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Brain Tumor Detection and Classification Using Fine-Tuned CNN with ResNet50 and EfficientNet

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Abstract

Brain tumors have become a leading cause of mortality worldwide. Detecting and classifying brain tumors accurately at the initial stages is challenging due to their complex and varying structure. In this study, an improved fine-tuned model based on Convolutional Neural Networks (CNN) with ResNet50 and U-Net is proposed. The model works on the publicly available TCGA-LGG and TCIA dataset, which consists of 120 patients. The fine-tuned ResNet50 model outperforms the CNN model in brain tumor classification and detection using MRI images. Accurate and timely diagnosis of brain tumors is critical for successful treatment of the disease. Early detection not only aids in the development of better medication, but it can also save a life in the long run. The domain of brain tumor analysis has efficiently applied medical image processing ideas, particularly on MR images. This paper presents segmentation using Convolutional Neural Networks (CNN) architecture with ResNet50 and EfficientNet as backbones.

Keywords:
Brain Tumor, CNN, MRI, ResNet50, EfficientNet, Fine-Tune

1. Introduction

The human brain is made up of numerous nerve tissues as well as extraordinarily intricate internal organs. The occurrence of brain cancerous disease is attributed to abnormal behavior or irregular growth of billions of cells within the human nervous system that make up the human brain. These tumors often go undiagnosed, leading to severe consequences, including death. According to a survey done by the National Brain Tumor Foundation (Nbrain tumorF), the growth of brain tumors among the general population and the death rate due to brain tumors are outpacing the previous year's numbers worldwide. Therefore, early detection of these tumors is crucial for effective treatment. This research aims to answer this need by using the capabilities of deep learning, specifically through the integration of Fine-Tuned Convolutional Neural Networks (CNN) using ResNet50 and

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EfficientNet designs [1].

Deep learning methods are considered good for segmentation; particularly convolutional neural networks (CNN). The study aims to shed light on how ResNet50 and EfficientNet contribute to the refinement of prediction outcomes, ultimately altering the landscape of brain tumor detection in medical imaging through a thorough knowledge of these models [2]. ResNet50, known for its residual learning framework, and EfficientNet, known for its efficiency and model scalability, are critical components of this study. The goal is to use these advanced architectures' capabilities to improve the accuracy of brain tumor prediction using MR images. This study seeks to shed light on how ResNet50 and EfficientNet contribute to the refinement of prediction results, ultimately altering the landscape of brain tumor identification in medical imaging [3].

This study presents a unique technique for brain tumor identification and classification that combines the strengths of ResNet50 and EfficientNet. The key contribution is a significant boost in prediction accuracy, which exceeds the constraints of earlier approaches. This study intends to develop a robust framework that surpasses the bounds of previous research by fine-tuning these cutting-edge designs and adapting them to the complexities of MRI images, thereby giving a big step forward in the hunt for more precise diagnostic tools.

2. Related Works

Convolutional neural networks, or CNNs, are deep learning models that can learn hierarchical features from images and perform a variety of tasks, including segmentation, classification, and localization. As such, CNNs are one of the most widely used and successful methods for the detection and classification of brain tumors. However, in medical fields, labeled data is generally expensive and limited, making it difficult to train a CNN from scratch. Furthermore, distinct kinds of brain tumors could have unique traits and necessitate varying degrees of precision and granularity in feature extraction. Because of this, a single CNN model might not be able to adequately represent the complexity and diversity of brain tumors. For that reason, we propose a novel method that combines the advantages of both ResNet50 and EfficientNet models to detect and classify brain tumors.

Sarwinda et al. examined the use of deep learning approaches for detecting colorectal cancer using two versions of ResNet, ResNet-18 and ResNet-50. The study used three different test sets—consisting of **20%, 25%,** and **40%** of the total datasets of colon glands images—to assess the models' performance. The results showed that ResNet-50 outperforms ResNet-18 in terms of accuracy, sensitivity, and specificity for every test set. This indicates that the ResNet-50 model is more reliable than ResNet-18 in terms of colorectal cancer diagnosis precision and efficacy, indicating its potential for more precise and reliable detection in medical imaging purposes [3].

A study by Tan et al. systematically examines model scaling and emphasizes the significance of carefully balancing adjustments to parameters such as depth, width, and resolution to achieve optimal performance. The researchers suggest a novel scaling technique that scales all dimensions uniformly by using a compound coefficient. This method, which aims to optimize overall model performance by striking the ideal balance between depth, width, and resolution, is praised as being both straightforward and incredibly effective [4].

