AI-DRIVEN PRECISION ONCOLOGY FOR BRAIN TUMOR DIAGNOSIS: A COMPREHENSIVE REVIEW OF ADVANCED METHODOLOGIES FROM 2024-2025

Abstract:
Manual interpretation of brain tumors from Magnetic Resonance Imaging (MRI) scans is a time-consuming, subjective, and variable process. Artificial Intelligence (AI) has been a revolutionary force that has changed this area, but the initial models have proven to have some serious challenges. This review comparatively analyzes the current best AI methods from the literature published in 2024 and 2025 for multi-class brain tumor classification. We assessed the transition from conventional Convolutional Neural Networks (CNNs) to newer, more advanced architectures, such as Vision Transformers (ViT), hybrid networks, where deep learning is paired with conventional machine learning, and strong ensemble models. The main topic of this review is the exploration of Explainable AI (XAI) and its importance in providing transparent and trustworthy decisions in the medical field. In addition, we deal with methods that strive to improve computer effectiveness and real-world usefulness by means of optimization inspired by the biological world and the implementation of new localization algorithms, such as YOLO. This survey highlights the most accurate and efficient methods that are ready for clinical application, especially their capability to overcome Indian healthcare inequalities by facilitating access to expert-level diagnosis.

Keywords: Precision Oncology, Brain Tumor, Artificial Intelligence, Deep Learning, MRI, Vision Transformer, Explainable AI (XAI), Ensemble Learning.

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INTRODUCTION

The diagnosis and treatment of brain cancer are the most demanding tasks in modern medicine. Manually interpreting MRI scans using radiologists, which is the standard for diagnosis, is a very time-consuming task that still requires high skills. This leads to subjectivity and potential diagnostic delays. The AI-powered brain tumor detection sector has greatly changed to meet the needs of the situation. Initially, research focused on the use of traditional machine learning classifiers supplemented with handcrafted features. Subsequently, the use of CNNs became the main theme. Through transfer learning, as well as the VGG16 and ResNet architectures, feature extraction was automated, and the deep learning accuracy was improved significantly. In addition to the fact that foundational deep learning models have their own challenges, which cover the problems that have been mentioned in the recent literature. The key problems discussed are as follows.

- **Insufficient number of classes for classification:** Initial works largely based on deep learning models were built mainly for binary classification (tumor vs. no tumor) and did not continue to develop further into solving multi-class problems of classifying the brain tumor into various types such as glioma, meningioma, and pituitary tumors, which is necessary for deciding the treatment course precisely.

- **The "Black Box" Problem:** The nature of deep learning models, which are not very transparent, leads to clinical trust being lost. If there is no explanation as to how the model reached a certain decision, then the doctors will not be sure and thus will not decide to rely on it when making decisions.
- **Computational and Data Demands:** These complex and modernized models usually utilize powerful computing machines and are trained on large datasets to produce their highest-performing models; hence, they are not always suitable for resource-poor clinical environments.
- **Classification vs. Localization:** Typically, there is a gap between an image classification task and the accurate localization of the tumor in the image, which is a very important step in surgical planning and radiotherapy.

This review systematically analyzes and compares novel methodologies developed between 2024-2025 designed to solve these specific problems. Current research has shifted towards more sophisticated and methodologically diverse approaches, including the application of Vision Transformers (ViT) to capture the global context in MRI scans, the creation of hybrid and ensemble models to boost performance, and a crucial focus on Explainable AI (XAI) techniques to make model decisions transparent and trustworthy for clinicians.

METHODOLOGY OF THE REVIEW

A systematic methodology underpins this review, ensuring a comprehensive analysis of the selected literature without bias creeping in somehow. The process entails a myriad of bewildering steps undertaken subsequently.

