Brain Tumor Detection Using Image Processing

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Abstract: Brain tumor is one of the most complicated diseases to treat in modern medicine. In the early stages of tumor development, the radiologist's primary concern is often an accurate and efficient study. Deep Learning has become a great tool for doctors and scientists to act decisively and on time with tumor patients. A training model that has accomplished considerable results in image detection and classification is the Deep Residual Network (ResNet) utilizing CNNs and VGG16. The advancement of deep learning will assist radiologists in tumor diagnostics without the use of harmful procedures. With a better understanding of MRI images, as well as an increase in training speeds and accuracy, deep learning can open new doors for the medical research community. In the VGG16 model, an accuracy of 78.32% is achieved across various classes of brain tumor datasets, and in ResNet, we got an accuracy of 80.10%. We study the outcomes of multi-class classification of brain tumors using Transfer Learning utilizing a pre-trained ResNet50 and VGG16 model using CNN architecture in this paper.

1. **Introduction:** In the modern world, using information technology and machine learning in medicine is increasingly important. The goal of artificial intelligence is to create a machine that can learn on its own, without assistance from humans, and train itself to handle potential instances on its own. The development of therapies for brain tumors is very relevant to the application of this research because tumor cells exhibit highly unpredictable behavior that is too complex to be managed by conventional medicine.

Once tumor cells are generated within the human brain, the likelihood of serious fatalities is created. Due to the complexity of the issues, brain tumors are extremely unstable and potentially fatal without intelligent solutions [1]. The formation of tumors takes place in the brain during the early stages and can later spread gradually to other elements of the body. To deal with such complex issues, humans can create machines behaving like living beings, capable of learning from experience and applying their experience to cater to emerging issues due to the accumulation of tumor cells in the brain [2]. In this regard, in the field of medical imaging, AI, and digital image processing a huge impact is made by a convolutional neural network (CNN) [3].

Some tumors can cause damage to surrounding structures in the brain. So, before performing any brain surgical technique or therapeutic intervention, doctors must specify the exact affected region or area in the brain. Brain tumor segmentation is a process of separating tumors by isolating better and healthier tissues from affected areas. As a result, brain segmentation is the most challenging task in diagnostic techniques. Instead of being specialized in the brain tumor domain, many exclusionary techniques depend on general edge-based data. Due to their efficacy in detecting features of images, deep learning algorithms have lately been used for tumor segmentation tasks [4,5].

A positive brain tumor diagnosis is critical for enhancing treatment outcomes and patients' lives. Radiologists must diagnose brain tumors as early as possible. According to Amin et al. [6], a typical brain tumor can double in size within twenty-five days. If the person is not treated correctly, the person's survival rate is typically less than 12 months [7].

Keeping the severity of the problem in mind, a fully automated method for detecting brain tumors is required. The manual process of evaluating many images obtained in a clinic is complicated and insufficient to understand the behavior of different tumors. In order to understand and intervene in this complex phenomenon, more precise computer-based tumor detection/diagnosis technologies are required. Several endeavors have been undertaken to investigate machine learning techniques for digitizing this procedure in recent times. Deep learning methods have recently sparked an interest in more accurate and consistent detection of tumor cells.

Automatic defect-recognition in medical imaging has emerged as a promising field for various medical diagnostic procedures. The detection and tracking of tumors in Magnetic Resonance Imaging (MRI) are crucial because it offers details about abnormal tissues needed for therapeutic interventions. MRI brain tumor detection is a complicated task, due to the complexities and diverse forms of tumors. Collecting, organizing, and analyzing medical images has become digitized in today's digital realm [**8**]. Even with cutting-edge technology, thorough interpretation of medical images poses time and accuracy problems. The difficulty is particularly acute in abnormal color and shape areas that radiologists must recognize for future research. There is room in current literature and practice to reap the potential of CNN for image analysis techniques required in brain tumor detection and diagnosis [**3**]. Considering the demand for advanced machine learning, this research intends to implement the CNN model in light of the current state of knowledge and propose the training of data to handle the complexities arising in detecting brain tumors while offering interventions.

