Brain Tumor Detection & Classification

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Abstract

This research aims to leverage advanced deep learning techniques for accurate identification and classification of various types of brain tumors, thereby facilitating timely evaluation by medical professionals. Through the exploration of image augmentation methods, we aimed to enhance model accuracy and generalize its performance by mitigating overfitting issues commonly encountered in conventional approaches. The employed augmentation strategies yielded promising results, achieving an impressive accuracy of 99.8%. Furthermore, we investigated the effectiveness of transfer learning techniques using pre-trained models such as ResNet50 and VGG19. By leveraging these established architectures, we observed substantial improvements, achieving accuracies of 97% and 95% respectively. Notably, this approach led to significant reduction in trainable parameters, consequently reducing the computational resources (CPU, GPU) utilization and training time. Moreover, the utilization of fewer trainable parameters allowed for training on smaller datasets, which is particularly advantageous in the context of healthcare data, known for its scarcity and expense. Overall, our findings demonstrate the efficacy of employing advanced deep learning techniques in medical image analysis, offering both improved accuracy and cost-efficiency.

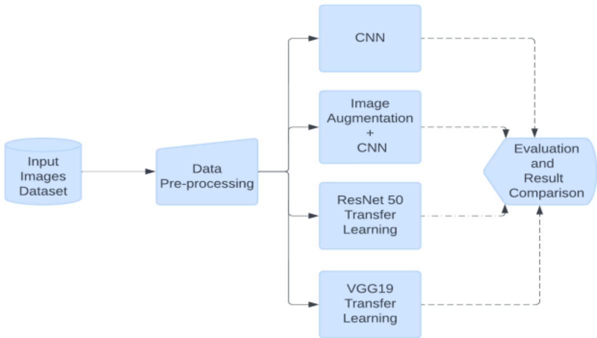

Fig. 1. *Methodology of classification process*

I. Introduction

A. Overview

Brain tumors pose a significant threat to human health, with potential life-threatening consequences. These abnormal masses of cells within the brain, whether benign or malignant, can exert pressure on the delicate organ, leading to severe damage and even fatality. Early detection and classification of brain tumors are crucial for effective treatment and patient survival. In this paper, we present a comprehensive approach to address this critical issue by leveraging deep learning techniques applied to Magnetic Resonance Imaging (MRI) data.

B. Motivation

The motivation behind our research stems from the critical need for timely and accurate diagnosis of brain tumors. With the rigid structure of the skull, any abnormal growth within the confined space of the brain can lead to increased intracranial pressure, potentially resulting in brain damage and life-threatening complications. Therefore, the early detection and classification of brain tumors are essential for initiating appropriate treatment strategies and improving patient outcomes.

C. Approach

Our research builds upon the foundation of a previously utilized convolutional neural network (CNN) model [2]. Our objective is to enhance the performance of this baseline model by employing various approaches. Central to our methodology is the implementation of a multi-task classification architecture, ensuring that the model effectively identifies and classifies tumors. Our workflow begins with an in-depth exploration of the dataset through exploratory data analysis, followed by preprocessing of the images to prepare them for model training. The baseline CNN model is then trained and evaluated to establish a benchmark. Subsequently, we apply image augmentation techniques and incorporate dropout layers to enhance the model's generalization capabilities. Additionally, we investigate the potential of transfer learning techniques utilizing the VGG19 and ResNet50 architectures to ascertain whether resources utilization can be effectively reduced. Through these steps, we aim to iteratively refine and optimize the performance of the CNN model. This comprehensive approach not only enhances model accuracy but also contributes to the efficient utilization of computational resources.

D. Dataset

Our experimental approach makes use of a large dataset [1] comprising 7023 human brain MRI scans. There are four classes in the dataset: pituitary, meningioma, glioma, and no tumor. To be more precise, we merge three smaller datasets—figshare, SARTAJ, and Br35H—to produce a varied set of MRI pictures that depict various tumor kinds. It is important to note that glioma class photos were not included in the SARTAJ dataset because of problems with categorization; instead, we used photographs from the figshare repository for this class. Training data comprise of 5712 images, testing and validation dataset comprised of 655 and 666 images respectively.

