Brain Tumor Detection using deep learning from scanned brain images

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***Abstract*—More advanced diagnostic aids are increasingly being demanded with the current surge of brain tumor prevalence, in which timely and accurate diagnosis is very critical.Traditional Conventional methods have much reliance upon manual interpretation of images tends to be slow and prone to errors.The most frequent and widely utilized machine learning model for image recognition is probably CNN. [1] This research presents a dual-approach methodology that will use deep learning techniques, most importantly Convolutional Neural Networks (CNNs), for the automation of the categorization of brain cancers from MRI scans. We have used for this the well-reputed VGG16 model, a pre-trained neural network very well known for its high reliability in robust image recognition, and another custom-built CNN model, smaller-sized, made for computation efficiency and fast deployment. The initial implementation of the VGG16 model achieved a modest validation accuracy of 73%. Despite efforts to improve performance through fine-tuning and data augmentation, no significant gains were observed. However, our custom model, 'Modfinal_model', demonstrated substantial improvement, achieving an impressive 97% accuracy in classifying MRI-based brain tumors. This work not only supports the use of sophisticated CNNs in medical image processing, but it also paves the way for future research into broad applications in healthcare diagnostics.**

***Index Terms*—Convolutional neural networks, VGG16, Medical image analysis, TensorFlow, Machine learning in Healthcare**

I. Introduction

Medical diagnostics are facing a severe challenge related to the detection and classification of brain tumors from MRI images. The problem has been a matter of grave concern, as brain tumors are the most common solid neoplasm occurring in American children and adolescents at a frequency of about 5,000 cases yearly. Since diagnosis often plays a pivotal role in the cure, it is very important to make an accurate diagnosis rapidly for the effective treatment of the disease. Current diagnosis is mainly manual interpretations of an MRI picture by a radiologist, which could be very time-consuming and error-prone. This has led to the shift towards the application of machine learning, in particular deep learning models such as convolutional neural networks (CNNs), which have revolutionized many fields by learning from experience without being explicitly programmed. These have applications in diverse areas like stock price prediction, facial recognition, and music genre classification. CNNs have also proved highly effective in dermatology, as recent studies have shown that they may reach the performance of expert dermatologists. This was done using Long Short-Term Memory (LSTM) networks to predict patient diagnoses from health records, where reinforcement learning produced personalized suggestions of what treatments to offer the patients. Neural networks, with deep learning models like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), are massively applied to domains such as image and speech recognition, natural language processing, and other works requiring pattern finding. CNNs have found broad success in applications such as facial recognition technologies and automated image captioning. Lawrence et al. (1997) utilized CNNs to identify faces with significant accuracy, a foundational study in using neural networks for biometric identification [2] .Shen et al. (2017) reviewed the use of deep learning for medical image analysis, highlighting its effectiveness in enhancing diagnostic accuracy for various diseases, including cancer.[3] The strengths are high accuracy of pattern recognition, and the possibility to learn very complex patterns. The weaknesses are the requirement of feeding in lots of data and huge computational resources. These models can also turn into black boxes with little understandability of their decisions.

Our project on brain tumor classification using CNNs relates closely to the applications of neural networks in medical imaging. Similar to Shen et al. (2017), we leverage deep learning to enhance diagnostic accuracy but specifically focus on brain tumors using MRI scans. Unlike linear regression and reinforcement learning, our approach utilizes a pre-trained VGG16 model adapted for image classification tasks, taking advantage of transfer learning to reduce the need for vast amounts of training data and computational resources. This strategic use of a pre-trained model addresses some of the typical weaknesses of neural networks, such as their demand for large labeled datasets and extensive training time, by utilizing learned features from ImageNet data. Thus, our method stands out by balancing the robust capabilities of deep learning with practical constraints encountered in medical settings.

