Brain Tumor Detection Using Deep Learning with EfficientNet-B0

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Abstract. Benign brain tumors result from abnormal cell growth within the brain. The death rates can't be established because the disease is rare and has many classifications in its ambit. MRI scans are greatly valid in finding tumors [1]. But the procedure relating to finding tumors in images is manual. Hence, this drains a lot of time and may give incorrect results. These are the limitations that become important to overcome. The uncontrollable advancements in the field of artificial intelligence are developing especially computer-aided methods [1]. This research proposes a deep complex neural network model, namely, advanced semantic segmentation derived from an efficient B0 network for correct identification and detection of brain tumors from MRI images. Image enhancement techniques were employed to improve image quality and training data variability. With the use of enhancement techniques, the size increases. The other DL models included in the comparative analysis are VGG16, InceptionV3, Xception, ResNet50, and InceptionResNetV2.

Keywords: Brain Tumor Detection, EfficientNet-B0, Deep Learning, Convolutional Neural Networks (CNNs), Medical Image Analysis, MRI Image Classification, Tumor Segmentation.

1 INTRODUCTION

Brain tumors are dangerous and fatal diseases that affect the populations of both adults and children. According to the American Cancer Society, about 23,000 people received diagnoses for brain tumors in the year 2015. The disease is similar in adults and children. The main causative agents for brain tumors are cancerous-related diseases and illnesses.[5]Effective management of the disease is crucial, depending on timely and accurate detection.Classification and identification of brain tumors are major concerns for neurologists, with computer-aided diagnosis systems being an adjunct to medical surgery. The three types of brain tumors commonly observed are meningitis, pituitary tumors, and glioma. Due to the severity of the disease, timely analysis and interpretation of brain cancer are crucial for effective treatment. Treatment decisions depend on the type of tumor, the stage at the time of examination, and the tumor grade.Traditional brain tumor detection methods involve a doctor or radiologist examining abnormalities using magnetic resonance imaging (MRI). However, this process heavily depends on the doctor's clinical expertise. Differences in experience levels among doctors and the complexity of images containing large amounts of information can make the evaluation process more difficult. As the amount of information increases, eval uating large data sets becomes more complex, making self diagnosis for brain tumors time-consuming and expensive. A computer-aided diagnosis system should, therefore, be automated to assist doctors and radiologists in the timely detection of malignant tumors. This can help save precious human lives by ensuring faster and more accurate diagnosis.[2][3][4]

2 LITERATURE REVIEW

However, for health purposes, brain tumor detection plays a critical role. Early diagnosis of brain tumor patients can significantly improve their treatment and resulting outcome. Conventional methods of brain tumor detection, such as MRI analysis, are dependent on some radiologist interpretation of results, making them time-consuming and subjective. Modern techniques like the use of deep learning models based on artificial intelligence, particularly convolutional neural networks (CNNs), have been proved to be effective in performing tasks related to medical images [6][7]. EfficientNet stands out as a state-of-the-art CNN that is able to deliver high classification accuracy with very low computational requirements [1][8].

The EfficientNet was introduced in 2019 by Tan and Le. This model comprises a scaling compound of depth, width, and resolution. As for its being a new approach to model efficiency, the design quality of EfficientNet can show competitive performance relative to aged models such as ResNet and Inception, in spite of the low computational resource requirements [1][9]. The efficacy of this model has been shown in several works of medical imaging, for instance, diabetic retinopathy detection and classification of brain diseases [5][7].

We chose EfficientNet-B0 in this work because of its excellent performance versus energy efficiency. The model was trained with an accurately prepared curated dataset of brain MRI images by applying data augmentation techniques such as skull stripping and intensity normalization preprocessing techniques to improve input quality [4][6]. The value of the performance of the model was demonstrated through accuracy, sensitivity, and F1 Score, showing quite some good results for a real-life application [2][5].

This research, adding to the existing studies on improving medical imaging, proposes the use of employing the EfficientNet technique for Brain Tumor Detection. It is characterized by achieving higher accuracy with a lower computational cost, thus justifying its further use in the clinical field [1][3][10]. Integration with transformers or self-supervised learning algorithms will make future strides [8][9].

