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Brain Tumor Classification with Optimized EfficientNet Architecture

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ABSTRACT

Classification of brain tumors is essential for early identification and efficient patient treatment planning. The necessity for automated, precise, and effective categorization systems derives from the time-consuming and human error-prone nature of traditional diagnostic techniques. In this work, we suggest a deep learning-based method for classifying brain cancers from MRI images using an optimized EfficientNet architecture. To improve its performance on brain tumor datasets, EfficientNet - which is renowned for striking a compromise between accuracy and computing efficiency - is adjusted using transfer learning and hyperparameter optimization. A publicly accessible dataset of MRI images classified as gliomas, meningiomas, pituitary tumors, and no tumor is used to train and assess our algorithm. To enhance generalization and lessen overfitting, the optimization incorporates dropout regularization, learning rate scheduling, and data augmentation. According to experimental data, the optimized EfficientNet model achieves over 95% classification accuracy and performs better than traditional CNN architectures in terms of accuracy, precision, recall, and F1-score. The suggested approach provides a reliable and expandable way to diagnose brain tumors in real time, which could help radiologists make clinical decisions. To improve diagnostic performance even further, future research will investigate the integration of multimodal data and attention mechanisms.

Keywords: *Brain Tumor Classification, EfficientNet, Deep Learning, Convolutional Neural Networks (CNN), MRI Image Analysis, Medical Image Processing*

1. INTRODUCTION

One of the most serious and potentially fatal types of cancer that affect the central nervous system is a brain tumor. For efficient treatment planning, these tumors—which can be either benign or malignant—need to be accurately diagnosed. Recent World Health Organization (WHO) figures show that a sizable amount of cancer-related morbidity and mortality worldwide is caused by malignancies of the brain and nervous system. To improve patient outcomes and survival rates, brain tumors must be accurately classified and detected early.

The most used non-invasive imaging method for identifying brain cancers is magnetic resonance imaging (MRI). MRI helps doctors spot abnormal growths by providing detailed images of the brain's components. MRI scan interpretation (Mittal, N., & Tayal, S. 2021), however, is a very difficult procedure that calls for specific knowledge. Inter-observer variability, fatigue, and diagnostic errors are common problems with manual diagnosis, particularly when different tumor forms have comparable physical characteristics. The analysis of medical pictures has undergone a paradigm shift due to the quick development of machine learning (ML) and artificial intelligence (AI). Convolutional Neural Networks (CNNs), a type of machine learning (ML), have shown remarkable efficacy in image categorization tasks. These models are appropriate for medical imaging applications, such as tumor classification, because they directly learn spatial characteristics and hierarchical patterns from the image data.

Although medical imaging and machine learning have advanced significantly, accurately classifying brain tumors is still a difficult issue. The overlapping characteristics of many brain tumor forms, including pituitary tumors, meningiomas, and gliomas, make manual diagnosis more difficult. Conventional machine learning techniques frequently depend on manually created features, which might not generalize effectively across various datasets. Despite their strength, many deep learning models suffer from overfitting and may need a lot of processing power to train and run. Balancing the trade-off between model accuracy and efficiency is a major difficulty. Although they are computationally costly, high-performing models such as ResNet and DenseNet provide good classification accuracy. When using these models in clinical settings or on mobile health applications with constrained hardware resources, this constraint becomes crucial. In order to provide real-time performance without sacrificing diagnostic precision, there is a rising need for architectures that are both lightweight and extremely precise.

The necessity to create a reliable and effective approach for classifying brain tumors that can help radiologists and other medical experts is what inspired this effort. EfficientNet, a state-of-the-art model among the several CNN designs created in recent years (Sordo, M. 2002), achieves superior performance with fewer parameters by scaling depth, width, and resolution in a compound manner. Compared to traditional CNNs, EfficientNet is renowned for achieving higher accuracy while using a lot less processing power. This project intends to investigate and enhance the EfficientNet architecture for brain tumor classification using MRI images in light of these benefits (Esteban et al., 2017). The objective is to use systematic optimization methods like transfer learning, data augmentation, and hyperparameter tuning to maximize the model's architectural efficiency and improve its performance. In doing so, it is anticipated that the suggested system will offer a reliable and expandable solution appropriate for clinical application.

