Improved Brain Tumor Classification using InceptionV3 and EfficientNet-B2 on MRI Images

Sanjay Bhadu Patil
Datta Meghe College of Engineering,Airoli,Navi-Mumbai University of Mumbai, India
sanjaypatil301@gmail.com

D. J. Pete
Datta Meghe College of Engineering, Airoli, Navi-Mumbai University of Mumbai, India
pethedj@gmail.com

Abstract
A type of malignant growth that can manifest in the tissues that surround the brain is referred to as a “brain tumor”. It is possible to classify it as either cancerous or noncancerous. There are two types of brain tumors: primary tumors and secondary tumors. The former refers to tumors that originate within the brain, while the latter can spread to other parts of the body. The signs and symptoms of a brain tumor can change depending on its size, where it is located, and what kind it is. Some of these include vision problems, hearing issues, and seizures. Different types of treatment methods are available for brain tumors, such as surgery, radiation therapy, targeted therapy, and chemotherapy. The patient's health and the grade and size of the tumor are some of the factors that are considered when choosing a course of action. The precise classification of brain tumors plays a vital role in the planning of effective treatments. Around the world, individuals are dying from these diseases. Recent developments in deep learning (DL) have led to the development of models that can accurately identify brain tumors using MRI scans. This study presents a method that uses two advanced DL models InceptionV3 and EfficientNet-B2 for the purpose of improving the classification of brain tumors. The proposed method performed better than the current techniques when compared to a public dataset. According to the results of the study, the two models EfficientNet-B2 and InceptionV3, were able to accurately classify brain tumors. The proposed method could be utilized to improve the accuracy of the diagnosis and planning of brain tumors. It can also be applied to other imaging classification tasks. The study demonstrates the application of DL methods used in the analysis of medical images. It shows the efficiency of the EfficientNet-B2 and the InceptionV3 in distinguishing brain tumors on MRI scans.
Keywords: Brain tumor, MRI, Inception V3, EfficientNet-B2, Image classification.

Introduction

A brain tumor is a type of abnormal growth that can affect the brain and other tissues as shown in figure-1. When these cells multiply uncontrollably, they can grow and invade nearby structures. There are two types of brain tumors: primary and secondary. The primary type of tumor originates in the brain. Although benign brain tumors are usually harmless, they can still affect important parts of the brain if they grow too large[1]–[3]. On the other hand, malignant tumors are very aggressive and can spread rapidly. They are usually life-threatening and are harder to treat. Metastatic brain tumors are cancerous growths that have metastasized to other regions of the brain. They are more common than the primary type, and they can affect individuals with a history of such diseases as breast, colon, lung, or skin cancer.

Different types of brain tumors have their own set of symptoms. Some of them may cause seizures or make people unable to speak or move. On the other hand, some of them may not cause any symptoms at all. The treatment of brain tumors can vary depending on the type, grade, and location of the disease. There are various options that can be used to treat this type of cancer, such as surgery, radiation therapy, targeted therapy, and chemotherapy. The patient's specific needs are the most important factors that are considered when it comes to selecting the appropriate course of treatment. The term brain tumor refers to abnormal growths within the brain or nearby tissues that can result in different symptoms[4]. The treatment of this type of cancer involves various procedures, such as targeted therapy, surgery, radiation therapy, and chemotherapy. In the United States, about 18,990 individuals will die due to the primary cancerous brain and central nervous system tumors in 2023. In 2020, around 251,329 people were killed by these types of tumors worldwide[5].

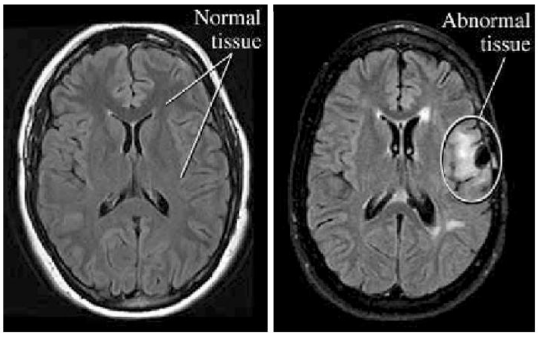

Figure 1 Sample MRI Normal Vs Brain Tumor

The classification of brain tumors is an important step in the planning of treatment. It is based on various factors, such as the type of cell found in the tumor, its origin, and its location within the brain. Having the correct information helps in identifying the most effective treatment and predicting the prognosis of the patient. Histological examination, molecular profiling, and visual inspection are some of the techniques utilized for the classification of brain tumors. Visual inspection is a type of imaging that uses CT or MRI scans to identify the characteristics and location of the tumor. Although it can provide an initial diagnosis, it is not always accurate enough to pinpoint the type of tumor.