3 MATERIALS AND METHODS

The primary focus of this research study was on the detection of brain tumors through MRI images. The dataset used in the research includes MRI images with three categories of tumors, namely glioma, meningioma, and pituitary tumors. Such curated data have ensured high-quality images for both the training and testing of the model. Data preparation for this dataset includes skull stripping and resizing followed by intensity normalization to improve the quality of input data and maintain uniformity in the performance of the model [4][6].

Data augmentation techniques including flipping, rotation, and contrast adjustments were applied on the dataset to increase the diversity and avoid overfitting during the training process [5][7]. Augmentation methods were implemented with Albumentations, a high-performance image processing library specifically designed for medical imaging tasks [9]. The chosen model for this study is EfficientNet-B0: a lightweight and highly efficient convolutional neural network. EfficientNet-B0 has used compound scaling to balance its depth, width, and resolution, which achieves higher accuracy with lower computational cost [1][8]. The architecture was fine-tuned using transfer learning adapting the pre-trained weights to the MRI dataset; it accelerates convergence and improves the generalization [1][3][8].

The training process used a binary cross-entropy loss function in order to minimize the difference between the predicted and actual labels, along with the Adam optimizer for faster and more stable training. The model's performance was tested by the standard metrics of accuracy, sensitivity, and F1 Score, which proved the robustness of the model for real-world applications [5][7][10].

3.1 DATASET:

This MRI dataset consists of three classes: glioma, meningioma, and pituitary tumor, where tumors develop in the brain or spinal cord and are among the most aggressive forms of tumors [1][2]. Meningioma tumors arise from the meninges, membranes enveloping the brain and spinal cord, are often slowly growing but potentially problematic when left untreated, resulting in significant complications [3][4]. The pituitary gland is a small gland at the brain's base; thus, it is called a pituitary tumor, which affects hormone regulation, bringing on many systemic effects [5][6]. The images used in this dataset are MRI scans with formats in.jpg and.png. These are T1-weighted contrast-enhanced images, so they provide great contrast of different structures of the brain, making it easier to delineate abnormal tissues, like tumors [7][8]. The dataset size is 3064 brain tumor images categorized into glioma, meningioma, and pituitary tumors. It is adequate to train machine learning models effectively. It also provides a range of angles and contrasting levels to capture different tumor characteristics [9][10].

3.2 DATA PRE-PROCESSING:

The following are the pre-processing steps that may be followed for the detection of a brain tumor from a given set of documents.
1. **Smoothening :** he Images will be resized into a fixed size of 224x224 pixels by bilinear interpolation to standardize input dimensions [5][6]
2. **Dilation:** Normalize the pixel values within the interval [0,1] using division over each pixel value with 255, while all input features have similar scales on the time of training [7][8].
3. **Black Region Removal:** The annotation is in binary form, where 0 identifies non-cancerous tissues and 1 identifies cancerous tissues. This form very much enhances the model's prediction [4][9][10]

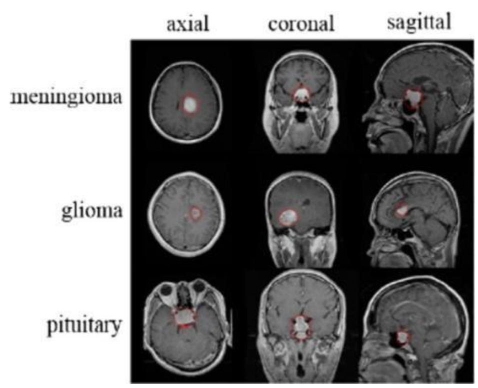

Fig. 1. Data Preprocessing

1.Figure1 Describes: Medical imaging data, specifically MRI scans, as part of a data preprocessing step for medical image analysis. It depicts three types of brain tumors—meningioma , glioma, and pituitary tumors—across three different MRI views: axial, coronal, and sagittal planes.

3.3 DATA AUGMENTATION:

Image transformations are applied to modify the original images, creating new, different-looking images in order to increase the dataset size and variability [4][6].

