An Approach for Classification & Detection of Brain Tumor Using CNN & VGG-16

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***Abstract*-- A brain tumor is an abnormal cell development in the brain, some of which can progress to cancer. MRI scans are the standard technique used to identify brain tumors. The abnormal tissue growth in the brain is discovered from the MRI scans. In this research, we'll use a variety of algorithms to identify brain tumors. This project's algorithms include: 1. The CNN Algorithm 2. VGG (16).In the initial CNN design, the accuracy of brain tumor detection approaches -99.33 percent. The second CNN model architecture achieves an accuracy of roughly 92.66 percent. Within the brain tumor images, the VGG-16 model is able to capture intricate details and relationships by stacking many convolutional and fully linked layers. The model can detect brain tumors with great accuracy thanks to its deep design. Numerous types of brain tumors can be accurately diagnosed with the VGG-16 model. An MRI image dataset was used to train it.**

***Index Terms*—CNN, VGG-16, Convolution, Pre-processing, Augmentation, Classification, Tumor, MRI, Detection, Data Extraction.**

1. Introduction

A brain tumour is a condition brought on by an abnormally large mass growing inside the brain. Our bodies normally make new cells which replace damaged and ageing ones in a controlled manner. However, tumour cells continue to grow uncontrollably in cases of brain tumours [1]. As previously said, because these brain tumours have an ability to spread and grow quickly, early detection is crucial. Additionally, in some complex cases, the classification stage after identification can be a complex and time-consuming task for doctors or radiologists. This is because it depends entirely on the availability of skilled medical professionals, which is challenging to provide in underdeveloped and few developing regions of the world. There are numerous ways to categorise brain tumours, such as primary and secondary tumours. About 70% of brain tumours are classified as primary tumours, with the remaining 30% being secondary tumours. The most common kind of brain tumours that start in the brain's glial cells are called gliomas. 30% of benign brain tumours and 80% of malignant brain tumours are gliomas. The WHO has classified gliomas into four classes, ranging from type I to IV. Grade I tumours are benign and resemble normal glial cells in texture greatly; Grade II tumours differ slightly from grade I, Grade III tumours are malignant and have abnormal tissue appearance, and Grade IV tumours are the most severe stage of gliomas and have visible tissue abnormalities.

A benign tumour called a meningioma develops slowly on the membrane that encases the brain and spinal cord inside the human skull. Meningioma tumours are mostly benign. However, the pituitary glands, which control hormone levels and processes in the body, are the source of pituitary tumours. It may be benign, cancerous, or benign and spread to the bones. Pituitary tumour complications can result in vision loss and a lifelong hormone shortage [2]. In an attempt to overcome this, the suggested approach offers an automated method that will determine whether the patient in issue has a brain tumour or not. With the help of this technology, the doctor may make decisions early on and start treatments earlier. The suggested method trains the model for this binary problem using MRI and the CNN and VGG-16 architecture [3].

In the presented approach, we expanded the dataset (MRI brain pictures), converted the raw data using a few data preparation processes, looked into two more deep learning models, CNN and VGG-16, and provided a comparative analysis in the results section. One can use any of these algorithms in their work, depending on factors like algorithm complexity, computing time, and other outcomes. With the help of this automatic detection technology, the doctor can begin treating patients earlier by making early decisions.

2. Literature Survey

In the work 'BRAIN TUMOR DETECTION USING DEEP LEARNING MODELS' S. Grampurohit, V. Shalavadi, V. Dhotargavi, M. Kudari & Mrs S. Jolad [1] emphasises how important artificial intelligence is to raising diagnostic precision. Several research works highlight the efficiency of convolutional neural networks (CNN) and architectures such as VGG-16 in MRI image analysis for accurate tumor diagnosis.

A. Kadam, S. Bhuvaji, S. Deshpande [2], proposed a "Brain Tumor Classification using Deep Learning Algorithms". For a comprehensive and comparative analysis of how various model types of network architectures fare against the four-class classification problem on the same dataset, they have developed and trained a variety of ANN and CNN models, including a variety of pre-trained Transfer Learning (TL) models.

