Branch of “Nazarbayev Intellectual Schools” AEO Nazarbayev Intellectual School of Physics and Mathematics in Uralsk

“Tumobrainor” — the desktop application for detecting and classifying brain tumors

Section: AI Programming

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Table of contents

Abstract

A brain tumor refers to the abnormal cell growth inside the brain, which can originate in any of its lobes without a predefined location. Magnetic Resonance Imaging (MRI) is vital in diagnosing these tumors, offering crucial insights into tumor morphology and precise localization. However, accurately classifying brain tumors from MRI scans remains challenging due to their heterogenous characteristics.

This study aims to leveraging deep learning algorithms within an application to improve the classification accuracy of MRI-based brain tumor diagnosis. The central hypothesis is that machine learning models can effectively identify and classify brain tumors using MRI images. To achieve this, we conducted a thorough review of existing literature on topics, data collection and preprocessing, model development and training, and app development. The novelty of the research is the app combining advanced segmentation techniques with deep learning ensemble algorithms, designed with a user-friendly interface, including real-time processing, medical guidelines, and statistical analysis.

The findings demonstrate high accuracy, sensitivity, and specificity, underscoring the model's robustness and potential for clinical use. These results provide a solid foundation for planning and targeted therapies.

Introduction

The human brain, the body's most complex organ, controls muscle movements and interprets sensory information like sight, sound, touch, taste, pain, etc. An abnormal cell growth inside the brain — brain tumor — disrupts these functions. Brain tumors represent one of the most critical challenges in modern neurosurgery with significant implications for patients' cognitive functions, well-being, and overall quality of life [1, 2]. The global impact of this condition is substantial, with 321,476 new cases of brain and central nervous system cancer in 2022 [3]. Information on the incidence of malignant brain tumors in Kazakhstan is limited; however, it has been reported that the incidence of malignant (central nervous system) CNS tumors increased in the period from 2004 to 2011 [4]. Of particular concern is that about 30% of all brain and central nervous system tumors are malignant, with glioblastomas accounting for 48.6%, diffuse/anaplastic astrocytomas for 11.8%, and other gliomas for 17.9% [5].

The objective of this work is to present an advanced AI-based application for brain tumor identification and classification, integrating with deep learning ensemble algorithms. This integration aims to enhance the accuracy and efficiency of MRI-based brain tumor diagnosis, addressing the complexities inherent in tumor classification due to their heterogeneous characteristics [6].

The methodology consists of three main phases:

1. **Literature Review**: A comprehensive review of existing literature on topic and deep learning architectures.
2. **Data Collection:** analysis of MRI datasets and preprocessing techniques used in successful implementations.
3. **Model Training and Validation:** implementation of a deep learning model using PyTorch framework for brain tumor classification. PyTorch was chosen for its dynamic computational graphs and extensive ecosystem of pretrained models, allowing for efficient model experimentation and optimization.
4. **Desktop Application Development:** creation of a user-friendly desktop application based on Flutter framework, with an intuitive interface for MRI image upload and analysis, medical guides, and statistical analysis.

This approach is particularly crucial given that cognitive dysfunctions associated with brain tumors are observed in 90% of patients with impairments arising not only from tumor location but also from surgical intervention, radiation therapy, and chemotherapy [7]. The complexity of diagnosis and treatment is further compounded by various factors affecting cognitive processes, including medications, anesthesia, infection, hormonal changes, stress, anxiety, depression, fatigue, and sleep disturbances [8]. The consequences of having this condition can be alleviated by an early identification of the disease, underscoring the need to develop the advanced classification technique.

Research section

Problem review

The human brain, as the body's most complex organ, regulates various physiological functions, including sensory integration. Brain tumors are among the most common global malignancies that disrupt these functions, leading to severe consequences, including death [9, 10]. While average cellular turnover involves programmed cell death and regeneration, Brain tumors cause uncontrolled cell proliferation, impairing brain functions. Brain tumors can be malignant or benign, with symptoms like fever, headaches, and cognitive decline, often leading to fatality [7]. The early and accurate detection of brain tumors is crucial for improved patient outcomes.

