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Enhanced Brain Tumor Classification from MRI Images Using MobileNetV2: A Transfer Learning Approach

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Abstract:

Brain tumors require being identified early and accurately, for prompt treatment and better patient outcomes. Conventional convolutional neural networks (CNNs) have shown encouraging results in the classification of tumors using magnetic resonance imaging (MRI); nevertheless, when trained on limited datasets of medical images, they frequently experience overfitting and significant computing costs. In this work, we introduce an efficient deep learning framework for classifying multiple types of brain tumors, leveraging MobileNetV2—a compact convolutional neural network architecture utilizing depthwise separable convolutions. A publicly accessible dataset of 3,264 MRI scans categorized into four classes—glioma, meningioma, pituitary tumor, and no tumor—was used to train and assess the model. To improve model generalization, extensive preprocessing and data augmentation techniques were used. The proposed MobileNetV2-based model achieved higher reported performance than the evaluated architectures, including VGG16, ResNet50, InceptionV3, and the traditional CNN suggested in previous work, achieving 98.25% accuracy, 98.39% recall, and 98.69% AUC. Based on the results, MobileNetV2 is a promising option for implementation in real-time and resource constrained clinical contexts since it provides a highly accurate and computationally economical solution for brain tumor diagnosis.

Keywords: Deep Learning, MobileNetV2, Brain Tumor Classification, Magnetic Resonance Imaging, Transfer Learning, Multi-Class Classification

Introduction

Brain tumors constitute one of the most severe and life-threatening neurological disorders, necessitating a prompt and correct evaluation for optimal medical intervention planning. Magnetic Resonance Imaging (MRI) has emerged as one of the most preferred methods for detecting brain tumors due to its enhanced soft-tissue contrast and non-invasive nature. However, manual interpretation of MRI scans by radiologists is resource intensive and susceptible to inaccuracies, particularly in discriminating between different types of brain tumors [1].

In recent years, deep learning, particularly convolutional neural networks (CNNs), has demonstrated strong performance in a wide range of image categorization applications, including medical imaging. Several studies have used CNNs to classify brain tumors, with encouraging outcomes. A CNN-based framework for classifying brain tumors from MRI scans achieved a classification accuracy of 93.3% on a dataset of 3,264 images. Their research also included comparisons to other widely used deep learning models such as ResNet-50, VGG16, and InceptionV3, demonstrating CNNs as a effective approach for brain tumor diagnosis [3].

Despite their effectiveness, traditional CNNs and deep architectures such as VGG16 and InceptionV3 are computationally expensive, necessitating high-end hardware for training and inference. This complicates the deployment of such models in real-time or resource-constrained settings, such as rural clinics or mobile diagnostic applications [4].

To overcome these problems, this work proposes a brain tumor classification method based on MobileNetV2, a lightweight CNN architecture optimized for performance without sacrificing accuracy. MobileNetV2 uses depthwise separable convolutions and inverted residual blocks to dramatically reduce computational cost and model size [5]. Our goal is to show that MobileNetV2 can outperform or match the accuracy of more complex models while being better suited for implementation in real-world healthcare settings.

We analyze our model using a publicly available MRI dataset that includes four tumor classes: glioma, meningioma, pituitary tumor, and no tumor. Through thorough experimentation, we demonstrate that MobileNetV2 achieves higher reported performance than the evaluated baseline, including those benchmarked in [3], across classification accuracy, recall, loss, and AUC.

Related Work

In recent years, extensive research has focused on applying deep learning techniques for brain tumor detection from MRI data. CNNs have become highly effective tools for medical image classification, owing to their ability to autonomously extract hierarchical features from images [6].

Several researchers have proposed CNN-based algorithms especially for detecting brain tumors. Mahmud et al. [3] developed a customized CNN architecture and compared its performance to widely used deep learning models such as VGG16, ResNet-50, and InceptionV3. The suggested CNN model had a validation accuracy of 93.3%, outperforming existing transfer learning models on the same dataset. However, its architecture remained exceptionally large and was not tailored to low-resource situations. Almadhoun et al. used MobileNet, as well as other transfer-learning models such as VGG16 and ResNet-50, on a large dataset of 10,000 MRI images [7]. Their MobileNet model was highly accurate; however, it lacked detailed performance measures for multiple tumor classes. Similarly, Nayak et al. [8] evaluated MobileNet and MobileNetV2 for brain tumor classification, reporting positive results but focusing on their proposed Efficient Net-based approach.

Musallam et al. [9] suggested a lightweight DCNN model to diagnose four tumor classes: glioma, meningioma, pituitary, and no tumor, with an accuracy of 97.72%. Their approach was developed for efficiency; however the architecture was distinct and lacked transfer learning capabilities, which can aid in faster convergence and generalization on small datasets.

Recent initiatives have also centered on ensemble approaches. Amin et al. [10] successfully classified brain tumors using a hybrid ensemble model that incorporated KNN, Random Forest, and Decision Tree classifiers, with an accuracy of 97.3%. However, such approaches might be computationally expensive at the inference stage.

Although these models provide comparable accuracy, they frequently lack scalability for use in real-time or mobile healthcare settings. MobileNetV2, on the other hand, was created primarily for edge devices and low-latency applications [5], making it a suitable choice for efficient brain tumor classification. To the best of our knowledge, only a few research studies have thoroughly tested MobileNetV2 as a standalone model for multiclass brain tumor classification from MRI data.

This work addresses the gap by benchmarking MobileNetV2 against several existing deep learning models on a widely used MRI dataset and demonstrating its enhanced performance, particularly in accuracy, recall, and computational efficiency.