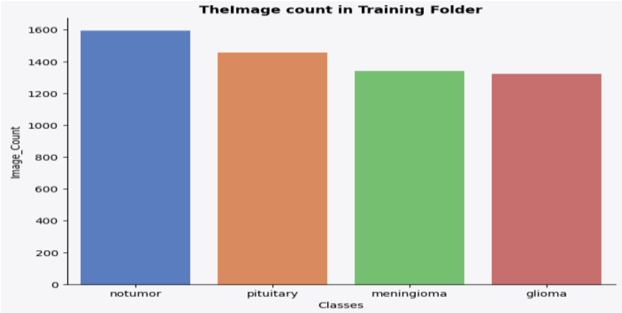

Fig. 2. Image distribution for different classes

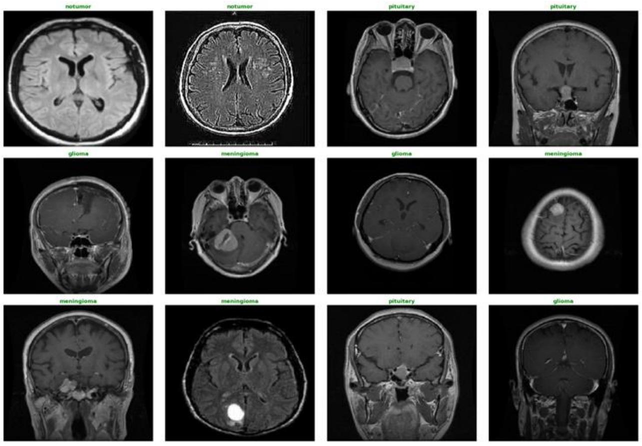

Fig. 3. Representative images from the dataset

II. Background

Brain tumors are a harmful medical disorder caused by abnormal cell development in the brain. Early and precise identification is critical for successful therapy and better patient outcomes. Traditionally, brain tumors are detected via medical imaging techniques such as Magnetic Resonance Imaging (MRI) scans, which are then analyzed by radiologists. However, this method can be time-consuming, subjective, and prone to human error.

In recent years, significant progress has been made in advancing brain tumor diagnosis through the analysis of MRI scans using deep learning techniques. Deep learning has emerged as a powerful tool. Several notable contributions have been made each addressing distinct aspects of tumor detection, segmentation, and classification.

Convolutional Neural Networks (CNNs) have opened up new paths for automated brain tumor diagnosis from MRI data. CNNs excel in image recognition applications because they can extract nuanced characteristics from complicated data, such as medical scans. Studies by Abdusalomov et al. [2] and Saeedi et al. [3] demonstrate the efficacy of CNNs in achieving high accuracy for brain tumor detection. This paves the way for utilizing CNNs as a reliable tool to assist radiologists in the diagnostic process. According to research, some CNN architectures, such as VGG [4] and ResNet [6], have produced encouraging results in brain tumor classification tasks. VGG models, are good in learning low-level characteristics from pictures. ResNet topologies solve the vanishing gradient problem, which is common in deep networks, by providing residual connections that allow for improved gradient flow during training. Rasheed et al. [5] explore image enhancement techniques to improve CNN performance for brain tumor classification, while Gómez-Guzmán et al. [7] propose novel CNN structures specifically designed for this task.

In summary, we aim to leverage the strengths of CNNs in image analysis while addressing potential challenges such as overfitting through techniques like dropout and data augmentation. These highlight the evolving landscape of brain tumor diagnostics, demonstrating the use of modern machine-learning approaches to improve the accuracy and efficiency of tumor identification, localization, and classification using MRI data.

III. Approach

A. CNN Model

Convolutional neural networks (CNNs) are a significant class of deep learning algorithms that are well-known for being efficient in picture recognition and classification applications. Our method makes use of CNNs for these purposes. CNNs can be identified by their convolutional, pooling, and fully linked layers arranged in a hierarchical architecture. While pooling layers downsample the feature maps to preserve important information and lower computational complexity, convolutional layers act as feature extractors, identifying complex patterns and features within the input images. These collected features are combined by fully connected layers, which also carry out the final categorization. Our model is trained robustly using a labeled dataset of brain MRI images. It minimizes the difference between projected and real labels by improving its parameters through gradient descent and backpropagation.

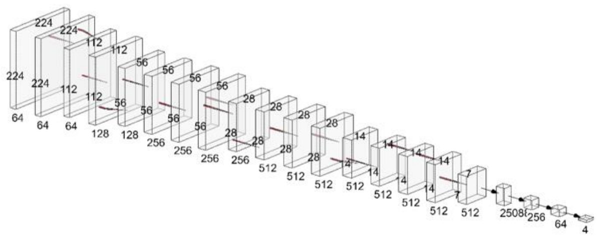

Fig. 4. CNN model Architecture

Fig. 5. CNN Train vs Loss Graph

Our CNN architecture forms the cornerstone of our model, comprising 13 convolutional layers and 5 max pooling layers. Each convolutional layer employs a 3x3 kernel size with "same" padding, ensuring consistency in output dimensions with the input image shape. Across these layers, we utilize varying numbers of filters—64, 128, 256, or 512—tailored to capture diverse features within the data. Consistency is maintained throughout the network by employing the ReLU activation function in all layers. This activation function introduces non-linearity, crucial for the model's ability to learn complex patterns effectively. Additionally, to streamline the processing of input images, max pooling layers are strategically inserted after every 2-3 convolutional operations, reducing spatial dimensions while preserving essential features. Following the convolutional layers, the flatten layer condenses the output from the last convolutional layer into a one-dimensional vector. This transformation prepares the data for input into the fully connected layers, facilitating higher-level feature extraction and classification. In the fully connected segment, two layers with 256 and 64 neurons respectively further refine the extracted features through ReLU activation. Finally, the last layer employs the softmax activation function, offering class probabilities for the four distinct classes under consideration.

