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Lightweight Deep Learning Framework for Brain Tumor Classification Using Feature Refinement

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***Abstract*—Accurate and efficient classification of brain tumors from MRI scans is critical for early diagnosis and treatment planning. While deep learning methods, including convolutional neural networks (CNNs) and transformers, achieve high accuracy, they often demand substantial computational resources, limiting their use in real-world clinical settings. This study proposes two lightweight models for multiclass brain tumor classification: a MobileNetV2-based model with a custom feature refinement head (MobileNetV2+RH) and a lightweight variant derived from MobileNetV2 with the same refinement head (CustomMobileV2+RH). Evaluated on a dataset of 7,023 MRI images across four classes—glioma, meningioma, pituitary tumor, and no tumor—both models achieved over 98% accuracy while using far fewer parameters than heavier state-of-the-art architectures. These results highlight that combining lightweight backbones with a refinement head yields high-performance, computationally efficient, and deployable solutions for MRI-based brain tumor classification.**

***Index Terms*—Brain Tumor Classification, MobileNetV2, Deep Learning, MRI, Lightweight Model**

I. Introduction

One of the most aggressive cancers affecting the central nervous system, primary brain tumors accounted for approximately 347,992 new cases and 246,253 deaths worldwide in 2019, significantly contributing to global cancer morbidity and mortality [1]. For better patient outcomes and efficient treatment planning, an early and precise diagnosis is essential. Because of its high-resolution soft tissue visualization and capacity to distinguish between distinct tumor forms, magnetic resonance imaging (MRI) is the main non-invasive method for identifying brain cancers, including gliomas, meningiomas, and pituitary tumors [2]–[4]. The significance of automated diagnostic systems is underscored by the fact that manual interpretation of MRI scans is time-consuming, requires a high level of knowledge, and is prone to human error.

Deep learning methods, particularly Convolutional Neural Networks (CNNs), have recorded remarkable success in MRI-based brain tumor classification [5]–[7]. Many existing approaches rely on fine-tuning pre-trained deep CNNs, which achieve high predictive accuracy but incur substantial computational costs, as all model layers remain trainable. Freezing the backbone network and training only the classifier layers can reduce training computational burden, but often results in suboptimal performance. On the other hand, fully custom CNNs trained from scratch may lower parameter count but typically struggle to achieve competitive classification accuracy [13]. More recent efforts employing transformer-based architectures [5] and attention mechanisms have demonstrated improved feature representation by capturing long-range dependencies, yet they dramatically increase parameter count and inference time, limiting their credibility for deployment in real-world clinical environments limited by resources.

To address these challenges, this work proposes two complementary approaches for efficient MRI-based brain tumor classification:

Firstly, we utilize a pre-trained lightweight architechture, MobileNetV2, as a frozen feature extractor, combined with a lightweight refinement head consisting of additional convolutional layers, residual connections, and separable convolutions.

Secondly, we design a MobileNetV2-derived lightweight variant with fewer inverse residual blocks relative to MobileNetV2, integrated with the same refinement head to further reduce both total and trainable parameters.

Finally, we evaluate the classification performance of these approaches on a publicly available dataset and compare their accuracy and parameter efficiency with both state-of-the-art models and benchmark CNN architectures to assess their suitability for practical implementation in clinical settings, particularly in machines with limited computational resources.

II. Related Work

Classification of Brain tumors utilizing MRI images has attracted significant attention due to the potential of deep learning methods to enhance diagnostic accuracy, reduce manual effort, and assist clinicians in early and precise diagnosis. Transfer learning has been widely employed to utilize pre-trained models and reduce the need for large training datasets while improving generalization. Liu and Wang [6] introduced MobileNet-BT, achieving 99.24% accuracy and F1-score in multiclass classification of glioma, meningioma, pituitary tumors, and healthy tissue, outperforming MobileNetV2, ResNet-18, EfficientNet-B0, and VGG16. Srinivas et al. [8] applied VGG-16, ResNet-50, and Inception-v3 on 233 MRI scans, achieving 96% accuracy with VGG-16. Mahjoubi et

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al. [7] utilized CNNs on 7022 MRI scans, reaching 95.44% overall accuracy, while Adewole Maruf et al. [9] evaluated 26 pre-trained CNNs on 3064 T1-weighted MRIs, with EfficientNetB3 achieving 98.98% accuracy. Gómez-Guzmán et al. [10] compared six pre-trained CNNs, finding that InceptionV3 acquired 97.12% accuracy, highlighting the efficiency and versatility of transfer learning for classifying brain tumors across different datasets and architectures.

