MindScan: Dual Deep Learning system of Brain Tumors Detection and Classification from MRI Scans

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This project presents MindScan, a web-based hierarchical deep learning system for automated brain tumor detection and classification from MRI images, using MobileNetV2 as the primary model. MRI scans were preprocessed with grayscale conversion, black-border cropping, CLAHE contrast enhancement, bilateral denoising, and intensity normalization to improve feature consistency and generalization. The pipeline employs a dual-stage architecture: a binary classifier detects tumor versus non-tumor cases, followed by a multi-class classifier distinguishing glioma, meningioma, and pituitary tumors. MobileNetV2 trained on preprocessed data achieved 99% validation accuracy for binary classification and 91.3% for multi-class classification. The web interface allows users to upload MRI images and receive real-time predictions, demonstrating reliable performance across diverse tumor types. These results highlight the effectiveness of combining preprocessing, a hierarchical architecture, and a lightweight CNN for accurate, efficient, and accessible brain tumor detection suitable for clinical and real-time applications.

1. INTRODUCTION

A. Problem

Brain tumors such as gliomas, meningiomas, and pituitary tumors remain difficult to diagnose early, and they often lead to severe health outcomes when detected late. Even experienced radiologists can misinterpret MRI scans, especially when small or subtle abnormalities are present. This challenge is more pronounced in regions with limited access to specialized radiological expertise, where delays and diagnostic errors are more common.

Traditional diagnosis depends heavily on human interpretation, which is time-consuming, costly, and prone to subjectivity. As a result, many patients do not receive timely and accurate assessments. There is a clear need for intelligent, automated systems capable of analyzing MRI scans with high precision, detecting minute patterns that may escape the human eye, and supporting clinicians in making faster, more reliable decisions.

B. Aim

The primary aim of this project is to develop an intelligent diagnostic system for brain tumor detection and classification using MRI images. The approach focuses on analyzing high-resolution brain MRI scans to automatically identify and differentiate between normal and abnormal cases. The system employs a dual-structured deep learning architecture, integrating both binary classification (normal vs. tumor) and multi-class classification (Glioma, Meningioma, Pituitary) models. This structure enables the system to first determine the presence of a tumor, and then accurately classify its specific type, enhancing diagnostic precision and clinical applicability. Furthermore, the project aims to integrate this model into a web-based platform called MindScan, providing an accessible interface for radiologists and healthcare professionals to facilitate early brain tumor detection, streamline diagnosis, and support remote medical assessment.

C. Related Work

Recent research on MRI-based brain tumor analysis focuses on improving diagnostic accuracy, segmentation quality, and model reliability. Three representative works illustrate the main directions in the field.

Explainable ConvMixer-Based Classification Models Selva Birunda et al. [1] in 2025 proposed EM-ConvMixer+Net, an explainable framework combining ConvMixer blocks with attention mechanisms to improve classification and interpretability. The model achieves high accuracy and provides visual explanations through Grad-CAM, but its multi-module architecture increases implementation complexity and computational cost.

YOLO-Based Real-Time Tumor Detection Nuthi Raju et al. [2] in 2025 introduced YOLO-Beta11, a lightweight model designed for real-time tumor detection. It integrates attention-enhanced modules and optimized loss functions, achieving strong precision and recall while keeping inference efficient. However, as a single-stage detector, it outputs bounding boxes rather than detailed tumor masks, limiting its use for tasks requiring pixel-level segmentation.

Hybrid VGG16–InceptionV3 Feature Fusion Models Jamaa et al. [3] in 2025 as well, developed a hybrid model that merges VGG16 and InceptionV3 features for multi-class tumor classification. This fusion improves generalization and boosts accuracy across tumor types. The drawback is the increased model size, which makes deployment slower and less suitable for resource-constrained clinical environments.

2. METHODOLOGY

A. Data

A.1. Data Overview

The experiments use the Brain Tumor MRI Dataset by Masoud Nickparvar from Kaggle [4], which includes MRI images labeled as glioma, meningioma, pituitary tumor, and no tumor. Although the dataset provider indicates uniform dimensions, verification confirmed that all images are consistently sized at 224×224. The original Training and Testing folders were merged into a single pool, and the final train–validation–test split was performed programmatically within the code. Since the images already share the same resolution, only normalization was applied before feeding them into the models. This setup ensures a clean, unified dataset suitable for both detection and classification tasks.

