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Automation of Brain Tumor Identification using EfficientNet on Magnetic Resonance Images

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Abstract

The general method for classification of brain tumors is through biopsy, but biopsy is performed only after a surgery where a small tissue is removed from the brain and examined under a microscope to determine if it is a tumor. Due to the advancement in technology especially in machine learning and artificial intelligence, it is possible for us to determine and classify a tumor without performing any surgery and feeding the present data of various MRI images to the machine for classification. Through our work, we put forward a technique for the detection of tumors by using EfficientNet, a pre-trained model using the approach of transfer learning. This paper focuses on three models from the family of models of EfficientNet namely EfficientNet-B2, EfficientNet-B3, and EfficientNet-B4. The proposed framework not only uses the pre-trained model to improve the performance of training a better model but also uses thresholding to improve the dataset for better accuracy and data augmentation for increasing the number of images in the dataset. Preliminary outcome shows that the family of models of EfficientNet performs better than previous CNN architectures because to scale all dimensions of depth, width, and resolution of an image with a constant ratio it uses the compound coefficient. The results also demonstrated that by scaling the baseline architecture the model is able to capture complicated features and thus the overall performance of the model is improved.

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Keywords: Transfer learning(TL); Data augmentation; Deep learning; Brain tumour; Convolutional neural network

1. Introduction

The application of machine learning in the domain of biomedical sciences has proven to be quite efficient since machine learning can describe the data better than biomedical models. It not only provides engineering solutions but also can be useful for advanced understanding [1], [2]. One such instance is the utilization of machine learning in the detection of brain tumour. Scientists are still working on one infallible cure for cancer at any stage of severity, but early detection of cancer might help in the prevention of death. Tumours are of two types benign and malignant. Benign tumours are noncancerous and do not metastasize which means they lack the ability to spread throughout the body. On the other hand, malignant tumours are cancerous, they can invade the nearby tissues and spread throughout the body forming other secondary tumours [3], [4]. There are various imaging technologies to obtain the

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required information for brain tumours like positron emission tomography (PET), Magnetic Resonance Imaging (MRI), and computed tomography (CT). Among all these technologies MRI is an extensively used technique on account of its advantageous characteristics. The use of 2D and 3D formats in the MRI provides relevant information about the shape, position, size, and type of brain. By developing a computer aided diagnosis (CAD) to automate the detection of a brain tumour the workload of manually reviewing the images which is a hectic and time-consuming process can be significantly reduced [5],[6],[7],[8]. The high inter and intra shape, contrast variations, and texture of the images obtained from MRI are a challenging problem to overcome [9], [10]. By using a traditional approach of machine learning (ML) techniques for classification the features would need to be manually extracted while the CNN models can extract the relevant features automatically, thus significantly improving the performance. Nevertheless, acquiring a large amount of data for training a deep learning-based model is a challenge [11], [12],[13]. To overcome this, this work provided a solution to use the concept of transfer learning to train a model on a large dataset and use that trained model with the dataset of brain images obtained from MRI to improve the accuracy and performance of the model.

In recent times a variety of work and research has been done on brain tumour detection using MRI for developing an automatic classification solution with high accuracy and performance. However, due to the contrast variations and different shape textures, it is still a challenge. Rao et al. [14] performed pixel-wise classifications by learning deep representations for each pixel based on its every modality (T1, T1c, T2, and Flair) thereafter combining them to form a multimodal representation for each pixel, and the classification is done using a CNN model achieving an accuracy of 67%. Afshar et al. [15] achieved an accuracy of 86.56% by using 1 CNN layer with 64 attributes maps and 16 capsules of primary type. Saxena et al. [16] proposed to use pre-trained models which included Vgg16, InceptionV3, and ResNet50. The highest accuracy of 95% was obtained with ResNet50 among all the transfer learning methods used. Using CNN-LSTM the highest accuracy of 84% was achieved with VggNet-LSTM by Shahzadi et al. [17]. By using Singular Value Decomposition (SVD) for classification El Abbadi et al. [18] achieved an accuracy of 96.66%. However, the dataset used by them only had 20 normal and 50 abnormal data. Mohsen et al. [19] proposed to combine discrete wavelet transform (DWT) which is a powerful feature extraction tool and principal component analysis (PCA) with Deep Neural Network Classifier achieving an accuracy of 93.94%. Çinar and Yildirim [20] proposed to use an improved model for the detection of brain tumours. They designed this improved model by using ResNet-50 as a base model from which the last 5 layers were removed and 10 new layers were added increasing the layers number from 177 to 182. The additional layers added in the order were Relu, BatchNormalization, Dropout, Fully connected, Relu, Max pooling, Fully connected, Classification and softmax layers. On this system, they obtained the maximal accuracy of 97.01%.