The authors H. Sultan, N. Salem, and W. Al-Atabany [3] of the Department of Biomedical Engineering at Helwan University in Cairo, Egypt, suggested "Multi Classification of Brain Tumor Images." Meningioma, glioma, and pituitary tumors are the three types of brain tumors that the authors classified in their work using CNN, along with their classifications and grades. Axial, coronal, and sagittal views were among the three different MRI views included in their initial dataset. Images on T1-weighted contrast-enhanced that included various grades of gliomas (Grades II, III, and IV) were included in the second dataset. These levels are then followed by the convolution layers and their activation functions (3 convolution, 3 ReLU, normalization, and 3 Max pooling layers). The accuracy of this suggested architecture was 98.7%.

Yuehao Pan, Weimin Huang et.al [4] proposed a “Brain Tumor Grading based on Neural networks and Convolutional Neural Networks”. This work uses baseline neural networks and several deep learning configurations to examine brain tumor grading using multiphase MRI data. This work utilizes the intrinsic learning capabilities of deep learning, in contrast to previous methods that depended on characteristics that were manually constructed. The results show that Convolutional Neural Networks outperform traditional Neural Networks in terms of grading performance by 18% when measured by sensitivity and specificity.

3. METHODOLOGY

3.1 Pre-processing of data:

Data pre-processing is the process of using pre-processing techniques to transform raw data into meaningful data. The methods of pre-processing that we have employed are:

Step 1: Import libraries.
Libraries like matplotlib, pandas, TensorFlow, NumPy, OS, and scikit-learn, among others, are imported.

Step 2: Augmenting data
The process of producing altered versions of the images in the dataset using methods like rotation and other adjustments is called "image data-augmentation." The photos are produced by the Image Data Generator class. There are various tumorous and non-tumorous images after augmentation.

Step 3: Bring in the enhanced information

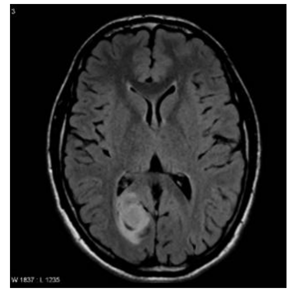


Fig 1. Original Image

Step 4: Convert the pictures to grayscale:
When working with CNNs and VGG16 for brain tumor detection, it's common to convert medical images (such as MRI scans) into grayscale. Grayscale images contain intensity information, which is often sufficient for medical imaging tasks.

Step 5: A sequence of erosions and dilations is used to eliminate noise. Erosion is the process of removing pixels from the image's edges. Dilation is the erosion process done in reverse, adding pixels to the image's edges. Gaussian blur is the method used to smooth the image.

Step 6: Take hold of the biggest shape:
The contour method is a technique used in image processing and computer vision to identify and outline the boundaries of objects or regions within an image. In the context of brain tumor detection using Convolutional Neural Networks (CNNs) and VGG16, the contour method can be applied after the CNN model processes the medical images.

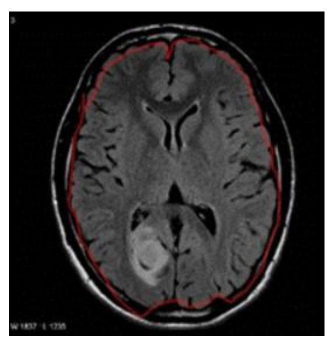


Fig 2. Find the largest contour

Step 7: Determine the contoured image's extreme points. The extreme points refer to the corner points of the bounding box around a detected contour. To find the extreme points of the contoured image in a brain tumor detection system using CNN and VGG16, you can use the boundingRect function in OpenCV. The boundingRect function returns the (x, y) coordinates of the top-left corner of the bounding box and its width and height.

