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TRANSFER LEARNING APPROACH USING EFFICIENTNET ARCHITECTURE FOR BRAIN TUMOR CLASSIFICATION IN MRI IMAGES

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Abstract

Researchers are focusing to automate the identification as well as diagnosis of brain tumors due to its rise. As we know that there is a diverse range in tumor functionalities, that's why multi-grading brain tumor classification has become a prominent research concern. Since tumor diagnosing process is extremely tedious when we implement it in a manual manner. Because the effectiveness of the prediction is associated here to radiologist's expertise, then there comes a computer-aided diagnostic system into picture. Hence, we need a methodology which requires less pre-processing as well as able to conduct effective implementation instead of traditional machine learning approaches. Currently transfer learning is very prominent in deep learning since it allows researchers to train deep neural networks with very little data. EfficientNet architectures are implemented to classify brain tumor. With the help of transfer learning, EfficientNet architectures are trained. Transfer learning based on CNN and by using EfficientNet B0 as well as EfficientNet B7 model that utilized weights from the ImageNet dataset to categorize between 4 common brain tumor categories such as no tumor, pituitary, meningioma, glioma brain tumors on publicly available dataset from kaggle has been implemented here in this research work. This dataset contains 3264 brain MRI images. Accuracy achieved using both the models which is calculated along with various performance measures such as Accuracy, precision, F1-score, specificity, sensitivity. Highest Accuracy achieved is 98%. The findings show that the approach can be used to classify brain tumors in several categories.

1. Introduction

Brain tumors are recognized as the 10th leading risk factor and reason of

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death in individuals as observed. Since the year 2000, June 8 has been marked as World Brain Tumor Day aimed at educating individuals about brain tumors. A brain tumor is a condition in which abnormal cells begin to proliferate uncontrollably in the brain or spinal cord. Based on genetic characteristics and histology, the World Health Organization (WHO) classified brain tumors into four groups (I, II, III, and IV) in 2016. When a brain tumor has progressed to a more advanced stage, the patient's life expectancy is reduced significantly. The major tests for tumor diagnosis and grade assessment include a neurological examination, imaging, biopsies, and biomarkers. Experts end up choosing magnetic resonance imaging (MRI) as a pre-and post-treatment imaging tool for determining the tumor's nature. It facilitates in surgical resection planning and disease status analysis. T1W (T1-weighted MRI), T1Wc (T1-weighted with contrast enhancement), T2W (T2-weighted), as well as T2Wc with fluid-attenuated inversion recovery (FLAIR) have all been used to study tissue features. The full tumor diagnosis is a time consuming and difficult process. Which might include several phases: (a) physical/neurological inspection, (b) tumor detection, (c) analyzing the tumor's surface area, thickness, and position (d) debridement surgery (along with biopsy), (e) tissue characterization as well as tumor categorization selection. Suitable strategy to classify tumor has always been biopsy. It visualizes tissue/cell properties, for example colours, patterns, configurations, and combinations to validate how deadly a tumor is. Doctors still depend on biopsy as being primary technique for stage assessment as well as to detect cancer. Biopsies on the other hand take time, and can be deadly as well as fatal as being intrusive.

As the number of cancer patients grows, we need a non-invasive, computer-aided diagnostic (CAD) tool that can accurately and consistently assess tumor grade in a short amount of time. Three types in brain tumors include pituitary adenoma, glioma as well as meningioma, which is according to where tumor is located in the brain. Brain tumors, like other types of tumors, are generally classified into two types: benign tumors, which are non-cancerous, and malignant neoplasms, which are very damaging and cancerous. The growth of these two kinds of tumors inside the skull puts pressure on the brain, which may be fatal to a person's life. In Figure 1 brain tumor MRI Images categories are shown.

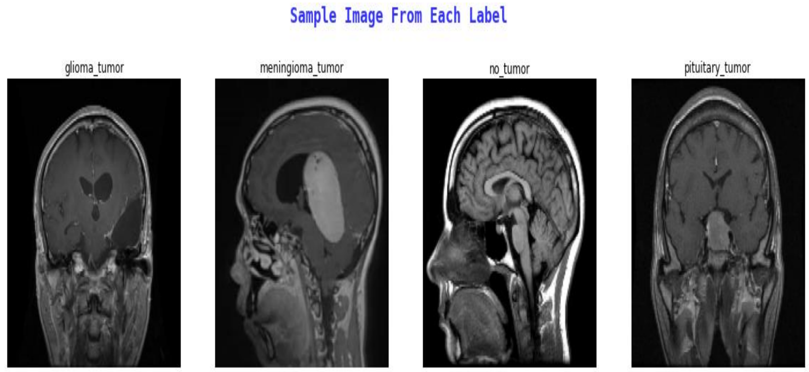

Figure 1. Brain tumor categories.