The use of Convolutional Neural Networks (CNNs) for diagnosing brain tumors using MRI data has been a significant area of research and has shown promising results in improving diagnostic accuracy and speed. Recent studies have focused on various CNN architectures like AlexNet, GoogLeNet, and ResNet50, with ResNet50 showing some of the highest accuracy rates in identifying brain tumor images[4].A comprehensive review of CNN techniques from 2015 to 2022 highlights their application in classifying brain tumors using MRI images. This review suggests that while many CNN-based methods demonstrate good performance, there is no clear consensus that any specific method outperforms others significantly, mainly due to variations in validation methods, performance metrics, and training data used in these studies[5].Additionally, advancements in deep learning techniques, including clustering and SoftMax classification, have been explored to further enhance the performance of CNNs in analyzing MRI images for brain tumor detection . This shows a continuous effort to refine and optimize deep learning methods for this critical application[6]Overall, the development of CNNs in the field of brain tumor diagnosis using MRI is evolving, with ongoing research addressing the challenges of clinical implementation and exploring future directions for this technology[6].These efforts are crucial for transitioning from experimental setups to practical, clinically applicable systems that can aid medical professionals in making more accurate and timely diagnoses.

Our project is specific to implementing pre-trained CNN model VGG16 for classification of brain MRI images into 'tumor' and 'healthy'. Pre-trained models are usually applied because they take up features learned from large datasets and can generalize well for specific tasks, especially if the dataset for that mission is relatively small. We are going to adapt the model to our needs by removing the head, which normally ends with layers that output dimensions not fit for our images, and train it with our own dataset, which comprises 4,514 MRI images.In addition, most existing works deploy models trained from scratch, we transfer learning, significantly reducing computational resources and time required for training. For this project, I expect that a fine-tuning of pre-trained networks to reach this twofold goal can be thus expected: maintaining the robustness of general features learned on large datasets, but at the same time reorienting it to the specificities needed for brain tumor detection.The methodology has proven to yield success in high validation accuracy and proving the model's generalization to new unseen MRI images. This method, apart from amplifying diagnostic accuracy, reduces time and cost for the completion of traditional methods of diagnosis and, altogether, can bring about improved patient outcomes with optimal utilization of medical resource settings.

II. Dataset

For this study we took a dataset from Kaggle[7] consisting of 4,514 MRI images. The full set of images is broken down into two groups: one with a brain tumor (2513 images) and the other that represents healthy brains (2087 images). The images were further partitioned into the training and validation datasets, which were intended to be used in training and testing the model, respectively. Training dataset: 3160 images,Validation dataset: 1354 images.This balanced dataset is important to train our models so that the deep learning algorithm can learn distinctive features effectively from both classes. In preparing the data for training with efficiency, some key pre-processing steps have been taken into consideration.

Examples from the dataset and features used: Generally, the examples in the dataset show MRI scans of well-defined boundaries of healthy tissue from brain images and the areas that are affected by a tumor as shown in fig.1. Among the features used by the neural network are edges, textures, and patterns both characteristic of normal brain structures and bearing the signature of tumors. These features are quite important for the CNN to really understand well in both classes.This is how all these parts work together in project setup.