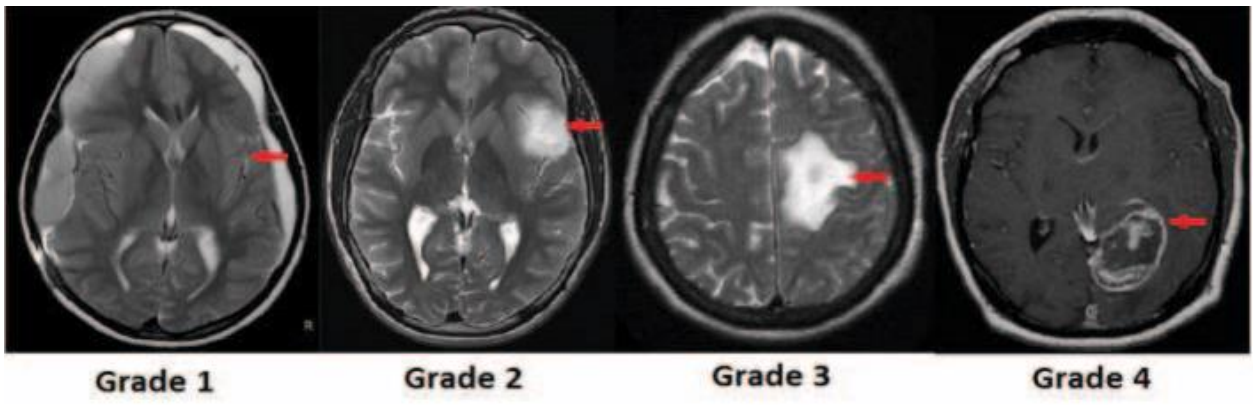

Figure 1. Grades of brain tumor (Astrocytoma) [11]

According to the diagnostic scheme of the World Health Organization (WHO) [12], the classification of tumors as grades I, II, III, and IV is based on various factors, such as correspondence of tumor cells to normal cells, rate of growth, and tumor margins. Among this classification, grade III is characterized by abnormal cells which infiltrate between neighboring cells, and the most malignant tumor grade IV shows rapid proliferation into surrounding tissues [13, 14]. The new classification of CNS tumors is based on phenotype/genotype expression and growth pattern and behavior [15].

Glioblastoma (GBM) represents a common and lethal form of CNS tumors [16], which radiographically is reflected by subregions of enhanced (ET) and non-enhanced tumors (NET), as well as peritumoral edematous/invasive tissue (ED). GBM creates by glial cells and grows by infiltrating surrounding tissues. The median overall survival for GBM patients remains 12–16 months [16].

Table 1 – Average indicators of psychometric tests [7].

Test		**Group**	
		Healthy	Brain Tumor (Kazakh)
The Functional Assessment of Cancer Therapy – Brain (FACT-Br)	Physical well-being	9,29 (6,21)	4,57 (3,27)
	Social/family well-being	20,71 (4,68)	17,57 (5,47)
	Emotional well-being	10,14 (5,49)	6,07 (1,59)
	Functional well-being	18,71 (6,42)	16,07 (6,26)
	Additional concerns	40,43 (7,16)	37,43 (9,10)
Mini-Mental State Examination, MMSE		24,31 (10,85)	25,71 (3,15
Montreal Cognitive Assessment, MoCA		22,50 (10,87)	20,14 (10,19)

Brain tumors profoundly impact patients' overall well-being and mental health, manifesting in severe physical, emotional, and cognitive challenges. For instance, the *Functional Assessment of Cancer Therapy–Brain (FACT-Br)*—a validated quality-of-life tool assessing physical, social, emotional, and functional domains—reveals significantly lower physical well-being scores in patients (4.57 ±3.27) compared to healthy individuals (9.29 ±6.21). Emotional well-being scores also decline (6.07 ±1.59 vs. 10.14 ±5.49). Cognitive assessments using the *Mini-Mental State Examination (MMSE),* a 22-item screen evaluating orientation, memory, attention, and language, show patients averaging 24.31 (±10.85) – below the 26-point threshold indicating preserved function. Similarly, the *Montreal Cognitive Assessment (MoCA),* a 30-point rapid screen for attention, memory, and executive function, yields lower patient scores (20.14 ±10.19) compared

to healthier groups (22.50 ±10.87), with scores ≤25 signaling impairment. Both tools have been linguistically adapted for Russian and Kazakh populations. A strong inverse correlation between emotional well-being and cognitive status (r = -0.634, p=0.003) underscores the interplay of psychological and cognitive decline. These findings, analyzed via Pearson's correlation, ANOVA, and Cronbach's alpha for test reliability, emphasize the necessity for integrated interventions addressing both mental health and cognitive deficits in brain tumor care [7].

