Brain Tumor Classification Based on its Presence & Position Using MRI Images

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Abstract

In this project, We will do The Brain Tumor Classification from Magnetic Resonance Imaging (MRI) images using different machine learning models based on the presence & positions of it. Since,the conventional method for tumor detection in MRI images is very time consuming, cost ineffective & inappropriate for large amount of data and MRI images contain noise due to operator intervention which can lead to inaccurate classification, hence Automated Detection of Tumor in MRI images is necessary as High Accuracy is needed when dealing with human life. So we will focus on the accuracy using different machine learning techniques.To get the accuracy as much as high, we shall use different models and compare the accuracies & consider the best suited model for this purpose.

1 Introduction

Brain is one of the vital organs in the human body, which consists of billions of cells. The abnormal group of cell is formed from the uncontrolled division of cells, which is also called as tumor.But the risk to death depends on the position of the brain tumor.The low grade brain tumor(grade I & grade II) is called Benign which is not cancerous.But the high grade brain tumor(grade III & grade IV) is called Malignant which is cancerous.

The benign tumors of low-grade I and II glioma are considered to be curative under complete surgical excursion, whereas malignant brain tumors of grade III and IV category can be treated by radiotherapy, chemotherapy, or a combination thereof. The term malignant glioma encompasses both grade III and IV gliomas, which is also referred to as anaplastic astrocytomas. An anaplastic astrocytoma is a mid-grade tumor that demonstrates abnormal or irregular growth and an increased growth index compared to other low-grade tumors. Furthermore, the most malignant form of astrocytoma, which is also the highest grade glioma, is the glioblastoma. The abnormal fast growth of blood vessels and the presence of the necrosis (dead cells) around the tumor are distinguished glioblastoma from all the other grades of the tumor class. Grade IV tumor class that is glioblastoma is always rapidly growing and highly malignant form of tumors as compared to other grades of the tumors.

Brain MRI image is mainly used to detect the tumor and tumor progress modeling process. This information is mainly used for tumor detection and treatment processes.MRI image gives more information about given medical image than the CT or ultrasound image. MRI image provides detailed information about brain structure and anomaly detection in brain tissue.

Brain MRI images are segmented and preprocessed to get the features dividing the entire image into different regions and thus the presence of the infected tumor is detected in the MRI images.

Tumors can be benign or malignant, can occur in different parts of the brain, and may be classified as primary or secondary. A primary tumor is one that has started in the brain, as opposed to a metastatic tumor, which is one that has spread to the brain from another area of the body.The incidence of metastatic tumors is approximately four times greater than primary tumors.Tumors may or may not be symptomatic: some tumors are discovered because the patient has symptoms, others show up incidentally on an imaging scan, or at an autopsy.According to the position the primary tumors can be classified into different types:

- **Glioma:** A glioma is a type of tumor that starts in the glial cells of the brain or the spine. Gliomas comprise about 30 percent of all brain tumors and central nervous system tumours, and 80 percent of all malignant brain tumours.
- **Meningioma:** Meningioma, also known as meningeal tumor, is typically a slow-growing tumor that forms from the meninges, the membranous layers surrounding the brain and spinal cord. Symptoms depend on the location and occur as a result of the tumor pressing on nearby tissue. Many cases never produce symptoms. Occasionally seizures, dementia, trouble talking, vision problems, one sided weakness, or loss of bladder control may occur.

- **Pituitary:** Pituitary adenomas are tumors that occur in the pituitary gland. Pituitary adenomas are generally divided into three categories dependent upon their biological functioning: benign adenoma, invasive adenoma, and carcinomas. Most adenomas are benign, approximately 35 % are invasive and just 0.1% to 0.2% are carcinomas. Pituitary adenomas represent from 10% to 25% of all intracranial neoplasms and the estimated prevalence rate in the general population is approximately 17% .

2 Literature review

In [1],the CNN is used in brain tumor classification which is divided into two phases such as training and testing phases. The number of images is divided into different category by using labels name such as tumor and non-tumor brain image etc. In the training phase, preprocessing, feature exaction and classification with Loss function is performed to make a prediction model. In the preprocessing image resizing is applied to change size of the image. Finally, the convolution neural network is used for automatic brain tumor classification by applying a. convolution filter in first layer;b. sensitivity reduction of filter by subsampling; c. Relu is used in the actiavtion layer & d. finally loss generation .The loss function is calculated by using gradient descent algorithm to generate the model parameters and the training accuracy got is 97.5 %.

