"In Pursuit of Technical Excellence"

PROJECT REPORT

On

"Brain Tumor Detection using Deep Learning"

For the Degree of

Bachelor of Technology in
Information Technology

By

Vinod Patil	**BE20F06F041**
Avijeet Salve	**BE20F06F053**
Bhagyashri Saundarkar	**BE20F06F055**
Shrutika Uikey	**BE20F06F066**

Under the Guidance of

Dr. Sangita Nemade

Department of Information Technology
GOVERNMENT COLLEGE OF ENGINEERING, AURANGABAD

CHHATRAPATI SAMBHAJINAGAR

(An autonomous Institute of Government of Maharashtra)

(2023-2024)

CERTIFICATE

This is to certify that the seminar entitled **“Brain Tumor Detection System using Deep Learning”** which is being submitted herewith for the award of the **‘Degree of Bachelor of Engineering’ in ‘Information Technology’** of Government College of Engineering, Aurangabad (Chhatrapati Sambhajinagar) by **Vinod Patil , Avijeet Salve , Bhagyashri Saundarkar , Shrutika Uikey**

Place: Chhatrapati Sambhajinagar

Date:

c

Dr. Sangita Nemade — **Project Guide**

Dr. Anjana Ghule — **Head of Department**

Dr. Sanjay Dambhare

Principal

Government College of Engineering,

Aurangabad (Chhatrapati Sambhajinagar)

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1. INTRODUCTION

1.1 BRAIN TUMOR DETECTION SYSTEM

The human body consists of many organs, and the brain is the most important and vital organ among them all. One of the most common causes of brain dysfunction is brain tumors. A tumor is nothing more than extra cells that grow out of control. Brain tumor cells grow in such a way that they eventually take up all the nutrients intended for healthy cells and tissues, causing brain failure. Currently, doctors identify the location and region of a brain tumor by manually reviewing MR images of a patient's brain. This leads to the inaccuracy of the tumor and is considered very time-consuming.Brain cancer is a very worrying disease that causes the death of many people. A brain tumor detection and classification system is available for early diagnosis. Cancer classification is the most difficult task in clinical diagnosis.This project deals with such a system that uses computer-aided methods to identify tumor blocks and classify tumor type using Convolution Neural Network Algorithm on MRI images of different patients.

Different types of images. Processing methods such as image segmentation, image enhancement and feature extraction are used to detect brain tumors in MRI images of cancer patients. Brain tumor detection using image processing techniques involves four steps: image preprocessing, image segmentation, feature extraction, and classification.Image processing and neural networks are used to improve brain tumor detection and classification in magnetic resonance imaging.

OVERVIEW OF BRAIN AND BRAIN TUMOR

The main part of the human nervous system is the human brain. It is located on the human head and is covered by a skull. The function of the human brain is to control all parts of the human body. It is a type of organ that allows humans to accept and tolerate all kinds of environmental conditions. The human brain enables people to act and share thoughts and feelings. This section describes the structure of the brain [2] for a basic understanding

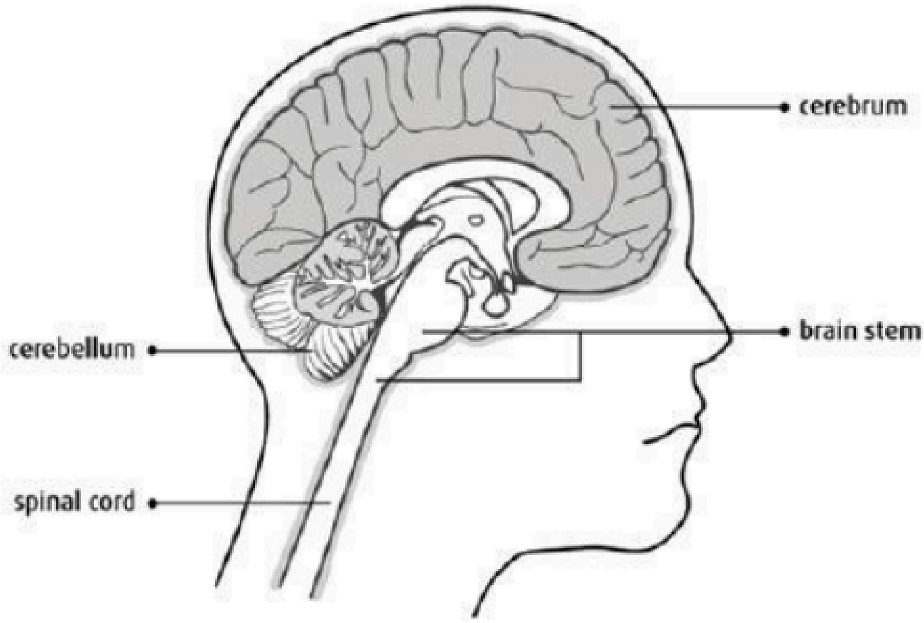


Fig.1: Basic Structure of the human brain [4]

Brain tumors are divided into two types: primary brain tumor (benign tumor) and secondary brain tumor (malignant tumor). A benign tumor is a type of cell that grows slowly in the brain, and a type of brain tumor is a glioma. It comes from non-neuronal brain cells called astrocytes. Primary tumors are less aggressive, but these tumors put a lot of pressure on the brain and therefore the brain stops working properly. Secondary tumors are more aggressive and spread more quickly to other tissues. A secondary brain tumor originates in another part of the body. This type of tumor has a metastatic cancer cell in the body that spreads to different parts of the body such as the brain, lungs, etc. A secondary brain tumor is highly malignant. Secondary brain tumors are mainly caused by lung cancer, kidney cancer, bladder cancer etc.

MAGNETIC RESONANCE IMAGING (MRI)

Raymond v. Damadian invented the first MRI in 1969. In 1977, the first MRI images for the human body were invented and the most advanced technology. Thanks to MRI, we can see the details of the internal structure of the brain and, based on this, look at the different tissues of the human body. The quality of MRI images is superior compared to other medical imaging methods such as x-rays and CT scans. MRI is a good method to detect a brain tumor in the human body. There are different types of MRI to map changes caused by a tumor, including T1-weighted, T2-weighted, and FLAIR (fluid-attenuated inversion recovery).

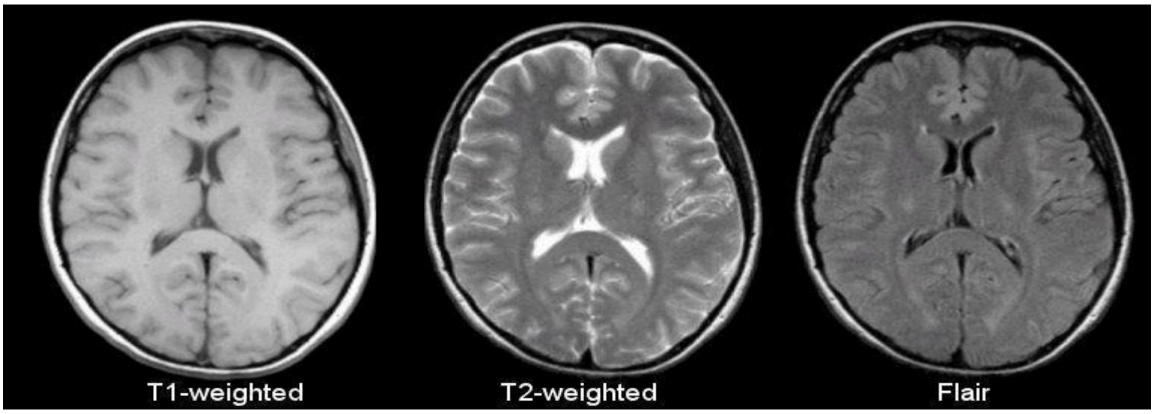


Fig 2: T1, T2, and Flair image [4]

The most common MRI sequences are weighted and T2-weighted. For T1, only one tissue type is white fat, and the two tissue types weighted for T2 are Shiny FAT and Water. T1-weighted repetition time (TR) is short in T2-weighted TE and long in TR. TE and TR are the pulse train parameters and mean repetition time and time to echo and can be measured in milliseconds (ms) [4]. Echo time represents the time from the center of the RF pulse to the center of the echo, and TR is the time between the TE repeating pulse train and the echo, as shown in the figure.

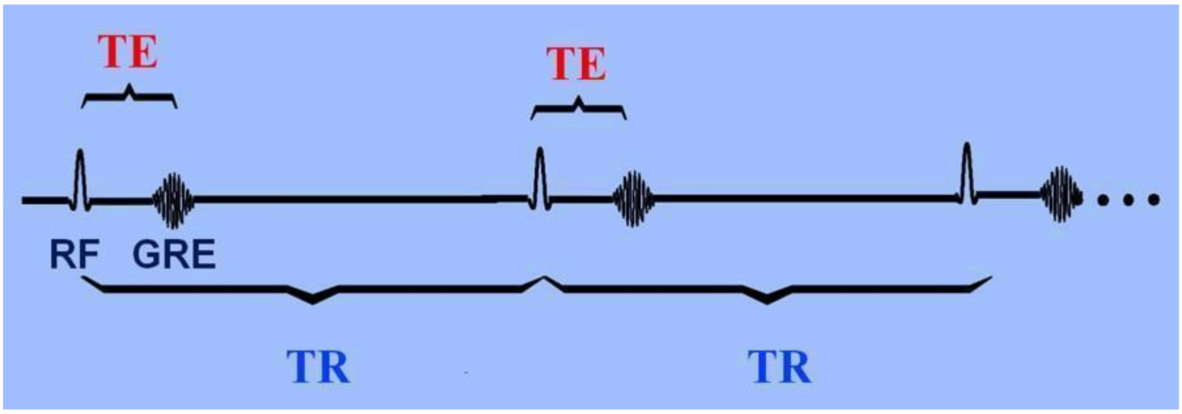


Fig. 3: Graph of TE and TR [6]

The third most frequently used sequence in FLAIR. The Flair sequence is almost identical to the T2-weighted image. The only difference is that TE and TR times are very long. Their approximate TR and TE times are shown in the table.

	TR (msec)	TE (msec)
T1-Weighted (short TR and TE)	500	14
T2-Weighted (long TR and TE)	4000	90
Flair (very long TR and TE	9000	114

Fig.4: Table of TR and TE time [2]

1.2 APPLICATION

- This application can accurately detect brain tumor
- It can correctly identify the tumor so that patients can receive the right treatment as soon as possible and protect life from danger This application is helpful to doctors for appropriate prediction as well as patients to take early-stage treatment.
- This application is also useful for doctors to make the correct forecast patients to start treatment at an early stage It is a user-friendly application

1.3 OBJECTIVE

- To study and identify the brain tumors and their causes using the proposed model
- To provide a solution appropriately by detecting brain tumors accurately at the early stages
- To evaluate the accuracy, efficiency, and performance of the proposed model for accurate detection of tumors

1.4 MOTIVATION

The main motivation behind Brain tumor detection is to not only detect tumors but it can also classify types of tumors. So it can be useful in cases such as we have to be sure the tumor is positive or negative, it can detect a tumor from an image and return the result tumor is positive or not. This project deals with such a system, which uses computer-based procedures to detect tumor blocks and classify the type of tumor using a Convolution Neural Network Algorithm for MRI images of different patients.

1.5 ORGANIZATION OF REPORT

Chapter 1 Gives a brief introduction to Brain tumor Detection and Classification using Deep Learning, its applications, the objective of the system, and its motivation.

Chapter 2 Contains a literature survey that provides a summary of individual papers.

Chapter 3 Provides an overview of existing work for Brain tumor detection and classification that has been done using CNN.

Chapter 4 Presents the tools, and technology used and dataset detail.

Chapter 5 Contains a conclusion about Brain tumor detection using deep learning

2. LITERATURE SURVEY

In the past, machine learning (ML) techniques were considered as the foundation to take over classification and mining tasks. Recently the less accuracy in prediction models and the critical nature of the medical data analyzation forced researchers toward new methods of brain tumor detection to improve classification accuracy. Consequently, deep learning (DL)[6].

In recent years, a lot of research has been directed toward the adaptation of deep learning models in diagnosing brain tumors. Academicians have put in their efforts and with the help of high-end computing devices, higher accuracy has been achieved. Convolutional neural networks (CNN), which include input, output, hidden layers, and hyperparameters, are often called Deep Learning (DL). DL requires large datasets, the requirement to design complex models, fine-tuning of hyper-parameters, and time and effort to training/testing. As per recent research, significant data augmentation methods like resizing, rotation, scaling, and transformation are enforced to tackle the big data availability problem. A trained NN is used in transfer learning techniques to extract similar properties from an application-specific dataset [5]. For brain tumor identification current TL methods like RESNET-100, VGGNET, Google-Net, AlexNet, etc. are applied. The principal causes of such disease are cancer-related ailment and morbidity. Effective handling of this disease is crucial which depends on its timely and accurate detection [6].