In the context of Kazakhstan, according to the study at the National Center for Neurosurgery, the majority (43.3%) of patients suffering from brain tumor had Grade 4 tumors, followed by Grade 3 (27.8%), Grade 2 (21.5%), and Grade 1 (7.5%). Grade 4 constituted glioblastoma only, while anaplastic astrocytoma was most prevalent in Grade 3. For Grade 2, diffuse astrocytoma had the highest proportion, and in Grade 1, it was pilocytic astrocytoma. A significant difference in survival can be seen only with Grade 4. The overall survival after 5 years of follow-up was 45.93%. Survival outcomes were worst in Grade 4 patients (15.64%) and best in Grade 2 patients (73.92%). Grade 1 had a 5-year survival of 68.57%, and Grade 3 survival was 63.97% [17]. The patients in the study had a median age of 41, mean age of 42.68 ± 13.49 years. The worst survival outcomes were observed among the oldest age group, where 21.83% of the sample survived 5 years since diagnosis [17].

Such drastic differences could be attributed to the lack of diagnostics in Kazakhstan. Currently, the diagnostics of brain tumors are based on histological tests and analysis; therefore, there is a possibility of misdiagnosis that results in false survival rates [17]. Another factor that might influence the survival rate is the younger age of the first diagnosis of the sample studied. Older age of diagnosis is a known risk factor for worse survival outcomes [18, 19] and is one of the variables that increases the risk of death in multivariable Cox regression for Grade 4 patients in the current sample [17].

Magnetic Resonance Imaging (MRI) is vital in diagnosing brain tumors, offering crucial insights into tumor morphology and precise localization. Despite its pivotal role, accurately classifying brain tumors from MRI scans is inherently complex due to their heterogeneous characteristics [6]. Through the synergistic amalgamation of sophisticated segmentation techniques and ensemble learning strategies, current research addresses the shortcomings of traditional methodologies, thereby facilitating more precise and efficient brain tumor classification.

Problem solving methods

We implemented a convolutional neural network (CNN) using the ResNet50 architecture for brain tumor classification, leveraging its deep structure (50 layers) and skip connections to mitigate vanishing gradients. CNNs excel in image-based tasks through hierarchical feature extraction via convolutional layers, ReLU activation, and pooling, followed by fully connected layers for classification.

The model was developed in Python using TensorFlow, with preprocessing including image resizing to 224×224 and pixel normalization (0-1 range). Training utilized the Adam optimizer and categorical cross-entropy loss over 30 epochs on a dataset of 3,064 MRI scans (glioma, meningioma, pituitary tumors) from the brain tumor dataset posted by Jum Cheng on figshare.com. Data augmentation (rotation, flipping, zooming) and early stopping were applied to enhance generalization and prevent overfitting.

Key libraries included NumPy for numerical operations, Pandas for data handling, and Matplotlib for visualization. Code execution and prototyping were streamlined via Jupyter

Notebook. The full implementation details and trained weights are available in the project repository. Regarding the application development, the code of "Tumobrainor" app was based on Flet UI that is built with Flutter.

Results

The brain MRI dataset was divided into training (70%), validation (20%), and testing (10%) subsets. During training, the model demonstrated consistent improvement, with training accuracy rising to 99.8% and validation accuracy reaching 99.5% by the final epoch. These trends, visualized in the accuracy progression graph, indicate stable learning without overfitting.

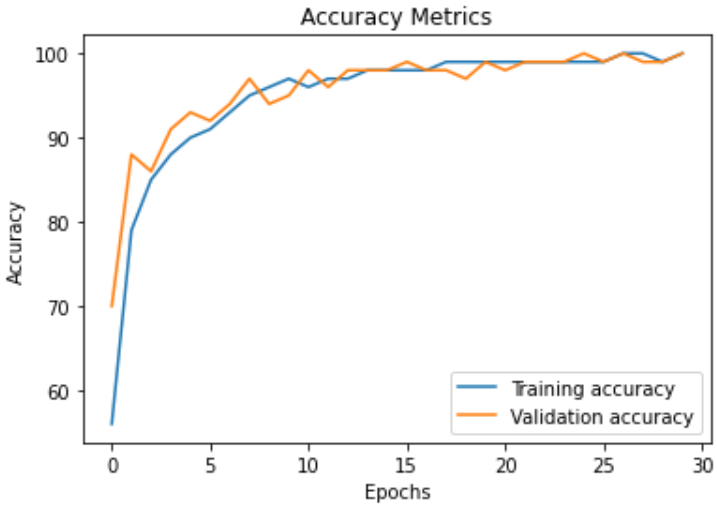

Figure 2. The Training and Validation accuracy graph

The brain MRI dataset was divided into training (70%), validation (20%), and testing (10%) subsets. During training, the model demonstrated consistent improvement, with training accuracy rising to 99.8% and validation accuracy reaching 99.5% by the final epoch. These trends, visualized in the accuracy progression graph, indicate stable learning without overfitting.