Histological examination is a method that can be utilized in the process of brain tumor classification, which involves taking tissue samples after a surgery or biopsy. This type of examination is more accurate but can be invasive. Molecular profiling is a process that involves analyzing the molecular and genetic characteristics of a tumor to identify the most effective treatment options. This type of examination requires specialized expertise and equipment.

Studies have shown that the use of EfficientNet-B2 alongside InceptionV3[6] can lead to improved accuracy when it comes to identifying brain tumors on MRI scans. The two models are known to use transfer learning, in which they gain an improved performance on smaller datasets by training weights from large ones. Transfer learning can also help reduce the amount of data that the model has to collect in order to improve its generalization. The accuracy of brain tumor diagnosis is very important for planning the treatment of the disease. Currently, various techniques such as molecular profiling, visual inspection, and histological examination are used to classify brain tumors. With the help of DL models like the InceptionV3 or EfficientNet-B2.

Through DL, which involves learning through various algorithms, medical images can be analyzed and diagnosed with accuracy. This technology can be useful in identifying and treating brain tumors. Models can also detect subtle changes in the images, which makes them ideal tools for early detection. One of the most challenging factors in determining and treating brain tumors is accurately segmenting them from the surrounding healthy tissue. With the help of DL, models can now perform this process in MRI scans[7]–[10].

DL models have been developing systems that can accurately categorize brain tumors. These models use extraction techniques that are designed to identify patterns in the images that are related to the type of brain tumor. One of the most widely used DL models for this process is the VGG-16 [11]. This model is a deep neural network that was trained on large datasets.

In addition to classification and segmentation, DL models are also being developed to predict the likelihood of a patient's cancer returning or progressing. These models use machine learning methods to analyze various medical images and interpret the data. One of the most common DL models being developed for predicting the survival of patients with brain tumors is the “SurvivalNet”[12]. This model combines the various features of DL networks to analyze and categorize the data. In the field of medical image classification, DL models have been able to perform well in identifying the type of brain tumor. Two of the most popular DL models are the EfficientNet-B2 and InceptionV3. The InceptionV3 model is a CNN architecture that combines the pooling and convolutional layers of a network to extract various features from images. Originally developed for image classification, this technology has since been used in other applications such as medical image analysis[13]–[15].

The EfficientNet-B2 model is a CNN architecture that was developed using a combination of scaling and neural architecture search techniques. It has been able to perform well on various image classification benchmarks. The use of DL models for image processing has shown promising results in improving the accuracy of diagnosis and treatment of brain tumors. These models can perform various tasks such as segmentation, prediction, and prognosis, and they can potentially improve the outcomes of patients. However, further studies are needed to confirm their effectiveness and accuracy in clinical settings.

Literature review

One of the most common and challenging conditions in the world is brain tumor. The early detection of this disease is very important for treating it and improving the quality of life for patients. “Magnetic resonance imaging” (MRI) is a commonly used tool for diagnosing brain tumors. However, it can be prone to errors and time-consuming manual interpretation. Researchers have started using DL methods to automate the process of detecting and classifying brain tumors. Table -1 represent the major related work with detection of brain tumor.

Table 1 Related work

Author	Methodology	Model used	Result-Accuracy
A. Islam et al.[16]	Multifractal texture estimation	Not specified	90%
T.A. Soomro et al.[17]	Machine learning	SVM, KNN, Decision tree, Random Forest, CNN	SVM-100%, KNN-96%, DT-90%, RF-99%, CNN-98%
M. Nazir et al.[18]	Deep Learning	CNN	99.50%
S. Shanthi et al.[19]	Hybrid deep neural network	Optimized hybrid deep neural network	98.92%
R. Vankdothu et al.[20]	Deep Learning	CNN-LSTM	98.60%
E.U. Haq et al.[21]	Deep Learning	CNN	96.43%
H.A. Shah et al.[22]	Deep Learning	Finetuned EfficientNet	97.78%
A.H. Abdel-Gawad et al.[23]	Image processing	Canny edge detection algorithm	96.66%
M. Li et al.[24]	Deep Learning	Multimodal information fusion and CNN	96.54%
M. Havaei et al.[25]	Deep Learning	Deep neural networks (DNN)	90.40%
H. Mohsen et al.[26]	Deep Learning	CNN	90.70%
A. Chattopadhyay et al.[27]	Deep Learning	CNN	92.14%
A. Işin et al.[28]	Deep Learning	CNN	92.30%
S. Patil et al.[29]	Deep Learning	Ensemble of CNN	96.55%