With recent developments in technology, In the research paper [5] S. Solanki, U. P. Singh, S. S. Chouhan, and S. Jain describe the purpose of their development as to combine feature selection approaches with machine learning to identify pre-illnesses. For the early diagnosis of early diseases in MRI, CT scan, and X-ray images, this system makes use of deep learning techniques and image processing technology. To make feature extraction more efficient, the dataset including defective images from several categories was pre-processed and segmented. In this model feature extraction is implemented by Masking used to eliminate the pixels. Setting the pixel value of a picture to zero or another background value is known as masking. Then the diseased section of the original picture is segmented using the K-means segmentation technique. The best characteristics from this dataset are then selected for accurate categorization via feature selection. Relief-f Attribute Evaluator (RAE), Principal Component Analysis (PCA), as well as Information Gain (IG), are the three techniques of feature selection used in this study. They have used the MRI Kaggle dataset and CNN built with Keras and Tensorflow with a fully-featured cross-platform application built with PyQt5 and MariaDB. To be more precise the accuracy or overall statistical analysis is shown in Table [2.1].

N. Noreen and S. Palaniappan [6] have proposed a model based on deep learning which uses different hyperparameters for training and optimizes these parameters during training by using the loss function and Adam optimizer. Progressively, the loss function learns to minimize the error in prediction with the aid of some optimization function. The main idea is to extract features from various layers of pre-trained models trained on our proposed dataset that are combined or concatenated to extract multiscale information from input images to further enhance the feature capability of the classifier model. The authors proposed model consists of 11 number of inception modules. The features were extracted from a fully connected layer and after the concatenation from different Inception blocks are passed to the classifier. Then they applied a softmax classifier on multilevel or fused features extracted features from the pre-trained DensNet201 model then these denseblocks extracted from the bottom layers of the pre-trained DensNet201 model produced multiscale and dense information from input images of brain tumor dataset for brain tumor multiclass classification. Based on the experimental evaluation, they have used three dense blocks from the pre-trained DensNet201 model which have a major contribution in the efficient classification of brain tumor dataset. As they have used combined approaches such as inception block and combined denset block their accuracies were indicated as 99.34% and 99.51% respectively.

A. Jabbar, S. Nassen, and other their collaborative Authors [7] have studied the challenges of diagnosing brain tumors using deep learning models, including developing efficient multitask models, addressing classification issues for diseases with limited data, and then proposed the Hybrid Caps-VGGNet Model to extract more detailed, discriminative and comprehensive features than the most powerful pre-trained deep learning models. They have used BraTs 2020 dataset as it uses multi-institutional pre-employable X-ray checks. In addition to this dataset, they have presented benchmark assessed on BRATS19 datasets HGG(High-Grade Glioma) and LGG(Low-Grade Glioma) source from The Cancer Gensome Atlas(TCGA). They have used MICCAI Barin Tumor Segmentation BraTs20 and BraTs19 datasets consisting of 3D MRI images of glioma patients. For the experiment, the training set of the 2020 dataset was used as the training and validation set, while the training set of the 2019 dataset was used as the test set. The remarkable accuracy of the author's model is 0.98 on the HGG and LGG datasets training accuracy is 0.99 and validation accuracy is 0.98 on the BraTs20 dataset.

S. Ahmad and P. K. Choudhary [9] have analyzed and investigated the performance of seven pre-trained CNN models i.e., VGG16, InceptionResNetV2, ResNest50, VGG19, Xception, InceptionV3 and DenseNet201 and further followed by five classifiers such as Support Vector

Machine, Random Forest, Decision Tree, AdaBoost, and Gradient Boosting. The relative performance of each feature extractor and classifier pair is tested to identify the best-performing model. In this investigation, the transfer learning models are used as standalone feature extractors and later on, the traditional classifiers are used to classify those features to detect the tumor from brain images. As a standalone feature extractor, the pre-trained network is used to process the images, and extract features and the fully connected layers (classification layers) are kept inactive. Authors have compared the corresponding results to select a best performing CNN model for the detection of brain tumors from MR images. And chooses to go with VGG19 SVM as it shows highest accuracy 99.39% in the investigation. The author's technique extended to the classification of tumor types like Glioma, Meningioma, and Pituitary using the MR image dataset.

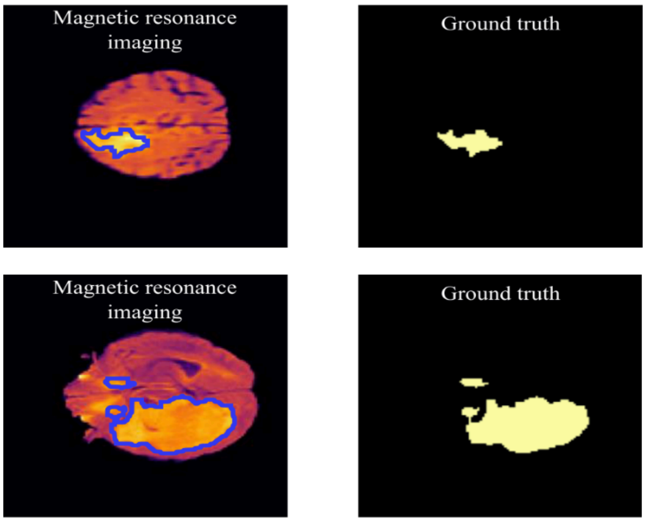


Fig. Example of Brain Tumors from [4]

2.1 Comparative performance Analysis of previous models:

Comparative analysis is done on following statistical analysis provided by them in research papers since 2020-2023.

- Accuracy = (TP +TN)/(TP + TN + FP + FN)
- Recall = TP/(TP + FN)
- Specificity = TN/(TN + FP)
- Precision = TP/(TP + FP)
- F1 score = (2 × Precision × Recall)/(Precision + Recall)

- FPR = FP/(FP+TN)
- Jaccard = TP/(TP + FP + FN)

Year	Topic	Network	Advantage	Disadvantage	Performance Analysis									
						TP	DSC	Precision	Recall	Jaccard	FPR	Specifi.	ACC	F1-Score
2023	Brain Tumor Detection and Classification Using Intelligence Techniques: An Overview	CNN	There is a method for categorization and segmentation that makes use of CNNs that is both efficient and effective.	Noise estimation is challenging. Technical issue defining exact prediction.		-	-	94.81%	95.07%	-	-	94.46%	95.4%	95.94%
2023	CrossTransUnet: A New Computationally Inexpensive Tumor Segmentation Model for Brain MRI(Model-1)	CrossTrans Unet	CrossTransUNet allows to reduce the computational cost of the models while achieving highly accurate segmentations, measured by DSC.	CrossTransUNet is one of the new cmodels so the model were not overtrained.		5.25	94.00%	-	-	-	-	-	99.51%	-
2023	Identification and Prediction of Brain Tumor Using VGG-16 Empowered with Explainable Artificial Intelligence	VGG16 empowered with LRP	DL method that facilitates the re-use of previously trained models and their learned approximations for new purposes.	Challenging to understand how the models arrive at some particular predictions		-	-	99.83%	99.92%	-	17%	99.83%	99.88%	99.8%
2022	Data Augmentation and Transfer Learning for Brain Tumor Detection in MRI	Component Analysis & ResNet50	Overtrained model for statistical analysis.	This model requires a large corpus of data for network to be generalized for high performance.	Training from Zero	-	-	96.92%	98.00%	-	-	98.00%	86.50%	87.56%
					Training from transfer learning	-	-	100%	100%	-	-	100%	92.00%	92.38%
2023	ResUNet+: A New Convolutional and Attention Block-Based Approach for Brain Tumor Segmentation.	UNet and ResUNet+	UNet has ability to extract local and global features at varying scale. - It can transfer the feature map of each encoder level to the decoder level with skip connections.	There are semantic gaps between the encoder and decoder in the classical UNet structure. Some features might be lost on addition of convolutional operation in UNet model.	Whole Tumor	-	88.90% (UNet) 92.80% (ResUNet+)	94.21% (UNet) 98.17% (ResUNet+)	93.63% (UNet) 98.46% (ResUNet+)	88.53% (UNet) 92.80% (ResUNet+)	-	94.74% (UNet) 99.96% (ResUNet+)	94.54% (UNet) 98.58% (ResUNet+)	-
					Enhancing Tumor	-	90.30% (UNet) 93.10% (ResUNet+)	92.23% (UNet) 96.33% (ResUNet+)	93.25% (UNet) 97.42% (ResUNet+)	89.13% (UNet) 92.15% (ResUNet+)	-	95.96% (UNet) 99.94% (ResUNet+)	93.65% (UNet) 97.75% (ResUNet+)	-
					Tumor Core	-	88.30% (UNet) 91.90% (ResUNet+)	93.51% (UNet) 97.41% (ResUNet+)	92.32% (UNet) 96.93% (ResUNet+)	88.27% (UNet) 91.32% (ResUNet+)	-	95.84% (UNet) 99.72% (ResUNet+)	94.53% (UNet) 98.46% (ResUNet+)	-
2022	Brain Tumor Classification Using Fine-Tuned GoogLeNet	GoogleNet, IoMT Enabled CAD	It connects the smart healthcare devices remotely and share the	While using ML Manual classification is quite challenging, requiring highly	Proposed Model	Glioma Tumor	TP - DSC -	96.02%	97.00%	-	-	96.00%	94.9%	94.3%
						Meningi-o	- -	93.78%	86.98%	-	-	98.19%		

	Features and Machine Learning Algorithms: IoMT Enabled CAD System.	System.	supportive information with medical experts.	professional radiologist and time intensive for large Magnetic Resonant Imaging (MRI) data classification.		ma Tumor									
						Pituitary Tumor	-	-	94.48%	97.10%	-	-	97.47%		
					GoogLeNet +SVM	Glioma Tumor	-	-	98.76%	97.24%	-	-	98.93%	97.6%	97.35%
						Meningi-oma Tumor	-	-	94.71%	95.80%	-	-	98.40%		
						Pituitary Tumor	-	-	98.40%	99.20%	-	-	98.30%		
					GoogLeNet+ K-NN	Glioma Tumor	-	-	98.41%	98.02%	-	-	98.63%	98.3%	98.3%
						Mening-io ma Tumor	-	-	95.55%	94.57%	-	-	98.65%		
						Pituitary Tumor	-	-	97.78%	99.10%	-	-	99.01%		
2022	MRI Image Based Relatable Pixel Extraction with Image Segmentation for Brain Tumor Cell Detection Using Deep Learning Model	Deep Learning model.	It uses Hough transform, which is a mechanism for automatically locating and segmenting anatomical structures of interest analysed the images for brain tumour detection	The handling of MRI scans of big size and complexity makes it a discouraging and challenging process for professionals to get information manually.	Meningioma		-	100%	100%	87.50%	-	-	100%	92.31%	
2022	Brain Tumor Identification using Dilated U-Net based CNN.	Dilated U-Net based CNN model	Semantic segmentation is deepened that has spatial information in the feature map which reduces the critical time	The deep features and handcrafted features were required to be fused for improving the results of classification.	-	-		93.4%	-	99.52%	-	-	99.81%	99.47%	69%
2022	On the Performance of Deep Transfer Learning Networks for Brain Tumor Detection Using MR Images.	SVM with VGG-19	Used Supervised learning algorithms to improve accuracy of brain tumor detection.	Here, the amount of computational complexity is quite high to train a deep convolutional neural network (DCNN) model using a massive dataset.	-	-	-	-	99.51%	99.27%	-	-	99.63%	99.39%	99.3%
2020	Brain tumor segmentation using K-means clustering and deep learning with synthetic data augmentation for classification	segmentation using k-means clustering and deep learning. Fine tuned VGG19	It uses synthetic data augmentation	Unavailability of large enough labeled MRI data for CNN training.	-	-	-	-	-	-	93.03%	-	96.02%	-	-