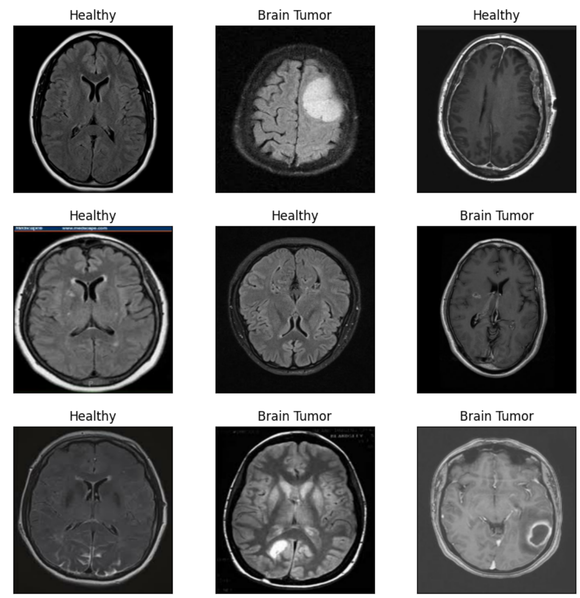

Fig. 1. MRI Scans of Brain showing Healthy and Tumor

Preprocessing and normalization were conducted on the images fed to a Convolutional Neural Network (CNN) VGG16 architecture-based.This model learns from and can generalize on the complex patterns characterizing brain tumors in MRI scans through the below-utilized features, distinguishing the 'healthy' class from the 'brain tumor' class. This structured approach in data set preparation and preprocessing ensures good quality and well-prepared data from which the neural network will have to learn; therefore, more accurate and reliable classification results can be accomplished. The images are very well pre-processed and labeled, thus laying a strong ground to train CNNs for exact classification of brain tumor images. For this problem, the image dimensions were set to be standard, hence having a constant input size for the CNN, which is one of the major steps in maintaining consistency during feature extraction over diverse images.There is additionally a metadata.csv file.

The metadata.csv file contains the following columns to describe the images in the dataset:

- Unnamed: 0: An index column.

- image: The name of the image file.
- class: The classification of the image, which in this example is 'tumor'.
- format: The file format of the image (JPEG, PNG, TIFF).
- mode: The color mode of the image (e.g., RGB, grayscale represented as 'L').
- shape: The dimensions of the image, represented as (width, height, channels).

This metadata provides an overview of the image properties, which are crucial for preprocessing steps in machine learning workflows, especially in ensuring compatibility with deep learning models.

Resizing: Resizing happened to all the images to a similar size, 381x362 pixels. That standardization is really important in ensuring that the neural network receives a given input of data of the same size, hence effective learning and feature extraction are greatly enhanced.

Data Normalisation: During normalization, all the images are normalized to scale their pixel values between 0 and 1. This is by rescaling every pixel value with 1/255, which ensures fast convergence during training due to a maintained common scale of all the input features.Data normalization is done in the sense that pixel values were rescaled, and a uniform image size was set for all inputs to be 381x362 pixels. This size was chosen so that the resizing was not done with a size so large that significant details present in the images within the dataset were lost.

III. Methods

The primary methodological approach in this study is to use deep learning to classify brain cancers based on MRI data. At first we used VGG16 neural network architecture, which has been pre-trained using the ImageNet data. VGG16 was chosen because of its shown performance in image identification tasks, providing it a strong foundation for transfer learning applications in medical imaging. Later we build an customized CNN Model.

A. VGG16 Architecture

Initially, 1,000 unique classes were intended to be identified using the VGG16 architecture. Its depth, comprising 16 layers which has 13 convolutional layers and 3 fully connected layers—allows for differentiation. VGG16 is renowned for its effectiveness and ease of use. It also does well on a wide range of computer vision applications, such as object identification and image classification. The architecture of the model shown in Fig.2. consists of a stack of convolutional layers, followed by layers of max-pooling that become deeper and deeper. By using this technique, the model is able to learn complex hierarchical representations of the visual input, which results in predictions that are more reliable and accurate. Because of its great performance and adaptability, VGG16 is still a popular choice for many deep learning applications, even if it is simpler than more current designs. [8]

For this project, the model was modified to meet the binary classification task of determining whether an MRI image exhibits symptoms of a brain tumor or not. This adaption requires changing the network's top layers.

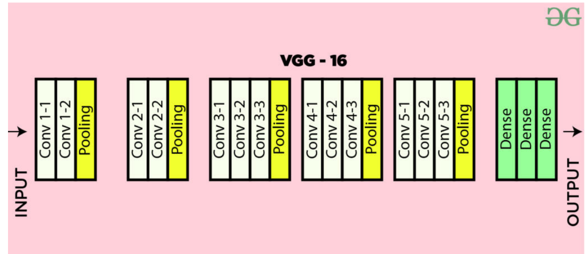

Fig. 2. VGG16 Architecture.[8]

To better meet the task's requirements, the original fully linked output layers of VGG16 were modified with a new setup:

Flattening Layer: This layer turns 3D feature maps into the 1D feature vectors required for binary classification.

Dense Output Layer: One dense layer with one neuron was added. It uses a sigmoid activation function to get a number between 0 and 1, indicating the chance that the MRI scan shows a brain tumor.