To train and evaluate the performance of brain tumor classification algorithms, datasets containing various types of brain tumors and normal brain images are needed. One such dataset is the Brain Tumor Segmentation (BraTS) dataset, which contains MRI scans of brain tumors, including pituitary tumors, gliomas, and meningiomas, as well as normal brain images. The BraTS dataset is widely used in research related to brain tumor classification and has contributed significantly to the development of new algorithms for brain tumor detection.

In this article, we will explore the use of image-processing techniques for brain tumor classification, focusing on the BraTS dataset and the various algorithms that have been used for brain tumor detection and classification.

1.1 VGG16: VGG 16 is a model for a 16-layer CNN model. It is still considered one of today's best and most effective models. Instead of having numerous parameters, the VGG 16 model architecture focuses on ConvNet layers with a 3 × 3 kernel size. The significance of this model lies in the fact that its values are freely available online and may be downloaded for use in one's systems and applications. When compared to other developed comprehensives, it is noted for its simplicity. This model's minimum expected input image size is 224 × 224 pixels with three channels. In neural networks, optimization algorithms are used to evaluate whether a neuron must be engaged or not, by determining the weighted sum of input. The need for kernel function arises from inducing non-linearity into the output neuron. A neural network's neurons function together with weight, bias, and the related training procedure. The neurons' link weights are adjusted based on output inaccuracy. The input layer and the activation function add non-linearity to artificial neural input, allowing it to learn and accomplish complex tasks