Table 2.1: Performance Analysis since 2020-23

3. EXITING WORK & PROPOSED WORKFLOW

3.1 OVERVIEW OF EXITING WORK

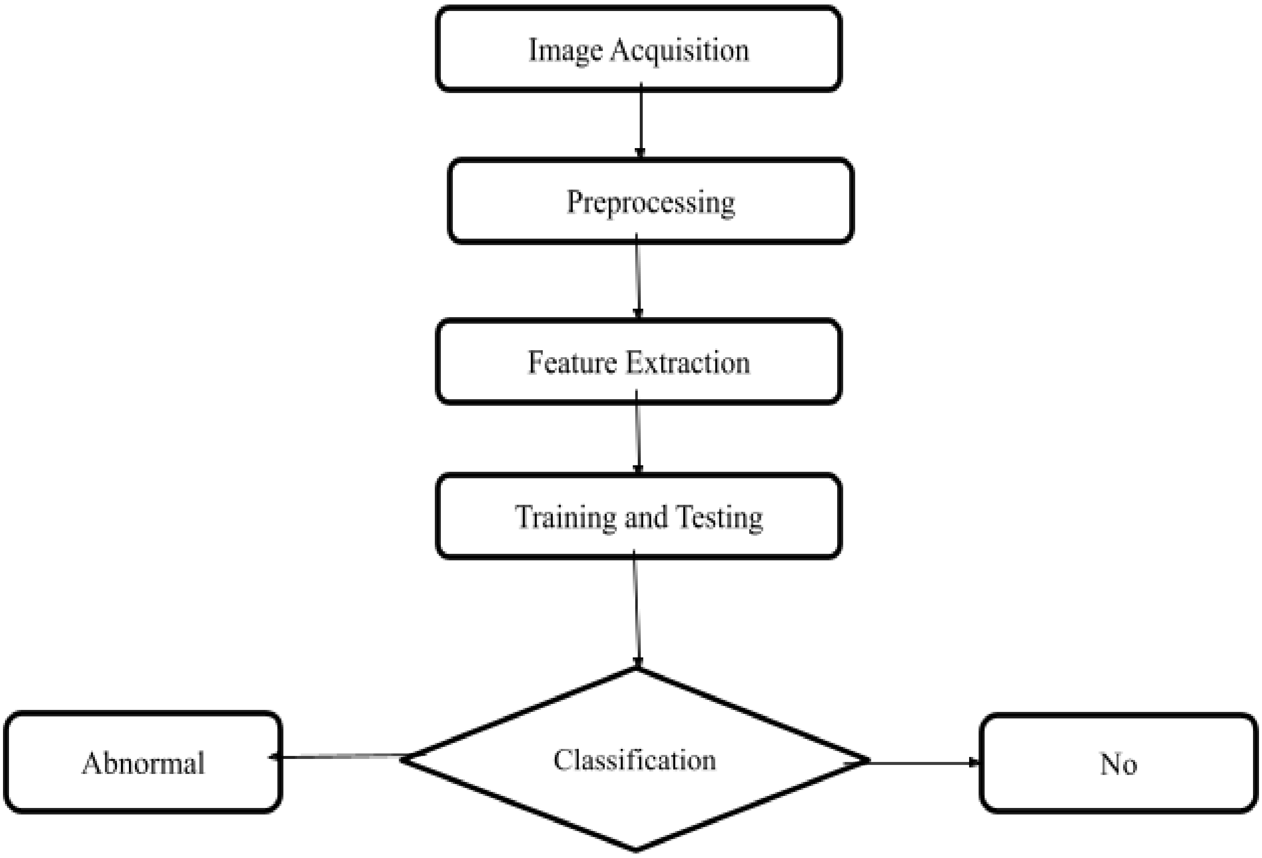


Fig.5. Workflow of brain tumor detection

- In the first stage, there is a computer-based procedure to detect tumor blocks and classify the type of tumor using an Artificial Neural Network Algorithm for MRI images of different patients
- The second stage involves the use of different image processing techniques such as histogram equalization, image segmentation, image enhancement, morphological operations, and feature extraction are used for brain tumor detection in the MRI images for cancer-affected patients
- This work introduces one automatic brain tumor detection method to increase the accuracy and decrease the diagnosis time

- **Image Preprocessing:** As input for this system is MRI, scanned image and contain noise. Therefore, our first aim is to remove noise from an input image. As explained in the system flow we are using a high-pass filter for noise removal and preprocessing.
- **Segmentation:** Region growing is the simple region-based image segmentation technique. It is also classified as a pixel-based image segmentation technique since it involves the selection of initial seed points.
- **Morphological operation:** The morphological operation is used for the extraction of boundary areas of the brain images. This operation is only rearranging the relative order of pixel value, not mathematical value, so it is suitable for only binary images. Dilation and erosion is the basic operation of morphology. Dilation is adding pixels to the boundary region of the object, while erosion is removing the pixels from the boundary region of the object.
- **Feature Extraction:** The feature extraction is used for edge detection of the images. It is the process of collecting higher-level information about an image such as shape, texture, color, and contrast.
- **Connected component labeling:** After recognizing connected components of an image, every set of connected pixels having the same gray-level values is assigned the same unique region label.
- **Tumor Identification:** In this phase, we have having dataset of previously collected brain MRIs from which we are extracting features. The knowledge base is created for comparison.

- In the first step we can take an image as input. In the image we used tumors in the image and only fat and water tissues in the images.
- In the second step convert the image to grayscale
    - Signal-to-noise
    - Complexity of the code
    - Learning image processing
    - Difficulty of visualization
    - Color is complex

- Then we convert the image to a binary image by thresholding.
    - Thresholding is the simplest method of image segmentation and the most common way to convert a grayscale image to a binary image.
    - In thresholding we select the threshold value and then the gray level value below the selected threshold value is classified as 0. and equal and greater than the threshold value are classified as 1.
- Find the number of connected objects
- Find the mask by assigning 1 to the inside and 0 to the outside of the object that shows brain region.
- Multiply the mask with T1, T2 and FLAIR MR images to get their skull-stripped MR image
    - T1 & T2: weighted MRI
    - FLAIR: fluid attenuated inversion recovery weighted MRI.
      Types of MRI images
        - T1: one tissue type is bright-FAT
        - T2: two tissue types are bright-FAT and water

3.2 PROPOSED WORKFLOW

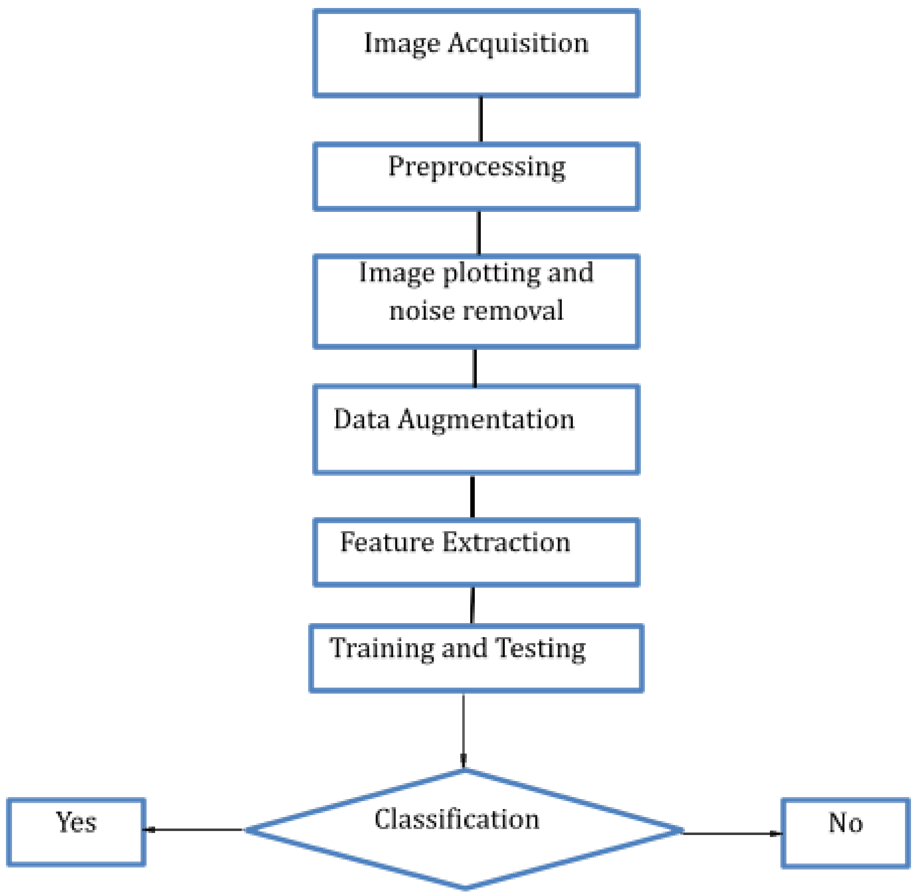


Fig. 7. Proposed workflow of brain tumor detection

The proposed system has five modules. Dataset, Pre-processing, Split the data, Build CNN model train Deep Neural network for epochs, and classification. In the dataset, we can take multiple MRI images and take one as the input image. In pre-processing the image encoded the label and resized the image. In splitting the data, we set the image as 80% Training Data and 20% Testing Data. Then build a CNN model train deep neural network for epochs. Then classify the image as yes or no if a tumor is positive then it returns yes and if the tumor is negative then it returns no.

At To begin with, Picture securing is done through pictures imported from Kaggle. We have put away close approximately 3000 pictures in our dataset.

The workflow of the proposed demonstrate to distinguish tumor start with picture preprocessing. As input for this framework is MRI, checked picture and whether contain tumor. Hence, our to begin with point is to evacuate commotion from an input picture. At that point we utilized morphological operations disintegration and weakening to identify boundaries and decrease commotion. To acknowledge the input from client picture ought to be in .jpg or in case it is in .png arrange we utilized extentions cv2 which makes a difference to perform imaging operations. On the off chance that it is colored picture it gets changed over to dark picture utilizing strategy rgbtogrey(img.jpg).

• Once more by resizing the pictures, we expanded our information. At that point at backend, we have made segments among preparing dataset in gather of 2. portion 1 named as "yes" and portion 2 as "no".

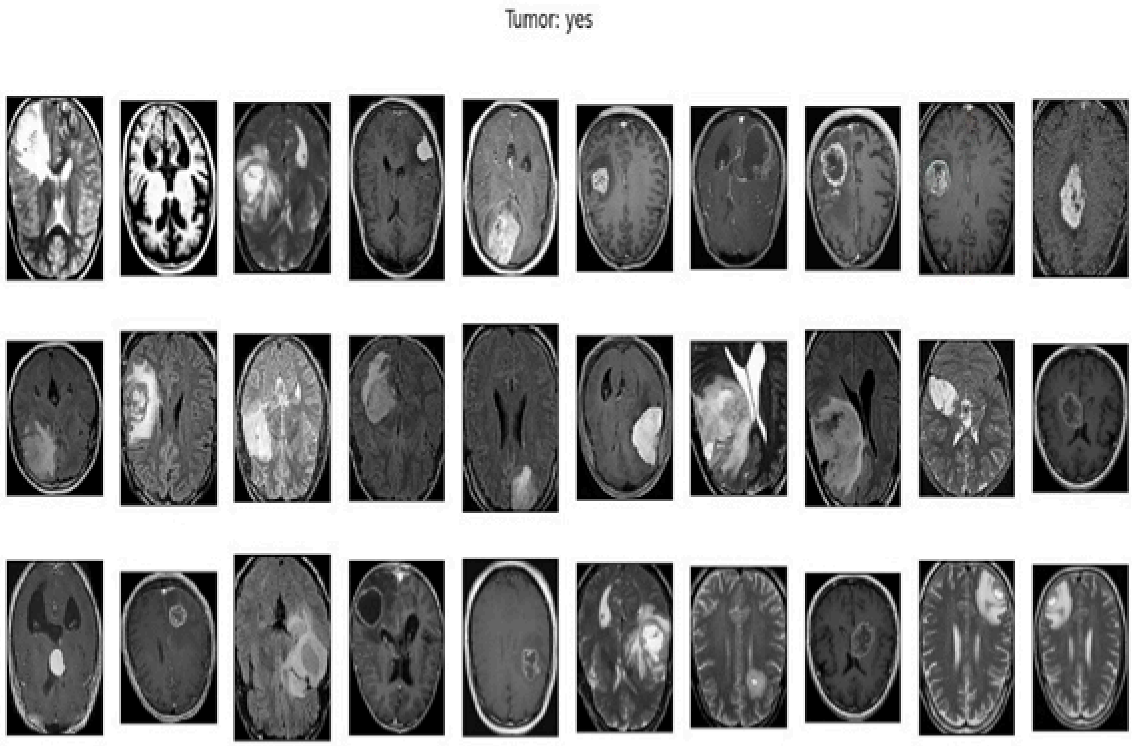
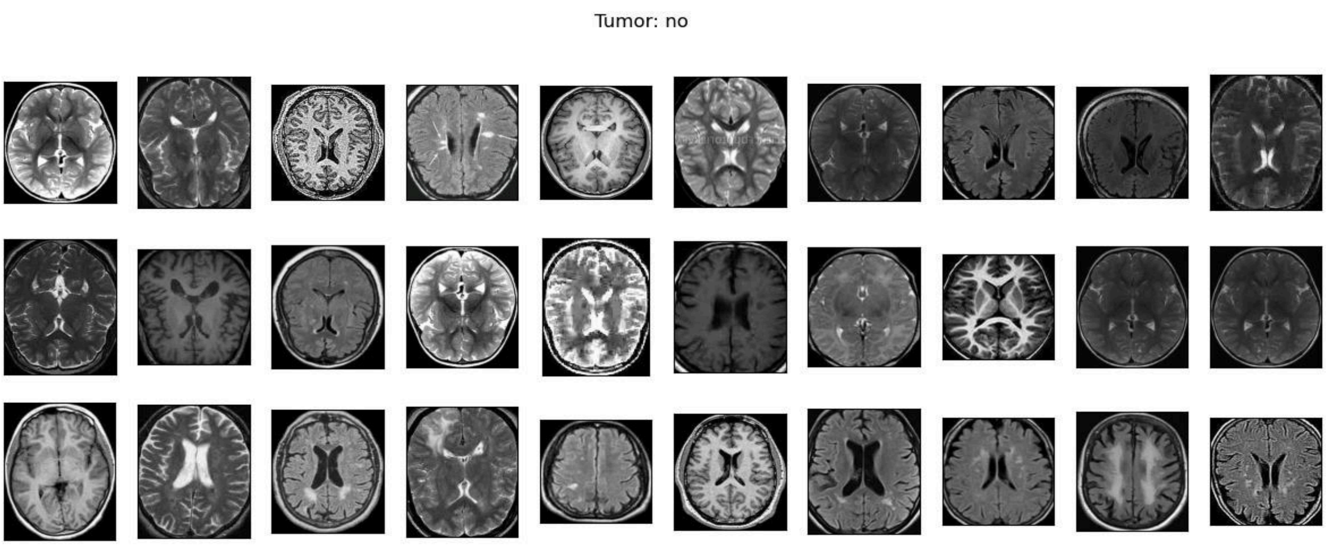