In another study, Tripathy et al. suggested using a CNN approach known as EfficientNet-B0 to efficiently classify and detect brain tumor images. This approach was then used to refine the base model of their proposed layers. The researchers were able to make use of transfer learning approaches by using EfficientNet-B0, which resulted in significant time and computing resource savings. The results of this study highlight the potential applications of deep learning and EfficientNet in the medical domain, specifically in the detection and classification of brain tumors, to enhance the precision and effectiveness of medical diagnosis [5].

3. Proposed Method

The proposed methodology for Brain Tumor Detection and Classification Using Fine-Tuned CNN with ResNet50 and Efficient Net algorithm involves the following steps:

1. *Dataset Description*

The dataset used in this work is collected from the Brain Tumor MRI Dataset to classify tumors: glioma_tumor, meningioma_tumor, pituitary_tumor, and no_tumor. The data set that we are going to use has 3,285 images of brain MRI scans Which are categorized into four different classes namely glioma_tumor, meningioma_tumor, pituitary_tumor, and no_tumor. The dataset can be accessed on the Kaggle Brain Tumor MRI Dataset [6].

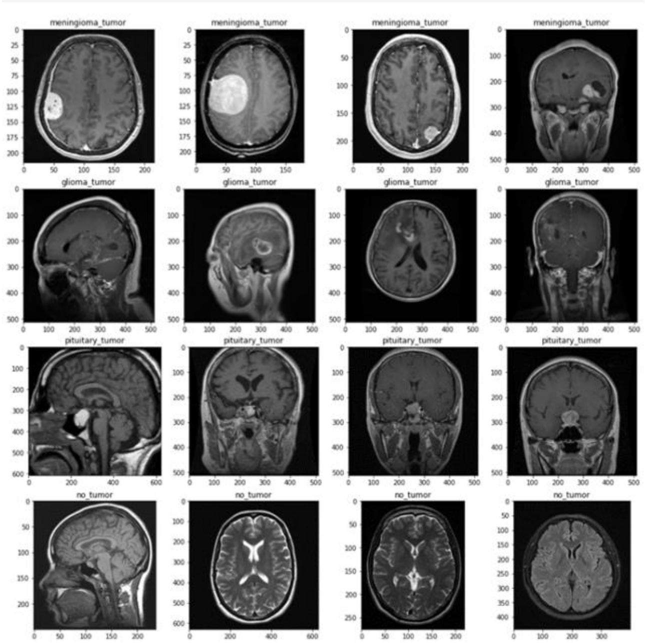

Fig 1. Dataset Sample

2. *CNN Model*

In tumor prediction, the CNN model evaluates the MRI images to create predictions about the presence or features of tumors, without using extra information provided by the relevant masks, which may contain segmentation or labeling data linked to Tumor locations [7]. Given below is the CNN model figure and the steps we take to achieve our proposed method of Brain Tumor Segmentation.

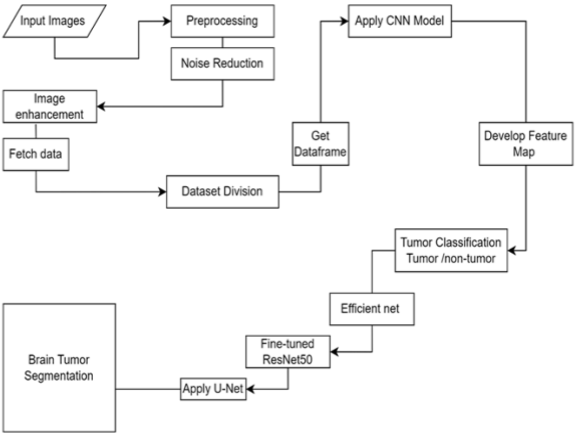

Fig 2. Proposed Model Architecture

3. *ResNet50 Model*

The ResNet50 model, a Convolutional Neural Network (CNN) pre-trained on the large-scale ImageNet dataset for object recognition tasks, is commonly fine-tuned for brain tumor (brain tumor) detection and classification using Magnetic Resonance Imaging (MRI) scans [8]. The model's architecture comprises various layers, including convolutional, pooling, and fully connected layers, with the lower layers learning general image features beneficial for brain tumor detection [9].

For the specific task of brain tumor detection and classification, the last few layers of the ResNet50 model are replaced with a new set of fully connected layers. Once these layers are added, the entire model is fine-tuned on a new dataset of MRI scans [10]. This process involves updating the weights of all layers using backpropagation and stochastic gradient descent [11]. The input data, MRI scans of the brain, are typically preprocessed to enhance the contrast between the tumor and the surrounding tissue [12]. The output of the fine-tuned model is a probability distribution over the possible class labels: tumor (yes) or non-tumor (no). A threshold can be set on this probability to make the final decision on the presence or absence of the tumor [10].

