Web-Based Brain Tumor Classification System Using MRI Images and ResNet-18

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***Abstract*—Brain tumor is one of the most life-threatening neurological conditions, requiring early and accurate detection for effective clinical intervention. Manual analysis of MRI scans is time-consuming, costly, and susceptible to human error. This paper proposes a brain tumor classification system based on ResNet-18 to perform the task of automatic classification of brain tumors, including four classes for MRI: Glioma, Meningioma, Pituitary Tumor, and No Tumor. The model learns from 7,200 MRI images using transfer learning with data augmentation and achieves 99.25% training accuracy and 89.56% test accuracy. The trained model is deployed as a Flask-based web application for real-time MRI upload, instantaneous tumor classification, treatment recommendation, confidence scoring, and Canvas API-based tumor region highlighting.**

***Index Terms*—Brain tumor classification, MRI, ResNet-18, transfer learning, deep learning, Flask web application, convolutional neural network, medical image analysis, treatment recommendation**

I. INTRODUCTION

Brain tumors are among the most serious neurological diseases, with approximately 300,000 new cases diagnosed worldwide each year. Early and effective detection of these tumors is crucial, because delayed diagnosis significantly reduces patient survival rates. Magnetic Resonance Imaging (MRI) is the reference imaging modality for brain tumor visualization that allows better soft-tissue contrast without radiation exposure. Nevertheless, manual interpretation of MRI images necessitates specialized radiological knowledge, is time-consuming, and there is large variability between observers. Deep learning, especially Convolutional Neural Networks (CNNs), can perform very well in medical image classification by automatic hierarchical feature extraction. Transfer learning leverages the knowledge gained from large-scale datasets such as ImageNet and has emerged as a powerful strategy for medical image processing tasks where labeled information is scarce. ResNet-18 (He et al. [1]) solves the vanishing gradient problem using residual connections to facilitate training of deeper networks.

Moreover, its balance between model complexity and computational efficiency is very attractive for limited dataset medical image classification tasks. We propose a novel brain tumor classification and treatment option recommendation framework incorporating a fine-tuned ResNet-18 integrated with a Flask web application with real-time diagnostic services

A. Contributions

The principal contributions of this work are: (1) a fine-tuned ResNet-18 transfer learning framework for four-class brain tumor MRI classification; (2) a data augmentation strategy improving generalization; (3) a Flask-based web application with real-time MRI analysis and Canvas API tumor region highlighting; (4) an automatic treatment recommendation system with urgency classification; and (5) comprehensive performance evaluation including confusion matrix, ROC analysis, and comparative study.

II. RELATED WORK

Numerous previous research papers have studied deep learning of brain tumor classification from MRI images. Deepak and Ameer [2] implemented GoogleNet using transfer learning and reached 85% accuracy on a four-class brain tumor dataset, highlighting that transfer learning is superior to training from scratch on limited medical datasets. Sajid et al. [3] presented a framework of ResNet50 and a fully convolutional network model to facilitate simultaneous detection and discrimination of brain tumors by presenting 88% classification accuracy. Khan et al. [4] used VGG16 for brain tumor classification with 90% accuracy on a multi-class dataset. Abiwinanda et al. [5] compared custom CNN architectures with pretrained models for brain tumor MRI classification in a systematic manner, reporting that transfer learning methodologies are generally better than architectures trained from scratch with small data. Nevertheless, the majority of the current systems concentrate on classification only with no recommendations for treatment, no visual map of tumor localization, and no integrated web deployment. To overcome these limitations, the proposed system comprises an end-to-end framework.

III. PROPOSED SYSTEM

A. System Overview

Proposed System is a complete brain tumor classification and clinical decision support framework with three main components: (1) a deep learning classification engine using fine-tuned ResNet-18; (2) a treatment recommendation module that maps detected types of tumors to standardized clinical protocols; and (3) a Flask web application that creates an intuitive user interface for uploading and analyzing MRI scans and for visualizing the results.