In section 3 details materials and techniques are provided. Section more focus on the data set used, and the model designed is extensively examined. The experiments performed and the results obtained are presented in Section 4. Lastly, the conclusion derived from this article is presented in Section 5.

2. Materials and Methods

This study had been carried out for detecting the presence of a brain tumour. Fig.1. illustrates the suggested framework. In the first stage, the images were pre-processed to eliminate irrelevant sections from each image, and the images were then augmented to increase the number of images in the dataset. In the second stage, the pre-processed MRI dataset was used to train the model obtained by using the weights of the pre-trained model. In the third stage of the experiment, the images were classified into images having the presence of tumour and images with no tumour.

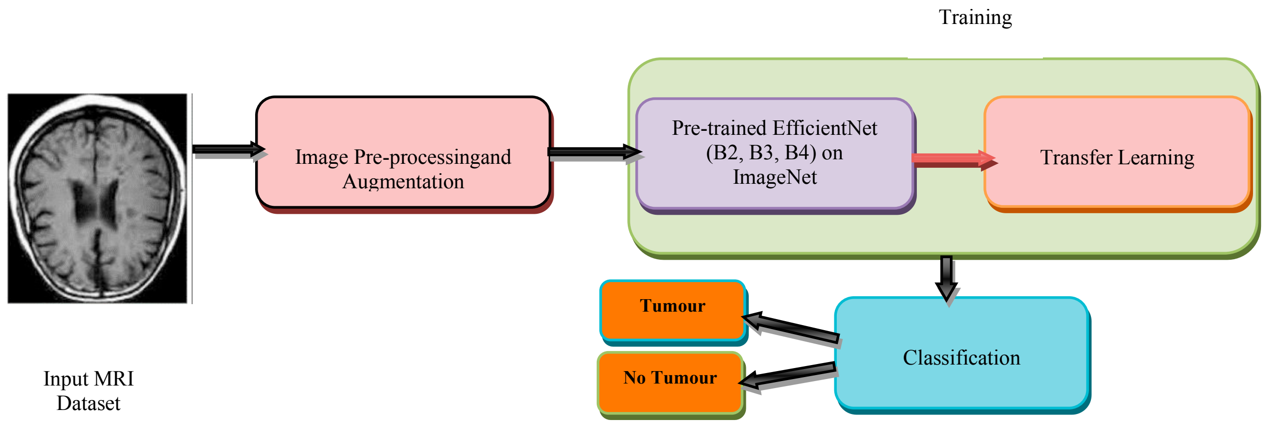


Fig.1. Workflow of proposed framework

2.1. Image Dataset and Image Pre-processing

The image dataset that was used in this proposed method was the brain tumour detection 2020 dataset collected from Kaggle. Out of the 3000 images present in the dataset, the number of images that contain tumours is 1500 and the remaining number of images without tumours is 1500. Therefore, this dataset consists of the normal class and tumour class. The images in the dataset contained many undesired spaces and corners entailing poor classifications. First and foremost, it is essential to crop the undesirable areas and keep only the relevant parts of the image. The images were cropped by finding extreme points in contours. After loading the original dataset, the magnetic resonance (MR) images are converted to grayscale and slightly blurred followed by the conversion of the MR images to binary images using thresholding. Thresholding allows for segmenting the brain region from the rest of the spaces. The largest contour of the threshold images was then found which we presume to be the brain region. We then find the four extreme points (extreme right, extreme left, extreme top, extreme bottom) as seen inFig.2. Hence, we finally crop the images using the information of the extreme points and contour. Different MR images in the dataset have different sizes, heights, and widths.