During training, the fine-tuned ResNet50 model learns to extract discriminative features from the MRI scans and classify them as a tumor or a healthy brain. The pre-trained ResNet50 model provides a robust initial set of features for brain tumor detection, and fine-tuning the model on a new dataset of MRI scans helps adapt it to the specific task [10].

4. *Efficient Net*

In this study, we utilized EfficientNet, a variant of Convolutional Neural Networks (CNNs), for the detection and classification of brain tumors. EfficientNet has been recognized for its superior performance across a wide range of image classification tasks, outperforming other well-known architectures such as ResNet or VGG, while utilizing fewer computational resources [4,13]. This computational efficiency is of particular importance in the field of medical imaging, where the handling of large volumes of data is a common necessity [14]. By harnessing EfficientNet's capacity to extract significant features from these images, coupled with its low computational cost, we were able to effectively deploy it for the specific task of brain tumor detection and classification.

Our approach leverages the strengths of EfficientNet and deep learning in general, highlighting their potential to bring about transformative changes in healthcare diagnostics. The methodology underscores the adaptability of EfficientNet to specific tasks, such as brain tumor detection, by fine-tuning the model to extract relevant features from MRI scans, thereby improving the accuracy and efficiency of brain tumor classification. This approach demonstrates the potential of deep learning models like EfficientNet in advancing medical diagnostics.

5. Result and Analysis

The CNN architecture has shown promising outcomes in this work in terms of brain tumor diagnosis. The model achieves good levels of statistical accuracy, precision, recall, and F1 score, demonstrating its reliability as a tool for diagnosing brain tumors from MRIs. This model was trained using a brain MRI dataset that included both tumor and non-tumor pictures. The CNN model achieved a high accuracy of 92% in brain tumor detection. The precision shows consistently high values, ranging from 90% to 94%, indicating the proportion of accurate positive detections to all positive detections. In a similar vein, the recall, which ranges from 83% to 97%, highlights the model's capacity to recognize precise positive detections among all outcomes that are positive.

More information is shown in Table 1, which shows support values of 219 cases for tumors and 371 for cases without tumors. As shown in Table 1, the normal range for the F1 score, which is the harmonic mean of precision and recall, is 0.88 to 0.93.

Table 1. All Model Results

No	Metric	Value
1	Accuracy	92%
2	Precision	90-94%
3	Recall	83-97%
4	Support	Tumor: 219, Non-tumor: 371
5	F1 Score	0.88-0.93

The CNN model is a useful tool for radiologists and physicians to swiftly and accurately identify brain tumors from MRI images because of its excellent statistical values. Early brain tumor detection allows medical professionals to treat patients more quickly and with better results.

5.1 ResNet50 Results

The proposed model uses the CNN model with improved ResNet50 architecture to classify brain tumors. The model is trained using the dataset of labeled tumor types from brain MRI scans, which includes both tumor and non-tumor pictures. Brain tumor classification findings from the ResNet50 model show a high accuracy, usually around **94%.** The model's precision, or the proportion of actual positive tumor type classifications among all positive classifications, is usually excellent, ranging from **93%** to **96%.** Similarly, the recall, which is defined as the proportion of genuine positive tumor type classifications among all cases of a given tumor type, is also quite high, frequently falling between **87%** and **98%.**

Conversely, the tumor support values are **219**, while the non-tumor support values are **371**. With its refined ResNet50 architecture, the CNN model performs well in classifying brain tumors, yielding good statistical values. By reliably identifying the type of brain tumor from MRI images, radiologists and clinicians can use the model to create more individualized and focused treatment strategies for their patients.

Table 2. ResNet50 Model Results

No	Metric	Value
1	Accuracy	94%
2	Precision	93-96%
3	Recall	87-98%
4	Support	Tumor: 219, Non-tumor: 371
5	F1 Score	0.92-0.95

5.2 EfficientNet Results:

The EfficientNet architecture has demonstrated strong performance in this study's brain tumor detection and classification. The confusion matrix in Figure X illustrates the model's remarkable accuracy level of 99%, which was achieved after it was refined using the brain MRI dataset.