- **Defining Scope & Research Questions:** Review focuses on AI methodologies for multi-class classification of brain tumors from MRI scans, with an emphasis on advanced architectures such as ViTs and hybrids.
- **Systematic Literature Search:** A comprehensive search was conducted in major academic databases, including IEEE Xplore, Google Scholar, and Elsevier, for peer-reviewed papers published between January 2024 and July 2025. The keywords included brain tumor and MRI alongside deep learning techniques, such as Vision Transformer and ensemble models with Explainable AI.
- **Inclusion and Exclusion Criteria:** Selection included only original peer-reviewed research applying specific AI models to human brain tumor data with clearly reported quantitative metrics and methodology.
- **Data Extraction and Thematic Synthesis:** Key information from ten selected studies was systematically extracted, including AI model architectures, datasets utilized, performance metrics, and various reported limitations. The data were subsequently amalgamated into thematic sections of this review quite haphazardly afterwards and grouped neatly.

ADVANCED MODEL ARCHITECTURES FOR ENHANCED CLASSIFICATION

Recent research primarily aims to improve the accuracy of multi-class brain-tumor classification systems quite significantly nowadays. Recently, a shift away from singular CNN models has occurred towards ensemble hybrids and Vision Transformers with greater complexity and robustness.

Ensemble Models

Ensemble learning aggregates predictions from multiple models, yielding a more accurate result than any single model typically produces. Hossain et al. (2024) conducted experiments and proposed an ensemble model named IVX16, which averages the predictions from three well-established transfer learning models: InceptionV3, VGG16, and Xception. In 2024, an ensemble model named IVX16 was proposed, which averaged predictions from three well-established transfer learning models: InceptionV3, VGG16, and Xception.

Tariq et al. (2025) presented a relatively modern alternative approach subsequently, who developed an ensemble combining a state-of-the-art CNN (EfficientNetV2) with a Vision Transformer (ViT). EfficientNetV2, a state-of-the-art CNN, combined with Vision Transformer ViT in an ensemble, was developed by 2025. CNN excel at capturing fine-grained local features and textures, whereas ViTs adeptly understand the global context and long-range dependencies within images.

Hybrid Models (Deep Learning + Machine Learning)

Hybrid models strike a balance between the automated feature extraction prowess of deep learning and the considerable efficiency of traditional machine learning classifiers. A pre-trained CNN serves as a sophisticated feature extractor, and its output is fed into a simpler classifier, such as KNN or SVM.

Researchers led by Kumar (2025) have apparently done some significant work and developed a hybrid approach using various CNNs (including VGG16 and ResNet) to extract features from MRI scans, which were then classified by an SVM. By 2025, a hybrid approach emerged, leveraging various CNNs, such as VGG16 and ResNet, for feature extraction from MRI scans, which an SVM then classified. This method attained a remarkably high accuracy of 97%, demonstrating the effectiveness of the combination in experimental conditions. Shahi et al. (2025) created a hybrid framework using AlexNet or ResNet-18 for feature extraction and an SVM for classification, explicitly showing that their hybrid model outperformed the standalone deep learning models in certain metrics. It behaved similarly under different conditions.

Vision Transformers (ViT) in Neuro-Oncology

Vision Transformers adapted from natural language processing successes have emerged as powerful tools for the effective analysis of medical images. ViTs fragment an image into various patches and scrutinize the relationships among them, thereby effectively capturing the global context across the entire image. Tariq et al. (2025) have shown this previously in their work, ViTs are a key component of next-generation models. By 2025, ViTs will likely remain a crucial part of models being developed for next-generation applications. However, their data-hungry nature remains a significant challenge. Hossain et al. (2024) found that when tested on a relatively small dataset, ViT models performed poorly and showed signs of overfitting, highlighting their dependency on massive datasets for effective generalization.

THE CRITICAL ROLE OF EXPLAINABLE AI (XAI)

For widespread adoption, AI models must be extremely trustworthy in high-stakes fields such as clinical medicine. The opaque inner workings of deep learning pose a significant hurdle in establishing trust pretty much everywhere nowadays. Explainable AI refers to techniques that make AI decisions completely transparent and somewhat interpretable by humans with a considerable technical background.