Fig. "YES" classified images

Fig. “NO” classified Images



3.2.1 Working of CNN model

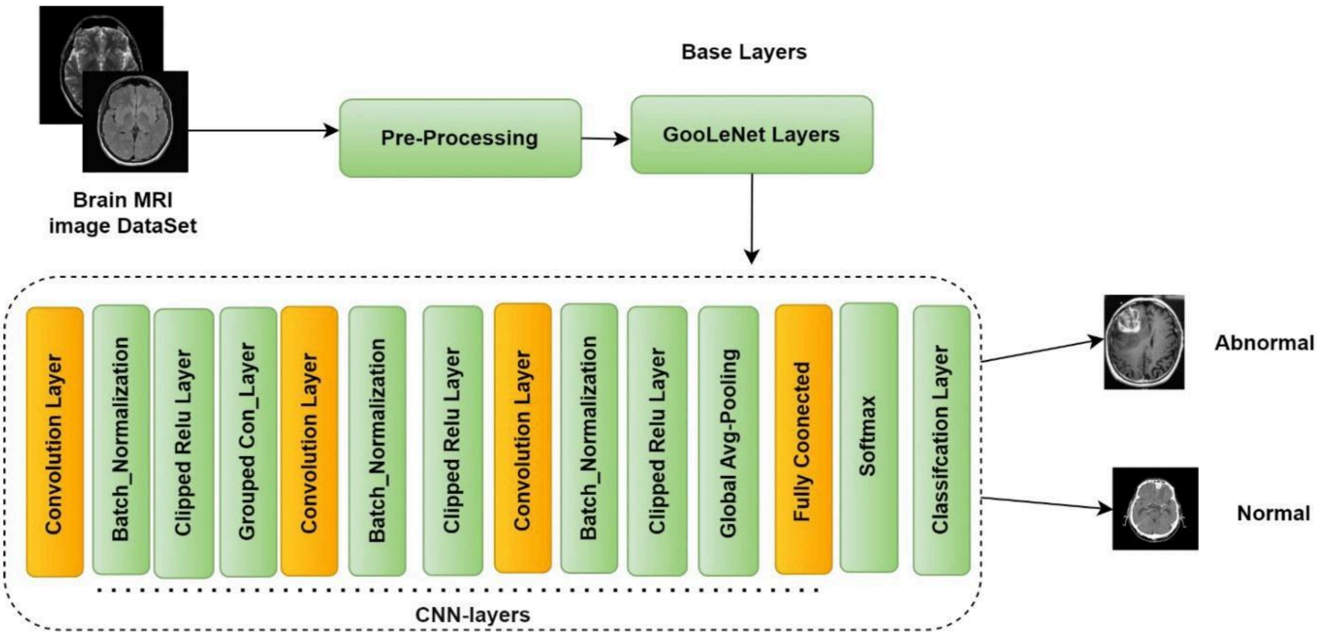


Fig.8.Working of CNN model for brain tumor detection [1]

Layer of CNN show:

o Convolution 2D

o MAX Poolig2D

o Dropout

o Straighten

o Thick

o Actuation

Convolution 2D: Within the Convolution 2D extricate the highlighted from the input picture. It gives the yield in a lattice shape.

MAX Poolig2D: Within the MAX surveying 2D it takes the biggest component from the amended highlight outline.

Dropout: Dropout is arbitrarily chosen neurons that are disregarded amid preparation.

Smooth: Smooth nourish yield into the completely associated layer. It gives information in list shape.

Thick: A Direct operation in which each input is associated with each yield by weight. It is taken after a nonlinear actuation work.

Enactment: It utilized the Sigmoid work and predicted the likelihood and 1.

● Within the compile demonstrate we utilized double cross entropy since we have two layers and 1.

● We utilized Adam optimizer within the compile demonstration.

Adam:

-Versatile minute estimation. It is utilized for non-convex optimization issues that straight forward to actualize.

Adam:-Adaptive moment estimation. It is used for non-convex optimization problems that straight forward to implement.

- Computationally efficient.

- Little memory requirement.

3.2.2 Working of VGG16 model

Transfer learning is a knowledge-sharing method that reduces the size of the training data, the time, and the computational costs when building deep learning models. Transfer learning helps to transfer the learning of a pre-trained model to a new model. Transfer learning has been used in various applications, such as tumor classification, software defect prediction, activity recognition, and sentiment classification. In this, the performance of the proposed Deep CNN model has been compared with the popular transfer learning approach VGG16.

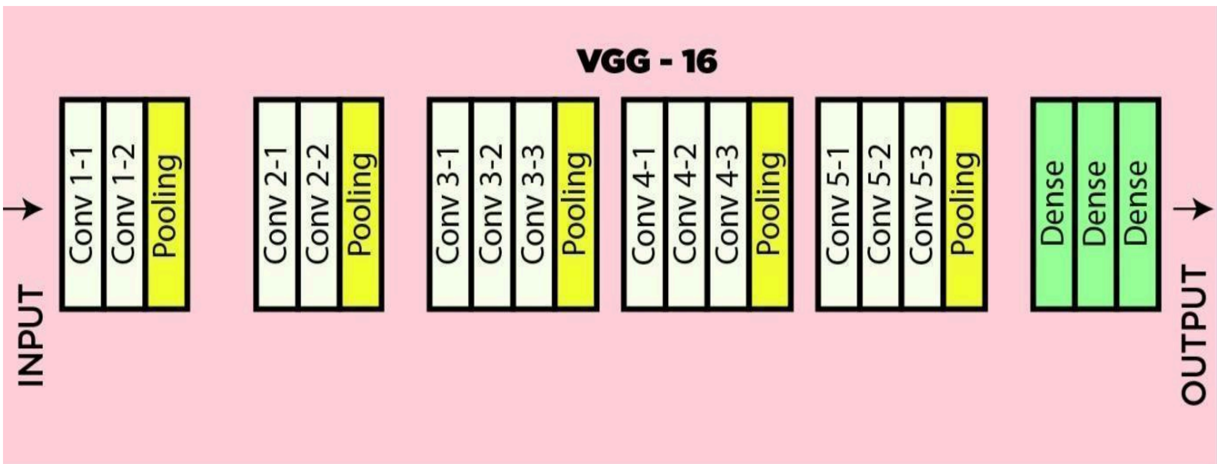


Fig.9. VGG16 layered architecture [16]

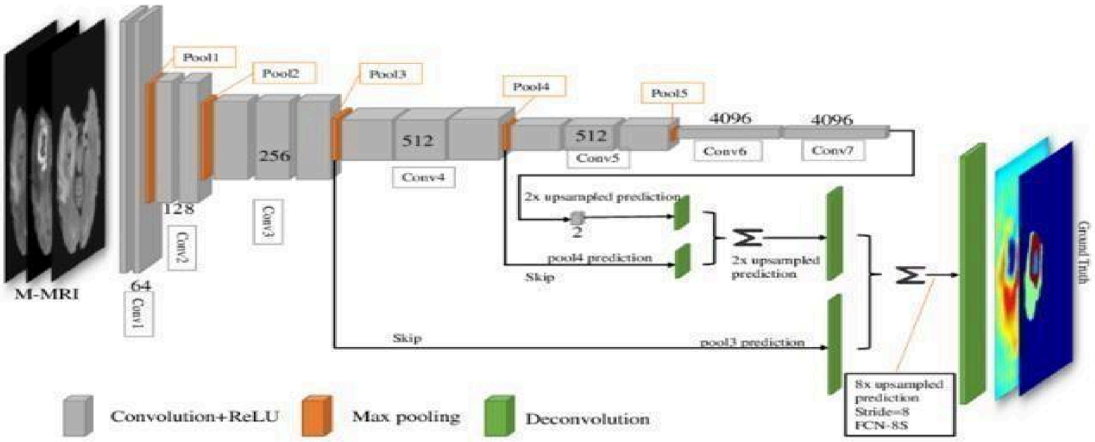


Fig.10.Working of VGG16 model for brain tumor detection [16]

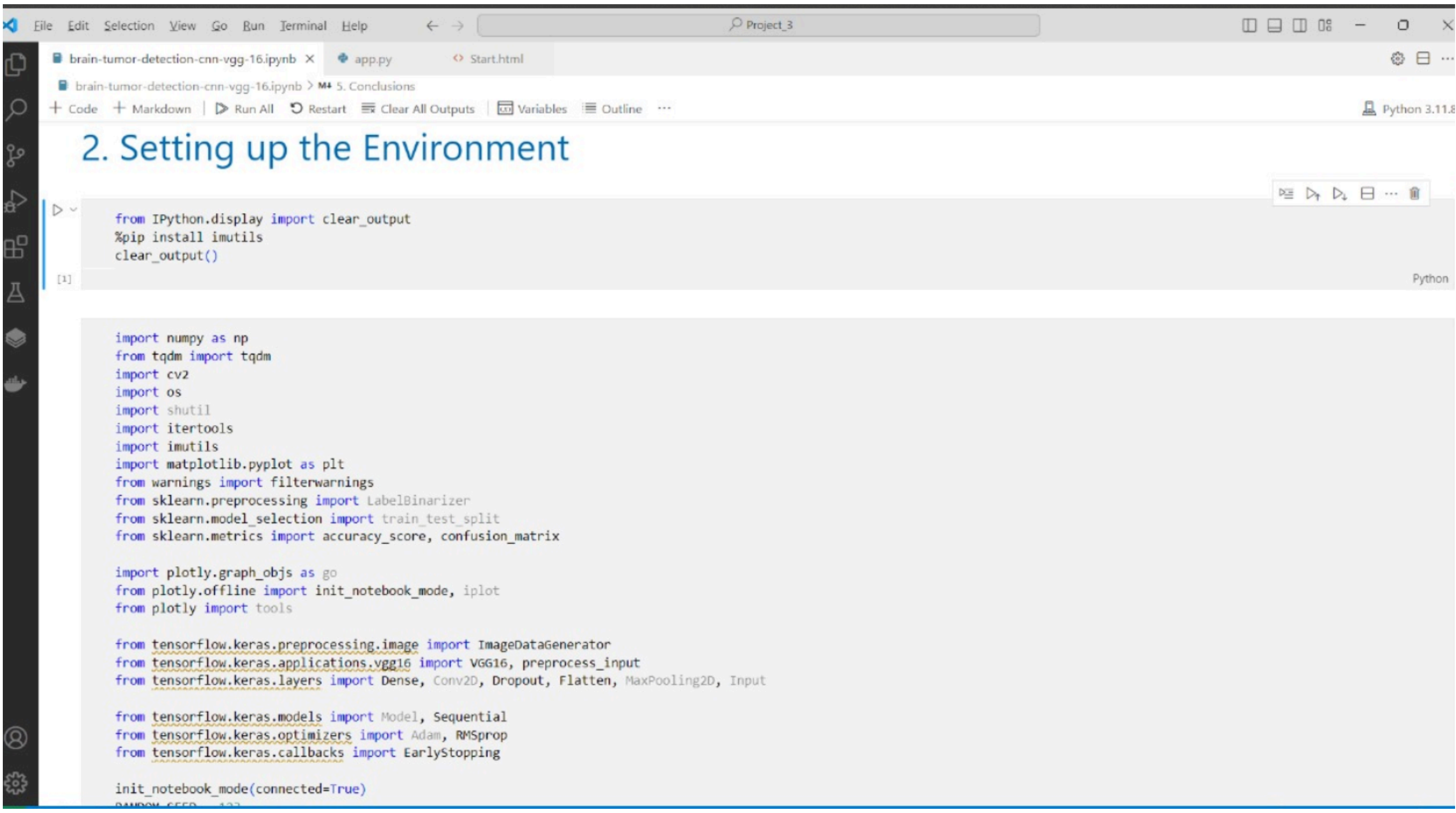
VGG16 is a convolutional neural network. The input of the 1 convolution layer is of fixed size 224 x 224 RGB image. The image is passed through a stack of convolutional layers, where the filters are used with a very small receptive field of 3×3 (which is the smallest size to capture the notion of left/right, up/down, and center). In the configurations, it also utilized 1×1 convolution filters, and it can be seen as a linear transformation of the input channels. The convolution stride is fixed to 1 pixel, and the spatial padding of convolution. The input layer is the spatial resolution preserved after convolution, i.e. the padding is 1 pixel for 3×3 convolution layers. Spatial pooling is carried out by five max-pooling layers, which follow some convolution layers (not all the conv. layers are followed by max-pooling). Max-pooling is performed over a 2×2 pixel window, with stride 2.