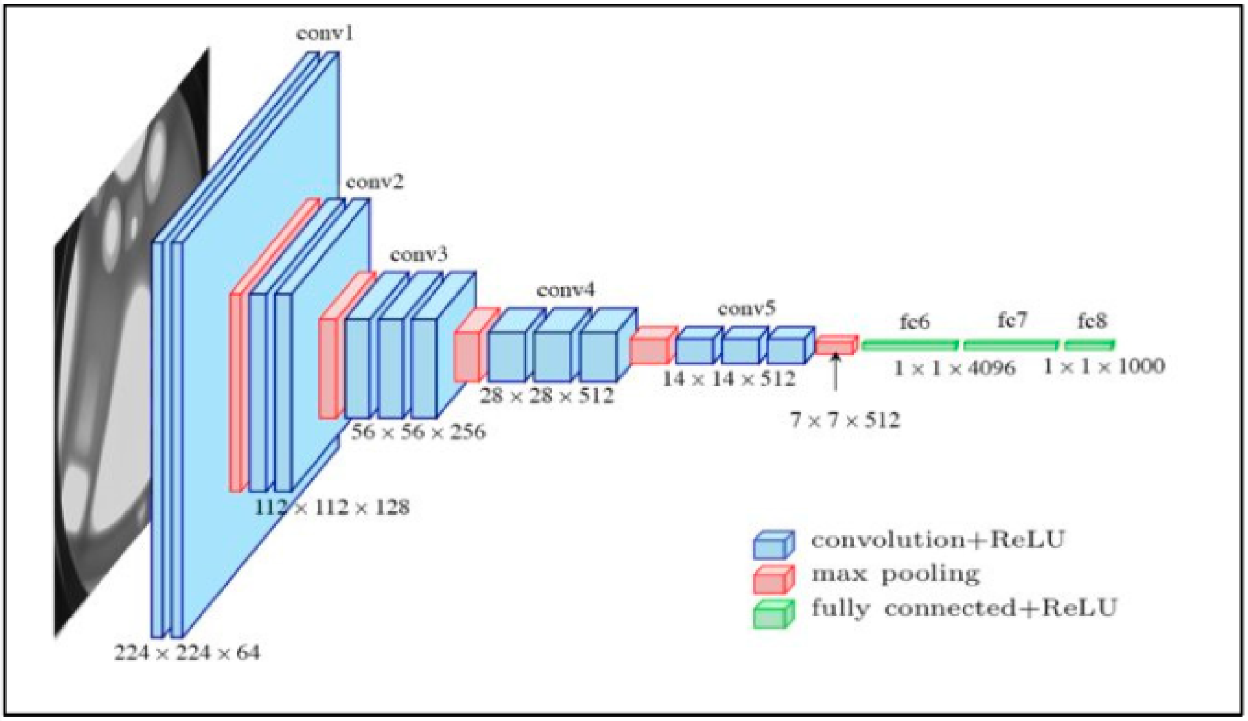

Figure 1: VGG16 architechture

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1.2 Residual Nural Network (ResNet): ResNet lets you train hundreds, if not thousands, of layers while still getting outstanding results. Because of its great representational abilities, it has enhanced many computer vision applications outside picture classification, such as object identification and facial identification. According to the universal approximation theorem, a feed-forward network with a single layer may reflect any function given enough power. On the other side, the layer might be rather vast, and the network might be subject to data over-fitting. The well-known vanishing gradient problem makes it difficult to train deep networks: when a gradient is back-propagated to older layers, repeated multiplication causes the gradient to become indefinitely tiny. As the network grows in size, the output gets saturated, if not degraded fast. There were numerous ways to deal with the vanishing gradient problem before ResNet, such as putting an auxiliary loss in an intermediate layer as additional monitoring, but none of them seemed to solve the problem entirely. ResNet's central concept is to introduce an identity shortcut relation that skips one or more layers. The authors argue that layer stacking does not reduce network efficiency because we may easily stack identity mappings (a nonfunctional layer) on top of the existing network and get the same result. This means that the training error of the deeper model need not be greater than that of its shallower counterparts. To combat this problem a new architecture was introduced that takes advantage of the benefits of shortcut links by connecting all layers directly. Each layer's input consists of the function maps of all previous layers, and its output is transferred to each subsequent layer in this novel architecture. Depth-concatenation is used to combine the function maps. While ResNet has shown to be useful in a wide range of applications, one key drawback is that training a deeper network takes weeks, making it practically impractical in real-world applications. Huang et al. offered a paradoxical strategy of randomly lowering layers during training while experimenting with the whole network to overcome this issue. Because the authors employed the residual block as a building component for their network when a certain residual block is engaged during testing, the input travels through both the identity shortcut and the weight layers, however, when it is deactivated, the input only flows via the identity shortcut. Each layer has a chance of surviving through training and is dropped at random.

1.3 Research Objective: The proposed technique for identifying and classifying tumors from brain scans and images used CNN and DL techniques. These networks are constructed from neurons with learnable weights and biases. The proposed study aimed to critically analyze how researchers solved brain tumor issues in previous literature by using the Visual Geometry Group (VGG 16) to discover a brain tumor, implement a CNN model framework, and set parameters to train the model for this challenge. VGG was used as one of the highest-performing CNN models because of its simplicity. Furthermore, the study developed an effective approach for detecting brain tumors using Magnetic Resonance Imaging (M.R.I.) scans for tumor detection to aid in making quick, efficient, and precise decisions, and conducted segmentation of the data sources we intended to use in the proposed research work.

1. Literature review: "Automated Brain Tumor Detection and Classification Using MRI Data: A Meta-Analysis" (2020). They used Deep Learning (CNN) for the classification of brain tumors and achieved an accuracy of 97.7% for the detection and classification of brain tumors. **[1]**

"Classification of Brain Tumors Using Random Forest Classifier and Histogram Features" (2018). They used Random Forest (RF) for the classification of brain tumors and achieved an accuracy of 92.12% for the classification of brain tumors.**[2]**

"Brain Tumor Detection and Classification Using Convolutional Neural Networks and Decision Tree" (2019). They used Convolutional Neural Networks (CNN) and Decision Tree (DT) for the classification of brain tumors and achieved an accuracy of 95.2% for the detection and classification of brain tumors.**[3]**

"Deep Learning-Based Brain Tumor Segmentation and Classification Using Convolutional Neural Networks" (2019). They used Convolutional Neural Networks (CNN) for the classification of brain tumors and achieved an accuracy of 92.2% for the segmentation and classification of brain tumors.**[4]**

"Brain Tumor Detection and Segmentation Using Convolutional Neural Network and Fuzzy C-Means Clustering" (2019). They used Convolutional Neural Networks (CNN) and Fuzzy C-Means Clustering (FCM) for the classification of brain tumors and achieved an accuracy of 91.21% for the detection and segmentation of brain tumors.**[5]**