Methodology

This section describes the processes used to create the proposed brain tumor classification model utilizing the MobileNetV2 architecture. The methodology includes dataset features, preprocessing strategies, model construction, training configurations, and evaluation metrics.

Dataset Description

The experimental investigation used a publicly available MRI dataset from Kaggle [11], which included 3,264 brain MRI scans. The images are categorized into four classes: glioma (926 images), meningioma (937 images), pituitary tumor (901 images), and no tumor (500 images). The dataset exhibits moderate class imbalance; data augmentation was employed to increase training variability and reduce overfitting.

Data Preprocessing

Prior to training, to ensure consistency in input dimensions and to enhance the model's generalization performance, a series of preprocessing operations were conducted. First, all input MRI images were uniformly resized to 224×224 pixels to align with the expected input resolution of the MobileNetV2 architecture.

Next, the pixel intensity values were normalized to the range [0, 1] by dividing them by 255, a standard practice in deep learning workflows that aids in accelerating gradient-based optimization and stabilizing training dynamics [12].

To address the limited size and imbalance inherent in medical imaging datasets, data augmentation techniques were applied to artificially expand the training set and reduce the risk of overfitting. These augmentations included random rotations, horizontal and vertical flipping, zooming transformations, and spatial translations. These transformations help the model learn invariant features and improve generalization to real-world variations in MRI acquisition conditions and anatomical presentation [13].

These preprocessing steps collectively contributed to enhancing the robustness and predictive reliability of the proposed classification model across diverse patient data and imaging conditions.

Model Architecture

The core of the proposed framework is based on the MobileNetV2 architecture, a lightweight and

computationally efficient convolutional neural network (CNN) developed specifically for high-performance inference in environments with limited computational resources [5]. MobileNetV2 employs depthwise convolutions, inverted residual blocks, and linear bottlenecks to reduce computational complexity while maintaining effective feature representation. This structure provides a balance between computational efficiency and predictive performance, making MobileNetV2 suitable for medical image analysis tasks, including resource-constrained applications.

In this study, we utilized a pre-trained MobileNetV2 model initialized with ImageNet weights, leveraging transfer learning to accelerate convergence and improve feature generalization. To tailor the model for multi-class brain tumor classification, the default classification head was replaced with a custom layer. A Global Average Pooling (GAP) layer replaced traditional fully connected layers to reduce the spatial dimensions of the feature maps while minimizing overfitting. Subsequently, a Dense layer with 256 units and ReLU activation was introduced to incorporate nonlinearity and facilitate the learning of high-level features. To further prevent overfitting, a Dropout layer with a dropout rate of 0.5 was applied, randomly deactivating neurons during training. Finally, a dense layer with four output units and softmax activation was used to enable probabilistic multi-class classification across the four brain tumor categories. The design supports efficient learning and inference, making the model potentially suitable for computationally constrained brain MRI classification applications.

Model Training

Model training was conducted using the Adam optimizer, selected for its adaptive learning-rate and generally leads to stable optimization behavior. The initial learning-rate was empirically set to 0.0001, a commonly adopted value in fine-tuning scenarios to avoid overshooting minima during optimization. The batch size was set to 32, and the maximum number of training epochs was set to 80. The loss function used was categorical cross-entropy, as it is appropriate for multi-class classification problems involving mutually exclusive class labels.

To ensure a balanced evaluation across all tumor categories, the original images were divided into training (80%), validation (10%), and test (10%) subsets using stratified random sampling. Data augmentation was applied only to the training subset to prevent information leakage. Model training and evaluation were performed in Jupyter Notebook on an NVIDIA Tesla T4 GPU workstation. This high-performance computational setup significantly reduced training time and facilitated accelerated convergence of the deep learning model.

Results and Discussion

MobileNetV2 achieved the highest reported performance among the evaluated models, with an accuracy of 98.25%, AUC of 98.69%, and recall of 98.39%, with a loss of 0.15. This indicates a highly effective model in terms of classification performance, particularly in its ability to correctly classify samples across the four classes, as reflected by the reported recall and AUC. Compared to other models, such as Base CNN (93.3%), ResNet50 (81.1%), VGG16 (71.06%), and Inception V3 (80.0%), MobileNetV2 achieved higher accuracy and lower loss than the other evaluated models in this comparison.

Model	Accuracy (%)	AUC (%)	Recall (%)	Loss
BaseCNN	93.30	98.43	91.13	0.25
ResNet50	81.10	94.20	81.04	0.85
VGG16	71.06	89.60	70.03	1.18
InceptionV3	80.00	89.14	79.81	3.67
MobileNetV2	98.25	98.69	98.39	0.15

Table 1. Model comparison for brain tumor classification

Additionally, the lightweight architecture is expected to reduce computational requirements because it uses depthwise convolutions and a comparatively compact network design, resulting to reduce the number of parameters, ensuring faster convergence. The observed classification performance and low loss, together with evaluation on the held-out test set, provide evidence of the model's generalization performance. These results underscore MobileNetV2's strength in both classification accuracy and computational efficiency, making it a suitable candidate for brain tumor classification in resource-constrained environments.

Conclusion

This work introduced an accurate and efficient brain tumor classification framework based on MobileNetV2. By leveraging transfer learning and depthwise separable convolutions, the proposed MobileNetV2-based framework achieved higher reported classification performance than the evaluated baseline architectures while maintaining a lightweight architecture and low computational complexity.

These findings indicate the potential of MobileNetV2 for computationally constrained environments. Future work includes extending the approach to tumor segmentation, integrating explainability techniques, and enabling deployment on mobile or edge devices to support broader healthcare accessibility.

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