Brain Tumor Classification using EfficientNet

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ABSTRACT
Accurate classification of brain tumors from magnetic resonance imaging (MRI) is essential for assisting clinical diagnosis and treatment planning. This study presents a deep learning–based approach for brain tumor classification using the EfficientNetB3 architecture. Transfer learning with initialization from weights learned on ImageNet is used, and the network is fine-tuned on a brain MRI dataset containing four classes: glioma, meningioma, pituitary tumor, and no tumor. The proposed system learns end to end to produce discriminative features from an image. Experimental results show that EfficientNetB3 achieves a test accuracy of 99%, with macro-averaged precision, recall (sensitivity), and F1-score of 99%. These results demonstrate the effectiveness of EfficientNetB3 for reliable and high-performance brain tumor classification.

Keywords
Deep learning, MRI, brain tumor classification, EfficientNetB3, medical imaging

1. INTRODUCTION
Humans can develop around 200 different types of abnormal tissue growth, known as tumors, which may be benign or malignant. Brain tumors are particularly dangerous because they involve abnormal growth within brain tissue, disrupting normal brain function. Over the past three decades, deaths caused by brain tumors have increased by nearly 300%, underscoring the urgency of effective diagnosis and treatment. If left untreated, brain tumors can be fatal, making early detection critical for improving survival rates. Because brain biopsies are complex and risky, magnetic resonance imaging (MRI) is widely used as a safer and reliable diagnostic method [1-10]. Gliomas are the most common type of brain tumor and originate from glial cells. They account for about 30% of all brain and central nervous system tumors and nearly 80% of malignant brain tumors [11]. According to the World Health Organization (WHO), gliomas are classified into four grades (I–IV). Grade I tumors are benign and closely resemble normal tissue, grade II tumors show slight abnormalities, grade III tumors are malignant with clear tissue irregularities, and grade IV tumors represent the most aggressive stage with severe abnormalities [11,12]. Meningiomas develop in the membranes covering the brain and spinal cord and typically grow slowly, with most being benign. Pituitary tumors arise from the pituitary gland, which regulates hormone secretion. These tumors may be benign or malignant and can lead to hormonal imbalances and vision problems [13]. Early detection and accurate classification of brain tumors are essential for proper diagnosis and treatment planning. Tumor grading is often complex and time-consuming for clinicians, requiring detailed visual inspection and comparison of tissue structures. This highlights the need for computer-aided diagnosis (CAD) systems to support early detection, reduce diagnosis time, and limit human error [11,12]. Recent advances in machine learning (ML), particularly deep learning (DL), have significantly improved medical image analysis. Techniques such as convolutional neural networks (CNNs) and autoencoders have shown strong potential in tumor detection, segmentation, and classification. However, existing DL-based approaches show variable performance across datasets, indicating that further improvement in model frameworks is still needed [14].

The system uses an accurate and fully automatic deep learning model to analyze brain MRI images. The system first determines whether a tumor is present and then classifies it into one of four types: glioma, meningioma, pituitary or no tumor. Deep learning models have shown strong performance in image classification tasks, particularly because they can automatically learn and extract meaningful features from images across their layers, making it easier for the classifier to distinguish between different tumor characteristics.

2. LITERATURE REVIEW
Seetha et al. [15] introduced a convolutional neural network (CNN) for the automatic classification of brain tumors from MR images. Their model employs a deeper architecture built with small convolutional kernels and low neuron weights to reduce computational complexity. Experimental results demonstrated that the proposed CNN achieved an accuracy of 97.5%, while maintaining lower complexity compared with other state-of-the-art methods. Ahmad Saleh et al. [16] reported a maximum accuracy of 98.75% using the Xception CNN model. The primary objective of their work was to enhance the effectiveness and reliability of MRI-based brain tumor classification and tumor type identification using artificial intelligence, CNNs, and deep learning techniques. Five pretrained models were evaluated in their study: Xception, ResNet50, InceptionV3, VGG16, and MobileNet. The study by Abd et al. [17] analyzed 25,000 brain MRI images using a deep convolutional neural network (DCNN) to identify different types of brain tumors. Their model achieved outstanding performance, reaching a training precision of 99.25%. Pashaei et al. [20] proposed a CNN-based classification framework composed of four convolution and normalization layers, three max-pooling layers, and a final fully connected layer. In their experiments, 70% of the dataset was used for training without data augmentation, while the remaining 30% was used for

testing with 10-fold cross-validation. The proposed model achieved a classification accuracy of 81.0%. Afshar et al. [21] presented a Capsule Network (CapsNet) model for brain tumor classification. To enhance classification accuracy, they modified the feature mapping process in the convolutional layer of the CapsNet architecture. By using a single convolutional layer with 64 feature maps, their model achieved a maximum accuracy of 86.56%. Ankita et al. [22] achieved the accuracy of 94% and 88% respectively using VGG16 and ResNet50 on a Imaging (MRI) dataset. In this paper, they propose comparative studies of various deep learning models grounded on different types of Neural Networks (ANN, CNN, TL) to primarily identify brain tumors and then classify them into Benign Tumor, Malignant Tumor or Pituitary Tumor.