2. Literature Survey

In [1], while using CE-MRI dataset through figshare, that analysis offers an integrated effective algorithm for three types of brain tumor categorization. Deep transfer learning has been used to characterize brain MRI images with the help of 9 architectures that are pre-trained. This research work introduced satisfactory results by using particular dataset in less time. Accuracy achieved is 98.71% which has surpassed all the current techniques.

In [2], Authors offers a technique that is based on artificial intelligence as well as transfer learning. In past studies, the multiclass technique was not used to classify brain tumors. Five clinically significant multiclass datasets had all been formulated, tested, as well as trained upon 7 techniques which are from machine learning as well as deep learning, especially regarding linear discrimination, support vector machine, decision tree, convolution neural network (AlexNet), naive bayes, ensemble, k-nearest neighbor, with the help of 3 protocols (K2, K5, and K10) to divide the dataset. For all multiclass datasets, the deep learning model CNN i.e. AlexNet outperforms other machine learning classifiers. With all cross validation Methods the maximum classification accuracy is 100%.

In [3], with the help of transfer learning and fine-tuning brain tumor has been classified. Transfer learning as well as fine-tuning (block wise) provides an alternative to employ a pre-trained CNN as feature extractor that helps in training a distinct classification algorithm. It also illustrates how learning from natural images may be used to analyze and classify brain MRI scans. It has been noticed that proposed technique proved to be great since handmade features are not utilized, preprocessing is less, and accuracy of 94.82% is attained when tested 5 times.

In [4], to classify low-grade gliomas and high-grade gliomas deep multi-scale 3D CNN architecture is implemented. By obtaining an overall accuracy of 96.49 % using the validation dataset, the suggested technique outperforms techniques that has been used in past.

In [5] Deep transfer learning networks with the help of 4 optimization algorithms i.e. RMSprop, Adam, Adadelta, SGD (Stochastic Gradient Descent) on figshare dataset whereas accuracy is calculated with the help of accuracy metrics and area under the curve. Transfer learning methods that are implemented here have performed very well as compared to past research works. Accuracy in ResNet50 with the help of Adadelta is 99.02 %.

In [6], brain tumors in 3 categories (glioma, pituitary and meningioma) have been classified here in this work utilizing AlexNet, VGGNet as well as GoogleNet CNN architectures. After that, it has been implemented with the help of transfer learning methods i.e. freezing and fine-tuning. Data augmentation techniques are included in order to increase dataset samples, improve results, and to reduce overfitting. Fine-tune VGG16 architecture achieved the maximum detection as well as classification accuracy 98.69%.

In [7], Authors compared several pre-trained DCNN models using transfer learning to classify brain tumors. Combining pre-trained DCNN models with transfer learning proved successful to gain high accuracy. Here AlexNet model achieved accuracy of 100%, 94% and 95.92% for all three datasets.

In [8], Authors discriminated brain tumor types with 94.2% accuracy using a tactic via genetic algorithm as well as CNN. Deep neural network was also used by [9] to categorize brain cancers at an accuracy of 96.13%.

In [10], Authors developed 2 different feature extraction perspectives: NLBP that also generated the key points dependent on an angle value and LBP that also assessed pixel value regarding relationship on pixel encompassing peers. As classifiers, they also used KNN, RF, ANN, AIDE as well as LDA. While including NLBP to extract all the features as well as KNN model, they seem to have been successful in obtaining the maximum accuracy of 95.56%.

In [11], the authors utilized convolutional neural network architecture and attained a classification accuracy of 84.19% for their classification task. Another technique suggested by [12] employed transfer learning as well as GoogleNet gained with classification accuracy of 97.1%. This approach obtained 97.1% classification accuracy.

[13] Segregated dataset among 2 groups: cancer and non-cancer tumors, biologists were using eight-layered CNN structure is implemented with 100% accuracy in binary classification.

The brain, that encompasses massive amounts of cell types, are among the most critical and delicate organs in the human body. The unconstrained segment and accumulation of undesirable cell gatherings within these even around brain is tumor. Above type cell seems to have the capacity to affect cognitive performance and destroys healthy cells [14]. Brain tumors are separated into two categories: high grade, III and IV as well as low grade, I and II in order to accurately analyze the constraints and different sorts of brain tumors is imperative for diagnostic imaging.