In [2],the RGB MRI image is converted to gray scale image and then median filter is applied for noise removal from brain MRI images.Then edges are detected from filtered image using canny edge detection.Then watershed segmentation is done for finding the location of the tumor in the brain image.Next the features are extracted using Gray Level Co-occurrence Matrix (GLCM) as it is robust method with high performance.The feature set formed by above specified method was applied to Multi-Layer Perceptron (MLP) and Naive Bayes for classification.

In [3],MRI images are applied to the CNN and the clustering alogrithm for the feature extraction is also used.classifiers such as the, Softmax Fully Connected layer classifier, RBF classifier and the DT classifier in the CNN architecture have been used to evaluate the efficiency of the proposed technique.The Softmax classifier has the best accuracy of 99.12% in the CNN.

In [4],Transfer learning has been used to classify the brain MRI images into the three categories glioma, meningioma,pituitary tumors.GoogleNet is used with two convolution layers, two pooling layers and nine inception modules, and a fully connected layer.Again, an inception module has six convolution layers and a pooling layer.They modified the last three layers of GoogLeNet so as to adapt it to the target domain. The fully connected (FC) layer in the original GoogLeNet was removed. Instead, a new FC layer with an output size of three was inserted. The softmax layer, following the FC layer, and the cross-entropy-based classification layer at the output were replaced with new ones.The hyperparameters of the model were tuned by minimizing the loss function. Adam was the chosen optimizer with the learning rate 0.0003.The mini-batch size was set to 30 and they got around 92% accuracy.

In [5],the task is carried by first pre-processing of given MRI image, then segmentation and finally performing morphological operation on that image.So the very first step in this method is the conversion of the input image i.e. MRI image to be pre-processed into a Grayscale image & then it is passed through the histogram equalization ,filtering.Next the images are given thresholds to be turned from gray-scale images to binary images.Finally the images are morphologically operated and then the image subtraction is done to remove the other region from the images to get the exact tumor locations in the images.

In [6], This work proposes the following DLAs to detect the Brain Tumor: (i) implementing the pre-trained DLAs, such as AlexNet, VGG16, VGG19, ResNet50 and ResNet101 with the deep-features-based SoftMax classifier; (ii) pre-trained DLAs with deep-features-based classification using decision tree (DT), k nearest neighbor (KNN), SVM-linear and SVM-RBF; and (iii) a customized VGG19 network with serially-fused deep-The base network is made of VGG-16 model [16] up to fully connected layerfeatures and handcrafted-features to improve the Brain Tumor detection accuracy.The VGG19 offers better classification accuracy compared to the alternatives, and hence conventional and customized VGG19 are then considered in this research to attain the better tumor detection accuracy.After selecting the VGG19 to solve the considered image examination problem, its performance enhancement is tried using the following approaches: (i) replacing the SoftMax classifier with DT, KNN, SVM-Linear and SVM-RBF classifiers, and (ii) enhancing the outcome of VGG19 using a new feature vector obtained by fusing the handcrafted and deep features.

In [7],An automatic brain tumor detection and classification method was implemented using Faster R-CNN algorithm. The VGG-16 architecture was chosen as a base network in Faster R-CNN for generating convolutional feature map to produce tumor region proposals followed by classification.The Faster R-CNN architecture consists of three main blocks namely RPN, Region of Interest (RoI) pooling and Region based Convolutional Neural Network (R-CNN) for object detection.The base network is made of VGG-16 model up to fully connected layer.Training of Faster R-CNN algorithm was done using Stochastic Gradient Descent (SGD) optimizer with learning rate of 0.01 and momentum of 0.9 where it is trained for 120 epochs with 1000 iterations per epoch giving the maximum accuracy of 98.4%.

In [8],the authors extracted features from the fully connected layer (FC7) of VGG19 and fed them into CFML.There are 19 layers and 144 million trainable parameters (weights) in the VGG19 architecture.Since the time complexity is very high for the training,hence they divided it into six blocks based on pooling layers.

In [9],, a deep convolutional neural net is pre-trained as a discriminator in a GAN to detect fake MR images produced by the generative model from genuine ones. In this manner,the discriminator will learn the structure of MR images and can extract robust features of an MRI scan.