Several studies have explored custom CNN architectures for enhanced feature extraction and tumor discrimination. Tiwari et al. [11] proposed a CNN on 7023 MRI images, achieving 99% accuracy, demonstrating that carefully designed networks can achieve high precision with moderate complexity. Ramdas Vankdothu and Hameed [12] used RCNN on 2870 images, achieving 95.17% accuracy, effectively combining recurrent and convolutional operations for better spatial feature modeling. Alwas Muis et al. [13] and Özkaraca et al. [14] explored deeper CNNs trained from scratch, attaining up to 97% accuracy and showing that fully custom architectures can be competitive with pre-trained models. Rasheed et al. [15] incorporated Gaussian-blur enhancement, skip connections, and regularization, reaching 97.84% accuracy, while Remzan et al. [16] achieved 98.27% accuracy using sequential CNNs. Zahoor et al. [17] developed Res-BRNet, integrating region- and boundary-focused operators to improve feature discrimination, achieving 98.22% accuracy. Zulfiqar et al. [18] and Waskita et al. [19] fine-tuned EfficientNet variants, achieving up to 99% test accuracy, highlighting the effectiveness of combining lightweight architectures with optimized fine-tuning strategies.

Hybrid and ensemble approaches have also been extensively investigated. Tonni et al. [20] combined nine pre-trained CNNs in a hybrid transfer learning framework with explainable AI, achieving 99.47% accuracy while providing interpretability through Grad-CAM and SHAP visualizations. Nassar et al. [21] applied majority voting across five CNNs on 3064 MRI scans, reaching 99.31% accuracy, demonstrating the benefits of leveraging complementary model strengths to reduce misclassification. Güler and Namlı [23] integrated deep learning and classical machine learning methods (SVM, KNN, LDA) on 7022 MRI images, achieving 100% accuracy and illustrating how ensemble strategies can improve robustness, reliability, and overall performance in multiclass brain tumors.

Transformer-based models have recently shown strong performance in medical image analysis. Reddy et al. [5] employed Fine-Tuned Vision Transformers on 7023 MRI scans and achieved 98.70% accuracy (FTVT-l16), outperforming ResNet-50 and EfficientNet-B0 by effectively capturing long-range spatial dependencies.

However, despite high accuracy, transformer- and ensemble-based models often involve large parameter sizes, high computational cost, and limited deployability on edge devices. To address these challenges, this work proposes lightweight CNN models with a refinement head that achieve competitive accuracy while significantly reducing parameters, training effort, and deployment cost—supporting practical clinical use.

III. Methodology

A. Proposed Approaches

1) MobileNetV2+RH:

a) Backbone: MobileNetV2 was chosen as the backbone due to its lightweight architecture and high representational capacity. It employs inverted residual blocks and depthwise separable convolutions, significantly reducing the parameter count while maintaining strong feature extraction. In this proposed approach, the pretrained base layers were frozen to utilize ImageNet features, enabling task-specific learning to be the model's primary focus in the subsequent layers.

b) Feature Refinement Head: A custom classification head was appended to the frozen backbone to refine features for brain tumor classification. It comprises convolutional layers followed by batch normalization and the ReLU function for activation, organized into residual blocks to ensure efficient gradient flow and to mitigate vanishing gradient issues. The residual connections also promote better feature reuse, enabling the network to learn low-level as well as high-level representations more effectively. A SeparableConv2D layer captures spatial correlations while maintaining a low parameter count. Global Average Pooling aggregates spatial features, followed by a fully connected layer consisting of 512 neurons and a dropout rate of 0.4. Finally, a softmax layer outputs probabilities across four brain tumor classes.

c) Overall Architecture: Fig. 1 illustrates the MobileNetV2+RH architecture, where the frozen backbone extracts features from preprocessed MRI images, refined through residual blocks, separable convolution, global average pooling, and dense layers before the softmax outputs four classes.