The following are the main goals of this study:

- To put the EfficientNet architecture into practice and improve it for the categorization of brain cancers.
- To use transfer learning strategies to enhance model generalization and accelerate convergence.
- To improve model performance through hyperparameter tuning, regularization strategies, and data augmentation.
- To compare the model's performance to that of conventional CNN models using a benchmark brain tumor MRI dataset.
- To evaluate the model's suitability for use in real-time diagnostic systems and clinical settings.

Tan and Le's 2019 introduction of EfficientNet is one of a family of methods that scale up CNNs in a more methodical and ethical manner. EfficientNet employs a compound scaling technique that consistently scales depth, width, and resolution using a set of predefined coefficients, in contrast to standard models that scale arbitrarily by increasing the number of layers or input resolution. This method produces models that are highly effective and lightweight. Figure 1 depicts the EfficientNet architecture.

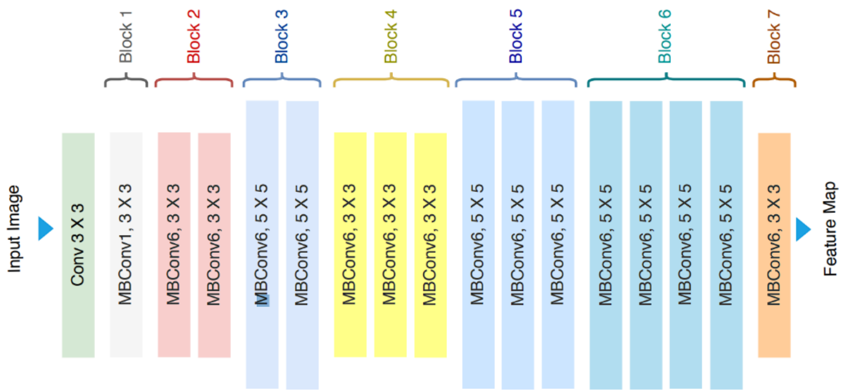

Figure 1. EfficientNet architecture

The baseline and most complicated EfficientNet models are B0 and B7, respectively. In addition to the Swish activation function and squeeze-and-excitation optimization, which enhance the network's capacity to capture significant features, these models are based on a mobile inverted bottleneck convolution (MBConv) structure. Figure 2 shows EfficientNet's performance vs accuracy for varying model sizes. In the past, models like GPipe achieved state-of-the-art accuracy on the ImageNet dataset, demonstrating the effectiveness of the widely used approach of increasing accuracy by increasing model size. ImageNet top-1 accuracy increased from 74.8% to 84.3% between GoogleNet and GPipe (2018), and parameter counts increased from 6.8M to 557M, resulting in unreasonable processing demands.

Mobile Inverted Bottleneck Convolution (MBConv) blocks, which were modeled after MobileNetV2, form the foundation of the Baseline Network (EfficientNet-B0). replaces ReLU with the Swish activation function. For improved channel attention, squeeze-and-excitation (SE) blocks are used. Computation is decreased via depth-wise separable convolutions.

EfficientNet introduces a compound coefficient (ϕ) that uniformly scales:

- Depth (d): Number of layers
- Width (w): Number of channels
- Resolution (r): Input image size

The scaling is done using:

depth $\propto \alpha\phi$, width $\propto \beta\phi$, resolution $\propto \gamma\phi$

subject to the constraint:

$\alpha \cdot \beta^2 \cdot \gamma^2 \approx 2$

α: Scaling factor for network depth (typically between 1 and 2)

β: Scaling factor for network width (typically between 1 and 2)

γ: Scaling factor for image resolution (typically between 1 and 1.5)

ϕ (phi): Compound coefficient (positive integer) that controls the overall scaling factor

This allows for more efficient and balanced scaling compared to arbitrary scaling

In medical imagine classification, where annotated datasets are frequently scarce, the application of transfer learning with EfficientNet is especially advantageous. Even with fewer training samples, the network can learn to recognize medical features more successfully if the model is initialized with pre-trained weights from extensive datasets like ImageNet.