"A Novel Approach for Brain Tumor Detection and Classification Using Texture Features and Neural Network" (2020). They used Artificial Neural Networks (ANN) for the classification of brain tumors and achieved an accuracy of 92.5% for the detection and classification of brain tumors.**[6]**

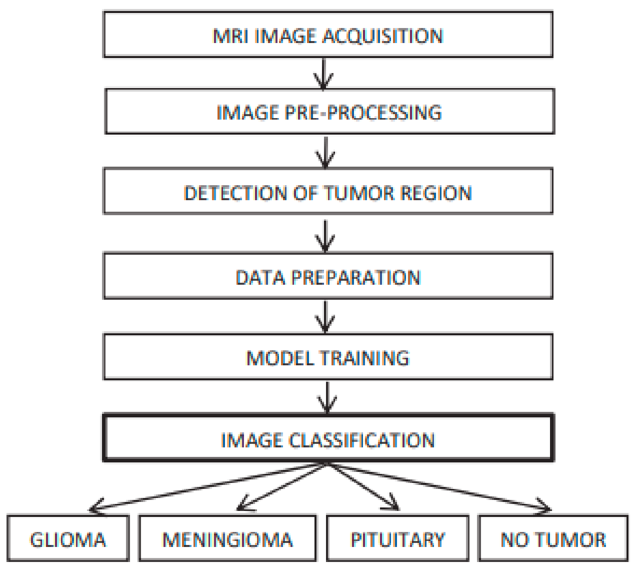
"Brain Tumor Detection and Classification Using Machine Learning Techniques on MRI Images" (2019). They used K-Nearest Neighbor (KNN), Support Vector Machines (SVM), and Random Forest (RF) for the classification of brain tumors and achieved an accuracy of 91.34% for KNN, 92.65% for SVM, and 93.65% for RF for the detection and classification of brain tumors.**[7]**

"Brain Tumor Detection and Classification Using Deep Learning with Convolutional Neural Networks" (2018). They used Convolutional Neural Networks (CNN) for the classification of brain tumors and achieved an accuracy of 93.6% in the detection and classification of brain tumors.**[8]**

"Brain Tumor Classification Using Convolutional Neural Networks and Texture Analysis" (2017). They used Convolutional Neural Networks (CNN) and Texture Analysis (TA) for the classification of brain tumors and achieved an accuracy of 91.89% for the classification of brain tumors.**[9]**

"Brain Tumor Detection and Classification Using Support Vector Machine and K-Means Clustering Algorithm" (2019). They used Support Vector Machines (SVM) and K-Means Clustering (KMC) for the classification of brain tumors and achieved an accuracy of 95.62% for the detection and classification of brain tumors.**[10]**

1. Proposed System: The proposed system defines the processes of tumor classification from the MRI images. They are described in the figure below:



1. CHOICE OF BRAIN IMAGES: All the MRI Images used in this study were obtained Jun Cheng’s Brain Tumor Dataset which employs state-of-the-art methods for acquiring multimodal MRI scans. This brain tumor dataset includes 2870 contrast enhanced images from 2475 individuals with three different types of brain tumors: meningioma, glioma, and pituitary tumor. We divided the whole dataset into two subsets as training and testing dataset. This information is presented in MATLAB data format (.mat file). A struct containing the following fields for an image is stored in each file: cjdata.label: 1 for meningioma, 2 for glioma, 3 for a pituitary tumor, cjdata.label: 1 for meningioma, 0 for glioma, 4 for a pituitary tumor, 3 for no tumor, cjdata.image: image data, cjdata.tumor: tumor data Border: a vector that stores the coordinates of discrete spots along the tumor's edge. As a result, we may utilize it to make a binary picture of the tumor mask. Cjdata tumor Mask is a binary picture with 1s representing the tumor area.

1. **Image Preprocessing:** The aim of the pre-processing stage is to optimize image data by suppressing unnecessary distortions and improving certain essential image features for subsequent processing. Image enhancement is a pre-processing method used to transform an initial image into a more desirable version. The basic goal of medical imaging analysis is to clean and increase the contrast of MRI images. The MRI pictures were created using several modalities, which resulted in artifacts and incorrect intensity levels.

