

Brain Tumor Classification using EfficientNet Models

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Abstract – A brain tumor refers to a cluster of aberrant brain cells in medical terms. The manual detection of brain tumor from brain MRI images is a difficult task, and sometimes it can cause misdiagnosis. Medical scanning has made it possible to detect brain tumors using imaging tools. They give clinicians a detailed image of the human brain. It is possible to detect early illnesses with sophisticated Artificial Intelligence and neural network classification models. In this paper, the brain tumor is detected from MRI brain images using a CNN model named EfficientNet. Four Efficient Net models i.e., EfficientNet B0, EfficientNet B1, EfficientNetB2, and EfficientNetB3 have been used for brain tumor classification. The performance of each model has been evaluated and the best model is found among the four models.

Key Words: Convolutional Neural Network, EfficientNet, Magnetic Resonance Image, Feature Extraction, Classification, Grey level run length matrix (GLRLM), Particle Swarm Optimization (PSO)

1. INTRODUCTION

A brain tumor is an abnormal mass of cells that proliferates and reproduces uncontrollably in the brain. To identify this disease and determine the type of brain tumor, doctors perform several tests [1]. The brain scan is used to analyze the tumor. The medical field has recently given increased attention to AI as a result of its successful applications. Classifying magnetic resonance images with artificial intelligence has gained much interest in medical image analysis. There are two general types of brain tumor classification. The first is the categorization of brain images into normal or abnormal classes, second is the classification of different stages of brain tumor.

This paper reviews and examines the brain tumor classification based on EfficientNet models. Here, based on the features extracted from the brain scan, an individual's MRI brain scan is categorized into either "tumor" or "no tumor." The methodology of brain tumor recognition using EfficientNet has been explained in are explained in Chapter 3. Chapter 4 shows the experimental results and performance comparison. The conclusion of the study is presented in Chapter 5.

2. LITERATURE REVIEW

A combination of the SVM classifier and Fuzzy C means has been used for detecting brain tumor in [2]. To obtain brain attributes, the grey level run length matrix (GLRLM) has been employed in this method. SVM classifiers are employed to determine whether a brain scan contains a tumor or not. The SVM classifier was trained by utilizing 96 of the 120 brain MRI scans and then tested using 24 remaining images. This method obtained a maximum of 91.66% accuracy in the classification task. The brain tumor was identified in [3] by utilizing the Naive Bayes Classifier. An evaluation of 50 brain scans found an overall accuracy of 94%, with an 81.25 percent tumor identification rate and a 100% non-tumor detection rate. Here, eight morphological traits and three intensity features have been derived from the segmented grayscale brain picture to categorize the tumor. The Naive Classifier is a supervised machine learning algorithm that is based on Bayes Probability theory.

In [4], two distinct deep learning-based methods for classifying and detecting brain tumors have been suggested. BRATS 2018 dataset has been used in this work. FastAi and YOLOv5 classification models were both accurate to 94.98 percent and 84.95%, respectively. Here, the classification model was constructed Based on ResNet34. To identify the brain tumor, [5] used a simple 8-layer convolutional neural network. A comparison of network performance with pretrained CNNs like VGG16, ResNet50, and InceptionV3 has been done to evaluate the network effectiveness. The proposed model achieved 96% training accuracy and 89% validation accuracy for brain tumor recognition. Here, the proposed system outperforms all other pretrained CNN models taken for comparison.

A brain tumor classification system based on Fuzzy C means algorithm and SVM have been proposed in [6]. Fuzzy C means algorithm is done for extracting brain features from MRI brain scan and SVM is used for classification of brain scan into 'tumor affected' or 'tumor not affected, class. The proposed detection system gives an accuracy of 97.89% accuracy. A brain image classification model that categorizes a person's brain scan into either the 'tumorous' or 'nontumorous' class has been implemented in [7] by utilizing Particle Swarm Optimization (PSO) based segmentation, and SVM classifier. PSO is used to partition the precise cancer region. A discrete wavelet transformation (DWT) is applied