In [10] the Fuzzy C-Means (FCM) segmentation is applied to separate the tumor and non-tumor region of brain. Also wavelet feature are extracted by using multilevel Discrete Wavelet Transform (DWT). Finally, Deep Neural Network (DNN) is incorporated for brain tumor classification with high accuracy. This technique is compared with KNN, Linear Discriminant Analysis (LDA) and Sequential Minimal Optimization (SMO) classification methods. An accuracy rate of 96.97% in the analysis of DNN based brain tumor classification but the complexity is very high and performance is very poor.

3 Proposed methodology

Our problem statement is to detect and classify tumors from the Brain MRI images.

3.1 Classification on Presence of Tumor

We are given a set of labelled data of MRI images with labels of tumor presence & absence.We divide the whole dataset into three datasets namely training testing and validation dataset with a division of percentage of 80% for training and 20% for testing.Within the 80% for training we too 10% for validation dataset. Now,since our aim is to detect whether the test images have the brain tumor or not we start by processing the data.
We have used different deep learning models in order to detect the presence of tumors :

- Vanilla CNN model from scratch where the data used is :
  - Without Augmentation
  - With Augmentation
- VGG-16
- ResNet50

3.1.1 Convolutional Neural Network(CNN)

The Convolution Neural Network (CNN) consists of input layer, convolution layer, Rectified Linear Unit (ReLU) layer, pooling layer and fully connected layer. In the convolution layer, the given input image is separated into various small regions.Element wise activation function is carried out in ReLU layer. Pooling layer is optional. We can use or skip. However the pooling layer is mainly used for down sampling. In the final layer (i.e) fully connected layer is used to generate the class score or label score value based on the probability in between 0 to 1.

Before implementing the models the pixel values of the images are transformed between 0 & 1.

In our case,we have used the same CNN model for the two types of the data one with augmentation & another without augmentation.

- Without Augmentation:

  The CNN Model.

  We have used 4 convolution layers with ReLu as the activation function and with a kernel size of (5,5) for the first layer and (3,3) for the next three layers with 4 max pooling layers.This is followed with 1 flatten,1 dropout layers along with 2 dense layers.The dense layers have the activation functions in the form of ReLu and sigmoid functions in the order.The last dense layer acts as the output layer with an output dimension of 1.

  Binary cross entropy has been used the loss function & Adam has been used as the optimizer with learning rate(LR) 0.01 .

- With Augmentation:

  We have used firstly the random flip layer and random rotation layer for the data augmentation & then we applied the same CNN model that we implemented for the without augmentation part that is the model with 4 convolution layers with 4 Maxpooling layers,1 flatten layer, 1 Dropout layer and 2 Dense Layers in that order.
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3.1.2 Well Built Architectures

In our case, we have used two well built architectures as :

- VGG-16:

  We have trained VGG 16 over our data where the data has been preprocessed & augmented by random flip & random rotation.The architecture of VGG-16 is provided in fig.1. Then, after applying VGG16 layers we applied 1 flatten layer to transform the tensor to a one dimensional tensor and then 1 dropout layer to reduce the parameters.Following this we used two 2 dense layers one with RELU and another with Sigmoid activation function.The last layer here acts as the output layer with 1 dimensional output.