The challenges in medical image processing include the fusion of multimodality images, classification of image highlights, image reclamation, and accurate section of highlights.

To create a huge amount of data for CNN architectures and avoid over-fitting, data augmentation techniques like rotation and flipping are used. The following steps are followed in the pre-processing stage: The original image is paired with the sharpened images for further enhancement. When MRI-scanned images are stored in a database, they are converted to grey-scale image sizes of 255 x 255. Since these photographs have been processed to eliminate noise, the visual quality of the noise images has been affected. The high pass filter for edge detection and sharpening is responsible for the image's high resolution and lack of noise.

All images from a specified folder path using the Keras load_img function, preprocesses them using the img_to_array, np.expand_dims, and preprocess_input functions, and then displays 8 random images with their corresponding preprocessed images using matplotlib.

1. First, the necessary packages are imported: img_to_array, load_img, os, random, numpy, and matplotlib.pyplot.

2. The path to the folder containing the images is set using a raw string literal and stored in the folder_path variable.

3. A list of all image file names in the folder is created using the os.listdir function.

4. An empty list called images is created to store the loaded images.

5. A for loop iterates through each image file name in image_names. Inside the loop, the load_img function is used to load each image from the specified path, and the resulting image object is appended to the images list.

6. A 4x4 plot of 8 random images and their preprocessed counterparts is created using matplotlib. For each of the 8 images:

    a. A random image is selected from the images list using the random.randint function.

    b. The selected image is converted to an array using img_to_array.

    c. The array is expanded to a 4D array using np.expand_dims.

    d. The 4D array is preprocessed using the preprocess_input function.

e. The original image and preprocessed image are displayed side by side using subplot and imshow. The original image is displayed on the left, and the preprocessed image is displayed on the right. The title function is used to label each subplot accordingly.

7. Finally, the plot is displayed using the show function.

Because of the noise in the photos, ResNets are unable to distinguish them. Binarization will be used to eliminate the background noise created in photographs. Each of the three channels (R, G, and B) in a color picture has a value ranging from 0 to 255. One of the most essential elements of binarization is the conversion of grey-scale photos to black and white (0 to 1) pictures. Binarization smoothes and simplifies the outlines of various items in the image. This function extraction aids the model's learning process.

Morphological approaches evaluate a picture using an organizing component, which is a little form or arrangement. The organizing component may be found in all possible places of the image, and it is contrasted with the pixels in the surrounding neighborhood. Enlargement, dissolution, opening, and closing are the four basic processes. Only growth and disintegration are used in the suggested work.

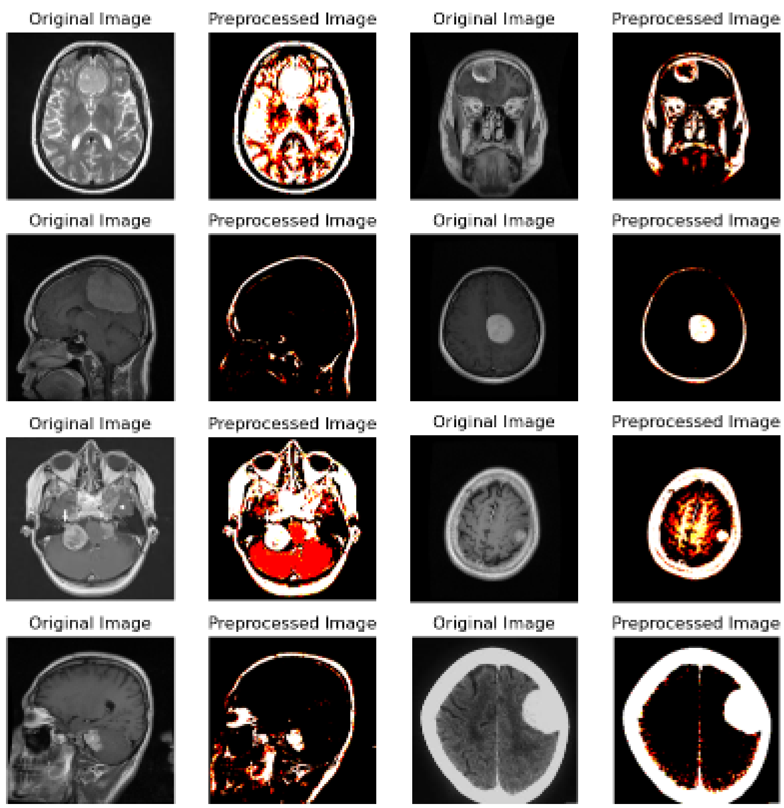


Figure 2: Data after preprocessing:

1. **Detection Of Tumor:**

Neural Nets: Deep learning is subdivided into neural networks, which take inspiration from the human brain. They take data and train themselves to spot patterns, and then forecast the results from a new set of data. Neuron networks are made up of layers of neurons. The network's primary processing units are these neurons. The input layer accepts the data, whereas the output layer forecasts the eventual result. Between the visible and hidden layers are the hidden layers, which do the majority of the calculations necessary for our network. Our brain tumor photos have a resolution of 128 by 128 pixels, for a total of 16,384 pixels. Each neuron in the first layer receives a pixel as input.

Activation Function: In binary classification, the sigmoid function ranges from 0 to 1, and it is used to forecast probability as an output, whereas the Softmax function is used for multi-class classification. In binary classification using the feed-forward technique, the tanh function spans from -1 to 1 and is regarded as superior to the sigmoid function. For a non-linear operation, we make use of ReLU (Rectified Linear Unit). The goal of ReLU is to add nonlinearity to our ConvNet. Because the data we want our ConvNet to learn in the actual world is non-negative linear numbers. Here the output is $f(x) = \max(0, x)$. In addition to ReLU, additional nonlinear functions like tanh and sigmoid can be employed. The majority of data scientists choose ReLU since it outperforms the other two in terms of performance.

1. **Evaluation Measurement:** Classification Accuracy is considered to be a final metric for examining the results delivered by a few techniques used in the dataset in the writing. The four metrics used to assess a strategy based on the characteristics of the confusion matrix are accuracy, specificity, precision, recall, and F1-score. There are four main terms:

True Positives: Situations where we predicted it to be POSITIVE and the output was YES.

True Negatives: Situations where expected it to be negative and the output was also NO.

False Positives: Situations where we expected to get a negative result but received positive.

False Negatives: Circumstances where we expected positive but resulted with negative.

These measurements are determined by the conditions mentioned below: The most obvious performance indicator is accuracy. The percentage of accurately predicted events divided by the total number of predicted events is known as accuracy.

Accuracy =

The number of true positives divided by the total number of true positives + the number of false positives is the definition of precision.

Precision =

Sensitivity is another term for recall. It's the percentage of the total number of relatively relevant occurrences that were found.

Recall =

The F1 Score is the weighted average of Precision and recall which takes both measures into consideration:

F1 Score = 2 x

When dealing with an uneven data collection, F1 Score is preferred over accuracy since it accounts for both false positives and false negatives. F-measures are used to balance the ratio of false negatives using a weighting parameter (beta) it is given as

F = P R

Sensitivity, specificity, and error rate are some of the other performance indicators that are employed. They allow us to assess the possibility of over- or under-estimation of tumor sub-regions. The error rate is the percentage of anticipated classes that are categorized wrongly by a decision model.