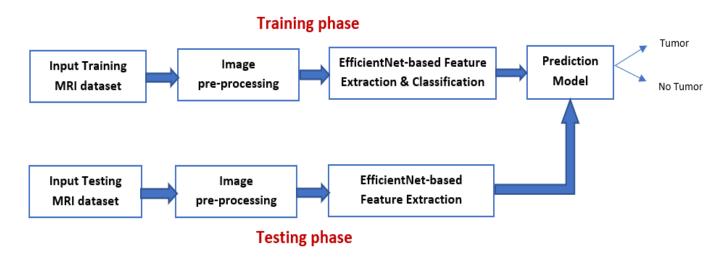


Fig.1: Block diagram of the proposed system

to the thirteen attributes that have been extracted to obtain brain features. Two SVM classifiers are used to classify brain images: a linear SVM and a radial basis function SVM. Here linear SVM gives an accuracy of 71% and radial basis SVM gives an accuracy of 85%.

3. METHODOLOGY

In this work transfer learning-based approach for classifying brain scans has been employed. EfficientNet models are used here for automatic feature extraction and classification of brain features. The brain tumor detection system consists of two phases. One is the training phase and the other is the testing phase. In the training phase, feature extraction and classification on the training data set are done to create a prediction model. In the testing phase, test data is fed to the prediction model to determine whether the person has the tumor or not. The main steps involved in both phases are i) input the MRI data ii) preprocessing iii) feature extraction and classification.

3.1 Input:

The two-dimensional Magnetic resonance image of an individual's brain is fed as the input to the system. The dataset is partitioned: as a training and testing set. Normally data is partitioned in 80:20 or 70:30 ratio. The dataset is collected from Kaggle.

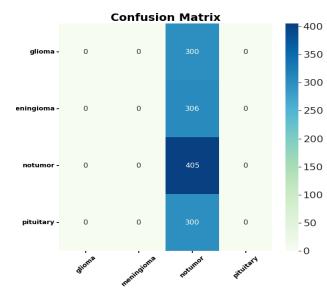
3.2 Pre-processing:

The two-dimensional MRI brain data are of non-uniform size. The EfficientNet architecture requires input dimensions of 224 \times 224. Therefore, the 2D brain images have been resized to a uniform dimension of 224 \times 224 \times 3.

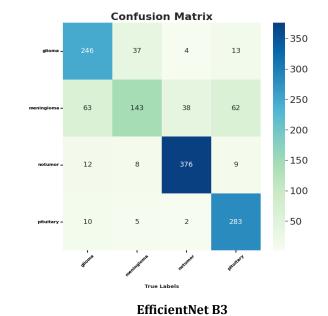
3.3 Feature extraction and classification:

Automatic feature extraction and classification of brain features for tumor detection is done by EfficientNet models. Four efficient models have been used here. They are EfficientNet B0, EfficientNet B1, EfficientNetB2, EfficientNet B3. The EfficientNet is a CNN architecture where every depth, width, and resolution parameter are scaled continuously by applying a compound coefficient. Here each dimension is consistently scaled with a predetermined set of scaling coefficients. This type of scaling increases model accuracy and efficiency [8]. There are 8 EfficientNet models i.e, EfficientNet B0-B7.Out of the 8 models EfficientNet B0-B3 has been used in this work. Every EfficientNet models have 5 modules. The number of sub-modules varies depending on the model. Mobile inverted bottleneck convolution layer, squeeze layer, and excitation layer makes up the core of EfficientNet. EfficientNet B0 consists of 18 convolution layers. Since they outperformed numerous other networks (including DenseNet, Inception, and ResNet) on the ImageNet test, EfficientNets are advised for classification jobs.