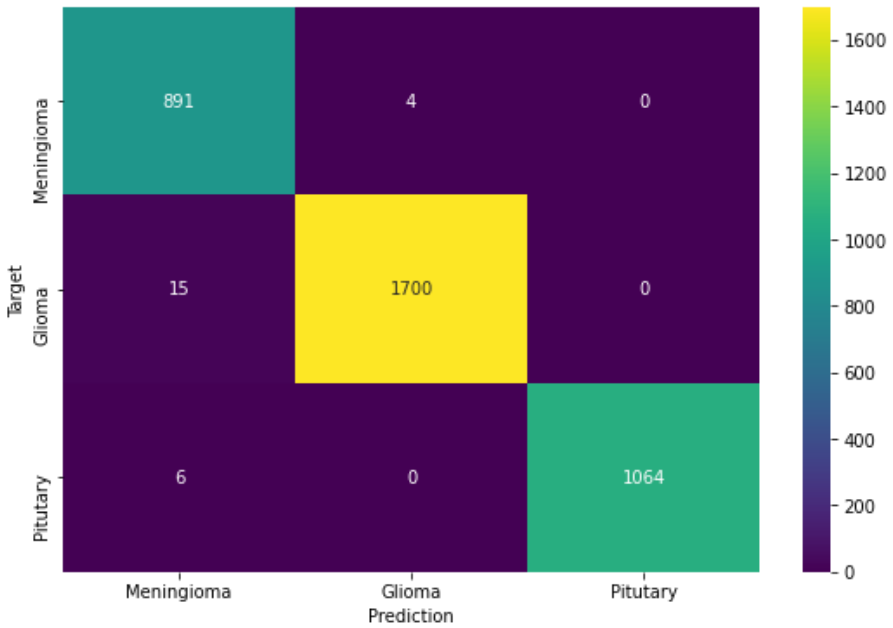

Figure 3. The Error Matrix of brain tumor types

The desktop application *Tumobrainor* was developed to enable interaction with the developed AI model, using the Flet framework for cross-platform GUI (graphical user interface) design and pandas/seaborn for data analysis and visualization.

It supports real-time analysis of glioma, meningioma, and pituitary adenoma cases, providing fast (at most 2 seconds) diagnostic predictions. This feature reduces reliance on manual radiological review, offering a quick and reliable tool for

This application, “Tumobrainor”, was developed using Python and its Flet framework. It offers the following functionality:

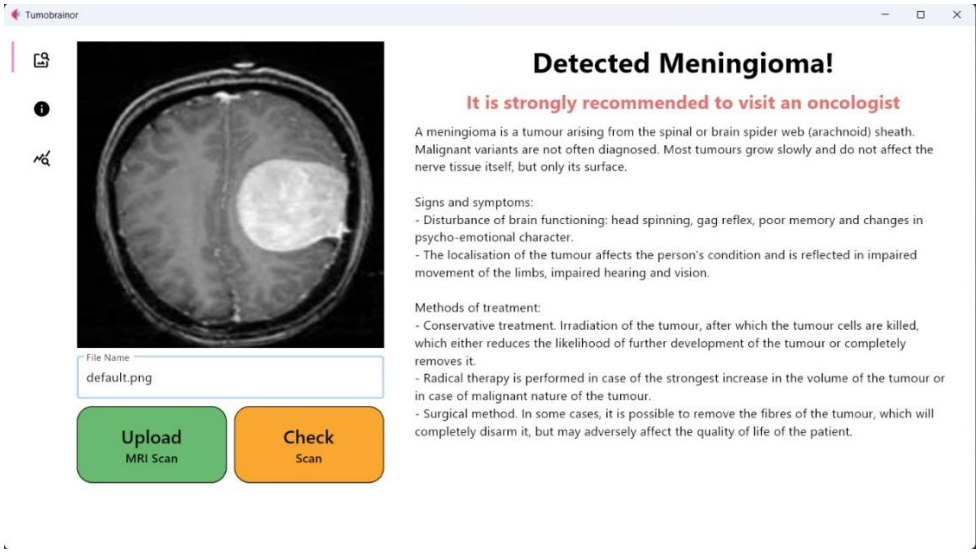

Figure 4. The Detection (Main) panel of Tumobrainor application

Detection and Classification of Brain Tumors. The app analyzes MRI images and predicts the disease within 2 seconds, making it both fast and convenient.

