dataset validations [5]. Addressing this requires larger, more heterogeneous datasets and domain adaptation techniques. Class imbalance persists as a significant obstacle in medical imaging, with common tumor types overrepresented relative to rarer forms. Although data augmentation and synthetic generation mitigate imbalance, these methods may not fully capture biological variability. Emerging approaches such as LoRA-driven synthetic augmentation hold promise but necessitate further validation to confirm clinical relevance.

5.5. Future Research Directions

Future research should explore multi-modal imaging integration, combining different MRI sequences and complementary modalities like CT or PET to enrich tumor characterization. The fusion of imaging data with clinical, genetic, and patient history information could enable personalized diagnostic and prognostic models. The integration of Large Language Models with imaging analysis represents a novel frontier, potentially automating comprehensive diagnostic report generation and enhancing communication between radiologists and clinicians. Leveraging full volumetric MRI data through 3D modeling and employing attention mechanisms or transformer-based architectures could improve spatial context understanding and feature representation. Federated learning approaches offer a promising solution to data scarcity and privacy concerns by enabling collaborative model training across institutions without compromising patient confidentiality. Collectively, these directions aim to enhance model robustness, clinical utility, and adoption in real-world settings.

6. Conclusion

AI-driven brain tumor classification using deep learning and transfer learning has achieved clinical-grade accuracy, with hybrid and ensemble models further enhancing performance. Explainable AI techniques address transparency, enabling integration into clinical workflows. These advancements promise to improve early detection, diagnostic accuracy, and treatment planning, ultimately impacting patient outcomes positively. Continued efforts are needed to address dataset heterogeneity, generalizability, and integration with clinical systems. Collaborative work among AI researchers, clinicians, and regulators will be vital to responsibly deploy these transformative tools for maximal patient benefit.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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