EfficientNet B0



EfficientNet B1



EfficientNet B2

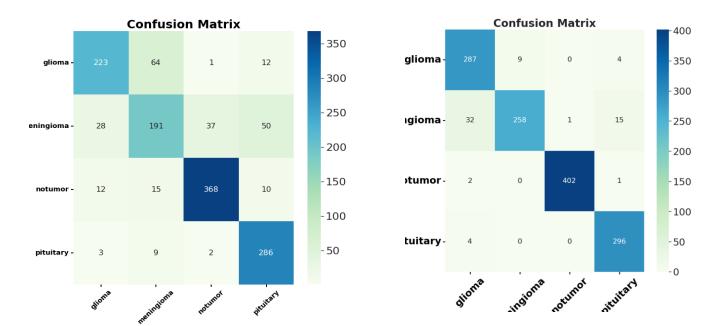


Fig 2: Confusion Matrix of EfficientNet models

0.8

Accuracy

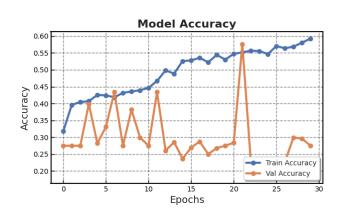
0.5

0.4

EfficientNet B0

EfficientNet B1

Model Accuracy







15

Epochs

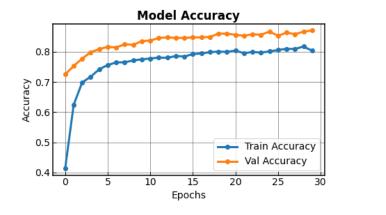
10

Train Accuracy

30

Val Accuracy

25



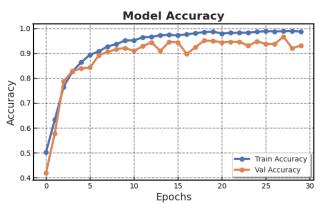


Fig 3: Accuracy Curves of EfficientNet models

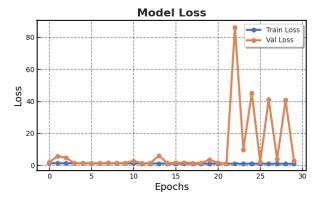
EFFICIENTNET MODEL	TRAINING ACCURACY	VALIDATION ACCURACY
EFFICIENTNET BO		
EFFICIENTNET B1	78.4%	85.2%
EFFICIENTNET B2		
EFFICIENTNET B3	98.89%	93.1%

Table 1: Accuracy of EfficientNet models

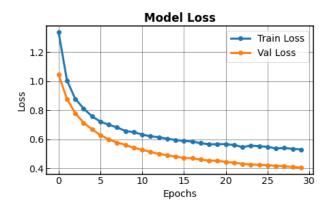


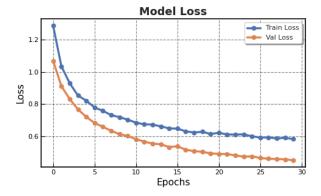
EfficientNet B0



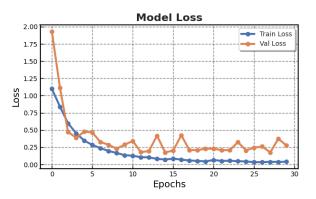


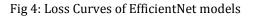






EfficientNet B3





EFFICIENTNET MODEL	ROC-AUC SCORE
EFFICIENTNET B1	0.8616
EFFICIENTNET B3	0.9639

Table 2: ROC AUC score of EfficientNet models

International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056

IRJET Volume: 09 Issue: 08 | Aug 2022

www.irjet.net

4. RESULTS

Two-dimensional MRI images from Kaggle which are resized to a uniform dimension of 224×224×3 are fed as input to the system. 5712 images were used for training and 1311 images were used for testing. Out of the four EfficientNet models, EfficientNet B3 provides higher accuracy in brain tumor classification task. EfficientNet B3 gives 98.8% training accuracy and 93.1% testing accuracy and outperforms all the other EfficientNet models. The least accurate was EfficientNet B0. This network model gives a low training accuracy score of 58.7% and a validation accuracy score of 27.5%. The accuracy and performance comparison of various models are given in Table 1 and Table 2.

5. CONCLUSION

An abnormal proliferation of brain cells can affect the brain's functionality. Detecting a brain tumor early can result in a faster response to treatment, increasing survival chances [8]. Brain tumors are often detected using MRI brain scans. With the development of AI methods, CNN, a deep learning approach, can be used to categorize MRI images for tumor determination. In this work, automatic brain tumor detection using four CNN EfficientNet models (EfficientNet B0-B7) has been done and found the best one. In comparison to EfficientNet B0-B2 models, EfficientNet B3 shows the best performance for brain tumor classification. In the future, EfficientNet B4-B7 can also be used to classify brain tumors and check if the accuracy of detection has increased.