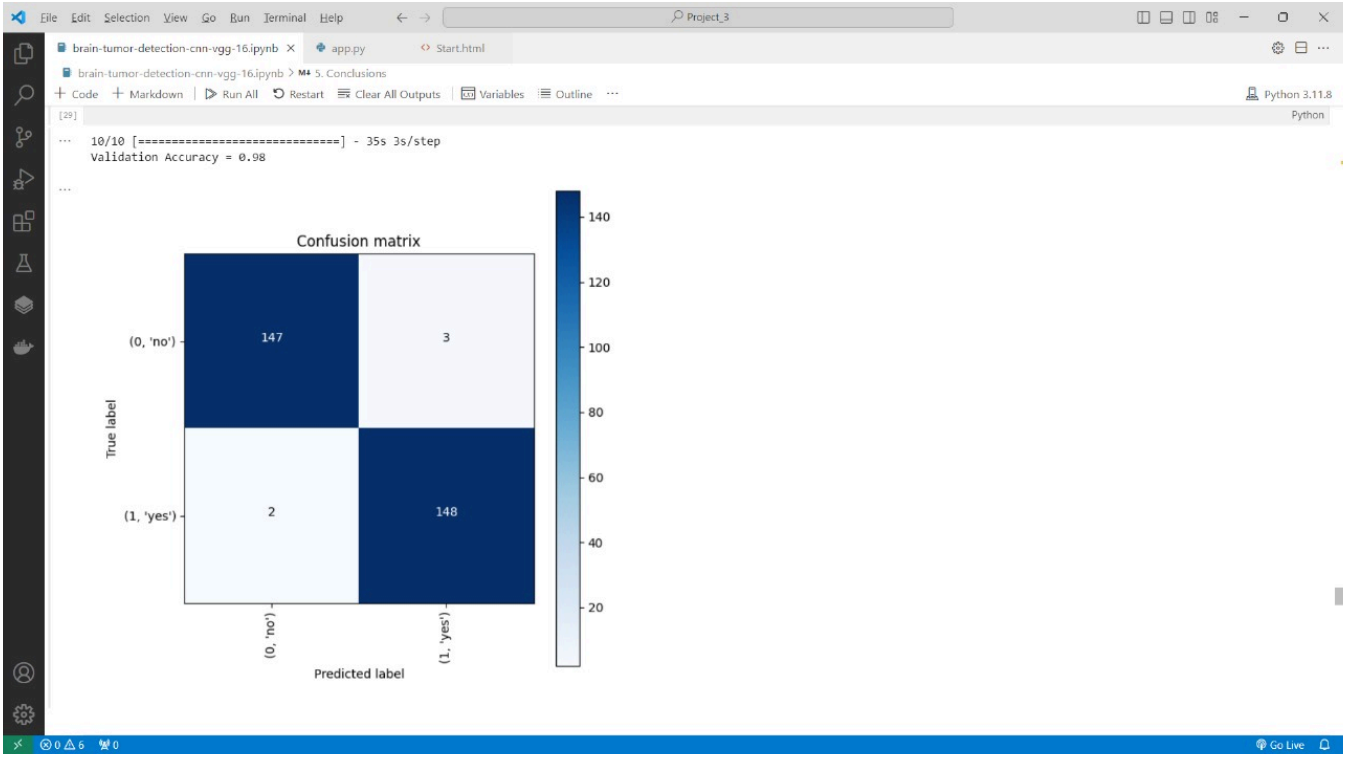
Three Fully-Connected (FC) layers follow a stack of convolutional layers which has different depth in different architectures the first two have 4096 channels each, the third performs 1000-way ILSVRC classification and it contains 1000 channels one for each class. The final layer is the soft-max layer. The configuration of the fully connected layers is the same in every network.

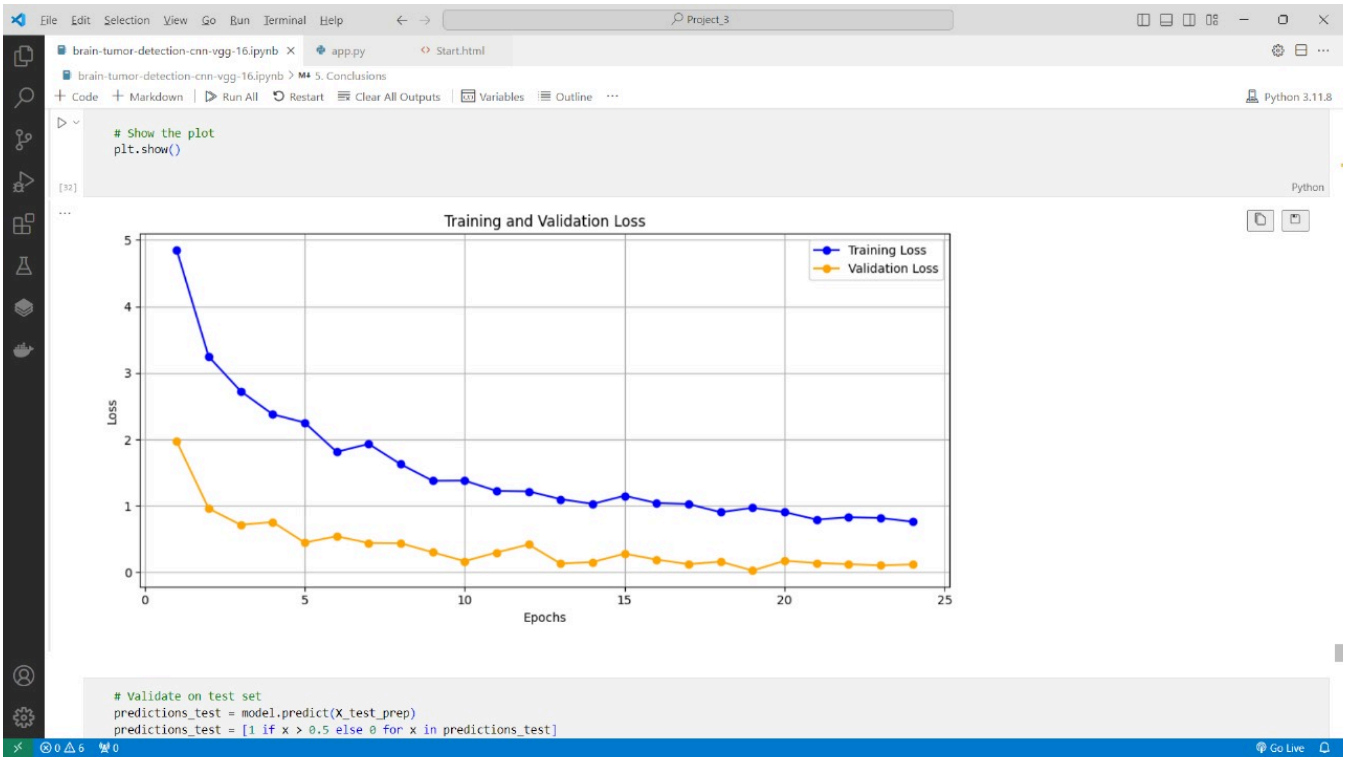
All hidden layers are equipped with the rectification (ReLU) nonlinearity. It is also noted that none of the networks (except for one) contain Local Response Normalization (LRN), such normalization does not improve the performance of the ILSVRC dataset, but leads to increased memory consumption and computation time.

3.2.3 Working of overall model:

We have started building our project from setting up the environment as shown below:




File Edit Selection View Go Run Terminal Help
Project_3
brain-tumor-detection-cnn-vgg-16.ipynb
app.py
Start.html
brain-tumor-detection-cnn-vgg-16.ipynb > M↓ 5. Conclusions
+ Code + Markdown | Run All Restart Clear All Outputs | Variables Outline ...
Python 3.11.8
[29]
Python
10/10 [==============================] - 35s 3s/step
Validation Accuracy = 0.98
Confusion matrix
(0, 'no')
(1, 'yes')
147
3
2
148
True label
Predicted label
140
120
100
80
60
40
20
Go Live


File Edit Selection View Go Run Terminal Help
Project_3
brain-tumor-detection-cnn-vgg-16.ipynb
app.py
Start.html
brain-tumor-detection-cnn-vgg-16.ipynb > M↓ 5. Conclusions
+ Code + Markdown | Run All Restart Clear All Outputs | Variables Outline ...
Python 3.11.8
# Show the plot
plt.show()
[32]
Python
Training and Validation Loss
Training Loss
Validation Loss
Loss
Epochs
0
5
10
15
20
25
1
2
3
4
# Validate on test set
predictions_test = model.predict(X_test_prep)
predictions_test = [1 if x > 0.5 else 0 for x in predictions_test]
Go Live

4. DATASET :

4.1: DATASET DETAIL

The dataset has 3000 images with different types of tumors and also includes images that have tissues of Fat or water. We are going to use a publicly accessible MRI dataset from Kaggle:
https://www.kaggle.com/navoneel/brain-mriimages-for-brain-tumor-detection

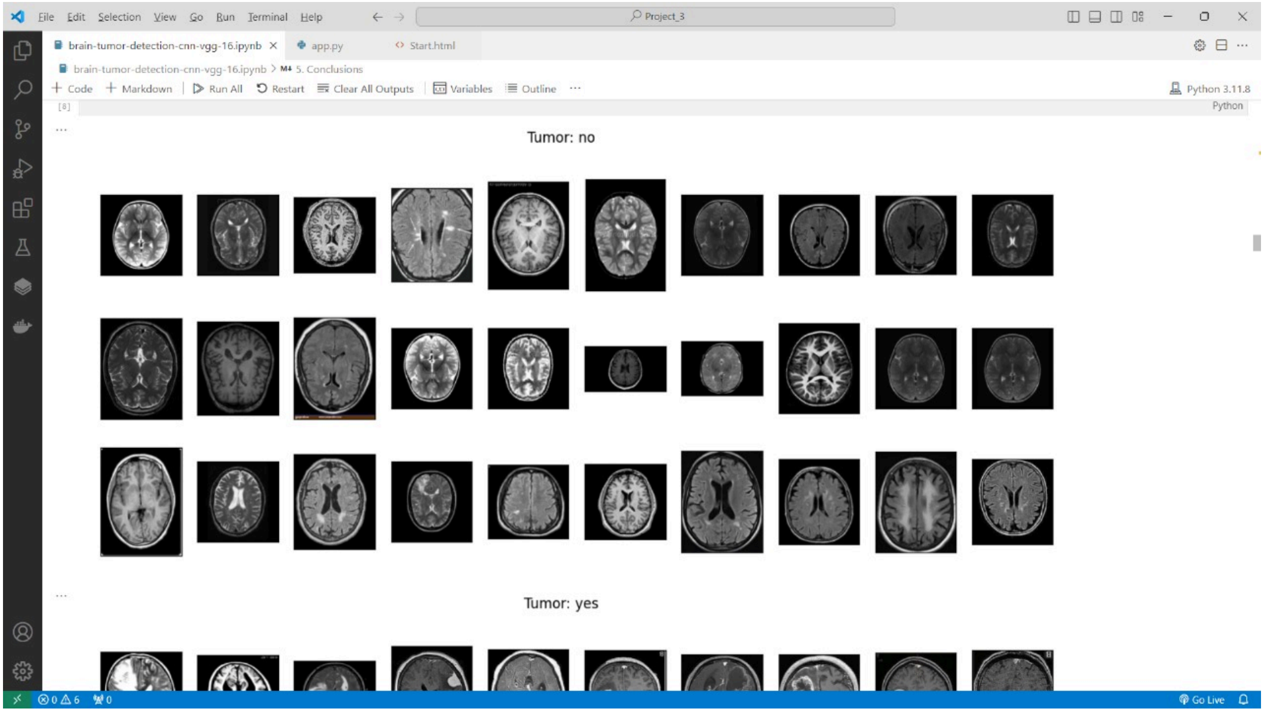
- Images will be stored in mainly two folders abnormal and normal which will be labeled as 'YES' and 'NO'
- It contains nearly 250 or more images of varying dimensions.
- Images are stored in grayscale jpg format as later on we can increase the size of the dataset by using data augmentation.

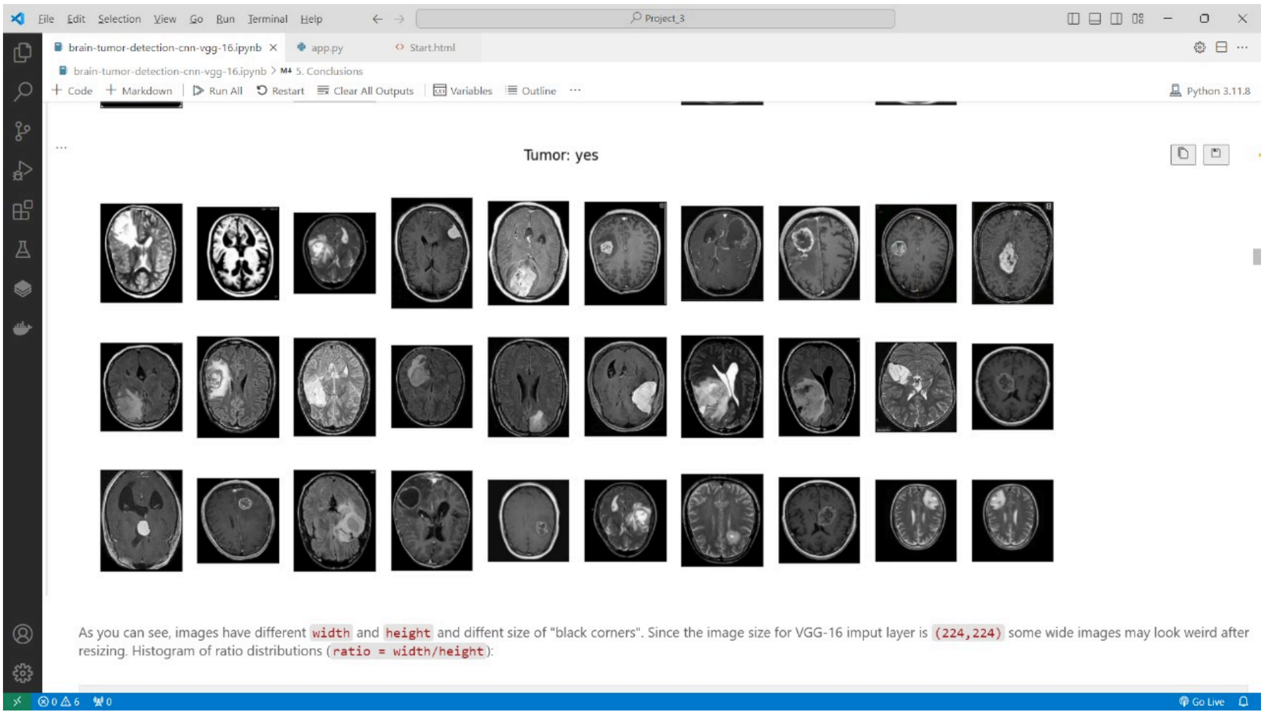
4.2: TOOLS & TECHNOLOGY USED

- **Python:** Python was the language of selection for this project. This was a straightforward call for many reasons.
  1. Python as a language has a vast community behind it. Any problems that may be faced are simply resolved with a visit to Stack Overflow. Python is among the foremost standard languages on the positioning making it very likely there will be straight answers to any question
  2. Python has an abundance of powerful tools prepared for scientific computing Packages like NumPy, Pandas, and SciPy area units are freely available and well-documented. Packages like these will dramatically scale back, and change the code required to write a given program. This makes iteration fast.