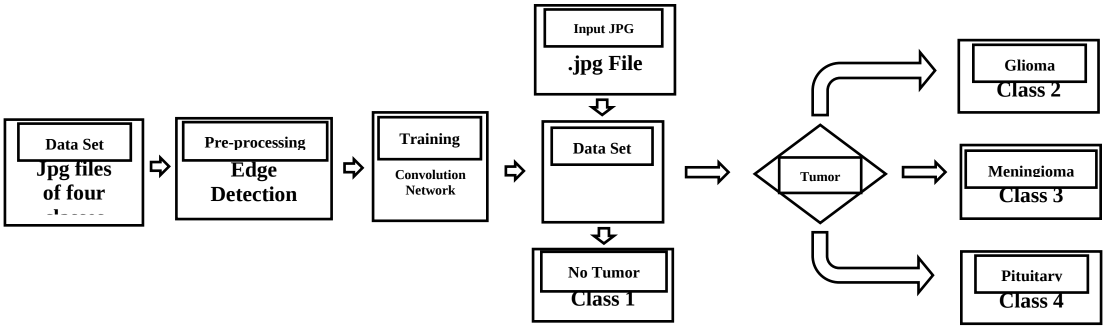


Fig 3. Architecture of Brain Tumor Detection Model

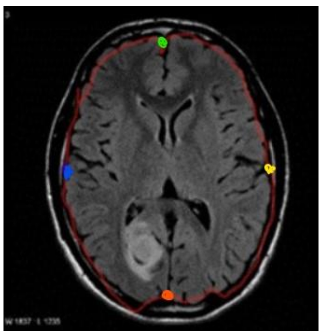


Fig 3. The extreme points of contour

Step 8: Adjust the picture's size

All the images before pre-processing were of different size, hence all the augmented images were resized to 240x240 for CNN and 224x224 for VGG-16.

Step 9: Use the extreme points to crop the photos.

Step 10: Dividing the dataset-

Divided data into four parts according to their tumor types [5].

3.2 Convolutional Neural Network (CNN):

In the latter half of the 20th century, significant advancements were made to the deep-structured learning model known as Convolutional Neural Networks (CNN). It simulates how the human brain is structured to process items. Additionally, studies demonstrate strong performance on CNN-based algorithms, particularly in the area of classifying 2D data.

Every layer in a CNN applies a distinct set of filters, usually hundreds or thousands of them, aggregates the output, and feeds it onto the network's subsequent layer [6].

A CNN automatically picks up these filters' values during training. CNN offers us two main advantages:

1. Local variance: Regardless of the object's location inside the image, we can identify it as containing an object according to the idea of local invariance.

By using "pooling layers," which locate areas of our input volume with a strong response to a filter, we are able to achieve this local invariance[7].

2. Compositionality: Every filter integrates a local pathway of lower-level information into a higher-level representation; this process enables our network to acquire deeper network knowledge and understand more complex features.

Kernel: In a huge image, a kernel is represented by a tiny matrix that moves from top to bottom and left to right. The neighborhood of each pixel in the input image is convolved with the kernel at that pixel, and the output is stored.

CNNs can learn filters to identify edges and blob-like structures in the network's lower levels. By using these edges and structures as 'building blocks', the CNNs can eventually identify high-level objects in the network's deeper layers.[8]

Convolutional neural network typically consists of below layers:

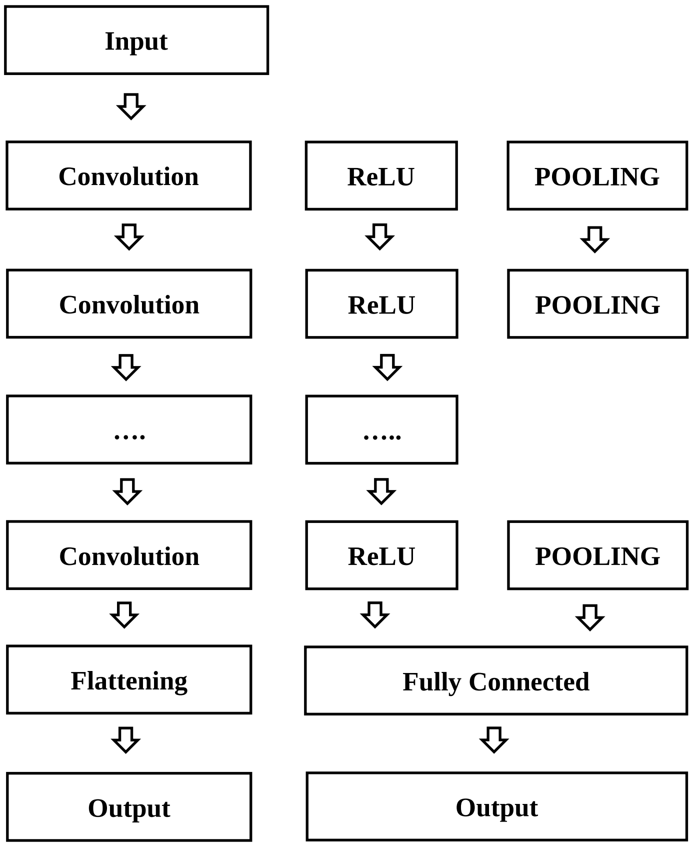


Fig 4. Flowchart of CNN Layers

1. *Input Layer:*
The photos have been downsized to 240x240 pixels, with depth=3 [the number of channels in the image] and height=240 and width=240 pixels [9].

2. *Convolution Layer:*
The convolution layer is considered as the core building block of a "Convolutional Neural Network". The parameter for the convolution layer is made up of K learnable filters, or kernels. In the work we have shown, we have employed 32 filters with a size of (7,7) in the convolution layer. The receptive field, or the local input volume region that each neuron is connected to, is denoted by the size (7,7) [10]. We've used a (7x7) receptive field, which means that for a total of 7x7x3 = 147 weights, each neuron will connect to a 7x7 local region via the image. We now have 32 two-dimensional activation maps after the input volume has been processed via all 32 filters. Thus, each element in the output volume represents the output of a neuron that "looks" at a limited portion of the input. In this way, the network "learns" to activate filters that recognise certain kinds of features. Due to the filter that was employed, the size of the image after the convolution operation is now (238, 238, 32) [11].

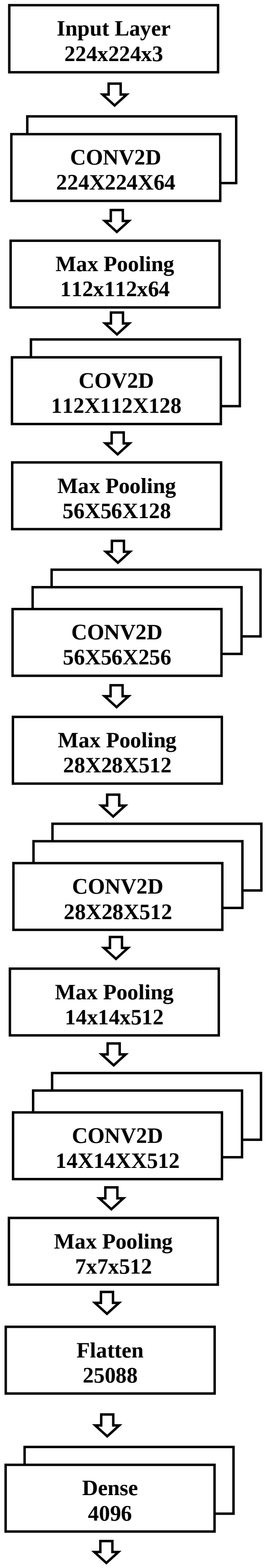
3. *Pooling Layer:*
Two techniques exist for decreasing the magnitude of an input volume.
1. Stride > 1 convolutional layer
2. Layers of Pooling
The principal role of the POOL layers is to gradually decrease the input volume's spatial dimensions, specifically its width and height. By doing this, we can lower the number of computations and parameters in the network. Control over fitting is another benefit of pooling.
In the pooling layer I, e Maxpooling, we have employed the Max function with the pool size of FxS, i.e. [receptive field size into stride].