We have used data augmentation to increase the number of pictures as the dataset used is not very huge. In data augmentation, random transformations are performed and various copies of an original image are created but with different scaling, orientation, and so on. By augmenting the dataset, the accuracy of the classification model is improved. In the data augmentation performed by us, we have used 8 augmentation strategies which are rotation, horizontal shifts, vertical shifts, scaling, shearing, brightness, and horizontal and vertical flipping. The dataset was subdivided into three sets in which 2000 images were used for the training sample, 600 images for the validation sample, and 400 images for the testing sample. The images were resized to the size of (180x180) pixels.

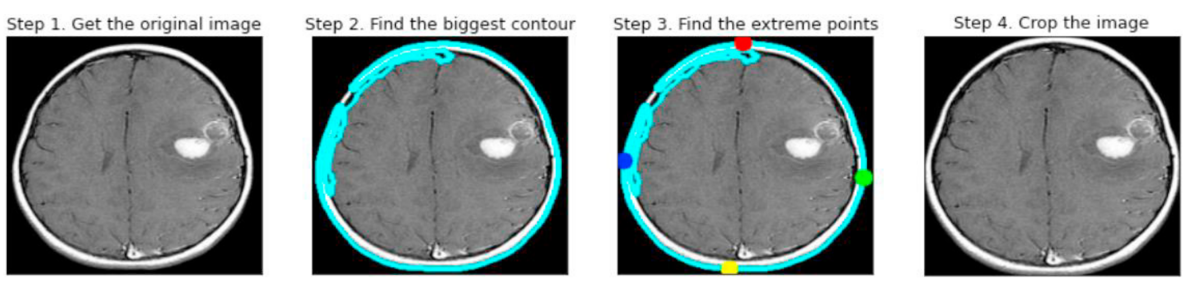


Fig. 2. Finding the extreme contours using thresholding and cropping the images

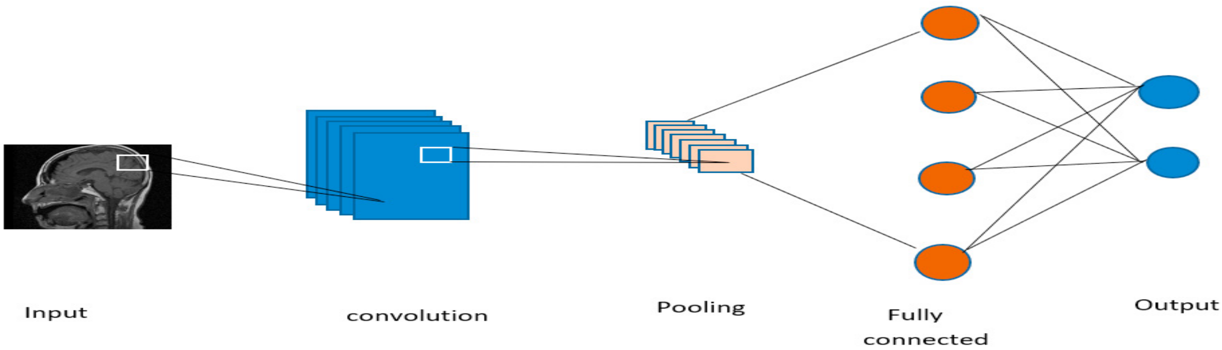


Fig. 3. Convolutional neural network (CNN) Architecture.

2.2. Convolutional Neural Network

CNN is a class of neural networks in deep learning which takes an input images and assigns bias and weight to a variety of objects in the image in order to classify them among one another. CNN reduces an image into a form that is easier to process without compromising the relevant and prominent features required for an accurate prediction, the architecture of CNN can be seen in Fig.3. The three main components of CNN are:

- A convolutional layer extract the low level and high level attributes. Now first convolutional layer is supervise for drawing out low level attributes and as we keep adding more convolutional layers the architecture is able to mine the high level attributes as well.
- A pooling layer is added to reduce the computing power to execute the data using reduction of dimensionality, in which the spatial size of the extracted feature is reduced.
- After applying the convolutional and pooling layer the model is successfully trained to understand the features. The final output is flattened and fed to a Fully Connected (FC) layer to classify images into different classes.