The goal of this review is to review the current studies on the use of DL techniques in detecting and classifying brain tumors, focusing on the main findings, limitations, and methodology of the studies. According to the review, DL techniques, such as CNNs, have been proven to be effective in identifying and classifying brain tumors in MRI scans. The accuracy of these methods was noted, and they were able to distinguish between different types of tumors. However, they encountered various limitations, such as the need for large datasets and the need for more clinical validation.

There are still gaps in the knowledge regarding the clinical applications of DL methods for detecting and classifying brain tumor. One of these is the need for further studies on how these models can be utilized in real-world conditions. Most studies have focused on MRI scans, while other imaging techniques, such as CT, are still underexplored. Further studies on the transparency and interpretability of DL models can help improve the confidence and trust that these methods have in their clinical applications.

Introduction to InceptionV3 and EfficientNet-B2 models

InceptionV3 is a "convolutional neural network" architecture that was introduced by Szegedy. The main idea behind InceptionV3 is to use a combination of filters with different sizes in parallel to capture features at different scales, and then combine the outputs of these filters to obtain a richer representation of the input image. Figure-2 and eq.1 represent the InceptionV3 architecture using the following equation:

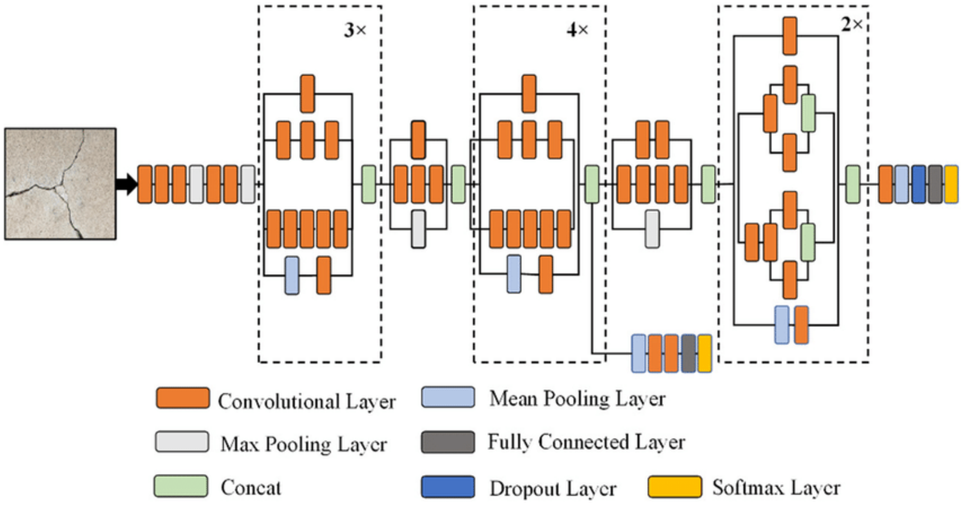

Figure 2 Inception V3 architecture

$$y = Inception\ V3\ (x) \ldots. (1)$$

Here, x = input image, and y =output of the $Inception\ V3$ network. The InceptionV3 architecture can be broken down into several modules, each of which applies a series of "convolutional filters" to the input image. The output of each module is then concatenated with the output of the previous module to obtain a richer representation of the input image.