Table 1: Comparative analysis with state-of-the-artworks

DL Model	Accuracy
CNN [15]	97.5%
Xception(CNN)[16]	98.75%
ResNet50[17]	95.33%
Densenet201[18]	68.71%
ResNet101[18]	74.09%
Mobilenetv2[18]	82.61%
SqueezeNet[19]	92.08%
CNN[20]	81.0%
CapsNet[21]	86.56%
VGG 16	86.83%
VGG 19	85.32%
CNN [43]	95%

[25], [27], [28], [30], [43], [44], [45], [46] focus on deep learning–based disease detection including lung disease, skin cancer, breast cancer, heart disease, Alzheimer's Disease Diagnosis and brain tumor classification, supporting the medical imaging of this work. [26], [29], [31], [48] address IoMT applications, smart sensor monitoring systems, healthcare cybersecurity, and secure medical data infrastructures. These technologies provide system-level support for deploying intelligent diagnostic models and real-time monitoring frameworks in complex operational environments. [36-40] shows model optimization through transfer learning, federated learning, reinforcement learning, and adaptive neural networks. [32], [33], [34], [35], [41], [42] enhance data reliability, communication efficiency, and large-scale processing through sensor data imputation, scheduling optimization, and high-performance architectures.

3. METHODOLOGY

This section will describe full details of the proposed methodology.

3.1 Dataset

This is a publicly available Brain Tumor MRI image dataset comprising a total image of 7023 brain MRI scans. The dataset consists of 2D brain MRI scans acquired from different patients and categorized into four clinically relevant classes.

3.1.1 Dataset Classes

The dataset contains four classes:

1. Glioma
2. Meningioma
3. Pituitary
4. No tumor

3.2 Distribution

Table 2: Image Distribution in the dataset

Class Levels	Training Set	Testing Set
Glioma	1321	300
Meningioma	1339	306
No tumor	1595	405
Pituitary	1457	300
Total	**5712**	**1311**

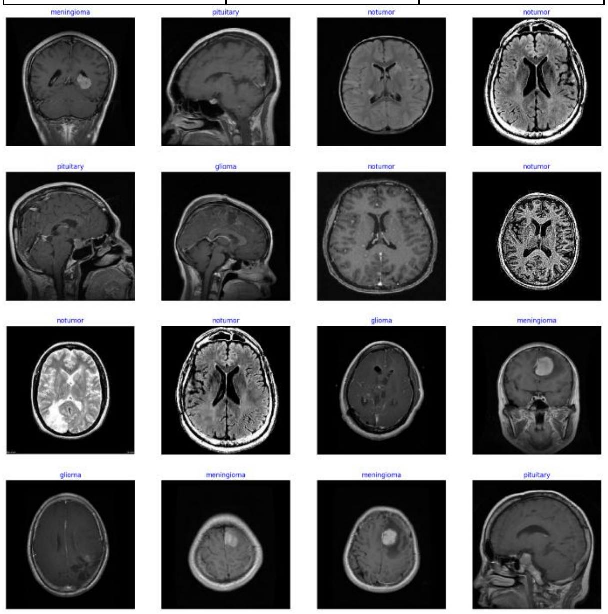

Fig 1: Visualization of Glioma, Meningioma, Pituitary, No tumor

3.3 Pre-Processing

To enhance the consistency of classification outcomes and the quality of extracted features, all dataset images undergo a preprocessing stage. Since deep learning models require extensive repetitive training, a large-scale image dataset is used to reduce the risk of overfitting and to improve generalization performance.

3.4 Resizing and Augmentation

All images were resized to 224 × 224 pixels, which significantly accelerates training and inference by reducing computational cost, without causing a noticeable degradation in model performance.

In this work, no explicit data augmentation is used. The dataset consists of a comparatively balanced number of samples from each class, with over 1,300 training images per tumor type. Additionally, since it involves MRI pictures, all pictures were taken with standardized medical imaging setup conditions, ensuring uniform orientation, scale, and anatomical structures among all samples, thus allowing a stable behavior during training as well as a high generalization capability of the model, since training and validation curves are nearly identical.

Brain tumor classification depends strongly on anatomical location, shape, and intensity patterns that are clinically meaningful. Applying aggressive augmentation techniques, such as large rotations or geometric distortions, may alter these structures and introduce unrealistic variations. For this reason, augmentation was intentionally avoided to preserve the medical validity of the images.