2.3. Transfer Learning

In general, by providing a very large dataset it can be notice the performance of CNN is finer compared to a small dataset. Ideally it is not always possible to train a model with a huge amount of data, the concept of transfer learning is used in such cases which is depicted in Fig.4. In transfer learning a model is pre-trained on a vast standard dataset (e.g., Image-Net [21]) which can then be used as an attribute extractor for a comparatively smaller dataset such as the MR images dataset. Transfer learning is being widely used in recent years in various fields like X-ray baggage security screening, lung pattern analysis and so on [22], [23], [24]. It improves the efficiency and provides a more generalized approach to leverage different algorithms for solving new challenges [25].

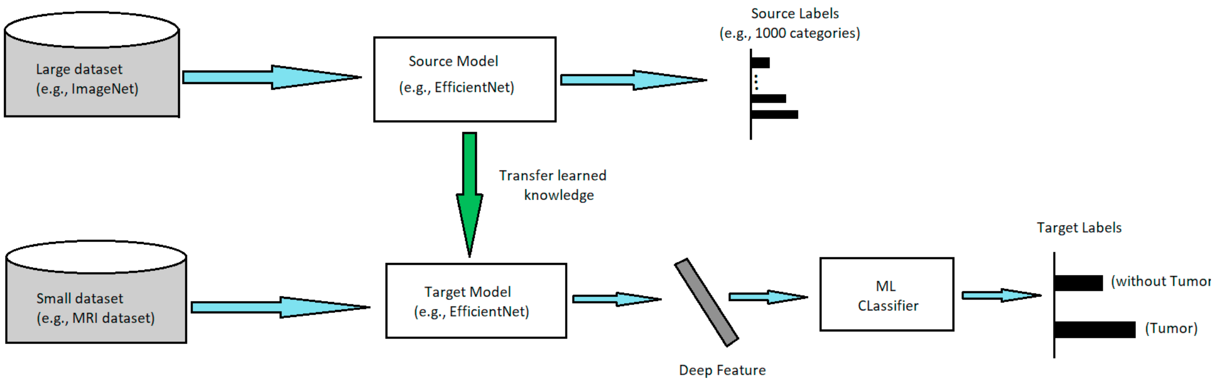


Fig. 4. The concept of Transfer Learning

2.4. EfficientNet Architecture

A variety of pre-trained models like VGG-16, ResNet50, and Inception V3 have been used in several fields for image classification. In 2019 a CNN architecture called EfficientNet [26] was introduced which uses compound coefficients for effective scaling. The architecture scales up the dimension of width, resolution and depth of resources available in a constant ratio without compromising the efficiency of the model. By using the AutoML MNAS framework for neural architecture search a new baseline network was developed on which the compound scaling method is dependent that improves both the accuracy and efficiency (FLOPS). This architecture uses mobile inverted bottleneck convolution (MBConv). With constant use of the compound scaling technique to scale up the baseline family of models was obtained (EfficientNet-B1 to EfficientNet-B7).

In this paper we have used EffecientNet-B2, EfficientNet-B3, and EffecientNet-B4 for brain tumour detection using an MR images dataset. After the pre-processing and augmentation of the images, the weights of the EfficientNet-B2, EfficientNet-B3, and EffecientNet-B4 were pre-trained on the Image-Net databank were used for better training of the model. We added a global max-pooling layer followed by a dropout operation with a rate of 0.2 to prevent over-fitting. Sigmoid was used as the activation function which applies a non-linear transformation to the input.

Sigmoid: $f(x) = \frac{1}{1+e^{-x}}$, $f(x) = f(x)(1 - f(x))$

In the fully connected (FC) layer loss function also called the error function is used to calculate the prediction error of the network. We have used the binary cross-entropy loss function.

Binary Cross-Entropy: $H_p(q) = -\frac{1}{N}\sum_{i=1}^{N} \quad y_i \, log \, log\big(p(y_i)\big) + (1 - y_i) log\,(1 - p(y_i))$

We have updated the weights of the layers using Adaptive moment estimation (Adam), an optimizer that compute the adaptive learning rate of each parameter. We run each method for 150 epochs.