The total number of trainable parameters in our model amounts to 21,154,180. This extensive architecture was trained over 20 epochs using the Adam optimizer with a learning rate set to 0.001. Throughout the training process, we employed accuracy as our primary evaluation metric, ensuring robust performance assessment across iterations.

This CNN model gave 97.2% training accuracy and 96.18% validation accuracy at end of 9^{th} epoch. As model run for 20 epochs, final results was 99.61% training, 96% validation and testing accuracy.

B. Image Augmentation

In deep learning, image augmentation is a commonly employed strategy to improve model performance, especially in situations where training data is scarce. Image augmentation makes the training dataset artificially larger by transforming the original photos in different ways. This helps keep the model from overfitting and enhances its capacity for generalization. Zooming in and out, rotating, moving, flipping, and modifying contrast and brightness are examples of common transformations. By adding variances to the training set, these changes enable the model to pick up more resilient and consistent characteristics.

During image augmentation, each training image underwent a series of transformations to enhance dataset diversity and improve model robustness. Specifically, we implemented image rotation within a range of 0 to 20 degrees, as well as width and height shifts by a maximum of 0.2. Additionally, zooming in and out was applied with a maximum score of 0.2. Horizontal flipping was incorporated using a nearest fill mode. For each training image we created 5 augmented images. Model is trained on 20368 images.

It's noteworthy that during width and height shifts, we ensured that the image was adjusted in a manner that prevented any loss of content. This was achieved by shifting the image left, right, up, or down while maintaining its entirety. Furthermore, we deliberately kept the zooming score low to minimize any potential distortion. Importantly, we refrained from employing image blur techniques due to the risk of losing valuable information, a practice deemed unsuitable for healthcare data. This meticulous approach to image augmentation aimed to enrich the dataset while preserving the integrity of the medical images.

After augmentation, we trained same CNN model as used before keeping all other parameters same. After 20 epochs, training accuracy achieved 99.43%, validation and testing accuracy 99.08% and 98.32% respectively. While evaluating the model performance, we make sure that we are measuring the performance on original training data (5712 images).

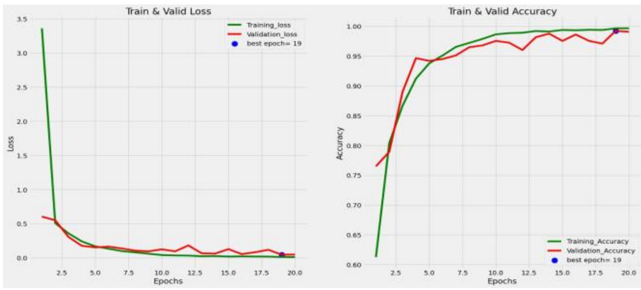

Fig. 6.*Train and Valid Loss Graph*

C. Transfer Learning

A deep learning technique called transfer learning uses a model that has been trained on one task to help with a related but unrelated task. It entails using the insight acquired from resolving one issue to another that is similar yet unrelated. Transfer learning in the context of image classification is taking a convolutional neural network (CNN) model that has already been trained, eliminating the last few layers, and adding new layers that are appropriate for the job at hand. By doing this, even with a small amount of training data, the model can rapidly adjust to new information and learn to correctly identify images.

We applied transfer learning in our implementation by using CNN models that have already been trained, like VGG19 and ResNet50. Large datasets like ImageNet, which include millions of tagged photos across thousands of classes, were used to train these models. By deleting the models' last classification layers and adding new ones that were suitable for our particular classification challenge, we modified these models for our brain tumor classification work. Compared to training a CNN from scratch, we were able to get good results on our brain tumor dataset with less training data and processing resources by taking advantage of the knowledge already embedded in these pre-trained models. By using this method, we were able to speed up the training process and get precise brain tumor image classifications.