2) CustomMobileV2+RH:

a) Backbone and Inverted Residual Blocks: The proposed backbone is a lightweight variant of MobileNetV2, specifically designed to reduce overall complexity while retaining strong feature extraction. Unlike the original MobileNetV2, which has 17 inverted residual blocks, our model uses only 11. To balance efficiency and representation power, the number of filters in certain blocks is adjusted (reduced in some layers and increased in others). Each block retains the core design of MobileNetV2, consisting of an optional expansion phase, depthwise convolution, projection phase, and residual connection where applicable. This modified backbone is trained from scratch to capture brain tumor–specific features directly from MRI images.

b) Feature Refinement Head: As with the MobileNetV2+RH model, the same feature refinement head is appended to the backbone, which ensures consistent features enhancement through residual convolutional layers for richer representations while using SeparableConv2D and Global Average Pooling for low-parameter classification.

c) Overall Architecture: Fig. 2 illustrates the architecture of CustomMobileV2+RH, where the modified MobileNetV2 backbone with 11 inverted residual blocks and adjusted filters extracts features from preprocessed MRI images, which are then enhanced by the feature refinement head before being classified by the softmax layer into four classes.

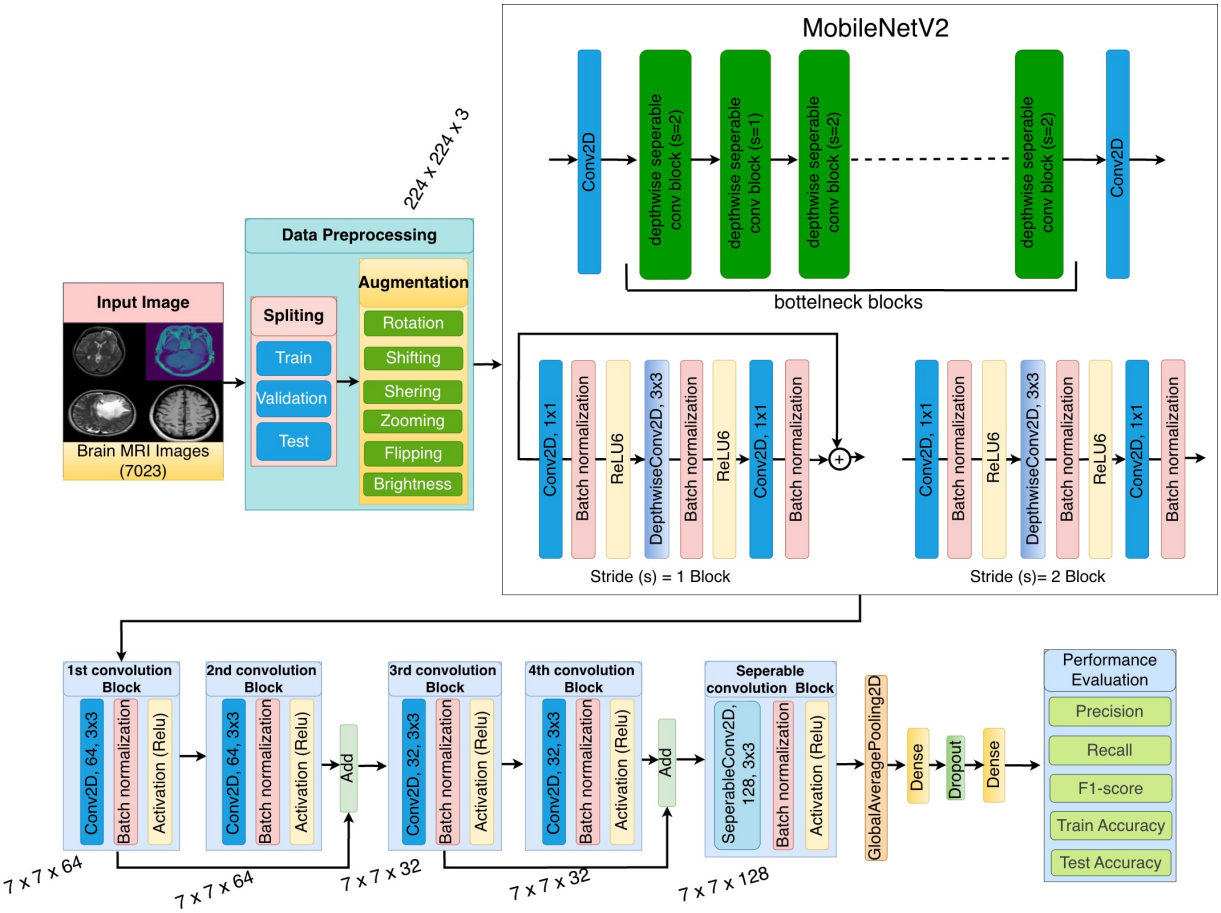

Fig. 1. MobileNetV2+RH model architecture for brain tumor classification.

B. Training Strategy

For the MobileNetV2+RH model, only the feature refinement head was trained while the backbone remained frozen. In contrast, the CustomMobileV2+RH was trained end-to-end from scratch. Categorical cross-entropy was used as the function for loss calculation to differentiate between the four classes. The models were trained on augmented data to improve generalization, and validation sets were used to monitor performance. Later, metrics including accuracy, precision, recall, F1-score, and confusion matrices were computed on the test set.