Khandaker et al. (2024) have perfectly demonstrated the dual goal of modern medical AI: achieving exceptional accuracy while ensuring interpretability. Exceptional accuracy and interpretability were perfectly demonstrated in 2024 by modern medical AI with its unique dual goal. They coupled high-performing DenseNet169, achieving an accuracy of 99.83% with a suite of XAI techniques, such as GradCAM, ScoreCAM, and LayerCAM. These tools generate visual heatmaps overlaying the original MRI and highlight specific pixels and regions that are heavily focused on for diagnosis purposes. Clinicians can now scrutinize model decisions thoroughly and validate their reasoning against their own deeply ingrained medical knowledge.

Hossain et al. (2024) and Kumar et al. (2025) used the XAI tools LIME (Local Interpretable Model-agnostic Explanations) and SHAP (Shapley Additive Explanations) to validate their models' predictions. Khan et al. (2024) introduced a novel framework that fuses XAI with formal methods, a concept from computer science used to provide mathematical guarantees of a system's correctness. In 2025, researchers employed the XAI tools LIME and SHAP to validate the predictions of their models with a considerable degree of interpretability.

EFFICIENCY, OPTIMIZATION, AND PRACTICAL APPLICATION

The practical deployment of AI models in real-world clinical settings, particularly in resource-constrained environments such as many parts of rural India, requires sheer computational efficiency.

Lightweight and Optimized Models

Shuvo et al. (2025), along with other researchers, directly addressed this challenge by creating a lightweight yet powerful hybrid network. A lightweight yet powerful hybrid network was created to address this challenge directly with considerable success. Their cascaded model employs an efficient CNN, namely MobileNetV2, for feature extraction, and a bio-inspired Bacterial Foraging Optimization algorithm selects discriminative features intelligently. A simple KNN classifier makes accurate final predictions with the selected features. State-of-the-art performance does not necessarily entail massive computational overhead, as evidenced by this remarkably accurate 99.16% efficient approach. Bedi et al. (2024) also contributes to this area by providing a straightforward comparison of several popular and relatively lightweight transfer learning models, including MobileNet-V2, ResNet, and Xception.

Tumor Localization with Object Detection

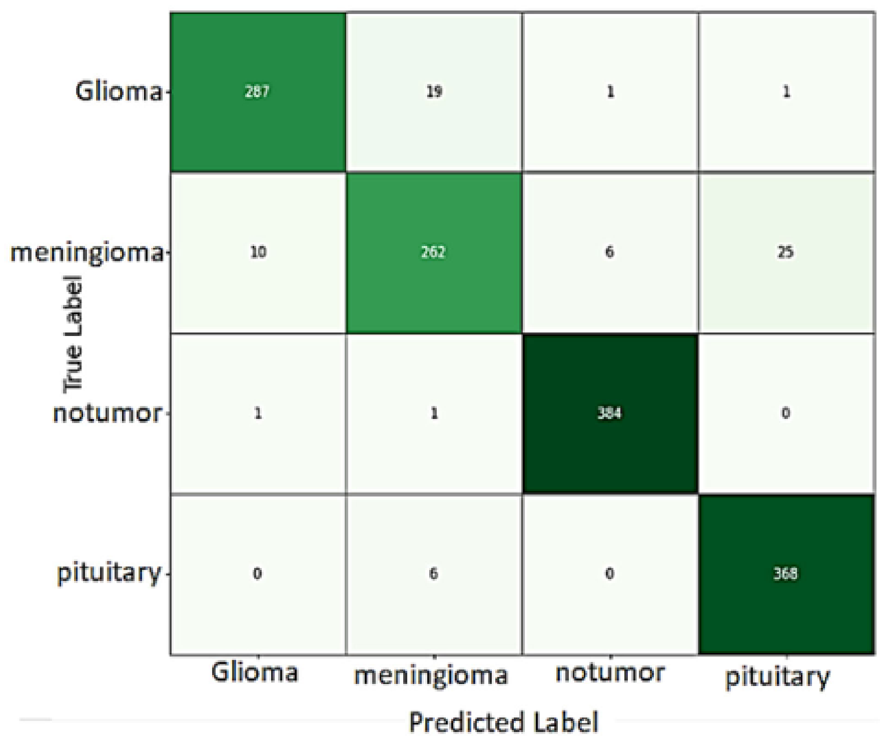
Precise diagnosis often necessitates the exact identification of tumor location boundaries for planning radiotherapy or surgery, rather than just classifying the tumor type. Dhabliya et al. (2024) furnished profound research findings and proposed a two-stage model that uses the YOLOv3 object detection algorithm. In 2024, they proposed a two-stage model utilizing the YOLOv3 object detection algorithm. YOLOv3 rapidly scans an image and draws bounding boxes around the detected tumors instead of laboriously classifying every single pixel. The localized region is subsequently passed into a separate CNN for classifying it as either a low-grade or potentially high-grade tumor.