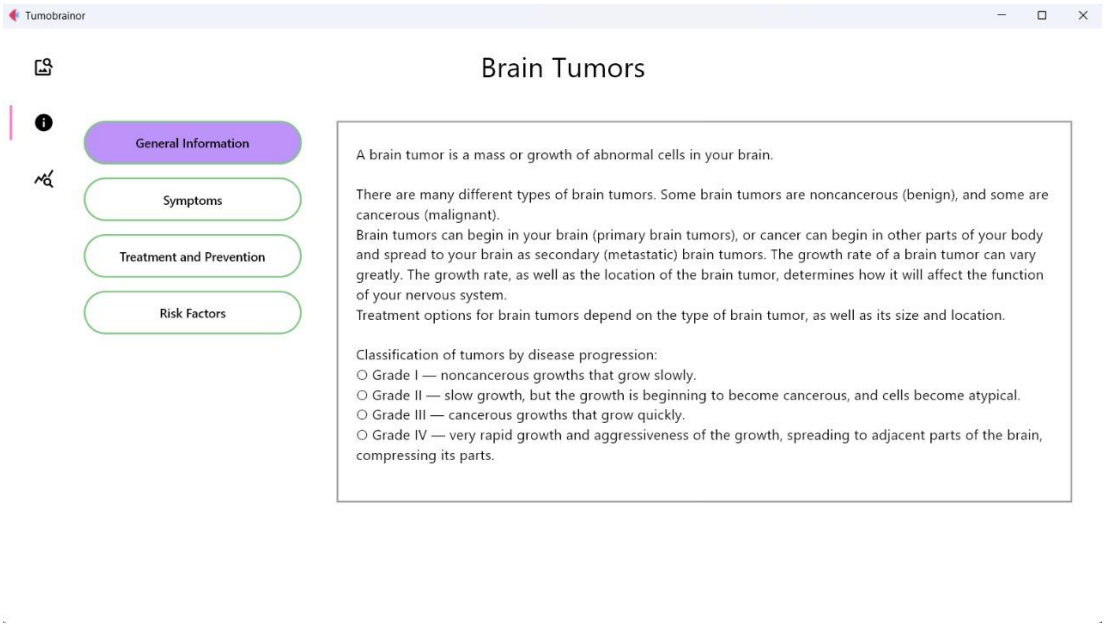

Figure 5. The Information panel of Tumobrainor application

Disease Information. It provides details about disease, its treatment, and prevention. This feature is presented in a separate tab with a user-friendly interface to raise awareness.