IV. Experimental Setup

A. Dataset

The conducted experiment was based on a dataset of 7,023 MRI scans that were divided into four classes: Meningioma (1,645 images), Glioma (1,621 images), Pituitary (1,757 images), and No Tumor (2,000 images). The open-source dataset used in this study was originally compiled and curated from three publicly available sources: Figshare, SARTAJ, and Br35H [22]. Afterwards, it was further divided into train, validation, and test sets in an 80:10:10 ratio. This split preserved enough samples for unbiased validation and testing while ensuring the use of a significant amount of data for model training. The distribution made it possible for the model to assess its generalization on unseen images and successfully capture a variety of tumor features.

B. Preprocessing

To match the input dimensions needed by the MobileNetV2 architecture, all images were reduced to 224×224 pixels. To ensure consistency with the pretrained weights obtained from ImageNet, the intensity of pixels were normalized via the preprocess_input function offered by MobileNetV2. This stage preserves numerical stability throughout training while helping the network in making efficient use of pretrained features.

C. Data Augmentation

The training set was driven through rigorous data augmentation techniques in order to enhance generalization and decrease overfitting. Images were randomly rotated within a range of $\pm 20°$, moved up to 10% of their dimensions in both the horizontal and vertical directions, and then sheared with a factor of 0.1. In order to account for orientation uncertainty, random horizontal flips and zoom operations up to 10% were added. The brightness was set between 0.8 and 1.2