3. Methodology

3.1 Proposed Method

3.1.1 Transfer Learning. Transfer learning is a technique that applies a framework knowledge gained through one dataset as the basis for a model trained on a different dataset as shown in figure 2 and figure 3. That process has been utilized in a wide range deep learning dimensions, such as image classification. A straightforward solution is to replace the classification layer with a framework trained on ImageNet, a dataset with some fourteen million pictures, then start training the framework with a more particular function. It thus empowers the system's beginning levels to extract highly explainable preferences from the huge dataset, designed to allow the adapted model's subsequent layers to include the nuances of the smaller dataset. Transfer learning can be considered for diversifying a neural network's base of knowledge. For illustration, a CNN model that can distinguish between a donkey and horse could be re-trained to increase its information or data and be able to identify buffalo as well, or it could be re-trained to distinguish between goat and wolves instead, reusing some of the non-inheritable data from learning to distinguish donkey and horse. A trained network might be a prerequisite for transfer learning. Transfer learning appears to require smaller dataset or knowledge inside the training dataset than consistent training. The key reasons for deploying transfer learning also provide a lack of research or knowledge, or even the timeframe involved in training a CNN from scratch.

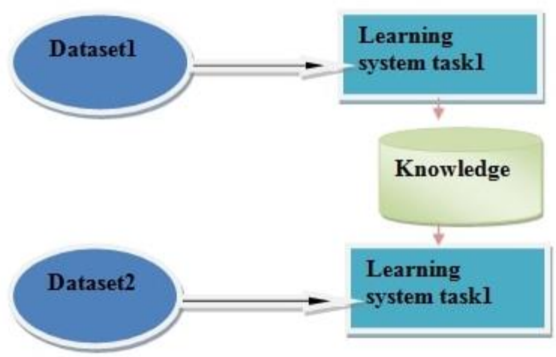

Figure 2. Transfer learning approach.

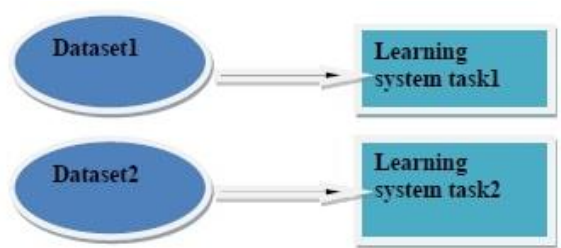

Figure 3. Traditional approach.

3.1.2 EfficientNet. EfficientNet are among the most accurate methods (permitting the minimal FLOPS for estimation) which really meets State-of-the-Art effectiveness across both ImageNet and conventional image classification transfer learning objectives, as originally created by Tan and Le in 2019 as shown in figure 4. EfficientNet delivers a family of models (B0 to

B7) that exhibit an interesting contrast of precision and accuracy on an array of products by presenting a hybrid method scaling the algorithm. Since 2012, ImageNet dataset models have risen highly robust, due to this achieved accuracy has been increased, although many are ineffective in terms of computational burden. The EfficientNet model may be regarded as a set of CNN models since it achieves highest accuracy i.e. 84.4% utilizing 66M parameters with the help of ImageNet classification task. EfficientNet produces quite robust outcomes via evenly expanding density, range, and sharpness. Under a given resource restriction, the initial step in the compound scaling technique is to look for a grid to determine the relationship between the multiple scaling dimensions of the baseline network. This method determines an appropriate scaling factor for the depth, breadth, and resolution parameters. The fundamental building element for EfficientNet is the inverted bottleneck MBConv, which was initially introduced in MobileNetV2, but is utilized somewhat more than MobileNetV2 owing to the higher FLOPS (floating point operations per second) budget. Blocks in MBConv are made up of a layer that expands and then compresses the channels, thus direct connections are utilized between bottlenecks with far fewer channels than expansion layers. When compared to standard layers, this design contains in-depth separable convolutions that reduce calculation by approximately K2 factor where k is the kernel size which specifies the width and height of the 2D convolution window.

