Grenze International Journal of Engineering and Technology, June Issue

Enhanced Brain Tumor Detection with Efficient Net: Leveraging Pre-trained Networks for Improved Classification Performance

Nagarjun A[1] and Manju N[2]
[1,2]Department of Information Science and Engineering, JSS Science and Technology University, Mysuru, India

***Abstract*—For timely diagnosis and treatment planning, brain tumors must be accurately categorized from medical images. EfficientNet model, a recent deep learning model for its fast processing of image classification problems, serves as the foundation of the novel approach we introduce in this paper for categorizing brain tumors. By proportionally scaling depth, width, and resolution with compound scaling, EfficientNet achieves peak accuracy within the model at reducing computational complexity. We apply the EfficientNet model to categorizing various types of brain tumours in MRI scans and evaluate its performance on a publicly available dataset of images of pituitary, meningioma, and glioma tumours. In order to warrant correct early diagnosis and treatment planning, brain tumours need to be properly classified through medical imaging. Here, we utilize the EfficientNet model, one of the advanced deep learning architectures that is widely recognized for its high-performance results in image classification, to introduce a new approach of brain tumour classification. Compound scaling, where the depth, width, and resolution are scaled equally, is how EfficientNet designs model accuracy with reduced computational complexity.**

***Keywords*— Brain Tumor, Medical imaging, Efficient Net, Deep learning.**

I. INTRODUCTION

Cancer occurs when cells develop abnormally and uncontrollably anyplace in the body. Lymphoma, lung, breast, skin, blood, and heart cancers are among the roughly 200 different forms of cancer.The leading cause of low life expectancy among many individuals of various ages and genders is brain tumors, a prevalent and severe disease. It usually happens when the brain's tissues suddenly and bizarrely extend. The quantity of these aberrant cells does not stay the same rather, they proliferate quickly and start to spread. The central nervous system controls a number of body processes [1]. Because the brain is essential for decision-making, brain tumors pose a major risk to human life. The improper development or buildup of brain cells is a hallmark of a brain tumor. The amount to which these tumors may impact a person's life depends on a number of variables, including the tumor's size, kind, location, and the availability of efficient treatment choices. These can arise in different parts of the brain and often don't show any symptoms until they get to more severe stages. For radiologists, it could be very hard to specify the precise location of a tumor. The brain tumor is typically found and imaged through the use of CT or MRI scans. For retrieval of brain cells for analysis, biopsy is usually done as an initial clinical procedure prior to brain surgery. Accurate brain tumor measurement and diagnosis are required in order not to incur any quality or technique flaw.

Grenze ID: 01.GIJET.11.2.715
© Grenze Scientific Society, 2025

Early detection of malignant cancers is required to enhance the medically improved outcomes of patients. Due to its high-quality imaging, MRI is the most used technique for the diagnosis of such malignancies. As it provides more specific information regarding the tumor, more precise diagnosis can be made particularly with contrast-enhanced MRI. Studies are ongoing to take advantage of the use of contrast agents and enhance MRI diagnosis even further.

The inside arrangement of organs, such as the brain, can also be seen by Computed Tomography (CT) scans. However, since MRI data are enormous in quantity, manually segmenting tumors that requires radiologists' knowledge is a highly challenging process. One of the brain tumors is glioma [2].

The remaining brain tumors are meningiomas and pituitary adenomas. Gliomas develop near glial cells, meningiomas develop near the outer cover of the brain, and pituitary tumors develop in the pituitary gland. Diagnosis is crucial to ensure proper treatment. The dramatic increase in brain tumor deaths over the past few years emphasizes the importance of diagnosis. Since biopsies may be hard to obtain on brain tumors, MRI is often used to diagnose such conditions.

II. LITERATURE REVIEW

The suggested approach [3] using VGG-16 and light-weight CNN models for tumor segmentation and classification of certain brain tumors like glioma, meningioma, and pituitary tumors. The model showed a high accuracy rate of 95.71% on the dataset, thus establishing the ability of CNNs to automate tumor classification and enhance diagnostic accuracy.

But the work does not cover comparisons with alternative state-of-the-art deep learning methods, which would have additionally contributed to analyzing its efficiency. The methodology adopted [4] utilized pre-processing methods to filter images for their quality, where 3x3 kernels were used to undertake segmentation operations. The loss function was optimized utilizing the Gradient Descent Algorithm for training the model efficiently. The findings highlight the ability of CNNs to detect brain tumors accurately but also underscore the need to optimize training time.

