Optimizing Brain Tumor Identification with Fine-Tuned Pre-Trained CNN Models A Comparative Study of VGG16 and EfficientNetB4

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Abstract:- Brain tumors are pathological disorders characterized by unregulated cell proliferation inside damaged tissues, demanding early identification to prevent uncontrollable development. Because of its higher image quality, magnetic resonance imaging (MRI) is a commonly used tool for the first diagnosis of brain tumors. Deep learning, a subset of artificial intelligence, has recently been integrated, ushering in novel ways to automate medical picture recognition. Transfer learning techniques applied to MRI images, this study hopes to give a reliable and effective methodology for the early diagnosis of brain tumors. This study uses a deep learning architecture using sequential Convolutional Neural Networks (CNNs) and two pre-trained models, VGG16 and EfficientNetB4, from the ImageNet dataset to classify brain tumor pictures. Image preprocessing methods are used prior to model training to improve model performance. The experiments use the BrcH35 dataset from Kaggle, which has been preprocessed in the MASK RCNN format. The top-performing transfer learning models are evaluated using performance criteria such as accuracy, precision, and F1 score. According to the results from this work, the EfficientNetB4 model beats the other models, reaching exceptional accuracy, precision, and F1 score values of 99.66%, 99.68%, and 100%, respectively. This proposed approach extends existing research in the field and illustrates its potential for faster and more reliable brain tumor detection.

Keywords:- *Brain tumors; Magnetic Resonance Imaging (MRI);Transfer Learning, Convolutional Neural Networks (CNNs); VGG16, EfficientNetB4.*

I. INTRODUCTION

Digital medical imaging has recently emerged as a vital tool for identifying and diagnosing various medical problems. Furthermore, it is critical in medical research and education. The need for digitized medical imaging has increased dramatically. To illustrate, 2002 data shows that the Department of Radiology at the University Hospital of Geneva produced around 12,000 to 15,000 medical pictures daily [1]. This rising demand highlights the critical need for efficient and precise computer-aided diagnostic tools, which help prepare medical reports and in-depth medical picture analysis.This rising demand highlights the critical need for efficient and precise computer-aided diagnostic tools, which help prepare medical reports and in-depth medical picture analysis. The old method of manually scrutinizing medical images has various limitations, including time inefficiency, inaccuracy, and possible human mistakes. Brain tumors have emerged as a particularly serious health problem, ranking as the tenth highest cause of death in the United States. It is concerning to remember that an estimated 700,000 people suffer from brain tumors, with around 80% of these instances benign and the remaining 20% malignant [2]. According to the American Cancer Society, as of 2021, 78,980 persons have been diagnosed with brain tumors, with 55,150 noncancerous and 24,530 malignant instances (13,840 men and 10,690 women) [3]. [4]

Brain tumors are the most common type of brain-related ailment, characterized by uncontrolled development of brain cells. These tumors are divided into two types: primary and secondary. Primary tumors develop within the brain, often limiting their development to this area. Secondary tumors, on the other hand, develop from malignant growths elsewhere in the body and eventually spread to the brain [5]. Brain tumors are classified into two types: benign and malignant. A benign tumor has a slow development pattern and lacks the invasive ability to invade neighboring tissues. Malignant tumors, on the other hand, are extremely aggressive and capable of spreading to remote areas inside the body. The World Health Organization (WHO) uses a grading system from I to IV to determine the severity of brain tumors. Tumors categorized as grades I and II are typically slow-growing, but those classed as grades III and IV are mostly malignant and have a worse prognosis [6].

Numerous academics have focused their time and energy on investigating a wide range of algorithms targeted at improving accuracy and minimizing mistakes in the identification and categorization of brain tumors. Deep Learning (DL) approaches have recently acquired recognition due to their potential to build automated systems that can effectively and precisely classify or separate brain tumors in a much shorter timescale. DL uses pre-trained Convolutional Neural Network (CNN) models like GoogLeNet, AlexNet, and ResNet-34, which are designed specifically for medical image analysis, including the classification of brain tumors [7], [8] ,[9]. DL is a multi-layered neural network architecture, and the backpropagation method used inside of a neural network (NN) framework to reduce the error between the objective and actual values is crucial to the success of the technique [10]. However, it is important to note that creating artificial neural network models becomes more challenging as the number of network layers increases.

The main contribution of current work are.