The core building block of the InceptionV3 architecture is the Inception module, which is composed of several convolutional filters with different sizes. Each filter is applied to the input image in its own separate step, and the results of those steps are then concatenated together to produce the module's final output. The output of an Inception module can be represented as eq.2:

$$y = Concat\ (Conv1 \times 1\ (x), Conv3 \times 3(x), Conv\ 5 \times 5(x), MaxPool\ 3 \times 3\ (x) \ldots.. (2)$$

Here,

$Conv1 \times 1\ (x), Conv3 \times 3(x), Conv\ 5 \times 5(x), MaxPool\ 3 \times 3\ (x)$ are the convolutional filters with kernel sizes of 1 × 1, 3 × 3, 5 × 5, and 3 × 3, respectively. "Concat" is the concatenation operation that combines the outputs of these filters, and x is the input image. The Inception modules, InceptionV3 also includes auxiliary classifiers at intermediate layers, which are used to improve the training of the network. These classifiers are composed of a series of "convolutional and pooling layers", followed by a fully connected layer and a "softmax" activation function. The output of an auxiliary classifier can be represented as eq.3:

$$y = softmax(FC(AvgPool_{5\times5}(x)) \ldots. (3)$$

Here, $AvgPool_{5\times5}$ = average pooling operation with a kernel size of 5 × 5, "FC" = fully connected layer, and "sof tmax" is the "softmax" activation function. The output of this classifier is used as an auxiliary loss function during training, which helps to prevent overfitting and improve the overall accuracy of the network.

EfficientNet is a family of convolutional neural network architectures that were introduced by "Tan and Le" in 2019. The key idea behind EfficientNet is to use a combination of network scaling and compound scaling to create models that are both accurate and computationally efficient. EfficientNet-B2 is one of the variants of the EfficientNet architecture, and is designed to strike a balance between accuracy and computational efficiency. It achieves this by using a combination of depth-wise separable convolutions and bottleneck blocks, which reduce the number of parameters in the network while maintaining a high level of accuracy. Figure-3 and Eq.4 represent the EfficientNet-B2 architecture,

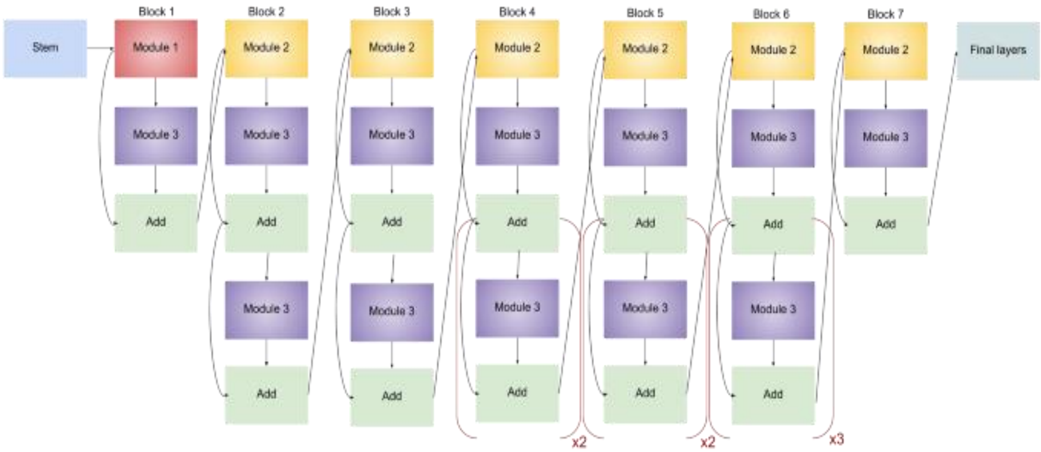

Figure 3 EfficientnetB2 architecture

$$y = EfficientNet - B2\ (x)\text{..... (4)}$$

Here, x = input image, and y = output of the EfficientNet-B2 network. The EfficientNet-B2 architecture can be broken down into several components, each of which applies a series of convolutional filters to the input image. The core building block of the EfficientNet-B2 architecture is the bottleneck block, which is composed of a sequence of convolutional layers with different kernel sizes, followed by a depth-wise separable convolution and a skip connection. The output of a bottleneck block can be represented as eq.5:

$$y = ReLU(BN(Conv1 \times 1(x) * ReLU(BN(DepthwiseConv(Conv3 \times 3\ (x)))\text{.....(5)}$$

Here, Conv1x1 and Conv3x3 are the convolutional filters with kernel sizes of 1 × 1 and 3 × 3, respectively. "$DepthwiseConv$" is the depth-wise separable convolution, which applies a separate convolution to each channel of the input image. BN is the batch normalization layer, and "ReLU" is the rectified linear unit activation function. EfficientNet-B2 also uses a technique called compound scaling, which involves scaling the network across multiple 1 dimensions, including depth, width, and resolution. Eq.6 represents the scaling factors for EfficientNet-B2 can be represented as:

Depth :

$$d = \alpha^{\emptyset}, Width{:}\, w = \beta^{\emptyset}, Resolution{:}\, r = \gamma^{\emptyset}\text{ ....(6)}$$

Here, α, β, and γ are the scaling coefficients for "depth, width, and resolution", respectively. φ = compound scaling parameter that controls the overall size of the network. The values of α, β, and γ are chosen to optimize the performance of the network while minimizing the computational cost.