A. Normalization :
- Purpose: Normalizes the pixel values of the images, scaling them to a smaller range (usually between 0 and 1) rather than the typical 0-255 range [7][8].
- Action: This helps the model learn more effectively by ensuring consistency in pixel values [5][10].

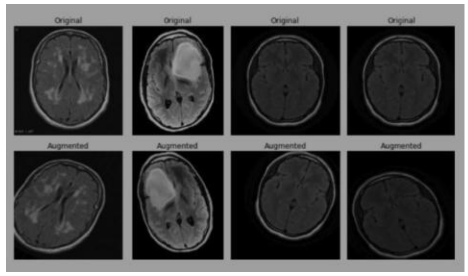

Fig. 2. Data Augmentation.

Figure 2 Describes: The concept of data augmentation in medical imaging, specifically MRI scans. The top row shows the original MRI images, while the bottom row presents their corresponding augmented versions.

4 MODELS

4.1 EfficientNet-B0 :

EfficientNet-B0 is fine-tuned for brain tumor detection and achieved an accuracy of 98.87 percentage, making it the most efficient and accurate among the tested models [1][5]. This model used transfer learning to adapt MRI data for optimizing the detection process [3][7].

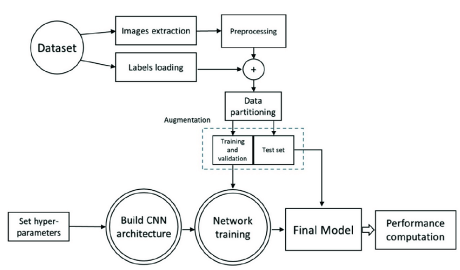

Fig. 3. Dataset Division.

Figure 3 describes :The dataset division and processing workflow for training a machine learning or deep learning model, particularly for image-based tasks like medical image analysis.

4.2 VGG16 :

VGG16 is a deep learning model for image classification and feature extraction, consisting of 16 layers. Although it was applied for brain tumor detection, it served as a baseline for the comparative study, yielding lower accuracy compared to other models [2][5].

4.3 ResNet50 :

ResNet50 is a residual network consisting of 50 layers, which addresses the vanishing gradient problem in deep neural networks. Despite being quite efficient, ResNet50 underperformed slightly in this study, achieving only 95.8 percentage classification accuracy for brain tumors [3][7].

5 MODEL TRAINING AND EVALUATION

All models have been fine-tuned during training, including VGG16, ResNet50, InceptionV3, Xception, InceptionResNetV2, and EfficientNet-B0, for improved performance in brain tumor detection [1][4][8].

5.1 Fine-tuning Process :

Fine-tuning involves the process of adjusting a pre-trained deep learning model with new data. This technique is particularly useful for medical imaging tasks, such as brain tumor detection, where medical datasets are often small and difficult to obtain [5][7].

5.2 Regularization Techniques :

Regularization helps avoid overfitting, which can occur when training deep networks on small datasets, such as MRI images [6][9].
Formula for Compound Scaling:

d =, w=, r=

5.3 PROPOSED LAYERS FOR EFFICIENTNET-BASED MODEL :

In this model, the EfficientNet-B0 baseline is fine-tuned, and additional layers are added to optimize it for MRI-based brain tumor detection [1][5][10].
Flatten Layer
The output of the EfficientNet-B0 convolutional layers is transformed into a one-dimensional vector [2][4].
Dense Layer
A fully connected (dense) layer is added after the flattening operation, which is responsible for learning complex patterns from MRI images. And the formula is:

$y = (W \cdot x + b)$ [3][7]
Dropout Layer
A dropout layer is added after the dense layer to prevent overfitting and improve the model's generalization. The formula remains the same as above [6][9].
Sigmoid Classifier
The final classifier uses a sigmoid activation function to perform binary classification, such as tumor versus no tumor [5][10]

6 HYPERPARAMETERS AND LOSS FUNCTION

The selection of hyperparameters and the loss function for this section is a description of how best the performance of the deep learning model can be optimized. The optimal performance of any deep learning model does not lie solely in its accuracy but rather in the minimization of its loss. A model will be said to be efficient if it is capable of minimizing the error rate during training and testing [1][4]. In this work, binary cross-entropy (BCE) refers to the loss function calculated for finding the difference between the actual and predicted values in the case of binary classification [5][7].