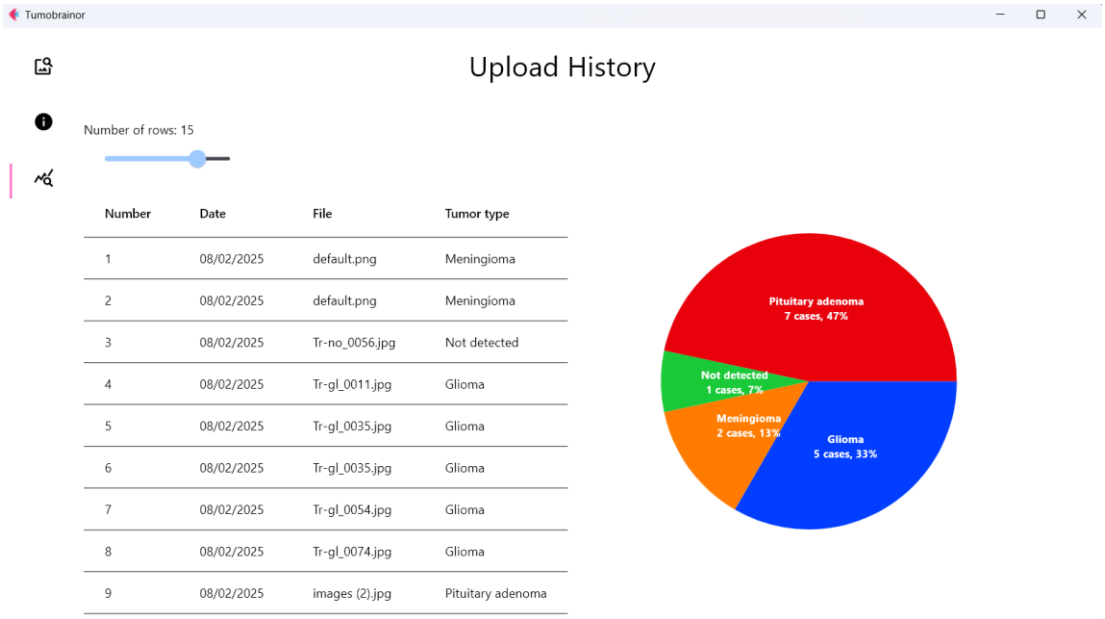

Figure 6. The Statisitcs panel of Tumobrainor application

Image Collection and Analysis. The application automatically saves the history of uploaded images and displays detailed statistics, showing the proportion of each disease. The statistics are interactive, allowing you to select the number of recent uploads you want to view.

The program shows significant potential to assist radiologists and neurologists in analyzing brain MRIs, initially for detecting and classifying suspicious lesions. With continued improvement, the AI could ultimately support more in-depth analysis and diagnosis.

The source code for the desktop application is available in this GitHub repository, and the resources for model training can be found in this separate GitHub repository.

Limitations

The deep learning-based brain tumor classification approach, despite its promise, faces several key constraints. The training data may inadequately capture real-world clinical variability, potentially limiting the model's generalization capabilities. Class imbalances in brain tumor datasets can skew model performance, particularly for rare tumor types. The substantial computational demands of these models may exceed available resources in many clinical environments. Most critically, the "black box" nature of deep learning algorithms makes it difficult for clinicians to understand and trust the decision-making process, hindering clinical adoption. Future research must tackle these challenges of data representation, computational efficiency, and model interpretability to develop clinically viable solutions.

The successful clinical implementation of deep learning models for brain tumour classification hinges on their robustness and generalization capabilities. Models must maintain consistent performance across diverse MRI protocols, scanner types, and patient populations - a significant challenge given the inherent variability in clinical settings. Despite using established techniques like regularization and early stopping, models trained on limited datasets remain susceptible to overfitting, compromising their reliability with new patients. The technical complexity of integrating these systems into existing hospital workflows presents additional hurdles, from developing intuitive interfaces to ensuring seamless communication with medical information systems. Overcoming these challenges is essential for establishing deep learning as a dependable tool in clinical practice.

Conclusion

This study successfully demonstrates the capability of an integrated deep learning approach to enhance the accuracy and efficiency of brain tumor classification using MRI scans. The findings highlight the effectiveness of convolutional neural networks (CNNs), particularly ResNet50, combined with advanced preprocessing and ensemble learning strategies, contributing to more precise medical diagnoses and improved healthcare outcomes. ResNet50's deep structure and skip connections enable it to handle complex image processing tasks, such as feature extraction and classification of heterogeneous brain tumors, achieving high training and validation accuracies of 99.8% and 99.5%, respectively.

The results reveal high accuracy, sensitivity, and specificity indices when applied to a dataset of 3,064 MRI scans encompassing glioma, meningioma, and pituitary tumors. These outcomes validate the model's robustness and potential for clinical applications, offering a solid foundation for surgical planning and targeted therapies. The development of the Tumobrainor application further enhances practical utility by providing a user-friendly interface for real-time tumor detection, disease information, and statistical analysis. This integration of advanced AI with accessible tools reduces reliance on manual radiological review, delivering a quick and reliable diagnostic solution.

However, challenges such as dataset bias, class imbalance, and the "black box" nature of deep learning models may hinder clinical trust and generalization. Addressing these issues requires refining training techniques, expanding dataset diversity, and developing explainable AI frameworks to ensure effectiveness across diverse clinical scenarios. The research confirms that tailored CNN architectures and ensemble learning strategies can significantly improve MRI-based brain tumor classification systems, paving the way for more accurate and personalized diagnostic tools.

Future work will focus on expanding these techniques to other forms of medical imaging, addressing computational efficiency for resource-limited settings, and continuing to refine the models to handle the variability and complexity of real-world clinical data. By overcoming these challenges, this research aims to establish deep learning as a dependable tool in clinical practice, ultimately improving global brain tumor care and patient outcomes.

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