3. Experiment Analysis

Three sets of experiments were carried out for brain tumour detection using the MR images dataset. In each set three different models of EfficientNet were utilized to classify the presence of tumour. One of the most important metrics used for the evaluation of a model's performance is the confusion matrix since other evaluation metrics can be derived from this table.

The confusion matrix is evaluated using four performance measures: True negative (TN), False positive (FP), False negative (FN), True positive (TP). Now TN reflects the number of MR pictures with no tumour which was correctly classified as no tumour. The FP reflects the number of MR images with no tumour that was misclassified as having the presence of tumour. The TP reflects the number of MR images with the presence of tumour that was correctly classified as having the presence of tumour. The FN reflects the number of MR images with the presence of tumour that was misclassified as having no tumour.

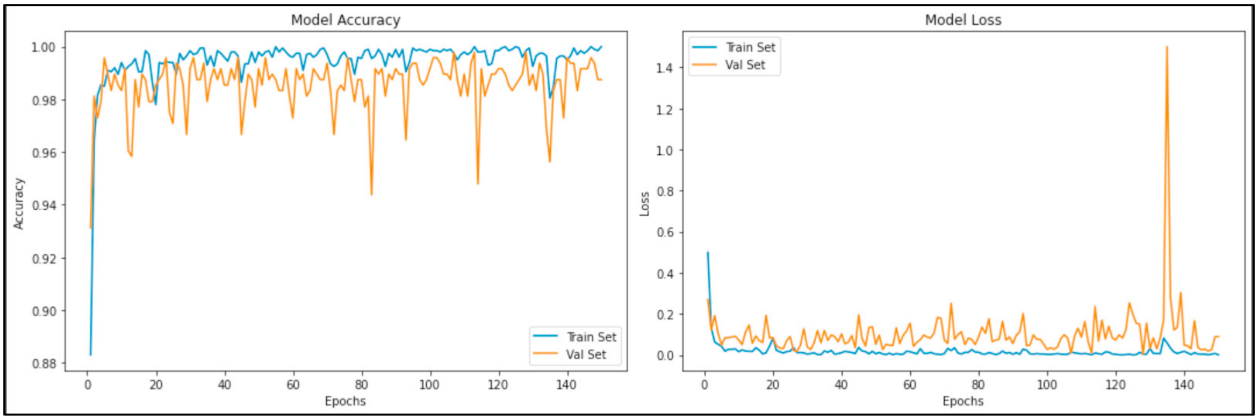
Accuracy: It gives us the fraction of predictions our model got right. It is the ratio of number of accurate predictions to entire number of predictions.
Accuracy = (TP + TN) / (TP + TN + FP + FN)

Sensitivity (Recall): It is the proportion of actual positives that got predicted correctly as positives.
Sensitivity/ Recall = TP / (TP + FN)
Precision: It gives the fraction of correctly identified positives out of all predicted positives.
Precision = TP / (TP +FP)

F1 score: It is the harmonic mean of precision and recall of the model. It considers both precision and recall for computation.
F1 score = (2 * Precision * Recall) / (Precision + Recall)

Specificity: It is the proportion of actual negatives that got predicted correctly as negatives.
Specificity = TN / (TN + FP)

In the first set of experiments, the weights of the pre-trained system EffecientNet-B2 were used. By training the network with the system, the accuracy and loss curves obtained are depicted in Fig 5. As it can be shown from Fig. 5 the training accuracy of the system is ~99%. The accuracy obtained on the validation set was 98.75% while the accuracy obtained on the test set was 100%. The performance criteria of EfficientNet-B2 are given in Table 1.



