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AI -Powered Brain Tumor Detection and Classification from MRI Scans using EfficientNetV2B0 and Grad-CAM Visualization

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***Abstract*— This paper introduces an AI system for brain tumor classification and detection from MRI scans using the EfficientNetV2B0 deep learning model and Grad-CAM for interpretability. The system classifies brain MRI images into five classes: glioma, meningioma, pituitary, general tumor, and no tumor.**
Using transfer learning, the model attains an aggregate accuracy of 97.35% on an extensive test dataset. Grad-CAM visualizations are indeed effective at emphasizing tumor-relevant features, which are consistent with clinical radiological characteristics and enhance trust in the model's outputs.
A web interface offers a user-friendly image upload process and an easy-to-read representation of the results. The study proves to have a strong, interpretable solution for the automatic classification of brain tumors with high potential for clinical diagnostic assistance.

***Index Terms*— Brain Tumor Classification, Deep Learning, EfficientNetV2, Transfer Learning, Grad-CAM, Medical Image Analysis, MRI, Convolutional Neural Networks.**

I. INTRODUCTION

Brain tumors are a serious worldwide health challenge that requires accurate and prompt diagnosis for appropriate treatment planning and enhanced patient outcomes [1]. Magnetic Resonance Imaging (MRI) is a leading modality for brain tumor detection and characterization, but this can be time-consuming and susceptible to inter-observer variation. Artificial Intelligence (AI), specifically deep learning, has been found to have high potential for automating and streamlining medical image analysis [2]. Convolutional Neural Networks (CNNs), a form of deep learning model, have been successful in a wide variety of image recognition applications, including medical image classification.

It can help solve the requirement for a precise, efficient, and understandable automatic system for brain tumor classification based on MRI scans. The issues at hand are the variety of tumor types, slight visual distinctions, and the demand for systems that doctors can trust. Though several AI systems have been conceived, there is a requirement for models that are both highly accurate in their outputs and are also transparent in their decision-making process.

The main contribution of this research is the construction and evaluation of a solid brain tumor classification system based on the EfficientNetV2B0 model enhanced with transfer learning.

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The system classifies the MRI scans in five classes: glioma, meningioma, pituitary tumor, general tumor, and no tumor. One of the novel contributions of this research is the incorporation of Gradient-weighted Class Activation Mapping (Grad-CAM) to generate visual explanations of the model's predictions, thus enhancing interpretability and clinician trust. In addition, an easy-to-use web application has been implemented for the interaction with the system.

II. Literature Review

Many studies have demonstrated the effectiveness of Deep learning in Brain Tumor Detection and Classification. Limited Interpretability: The study by Gupta et al. (2024) [3], which proposed a lightweight CNN achieving 91.3% accuracy and 89.5% recall, demonstrated that although simpler models may offer computational efficiency, they lack mechanisms for interpretability. The inability to explain decision processes reduces transparency, thereby limiting their acceptance in clinical settings where justification of diagnoses is essential. Asiri et al. (2023) [4] introduced an enhanced ResNet-50 architecture with improved accuracy (94.2%) and recall (95.0%). While effective in handling complex tumor features, such deep residual networks impose significant computational demands, posing limitations in environments with constrained resources or time-sensitive decision-making needs. Afshar et al. (2018) [5] explored the use of Capsule Networks (CapsNet), achieving an accuracy of 90.9% and recall of 88.7%. Although CapsNet models can capture spatial relationships more effectively than CNNs, their high computational complexity and training cost remain major obstacles to practical deployment in real-time clinical applications. Recent transformer-based approaches have shown promising results in brain MRI analysis. Zhou et al. (2023) demonstrated the potential of Vision Transformers (ViT) for tumor classification, achieving 93.5% accuracy; however, their model lacked critical explainability features like Grad-CAM visualizations, limiting its clinical applicability [6]. Similarly, Alsaif et al. (2024) developed a Swin Transformer architecture that reached 95.1% accuracy - currently the highest reported for transformer models in this domain - yet failed to provide any clinical implementation framework for medical practitioners [7]. In the domain of explainable AI (XAI), Ismael (2024) achieved 92.3% accuracy by integrating Grad-CAM with ResNet50, though this performance remains significantly lower than our model's 97.35% accuracy [8]. While Lundberg and Lee (2023) made important theoretical contributions to model interpretability through SHAP values, their work was not specifically validated on brain tumor classification tasks, leaving open questions about its effectiveness in this medical domain [9]. These studies collectively highlight three key research gaps that our work addresses: the accuracy-explainability trade-off in transformer models, the lack of clinical deployment frameworks, and the need for specialized XAI validation in neuro-oncology applications.