It focuses on a comprehensive approach integrating MRI-based tumor segmentation with survival prediction models. Using a deep learning-based segmentation technique, the authors extracted 4,524 features from the segmented tumor regions, ensuring detailed characterization of the tumor's morphology and intensity patterns. To refine the features, a decision tree-based feature selection process and cross-validation were employed. For survival prediction, a random forest model was utilized to classify patients into short-survivor, mid-survivor, and long-survivor categories, achieving a classification accuracy of 61%. Despite this promising result, challenges such as under-segmentation of tumor regions were noted, potentially affecting the overall model's performance. The model employs pre-processing techniques to enhance MR images and subsequently uses CNN for feature extraction and analysis.

The study reports a high detection accuracy of 92.78% and an impressive 97.9% accuracy for tumor classification, showcasing the efficacy of CNNs in this domain. However, the paper lacks specific details about the CNN architecture used, making it difficult to replicate or assess the model's complexity [5][6]. It presents a hybrid approach combining AdaBoost, Random Forest algorithms along with Otsu's Thresholding technique is used for image segmentation, ensuring accurate delineation of tumor regions. AdaBoost achieved a superior accuracy of 95%, outperforming the Random Forest model.

While the results are promising, the study provides limited information regarding the specific implementation details of the AdaBoost and Random Forest algorithms, making it difficult to reproduce the results. Furthermore, the paper lacks comparisons with more advanced deep learning. The study focuses on three types of tumors: glioma, meningioma, and pituitary gland tumors, along with healthy brain images. The authors propose a 2D Convolutional Neural Network (CNN) and a convolutional auto-encoder network for brain tumor classification [7] [8].

Both networks were trained using specific hyperparameters, achieving an impressive 96.47% training accuracy, and the auto-encoder reaching 95.63% which leverages transfer learning. The approach utilizes two pre-trained models, DenseNet121 and ResNet101 [9], for feature extraction and classification. DenseNet121 achieved an accuracy of 95%, outperforming ResNet101.

This demonstrates the effectiveness of DenseNet121 [10] in capturing complex tumor features for multi- type classification tasks. However, the paper provides limited details regarding the specific implementation of these models, such as the layers used or the training process, which hinders a comprehensive understanding of the methodology. Despite this, the results indicate the potential of transfer learning and deep feature fusion in enhancing brain tumor classification accuracy.

III. METHODOLOGY

Early brain tumor detection can be difficult; however, Fig. 1 illustrates how deep learning is widely used to categorize the four different kinds of brain tumor images. EfficientNet has surpassed the use of conventional deep learning algorithms such as CNN in tests of object detection and classification.

A. Dataset

The dataset is screened from the brain tumor MRI repository which is classified into four classes namely meningioma, pituitary, glioma and no tumor consisting of 7,023 MRI images.

B. Data-Preprocessing

By employing visual components such as graphs, charts, and maps, data visualization tools facilitate the identification of patterns and anomalies in data. The dataset of brain MRI images is divided into four classes in Figure 1.

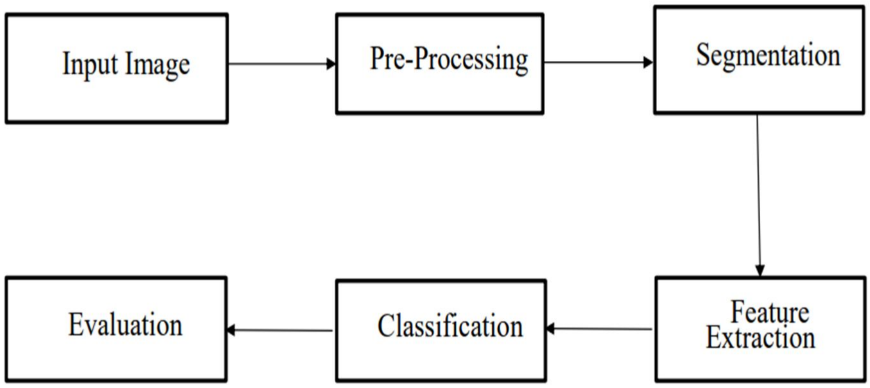

Fig. 1. Methodology

C. Image Segmentation Using Decoder and Encoder

Segmenting an image entail separating the foreground from the background or arranging pixels in groups based on how similar their colours or shapes.

Encoder: This is where max pooling and convolutions are carried out. We removed 16 convolutional layers from the original fully linked layers. While performing 2 × 2 max pooling, the corresponding max pooling indices are saved.

$\alpha : X \rightarrow F$

$\beta : F \rightarrow X\ \varphi$

$£ = \arg\min ||\, X - (£ \circ \varphi)\, X^2 ||$ (1)

The original data X is mapped to a latent space F in the encoder function, denoted by α We utilize the decoder function, denoted by £ , to extract the data from the bottleneck. In this case, the outcome is identical to what you get when you entered it. We try to reconstruct the original image, which is provided in Eq. (1), following some typical nonlinear compression. Equation (2) provides the activation function, which is used to transfer the standard neural network function and represents the latent dimension z in the encoding network.