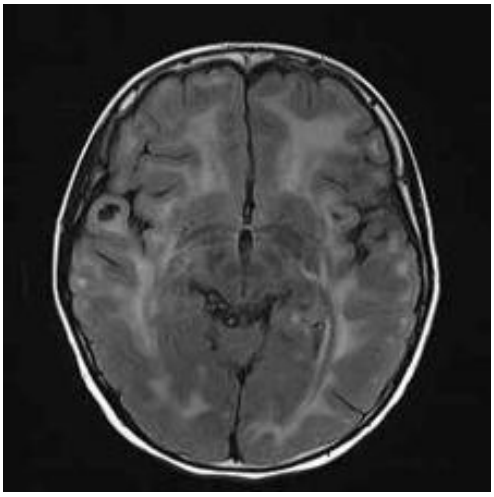

Fig. 1. Normal brain MRI scan with symmetrical structure and no visible abnormal growths or irregularities.

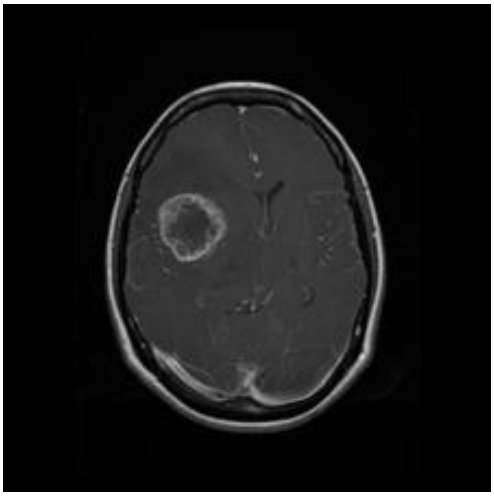

Fig. 2. MRI scan showing an abnormal brain region characterized by irregular mass and tissue deformation, indicative of a brain tumor.

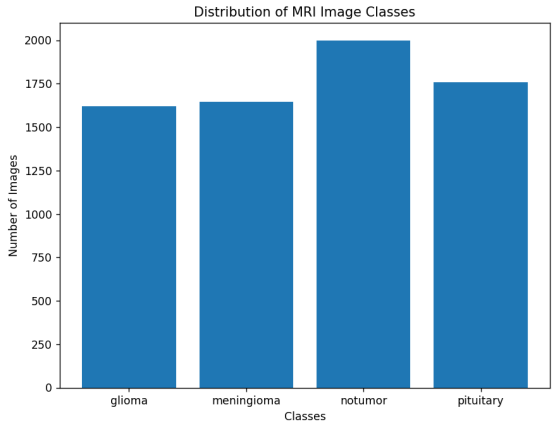

Fig. 3. This graph shows the distribution of the 4 classes, normal and 3 abnormal classes through the dataset

A.2. Data Preprocessing

The original MRI dataset presents substantial variability in resolution, field-of-view, contrast distribution, and noise levels across subjects and acquisition devices. To obtain standardized, noise-reduced, and contrast-enhanced inputs suitable for CNN-based tumor classification, we designed a deterministic preprocessing pipeline applied to every image in dataset. All steps were implemented in Python using OpenCV.

The complete pipeline consists of the following stages:

1. **Grayscale Loading** All MRI slices were loaded in grayscale using OpenCV. This ensures a uniform single-channel input representation across all samples.

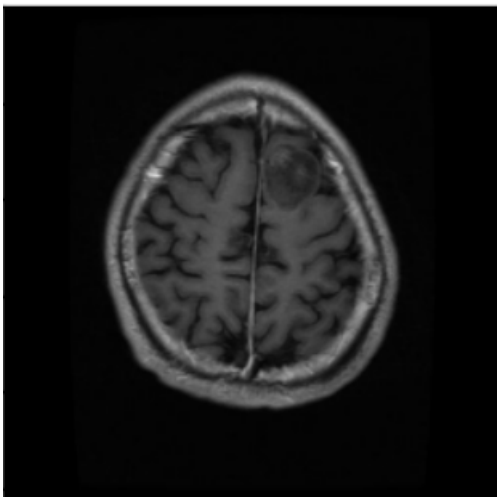

Fig. 4. Original input MRI

2. **Automatic Black-Border Cropping** Many MRI images contain large black margins surrounding the head. To remove these regions, we applied a morphological bounding-box cropping. This step isolates the brain region, reduces irrelevant background, and improves consistency across scans.