1. Result:

Results from Trained Model

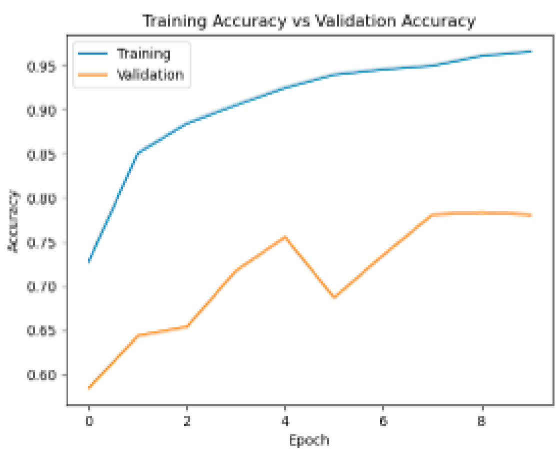


Figure 3: Obtained Accuracy Results of VGG16

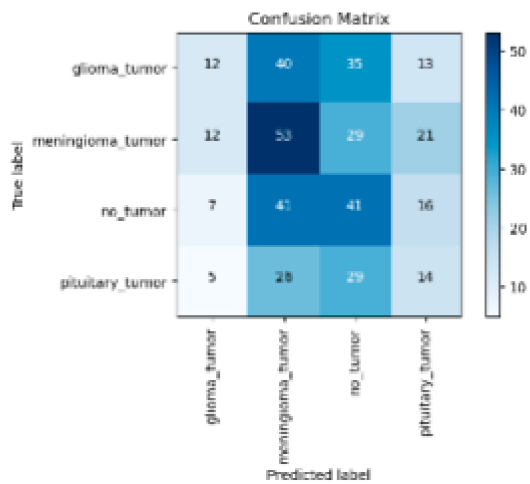


Figure 4: Confusion matrix of VGG16

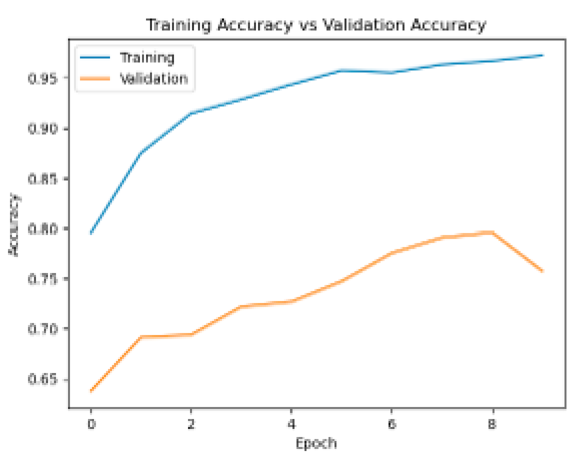


Figure 5: Obtained Accuracy Results of ResNet

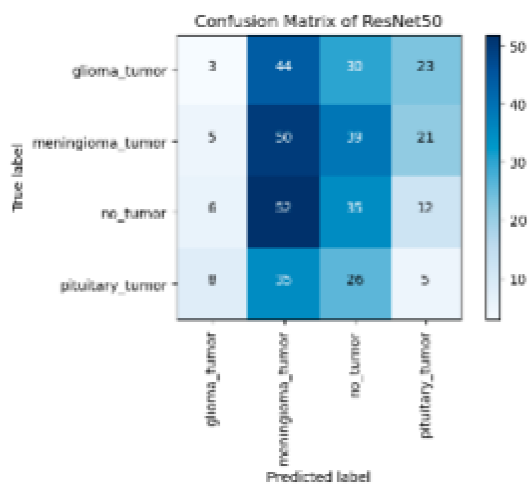


Figure 6: Confusion matrix of ResNet

1. Conclusion: In the field of medicine, brain image classification is critical in surgical preparation and treatment planning. We proposed a method for classification and tumor location detection using Deep Residual Networks (ResNet) and VGG16 in this paper. Our model assists in anticipating a patient's Brian Tumor with greater exactness, particularity, precision, and analysis, all of which are important in the restorative world. In the VGG16 model, an accuracy of 78.32% is achieved across various classes of brain tumor datasets, and in ResNet, we got an accuracy of 80.10%. We have compared the outcomes of multi-class classification of brain tumour using Transfer Learning utilising pre-trained ResNet50 and VGG16 model using CNN architecture in this paper.

1. Future Work: In the future, the proposed study could be expanded to include various types of modalities for detecting tumors, as well as the optimization method used to improve classification accuracy. Employing classifier boosting approaches such as utilizing larger amounts of photos with more data augmentation, hyperparameters, and training for a longer duration i.e. using more epochs, adding more applicable layers, and so on, you may improve testing accuracy and computation time. We may utilize U-Net architecture instead of CNN for more complicated datasets, where the max-pooling layers are simply replaced by up-sampling ones. We eventually want to employ very large and deep convolutional nets on video sequences, where the temporal structure gives very useful details that are missing or less visible in static pictures.

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