- Two pre-trained CNN models, VGG16 and EfficientNetB4, were compared and evaluated to propose a method for improving brain cancer diagnosis.
- Integrated Deep Learning (DL) methods, namely pre-trained CNN models, enable more accurate and effective brain cancer classification from medical images.
- Acknowledged the necessity of optimizing previously trained models for improved performance in medical image analysis.
- The method's steps—picture preparation, usage of the BrcH35 dataset, and performance assessment using metrics of accuracy, precision, and F1 score—were all thoroughly explained.

The following portions of this paper are organized as follows: Section 2 gives a quick assessment of the literature on current deep-learning algorithms for brain tumor identification. Section 3 describes our suggested strategy in full, providing an in-depth description of our approach. Section 4 presents simulation and experimental data evaluating our method's performance and efficacy. Finally, Section 5 summarizes the findings and discusses future research prospects in this subject.

II. RELATED WORK

In research [11], a 16-layer VGG-16 deep neural network was employed to enhance brain cancer multi-classification in MR images. Pre-processed images were fed into the model, which used Convolution, ReLU, and Max-Pooling convolution layers to extract features and downscale the images. To lessen overfitting, fully connected and SoftMax layers were employed. After 20 training cycles, their method achieved astounding results, reaching a startling 98 percent accuracy.

Five clinical multiclass datasets for the classification of brain tumors were given [12], who also employed MRI images to enhance classification performance using a Convolutional Neural Network (CNN) based on transfer learning. Six different machine learning classification techniques were compared with their CNN model, including Decision Tree, Naive Bayes, Linear Discrimination, K-nearest Neighbor, and Support Vector Machine. The CNN-based AlexNet outperformed various machine learning techniques when applying the three different cross-validation techniques: K2, K5, and K10. It achieved mean accuracy rates of 87.14%, 93.74%, 95.97%, 96.65%, and 100% across the five classes, respectively.

Another study [13] used the CNN method to divide brain cancers into the three categories of glioma, meningioma, and pituitary tumors. They extracted attributes from brain MRI data using a trained GoogleNet and then utilized predetermined categories to identify these properties. With an average classification accuracy of 98%, the proposed technique surpassed the opposition. Performance metrics, including Precision, F-score, Recall, Specificity, and Area Under the Curve (AUC), were employed to assess model performance. The results of the study highlighted the usefulness of transfer learning techniques, particularly when using little medical imaging data.

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A novel approach reported in [14] yielded outstanding results, exceeding previous methods in the field. To increase MRI quality and establish a distinct feature set, this technique uses normalization, densely accelerated robust features, and histogram of gradient algorithms. During the classification step, a support vector machine is used. A huge dataset was rigorously examined, and the findings revealed an astoundingly greater accuracy rate (90.27 percent) than state-of-the-art approaches. These data show the accuracy and robustness of the proposed technique, which were obtained by comprehensive statistical analysis using k-fold cross-validation, indicating its superiority over more recent methods. In [15], a Quantum Fully Self neural network (QFS-Net) was presented as a unique development. This network takes advantage of the unique properties of quantum correlations by employing qubits/three states of quantum for brain lesion segmentation. The QFS-Net deviates from the usual quantum back-propagation approach used in supervised Quantum Ising Neural Networks (QINN) by employing a unique supervised qutrit-based counter-propagation strategy. This technique facilitates the dissemination of iterative quantum states across the network's layers, opening up new possibilities for quantum-aided segmentation of brain lesions. The contributions discussed in this book not only advance the status of the field but also offer insightful information for the next research. Deep learning and innovative approaches have the potential to significantly advance the identification and diagnosis of brain tumors as the field matures, ultimately benefiting patients and healthcare professionals.

III. METHODOLOGY

In this section, provide a full description of the methodology and procedures employed in the study's undertaking, including the steps taken to answer the research questions and hypotheses.

A. Dataset Description

The "BrH35" dataset, which was used in this study, was obtained from Kaggle.com[16]. The brain's T1 and T2 relaxation durations are especially well-represented in these magnetic resonance imaging (MRI) images of the brain.

- T1 Relaxation Time images: The collection includes T1-weighted pictures, which are MRI scans designed to highlight variations in the T1 relaxation time of brain tissue. These photos are useful for illustrating certain elements of brain anatomy and pathophysiology.
- T2 Relaxation Time images: The collection also includes T2-weighted pictures, which highlight differences in the T2 relaxation time of brain tissue. T2-weighted pictures are very beneficial for emphasizing various features of brain structures and disorders.