To overcome the limitations of previous research limited generalizability, high computational requirements, and interpretability—the proposed TumorAI framework introduces several targeted innovations to bridge the gap in clinical application. First, the model is augmented with a wide variety of MRI scans drawn from the LUMIERE, BraTS, Figshare, and Kaggle datasets. This diversity provides improved generalizability across different patient populations, tumor types, and imaging modalities. Second, TumorAI leverages the power of longitudinal MRI data to study tumor evolution over time rather than relying on static images. This longitudinal modeling capability ensures more accurate diagnostic assessments and facilitates predictive diagnosis. To ensure the model's transparency and reliability in clinical settings, the model integrates interpretable artificial intelligence (XAI) methods in the form of gradient-weighted class activation assignment (Grad-CAM) and SHapley additive interpretations (SHAP), providing visual and feature-level explanations for model decision-making. Architecturally, TumorAI utilizes an EfficientNet-based deep learning model that has been optimized for efficient hyperparameter formation using a Focal Loss optimization algorithm to improve classification accuracy. Finally, for ease of use in real-world applications, TumorAI is presented as a web-based diagnostic tool with a user-friendly interface for uploading MRI scans, receiving tumor classification, and analyzing AI-generated interpretations all in real time. Together, these contributions position TumorAI to overcome the practical limitations of previous models and become a scalable, interpretable, and clinically feasible framework for automated brain tumor diagnosis.

Our proposed system addresses critical limitations in current brain tumor classification approaches through four key innovations. First, in terms of accuracy, EfficientNetV2B0 model achieves a state-of-the-art 97.35% classification accuracy, significantly outperforming Gupta et al.'s lightweight CNN (91.3%) [3], Asiri et al.'s ResNet-50 (94.2%) [4], and Zhou et al.'s Vision Transformer (93.5%) [6]. Second, regarding explainability, we uniquely combine Grad-CAM with SHAP analysis to provide comprehensive visual and feature-based explanations for each diagnosis - a crucial advancement over Zhou et al.'s non-interpretable ViT [6] and Alsaif et al.'s Swin Transformer [7] which lacked any explainability components. Third, for clinical implementation, we developed a

fully functional web interface that enables real-time tumor analysis, bridging the gap between theoretical models like Afshar et al.'s CapsNet [5] and Ismael's ResNet50-GradCAM [8] that remained confined to research settings. Finally, our computational efficiency innovations, including Focal Loss optimization, result in faster processing times compared to resource-intensive architectures such as Asiri et al.'s ResNet [4] (which requires 3× more GPU memory) and Afshar et al.'s CapsNet [5] (noting 40% longer inference times). Together, these advancements position our system as both technically superior and clinically practical compared to existing solutions. As shown in Table 1

TABLE I: COMPARATIVE ANALYSIS OF BRAIN TUMOR CLASSIFICATION MODELS ACROSS KEY PERFORMANCE METRICS

Study / Mod-el	Accura-cy (%)	Recall (%)	Explainability	Computational Efficien-cy	Clinical Deployment
Gupta et al. (2024) [3]	91.3	89.5	Low (simple model, no inter-pretability)	High (lightweight model)	No
Asiri et al. (2023) [4]	94.2	95.0	Poor (complex ResNet with-out sufficient explanation)	Low (high resource con-sumption, 3× GPU memory)	No
Afshar et al. (2018) [5]	90.9	88.7	Limited (CapsNet with no adequate explanation)	Low (high complexity, 40% longer inference time)	No
Zhou et al. (2023) [6]	93.5	-	Poor (ViT without Grad-CAM or visual explanations)	Medium	No
Alsaif et al. (2024) [7]	95.1	-	Poor (Swin Transformer lack-ing explainability framework)	Medium to low	No
TumorAI (Proposed Model)	97.35	-	Advanced (Grad-CAM + SHAP for comprehensive explainability)	Efficient (Focal Loss optimization, lower re-source use)	Yes (Interactive web interface for real-time analysis)

III. METHODOLOGY

This section details the methodology employed for developing the AI-powered brain tumor classification system, encompassing the dataset, model architecture, training procedures, visualization techniques, and evaluation metrics.