4. *Fully Connected Layer:*
The fully connected layers are used for making predictions based on the extracted images by convolution layer. Below are some layers used in our work: The Flatten layer is used to flatten the output from the convolutional layers into a 1D array [12]. Dense layers with ReLU activation functions are added to capture complex relationships in the data. The final Dense layer with SoftMax activation is used for multi-class classification.

5. *Output Layer:*
In this brain tumour classification problem, the four classifications 'glioma_tumor', 'meningioma_tumor', 'no_tumor', and 'pituitary_tumor' indicate various tumour forms. Each class is given a probability by the output layer with SoftMax activation, and the class with the highest probability is predicted to be the final output [13].

3.3 VGG-16 Architecture:

The Visual Geometry Group (VGG) network was introduced by Simonyi and Zisserman in the 2014 paper, "Very deep convolutional network for large scale image recognition". VGG16 (Visual Geometry Group 16) is a CNN (Convolutional Neural Network) architecture which is being designed for image classification [14]. It was created by the University of Oxford's Visual Geometry Group and debuted in the 2014 ImageNet Large Scale Visual Recognition Challenge (ILSVRC) competition. Because of the VGG16 architecture's efficiency and simplicity, it became well-liked. In the ILSVRC 2014 competition, VGG16 demonstrated the competitiveness of deep learning models for image classification problems. Although VGG16 is no longer the most accurate or efficient architecture—ResNet and Efficient Net, for example—it is still a commonly used benchmark and a useful starting point for learning about deep convolutional neural networks [15]. The VGG-16 architecture used in our model is:



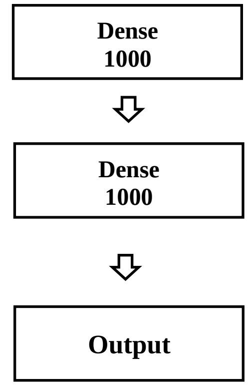


Fig 5. Flow Diagram of VGG16 Architecture

Two distinguishing features of the VGG family of convolutional neural networks are as follows:

1. Only 3X3 filters are used by any of the network's convolution layers.
2. Prior to performing a pool operation, stacking numerous convolution + RELU layer sets (the number of consecutive convolution layers + RELU layers typically grows the deeper we go).

Rather than utilizing the transfer learning technique, we constructed the VGG-16 architecture and made the required modifications to get more accuracy in the work that is being delivered [16].

An outline of the VGG16 architecture is provided below:

1.Input Layer: Takes in the picture input.

2.Convolutional Layers (13 layers): An activation function known as a Rectified Linear Unit (ReLU) follows each convolutional layer. These layers make use of tiny 3x3 convolutional filters. The deeper the network, the more filters there are.

3.Pooling Layers (5 layers): To minimize spatial dimensions, VGG16 makes use of max-pooling layers.

4.Fully Connected Layers (3 layers): These layers generate the final output by processing the high-level characteristics that the convolutional layers extracted.

5.Output Layer: When producing class probabilities for image classification, a SoftMax activation function is typically utilized [17].

3.4 Dataset:

A medical imaging method called magnetic resonance imaging (MRI) is used in radiology to create precise two- or three-dimensional pictures of the brain and brainstem. Two-dimensional T1-weighted contrast-enhanced pictures are included in the database. Three distinct perspectives are included in the dataset: sagittal, coronal, and axial views. Four classes were created from these photos [18]. For each form of tumor, the number of pictures collected is:

Type	Training Sample	Testing Sample	Total
Glioma	250	100	350
Meningioma	250	115	365
No Tumor	246	105	351
Pituitary	249	74	323

Table 1. Initial Dataset

4. Results

Results from VGG-16:

The following can be deduced from the VGG-16 result plots: Even though the accuracy rate is increasing up to 100% (Fig.7), we have estimated the best model at the 17th epoch, yielding 97.16 percent training accuracy and 97.42 percent validation accuracy. After the 17th epoch, validation accuracy was gradually decreasing even though accuracy was increasing [19].