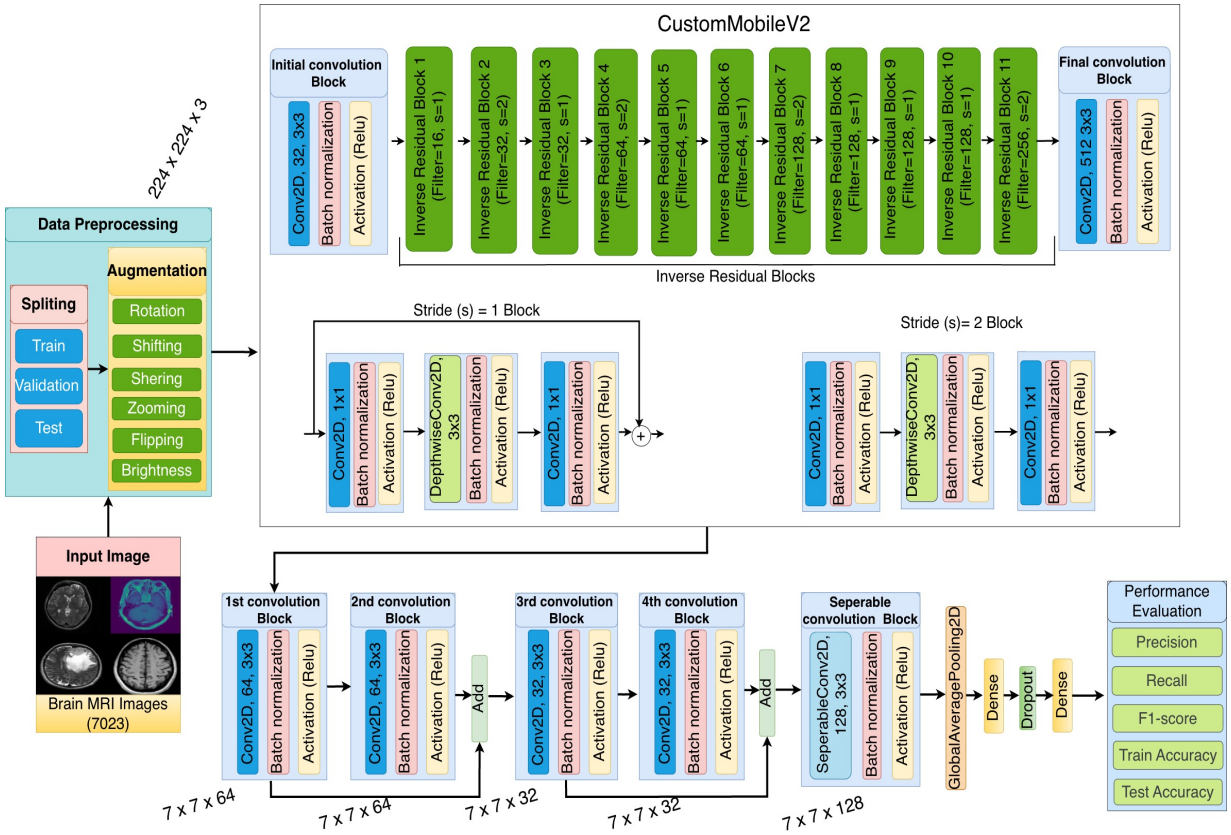

Fig. 2. CustomMobileV2+RH architecture for brain tumor classification.

to mimic variations in the intensity of an MRI scan. Nearest-neighbor filling was utilized to deal with vacant pixels in all enhanced photos. These augmentations prompted the model to learn robust and invariant characteristics across a range of imaging settings by mimicking real-world variances in MRI acquisition.

D. Training Environment

All experiments were conducted using TensorFlow and Keras on a system with dual NVIDIA Tesla T4 GPUs. The training pipeline was implemented in Python 3.10, ensuring compatibility with modern deep learning libraries to guarantee reproducibility of the training process

E. Hyperparameters and Callbacks

Models with a batch size of 32 were trained across 150 epochs. An initial learning rate of 0.0001 was applied to the Adam optimizer. Among the callbacks were ModelCheckpoint, which saved the top-performing model based on validation loss, and ReduceLROnPlateau, which dynamically decreased the learning rate when validation loss plateaued.

V. Results and Discussion

A. Classification Performance

Table I compares frozen pretrained CNN models with the proposed MobileNetV2+RH and CustomMobileV2+RH architectures. Traditional models, limited to ImageNet features, achieved moderate accuracy (∼90–92%), while the proposed models reached 98.44% and 98.86%, respectively. Both also delivered higher precision, recall, and F1-scores, confirming that the RH head effectively refines feature representations for brain tumor classification.

TABLE I
Performance comparison with traditional deep CNN models

Model	Precision	Recall	F1-Score	Accuracy
MobileNetV2	91.67%	91.61%	91.48%	91.61%
EfficientNetB0	89.59%	89.63%	89.44%	89.63%
DenseNet201	95.04%	95.02%	95.02%	95.02%
NASNetMobile	86.23%	86.50%	86.15%	86.50%
Xception	92.02%	92.04%	92.00%	92.04%
ResNet50	92.27%	92.32%	92.21%	92.32%
VGG16	90.10%	90.05%	90.00%	90.05%
InceptionV3	90.39%	90.48%	90.35%	90.48%
MobileNetV2+RH	**98.44%**	**98.44%**	**98.44%**	**98.44%**
CustomMobileV2+RH	**98.87%**	**98.86%**	**98.86%**	**98.86%**

B. Training and Validation Trends

Figures 3 and 4 illustrate the training and validation accuracy and loss curves for the MobileNetV2+RH and CustomMobileV2+RH models, respectively. Both models exhibit smooth convergence with minimal overfitting in MobileNetV2+RH, demonstrating strong generalization. The proposed refinement head contributed to refining feature representations from pretrained and custom backbones, allowing superior performance without requiring full fine-tuning.