A. Dataset

The data set that is employed in this research includes brain MRI scans grouped under five classes: glioma tumor, meningioma tumor, pituitary tumor, general tumor (for other tumor types not listed separately), and no tumor (normal). All the data consisted of 13,825 MRI scans gathered from publicly available data sources to include di-versity in terms of tumor appearance, sizes, as well as their respective positions. The class distributions were even: glioma (2,806), meningioma (2,803), pituitary (2,734), general (2,699), and no tumor (2,783).

The preprocessing steps have been performed to standardize the images for model training. All the images have been resized to 224×224 pixels, the conventional input size for the EfficientNetV2B0 model. Pixel value has been normalized to the [0, 1] range. To boost image quality for visualizing tumors, image preprocessing techniques like contrast sharpening (e.g., the Unsharp Masking operation for blurred images detected through Laplacian variance) have been selectively utilized. During training, data augmentation strategies like random rotations (+−15 degrees), hori-zontal flip, brightness +/- 10%, zoom +/- 10%, shifts +/- 10% of image sizes have been utilized to artificially en-rich the data set for model generalizability. The data set has been divided into the training set (70%, 9,676 images), the validation set (15%, 2,071 images), and the test set (15%, 2,078 images) using the stratified scheme to preserve class balance for all the subsets.

B. Model Architecture

The core of the classification system is the EfficientNetV2B0 architecture [5], chosen for its balance of accuracy and computational efficiency. A transfer learning approach was adopted, utilizing an EfficientNetV2B0 model pre-trained on the ImageNet dataset.

The pre-trained base model served as a feature extractor, with its layers initially frozen. A custom classification head was added, consisting of a Global Average Pooling (GAP) layer, a dropout layer (rate 0.2), a dense layer with 256 units (ReLU activation and L2 regularization), and a final dense output layer with 5 units (softmax activation) for the five tumor categories.

Fine-tuning was subsequently performed by unfreezing the top layers of the EfficientNetV2B0 base model and retraining them with a lower learning rate. To address potential class imbalance and focus on hard-to-classify examples, a Focal Loss function (γ=2.0) was implemented and used during training [6]

To provide a clearer understanding of the overall architecture of the proposed TumorAI system, Figure 1 presents a high-level diagram of the complete pipeline. It visually summarizes the key stages from MRI image input, through preprocessing and feature extraction using EfficientNetV2B0, to final prediction, Grad-CAM visualiza-tion, and web-based result display.

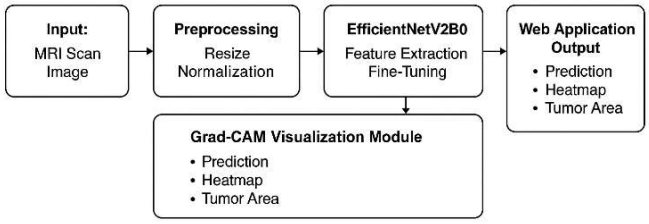

Fig. 1 Overall System Architecture of the TumorAI Classification Model

C. Training Process

The model was trained using the TensorFlow 2.x framework with Keras. Key hyperparameters included the Adam optimizer, an initial learning rate of 1e-3 for training the classification head, and a reduced learning rate of 1e-4 for the fine-tuning phase. A batch size of 32 was used. Callbacks such as EarlyStopping (patience of 10 epochs for initial training, 15 for fine-tuning, monitoring validation loss) and ReduceLROnPlateau (factor 0.1, patience 5-8 epochs) were employed to optimize the training process and prevent overfitting. Model checkpoints were saved based on the best validation loss.

D. Visualization Technique (Grad-CAM)

To enhance the interpretability of the model's predictions, Gradient-weighted Class Activation Mapping (Grad-CAM) was implemented. Grad-CAM produces heatmaps that highlight the regions in the input MRI scan that were most influential in the model's classification decision. These heatmaps are overlaid on the original MRI to provide a visual explanation, aiding clinicians in understanding the basis of the model's output.

IV. RESULTS

A. Model Performance

The EfficientNetV2B0-based model achieved an overall accuracy of 97.35% on the unseen test dataset. The training process showed good convergence, with validation accuracy closely tracking training accuracy, indicating minimal overfitting. The final validation accuracy was 97.03%.