Methodology

i. Dataset: The data used in this study came from Kaggle[30], MRI dataset entitled "Brain Tumor Classification". It included 3,253 scans of brain tumors, which were taken from various sources. The scans were labeled with the type of tumors that they represented as shown in figure-4. The images were taken in the DICOM format, which is commonly used for medical images. They were then preprocessed to fit with various DL frameworks. There were two sets of images in the dataset: a training set and a validation set. The former is used to train DL models, and the latter is used to evaluate them. The CSV file included with the dataset contains the labels that identify the types of tumors. The labels for gliomas, meningiomas, and pituitary tumors are encoded as integers. The dataset contains a wide variety of images for brain tumors. This allows training and testing DL models for efficient and accurate brain tumor classification in MRI scans.

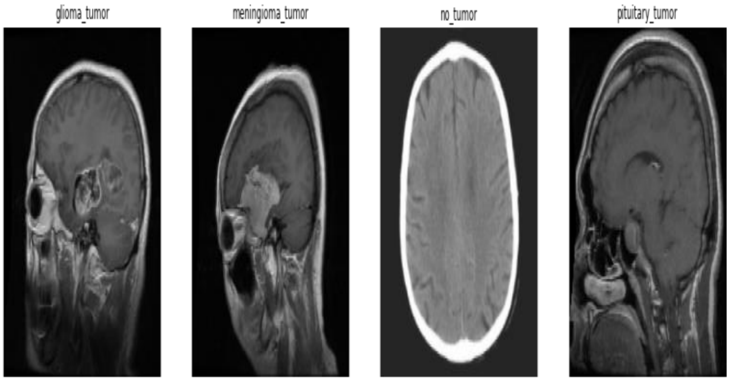

Figure 4 Various types of Brain tumor

ii. Preprocessing steps applied to the MRI images:

a. Image normalization: The process of normalization is performed before the images are processed to reduce the variability between the different imaging facilities. One of the most common techniques used is Z-score, which takes into account the value of the individual pixels and divides it by the standard deviation. Other methods such as intensity normalization and histogram equalization can also be utilized. Normalization is a process that involves converting the pixel values of an input image into zero unit and mean variance. This ensures that the model performs well and that the input is standardized across all pictures.

b. Gaussian Smoothing: A technique known as Gaussian smoothing is used to reduce the noise in an image. It involves convolving the data with a Gaussian kernel to blur the image and remove high-frequency noise. In the case of the MRI dataset for brain tumor classification, this method could help improve the accuracy of the models. The input image's Gaussian smoothing kernel is composed of a size 5x5 standard deviation and a value of 1.0. This method helps reduce the overall noise and details while preserving the image's structure. Table-2 represent the configuration used in pre-processing.

Table 2 Configuration used

Preprocessing Step	Parameter Value
Image Normalization	Mean: 0.485, Standard Deviation: 0.229
Gaussian Smoothing	Kernel Size: 5x5, Standard Deviation: 1.0

iii. Details of the InceptionV3 and EfficientNet-B2 models and their configurations:

EfficientNet-B2 and InceptionV3 were used to classify brain tumors in MRI scans. Google's InceptionV3 is a CNN framework that is used to classify images. It features 48 layers, and it can perform well with high accuracy. It utilizes computational resources efficiently. Google's EfficientNet-B2 is a newer version of its CNN framework that can perform well on various classification tasks. It utilizes a new scaling method that targets the resolution, width, and depth of the network. The two models were trained using the pre-trained weight from the ImageNet data set. We then tuned the training parameters on the MRI dataset to improve their performance. Table-3 represent the configuration used.