i) Transfer Learning with VGG19

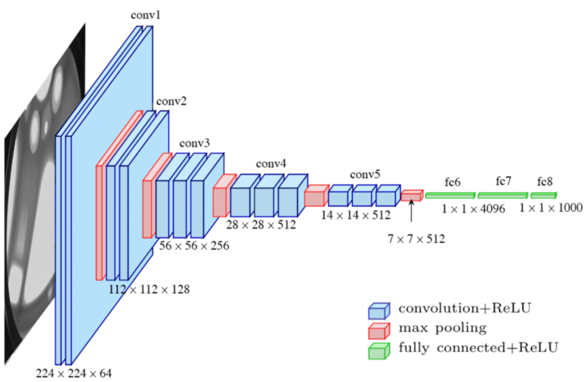

Fig. 7. *VGG19 model Architecture*

Source: *Medium[9]*

VGG19 is a convolutional neural network architecture characterized by its deep structure consisting of 19 layers. It follows a simple yet effective design philosophy with repeated 3x3 convolutional layers, followed by max pooling layers for spatial down sampling. The network progressively increases the number of filters in each convolutional layer, culminating in fully connected layers for classification. VGG19 is renowned for its ability to extract intricate features from images, making it a popular choice for various computer vision tasks.

For our problem, we unfreeze last 5 layers and added 1 convolution and fully connected layer with 2 dense layers and 2 dropout layers. We trained the model with 20 epochs, and we get very good results with 99.49% training, 98.2% testing and validation accuracy. Moreover, trainable parameters are 12,651,140. Which are almost 60% of baseline CNN model.

ii) Transfer learning with ResNet50

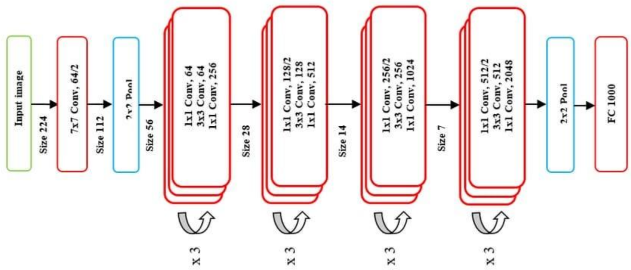

Fig. 8. *ResNet50 model Architecture*
Source: *Towards Data Science[8]*

ResNet50 is a deep convolutional neural network architecture comprising 50 layers, notable for its innovative residual connections. These connections allow the network to bypass certain layers, mitigating vanishing gradient issues and facilitating training of extremely deep networks. ResNet50 features a series of convolutional layers followed by global average pooling and fully connected layers for classification. Its design enables efficient learning of intricate features, making it widely adopted for image recognition tasks, particularly in domains where depth and accuracy are paramount.

For our problem, we unfreeze only dense layer and added dense and dropout layer. After training for 20 epochs, we get training accuracy of 95.99 %, testing & validation accuracy of 94.20 %. Total trainable parameter is 1,051,140 which are just 5 % of trainable parameter of baseline CNN model.

III . Experimentation and Results

A. Experimental Setup

We trained baseline CNN model and note down the model parameters. Then we train the model with augmented data, also with transfer learning techniques with VGG19 and ResNet50 architectures. Then we compare all the results together.

B. Results

Sr. No	Model	Training Accuracy	Testing Accuracy	Validation Accuracy	Trainable parameters	Training Time (Sec)
1	CNN model	0.9961	0.9600	0.9600	21,154,180	1660
2	Image Aug. + CNN	0.9943	0.9832	0.9908	21,154,180	5740
3	VGG19 (Transfer Learning)	0.9949	0.9820	0.9800	12,651,140	800
4	ResNet50 (Transfer Learning)	0.9599	0.9420	0.9420	1,051,140	480

V. Conclusion

The experiment underscored the efficacy of CNN architecture and transfer learning in the context of brain tumor classification. While the baseline CNN model demonstrated high accuracy during training, its performance on testing and validation datasets was suboptimal. However, the implementation of image augmentation proved instrumental in enhancing model performance by mitigating overfitting and promoting generalization. Furthermore, leveraging transfer learning techniques, particularly with VGG19, resulted in a substantial reduction of up to 60% in trainable parameters without compromising performance. Although transfer learning with ResNet50 also reduced trainable parameters significantly, it slightly impacted performance. Notably, transfer learning not only enhances model efficiency but also reduces training time and computational resources, underscoring its practical utility in medical image analysis.

Limitations:

1. Data Quality and Quantity: The efficacy of the models heavily depends on the quality and quantity of available data. Insufficient access to diverse and well-annotated datasets may limit the models' ability to generalize and impact their performance.

2. Model Generalization: Despite employing techniques like image augmentation and transfer learning to enhance model generalization, there may persist challenges in adapting to new data or varying imaging conditions. Fine-tuning hyperparameters or exploring alternative model architectures might be necessary to overcome these limitations.

3. Resource Constraints: Although transfer learning helps reduce trainable parameters, training deep learning models still demands significant computational resources and time. Limited access to high-performance computing infrastructure may hinder the efficient deployment and iteration of models.

Future Work:

Exploring alternative transfer learning strategies using additional state-of-the-art pretrained models could potentially enhance the performance of the model.

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