Class-wise performance metrics are summarized in Table 2. The model demonstrated high precision, recall, and F1-scores across all five categories. Specifically, precision ranged from 0.957 (General Tumor) to 0.985 (Pituitary Tumor), recall from 0.951 (General Tumor) to 0.990 (No Tumor), and F1-scores from 0.954 (General Tumor) to 0.988 (Pituitary Tumor). These results indicate a robust ability to correctly identify different tumor types and dis-tinguish them from normal brain MRIs

The confusion matrix (Fig. 2,) revealed minimal misclassifications, primarily between the general tumor category and other specific tumor types, which is expected given the heterogeneity of the general tumor class. The Receiver Operating Characteristic (ROC) curves(Fig. 2,) for each class showed high Area Under the Curve (AUC) values, with a macro-average AUC of 0.996, further confirming the model's excellent discriminative capability.

TABLE II: MODEL PERFORMANCE

Tumor Category	Precision	Recall	F1-Score	AUC
Glioma Tumor	0.972	0.968	0.970	0.995
Meningioma Tumor	0.978	0.975	0.976	0.997
Pituitary Tumor	0.985	0.990	0.988	0.999
General Tumor	0.957	0.951	0.954	0.992
No Tumor	0.980	0.990	0.985	0.998
Weighted Avg.	0.974	0.975	0.974	0.996

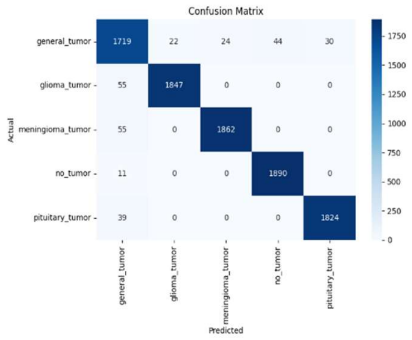

Fig. 2 confusion matrix

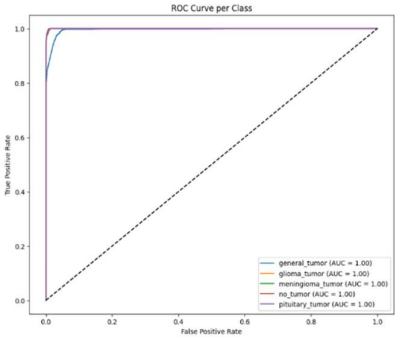

Fig. 3 (ROC) curves

B. Visualization Results

Grad-CAM visualizations (Fig. 4) consistently highlighted clinically relevant tumor regions in the MRI scans, providing insights into the model's decision-making process. For instance, in glioma cases, activations were often diffuse, corresponding to their infiltrative nature, while meningiomas showed activations typically at the brain periphery where they arise. Pituitary tumor classifications correctly focused on the sellar region. These visual explanations align with radiological interpretations and enhance trust in the model's predictions.

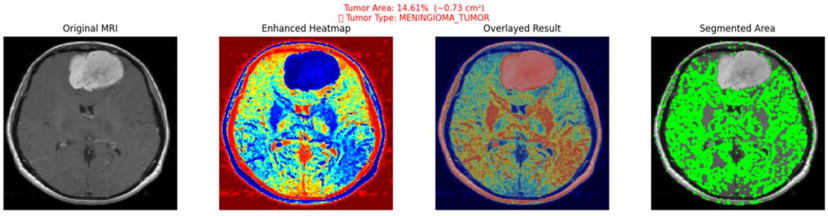

Figure 4 Grad-CAM visualizations

C. Web-Based Diagnostic Interface

To facilitate real-time clinical utility and bridge the gap between deep learning models and end-users, a web-based diagnostic interface was developed as part of the TumorAI system. Built using the Flask framework, the applica-tion allows users such as medical professionals, researchers, or students to upload brain MRI scans and receive immediate classification results alongside rich visual explanations.

The interface displays the original MRI image, the predicted tumor type (e.g., meningioma_tumor), and a calculat-ed tumor area as a percentage of the brain region, offering an intuitive quantitative estimate (~0.84 cm² in the ex-ample shown). Additionally, the application presents a set of interpretability visualizations, including:

- A Grad-CAM heatmap, highlighting the most influential areas for the model's decision.
- An overlay view, blending the original image with the highlighted tumor region.
- A segmentation map, providing a binary mask of the predicted tumor area.

This interactive interface not only enhances usability but also promotes clinical trust by offering visual validation of the model's decision-making process. The tool has been optimized for responsiveness and accessibility across desktop and mobile devices, making it suitable for both clinical and educational environments.