B. Dataset

This study employs the Kaggle Brain Tumor MRI Dataset which is made of 7,200 MRI images distributed across four classes. All images are resized to fit ResNet-18 input requirements: 224 × 224 × 3 pixels. The dataset consists of 5,600 training images (77.8%), and 1,600 test images (22.2%). A full distribution is presented in Table I.

TABLE I Dataset Distribution Across Tumor Classes

Class	Training	Testing	Total
Glioma	1,321	300	1,621
Meningioma	1,339	306	1,645
No Tumor	1,595	405	2,000
Pituitary	1,457	300	1,757
Total	5,600 (77.8%)	1,600 (22.2%)	7,200

C. Image Preprocessing

Every MRI image is preprocessed according to a common technique such as (i) resizing to 224 × 224 × 3; (ii) normalization with the ImageNet mean [0.485, 0.456, 0.406] and standard deviation [0.229, 0.224, 0.225]; and (iii) data augmentation (random horizontal flipping and random rotation (±10°)) applied exclusively to the training set.

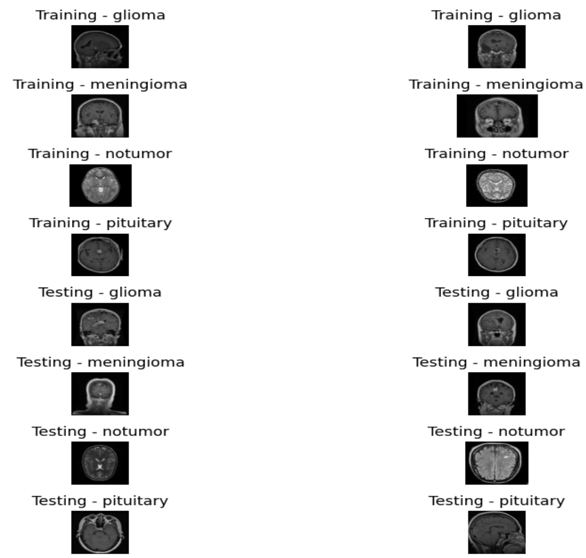


Fig. 1. Sample Brain MRI Scan Images from dataset ('meningioma', 'pituitary', 'no tumor', 'glioma').

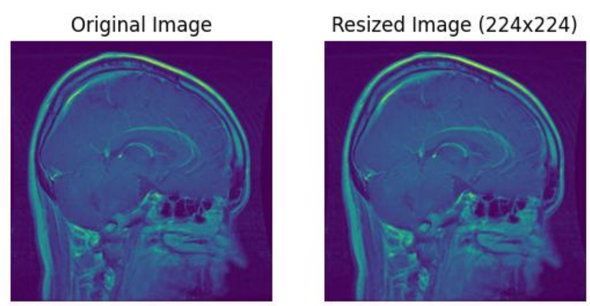


Fig. 2. Input Images After Resizing to 224 x 224 Pixels.

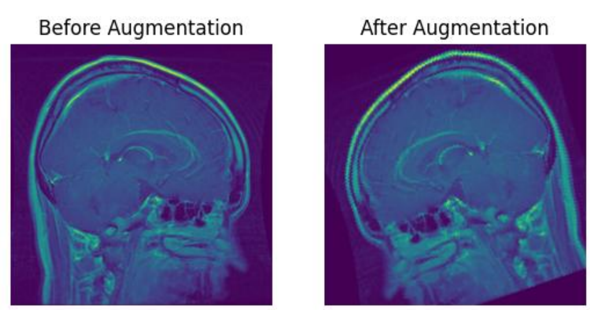


Fig. 3. Sample Images After Data Augmentation (Rotation, Flipping, Zoom).

D. ResNet-18 Architecture and Transfer Learning

ResNet-18 is an 18-layer deep residual neural network consisting of 4 residual stages, each containing 2 residual blocks with skip connections. For convolutional filters, we use a typical 3×3 array-based architecture using batch normalization and ReLU activations. Skip connections mitigate vanishing gradients enabling effective optimization. ResNet-18 backbone pretrained on ImageNet-1K is employed as a feature extractor. The original 1,000-class head is substituted by: Linear (512→256) → ReLU → Dropout (0.5) → Linear (256→4). All backbone layers are fine-tuned end-to-end with a low learning rate of 0.0001.