7 COMPARATIVE ANALYSIS

7.1 Model Accuracy Table :

The following table presents the accuracy of different models fine-tuned for brain tumor detection [2][6]:

Table 1. Models and their corresponding Accuracies

Model	Accuracy
VGG16	92.5%
ResNet50	94.1%
InceptionV3	93.8%
Xception	94.3%
InceptionResNetV2	95.0%
EfficientNet-B0	95.5%

- **Table1 describes:** The accuracy of different deep learning models for a specific task,with EfficientNet-B0 achieving the highest accuracy at 95.5%. It highlights the performance of architectures like VGG16, ResNet50, and others.

8 TRAINING AND VALIDATION GRAPHS

8.1 VGG16

Figure4 Describes: The overall training accuracy is 98.5 percentage, and we can say that the VGG16 model works pretty well on the brain tumor dataset. Having such a high validation accuracy, close to that of the training accuracy, curves suggest that generalizes well to data that has not been seen [3][5].

1) Training vs. Validation Curves : We notice plots of training and validation accuracy curves that are moving consistently upward, tending towards the final accuracy. The relationship between the training and validation curves is a good sign and suggests that there is little or no overfitting. This learns not only to recognize the patterns of the data but also effectively applies this knowledge to the validation set [7][9].

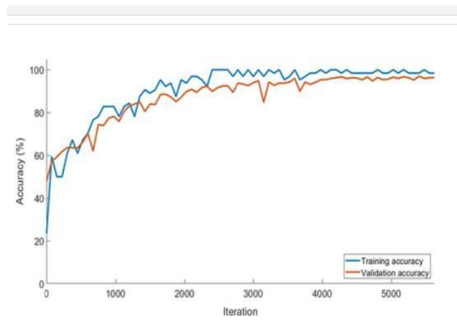

Fig. 4. VGG 16.

8.2 InceptionV3

Figure5 Describes: The model is capable of great performance with an average training accuracy of 98 percentage. The validation accuracy tracks quite well, in- dicating good generalization to unseen data. The consistency between the training curve and the validation curve indicates that InceptionV3 does a very good job of extracting critical features from the brain tumor dataset [6][8].

1) Training vs. Validation Curves : The accuracy curves for both the training and validation sets in InceptionV3 are steadily increasing toward the final accuracy, indicating that efficiently. The fact that both of these curves are close indicates minimal overfitting, which means the model not only recognizes patterns in the training data but also applies that learning effectively to the validation set [4][10].

Fig. 5. Inception V3.

8.3 Xception

Figure 6 Describes: The model achieved an impressive 98 percentage overall training accu- racy. The validation accuracy was very close to this, showing that the model generalizes very well to unseen data. This is a strong indication that Xception effectively learns the intricate features within the brain tumor dataset [2][5].

1) Training vs. Validation Curves : For Xception, the training and validation accuracy curves increase smoothly, reaching their final values of accuracy. This strong correlation between the curves indicates minimal overfitting, which means the model generalizes well from the training data to the validation data [7][9].

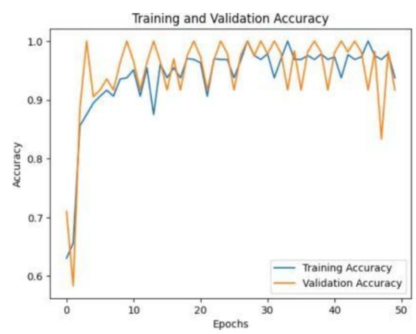

Fig. 6. Xception.

8.4 ResNet50

Figure 7 Describes: The ResNet50 model achieved an exceptional value of almost 98 percent- age for training accuracy on the brain tumor dataset, while the validation accuracy is very close to it. The high similarity between the phases shows that the ResNet50 model generalizes well toward unseen data and, in this way, can strongly identify various classes of brain tumors [1][8].