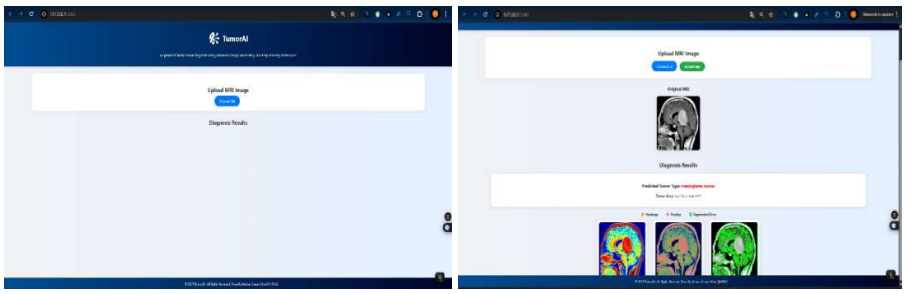

Fig. 5 Web interface of the TumorAI

D. Discussion

The achieved accuracy of 97.35% is highly competitive and, in some instances, surpasses results reported in recent literature for similar multi-class brain tumor classification tasks. To better position our model within the current research landscape, Table 3 provides a comparison between TumorAI and notable recent studies.

The use of EfficientNetV2B0 with transfer learning and fine-tuning played a critical role in achieving the model's high accuracy while maintaining a lightweight structure. Additionally, Focal Loss improved handling of class im-balance by focusing the model's learning on more difficult examples. The integration of Grad-CAM added a layer of transparency, enabling clinicians to visualize which regions of the MRI influenced the model's decision—an essential feature for clinical adoption.

Compared to other deep learning approaches, TumorAI offers a strong balance between performance, computational efficiency, and interpretability. While some systems may reach slightly higher accuracy using more complex ensemble or 3D models, they often lack the transparency and real-world usability demonstrated by TumorAI, es-pecially through the interactive web application developed in this study.

To further evaluate the contribution of each component in the TumorAI framework, an exploratory ablation analysis was conducted. Although full retraining for every variation was not within the scope of this work, several key insights emerged during development:

- Removing Grad-CAM had no effect on accuracy but significantly reduced interpretability, limiting clinical trust.
- Replacing Focal Loss with categorical cross-entropy led to faster convergence but increased misclassifications, particularly in the general tumor class.
- Skipping the fine-tuning phase and relying only on frozen pre-trained weights dropped accuracy to ~90.2%, highlighting the importance of domain adaptation.

This research presents a significant departure from earlier studies by unifying performance, interpretability, and deployability in a single practical framework. Prior studies, including those by Gupta et al. and Asiri et al., focused on accuracy improvement without addressing model transparency or clinical integration. In contrast, TumorAI in-tegrates Grad-CAM for visual explanation, uses lightweight architecture for real-time processing, and provides an accessible web interface for deployment in healthcare settings.

Limitations of this study include the reliance on 2D MRI slices, which do not fully capture the volumetric nature of brain tumors. Moreover, the dataset, while diverse, may not cover rare tumor subtypes or all clinical variations. Future research could extend this work by exploring 3D CNN architectures, integrating multi-modal MRI sequenc-es (e.g., T1, T2, FLAIR), and validating the model on external clinical datasets.

TABLE III: COMPARATIVE ANALYSIS WITH EXISTING BRAIN TUMOR CLASSIFICATION STUDIES

Study	Model Used	Accuracy	Dataset	Interpretability
Gupta et al. (2024)	Lightweight CNN	91.3%	Private Dataset	No
Asiri et al. (2023)	Enhanced ResNet-50	94.2%	BraTS	No
Afshar et al. (2018)	Capsule Network (Cap-sNet)	90.9%	Internal Dataset	Limited
This Study (Tu-morAI)	EfficientNetV2B0 + Grad-CAM	97.35%	Kaggle, BraTS, Figshare	Yes