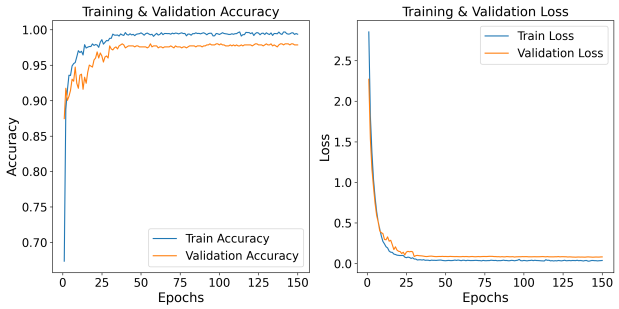

Fig. 3. Train-validation accuracy and loss curves of MobileNetV2+RH model.

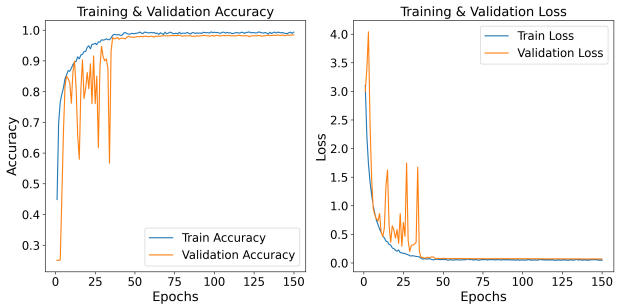

Fig. 4. Train-validation accuracy and loss curves of CustomMobileV2+RH model.

C. Confusion Matrix Analysis

Figures 5 and 6 present the confusion matrices of the MobileNetV2+RH and CustomMobileV2+RH models. Both models achieved balanced classification performance across all four classes: glioma, meningioma, pituitary tumor, and no tumor. The CustomMobileV2+RH demonstrated slightly fewer misclassifications, with pituitary being perfectly classified, but particularly in distinguishing no tumor, MobileNetV2+RH performed slightly better.

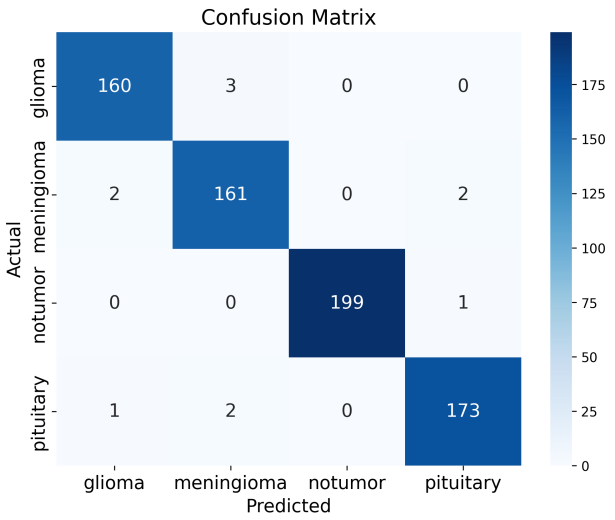

Fig. 5. Confusion matrix of MobileNetV2+RH model on the test set.

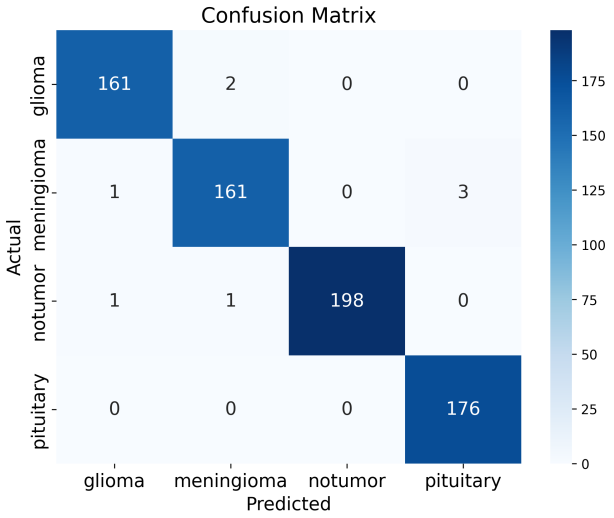

Fig. 6. Confusion matrix of CustomMobileV2+RH model on the test set.