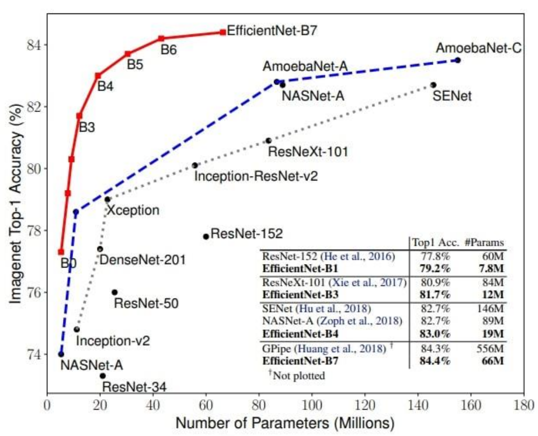

Figure 4. EfficientNet and CNN models comparison [15].

4. Experiments

After partitioning the dataset into training, validation and test sets, the method is intended for loading and obtaining images and labeling from raw datasets followed by preprocessing and augmentation strategies. The suggested experiment's framework is then outlined preceded by hyper-parameter setup, regularization approaches and optimization technique. And then estimations for network training and performance are generated.

4.1 Dataset. In this proposed architecture brain MRI images are used from kaggle publicly available dataset. In this dataset total 3264 images are used. And we divide dataset into 2870, 394 training as well as test set respectively as shown in table 1 and 2 respectively.

Table 1. Training data.

Tumor	Images
Meningioma	822
Glioma	826
Pituitary	827
No tumor	395

Table 2. Testing Data.

Tumor	Images
Meningioma	115
Glioma	100
Pituitary	74
No tumor	105

The initial stage is to upload the image data in the directories to a Python list then resize the list and subsequently transform it to numpy arrays. Image size is 150×150. For data augmentation we used ImageDataGenerator here in this work to classify brain MRI images. When the problem isn't really simplified well enough in machine learning from training to new dataset then this is considered as overfitting. It is one of the trickiest difficulties in applied machine learning that you might recognize.

Though first ever point is to understand exactly your model's overfitting. This is the time when perfect cross-validation comes into picture. You can avoid this by applying regularization or training with more data after you identify the problem. However, you may not have additional information to add to your initial data set sometimes. It could also be the wrong path to acquire and label additional data points. It is certainly going to bring better results in many cases, but it will take a long time and cost a great deal of time in terms of work. Data augmentation (DA) emerges around here. If you want to avoid overfitting or if the initial dataset is too small to train on or perhaps even if you'd like to get more performance out of your model using DA is a recommended approach. Then dataset is divided into 2 parts training and testing. The dataset through which the study has been conducted (biases as well as weights) such a data has been used and learned by the model this is called training dataset. The test set is almost always used to review measurement models. Once switching the labels to numerical values applied one hot encoding on them.

Modifying the model weights from pre-trained model derived for popular computer vision benchmark datasets, such as the ImageNet image recognition tasks, is one approach to speed up this process. Top-performing models may be downloaded and used right away or they can be included into a new model to solve your own computer vision issues. The EfficientNetB0 as well as EfficientNet B7 model is utilized that would take weights from the ImageNet dataset. Top option is set to False, which means the network doesn't include the pre-built model's top layer/output layer allowing us to create our own output layer based on our use case. GlobalAveragePooling2D, Dropout and dense layer are added to the model. Global Average Pooling 2D is such a layer that works in a similar way to the Max Pooling layer in CNNs except for maybe that it pools utilizing Average values rather than Max values. This tremendously minimizes the overall strain on the computer all through training. Dropout layer removes most of the neuron from the layer at each stage allowing the neurons to be more independent. It aids in the avoidance of overfitting. The neurons that will be omitted are chosen at random. The rate parameter is the probability of a neuron activity being set to 0 and therefore the neuron being dropped out. Dropout is among the most popular regularization methods. At every training epoch, we eliminate neurons from the network at random.

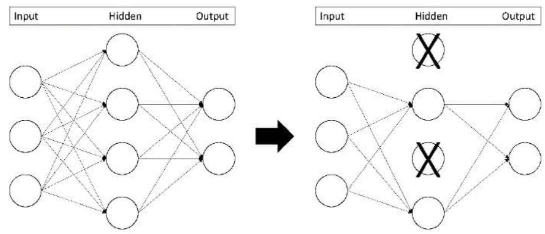

Figure 5. Before and after drop out.