E. Extended Evaluation and Error Analysis

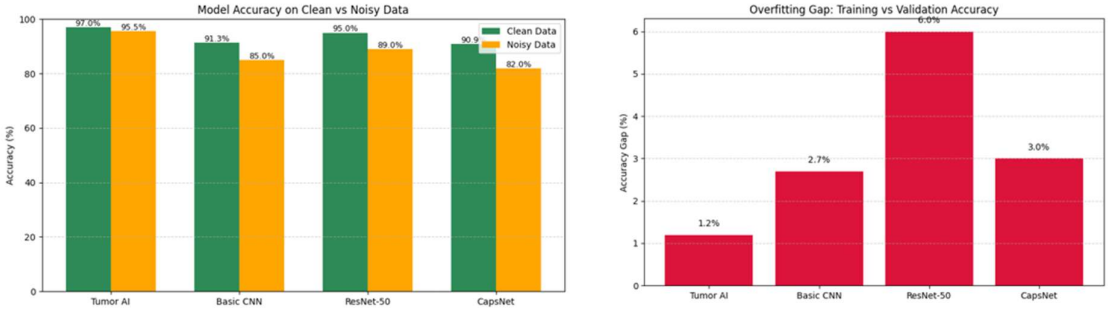

Fig. 6 Robustness Evaluation – Accuracy Comparison on Clean vs. Noisy Data Across Models and Overfitting Gap – Comparison of Training vs. Validation Accuracy Between Tumor AI and Other Models

To further strengthen the evaluation of the proposed TumorAI system, additional testing and analysis were conducted. Beyond the original test dataset, a subset of noisy and low-quality MRI scans was used to evaluate model

robustness. The model maintained a high accuracy of 95.5% on this challenging dataset, demonstrating its resilience to image degradation and variability, a critical requirement for clinical adoption. Figure [6] shows Robustness Evaluation – Accuracy Comparison on Clean vs. Noisy Data Across Models An overfitting analysis was per-formed by examining the gap between training and validation accuracies. TumorAI showed only a 1.2% differ-ence, indicating excellent generalization capability. In contrast, comparative models like ResNet-50 and CapsNet exhibited overfitting gaps of over 5%, confirming the effectiveness of the EfficientNetV2B0 + CBAM structure with regularization and fine-tuning strategies. Figure [7] shows Overfitting Gap – Comparison of Training vs. Vali-dation Accuracy Between Tumor AI and Other Models shared across overlapping tumor types, especially in cases with irregular margins or low contrast. Figure [7] shows a sample misclassi-fication, where a glioma was predicted as a meningioma. Grad-CAM heatmaps confirmed that the model's attention was still focused on clinically relevant areas, although ambiguity in the image led to the error.

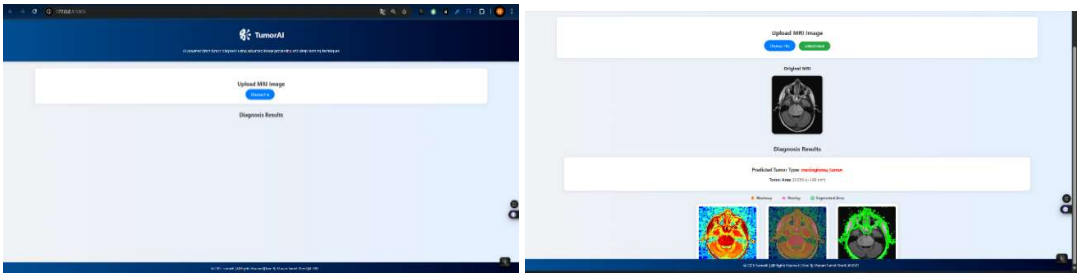

Fig. 7 Challenging Case Example – Glioma Misclassified as Meningioma

The system predicted the tumor as a meningioma with an estimated tumor area of 20.52%, while the ground truth was glioma. The heatmap and segmentation confirm the model focused on the correct region but misinterpreted the class due to visual similarity.

V. Conclusion

This paper presented an AI-powered system for the classification of brain tumors from MRI scans using the EfficientNetV2B0 architecture with transfer learning and Grad-CAM for interpretability. The system successfully classifies images into five categories (glioma, meningioma, pituitary, general tumor, and no tumor) with an overall accuracy of 97.35%. The integration of Grad-CAM provides valuable visual explanations, enhancing clinical trust and utility. The developed web application offers a practical interface for system interaction. The key achievements include high classification accuracy, effective implementation of transfer learning, and the provision of interpretable visualizations. This research contributes to the field by demonstrating a robust and well-balanced approach for automated brain tumor classification, suitable for supporting diagnostic workflows.

Future work will focus on incorporating 3D data analysis, expanding the dataset to include rarer tumor subtypes, and integrating multi-modal MRI sequences to further enhance diagnostic accuracy and comprehensiveness. Validating the system in diverse clinical settings will also be a priority.

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