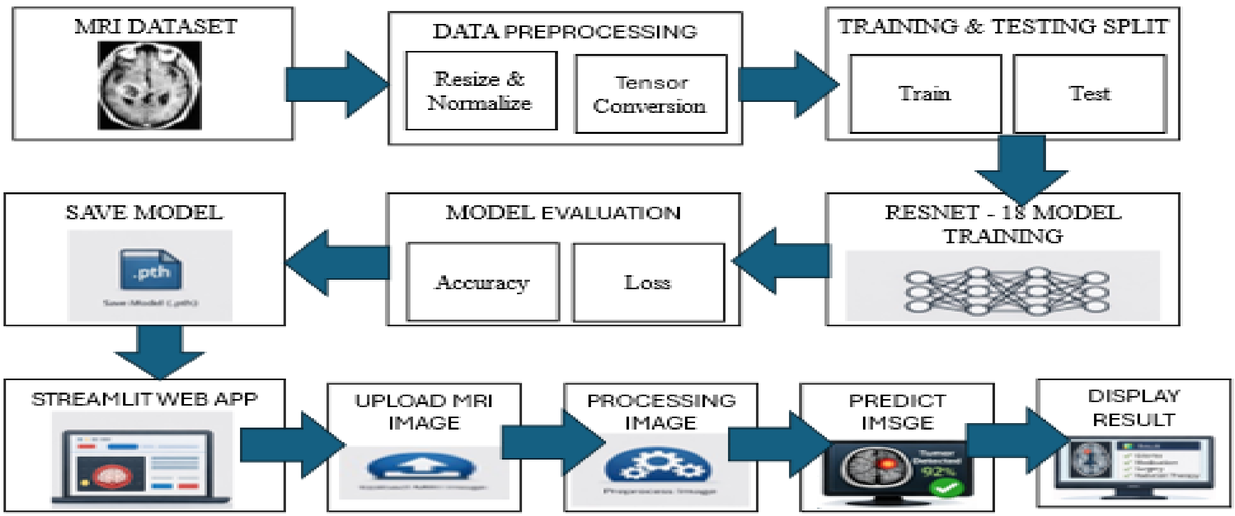


Fig. 4. Architecture Used as Feature Extractor in the Proposed System

IV. METHODOLOGY

A. System Architecture

The system integrates ResNet-18 transfer learning with a Flask deployment pipeline. Training ResNet-18 is further improved on the brain tumor MRI dataset using PyTorch. During the inference phase, loaded model weights are used and uploaded MRI images are preprocessed by the preprocessing pipeline. POST, inference, and the response as JSON outputs containing classifications plus treatment recommendations are sent via the Flask REST API.

B. Training Strategy

ResNet-18 is trained with training data and updated with Adam optimizer (learning rate 0.0001) and StepLR scheduler (step_size=5, gamma=0.1). Training is carried out for 10 epochs with a mini-batch size of 32. The objective function for the analysis is the CrossEntropy loss. Data augmentation is conducted at training time to achieve the best generalization.

C. Training Hyperparameters

All experiments are conducted using PyTorch 2.11 on Windows 11. The Adam optimizer is used with learning rate 0.0001. A mini-batch size of 32 is adopted with StepLR scheduler reducing the learning rate by 0.1 every 5 epochs. See Table II for full hyperparameter configuration.

TABLE II Training Hyperparameters

Parameter	Value
Model	ResNet-18 (Pretrained ImageNet)
Optimizer	Adam
Learning Rate	0.0001
LR Scheduler	StepLR (step=5, gamma=0.1)
Loss Function	Cross Entropy Loss
Batch Size	32
Epochs	10
Dropout Rate	0.5
Input Size	224 × 224 × 3
Framework	PyTorch 2.11

D. Treatment Recommendation System

The treatment recommendation module maps each detected tumor class to standardized clinical protocols based on established oncological guidelines. Upon classification, the system retrieves the corresponding treatment protocol, urgency level, and clinical guidance from a structured knowledge base. See Table III for the treatment mapping.