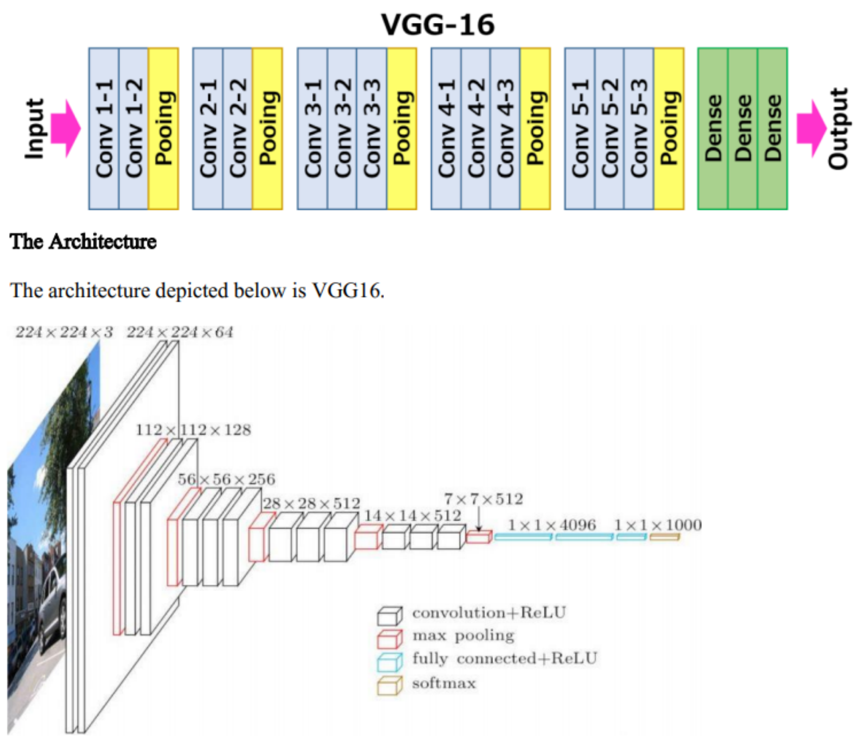

Figure 1: Vgg-16 Architecture

  Image Source: https://www.mygreatlearning.com/blog/introduction-to-vgg16/

- ResNet50:

  We have trained VGG 16 over our data. We first preprocessed & augmented the dataset by using random flip & random rotation.The architecture of ResNet50 is provided in fig.2. Then, after applying resnet50 layers we applied 1 flatten layer to transform the tensor to a one dimensional tensor and then 1 dropout layer to reduce the parameters.Following this we used two 2 dense layers one with RELU and another with Sigmoid activation function.The last layer here acts as the output layer with 1 dimensional output. We have used binary cross-entropy & Adam as loss function & Optimizer respectively with LR 0.01.

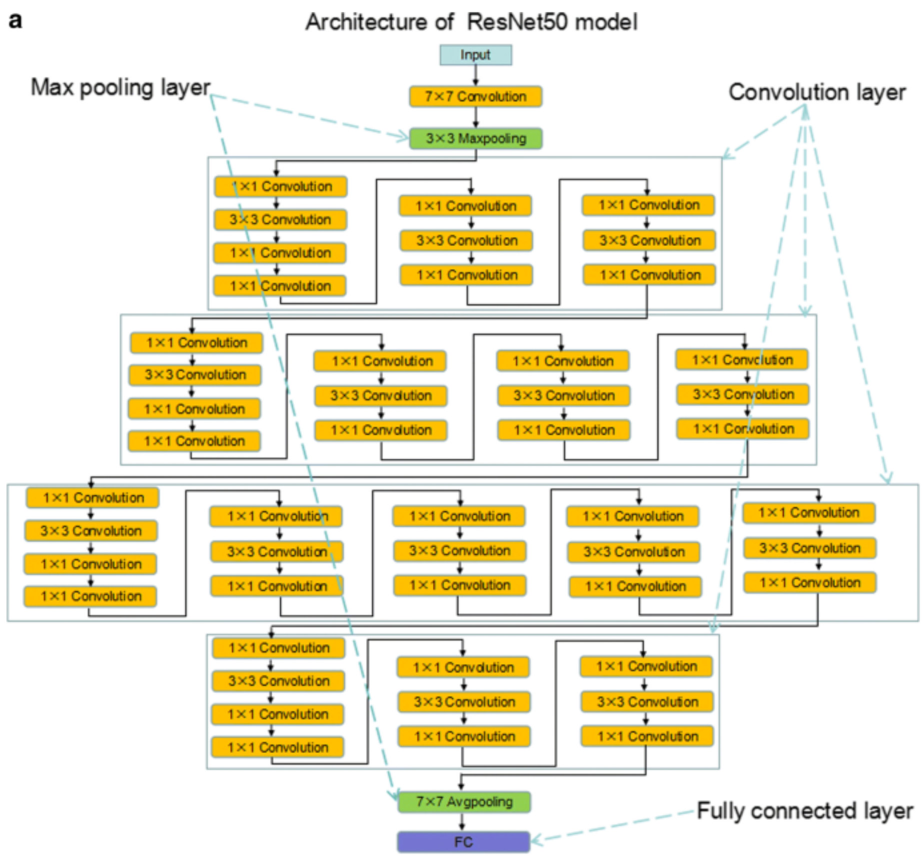

Figure 2: ResNet Architecture

Image Source: https://www.researchgate.net/figure/The-architecture-of-ResNet50-and-deep-learning-model-flowchart-a-b-Architecture-of$_{f}ig1_{3}$34767096

Then we compare the model losses and accuracies to choose the best model among these.