Data augmentation can be useful in situations where training data are sparse, highly imbalanced, or come from multiple sources with different data acquisition regimes. The exploration of data augmentation techniques and domain generalization methods in this situation could be investigated in future work.

3.5 EfficientNetB3

EfficientNet is a family of convolutional neural networks designed to achieve optimal accuracy while maintaining computational efficiency through compound scaling of network depth, width, and resolution. EfficientNetB3 represents a balanced configuration within this family and is well suited for high-resolution image classification tasks. Its architecture enables efficient feature extraction while significantly reducing parameter redundancy compared to traditional deep CNNs.

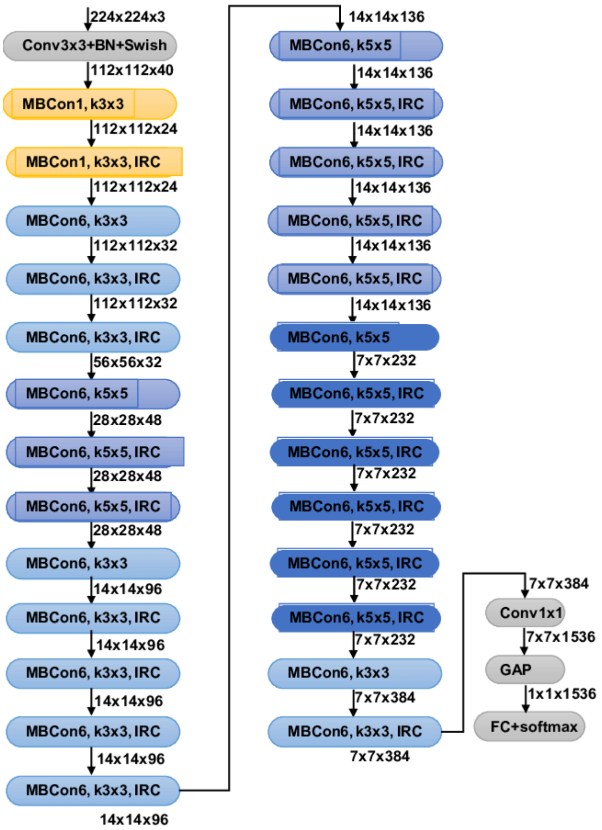

Fig 2: Illustration of the EffecientNet-B3 architecture. (10,3646 million weights). IRC means there is inverted residual connection.

EfficientNetB3 is employed as a pre-trained backbone using weights initialized from the ImageNet dataset. The top classification layers are excluded, allowing the network to act as a deep feature extractor. Input images of size 224 x 224 x 3 are fed into the base model, and global max pooling is applied to aggregate spatial features into a compact representation.

On top of the EfficientNetB3 backbone, a batch normalization layer is added to stabilize training and improve convergence. This is followed by a dense layer with 256 neurons using LeakyReLU activation, combined with L1 and L2 regularization to control model complexity and prevent overfitting. A dropout layer with a rate of 0.50 is incorporated to enhance generalization. The final classification layer consists of four neurons with softmax activation, corresponding to the four target classes.

The model is trained using the Nadam optimizer with a learning rate of 0.001 and categorical cross-entropy loss. Training is conducted for 7 epochs. Despite the shorter training duration compared to the custom CNN, the EfficientNetB3 model demonstrates superior performance due to its rich pre-trained feature representations.

Table 3 illustrates the basic parameters used in order to train the EfficientNetB3 model where Nadam optimizer is used. Categorical Cross-entropy is used as loss function.

Table 3: Parameter for the EfficientNetB3 Transfer Learning model

Method	Value
Type of Learning	Transfer Learning
Pretrained Weights	ImageNet
Base Architecture	EfficientNetB3
Trainable Layers	All layers
Optimizer	Nadam
Learning Rate	0.001
Hidden Activation Function	LeakyReLU
Output Activation Function	Softmax
Loss Function	Categorical Cross-Entropy
Batch Size	32
Input Image Size	224 × 224 × 3
Number of Classes	4
Epochs	7
Dropout Rate	0.50

Algorithm: EfficientNetB3 for tumor classification

- Load the EfficientNetB3 model pre-trained on ImageNet without the top layer, setting the input shape to 224 × 224 × 3 and using 'max' pooling.
- Add a BatchNormalization layer to stabilize and speed up the training process.
- Append a fully connected Dense layer with 512 units, applying L2 and L1 regularization to prevent overfitting.
  Use LeakyReLU as the hidden activation function.
- Include a Dropout layer with a rate of 0.50 to reduce over-reliance on specific neurons, enhancing generalization.

- Add another Dense layer with 256 units, also with L2 and L1 regularization, followed by the LeakyReLU activation function.
- Insert a second Dropout layer with a rate of 0.50 to further enhance model robustness.
- Add a Dense output layer at the end of the model architecture, with a number of units equal to the total classes in the dataset. Apply SoftMax activation to enable multi-class classification, ensuring that the model outputs probability distributions across all classes.
- Create the model by utilizing the Nadam optimizer, setting the learning rate to 0.001. Employ the categorical_crossentropy loss function and monitor accuracy as the performance metric.