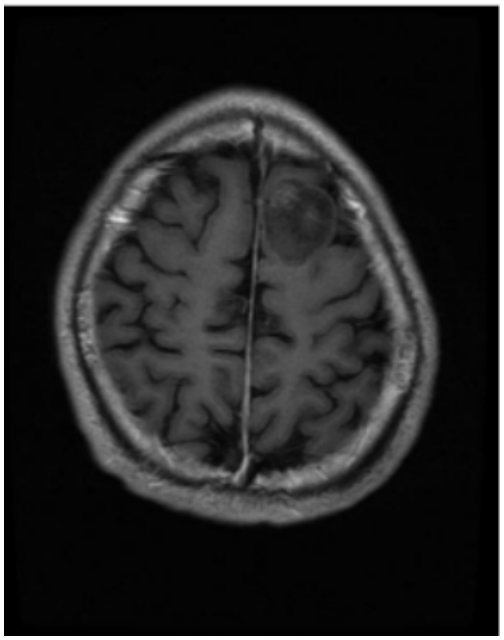

Fig. 5. Output after black-border cropping

3. **Local Contrast Enhancement (CLAHE)** To handle contrast heterogeneity between MRI scanners, we applied Contrast Limited Adaptive Histogram Equalization (CLAHE) with the following parameters: CLAHE locally boosts visibility of structures by enhancing edges and intensities without amplifying noise excessively.

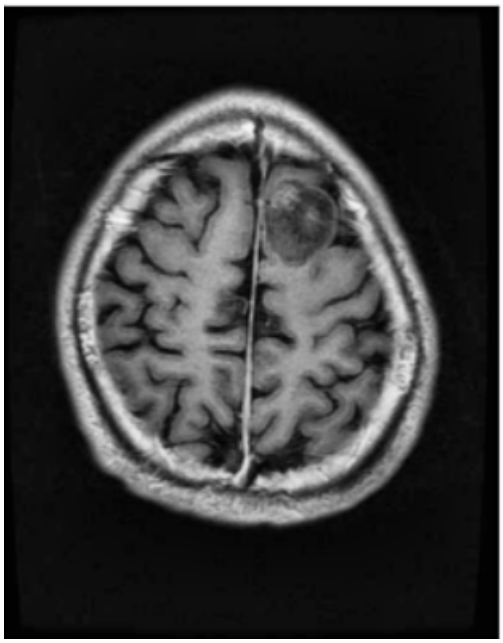

Fig. 6. Output after CLAHE

4. **Edge-Preserving Denoising (Bilateral Filter)** Following contrast enhancement, residual noise is smoothed using a bilateral filter: This filter reduces noise while preserving anatomical edges, unlike Gaussian blur which smooths edges away.

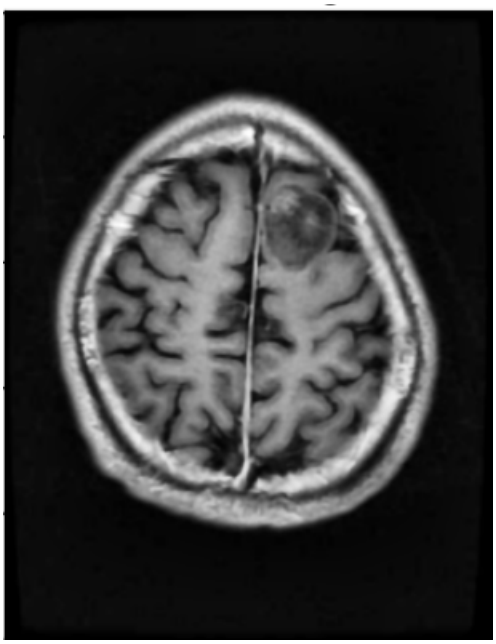

Fig. 7. Output after bilateral filtering

5. **Intensity Normalization** Before saving the preprocessed images, each image was normalized to the range [0, 1], This normalization ensures stable numerical behavior during model training and keeps pixel intensities consistent across the dataset. These preprocessed images were then saved back as uint8 images (scaled back to 0–255 only for storage), while the internal normalized representation is used for model input.

6. **Secondary Normalization (Step 2: Conversion to .npy for Training)** A second normalization stage was executed to prepare the final model input.