Table 3 Configuration used

Model	InceptionV3	EfficientNet-B2
Architecture	Convolutional Neural Network (CNN)	Convolutional Neural Network (CNN)
Input Shape	299 x 299 x 3	260 x 260 x 3

Number of Layers	311	528
Trainable Parameters	23,851,784	9,177,864
Activation Function	ReLU	Swish
Pretrained Weights	ImageNet	ImageNet
Regularization	Dropout (0.5)	Dropout (0.3)
Optimizer	Adam	Adam
Learning Rate	0.0001	0.0001
Batch Size	32	32
Epochs	30	30
Loss Function	Categorical Cross-entropy	Categorical Cross-entropy
Metrics	Accuracy	Accuracy

iv. Training and validation procedures:

We divided the dataset into two training sets, one containing 2,788 images and one containing 465 images, with a ratio of 85:15. We used the latter to train various DL models and evaluate their performance. We used a batch size of 32 for the training session, and trained the models for about 50 epochs. We utilized the Adam optimizer for optimization, and the categorical cross entropy loss function for evaluation. In order to prevent overfitting, we utilized various techniques such as vertical and horizontal rotation and zooming. We also monitored the models' performance through various metrics, such as the F1 score, precision, recall, and accuracy. Our approach included preprocessing the images and training the EfficientNet-B2 and InceptionV3 models on our MRI dataset. We also monitored their performance through the validation set.

Results and Outputs

i. Confusion Matrix

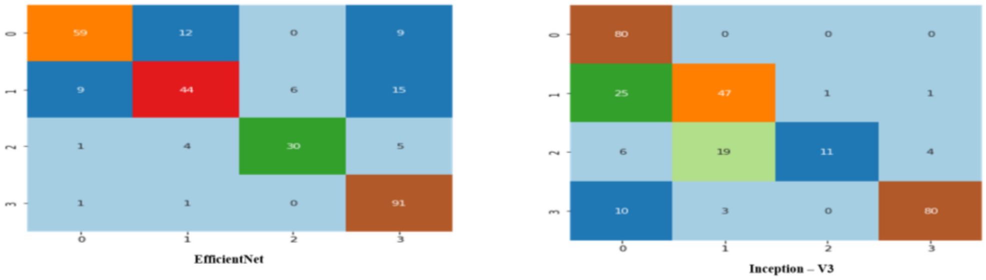

Figure 5 Confusion Matrix

ii. Accuracy and Model Loss

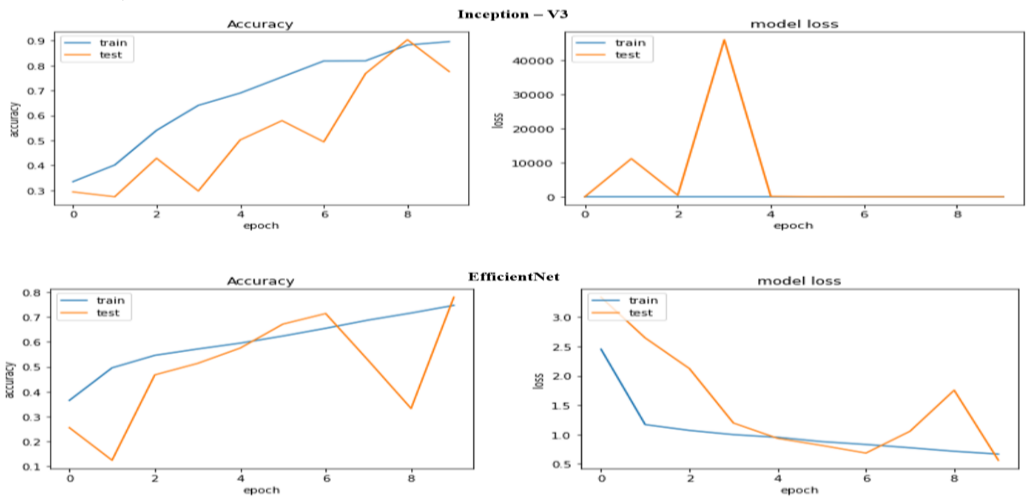

Figure 6 Accuracy and Model Loss

iii. Evaluation Metrices

Table 4 Evaluation Parameters

	EfficientNet	Inception-V3
Accuracy	78	76
Precision	76	94
Recall	98	86
F1-Score	85	90