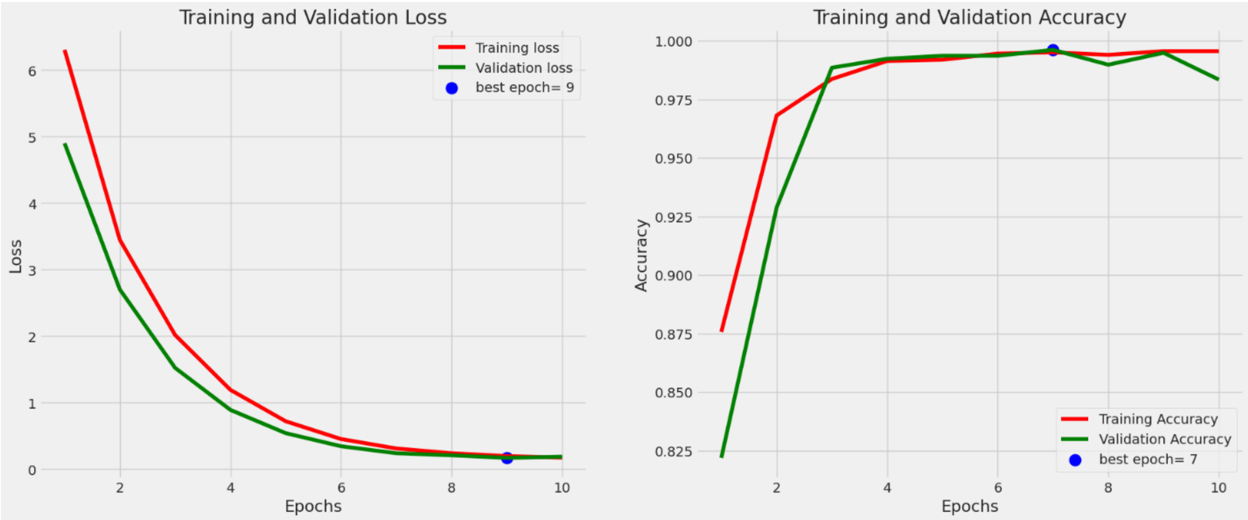

Fig 3: Learning Curve of EfficientNetB3

4. RESULTS

Figure 2 shows the learning curves of the EfficientNetB3 model, where both training and validation loss decrease rapidly and smoothly during the initial epochs, reaching low and closely aligned values by around epoch 9, indicating stable convergence. Training and validation accuracy rises sharply and remain consistently high, approaching nearly 100% with only minor fluctuations, and the best validation accuracy is achieved around epoch 7. The close overlap between training and validation curves throughout training suggests minimal overfitting and strong generalization performance, demonstrating that EfficientNetB3 learns discriminative features efficiently and converges faster than the CNN model.

Table 4: Performance for EfficientNetB3

Class	Precision	Recall	F1-Score
Glioma	0.99	0.99	0.99
Meningioma	1.00	0.98	0.99
No Tumor	1.00	1.00	1.00
Pituitary	0.98	1.00	0.99
Overall accuracy			0.99

Table 5: EfficientNetB3 with Other Models

DL Model	Sensitivity	Precision	Accuracy
EfficientNetB3	99.0%	99.0%	99.0%
CNN [15]	-	-	97.5%
Xception(CNN)[16]	-	-	98.75%
ResNet50[17]	-	-	95.33%
Densenet201[18]	67.46%	-	68.71%
ResNet101[18]	67.23%	-	74.09%
Mobilenetv2[18]	80.32	-	82.61%
SqueezeNet[19]	-	-	92.08%
CNN[20]	-	-	81.0%
CapsNet[21]	-	-	86.56%
CNN [43]	96%	96%	95%

5. CONCLUSION

This study presents a deep learning–based framework for brain tumor classification using the EfficientNetB3 architecture applied to MRI images. The approach leverages transfer learning to effectively learn discriminative features from limited medical imaging data and demonstrates the suitability of modern lightweight convolutional networks for brain tumor image analysis. The use of fine-tuning allows the model to adapt pretrained knowledge to the target domain, highlighting the advantages of transfer learning over conventional training strategies when data availability is constrained. The proposed method shows strong potential for integration into computer-aided diagnosis systems to support clinicians in brain tumor assessment. The effectiveness of such systems depends on appropriate model selection and training strategies, as improper transfer learning choices may lead to negative transfer. Therefore, further research is encouraged to explore optimal network selection, fine-tuning strategies, and broader clinical validation for brain tumor imaging tasks.

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