$Z = ¥\,(Wx + b)$ (2)

This can also be used to characterize the decoding network, while Eq. (3) provides a large variety of weights, biases, and activation functions.

$X^1 = ¥^1\,(W^1 z + b^1)$ (3)

Decoder: The decoder performs convolutions and up sampling. At the end of each pixel is a softmax classifier. The encoder layers remember their maximum pooling indices before sampling. Ultimately, each pixel's class is predicted using a K-class softmax classifier. The segmented image is shown in Fig 2.

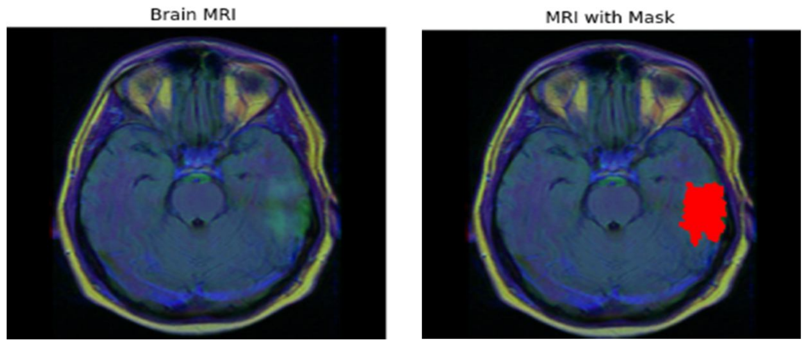

Fig. 3 Segmentation of Brain MRI image

IV. SYSTEM IMPLEMENTATION

Convolutional Neural Networks are designed to take into consideration the spatial structure of the input. CNN's hidden layers frequently include convolutional, pooling, fully connected, RELU (activation function), and normalizing layers. The features are automatically extracted. The CNN architecture of brain MRI images is shown in Figure 3

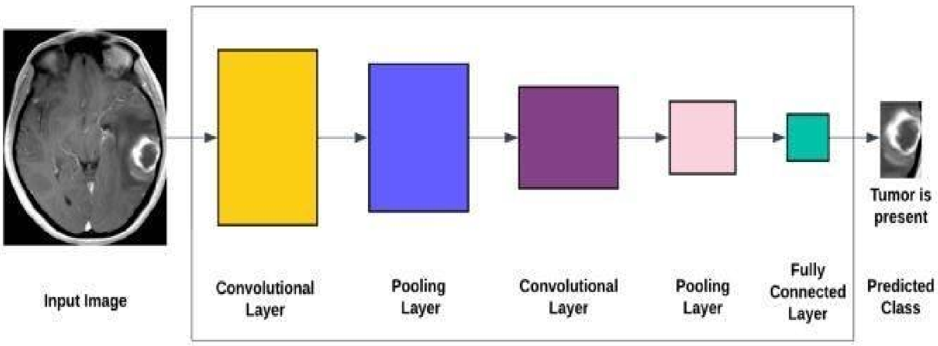

Fig. 3 CNN architecture for Brain MRI images

The model underwent 30 epochs of training with a learning rate of 0.001. The training and validation accuracy learning curves are plotted over 30 epochs in Figure 4, and the loss is displayed in Figure 5. As the validation loss is noticed more often, the training accuracy decreases, but it increases with each iteration. The obtained model's accuracy is 92.30%.

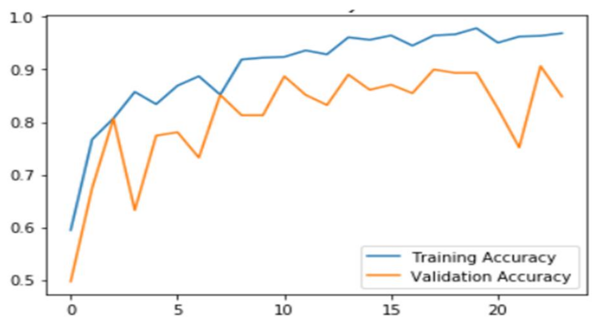

Fig. 4 CNN model accuracy

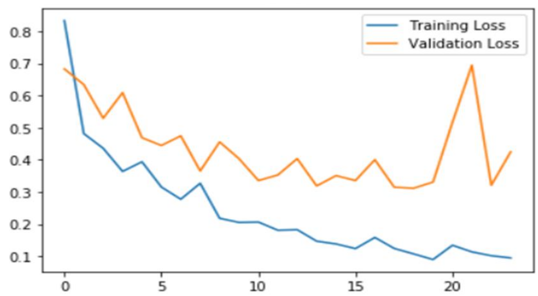

Fig. 5 CNN model loss

The model is trained for 30 epochs with a learning rate of 0.001 using EfficientNetB0. The training and validation accuracy learning curve is plotted over 30 epochs in Figure 6, and the loss is shown in Figure 7. The training accuracy increases but decreases with each repetition as the validation loss is observed more frequently. The model's obtained accuracy is 99.50%.

