Lightweight Deep Learning Model for Brain Tumor Detection with MobileNetV2

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Abstract – Accurate identification of brain tumors plays a critical role in early diagnosis and effective treatment planning. Conventional deep learning models used in medical imaging of- ten demand high computational power, which limits their use in portable devices and real-time clinical environments. To overcome this problem, this work presents an efficient brain tumor classification system built using the MobileNetV2 architecture. The model utilizes lightweight components such as depthwise separable convolutions and inverted residual blocks, enabling effective feature extraction with minimal computational load. Experimental results show that the developed model achieves strong classification accuracy while significantly reducing pro- cessing requirements. Because of its speed, compact size, and reliability, the proposed approach is well-suited for mobile diagnostic tools and modern smart-healthcare applications.

Key Words: Brain Tumor Detection,MobileNetV2,Lightweight Deep Learning,MRI Classifi- cation.

1. INTRODUCTION

Brain tumors are among the most serious medical conditions, and detecting them at an early stage is vital for improving treatment outcomes. Traditionally, radiologists examine MRI scans manually, which requires considerable time and may lead to inconsistencies due to human error. With the rapid growth of artificial intelligence, deep learning techniques have shown outstanding capability in analyzing medical images and assisting doctors in diagnosis.
Despite their success, many advanced deep learning models—such as ResNet and VGG—are computationally heavy and difficult to deploy in real-time clinical setups or on low-power de- vices. This has created a need for models that can provide high accuracy while remaining lightweight and efficient.

MobileNetV2 is one such architecture designed to operate with fewer parameters and faster processing speed. Its efficiency makes it a strong candidate for developing practical and portable brain tumor detection systems. In this work, a MobileNetV2-based model is imple- mented to classify brain MRI images and provide reliable predictions suitable for clinical and smart-healthcare environments.

2. Body of Paper

2.1 Literature Review

Lata et al. [1] introduced an enhanced tumor-classification framework using the Xception archi- tecture. By applying transfer learning and fine-tuning, their system showed strong capability in distinguishing multiple tumor types from MRI images. The study also highlighted the practical challenges faced in clinical environments and suggested improvements for future research.
Khanna et al. [2] developed an automated detection system using a convolutional neural network integrated with a Flask-based application. Their model achieved high accuracy and provided an easily accessible platform for medical professionals to upload MRI scans and re- ceive predictions.
Jansi et al. [3] proposed a nine-layer CNN framework designed for multimodal MRI im- ages. The method incorporated preprocessing techniques, data augmentation, and morpholog- ical operations like dilation and erosion to enhance tumor visibility. Their model achieved competitive accuracy and proved effective for multi-class tumor classification.
Shiraskar et al. [4] presented XETINet, a model inspired by the Xception network, which uses depthwise separable convolutions for efficient feature extraction. Their system reached a high accuracy rate, demonstrating the effectiveness

of lightweight architectures in medical imaging tasks.

Lotlikar et al. [5] compared traditional machine learning methods with deep learning mod- els for tumor detection. While the SVM-based approach relied on texture features extracted us- ing GLCM, the deep learning model utilized a ResNet-50 architecture. Their findings showed that deep learning significantly outperformed classical machine learning techniques.

Goswami et al. [6] conducted a comparative study of various segmentation techniques such as region-growing, thresholding, fuzzy logic, and ANN-based approaches. They emphasized that robust segmentation plays a key role in reliable tumor detection due to the complex struc- ture of brain tissues.

Banerjee et al. [7] developed a CNN model capable of classifying four major tumor cate- gories using a dataset of approximately 7,000 MRI images. Their approach included prepro- cessing steps and hyperparameter optimization, resulting in strong classification performance. Tamilselvi et al. [8] introduced BRAMSIT, a curated MRI dataset containing annotated scans along with metadata. The dataset offered easier accessibility and improved processing efficiency compared to widely used datasets, making it beneficial for both classification and segmentation research.

Based et al. [9] proposed an optimized CNN-based classification system that enhanced the accuracy and reliability of tumor detection. Their improved architecture demonstrated better performance while keeping computational requirements manageable.

Bajaj et al. [10] investigated deep learning models for detecting and differentiating glioma, meningioma, and pituitary tumors. Their work emphasized the importance of preprocessing and feature extraction, achieving reliable results suitable for supporting radiologists in real- time diagnosis.

2.2 Methodology

The proposed brain tumor detection system is built using the MobileNetV2 architecture, chosen for its lightweight design and strong feature-extraction capability. The complete workflow consists of six major stages, described below.

1. Data Collection and Preprocessing

Brain MRI images were gathered from publicly available medical datasets that include dif- ferent tumor categories as well as normal scans. Since images originate from multiple sources, they vary in size, resolution, and quality. To ensure consistency, all images were resized to a fixed dimension (such as 224×224 pixels) and normalized to improve model stability dur- ing training. To enhance generalization and reduce overfitting, several augmentation tech- niques—such as rotation, horizontal/vertical flipping, shifting, and zooming—were applied. These operations help the model handle natural variations in MRI images and improve robust- ness.