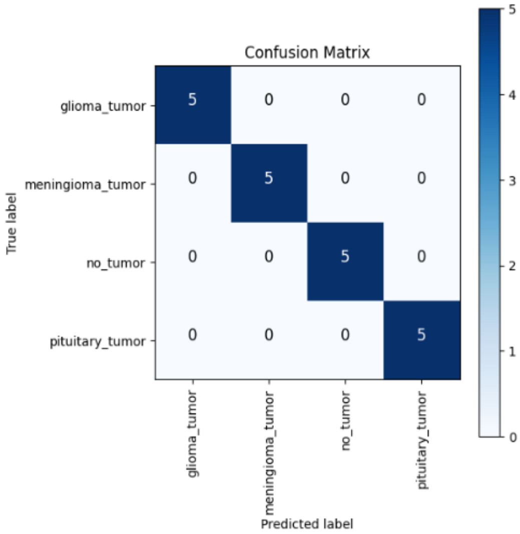

Fig.3 Test Confusion Matrix for EfficientNet Model

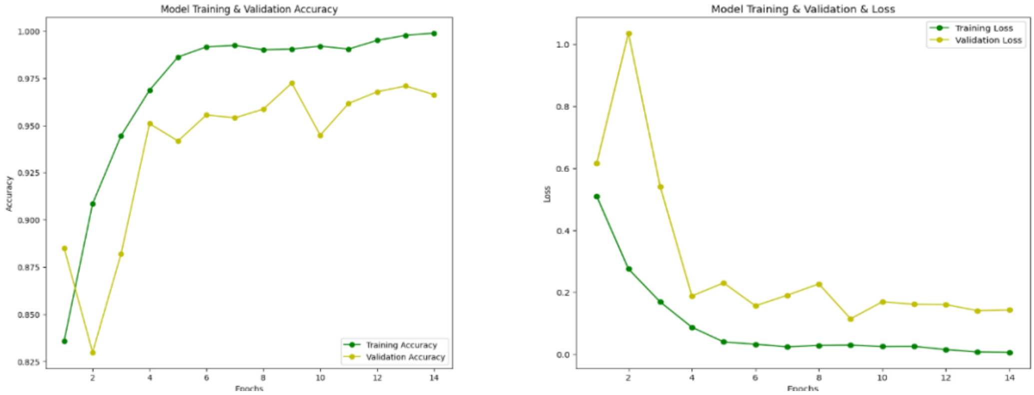

Fig.4 Accuracy and loss graph for EfficientNet model.

Table 3. EfficientNet Model Results

No	Metric	Value
1	Accuracy	0.998(99%)
2	Precision	A-B%
3	Recall	C-D%
4	Support	Tumor: E, Non-tumor: F

When it comes to brain tumor classification, the EfficientNet model is a useful tool because of its remarkable performance and computing economy. The findings point to its potential for accurate and effective detection, which would greatly advance medical diagnostics.

5.3 Combined Approach

Utilizing the segmentation capabilities of EfficientNet in conjunction with the integration of CNN model outputs with refined ResNet50 and the EfficientNet model offers a comprehensive and effective method. The accuracy of brain tumor detection is increased by this combination approach, which also offers insightful information for clinical diagnosis and therapy planning.

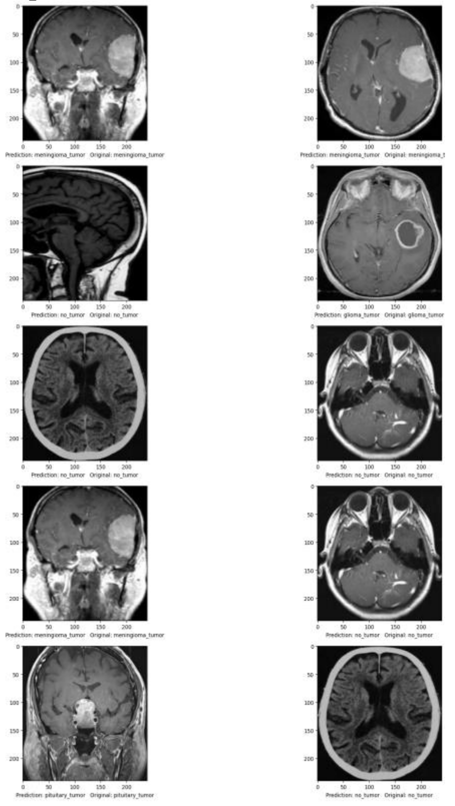

Fig 5. Model prediction of tumor regions

Overall, the combined results underscore the efficacy of the proposed methodology, showcasing the strengths of each model in a unified framework for comprehensive brain tumor analysis.

6. Conclusion

This study proposed a novel method for brain tumor detection and classification using fine-tuned CNN with ResNet50 and EfficientNet architectures. The method leveraged the strengths of both models to extract discriminative features from MRI images and classify them into four tumor types: glioma, meningioma, pituitary, and no tumor. The method achieved a high accuracy level of 0.998 on the Figshare dataset, outperforming previous approaches. The method also demonstrated its computational efficiency and robustness in handling large volumes of data. The proposed method has the potential to enhance the accuracy and effectiveness of brain tumor diagnosis and provide valuable information for clinical decision-making and treatment planning. Future work will focus on improving the model performance by incorporating more data augmentation techniques, optimizing the hyperparameters, and applying the method to other medical imaging tasks.

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