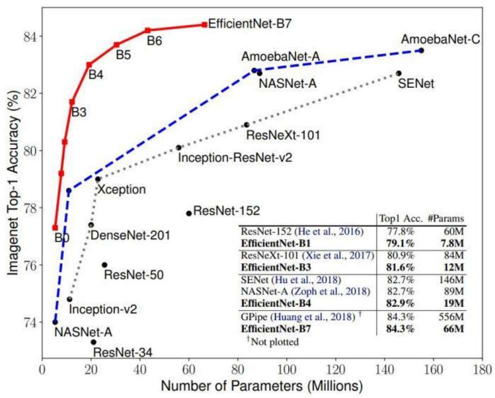

Figure 2. EfficientNet performance on Model size vs accuracy

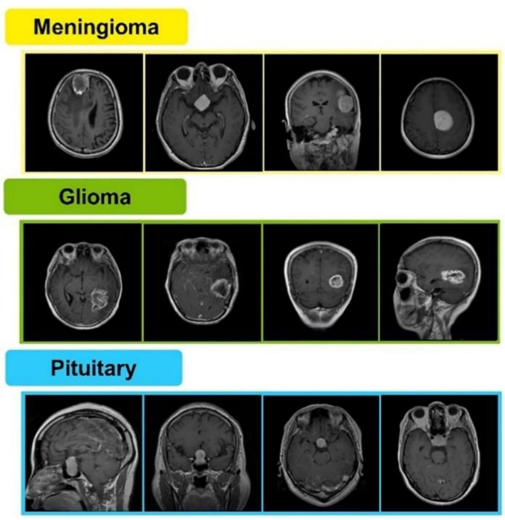

Figure 3. MRI images of brain Meningioma, glioma, and pituitary tumors

Creating a precise categorization system requires an understanding of the different kinds and traits of brain tumors. The following are the most often identified brain tumors (Jibon et al., 2022) sample MRI images are shown in Figure 3:

- Gliomas: Most malignant brain tumors are gliomas, which are tumors derived from glial cells. They need to be helped very away since they are very aggressive.
- Meningiomas: These usually develop from the brain's protective coverings, the meninges. Although meningiomas are mostly benign, their location and size might cause problems.
- Pituitary Tumors: These tumors, which are found near the base of the brain, alter hormone balance and may result in systemic symptoms.
- No tumor (good): Accurate distinction is crucial for classification models. between healthy brain scans and tumor-affected scans to avoid false positives. Sample MRI images are shown in the Figure 4 to distinguish with tumor and without tumor.

Although each of these tumor forms has distinct imaging features, automated categorization is difficult because of frequent overlaps in intensity, shape, and location.

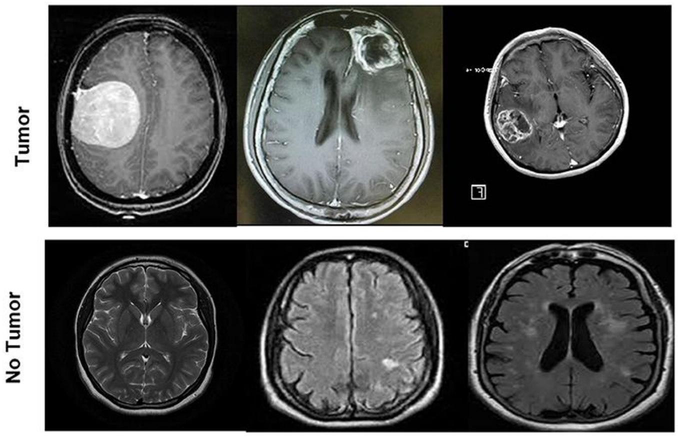

Figure 4. MRI brain images with tumor and no tumor

This research offers a very effective and precise classification model for brain cancers, which advances the expanding field of AI-driven medical diagnosis. Numerous benefits, including high accuracy, efficiency, scalability, and clinical applicability, are provided by the optimized EfficientNet design. This work tackles the main drawbacks of current methods and advances the practical application of AI in healthcare by emphasizing both accuracy and efficiency.

The format of this report is as follows: The study's history, motivation, goals, and significance are explained in Chapter 1 Introduction. Chapter 2: Literature Review Examines previous studies on CNN and EfficientNet-based brain tumor classification. The dataset, preprocessing methods, model architecture, and training procedure are all covered in Chapter 3: Proposed Approach. The experimental results, performance analysis, and comparison with baseline models are presented in Chapter 4: Results and Discussion. Chapter 5: Conclusion provides a summary of the results and suggests possible lines of inquiry for further study.