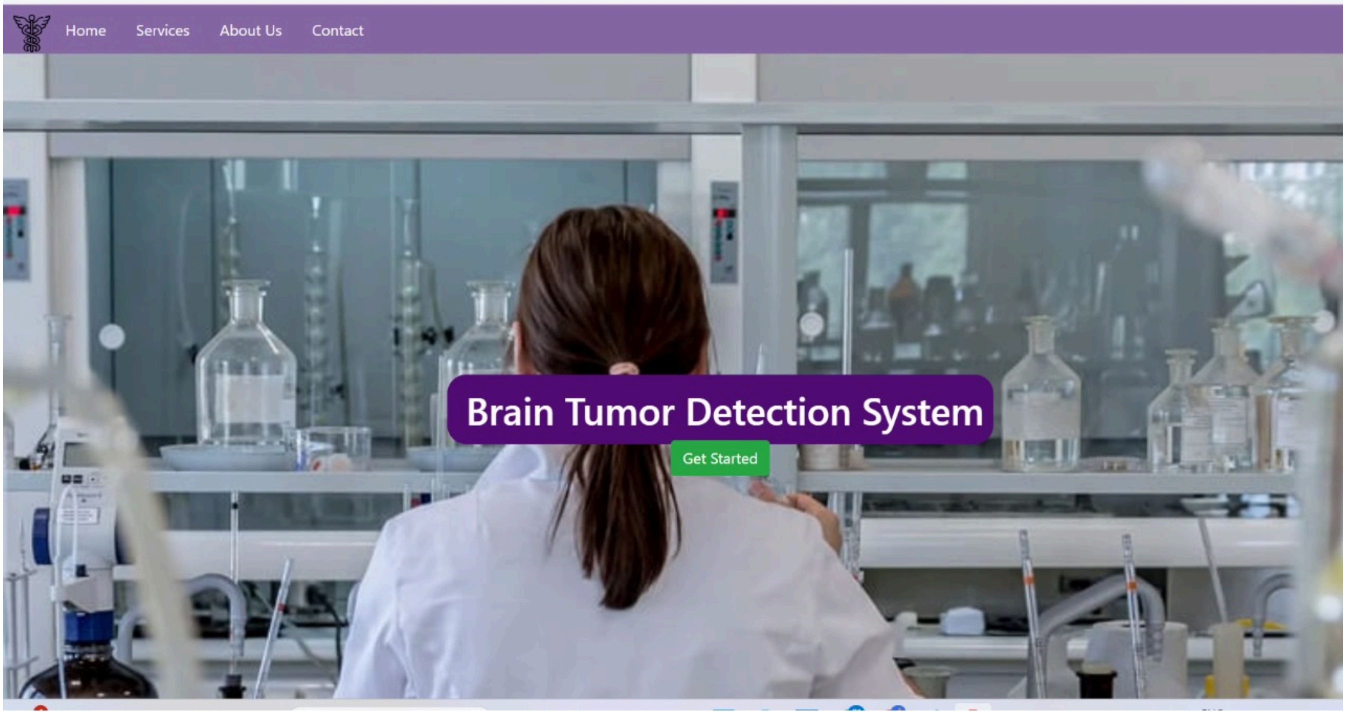
- **Jupyter Notebook:** The Jupyter Notebook is an open-source web application that enables you to make and share documents that contain live code, equations, visualizations, and narrative text. It includes data cleaning and transformation, numerical simulation, statistical modeling, data visualization, machine learning, and much more.

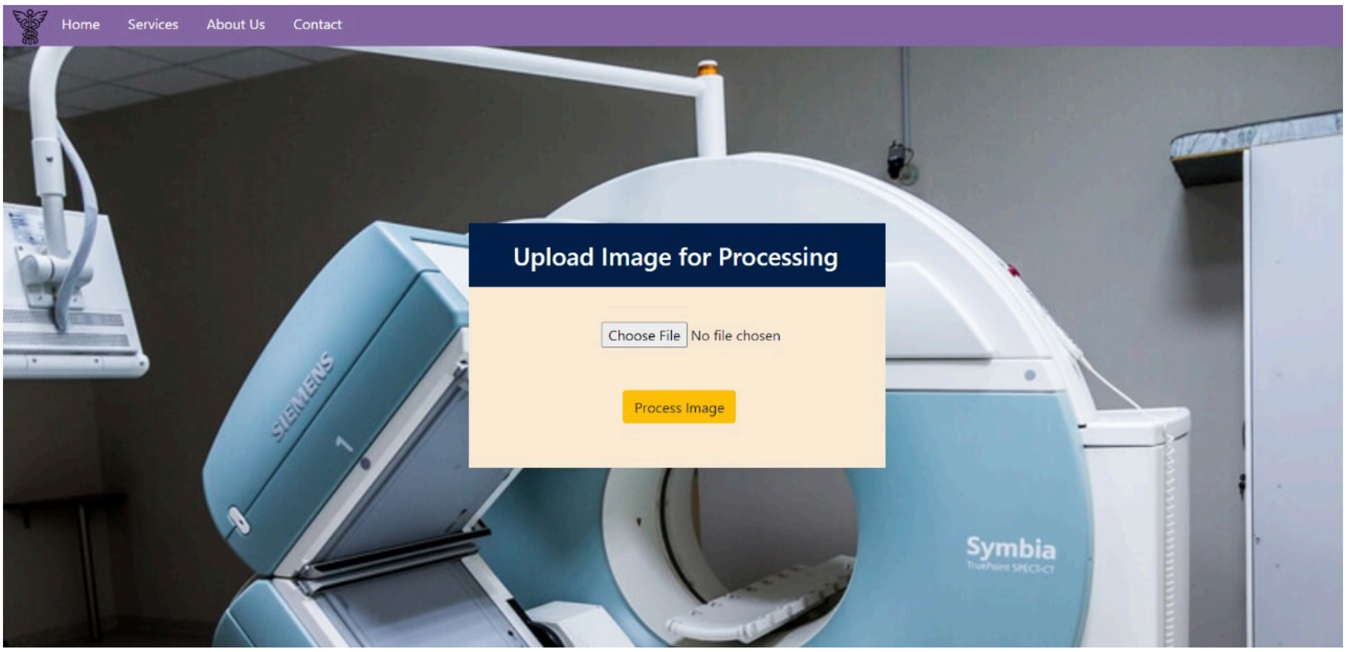
- **Keras:** Deep learning is a branch of artificial intelligence concerned with solving highly complex problems by emulating the working of the human brain. In deep learning, we use neural networks which use multiple operators placed in nodes to help break down the problem into smaller parts, which are each solved individually. But neural networks can be really hard to implement. This problem is taken care of by Keras, a deep learning framework.
- **PIL:** Python Imaging Library (expansion of PIL) is the de facto image processing package for Python language. It incorporates lightweight image processing tools that aids in editing, creating and saving images.
- **Flask:** Flask is a web framework, it's a Python module that lets you develop web applications easily. It has a small and easy-to-extend core: it's a microframework that doesn't include an ORM (Object Relational Manager) or such features.
- **Sklearn:** Scikit-learn (Sklearn) is the most useful and robust library for machine learning in Python. It provides a selection of efficient tools for machine learning and statistical modeling including classification, regression, clustering and dimensionality reduction via a consistent interface in Python. This library, which is largely written in Python
- **TensorFlow:** TensorFlow is an open-source software library. TensorFlow was originally developed by researchers and engineers working on the Google Brain Team within Google's Machine Intelligence research organization for the purposes of conducting machine learning and deep neural networks research

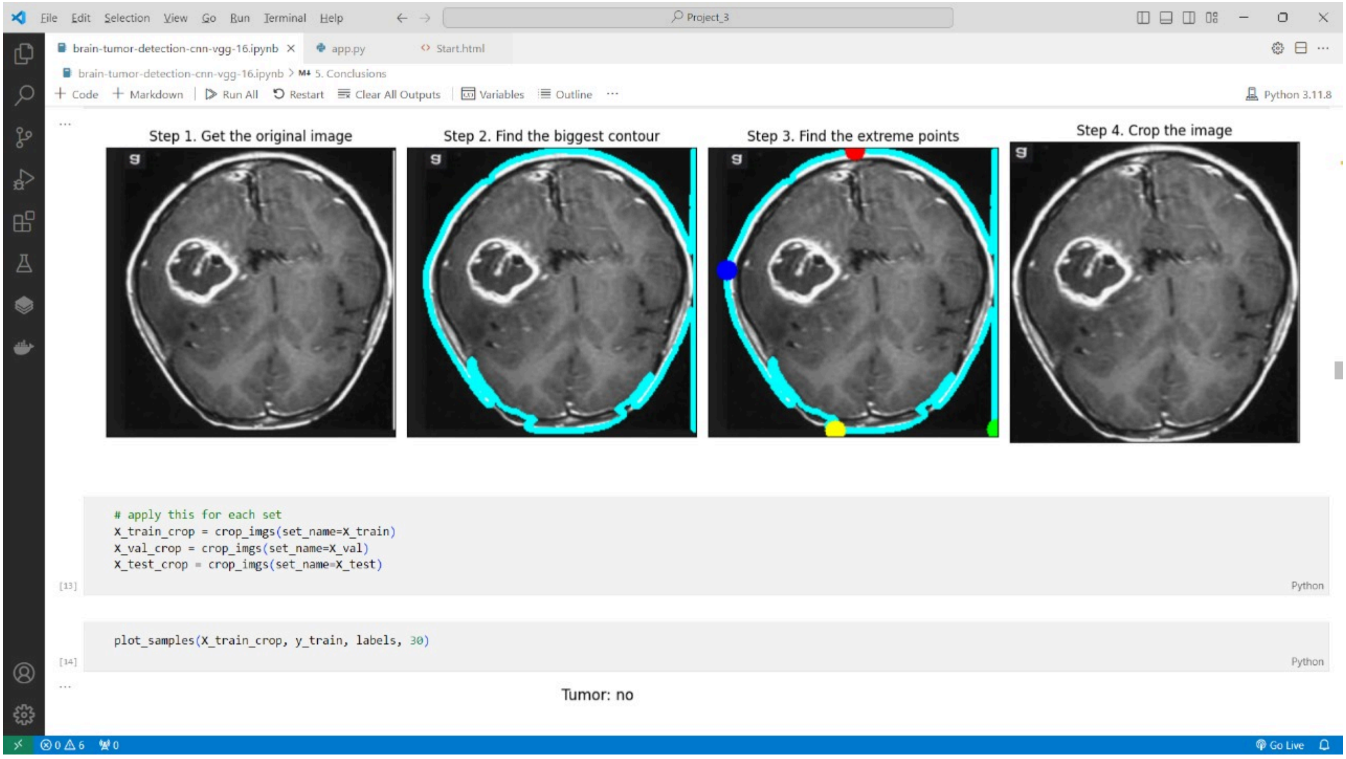

brain-tumor-detection-cnn-vgg-16.ipynb
app.py
Start.html
Project_3
Python 3.11.8
Tumor: no
Tumor: yes


brain-tumor-detection-cnn-vgg-16.ipynb
app.py
Start.html
Project_3
Python 3.11.8
Tumor: yes
As you can see, images have different width and height and diffent size of "black corners". Since the image size for VGG-16 imput layer is (224,224) some wide images may look weird after resizing. Histogram of ratio distributions (ratio = width/height):