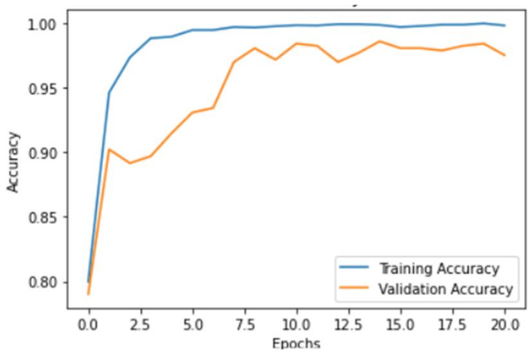

Fig. 6. EffiecientNetB0 model accuracy

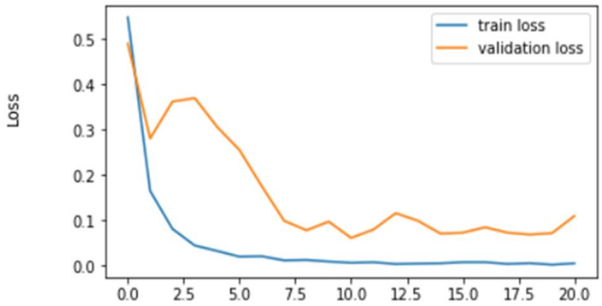

Fig. 7. EffiecientNetB0 model loss

TABLE 1. COMPARISON OF TRAINING THE MODEL

Architecture	**Accuracy**
CNN	92.30
EffiecientNetB0	99.50

V. CONCLUSION

The term "brain tumor" refers to a mass of abnormal brain cells. It usually happens when the brain's tissues suddenly and bizarrely extend. The quantity of these aberrant cells does not stay the same; rather, they proliferate quickly and start to spread. The central nervous system controls a number of body processes. Because the brain is essential for decision-making, brain tumors pose a major risk to human life. The improper development or buildup of brain cells is a hallmark of a brain tumor. The amount to which these tumors may impact a person's life depends on a number of variables, including the tumor's size, kind, location, and the availability of efficient treatment choices. Early brain tumor detection can be difficult, however deep learning is widely used to categorize the four different kinds of brain tumors like meningioma, pituitary, glioma and no tumour were screened from Brain MRI images dataset repository consisting of 7,023 MRI images. In object detection and classification tests, efficientNet has outperformed all other approaches using deep learning techniques like Convolutional Neural Networks (CNN). Data pre-processing tasks like encoder and decoder were employed. The model was trained with the learning rate of 0.001 for 30 epochs. The accuracy of the model obtained is 92.3% for CNN where as in EfficientBetB0 the training accuracy obtained is 99.5% with a learning rate of 0.001 for 30 epochs.

REFERENCES

[1] Waghmare V.K, Kolekar M.H. (2020) "Brain Tumor Classification Using Deep Learning."
[2] Oneza Tehreem Khan and Rajeswari D (2021) "Brain Tumor detection Using Machine Learning and Deep Learning Approaches"
[3] Li Sun, Songtao Zhang, Hang Chen, and Lin Luo (2022) "Brain TumorSegmentation and Survival Prediction using Multimodal MRI Scans with Deep learning Algorithms"
[4] Hameed, F.L., & Dakkak, O. (2022) "Brain Tumor Detection and Classification Using Convolutional Neural Network (CNN)"
[5] Khan, M.F., Khatri, P., et al. (2022) "Detection of Brain Tumor from the MRI Images using Deep Hybrid Boosted based on Ensemble Techniques.
[6] Narayanan Krishnasamy, Thangaraj Ponnusamy (2023). "Deep learning-based robust hybrid approaches for brain tumor classification in magnetic resonance images."
[7] Soheila Saeedi, Sorayya Rezayi, Hamidreza Keshavarz and Sharareh R. Niakan Kalhori (2023) "MRI-based brain tumor detection using convolutional deep learning methods and chosen machine learning techniques.
[8] Mukul Aggarwal, Amod Kumar Tiwari, M Partha Sarathi and Anchit Bijalwan (2023) "An early detection and segmentation of Brain Tumor using Deep Neural Network"
[9] Chen, W., Tan, X., Zhang, J., Du, G., Fu, Q., & Jiang, H. (2024) "A robust approach for multi-type classification of brain tumor using deep feature fusion"
[10] Da Ma,Hao Zhang,Hei Wang (2024) "Deep learning methods and applications in brain imaging for the diagnosis of neurological and psychiatric disorders.