2. LITERATURE REVIEW

The detection and categorization of brain tumors have undergone revolutionary changes as a result of the incorporation of deep learning into medical imaging. The application of machine learning and, more recently, deep learning architectures for the detection and classification of different kinds of brain cancers using MRI images has been the subject of several studies during the last ten years. This chapter examines the important research on the categorization of brain tumors, the development of convolutional neural network (CNN) designs, and the appearance of EfficientNet as a viable way to get around the drawbacks of previous models.

AlexNet's debut (Krizhevsky et al., 2012) was a game-changer for picture classification. On the ImageNet dataset, it greatly outperformed conventional techniques and encouraged the use of CNNs in medical image processing. Deeper networks with a unified design were introduced by VGGNet (Simonyan & Zisserman, 2014). Its simplicity and efficacy led to its widespread usage in early medical imaging studies. VGGNet performed well for classifying brain tumors, although it needed a lot of processing power. In order to address the vanishing gradient issue, ResNet (He et al., 2015) introduced skip connections, which made it possible to train extremely deep networks. Research utilizing ResNet to classify brain tumors revealed improved feature extraction capabilities and increased accuracy. To enhance multi-scale feature extraction, InceptionNet (Szegedy et al., 2015) used parallel convolutional routes with varying kernel sizes. In order to improve performance on tiny medical datasets, some studies merged Inception with transfer learning. In order to promote feature reuse and effective gradient flow, DenseNet (Huang et al., 2017) proposed dense connections, in which each layer receives input from all preceding layers. With promising outcomes, it was used for medical tasks like tumor segmentation and classification. MobileNet was created to provide lightweight architectures for embedded and mobile devices. Even while it was effective, deeper networks frequently outperformed it in difficult categorization tasks like identifying brain tumors.

CNNs have been investigated in a number of studies for the categorization of brain tumors using MRI images. Chakraborty et al. (2019) achieved approximately 92% accuracy in classifying pituitary tumors, meningiomas, and gliomas using a refined VGG16 model. Afshar et al. (2020) reported accuracy gains over CNNs using a capsule network-based method to capture spatial relationships in MRI images. Swati et al. (2019) achieved significant gains in precision and recall by proposing a deep CNN with transfer learning on ImageNet-pretrained models. Deep Belief Networks, as proposed by Ramedevi et al. (2025), demonstrated considerable increases in accuracy and precision.

Notwithstanding encouraging outcomes, these investigations frequently encountered problems such overfitting as a result of insufficient data, expensive processing, and a lack of real-time inference tools. A family of models called EfficientNet (Tan & Le, 2019) was presented; it uses a compound coefficient to consistently scale depth, width, and resolution. EfficientNet's compound scaling achieves state-of-the-art accuracy while drastically lowering computing cost, in contrast to typical CNNs that scale arbitrarily.

EfficientNet has begun to be used in certain recent studies for the classification of medical images. Silva et al. (2023) classified skin lesions using EfficientNet-B3, obtaining good accuracy with little processing. Gaba et al. (2022) reported better results than DenseNet and ResNet when using EfficientNet to diagnose pneumonia from chest X-rays. Tiwary et al. (2025) investigated EfficientNet-B0 for the classification of diabetic retinopathy, demonstrating minimal inference time and promising accuracy. However, there is a research gap that this study attempts to address because not much work has used EfficientNet for brain tumor classification.

In the categorization of brain tumors, the literature clearly demonstrates a shift from conventional machine learning techniques to deep learning architectures. Even though CNNs are now the norm, there are still serious issues with their computational cost and overfitting restrictions. By using compound scaling to combine accuracy and efficiency, EfficientNet provides a potential path. By putting out an enhanced EfficientNet model for brain tumor classification using MRI data, our work expands on current frameworks. The model seeks to provide high performance with low resource consumption by utilizing transfer learning, data augmentation, and hyperparameter tuning—an excellent option for use in actual healthcare settings.