VISUALIZATIONS AND KEY DATA FROM REVIEWED LITERATURE

Key figures and tables extracted from selected reference papers are presented here, substantiating the findings of this review with various visualizations. The elements presented here furnish evidence directly related to the performance and methodologies employed by the models discussed alongside their interpretability.

From Tariq et al. (2025): Ensemble Model Performance

EfficientNetV2 and Vision Transformer (ViT) are combined innovatively in this study, yielding a somewhat groundbreaking key contribution. The confusion matrices are presented in (Fig. 1). The performance of the individual models and the final ensemble model is demonstrated in detail. The ensemble model exhibited markedly fewer misclassifications, particularly in challenging glioma and meningioma classes, validating the effectiveness of combining two disparate architectures.



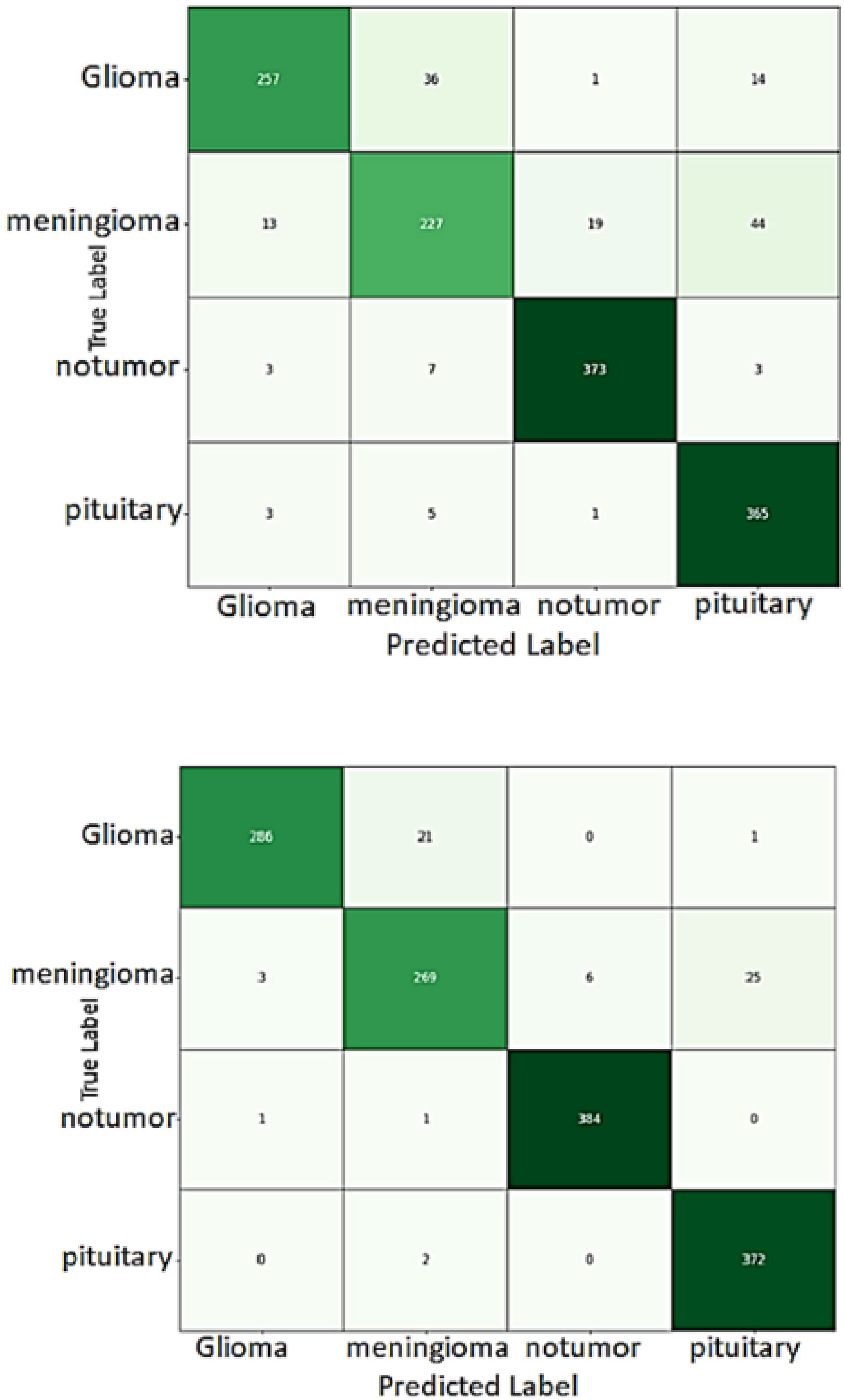


Fig. 1: EfficientNetV2 and Vision Transformer matrices starkly contrast with the final Geometric Mean model's surprisingly superior performance metrics overall.

- **EfficientNetV2 Matrix:** Strong performance is evident with 287 glioma cases and 384 ‘notumor’ cases classified correctly, but 36 meningioma cases were misclassified as glioma.
- **Vision Transformer Matrix:** Performs less effectively, correctly classifying only 257 glioma cases and misclassifying 64 meningioma cases.