(a) (b)

Fig.5. (a) Training and validation accuracy curves. (b) Training and validation loss curves for EfficientNet-B2

Table 1. Performance Criteria of EfficientNet-B2

Criteria	Estimates
Accuracy	100
Sensitivity	1
Specificity	1
F- score	1

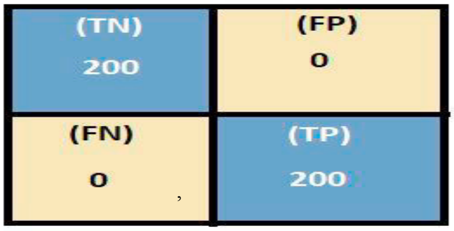
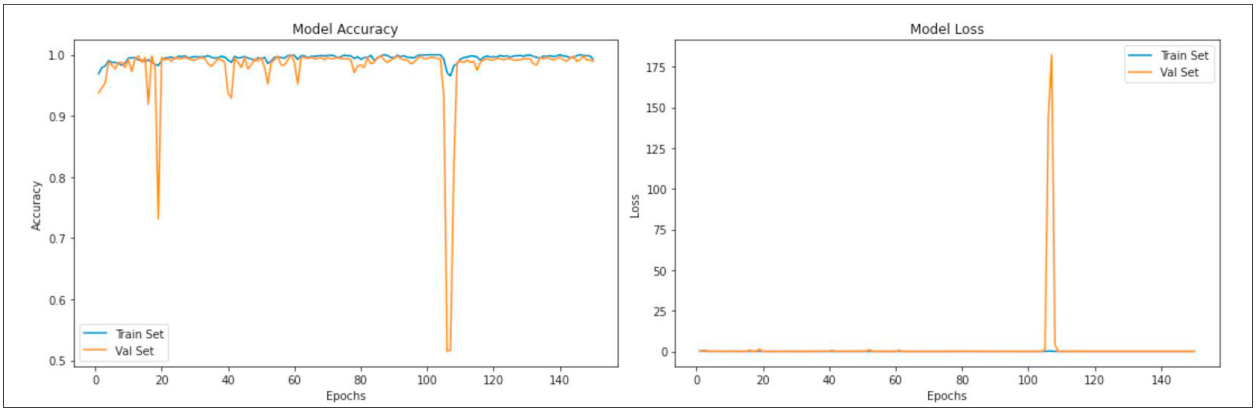


Fig.6. Confusion Matrix for EfficientNet-B2

Now in second phase of experiments, the weights of the pre-trained model EffecientNet-B3 were used. By training the network with the model the accuracy and loss curves obtained are depicted in Fig 7. As it can be seen from Fig 7. the training accuracy of the model is ~99%. The accuracy obtained on the validation set was 98.33% while the accuracy obtained on the test set was ~99%. The performance criteria of EfficientNet-B3 are given in Table 2.



(a) (b)

Fig.7. (a) Training and Validation Accuracy Curves. (b) Training and Validation Loss Curves for EfficientNet-B3

Table 2. Performance Criteria of EfficientNet-B3

Criteria	Estimates
Accuracy	99
Sensitivity	0.985
Specificity	0.995
F- score	0.989

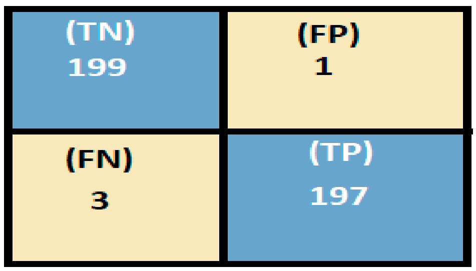
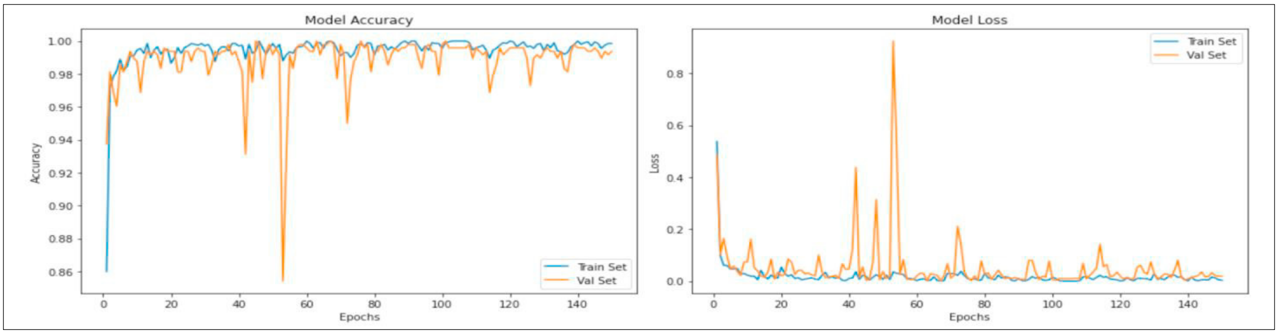