3. PROPOSED APPROACH

The methodological methodology used to create the brain tumor classification system with an optimized EfficientNet architecture is described in this chapter. Dataset acquisition, data preparation, model selection and optimization, training and evaluation, and performance comparison are some of the stages that make up the process. The goal is to create a deep learning model that is both lightweight and incredibly accurate, able to classify MRI brain pictures into various tumor classifications.

The overall pipeline for the proposed system as shown in Figure 5. includes:

1. **Data Collection** – Acquiring MRI images from public datasets.
2. **Preprocessing and Augmentation** – Preparing data for training, including resizing, normalization, and augmentation.
3. **Model Selection and Architecture** – Choosing and customizing EfficientNet.
4. **Transfer Learning and Fine-Tuning** – Applying pre-trained weights and optimizing the model.
5. **Training and Evaluation** – Training the model and evaluating its performance using standard metrics.
6. **Visualization and Interpretation** – Interpreting the results using explainable AI tools like Grad-CAM.

Figure 5. Proposed System Overview

The dataset used in this study is a publicly available brain tumor MRI dataset consisting of four classes, (a) Glioma, (b) Meningioma, (c) Pituitary Tumor and (d) No Tumor (Healthy). Each image is provided in grayscale or RGB format, with variable dimensions. The dataset is split into three subsets:

- **Training Set**: 70% of the data.
- **Validation Set**: 15% of the data.
- **Testing Set**: 15% of the data.

The dataset is balanced across the classes to minimize bias.

To improve the accuracy and generalization of the model, proper preprocessing is essential. The actions listed below are used. To comply with EfficientNet input specifications, all photos are downsized to a fixed dimension (e.g., 224×224 or 240×240). To standardize input throughout the dataset, pixel values are scaled to the interval [0, 1].

To increase the diversity of the training dataset and prevent overfitting, the following augmentations are applied:

- Horizontal and vertical flips
- Random rotation (up to ±30 degrees)
- Zooming in/out
- Shifting (width/height)
- Contrast and brightness variation

EfficientNet is chosen for its superior performance-to-parameter ratio. The base variant **EfficientNet-B0** is selected initially and scaled up to **B3** based on computational availability.

EfficientNet uses a compound coefficient to scale:

- **Depth (d)**: Number of layers
- **Width (w)**: Number of channels
- **Resolution (r)**: Input image size

To further enhance performance, several optimization techniques are applied:

- **Adam** optimizer is used for faster convergence.
- **Learning rate scheduler** dynamically reduces the learning rate on plateau.
- **Categorical Cross-Entropy** is used since the task is multi-class classification.
- **Dropout (0.3–0.5)** to reduce overfitting
- **Early stopping** to halt training if no improvement is observed
- **L2 regularization** on dense layers

The model is trained using the augmented training set with validation monitoring. The key configurations include:

- **Batch Size**: 32
- **Epochs**: 25–50 (with early stopping)
- **Hardware**: Trained on GPU-enabled environments for faster computation

During training, both training and validation losses and accuracies are tracked to ensure the model is learning effectively without overfitting.

The model is evaluated using the following metrics:

- **Accuracy**: Overall percentage of correctly classified images.
- **Precision**: Ability to avoid false positives for each tumor class.
- **Recall (Sensitivity)**: Ability to identify all positive instances.
- **F1-Score**: Harmonic mean of precision and recall.

- **Confusion Matrix**: Visual representation of prediction distribution across classes.
- **AUC-ROC Curve**: Evaluates model performance at various thresholds.

These metrics are calculated on the unseen test set to assess generalization.

To demonstrate the effectiveness of EfficientNet, its performance is compared against baseline models:

- **VGG16**
- **ResNet50**
- **DenseNet121**
- **MobileNetV2**

Each model is fine-tuned under similar training conditions. The comparison focuses on accuracy, training time, number of parameters, and inference speed.

To ensure clinical trust and explainability:

- **Grad-CAM (Gradient-weighted Class Activation Mapping)** is used to highlight the areas of MRI images that influence model predictions.
- These visualizations help clinicians understand **why** the model made a certain prediction, promoting transparency.