A.3. Dataset Configuration for Classification Tasks

To prepare the dataset and configurate it for classification task, we followed these methods as follow:

Tumor vs No-tumor Binary Classification For implementing binary classification we splitted the dataset to contains all 2000 sample of no tumor class and a chunk of each tumor class, and to make the dataset balanced between tumor and no tumor we managed to take 667 sample of each three tumor classes which resulted of 2001 sample.

Three-Class Tumor-Only Classification To classify tumor type, samples from the notumor category are excluded. The model learns to discriminate between:

- glioma
- meningioma
- pituitary tumor

This configuration focuses strictly on tumors and corresponds to clinical tasks requiring tumor-type identification after a positive detection.

Train, Validation, and Test Split The binary dataset is then split into training, validation, and test sets using a reproducible

random seed. Stratified sampling ensures that both classes maintain the same proportion in all splits. This workflow prevents overfitting, stabilizes learning, and provides a consistent framework for both binary and three-class classification tasks.

B. Models

B.1. Pipeline

The architecture follows a two-stage approach. First, a binary classifier determines whether an MRI scan is abnormal or normal. This step filters out healthy cases, **reducing unnecessary computation for normal images and improving overall detection efficiency**. If the scan is classified as abnormal, it is passed to a multi-class classifier that distinguishes between the specific tumor types—glioma, meningioma, or pituitary tumor. This hierarchical design simplifies the classification task, allows the models to focus on relevant features at each stage, and improves both accuracy and interpretability. [5]

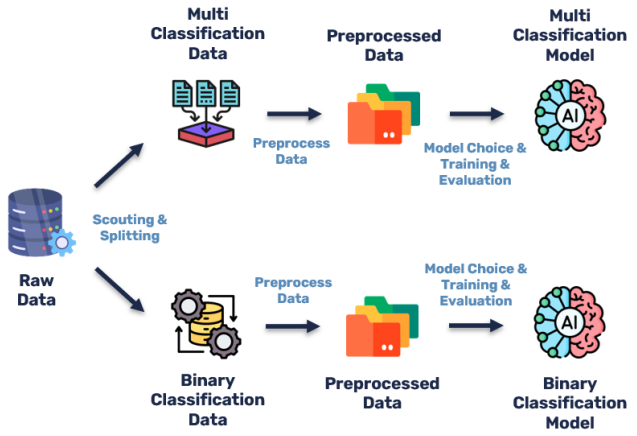

Fig. 8. Pipeline of models

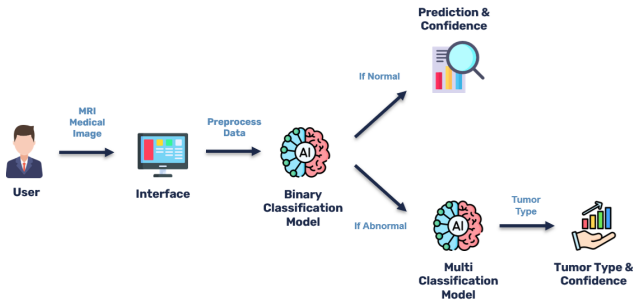

Fig. 9. User senario

B.2. MobileNetV2

MobileNetV2 is a lightweight convolutional neural network designed for efficient performance on mobile and embedded devices. Introduced by Sandler et al. [6] in 2018, it uses inverted residual blocks with linear bottlenecks, preserving representational power while reducing computation. MobileNetV2 has around 3.4 million parameters and a model size of approximately 14 MB, making it highly compact compared to larger architectures like EfficientNetV2B0. It provides a strong balance of accuracy and speed, supporting real-time inference with low memory and computational requirements. Its main limitation is that it may not achieve the highest accuracy on very challenging datasets compared to larger models.

B.3. ResNet18

ResNet18 is a convolutional neural network introduced by He et al. [7] in 2016 that employs residual learning to facilitate the training of deeper networks. It consists of 18 layers with skip connections that allow gradients to flow more effectively during backpropagation, addressing the vanishing gradient problem common in deep architectures. ResNet18 has approximately 11.7 million parameters, making it larger than MobileNetV2 but still relatively lightweight compared to deeper ResNet variants. It offers a strong trade-off between accuracy and computational efficiency, making it suitable for tasks requiring reliable feature extraction with moderate resources. Its main limitation is that it may be slower than extremely compact models on mobile or embedded devices.