4.3 UI snapshots

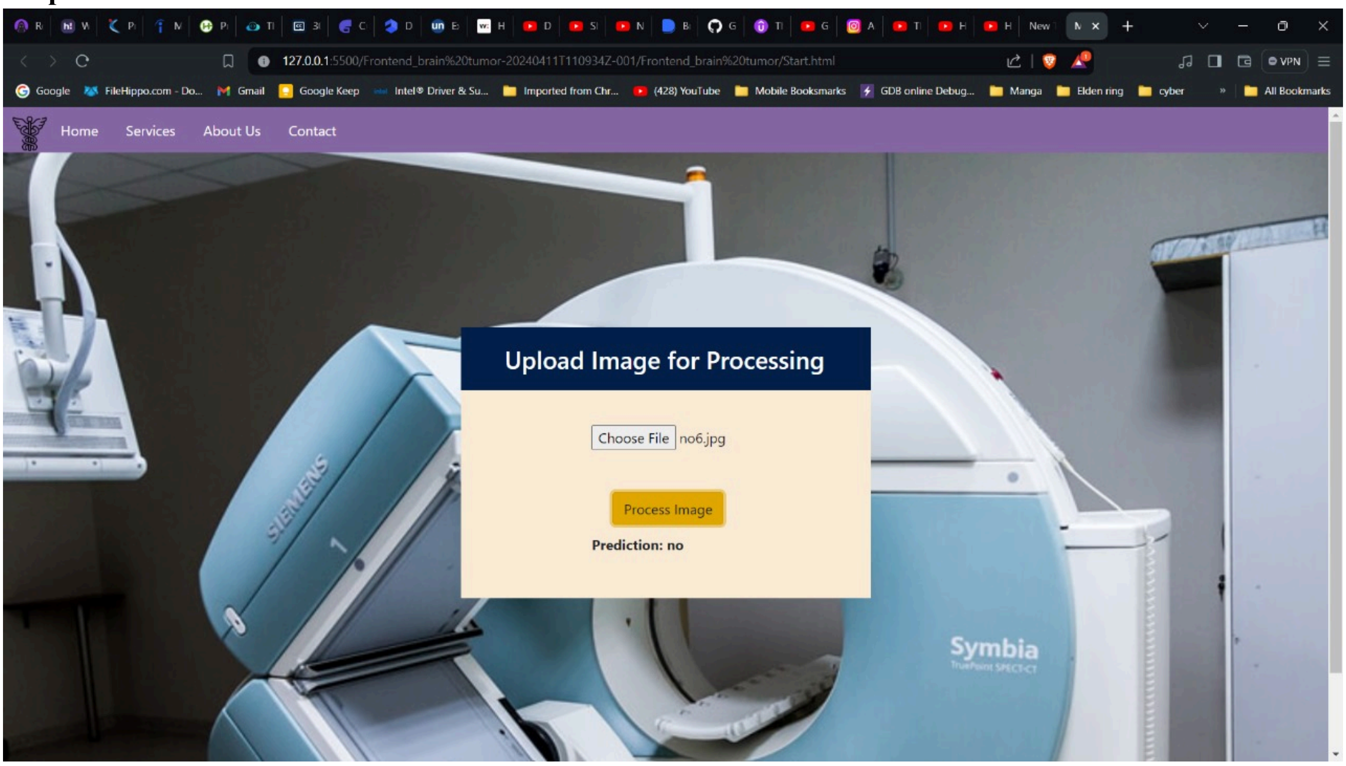




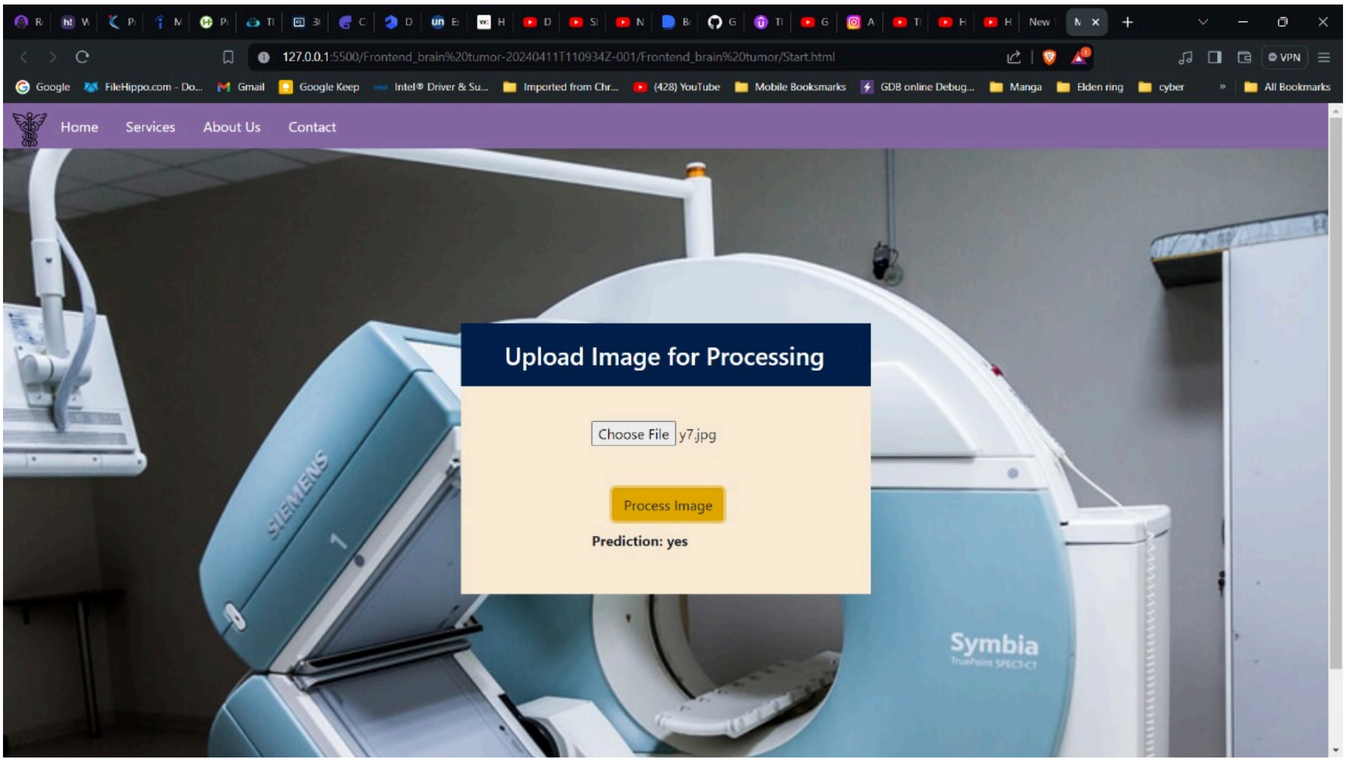


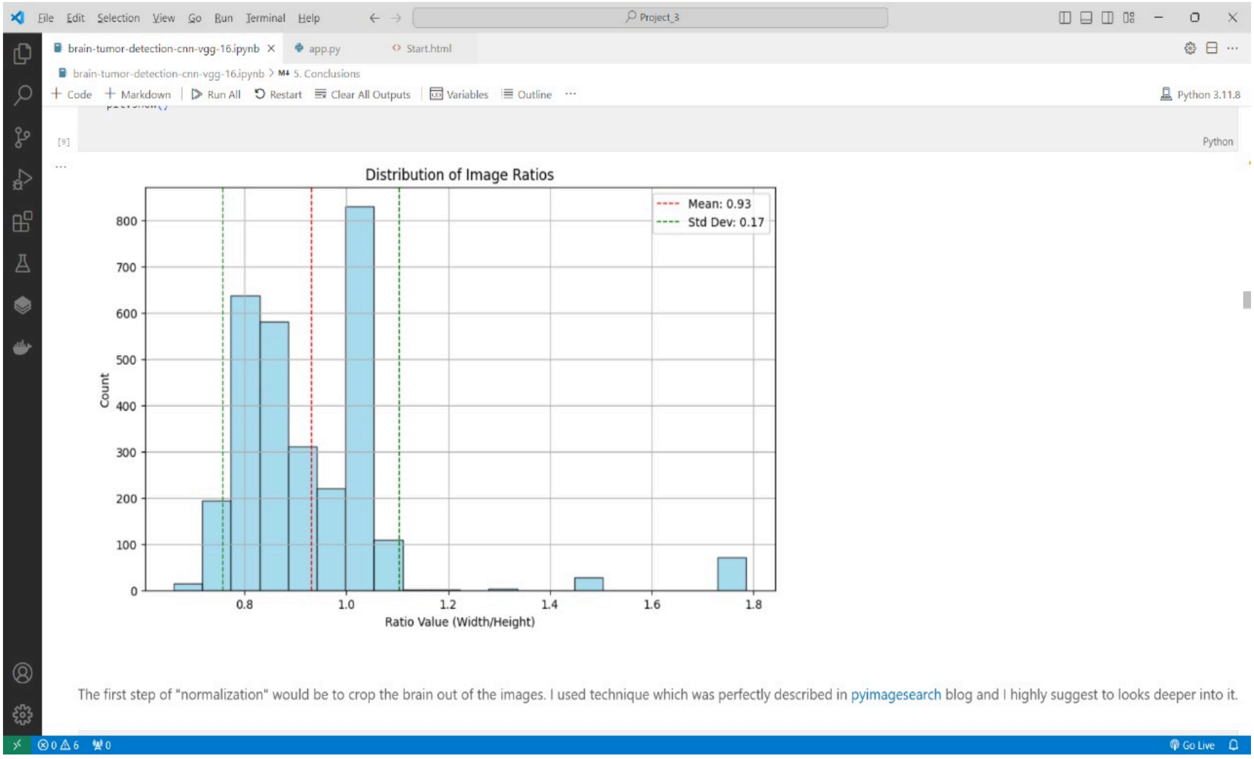
brain-tumor-detection-cnn-vgg-16.ipynb
app.py
Start.html
Step 1. Get the original image
Step 2. Find the biggest contour
Step 3. Find the extreme points
Step 4. Crop the image
# apply this for each set
x_train_crop = crop_imgs(set_name=X_train)
x_val_crop = crop_imgs(set_name=X_val)
x_test_crop = crop_imgs(set_name=X_test)
plot_samples(X_train_crop, y_train, labels, 30)
Tumor: no

Output:



Home
Services
About Us
Contact
Upload Image for Processing
Choose File
no6.jpg
Process Image
Prediction: no


Home
Services
About Us
Contact
Upload Image for Processing
Choose File
y7.jpg
Process Image
Prediction: yes


brain-tumor-detection-cnn-vgg-16.ipynb
app.py
Start.html
Distribution of Image Ratios
Mean: 0.93
Std Dev: 0.17
Count
Ratio Value (Width/Height)
The first step of "normalization" would be to crop the brain out of the images. I used technique which was perfectly described in pyimagesearch blog and I highly suggest to looks deeper into it.

5. Performance Analysis of Proposed Model:

The analysis is done on following statistical entities.

- Accuracy = (TP +TN)/(TP + TN + FP + FN)
- Recall = TP/(TP + FN)
- Specificity = TN/(TN + FP)
- Precision = TP/(TP + FP)
- F1 score = (2 × Precision × Recall)/(Precision + Recall)
- FPR = FP/(FP+TN)
- Jaccard = TP/(TP + FP + FN)

In our proposed model, while training the images there is a graph showing training accuracy and validation accuracy as below:

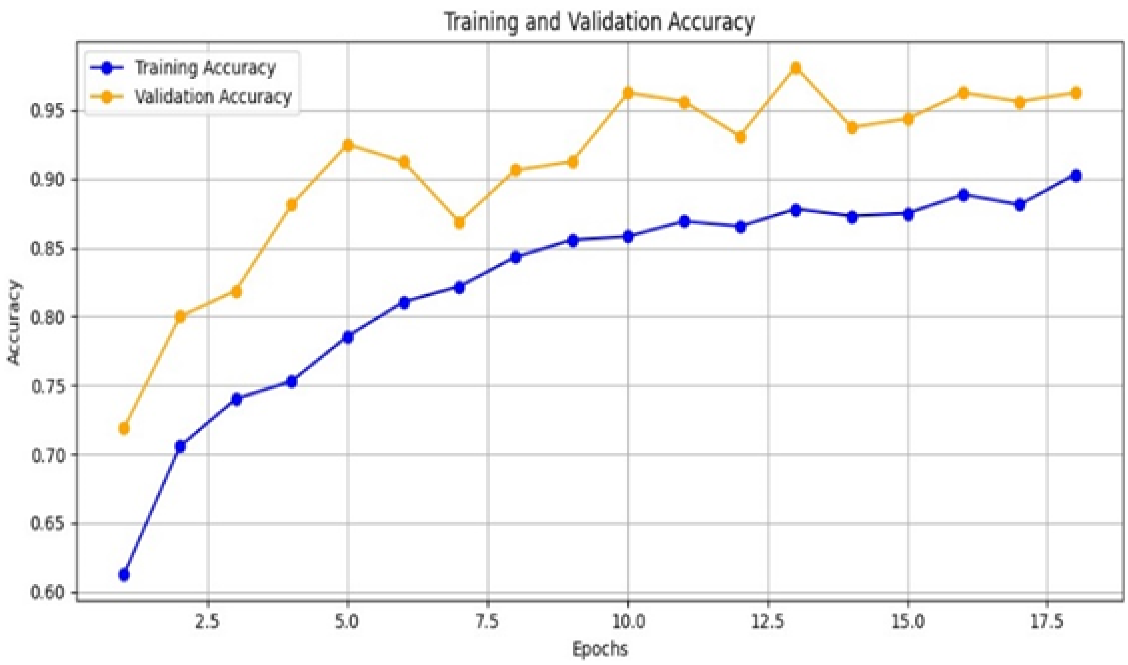


Fig. Graph showing Training and Validation accuracy

Based on the prediction of images, images get labeled as actual class and predicted class values by assigning values 0 or 1. Shown as follows:

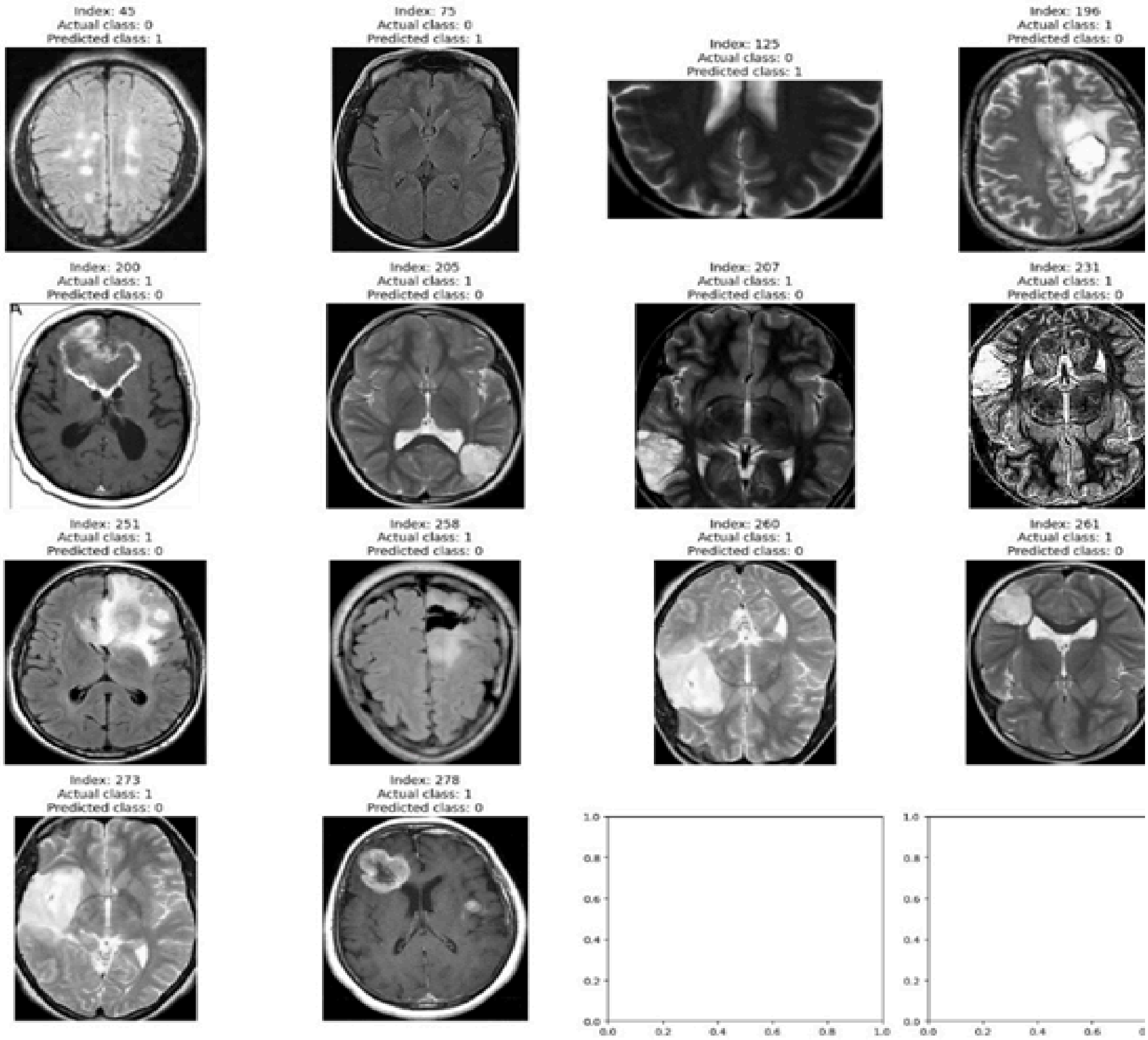


Fig. Classification of images in actual and predicted class

Near about we have analyzed 2 sets of epochs. For the very first one we took 10 epochs after running it successfully we found statistical entities from the following generated confusion matrix:

Accuracy = (TP +TN) / (TP + TN + FP + FN)

= 145+145/145+145+4+4

= 0.9773

Recall = TP/(TP + FN)

= 145/150

= 0.9733

Specificity = TN/(TN + FP)

= 145/150

= 0.9733

Precision = TP/(TP + FP)

= 145/150

= 0.9733

F1-Score = (2×Precision×Recall)/(Precision+ Recall)

= 2*0.9733*0.9733/0.9733+0.9733

= 0.4595

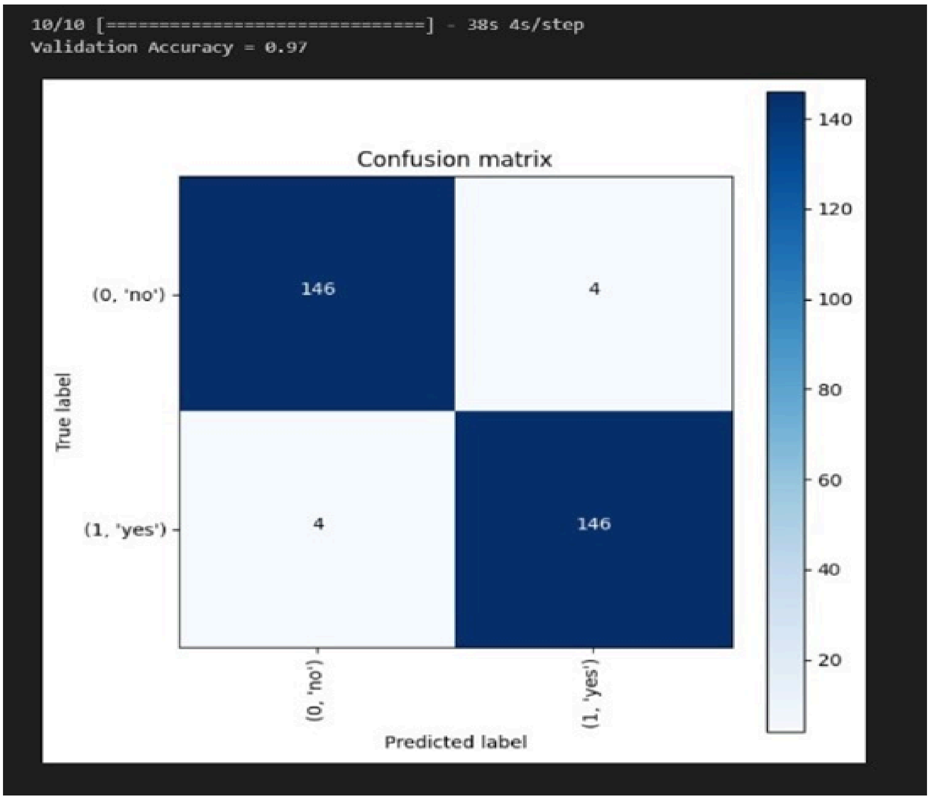


Fig. Confusion Matrix 1

The second one we took a set of 75 epochs after running it successfully a confusion matrix get generated as shown:

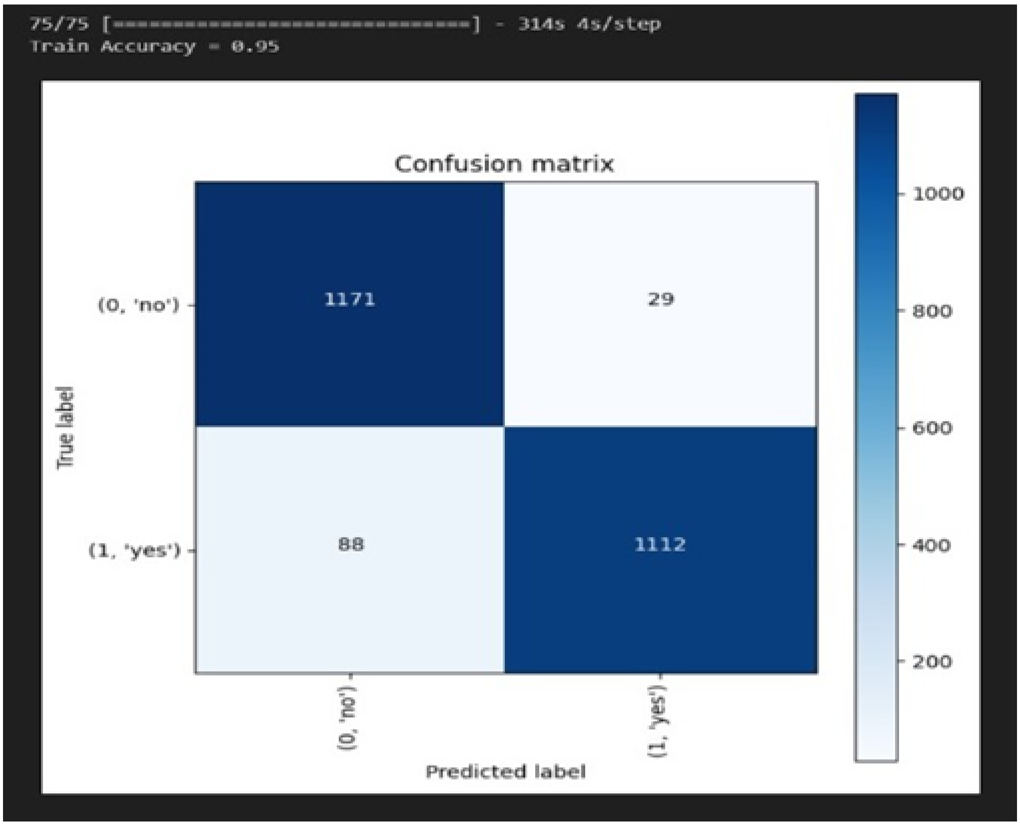


Fig. Confusion Matrix 2

From the above confusion matrix, we have predicted statistical entities as:

Accuracy = (TP +TN) / (TP + TN + FP + FN)

= 1112+1171/1112+1171+88+29

= 2283/2400

= 0.95125

Recall = TP/(TP + FN)

= 1112/1200

= 0.92555

Specificity = TN/(TN + FP)

= 1171/1200

= 0.9758

Precision = TP/(TP + FP)

= 1112/1141

= 0.9745

F1-Score =(2×Precision×Recall)/(Precision+ Recall)

= 2*0.9745*0.9255/0.9745+0.9255

= 0.9499

So , the accuracy of the our model is **97.3%.**

6. CONCLUSION

In brain tumor detection we have studied feature-based existing work. In feature, we have studied image processing techniques like image pre-processing, image segmentation, feature extraction, and classification. And also study deep learning techniques CNN and VGG16. In this system we have to detect whether the tumor is present or not if the tumor is present then the model returns yes otherwise it returns no. we have compared CNN with the VGG 16 Model. The result of the comparison VGG 16 is more accurate than CNN. However, not every task is said to be perfect in this development field even more improvement may be possible in this application. I have learned so many things and gained a lot of knowledge about the development field.

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APPENDIX ABBRAVIATION

Sr No.	Abbreviation	Meaning	
1	CNN	Convolutional neural network	
2	MRI	Magnetic resonance imaging	
3	FLAIR	Fluid attenuated in version recovery weighted	MRI
4	TR	Time repetition	
5	TE	Pulse sequence parameter	
6	VGG 16	Visual Geometry Group	
7	FC	Fully connected layer	
8	ReLU	Rectified linear unit	
9	LRN	Local response normalization	
10	SVM	Support vector machine	
11	KNN	K nearest neighbor	

ACKNOWLEDGEMENT

We would like to take this opportunity to sincerely thank Dr.Sangita Nemade, our guide and assistant professor in the Department of Information Technology at the Government College of Engineering, Chhatrapati Sambhaji Nagar, for her direction and assistance during the study for our project. We could not have done this without her gracious advice and assistance. We appreciate her prompt input, which enabled us to efficiently monitor and plan the process. Her ideas, time, and support enabled us to finish our assignment quickly and effectively. We also thank Dr. Versha Gaikwad for her support, for creating a wonderful learning atmosphere, and for providing the necessary resources.

We are grateful to all of my B.E. instructors as well as Dr. Anjana Ghule, Head of the Department of Information Technology at the Government College of Engineering Chhatrapati Sambhaji Nagar, for their insightful counsel. We also sincerely appreciate the participation of all of the faculty members, non-teaching personnel, and friends.

Vinod Patil	BE20F06F041
Avijeet Salve	BE20F06F053
Bhagyashri Saundarkar	BE20F06F055
Shrutika Uikey	BE20F06F066

(Department of Information Technology)

Government College of Engineering, Aurangabad (Chhatrapati SambhajiNagar)

DECLARATION

We thus certify that, with Dr. Sangita Nemade's assistance, we developed, finished, and wrote the dissertation titled **"Brain Tumor Detection System using Deep Learning".** We have followed all ethical and academic guidelines and acknowledged the usage of all materials in this endeavour. Any data, thoughts, or ideas that came from other people have been properly referenced in accordance with the guidelines.

Date:

Place: Chhatrapati SambhajiNagar

Vinod Patil	**Avijeet Salve**
(BE20F06F041)	**(BE20F06F053)**
Bhagyashri Saundarkar	**Shrutika Uikey**
(BE20F06F055)	**(BE20F06F066)**