Fig.8. Confusion Matrix for EfficientNet-B3

In the third set of experiments the weights of the pre-trained system EffecientNet-B4 were used. By training the network with the model the accuracy and loss curves obtained are depicted in Fig.9. As it can be shown in Fig 9. the training accuracy of the model is ~99%. The accuracy obtained on the validation set was 99% while the accuracy obtained on the test set was 99.5%. The performance criteria of EfficientNet-B3 is given in Table 3. Experimental outcomes strongly suggest that the EfficientNet-B2 method can be more effective and can improve significantly overall detection of the Computer-Aided Diagnosis (CAD) system especially for MRI brain images. Compare to other deep learning approach, performance criteria of EfficientNet-B2 technique gain more accuracy.



(a) (b)

Fig.9. (a) Training and validation accuracy Curves. (b) Training and validation loss Curves for EfficientNet-B4

Table 3. Performance Criteria of EffecientNet-B4

Criteria	Estimates
Accuracy	99.5
Sensitivity	0.99
Specificity	1
F- score	1

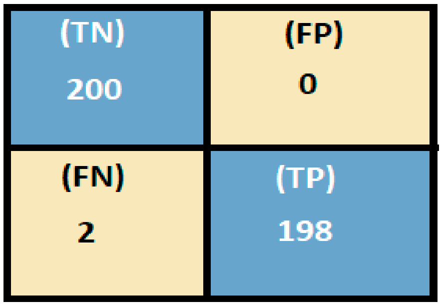


Fig. 10. Confusion Matrix for EfficientNet-B4

Some works of other authors in the detection of brain tumour along with our work are mentioned in Table 4. It shows the comparison of outcomes between the proposed method and existing methods.

Table 4. Some works of other authors in detection of brain tumour

author	year	methods	Accuracy (%)
Rao et al. [1]	2015	Enhanced Technique	67.0
Abbadi et al. [20]	2016	SVD	96.6
Mohsen et al. [19]	2017	DWT	93.9
Shahzadi et al. [17]	2018	VggNet-LSTM	84.0
Afshar et al. [15]	2018	Enhanced Technique	86.5
Saxena et al. [16]	2020	ResNet-50	95.0
Çinar& Yildirim	2020	Improved Model	97.0
Proposed Method	2022	EfficientNet	99.5

5. Conclusion

The paper aimed to detect brain tumours using convolutional neural networks (CNN) and MR images as a dataset. In our proposed framework we used a pre-trained model which is EfficientNet that involved the basic of TL to overcome the limited number of samples and also prevented manually scaling the model for training. By using EfficientNet architecture for the detection of brain tumours we obtained better results than existing CNN architectures. In this framework, the images were resized, cropped, and augmented to further enhance the training accuracy of the system. The use of EfficientNet-B2, EfficientNet-B3, and EfficientNet-B4 from the family of models of EfficientNet presented a consistent improvement in the accuracy of the models. While ResNet can be scaled up from ResNet-18 to ResNet-200 to achieve better accuracy when more resources are made available, it is still tedious to manually tune the methods and still not obtain a greatly optimized result. As seen in the ResNet-50 obtained an accuracy of 95% for tumour detection which is less compared to each of the three models of EfficientNet. We see that in order to scale up efficiently all the dimensions of width, perseverance and depth of the image should be scaled together with an optimal balance and not just scaled individually. Due to the huge reduction in computations required with EfficientNet, it opens up new opportunities for convolutional neural networks to be used in mobile phones. We can further improve the performance by using the EfficientNet-B7 model which captures richer and more complex features. The proposed system can be extended to classify the different stages of a brain tumour in the future.

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