B.4. EfficientNetV2B0

EfficientNetV2B0 is a state-of-the-art convolutional neural network that employs compound scaling of depth, width, and resolution to optimize accuracy and efficiency. It is designed to achieve high performance with fewer parameters and reduced computational cost compared to traditional large models. The architecture incorporates advanced features such as fused MB-Conv blocks and progressive learning rate scaling, making it well-suited for a variety of image classification tasks while maintaining a balance between model size, speed, and representational power. [8]

C. Web Interface

The MindScan web interface provides a user-friendly platform for AI-based brain tumor detection. The frontend, built with HTML, CSS, and JavaScript, allows users to upload MRI images and receive predictions instantly. The backend, implemented in Python, processes the images and generates model outputs in real time through a lightweight API. [9], enabling fast, reliable, and accessible brain tumor analysis directly from the browser.

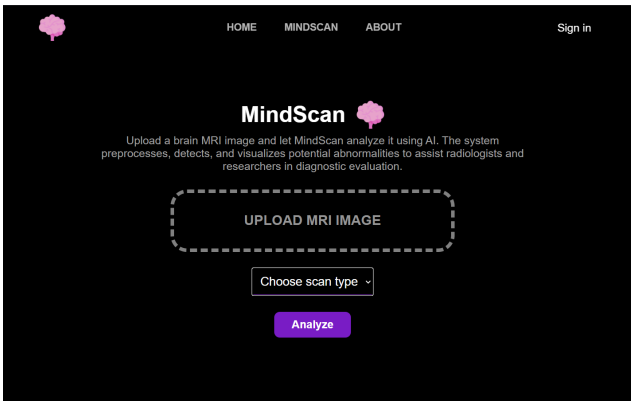

Fig. 10. MindScan interface.

3. RESULTS

A. Binary Classification with MobileNetV2

A.1. Applied on data not preprocessed

We trained MobileNetV2 as a binary classifier to distinguish between normal and abnormal MRI scans. The model achieved rapid convergence, reaching a training accuracy of 99.8% and a

validation accuracy of 98.1% after 10 epochs. F1-score, precision, and recall metrics followed similar trends, with the final validation F1-score reaching 0.981, demonstrating that MobileNetV2 can reliably detect abnormal scans. The training process was stable, with steadily decreasing loss, highlighting the efficiency and suitability of MobileNetV2 for real-time binary classification tasks.

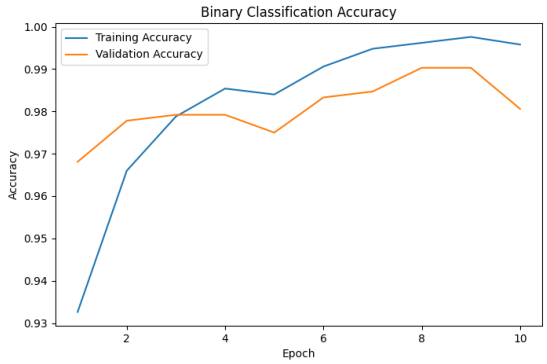

Fig. 11. The curve of the binary classification accuracy

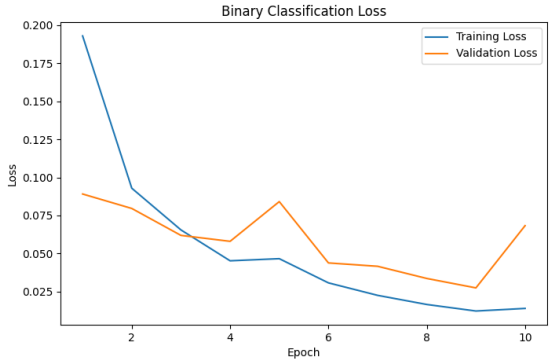

Fig. 12. The curve of the binary classification loss on preprocessed

A.2. Applied on preprocessed data

The model trained on the preprocessed dataset showed a clear improvement in both stability and overall performance. Starting from an initial accuracy of 91%, MobileNetV2 quickly progressed to 99% training accuracy and 99% validation accuracy by the final epoch. Loss values consistently decreased for both training and validation sets, and the high precision, recall, and F1-scores remained closely matched across epochs, indicating balanced predictions with minimal overfitting. Compared to the non-preprocessed experiment, the preprocessed version converged more cleanly, exhibited smoother accuracy and loss curves, and achieved slightly higher final validation performance. These results confirm that preprocessing enhanced feature consistency and helped the model generalize better while maintaining rapid convergence.