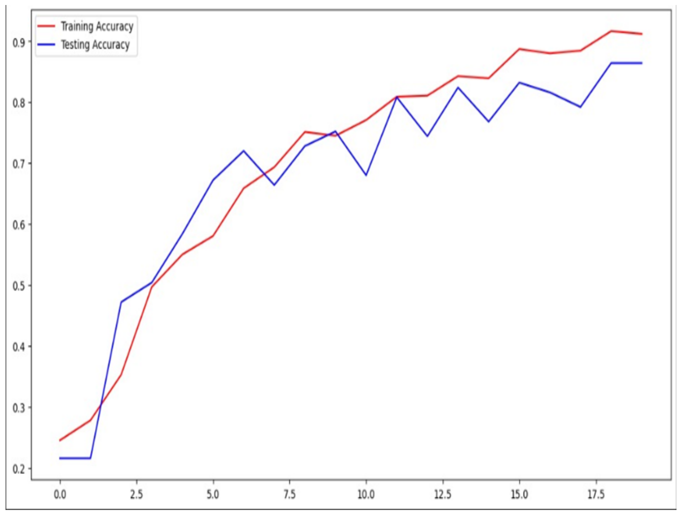


Fig 6. Accuracy Chart

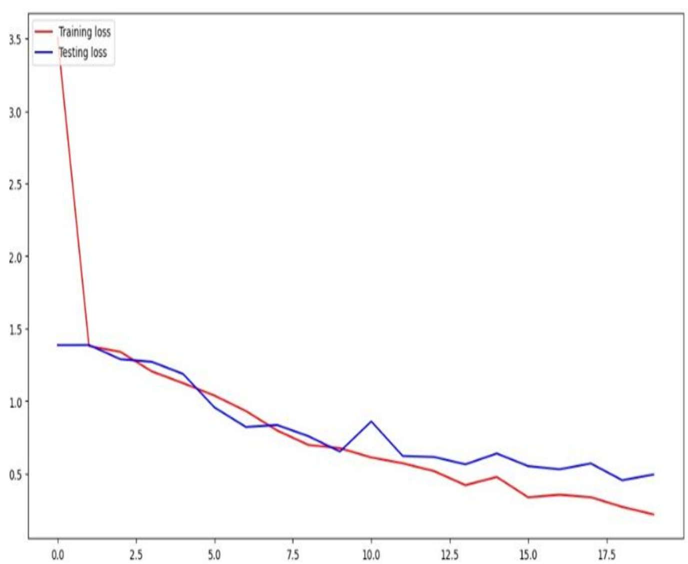


Fig 7. Loss Chart

In fig 6 and 7 blue color refers to Training loss and Training accuracy and orange lines represent Testing loss and Testing accuracy.

Parameterized comparison of CNN and VGG16 outputs:

Parameter	CNN	VGG-16
No. of images	Total - 1389 Training - 995 Test - 394	
Time consumed [From pre-processing Till obtaining results]	0:5:03 [5mins: 3secs] GPU (GOOGLE COLAB)	0:15:25 [15mins:25secs] GPU (GOOGLE COLAB)
Epochs carried out	20	
Accuracy	0.9336	0.9716
Loss	0.589	0.112

Table 2. Comparison of CNN & VGG16

5. Conclusion

In conclusion, a major development in medical imaging has been made with the use of Convolutional Neural Networks (CNN) and the VGG16 architecture in brain tumor diagnosis. From complex radiological data, these advanced algorithms have shown amazing efficiency and accuracy in finding and categorizing brain tumors. Their capacity to identify minute patterns and characteristics in medical images has improved diagnostic accuracy and made detection earlier and more dependable. The incorporation of CNN and VGG16 into medical procedures has the potential to significantly enhance patient outcomes by providing prompt, precise diagnosis and intervention, particularly as technology advances. The convergence of medical imaging and artificial intelligence signals a new chapter in proactive healthcare and highlights the revolutionary potential of these cutting-edge technologies.

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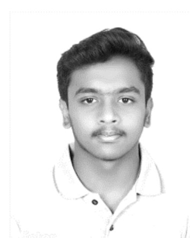

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