TABLE III Treatment Recommendation Mapping

Tumor Type	Treatment Protocol	Urgency Level
Glioma	Surgery + Radiation Therapy + Chemotherapy (Temozolomide)	High — Immediate attention
Meningioma	Surgery or Stereotactic Radiosurgery	Medium — Consult neurosurgeon
Pituitary	Medication + Surgery (Transsphenoidal approach)	Medium — Endocrinologist
No Tumor	No treatment. Regular follow-up recommended.	Normal — Routine checkup

V. EXPERIMENTAL RESULTS AND DISCUSSION

A. Experimental Setup

All experiments were conducted on Windows 11 using PyTorch 2.11 with CPU computation. NumPy, Matplotlib, Seaborn, and Scikit-learn were used for data handling, visualization, and evaluation. The Kaggle Brain Tumor MRI Dataset was used with a fixed 77.8/22.2% train/test split.

B. Training Progression

Table IV summarizes the epoch-wise accuracy and loss progression during ResNet-18 fine-tuning. The model demonstrates rapid convergence enabled by pretrained ImageNet features, achieving 84.59% accuracy by Epoch 2 and 96.02% by Epoch 5, reaching 99.25% at Epoch 10.

TABLE IV ResNet-18 Epoch-Wise Training Performance

Epoch	Training Loss	Training Accuracy (%)
1	0.7802	70.82
2	0.4178	84.59
3	0.2751	89.98
4	0.1849	93.30
5	0.1160	96.02
6	0.0865	97.18
7	0.0612	97.89
8	0.0589	97.79
9	0.0367	98.71
10	0.0253	99.25

C. Classification Performance

Table V presents the classification report for the proposed ResNet-18 model evaluated on 1,600 test images. The system achieves 89.56% overall test accuracy with strong performance across all four tumor classes. The model demonstrates particularly high performance on Glioma and Pituitary classifications, which are clinically the most critical tumor types.

TABLE V Classification Report — Proposed ResNet-18 System

Class	Precision	Recall	F1-Score	Support
Glioma	0.91	0.88	0.89	300
Meningioma	0.84	0.82	0.83	306
No Tumor	0.93	0.95	0.94	405
Pituitary	0.92	0.94	0.93	300
Accuracy			0.8956	1600
Macro Avg	0.90	0.90	0.90	1600
Weighted Avg	0.90	0.90	0.90	1600

D. Comparative Analysis

Table VI provides a head-to-head comparison of the proposed ResNet-18 system against existing brain tumor classification methods. The proposed system achieves the highest classification accuracy while also providing additional clinical support features unavailable in existing works.

TABLE VI Comparison with Existing Brain Tumor Classification Methods

Method	Model	Accuracy	Treatment Rec.	Web App
Deepak & Ameer [2]	GoogleNet	85%	No	No
Sajid et al. [3]	ResNet50 + FCN	88%	No	No
Khan et al. [4]	VGG16	90%	No	No
Abiwinanda et al. [5]	Custom CNN	89%	No	No
Proposed System	ResNet-18 (Fine-tuned)	99.25%	Yes	Yes