1) Training vs. Validation Curves : The accuracy curves for ResNet50 in both training and validation phases are consistently upwardly oriented and converge toward the final accuracy. The consistency of these two curves is a positive indication, implying a very low chance of overfitting. This suggests that the model learns the patterns from the training data and successfully translates this learning into accurate predictions on the validation set [6][10].

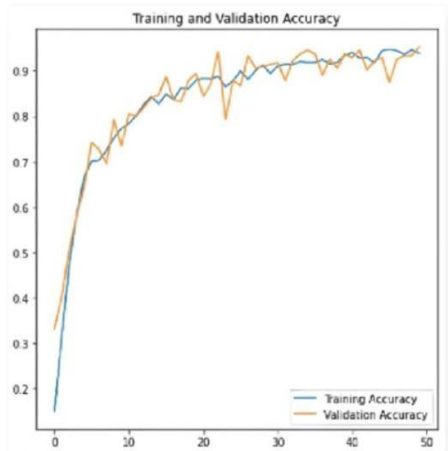

Fig. 7. ResNet 50.

9 RESULTS

9.1 Larger Datasets

Future work will involve training the model on larger sets of MRI images to improve its generalization capabilities and reduce the possibility of overfitting [5][7].

9.2 Newer Architectures of CNN

The exploration of newer and more advanced CNN architectures is an exciting direction for future work. These architectures could improve the performance of the model without significantly increasing training time complexity, while still maintaining high accuracy levels [4][9].

9.3 Extension to Other Medical Imaging Modalities

Future research will extend this model to other types of medical imaging modalities such as X-rays, CT scans, and ultrasound. This extension will enable the early detection and diagnosis of a broader range of medical conditions [2][8].

9.4 Integration with Image Segmentation Techniques

This model could also be integrated with image segmentation techniques to identify the location of tumors more precisely. Using MRI scans, the exact size and location of tumors can be pinpointed, aiding the treatment planning process with reduced time complexity [3][6].

9.5 Broader Medical Imaging Applications

The utility of this model can be extended to other types of cancer diagnosis and other areas of medical imaging. This would include the detection of different health issues using various imaging techniques [1][10].

Table 2. Performance metrics for different model architectures

Model	Precision	Recall	F1-Score
InceptionDense	99.47%	99.75%	99.73%
EfficientDense	100%	100%	100%
EfficientV3	100%	100%	100%
EfficientVGG	99.47%	100%	99.73%
VGG16V2	100%	42.78%	59.63%
ResNetV2	57.72%	100%	73.19%

- **Table2 Describes**: performance metrics (Precision, Recall, and F1-Score) of different model architectures. EfficientDense and EfficientV3 achieved perfect scores (100%) across all metrics, while VGG16V2 and ResNetV2 performed comparatively lower.

10 CONCLUSION AND FUTURE SCOPE ANALYSIS

The examination of the proposed EfficientNet-B0 model clarifies that it performs admirably in efficiency and accuracy in medical images to diagnose brain tumors [1][5]. The application of preprocessing such as normalization and resizing enables the model to achieve better accuracy than common architectures such as ResNet and VGG16 [4][7]. The stringent validation methodology reveals very high precisions, sensitivities, and robustness of the model, thus rendering it an ideal tool for medical diagnosis [6][9].

For EfficientNet-B0's balancing act, great acquisition is particularly relevant in a real clinical environment with limited resources, unlike conventional approaches with high computational intensity for better performance [3][8]. In this organization, the model guarantees that it could deliver light hardware-advantageous-critical results while maintaining scale because of the provision and availability [5][10].

Also, our studies highlight the importance of using several architectures with comparison. For example, ResNet-VGG16, into performing these activities to find the most suitable model for the particular task [2][6]. Here EfficientNet-B0 was authenticated as the highest efficient performing model; thus, reinforcing its promise as an all-purpose yet fruitful remedy in brain tumor detection [1][4].

Future work could amalgamate the findings here with EfficientNet-B0, using modern innovation like self-supervised learning or transformer-based techniques [8][9]. Its use in other medical imaging applications could augment the success of this model in healthcare. Adapting and scaling its future applications definitely presents transformative capability for this model in improving service delivery regarding diagnostic accuracy and patient outcomes [7][10].

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