- **Geometric mean ensemble matrix :** Performed exceedingly well overall. It correctly classifies 280 glioma cases, fewer than EfficientNetV2 alone, but boosts meningioma classification significantly, identifying 269 cases correctly and reducing misclassifications drastically. Ensemble methods create a relatively balanced classifier, and the reliability increases noticeably with this approach.

From Shuvo et al. (2025): Lightweight Model Performance
The potency of optimization is underscored in this study. A comparison of various cascaded networks is presented in Table 1. MobileNetV2 paired with BFO and KNN exhibited the highest accuracy at 99.16%, and BFO step markedly boosted performance via pertinent feature selection.

Table 1: Performance of MobileNetV2 with Various Classifiers (Shuvo et al., 2025)

Classifier	Accuracy (%) W/O BFO	Accuracy (%) with BFO	Precision (%) with BFO	Recall (%) with BFO	F1-Score (%) with BFO
SVC	97.35	97.4	97.68	97.24	97.43
RF	93.3	92.86	93.62	92.38	92.92
XGB	95.77	95.72	96.14	95.45	95.78
KNN	98.09	99.16	99.25	98.91	99.13
LR	95.06	96.03	95.42	96.12	95.26

This table shows that the K-Nearest Neighbours (KNN) classifier, when combined with MobileNetV2 and BFO, yielded the best performance across all metrics.

From Khandaker et al. (2024): Explainable AI (XAI) Visualizations
This paper exhibits considerable strength, owing largely to its intensely interpretative focus. Figure 2 illustrates the output from four disparate XAI techniques applied against the DenseNet169 model with considerable intricacy. Heatmaps provide crucial transparency for clinicians by vividly visualizing the model's reasoning beneath the layers of a complex neural network architecture.