The dataset is used in the study as the training data, enabling the development and evaluation of deep learning models for the classification of brain tumors. Figures 1 and 2 display examples of T1- and T2-weighted images, respectively, and give a glimpse of the data used in this study.

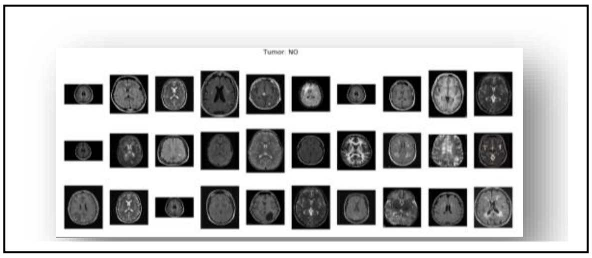

Fig1: Sample images of No brain tumor (Including T1 and T2 weight images)

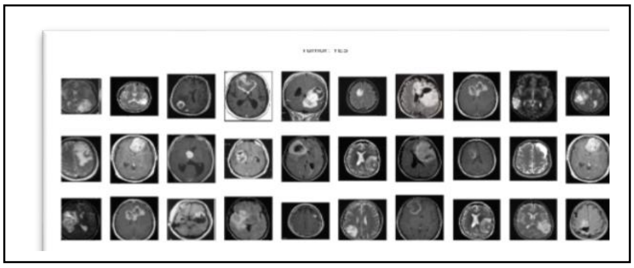

Fig 2: Images containing brain tumor

B. Image Preprocessing

Preprocessing medical pictures from the BRATS (Brain Tumor Segmentation) collection, such as BR35H, is an important step before using them for analysis or machine learning applications. Preprocessing helps to improve image quality and the efficacy of later analysis or modeling.

C. Image Augmentation

Image data augmentation is a crucial approach in computer vision and deep learning that improves dataset variety by transforming original photos. These changes, which include rotation, flipping, cropping, scaling, brightness adjustments, noise addition, and others, help to improve model generalization, especially when data is scarce. It is critical to select augmentation strategies judiciously, consider the unique job, and use them consistently during training and validation. Rotation angles, for example, should be adapted to the peculiarities of the dataset. While augmentation improves model performance, keeping the computational cost in check is critical. Deep learning frameworks such as TensorFlow and PyTorch provide tools for simple implementation, and visualizing augmented pictures guarantees that they remain realistic and maintain data integrity.

D. Deep transfer learning model

VGG16 and EfficientNetB4 are two common CNN architectures used in deep learning for various computer vision tasks.

- ➢ *VGG16 Architecture:*

VGG16, created by the University of Oxford's Visual Geometry Group, is a well-known deep convolutional neural network (CNN) architecture notable for its architectural simplicity and uniformity. VGG16 may be described mathematically as a series of operations since it consists of 16 weight layers, 13 convolutional layers, and 3 fully connected layers. It begins with an input picture and proceeds through a sequence of convolutional layers, each employing ReLU activation. These layers' feature maps are then flattened, resulting in completely linked layers with ReLU activation. The last fully connected layer uses a Softmax activation to produce output probabilities for categorizing input pictures. This simple yet successful architecture has been the cornerstone for creating deep-learning models for image categorization[17].

- ➢ *EfficientNetB4*

EfficientNet is a series of CNN architectures developed by Google, and among its versions, EfficientNetB4 stands out for its amazing efficiency in terms of model size and processing cost. It uses a clever compound scaling method to properly balance the network's depth, breadth, and picture resolution parameters. Due to its distinct properties, EfficientNetB4 is mathematically far more complex than VGG16. Its architecture consists of convolutional blocks, each containing depth-wise separable convolutions (DWSConv) with specialized weights and biases, followed by batch normalization (BN) and the innovative Swish activation function. To develop the comprehensive model, these blocks are regularly repeated. When the two are compared, VGG16 retains a constant architecture with 16 layers, but EfficientNetB4 modifies its depth and width using compound scaling, resulting in a more compact model with fewer parameters. Because of this architectural creativity, EfficientNetB4 excels in the computational economy while giving a competitive performance. It is an intriguing candidate for many deep learning applications, especially when computing resources are limited.