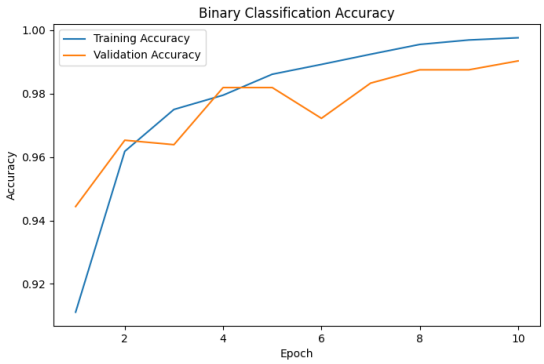

Fig. 13. The curve of the binary classification accuracy on preprocessed data

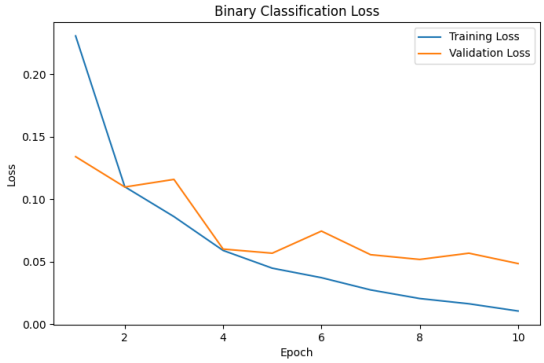

Fig. 14. The curve of the binary classification loss

B. Multi-Class Classification with MobileNetV2

B.1. Applied on data not preprocessed

MobileNetV2 was trained to classify abnormal MRI scans into glioma, meningioma, or pituitary tumor categories. The model showed steady improvement over 10 epochs, reaching a training accuracy of 95.4% and a validation accuracy of 87.3%. F1-score, precision, and recall on the validation set were similarly high, indicating that the model reliably distinguishes between different tumor types. The training and validation loss decreased consistently, suggesting effective learning and good generalization, although the validation performance is slightly lower than training, which is expected in multi-class tasks due to higher complexity.

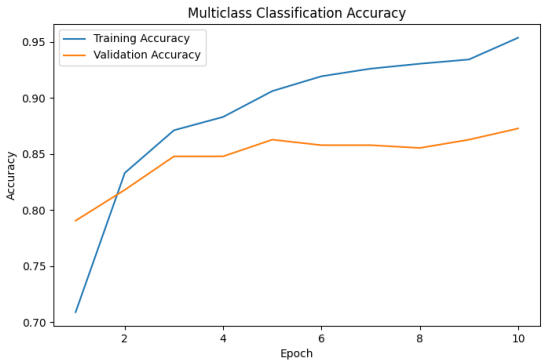

Fig. 15. The curve of the multi-class classification accuracy

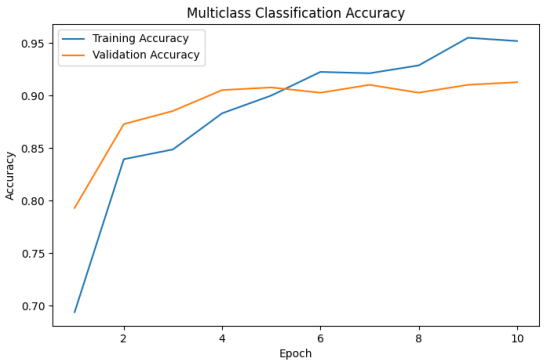

Fig. 17. The curve of the multi-class classification accurac after preprocessingy