Limitations of VGG16: [8]

- Training is extremely slow
- It takes around 528 MB for the VGG-16 trained ImageNet weights. It is therefore inefficient as it consumes a lot of bandwidth and storage space.
- The increasing gradient problem is caused by 138 million factors.

B. Modified VGG16 Model

At first we Loaded pre-trained model VGG16: Loads model with weights pre-trained and Removed the fully connected layers of the model so that it is adaptable to new output classes. and then we Set the trainable layers: The initial num_frozen_layers' weights are set to non-trainable (layer.trainable = false) to preserve the learned generic features, while later layers can be fine-tuned to the more specifics of the new data. New model construction was done by Rescaling the images and performed preprocessing. Later we added three convolutional layers followed by Pooling and flattening layer and then Output layer which is dense layer which outputs single value Later the number of frozen layers is set to 7 and initial convolutional layers remain unchanged as they capture the features useful for image processing. Builded and trained a neural network model(new constructed model) for binary classification.

C. Customized CNN architecture

Aside from utilizing a complicated model such as VGG16, we tested a simpler customized convolutional neural network (CNN) architecture to see if a less complex model might provide equivalent results. We defined it as Modfinal_model. This model was created from scratch and has less convolutional layers as shown in fig.3. It has 5 convolutional layers, 5 maxpooling layers followed by one dropout layer and 1 flattening layer and 2 Fully connected layers(Dense layer). The objective for investigating a simpler model was to strike a compromise between computing efficiency and predictive performance, which is critical for real-world applications when resources are constrained.

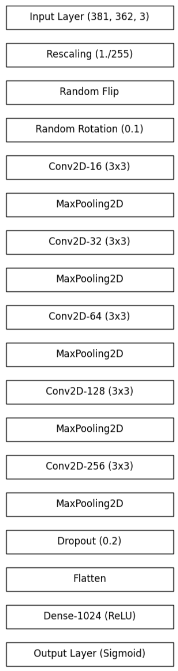

Fig. 3. CNN(Modfinal_model) Architecture.

IV. Experiments

We conducted experiments on a dataset of 4514 MRI scanned images from Kaggle, which were divided into Tumor and Healthy classes. In the preprocessing phase, we rescaled the image dimensions to 381 x 362 x 3 average dimensions of images so that we can maintain a standard image size and divided them into training and validation sets(helps to see how well the model is generalizing to unseen data). Learning rate was set to 0.001. Batch size was set to 32. Initially we used the VGG16 model, the model is loaded without a top layer, is suited to the average dimensions of our photos, and includes pre-trained ImageNet weights. And defined a function 'tumor_classifier' to build a custom model based on VGG16 for tumor classification.However,its performance was insufficient for our needs. As a result, we created a bespoke model based on the VGG16 architecture, which included additional convolutional layers, pooling, and flattening layers to produce a binary classifier.

Hyperparameter adjustment was critical to optimizing model performance. No.of frozen layers is set to 7 and initial convolutional layers remain unchanged as they capture the features useful for image processing. We experimented with batch size and epochs, first training for 10 epochs and then increasing to 20 epochs, as well as implementing data augmentation and regularization strategies. Despite these efforts, the first VGG16 model had a validation accuracy of 73%, and fine-tuning and data augmentation produced no substantial gains. we got 45% and 54% respectively. We adjusted the learning rate during training to increase model performance. This parameter adjustment enabled us to determine the ideal value for minimizing the loss function.

After identifying performance issues, decide to modify the model architecture by reducing the number of layers and employing fewer filters in convolutional layers to reduce overfitting and computational demand. VGG16 contains 16 layers (13 convolutional and 3 fully linked). Has over 138 million parameters, making it computationally demanding and potentially prone to overfitting on smaller datasets. The newly defined model (Modfinal_model) is noticeably simpler. It starts with numerous convolutional layers, then moves on to max pooling layers and eventually a dropout layer before flattening and adding dense layers. Convolutional layers use fewer filters (from 16 to 256 across layers) than VGG16, which progresses from 64 to 512.

Our final model, Modfinal_model, attained an astounding 97% accuracy after 30 epochs of training. This highlights the necessity of tailoring model architectures and training procedures to individual tasks, particularly in medical image categorization.In the following sections, we will look deeper into the implications of these findings and their applications in clinical situations.