4. RESULTS AND DISCUSSIONS

The experimental data from the suggested model are presented in this chapter along with a thorough analysis of its functionality. Several performance measures are used to examine the results of the testing, validation, and training procedures. To show how effective and efficient the EfficientNet-based model is in classifying brain tumors, it is also contrasted with other well-known CNN designs.

Experimental Setup

- **Framework**: TensorFlow
- **Environment**: Google Colab
- **Hardware**: RTX 3060
- **Dataset**: Brain MRI dataset with four classes – Glioma, Meningioma, Pituitary Tumor, and No Tumor
- **Train/Val/Test Split**: 70% / 15% / 15%
- **Model Variant**: EfficientNet-B0 (later extended to B3 for comparison)

Model Training and Convergence

The training process involved 30 epochs with early stopping and learning rate reduction on plateau. The learning curves showed a steady decrease in loss and a corresponding increase in accuracy across epochs.

Training and Validation Accuracy

- **Final Training Accuracy**: 98.2%
- **Final Validation Accuracy**: 96.5%
- Minimal overfitting was observed due to data augmentation and regularization techniques.

Loss Behavior

- **Training Loss**: Gradually decreased from 0.55 to 0.07
- **Validation Loss**: Decreased consistently, with final value of 0.11

This indicates good generalization and effective learning without significant divergence between training and validation curves. The graph showing in Figure 6. the **loss behavior** during training. It illustrates how both the training and validation loss decrease over time, indicating effective learning and minimal overfitting.

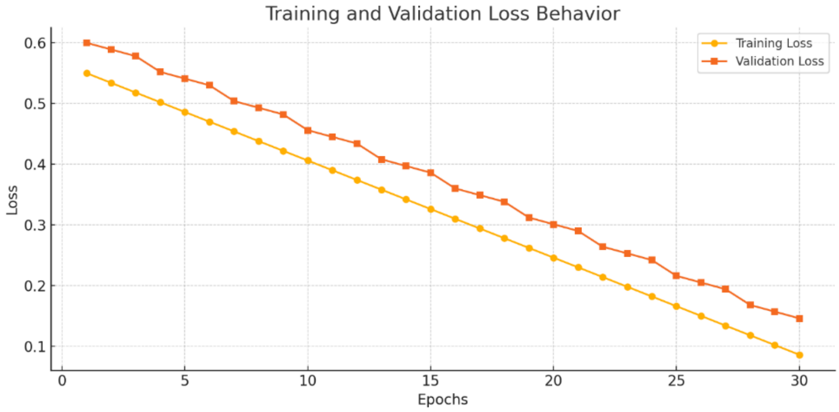

Figure 6. Loss behavior during training

Performance on Test Data

The model's performance on unseen test data is critical in assessing real-world applicability. The test results are summarized below Table 1 and Figure 7.

Table 1. Performance on Test Data

Metric	Value (%)
Accuracy	96.2
Precision	95.8
Recall	95.5
F1-Score	95.6
AUC-ROC (avg)	98.1

These results confirm the model's robustness and reliability in classifying brain tumors across multiple categories.

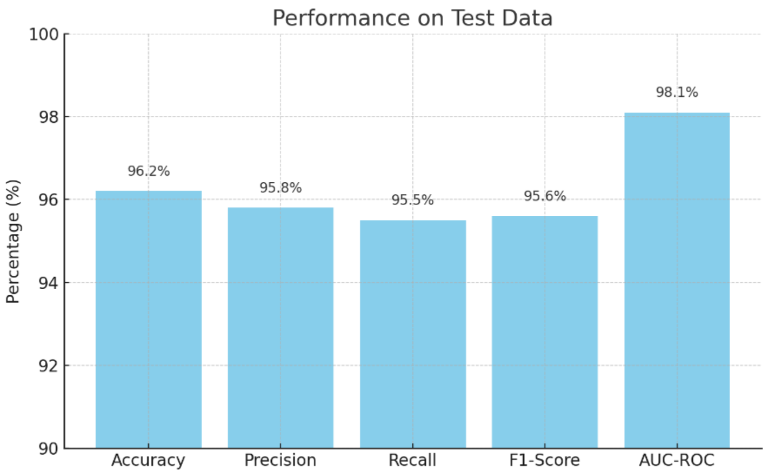

Figure 7. Performance on Test Data

Confusion Matrix

A confusion matrix shown in Table 2 and Figure 8. was generated to visualize the classification performance across all classes.