3.2 Classification of Tumor Based on its Position

Our second problem is to classsify the tumors on the basis of its position. We are given another set of labelled data with four labels viz. Glioma, Meningioma,pituitary,no tumor with the training & testing datasets separately.We took a validation split with a factor of 0.2 within the training set.We have then done the preprocessing & data augmentation.Then we have used different models:

- Vanilla CNN model from scratch where the data used is :
  - Without Augmentation
  - With Augmentation
- ResNet
- Efficient-Net

Data Preprocessing:

The extreme points of the images are found out & then a rectangular portion is cut out of them.Thresholding the images,a series of erosions & dilations are performed to remove any small regions of noise.In the thresholded images contours are found out and the largest one is grabbed resulting in noise free cropped cleaned images .

In our case,we have used the same CNN model for the two types of the data one with augmentation & another without augmentation.

- Without Augmentation:

  The CNN Model.

  We have used 4 convolution layers with ReLu as the activation function and with a kernel size of (5,5) for the first layer and (3,3) for the next three layers with 4 max pooling layers.This is followed with 1 flatten,1 dropout layers along with 2 dense layers.The dense layers have the activation functions in the form of ReLu and sigmoid functions in the order.The last dense layer acts as the output layer with an output dimension of 1.

Binary cross entropy has been used the loss function & Adam has been used as the optimizer with learning rate(LR) 0.01 .

- With Augmentation:

  We have used firstly the random flip layer and random rotation layer for the data augmentation & then we applied the same CNN model that we implemented for the without augmentation part that is the model with 4 convolution layers with 4 Maxpooling layers,1 flatten layer, 1 Dropout layer and 2 Dense Layers in that order.

  .

3.2.1 Well Built Architectures

Here two well built architectures used are:

Data Augmentation:

The data is first augmented through rotation, width shifting , height shifting and horizontal flipping in order to decrease the possibility of overfitting of the data.

- ResNet:

  We have trained ResNet50 model over our data.The architecture of ResNet is provided in fig.2. After that we applied Global average pooling layer which applies average pooling on the spatial dimensions until each spatial dimension is one, and leaves other dimensions unchanged. This is followed by a dropout layer and a dense layer giving an output of dimension 4 with an activation function of softmax.

  At last we have applied categorical Cross-entropy loss, and Adam as optimizer with LR 0.0001.

- Efficient-Net:

  We have trained Efficient-Net model over our data. The architecture of Efficient-Net is provided in fig.3. After that we applied Global average pooling layer which applies average pooling on the spatial dimensions until each spatial dimension is one, and leaves other dimensions unchanged. This is followed by three dense layers giving outputs of dimensions 1024,1024 and 512 respectively and having activation functions as ReLu.This is followed by a Dropout layer to decrease the number of parameters.And at last there is a dense layer acting as the output layer to give an output of dimension 4 using the sigmoid activation function.

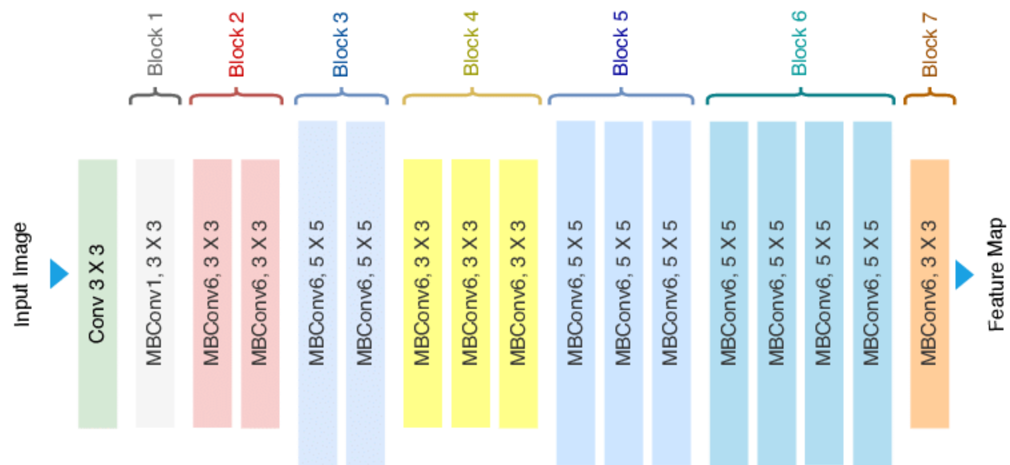

Figure 3: Efficient-Net Architecture

Image Source: https://www.researchgate.net/figure/Architecture-of-EfficientNet-B0-with-MBConv-as-Basic-building-blocks$_{f}ig4_{3}$44410350

At last we have applied categorical Cross-entropy loss, and Adam as optimizer with LR 0.0001.