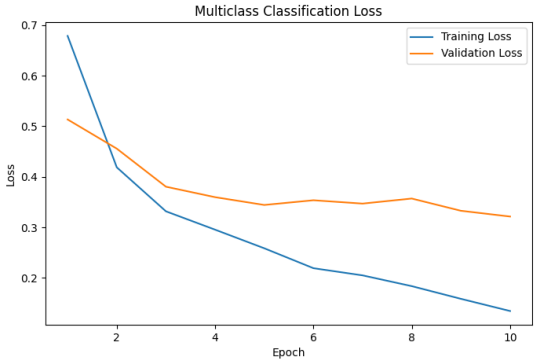

Fig. 16. The curve of the multi-class classification loss

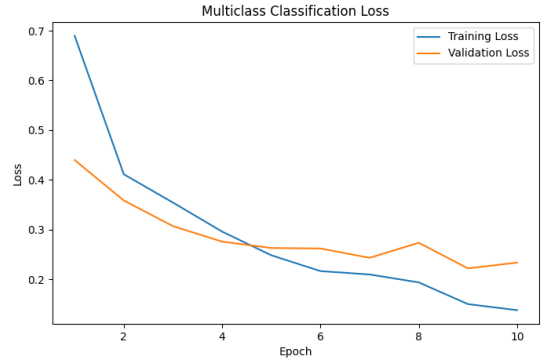

Fig. 18. The curve of the multi-class classification loss after preprocessing

B.2. Applied on preprocessed data

Training the multiclass classifier on the preprocessed images led to a clear improvement in learning stability and overall performance. The model began with an accuracy of 69% but quickly progressed, reaching over 90% validation accuracy by the fourth epoch and stabilizing around 91% in the final iteration. Precision, recall, and F1-score followed the same trend, showing consistent and balanced predictions across all tumor categories. The loss steadily decreased for both training and validation sets, and the gap between them remained small, indicating controlled generalization without overfitting. Compared to the non-preprocessed setup, the preprocessed data enabled smoother convergence and higher final performance, confirming that the preprocessing pipeline strengthened feature quality and improved the model's ability to differentiate between the three tumor types.

C. Binary Classification with ResNet18

We trained ResNet18 as a binary classifier to distinguish between tumor and non-tumor MRI scans. The model converged quickly, achieving a test accuracy of 98%. Precision, recall, and F1-score metrics indicate strong discriminative ability, with precision for tumor and non-tumor at 1.00 and 0.93, recall at 0.97 and 1.00, and F1-score at 0.98 and 0.97, respectively. However, a noticeable gap between training and validation performance suggests some overfitting, likely due to the relatively small dataset size compared to ResNet18's large capacity. Dropout, early layer freezing, and balanced sampling mitigated overfitting to some extent, but the model's complexity exceeds the amount of available data, limiting generalization in edge cases.

D. Multi Classification with ResNet18

ResNet18 was trained to classify tumor MRI scans into glioma, meningioma, and pituitary tumor categories. The model reached 97% test accuracy, with pituitary tumors identified with near-perfect reliability. Most misclassifications occurred between glioma and meningioma due to their visual similarity. While precision, recall, and F1-score metrics were high across all classes, the large network exhibited signs of overfitting, with training accuracy consistently higher than validation accuracy. Fine-tuning only higher layers, combined with dropout and weight decay, helped control overfitting, but the relatively small dataset limited ResNet18's full generalization potential for multi-class tumor differentiation.

E. Binary Classification with EfficientNetV2B0

Training and fine-tuning a large architecture like EfficientNetV2B0 on a relatively small dataset can easily lead to dramatic overfitting. The model's high capacity allows it to memorize training samples rather than generalize to unseen data, which can significantly reduce its reliability for brain tumor detection tasks when dataset size is limited.

F. Web Interface Demo

We conducted tests and demos using the MindScan interface with sample MRI images randomly from random internet sources for all tumor classes and no tumor class. The system successfully analyzed each case, providing accurate predictions and demonstrating reliable performance across different tumor types.