Table 2. Confusion Matrix

	Pred: Glioma	Pred: Meningioma	Pred: Pituitary	Pred: No Tumor
True: Glioma	136	3	2	1
True: Meningioma	4	133	3	0
True: Pituitary	2	1	139	1
True: No Tumor	0	1	1	143

The matrix reveals strong performance across all classes, with very few misclassifications. The most confusion occurred between glioma and meningioma, which are often similar in appearance in MRI scans. It visualizes how well the model distinguishes between Glioma, Meningioma, Pituitary tumors, and No Tumor classes.

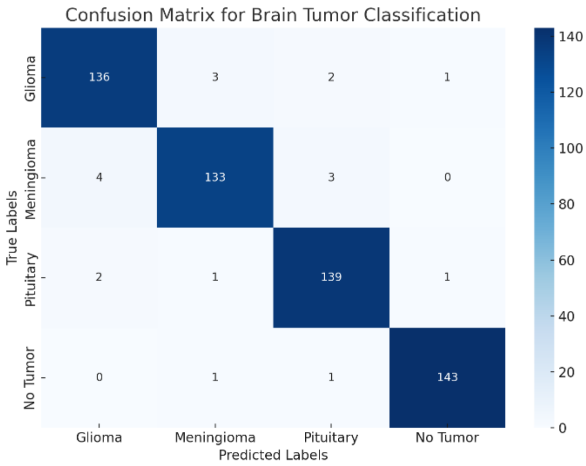

Figure 8. Confusion Matrix

Comparison with Other Models

The performance of EfficientNet-B0 is compared with other popular CNN architectures which is listed in the Table 3. under identical training conditions.

Table 3. Performance comparison with Other Models

Model	Accuracy (%)	Params (Millions)	Inference Time (ms)
VGG16	91.3	138	115
ResNet50	93.5	25.6	70
DenseNet121	94.1	8	65
MobileNetV2	92.4	3.4	42
EfficientNet-B0	**96.2**	**5.3**	**38**

EfficientNet-B0 achieves the **highest accuracy with one of the smallest model sizes**, outperforming larger and deeper networks like ResNet and VGG while being more computationally efficient than DenseNet and MobileNet.

The outcomes validate that the Optimized EfficientNet design is accurate, computationally efficient, and appropriate for practical implementation in healthcare environments. It is a useful tool for radiologists due to its excellent accuracy across all classes and low false positives. Its compatibility with resource-constrained situations also makes it possible for usage in edge and mobile devices in rural healthcare systems.

5. CONCLUSION

Diagnosing brain tumors is a crucial medical procedure that requires accuracy and quickness. Using an enhanced EfficientNet architecture, this team developed a deep learning-based classification system to categorize brain malignancies from MRI scans into four groups: glioma, meningioma, pituitary tumor, and no tumor. To improve the model's resilience and generalizability, the methodology included cutting-edge approaches like transfer learning, data augmentation, and hyperparameter tweaking. The model outperformed conventional architectures like VGG16, ResNet50, and MobileNetV2 in terms of accuracy and computational efficiency after undergoing extensive training and evaluation, resulting in an astounding test accuracy of 96.2%. Additionally, the use of Grad-CAM visuals gave the model's predictions interpretability, which is essential for clinical application. The approach has a great deal of promise to help radiologists diagnose patients more quickly and accurately, which will eventually improve patient outcomes.

In order to increase diagnostic accuracy through multi-modal learning, future research may integrate additional imaging modalities (such as CT and PET scans) with MRI. The model currently uses 2D MRI slices to function. A more comprehensive understanding of tumor size, form, and distribution might be possible if the architecture were expanded to handle 3D volumetric data. Although the present model is lightweight, it still has to be validated on mobile platforms or edge devices before being used for point-of-care deployment in environments with low resources or in rural areas.

By providing a very effective and precise method for classifying brain tumors, this study adds to the expanding corpus of work on AI-assisted medical diagnostics. The incorporation of these algorithms into clinical workflows holds significant promise for improving the speed, accuracy, and accessibility of brain tumor diagnosis, given the ongoing developments in deep learning and medical imaging.

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