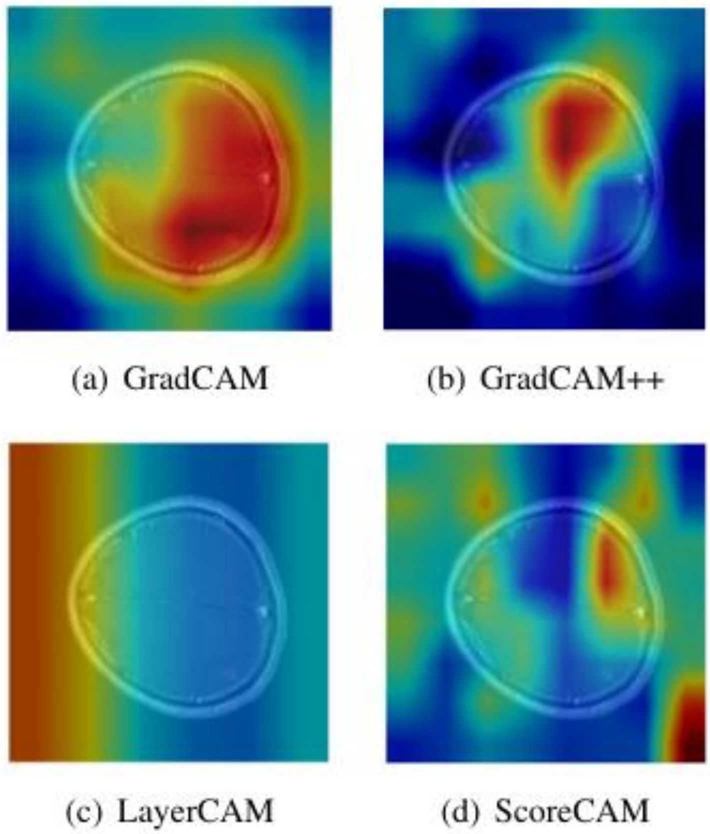


Fig. 2: Four XAI methods, namely GradCAM, GradCAM++, LayerCAM, and ScoreCAM, provide visual explanations highlighting the model's focus area for effective brain tumor diagnosis.

Four heatmaps generated by various XAI methods, including GradCAM and ScoreCAM, are displayed on the same brain MRI quite effectively.

- **GradCAM:** A large intense red blotch appears directly over the tumor, indicating this region as the primary focus for model decision-making purposes.
- **GradCAM++ and ScoreCAM:** Produce refined heatmaps displaying activation focused within tumor boundaries.
- **LayerCAM** : Activations from multiple layers are visualized thoroughly, offering a super-detailed glance at the features that the model identifies internally. All four methods confirmed the model accuracy, focusing on pathological image areas.

From Dhabliya et al. (2024): Tumor Localization with YOLOv3

Localization occurs first in a two-step process, and then classification follows fairly naturally in this particular instance. Figure 3 illustrates the workflow graphically, showing the object detection model pinpointing the tumor location initially within a medical imaging context rather crudely.

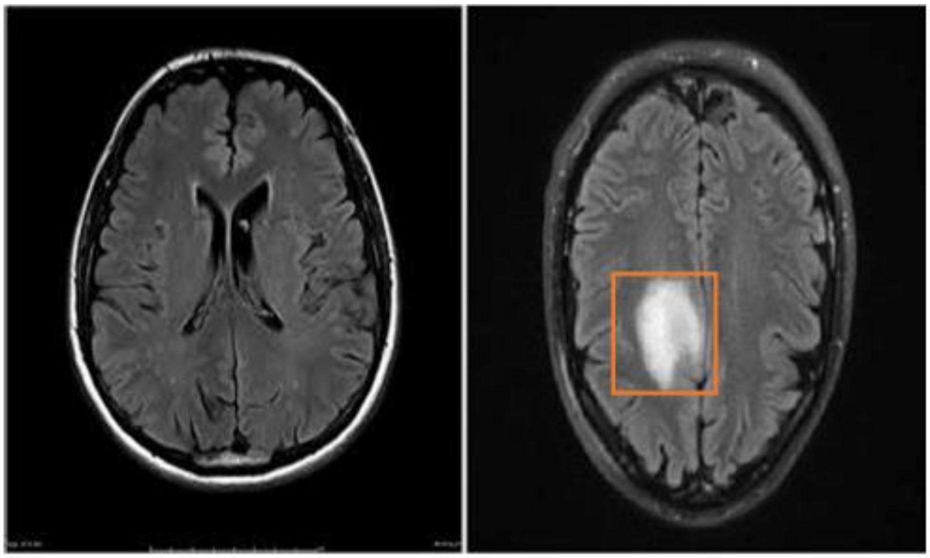


Fig. 3: Example of brain-tumor localization. An MRI image displays the tumor presence highlighted by the YOLOv3 algorithm inside a bounding box around it very accurately.