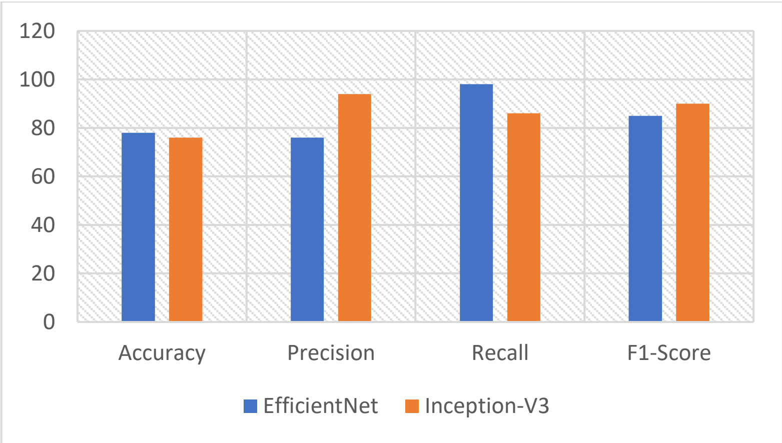

Figure 7 Graphical representation of evaluation parameters

Table 5 Sensitivity and Specificity

	EfficientNet	Inception-V3
Sensitivity	97.7	99.5
Specificity	97.84	86.02

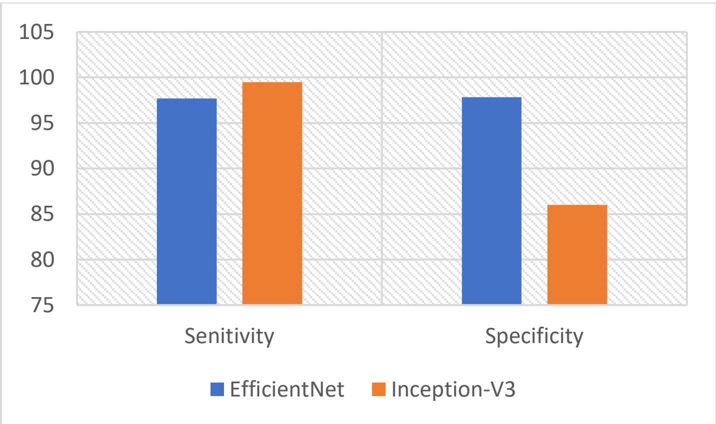

Figure 8 Graphical representation of sensitivity and Specificity

The results depicted in table- 4,5 and figure-5,6,7,8 InceptionV3 had an accuracy of 76%, while EfficientNet-B2 managed to achieve an accuracy of 78%. This indicates that the latter is better suited for this type of task as it can more accurately classify brain tumors. InceptionV3 performed better than EfficientNet-B2 in terms of precision. It had a score of 94%, which is higher than the latter's 76%. It also has a lower false-positive rate. The recall score is a measure of how many cases of brain tumors were correctly identified. Compared to InceptionV3, EfficientNet-B2 was able to get a recall score of 98%, which shows that it is more adept at identifying such cases. The F1 score, which represents the harmonic mean between recall and precision, was given to InceptionV3 by an algorithm with a score of 90.8%, as opposed to 85% for EfficientNET-B2. This indicates that InceptionV3, when it comes to handling recall and precision, is better than EfficientNet-B2. InceptionV3 was able to achieve a specificity score of 87.82% and a sensitivity score of 97.94%, which indicates that it is better at identifying brain tumors. On the other hand, EfficientNet-B2 was able to achieve a sensitivity of 97.7% and an accuracy of 97.84%. The results indicate that EfficientNet-B2 and InceptionV3 are good candidates for classification of brain tumors on MRI scans. EfficientNet-B2 performed better in terms of specificity, sensitivity, and accuracy, but InceptionV3 was able to perform better in terms of F1 score and precision. These findings have important implications for the treatment and diagnosis of brain tumors.

Conclusion and Future scope

The results of this study revealed that DL models can accurately identify brain tumors using MRI scans. The two models, EfficientNet-B2 and InceptionV3, were able to achieve high accuracy. InceptionV3 performed better on F1-score and precision. The ability of DL models to accurately identify brain tumors is a significant advance in the field of oncology. It enables the timely diagnosis and appropriate treatment of patients with this disease. One of the main directions that researchers are working on is to develop hybrid systems that combine the strengths of the two DL models. This method could lead to the development of a more accurate and robust classification model. In addition, other methods such as reinforcement learning and transfer learning could also be used to improve the accuracy of the models. The findings of this study demonstrate the potential of deep neural networks to improve the classification of brain tumors using MRI images. It also proposes the development of a hybrid system that combines the strengths of these models.

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