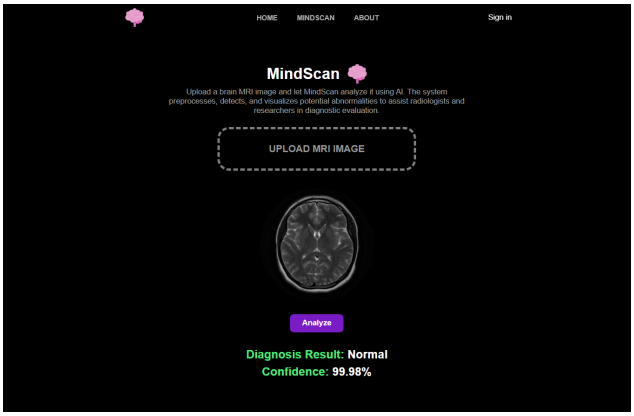

Fig. 19. Test in MindScan interface on a normal sample

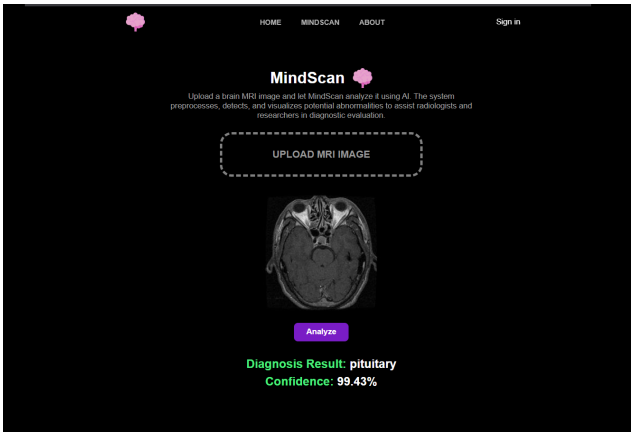

Fig. 20. Test in MindScan interface on an abnormal sample

4. DISCUSSION

A. MobileNetV2

A.1. Applied on data not preprocessed

The MobileNetV2-based pipeline performed well for both binary and multi-class brain tumor classification. Binary classification achieved near-perfect metrics, while multi-class classification reached 87.3% validation accuracy, showing reliable tumor type identification. The hierarchical design proved efficient, and MobileNetV2's compact size supports fast, web-based deployment. Slight gaps between training and validation suggest that more data or augmentation could further improve generalization.

A.2. Applied on preprocessed data

Applying preprocessing led to clear improvements in stability and overall performance for both binary and multiclass classification. The binary model reached 99% validation accuracy with smooth convergence and minimal gaps between training and validation curves, indicating strong generalization. The multiclass model also benefited, achieving over 91% validation accuracy and maintaining consistent precision, recall, and F1-scores across all classes. Loss decreased steadily in both tasks, and the training process became more stable compared to the non-preprocessed setup. These results show that preprocessing enhanced feature clarity, improved convergence, and strengthened MobileNetV2's ability to distinguish brain tumor types.

B. Comparison

MobileNetV2 trained on preprocessed data demonstrated the best overall performance for both binary and multi-class brain tumor classification. The model achieved 99% validation accuracy for binary classification and 91.3% for multi-class classification, with smooth convergence and minimal overfitting. Preprocessing clearly improved stability, generalization, and feature consistency, allowing the model to reliably distinguish tumor types. Its compact size and efficiency also make it ideal for real-time, web-based deployment, confirming MobileNetV2 on preprocessed data as the optimal choice for this project.

Table 1. Training and Validation Metrics Across Epochs for MobileNetV2 and ResNet18[a]

Model / Data	Train Acc	Val Acc	Train Loss	Val Loss
Binary Classification				
MNV2 (Raw)	0.9958	0.9806	0.0139	0.0683
MNV2 (PP)	0.9976	0.9903	0.0105	0.0485
Multi-Class Classification				
MNV2 (Raw)	0.9538	0.8728	0.1346	0.3215
MNV2 (PP)	0.9519	0.9127	0.1377	0.2334

[a] Abbreviations: MNV2 = MobileNetV2, PP = Preprocessed, Acc = Accuracy, Val = Validation.

5. LIMITATIONS AND FUTURE WORK

Despite the strong performance of MindScan, several limitations exist. The dataset used is relatively small and sourced from a single public repository, which may limit the model's generalization to diverse clinical populations. Additionally, the current system focuses solely on classification and does not provide tumor segmentation, which could be valuable for treatment planning and surgical guidance. Future work could address these limitations by incorporating larger, multi-center datasets to improve generalization, adding automated tumor segmentation capabilities, and exploring 3D MRI analysis. Further validation in real-world clinical settings would also strengthen the system's reliability and applicability.

6. CONCLUSION

In this work, we developed MindScan, a web-based AI system for brain tumor detection and classification using MRI images. The proposed hierarchical approach—binary classification to detect abnormalities followed by multi-class classification to identify tumor types—demonstrated strong performance, with MobileNetV2 achieving high accuracy, F1-score, precision, and recall. The system provides real-time, reliable predictions while remaining lightweight and suitable for web deployment. These results highlight the potential of AI-assisted tools to

support early and accurate diagnosis of brain tumors, improving clinical decision-making and patient outcomes. Future work could focus on expanding the dataset, adding segmentation capabilities, and validating the model across diverse clinical settings.

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