Dense layer is the output layer that sorts the image into one of four categories. It makes use of the softmax function, which is a sigmoid function generalized. After that model is compiled Adam optimizer is used. Callback functions are added to the model for training. Here epoch is 50 and batch size is 40. TensorBoard, ModelCheckpoint and ReduceLROnPlateau callback functions are used here. A callback is a version of attribute which are used to facilitate motives at discrete periods of the learning phase. TensorFlow comes with a simulation tool called TensorBoard. The ModelCheckpoint callback has been used in terms of dealing with model.fit () training to access a methodology or weights at a given step so that the model or weights are sometimes stacked eventually to undergo training either from saved state. Keras alternatively also seems to have a ReduceLROnPlateau callback that diminishes the learning rate from a certain portion when it reaches a plateau. Out of the four main occurrences, the largest value in each row indicates the expected output. So that we can determine the index associated with the expected outcome using argmax. In this 0, 1, 2 and 3 depicted as 0 - Glioma Tumor, 1 - Meningioma Tumor, 2 - No Tumor, 3 - Pituitary Tumor. Argmax is a prerequisite for ensuring the parameter that produces the target function's optimal solution. In machine learning Argmax has often been used to choose the class with the highest projected probability.

4.2 Performance Measures. Confusion Matrix: figure 9 and figure 12 shows confusion matrix for both models EfficientNet B0 as well as EfficientNet B7. Basic architecture of confusion matrix is also there which is with respect to predicted as well as actual values that are shown in figure 6.

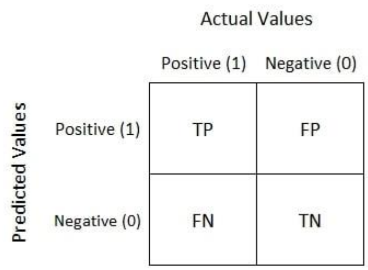

Figure 6. Basic Confusion matrix.

The sensitivity of a classifier is expressed as the fraction between the amount of data that was suitably classified correctly and the amount of data that was really positive. The specificity of a classifier is expressed as the fraction between the amount of data that was suitably classified negative and the amount of data that was really negative precision is from all positive points how many are still properly categorized as positive. TP accurately classified by a diagnosis test is known as sensitivity, also known as recall. It measures how efficient this classifier has been in order to classify tumor categories. The true negative ratio (TNR) of a diagnostic test indicates the classifier's capacity to foresee the negative condition. The positive predictive rate (PPR) is known as precision. The F1-Score is a metric that measures recall and precision in classification. The proposed method's overall classification accuracy in terms of TP and TN is called accuracy.

Precision, Sensitivity, Specificity, and Accuracy have been calculated as follows.

$$\text{Recall} = \frac{TP}{Tp + FN} \qquad \text{Sepecificity} = \frac{TP}{TN + FP}$$

$$\text{Precision} = \frac{TP}{Tp + FN} \quad F1\,score = 2^{*}(\text{Precision} * \text{Recall})/(\text{Precision} + \text{Recall})$$

$$\text{Accuracy} = \frac{TP + TN}{Tp + FP + FN + TN}$$

The number of positive predicted occurrences that are really positive is known as True Positive (TP). True Negative (TN) refers to the number of predicted negative cases that are also true negative. False Negative (FN) is the number of predicted negative cases that turn out to be positive, also known as (type 2) error. False Positive (FP) is the number of predicted positive cases that turn out to be negative, also known as (type 1) error.

5. Results

(i) EfficientNet B0 with epoch = 50, batch size = 40

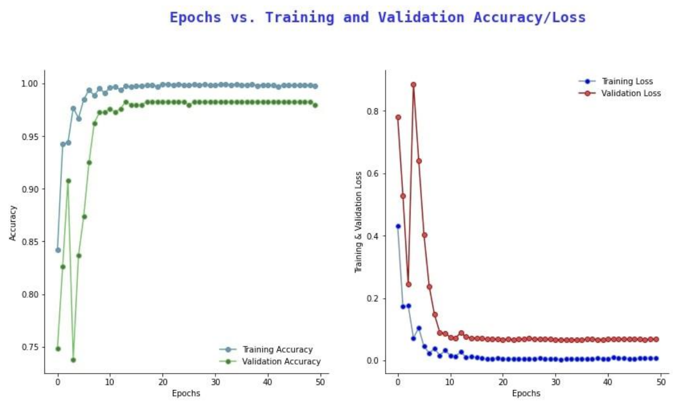

Figure 7. Training and validation Accuracy and loss Plot.

	precision	recall	f1-score	support
0	0.96	0.96	0.96	93
1	0.96	0.96	0.96	95
2	0.98	1.00	0.99	52
3	0.98	0.97	0.97	87
accuracy			0.97	327
macro avg	0.97	0.97	0.97	327
weighted avg	0.97	0.97	0.97	327

Figure 8. Precision, recall, F-score, support.