D. Comparison with State-of-the-Art (SOTA)

Compared to state-of-the-art methods in Table **??**, including transformer-based FTVT variant, CNNs, and ensembles, the proposed models achieve competitive accuracy with far fewer parameters. FTVT-b16 reaches 98.09% accuracy with 89.2M parameters, and EfficientNet variants require 7–23M for 95–98% accuracy. In contrast, CustomMobileV2+RH achieves 98.86% with only 1.7M parameters, while MobileNetV2+RH reaches 98.44% with 0.87M trainable (3.1M total) parameters. Although MobileNet-BT reports slightly higher accuracy (99.24%) with 3.5M parameters, both proposed models outperform heavier SOTA approaches in efficiency–accuracy trade-off, with CustomMobileV2+RH suited for low-resource deployment and MobileNetV2+RH for faster training.

E. Discussion

The two proposed models emphasize different strengths. CustomMobileV2+RH delivers the highest accuracy with minimal total parameter count, making it well-suited for deployment on resource-limited devices, achieving both inference and training efficiency. MobileNetV2+RH offers nearly the same accuracy with fewer trainable parameters, favoring faster training and experimentation despite its larger overall size.

Considering accuracy and deployment feasibility, CustomMobileV2+RH stands out as the preferred model, with MobileNetV2+RH serving as a practical choice when training efficiency is the priority.

VI. Conclusion

In this study, we proposed two efficient models for MRI-based brain tumor classification: MobileNetV2+RH, integrating a frozen pretrained backbone with a lightweight refinement head, and CustomMobileV2+RH trained from scratch. The refinement head was designed to enhance feature extraction while keeping parameters low, and a preprocessing pipeline comprising normalization, scaling, and data augmentation improved generalization across the merged multi-source dataset.

TABLE II
COMPARISON OF THE PROPOSED MODELS WITH EXISTING LITERATURE

Model	Paper	Accuracy	Precision	Recall	F1-Score	Trainable Parameters	Total Parameters
MobileNet-BT	X. Liu and Z. Wang (2024) [6]	99.24%	99.24%	99.24%	99.24%	3.5 M	3.5 M
FTVT-b16	Reddy et al. (2024) [5]	98.09%	98.93%	92.67%	95.70%	89.2 M	89.2 M
CNN	Mahjoubi et al. (2023) [7]	95.44%	95.00%	95.25%	96.25%	7.7 M	7.7 M
VGG16 + ResNet152V2	Tonni et al.(2025) [20]	97.00%	96.00%	96.50%	96.89%	138 M	138 M
Custom CNN	Alwas Muis et al.(2023) [13]	84.00%	64.20%	84.30%	72.90%	0.03 M	0.03 M
Proposed Model	Rasheed et al.(2023) [15]	97.85%	97.85%	97.90%	97.84%	1.7 M	1.7 M
Xception Model	Amarnath et al.(2024) [24]	98.17%	98.17%	98.17%	98.17%	22.9 M	22.9 M
MobileNetV2+RH	**Our proposed model 1**	**98.44%**	**98.48%**	**98.44%**	**98.44%**	**0.87 M**	**3.1 M**
CustomMobileV2+RH	**Our proposed model 2**	**98.86%**	**98.87%**	**98.86%**	**98.86%**	**1.7 M**	**1.7 M**

Both the models gained high accuracy, precision, recall, and F1-score while maintaining much lower computational complexity than heavier CNNs and transformer-based methods. CustomMobileV2+RH delivered slightly higher accuracy (98.86%) with minimal total parameters (1.7M), making it especially appealing for deployment on resource-limited systems. MobileNetV2+RH achieved nearly comparable accuracy (98.44%) with fewer trainable parameters (0.87M), enabling faster training and efficient experimentation, which is advantageous during model development.

These results demonstrate that combining lightweight architectures with a customized refinement module and effective preprocessing can deliver reliable and scalable brain tumor classification. However, the models have not yet been validated on real-world clinical images. Future work may explore explainable AI, multimodal imaging, inference analysis, edge-device deployment, and validation with clinical data to further strengthen interpretability, generalizability, and accessibility in healthcare.

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