REFERENCES

- https://www.mayoclinic.org/diseasesconditions/brain-tumor/symptoms-causes/syc-20350084
- [2] Parveen and A. Singh, "Detection of a brain tumor in MRI images, using a combination of fuzzy c-means and SVM," 2015 2nd International Conference on Signal Processing and Integrated Networks (SPIN), 2015, pp. 98-102, DOI: 10.1109/SPIN.2015.7095308.
- [3] H. T. Zaw, N. Maneerat and K. Y. Win, "Brain tumor detection based on Naïve Bayes Classification," 2019 5th International Conference on Engineering, Applied Sciences and Technology (EAST), 2019, pp. 1-4, DOI: 10.1109/ICEAST.2019.8802562.
- [4] N. M. Dipu, S. A. Shohan and K. M. A. Salam, "Deep Learning Based Brain Tumor Detection and Classification," 2021 International Conference on Intelligent Technologies (CONIT), 2021, pp. 1-6, DOI: 10.1109/CONIT51480.2021.9498384.
- [5] Khan, H. A., Jue, W., Mushtaq, M., & Mushtaq, M. U. (2020). Brain tumor classification in MRI image using convolutional neural network. *Math. Biosci. Eng*, 17(5), 6203-6216.

- [6] A. Halder and O. Dobe, "Detection of tumor in brain MRI using fuzzy feature selection and support vector machine," 2016 International Conference on Advances in Computing, Communications and Informatics (ICACCI), 2016, pp. 1919-1923, DOI: 10.1109/ICACCI.2016.7732331.
- [7] A. Dixit and A. Nanda, "Brain MR Image Classification via PSO based Segmentation," 2019 Twelfth International Conference on Contemporary Computing (IC3), 2019, pp. 1-5, DOI: 10.1109/IC3.2019.8844883.
- [8] T. Mantha and B. Eswara Reddy, "A Transfer Learning method for Brain Tumor Classification using EfficientNet-B3 model," 2021 IEEE International Conference on Computation System and Information Technology for Sustainable Solutions (CSITSS), 2021, pp. 1-6, DOI: 10.1109/CSITSS54238.2021.9683036.
- [9] K. Duvvuri, H. Kanisettypalli and S. Jayan, "Detection of Brain Tumor Using CNN and CNN-SVM," 2022 3rd International Conference for Emerging Technology (INCET), 2022, pp. 1-7, doi: 10.1109/INCET54531.2022.9824725.
- [10] M. Gurbină, M. Lascu and D. Lascu, "Tumor Detection and Classification of MRI Brain Image using Different Wavelet Transforms and Support Vector Machines," 2019 42nd International Conference on Telecommunications and Signal Processing (TSP), 2019, pp. 505-508, doi: 10.1109/TSP.2019.8769040.
- [11] M Monica Subashini and Sarat Kumar Sahoo, Brain MR Image Segmentation for Tumour Detection using Artificial Neural Networks, vol. 5, no. 2, Apr-May 2013.
- [12] G. Karayeğen and M. F. Akşahin, "Brain Tumor Prediction with Deep Learning and Tumor Volume Calculation," 2021 Medical Technologies Congress (TIPTEKNO), 2021, pp. 1-4, doi: 10.1109/TIPTEKN053239.2021.9632861.
- [13] V. Zeljkovic et al., "Automatic brain tumor detection and segmentation in MR images," 2014 Pan American Health Care Exchanges (PAHCE), 2014, pp. 1-1, doi: 10.1109/PAHCE.2014.6849645.
- [14] K. T.K. and S. Xavier, "An Intelligent System for Early Assessment and Classification of Brain Tumor," 2018 Second International Conference on Inventive Communication and Computational Technologies (ICICCT), 2018, pp. 1265-1268, doi: 10.1109/ICICCT.2018.8473297.
- [15] G Rajesh Chandra, Kolasani Ramchand and H Rao, "Tumor detection in brain using genetic algorithm", *7th International Conference on Communication Computing and Virtualization Elsevier*, 2016.