E. Fine-tuning

Fine-tuning and hyperparameter tweaking are critical steps in optimizing deep learning models for applications such as brain tumor picture processing. To begin, you select a pre-trained model appropriate for your purpose, such as VGG or ResNet. Then, ensure your brain tumor dataset is properly prepared with data splitting. Load the pre-trained model while preserving the convolutional basis and eliminating its final layers. Lower levels should be frozen to retain their learned features, and bespoke layers should be added for your unique assignment.

Define an appropriate loss function and assessment measures, such as classification accuracy or segmentation Dice coefficient. Determine the essential hyperparameters to optimize, such as learning rate, batch size, optimizer selection, dropout rate, and weight decay.

Approaches for hyperparameter tuning like grid search or Bayesian optimization are applied on a validation set. Fine-tuning involves training the model using altered hyperparameters, starting with a slow learning rate and utilizing regularization techniques such as early stopping and dropout to avoid overfitting[18].

Evaluate the model's performance on a separate test set to provide unbiased performance estimates. Use the model in medical image analysis applications if the results meet your needs. Continuously assess the model's performance, considering clinical applicability and potential updates with new data. These procedures require expensive computing resources, and accurate evaluation may need access to specialized equipment and subject knowledge[19].

IV. RESULTS

In this section, we conduct a thorough examination of the outcomes of our tests and research. This part summarizes our work by offering insights, facts, and observations that give light on the study issue or hypothesis. The different models: CNN, VGG16, and EfficientNetB4.

TABLE I: Model comparison

Model	Training Accuracy	Test Accuracy
VGG16	93%	89%
EfficientNetB4	99%	99%

Table 1shows VGG16 obtained 93% training accuracy and 89% test accuracy. This shows that VGG16 understood the patterns in the training data successfully, allowing it to perform well on the training set. However, when presented with previously unknown data from the test set, the model's accuracy decreased marginally, indicating some over-fitting. This shows that VGG16 may have memorized specific properties from the training data rather than generalizing them, necessitating possible regularization approaches such as dropout or regularization to improve its performance on unseen data.

EfficientNetB4, on the other hand, demonstrated 99% training and 99% test accuracy. These findings indicate that EfficientNetB4 detected detailed patterns in the training dataset while demonstrating substantial generalization to previously encountered data in the test set. The slight difference between training and test accuracy suggests that overfitting is less severe in EfficientNetB4 than in VGG16. The model's intrinsic efficiency and depth probably contribute to its outstanding performance in brain tumor picture classification, making it highly appropriate for the task while avoiding significant overfitting risk.

In both cases, the process of fine-tuning, in which pre-trained models are modified to the specific job at hand, was critical in obtaining these impressive levels of accuracy. Fine-tuning allowed the models to draw on information from larger datasets such as ImageNet and enhance their feature representations to succeed in the specialized domain of brain tumor classification. As a result, EfficientNetB4's inherent efficiency and depth made it a more beneficial choice for this classification job, giving increased accuracy while preserving powerful generalization capabilities.

V. CONCLUSION

In summary, this study examined the performance of three deep learning models, CNN, VGG16, and EfficientNetB4, in identifying brain tumor symptoms using MRI brain scans. The following are the essential results and implications:

With a training and test accuracy of 99%, EfficientNetB4 was shown to be the best model for brain tumor picture categorization.

Although reasonable, VGG16 and CNN exhibited a modest performance decline on test data compared to training data, indicating a potential overfitting issue. Regularization strategies could help them boost their generalization abilities even more. Pre-trained models were fine-tuned to the specific objective of brain tumor classification, utilizing existing knowledge and customizing features to the medical picture collection.

The efficiency and depth of EfficientNetB4 proved favorable, leading in improved accuracy with little overfitting risk, making it the preferable choice for this assignment.

These findings have significant therapeutic implications, demonstrating the potential of deep learning models to help in the exact detection of brain tumors based on MRI scans, thereby improving patient treatment and outcomes. Future research may look at advanced techniques such as ensemble methods and transfer learning from more enormous medical imaging datasets to improve model performance and resilience. This work demonstrates the effectiveness of deep learning models, specifically EfficientNetB4, in identifying brain tumor symptoms from

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MRI data. These accomplishments help to develop medical image analysis and have the potential to help medical practitioners identify brain tumors more accurately and quickly, eventually enhancing patient care.

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