This figure contains two MRI images.

- **Left Image:** Brain MRI scan classified as tumor-free.
- **Right Image:** MRI of the brain reveals a tumor. The YOLOv3 algorithm successfully draws a red bounding box directly around the tumor, precisely localizing the region of interest before sending it for classification. This showcases the model's ability remarkably by not only categorizing data but also effectively pinpointing anomalies.

From Hossain et al. (2024): Ensemble vs. Single Model and LIME Validation

An ensemble model decisively outperforms its constituent parts according to some study findings in various scenarios. Figure 4 displays the accuracy curves for several models, while Figure 5 leverages LIME validation to scrutinize the model focus.

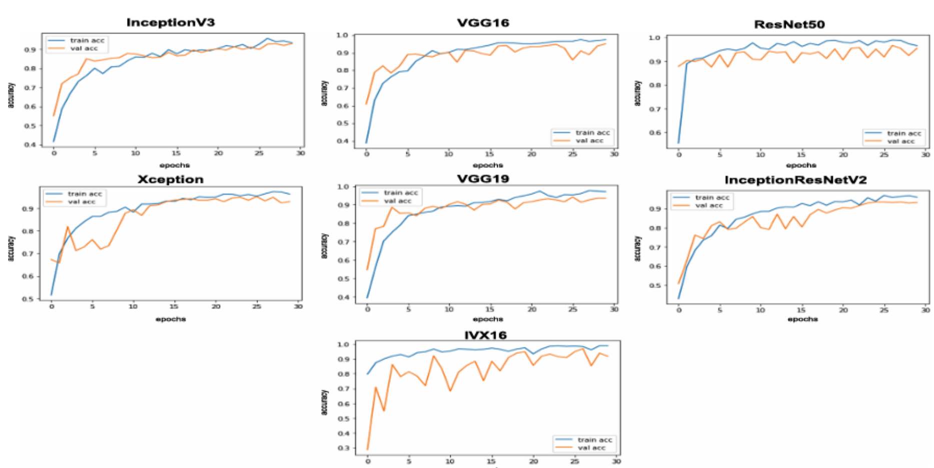


Fig. 4: The six transfer learning models and the IVX16 ensemble model exhibited performance curves with superior results, with the latter performing remarkably.

Seven different models were plotted over 30 epochs with varying validation accuracies and remarkably inconsistent training accuracy trajectories. The orange line representing the IVX16 ensemble model achieves higher validation accuracy and stability, far surpassing other individual transfer learning models, such as InceptionV3 and VGG16.