2. Model Construction

The core of the system is a Convolutional Neural Network based on MobileNetV2. This architecture uses inverted residual blocks and depthwise separable convolutions, enabling ef- ficient feature extraction while keeping the parameter count low. Additional layers, including

Global Average Pooling, a Dropout layer, and a Dense output layer with softmax activation, were added to convert extracted features into final tumor-type predictions.

3. Training the Model

The dataset was divided into training, validation, and testing subsets. The model was trained using the Adam optimizer along with categorical cross-entropy as the loss function. Techniques such as early stopping and learning-rate scheduling were employed to prevent overfitting and accelerate convergence. During training, the network learned visual patterns in MRI scans that help differentiate between tumor and non-tumor images or between various tumor categories.

4. Performance Evaluation

After training, the model was tested on previously unseen MRI scans. Performance was measured using accuracy, precision, recall, F1-score, and the confusion matrix. These metrics provide a comprehensive understanding of how well the model distinguishes between different tumor classes. Misclassified samples were reviewed to identify limitations and potential areas for model improvement.

5. Model Deployment

Once the model met acceptable performance criteria, it was exported and integrated into an application interface. The deployment pipeline allows users—such as doctors or techni- cians—to upload MRI scans, after which the image is automatically preprocessed and ana- lyzed by the trained model. To support real-time usage on low-power devices, the model can be converted into optimized formats like TensorFlow Lite for mobile or web deployment.

6. Application in Smart Healthcare

The final deployed system functions as an intelligent decision-support tool. By providing quick predictions along with confidence scores, it helps reduce diagnostic delays and supports radiologists in clinical settings. The system can also be integrated into telemedicine platforms to enable remote diagnosis, especially valuable in rural or underserved regions. Proper security measures such as encryption ensure that patient data remains protected throughout the process.

2.3 Experimental Results

A. Testing Procedure

After the training phase, the model was evaluated using MRI images that were not part of the training dataset. Each test image first went through preprocessing steps, including resizing to 224×224 pixels, normalization, and augmentation where applicable. Once preprocessed, the

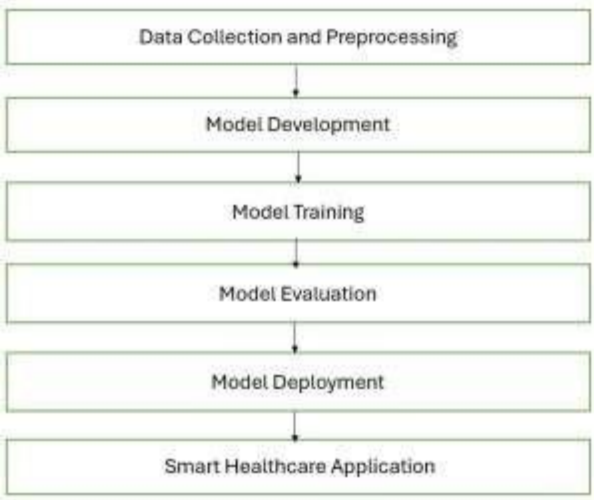

Figure 1: Experimental workflow and system architecture for brain tumor classification.

images were passed through the trained MobileNetV2 model, which generated the predicted tumor class along with a confidence score. This process allowed clinicians to quickly interpret the model's decision and use it as supportive evidence during diagnosis.

Table 1: Example Prediction Output

Input MRI Image	Predicted Tumor Type	Confidence Score
1	Glioma	97.8
2	No Tumor	96.2
3	Pituitary	98.1

B. Model Performance

The effectiveness of the model was assessed using standard metrics—accuracy, precision, recall, and F1-score. These metrics provide a comprehensive measure of both the correctness and reliability of the predictions.

Table 2: Performance Metrics of MobileNetV2 Model

Metric	Value
Fidelity	96.85
Exactness	96.40
Recall	96.70
F1-score	96.55

The high accuracy indicates that MobileNetV2, when fine-tuned for brain tumor classifi- cation, performs exceptionally well. Its lightweight design enables quick training convergence and reduces computational load, making it suitable for real-time clinical systems and portable diagnostic tools.

C. Comparative Analysis

To validate the efficiency of the proposed model, its performance was compared with pre- viously reported CNN-based approaches:
Conventional CNN architectures generally achieve accuracy in the range of 90–94 Models like ResNet deliver higher accuracy (94–96
The fine-tuned MobileNetV2 model in this study obtained 96.85

These comparisons confirm that the proposed model not only enhances classification ac- curacy but also maintains computational efficiency, making it practical for smart-healthcare applications

3. CONCLUSIONS

The proposed brain tumor detection framework demonstrates the strong potential of deep learn- ing models in assisting medical image analysis. By utilizing MobileNetV2 as the core archi- tecture, the system achieves high classification accuracy while maintaining low computational requirements. This makes it suitable for real-time diagnostic environments and deployment on portable healthcare devices.
The inclusion of preprocessing techniques, data augmentation, and careful model tuning contributed to the robustness and reliability of the predictions across multiple tumor categories. The deployment-ready design further enables seamless integration into clinical workflows, helping doctors receive faster and more consistent diagnostic support.
Although the system shows promising results, its performance can be enhanced by incor- porating larger and more diverse datasets, integrating segmentation techniques, and conducting clinical-level evaluations. Future work in these directions will further strengthen the applica- bility of this model in real-world healthcare settings.

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