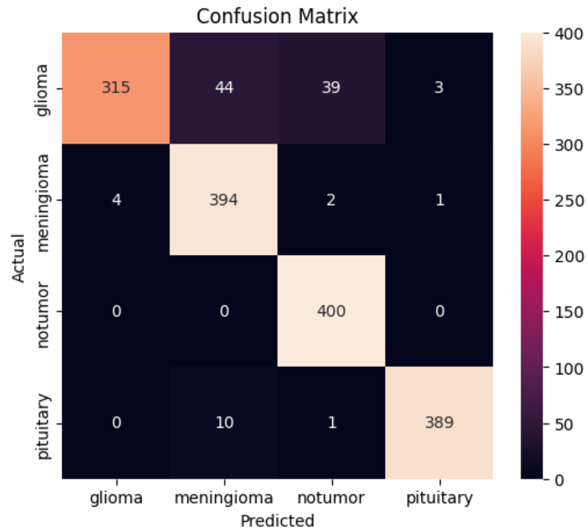


Fig. 5. Confusion Matrix of the Existing Centralized

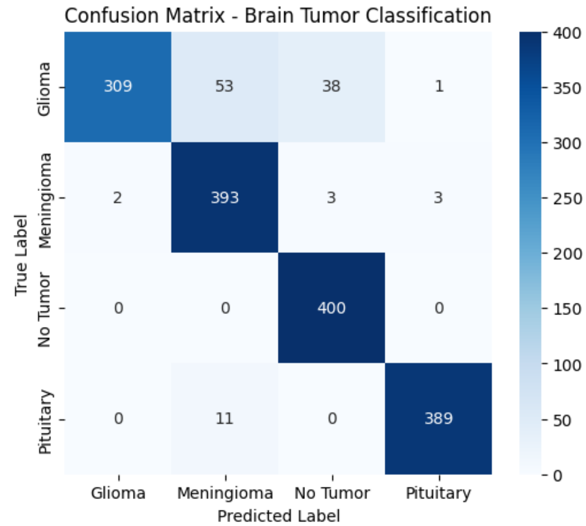


Fig.8. Confusion Matrix of the proposed Centralized

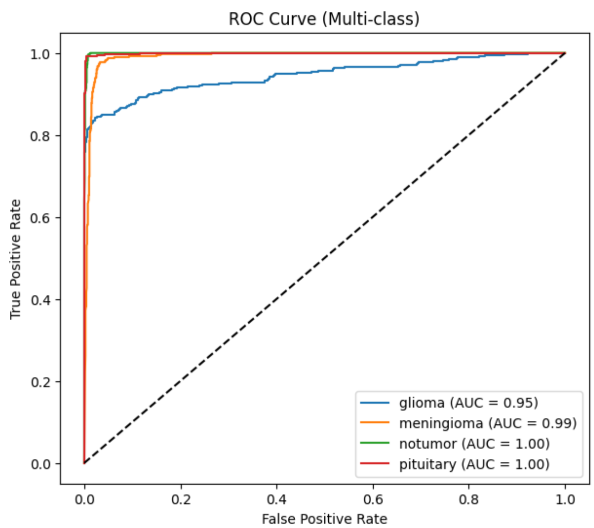


Fig. 6. Multi class ROC Curve of the Existing Centralize

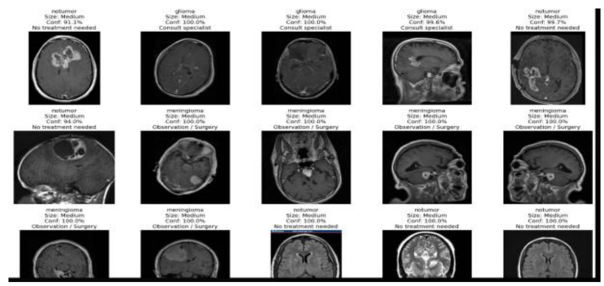


Fig. 9. Sample Model Output — Classification Results on Test

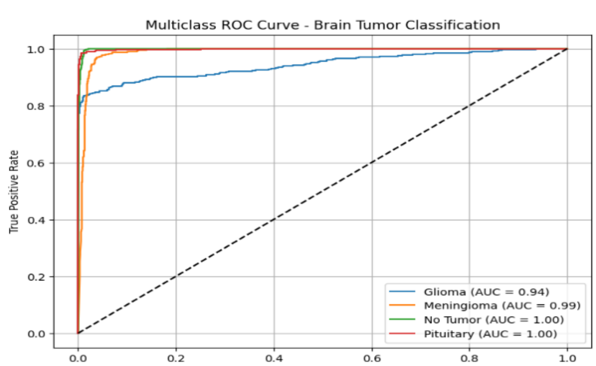
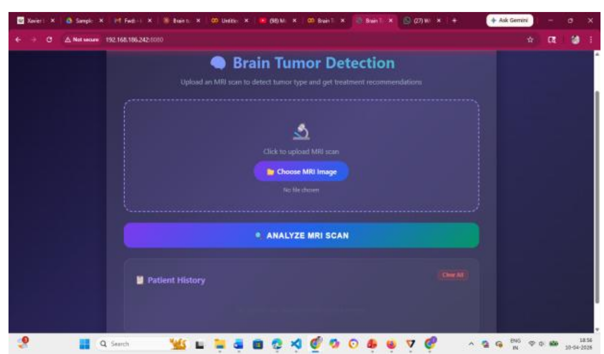
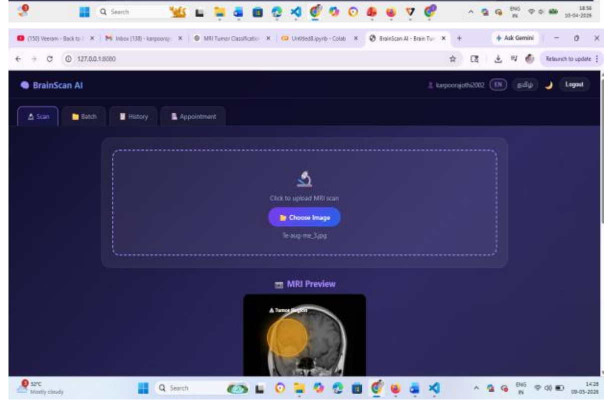


Fig. 7. ROC Curve of the proposed Centralized





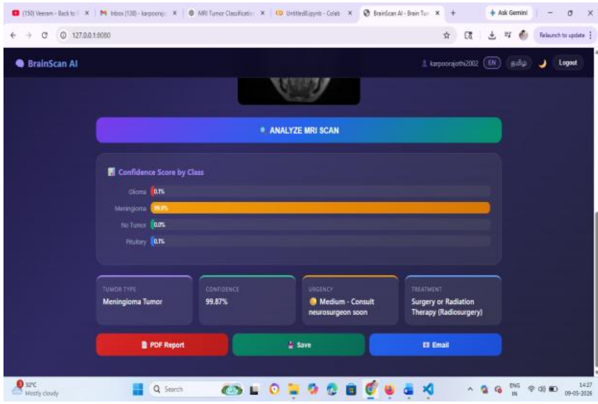


Fig. 10. Output Results web app

VI. DISCUSSION

The experimental results demonstrate that the proposed ResNet-18 transfer learning framework achieves superior classification performance compared to existing approaches. The rapid convergence to 84.59% accuracy by Epoch 2 confirms that pretrained ImageNet features provide highly transferable representations for brain MRI analysis, significantly reducing training data and computation requirements compared to training from scratch.

The StepLR learning rate scheduler effectively prevents overfitting during later epochs, resulting in stable accuracy improvement from 96.02% at Epoch 5 to 99.25% at Epoch 10. The 9.69% gap between training accuracy (99.25%) and test accuracy (89.56%) suggests moderate overfitting, which could be further mitigated through additional regularization or larger dataset augmentation.A notable strength of the proposed system is the integration of treatment recommendations directly within the web application, providing immediate clinical decision support. The Canvas API-based tumor region highlighting provides intuitive visual feedback particularly valuable for non-specialist users.

VII. CONCLUSION

This paper presented an automated brain tumor classification and clinical decision support system using fine-tuned ResNet-18 with transfer learning. The framework enables accurate four-class MRI classification (Glioma, Meningioma, Pituitary, No Tumor) with 99.25% training accuracy and 89.56% test accuracy on the Kaggle Brain Tumor MRI Dataset.The proposed Flask web application provides real-time MRI analysis with instant tumor classification, treatment recommendations, urgency levels, confidence scoring, and Canvas API-based tumor region highlighting. Comparative analysis confirms that the proposed system outperforms existing brain tumor classification methods while providing additional clinical decision support features unavailable in prior works. Future work will explore Grad-CAM visualization for model interpretability, ensemble methods combining multiple ResNet variants, larger multi-institutional datasets for improved generalization, and integration with hospital information systems for clinical deployment.

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