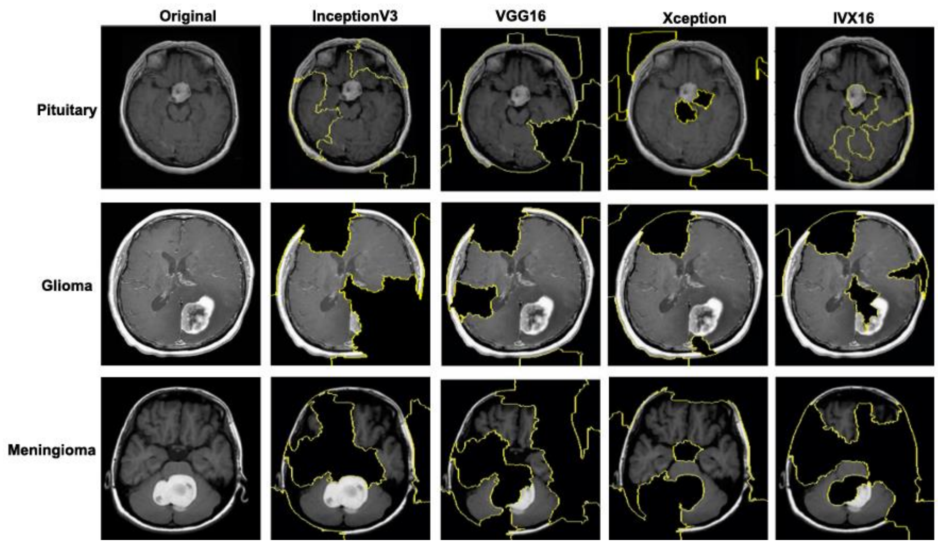


Fig. 5: Tumor types exhibit varying LIME visualizations across distinct categories. The IVX16 ensemble model correctly identified the tumorous region in the final column with reasonably high accuracy.

The LIME outputs were visualized in a grid format across four disparate models for pituitary tumors and Glioma and Meningioma tumor types.

- The first three columns for each tumor type show varied localizations across the InceptionV3, VGG16, and Xception models, with highlighted areas often outside the actual tumor boundaries.
- **The IVX16 Ensemble** column provides the most accurate visualization, consistently with the highlighted yellow boundary correctly enclosing the tumorous region. Visually, this validates the ensemble model predictions based on the correct pathological features.

DISCUSSION AND IMPLICATIONS FOR THE INDIAN CONTEXT

Research from to 2024-2025 heralds a pronounced shift towards crafting AI systems that are simultaneously accurate, trustworthy, and clinically efficient. The trend is moving away from monolithic black box architectures towards solutions that are fairly modular and highly optimized for specific tasks. Ensemble and hybrid models prove highly effective, and the integration of XAI becomes a standard necessity rather than a belated afterthought.

Such advancements have profoundly impacted Indian healthcare. A severe shortage of trained radiologists and neuro-oncologists exists, especially in rural areas, creating a significant bottleneck in diagnosis. AI models, particularly lightweight and efficient ones, can serve as powerful assistive tools for general physicians and radiologists in such overseas regions.

- **Democratizing Expertise:** Accurate multi-class classification from MRI scans by an AI system provides crucial expert-level insights for doctors in district hospitals, enabling faster referrals.
- **Standardizing Care:** AI furnishes objective analyses that are extremely helpful in reducing the diagnostic variability rampant across diverse medical centers with varying levels of expertise.
- **Optimizing Resources:** These tools help clinicians prioritize critical cases by providing accurate automated first readings and localizing tumors, thus optimizing the use of limited healthcare resources.

CONCLUSION AND FUTURE DIRECTIONS

Significant advancements in AI for brain tumor diagnosis stem largely from the intelligent fusion of diverse methodological approaches. Hybrid and ensemble models achieve the highest accuracy for complex multi-class classification problems, especially those integrating the local feature extraction process of CNNs with the global contextual understanding of vision transformers.

The integration of Explainable AI has become crucial for garnering clinical trust and facilitating adoption, thereby shifting the focus from performance alone to transparency and human-machine collaboration. Powerful models are being developed with computational efficiency, making advanced diagnostic tools more accessible in diverse clinical practices surprisingly quickly.

Future research should focus on the following key areas:

- **Larger and More Diverse Datasets:** Performance of models such as ViTs relies heavily on the availability of copious amounts of fairly diverse data. The creation of ethnically diverse datasets involving multiple institutions is crucial for training robust models with broad generalizability.
- **Multi-Modal Data Integration:** Future models will likely incorporate diverse data types, such as histopathology slides, genomic data, and various facets of patient clinical history, rather than haphazardly.
- **Longitudinal Studies:** AI models must be developed and validated for tracking tumor progression over time, not just for making the initial diagnosis of tumors.
- **Clinical Integration and Trials:** Ultimate goals manifest as profoundly impactful real-world outcomes very slowly over time. Prospective clinical trials validating AI models in live workflows rigorously assess their impact on patient outcomes pretty thoroughly nowadays.

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