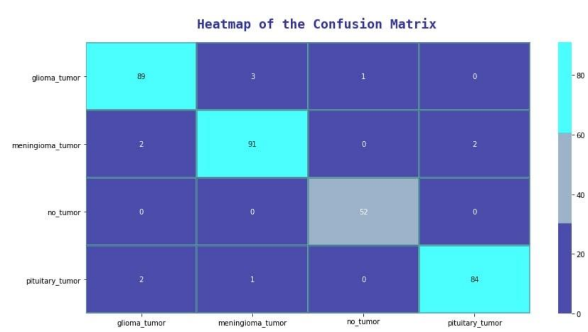

Figure 9. Confusion Matrix of Proposed EfficientNet B0 model.

(ii) EfficientNet B7 with epoch = 50, batch size = 40

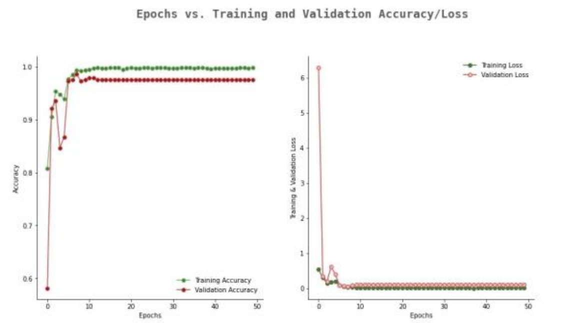

Figure 10. Training and validation Accuracy and loss Plot.

	precision	recall	f1-score	support
0	0.98	0.96	0.97	93
1	0.98	0.97	0.97	95
2	0.95	1.00	0.97	52
3	0.99	0.99	0.99	87
accuracy			0.98	327
macro avg	0.97	0.98	0.98	327
weighted avg	0.98	0.98	0.98	327

Figure 11. Precision, recall, F-score, support.

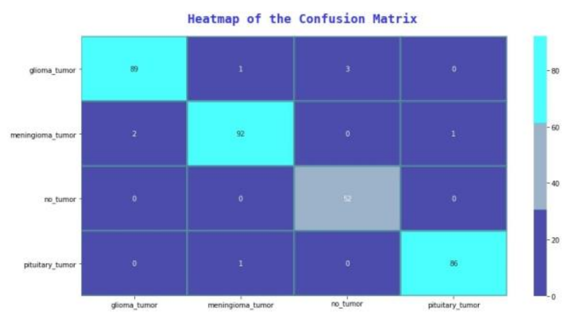

Figure 12. Confusion Matrix of Proposed EfficientNet B7 model.

6. Conclusion

For image processing and pattern identification deep learning approaches have been emerged in recent times. An automated kind of mode is proposed in this paper to classify MRI images of tumor of brain on publicly available Data set of kaggle. In this study EfficientNet deep learning architecture (EfficientNet B0 and EfficientNet B7) is proposed to classify the brain tumor into 4 types meningioma, glioma, pituitary, no tumor. It yields satisfactory accuracy with a constrained amount of training inputs and epochs, permitting for a faster processing time. EfficientNet architecture is trained using transfer learning approach. EfficientNet B0 and EfficientNet B7 model to categorize between 4 common categories such as no tumor, pituitary, meningioma, glioma brain tumors on publicly available dataset from kaggle. This dataset contains 3264 brain MRI images. Accuracy achieved is 98% using both the models which is calculated along with accuracy, precision, F1-score, specificity, sensitivity.

7. Future Scope

In the future, a new convolutional neural network design and transfer leaning with a different architecture may be used to classify brain tumors with greater accuracy and outcomes. Computer aided diagnosis (CAD) and deep learning methods may also be used to determine the form and size of a tumor. It has been observed that we can use vision Transformer technique to classify brain tumor. It is an emerging technique with good results. The Vision Transformer is an image classification strategy that utilizes a Transformer kind of design to classify over image patches. An image is broken down into tiny patches. A flattened vector (2D to 1D) of neighboring pixels from a patch with a particular size should be used as the input sequence. Each flattened piece is put into a linear projection layer ultimately in a "Patch embedding". The picture's positioning metadata is then conserved by attaching position embeddings to the succession of image patches in a linear fashion. It adds information to the sequence understanding of the relative or absolute positions of the picture patches. According to the orientation of the image patch, an incremental learnable (class) embedding is appended to the sequence. Despite having updated by self-attention, this class embedding is utilized to examine the initial image's class. Simply stacking an MLP Head on top of the Transformer at the region of the extra learnable embedding that we added to the sequence is enough to do the classification.

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