V. Results and discussion

The evaluation metrics of multiple models on the validation set indicated a range of accuracy and to see how well they classified brain tumor images. The initial VGG16 model had a validation accuracy of 73%, which indicated moderate performance but fell short of our expectations. Fine-tuning the VGG16 model resulted in reduced accuracies, with 45% and 54% attained after 10 and 20 epochs, respectively. This shows that the model struggled to master the dataset's complexities, even after making modifications. Similarly, despite using data augmentation and regularization techniques, the accuracy remained at 54%, showing slight increase in generalization.

Our modified model, Modfinal_model, showed remarkable improvement, reaching 97% accuracy after 30 epochs of training. This shows that reducing the model architecture and allowing for more training iterations resulted in improved performance. The table below summarizes the comparison of different models' performances.

Model	**Validation Accuracy**
VGG16	73%
Fine-tuned model (10 epochs)	45%
Fine-tuned model (20 epochs)	54%
Data augmented and regularized model	54%
Final model (Modfinal_model)	97%

These findings show the need of carefully selecting and adapting model architecture and training procedures to achieve peak performance in medical image classification tasks. While pre-trained models such as VGG16 give a good foundation, fine-tuning and augmenting data may not always result in significant gains. Instead, simplifying the model architecture and allowing for more training iterations can lead to better results, as seen by our final model's performance.

The experiments showed that, while pre-trained models such as VGG16 give a good starting point, fine-tuning and data augmentation strategies may not necessarily result in significant improvements in brain tumor detection accuracy and altering the learning rate was critical in improving model performance. By fine-tuning this parameter, we were able to obtain the best value that minimized the loss function, resulting in higher accuracy in detecting brain tumors from MRI examinations.Despite efforts to improve the VGG16 model, the accuracies obtained were small, demonstrating the need for new methodologies. Our reduced model, Modfinal_model, obtained an impressive 97% accuracy after 30 epochs, demonstrating the importance of model architecture and training procedures in generating superior performance. More study is needed to evaluate the model's performance on larger datasets and determine its clinical application in supporting radiologists in brain tumor identification.

VI. Conclusion

Finally, our study proved the potential of deep learning algorithms for detecting brain tumors from scanned pictures. We started with a pre-trained VGG16 model and iteratively improved our technique through changes to hyperparameters and model architectures. Our results demonstrated that model simplicity and appropriate training iterations are critical for achieving high tumor detection accuracy.

The final model, Modfinal_model, scored an excellent 97% accuracy on the validation set, surpassing the basic VGG16 model and other variants. This demonstrates the efficiency of fine-tuning model architectures to fit the task at hand.

In the future, numerous options will be implemented to improve the performance of the models and applicability. First, testing on bigger and more different datasets is necessary to confirm that the model can be generalized across patient populations and different types of imaging. Furthermore, incorporating advanced strategies such as attention mechanisms or assembling several models may increase performance even further.

Furthermore, incorporating clinical data such as patient history or additional imaging modalities (e.g., functional MRI) may improve the model's diagnostic skills and aid in clinical decision-making. Finally, applying the model in real-world clinical settings and assessing its effectiveness in supporting radiologists could provide useful information on its practical applicability and impact on patient care.

In conclusion, our study shows the use of machine learning has the ability to improve brain tumor identification, and future study in this field has promise for improving patient outcomes and developing medical imaging technologies.

Contributions

This section details the specific contributions of each team member to the project, emphasizing the collaborative effort and the unique roles each individual played.

Kusuma Korada: Played a key role in Data gathering, preparation, Exploratory data analysis and auto-tuning. Responsible for documenting the Abstract, Introduction and dataset.

Nikhil lakkireddypalli: Led the implementation and fine-tuning of the VGG16 model, assessing its performance and making critical adjustments. Responsible for documenting the Results, Discussion and conclusion.

Pooja sree Bolisetty: Developed the custom CNN model, ”Modfinal_model”, from scratch, integrating advanced neural network techniques. Responsible for documenting the Methods and Experiments.

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