4 Experimental result

- Datasets we have used for our project
  - https://www.kaggle.com/datasets/ahmedhamada0/brain-tumor-detection
  - https://www.kaggle.com/datasets/sartajbhuvaji/brain-tumor-classification-mri
- Experimental settings and Experminetal Results

Detection Of Brain Tumor Using MRI Images by different Models

Models	Parameters	Settings (Values)	Training Accuracy	Validation Accuracy	Testing Accuracy
1. Vanilla CNN (Without Augmentation)	1. Initial Learning Rate 2. Optimizer 3. Loss Fn. 4. Batch-size 5. Maxm. Epochs	0.01 Adam. Binary Cross entropy. 64 20	95.29 %	96.55 %	94.82 %
2. Vanilla CNN (With Augmentation)	1. Initial Learning Rate 2. Optimizer 3. Loss Fn. 4. Batch-size 5. Maxm. Epochs	0.01 Adam. Binary Cross entropy. 64 20	78.89 %	83.62 %	81.52 %
3. VGG-16	1. Initial Learning Rate 2. Optimizer 3. Loss Fn. 4. Batch-size 5. Maxm. Epochs	0.01 Adam. Binary Cross entropy. 64 20	96.49 %	98.28 %	97.06 %
4. ResNet 50	1. Initial Learning Rate 2. Optimizer 3. Loss Fn. 4. Batch-size 5. Maxm. Epochs	0.01 Adam. Binary Cross entropy. 64 20	100 %	99.14 %	99.48 %

Classification Of Brain Tumor Using MRI Images by different Models

Models	Parameters	Settings (Values)	Training Accuracy	Validation Accuracy	Testing Accuracy
1. Vanilla CNN (Without Augmentation)	1. Initial Learning Rate 2. Optimizer 3. Loss Fn. 4. Batch-size 5. Maxm. Epochs	0.01 Adam. Binary Cross entropy. 64 20	92.84 %	86.54 %	82.33 %
2. Vanilla CNN (With Augmentation)	1. Initial Learning Rate 2. Optimizer 3. Loss Fn. 4. Batch-size 5. Maxm. Epochs	0.01 Adam. Binary Cross entropy. 64 20	70.91 %	75.95 %	65.96 %
3. ResNet	1. Initial Learning Rate 2. Optimizer 3. Loss Fn. 4. Batch-size 5. Maxm. Epochs	0.0001 Adam Categorical cross entropy 64 12	99.74 %	99.31 %	89.86 %
4. Efficient Net	1. Initial Learning Rate 2. Optimizer 3. Loss Fn. 4. Batch-size 5. Maxm. Epochs	0.001 Adam Categorical cross entropy 32 12	99.87 %	98.16 %	89.74 %

Start of art: For the Detection of the Tumors using MRI images,in [1],the authors got 97.5 % using CNN,where we have got the best accuracy of 99.48 % using ResNet-50.

For the case of Classification of Tumors using MRI images,in [4],the authors got 98% as best accuray using TL, where we have got 89.86 % as best accuracy using ResNet.

Inference:

From the above two tables it is clear from the testing accuracies that in the pre- determined experimental setup in both cases the Resnet performs the best.

However through building the Vinilla CNN models from the scratch we see that though we could not reach upto the accuracies attained by the well built models however still they performed really well.

Also though in case of Augmentation we face a decline in accuracies in both the problems for Vanilla CNN but it can also be seen that due to augmentations the testing accuracy is way more close to training accuracy (even better than training accuracy in case of detecting brain tumors).

5 Summary

At the beginning of the project we started our journey with the aim of detecting and classifying the brain tumors from the given labelled data sets of the Brain MRI images.We implemented different deep learning models in order to detect as well as to classiffy the brain tumors. The first part of the project deals with the detection of the brain tummors.

We implemented 3 types of models namely :

- 3 layered Vanilla CNN from scratch where the data used is :
  - Without Augmentation
  - With Augmentation
- VGG-16
- ResNet50

From the accuracy table for detection we choose the ResNet50 model as the best model because it gives the best accuracy of 99.48% over the testing data.

The second part of the project deals with the classificaion of the brain tummors. We implemented 3 types of models namely :

- 3 layered Vanilla CNN from scratch where the data used is :
  - Without Augmentation
  - With Augmentation

- VGG-16
- ResNet50

From the accuracy table for classification we choose the ResNet50 model as the best model because it gives the best accuracy of 89.86% over the testing data.

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