

# **Brain tumor segmentation and classification using deep neural network and an interactive GUI interface to estimate the psychological effects on its removal**

Submitted in partial fulfilment of the requirements for the award of  
Master of Engineering degree in Embedded Systems and IoT

by

B. Kavitha (39108002)



**DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING  
SCHOOL OF ELECTRICAL AND ELECTRONICS ENGINEERING**

**SATHYABAMA INSTITUTE OF SCIENCE AND TECHNOLOGY  
(DEEMED TO BE UNIVERSITY)**

**Accredited with Grade "A" by NAAC**

**JEPPIAAR NAGAR, RAJIV GANDHI SALAI, CHENNAI - 600 119**

**APRIL 2021**



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**DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING**

**BONAFIDE CERTIFICATE**

This is to certify that this Project Report is the bonafide work of  
B.KAVITHA(39108002) who carried out the project entitled “**Brain Tumor Segmentation  
And Classification Using Deep Neural Network And An Interactive GUI Interface To  
Estimate The Psychological Effects On Its Removal**” under my supervision from  
December 2020 to April 2021

**Internal Guide**

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**Submitted for Viva voce Examination held on 17/04/2021**

**Internal Examiner**

**External Examiner**

## **DECLARATION**

I, B. Kavitha (39108002), hereby declare that the Project Report entitled “**Brain tumor segmentation and classification using deep neural network and an interactive GUI interface to estimate the psychological effects on its removal**” done by me under the guidance of Mrs. R. Shakthi Prabha is submitted in partial fulfilment of the requirements for the award of Master of Engineering degree in Embedded Systems and IoT.

**DATE:** 17/04/2021

**PLACE:** Chennai

B.Kavitha

**SIGNATURE OF THE CANDIDATE**

## ACKNOWLEDGEMENT

I am pleased to acknowledge my sincere thanks to Board of Management of **SATHYABAMA** for their kind encouragement in doing this project and for completing it successfully. I am grateful to them.

I convey my thanks to **Dr. N. M. Nandhitha, M.E., Ph.D.**, Dean, School of Electrical and Electronics Engineering and **Dr. T. Ravi, M.E., Ph.D., Head of the Department, Dept. of Electronics and Communication Engineering** for providing me necessary support and details at the right time during the progressive reviews.

I would like to express my sincere and deep sense of gratitude to my Project Guide **Mrs. R. Shakthi Prabha** for her valuable guidance, suggestions and constant encouragement paved way for the successful completion of my project work.

I wish to express my thanks to all Teaching and Non-teaching staff members of the Department of Electronics and Communication Engineering who were helpful in many ways for the completion of the project.



## **ABSTRACT**

Brain being the important functional unit of our nervous system, the brain tumor nearly means that part or the whole of our entire living and function is endangered and might get compromised if left untreated. Hence, segmenting and classifying the tumorous portion of brain from an MRI image are the crucial tasks. This paper focuses on achieving that to the optimal level. Various image techniques such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI) and ultrasound image are used to evaluate the tumour in a brain. In this work MRI images are used to diagnose tumour in the brain. Since the manual classification takes more time, the automatic classification has been gaining more attention and momentum recently. But it faces a serious concern with respect to the accuracy it provides. Hence trusted and automatic classification scheme are essential. The automatic brain tumour classification is very challenging task in large spatial and structural variability of surrounding region of brain tumour. In this work, automatic brain tumour classification is provided by three Deep Neural Networks – ResNet50, VGG16 and VGG19. And a performance analysis is done. Experimental results show that the VGG19 architecture archives a rate of 93% accuracy with low complexity compared with the all-other state of arts method.

### **Key points:**

Brain tumor, MRI, Automatic Classification, Deep Neural Network, ResNet50, VGG16, VGG19

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# CHAPTER 1

## INTRODUCTION:

Brain is one of the vital organs in the human body, which consists of billions of cells. The abnormal group of cells is formed from the uncontrolled division of cells, which is also called as tumour. Neurologists classify manually the brain MR images using the World Health Organization (WHO) classification criteria into two types such as low grade (grade1 and grade2) and high grade (grade3 and grade4) tumour. Low grade brain tumour is also called as benign tumour. Similarly, the high-grade tumour is also called as malignant tumour. Benign tumour is not cancerous. Hence it doesn't spread to other parts of the brain. However, the malignant tumour is a cancerous tumour. So, it spreads rapidly with indefinite boundaries to other region of the body easily. It leads to immediate death. Brain MRI image is mainly used for tumour detection and treatment processes. MRI images are more detailed than CT or ultrasound image. In MRI the brain structure can be clearly delineated and anomaly in the brain tissue can be easily detected. Scholars offered brain MRI images from the time when it became possible to scan and freight medical images to the computer for finding and type cataloguing brain tumours. Neural Networks (NN), Support Vector Machine (SVM) and such methods are used for their good enactment of the proposed work over the most recent few years.

## CHAPTER 2

### OBJECTIVES:

- **Machine learning and convolutional neural networks CNNs** work by using an input, convolving this input with a filter and giving an output. The general overview of this process is not as simple and as general as that. Additional steps are also needed to produce a fully functional CNN. The network is first trained to a dataset. This is termed machine learning. The training is iterated several times. The number of iterations is based on the how close the output is to the expected result.
- **Data augmentation** is mainly used to increase the diversity of data available for training without actually collecting new data. MRI images can be translated, cropped and rotated to some particular degree. The neural network will not identify the patterns within the input dataset that has been morphologically changed. The over-fitting problem is reduced by data augmentation process. It is also estimated to improve the prediction accuracy in the range of 1% to 3%.
- **Dropout** is a method whereby nodes in the convolutional neural network are briefly dropped. When the network is trained iteratively, the powerful connections are learned more while the weaker ones are ignored. As iterations progresses, not all the node connections stay alive. Some would become obsolete and hence stop participating. The input and the output neuron of such nodes are established to zero. It helps to increase the validation accuracy. Though it may require to double the number of iterations required to converge, the training time taken for epoch is less.
- **Batch normalisation** is a process of dividing the weighting power of all nodes that have a high bias and converting it into conventionally lower values. It also helps to reduce the memory requirement.

- **Pooling** is the process of down sampling the image. The pixel values are averaged or the resolution is degraded in order to train the CNN to identify features that are imprecise. The insignificant details are left to be ignored.
- **Brain tumour segmentation** is a hot point in the research field of computer science with bio medical. The Brain tumor segmentation is useful in assessing the tumor growth and to localize the region of tumor affected area. That can help in the treatment processes and also to evaluate the responses, to assist in computer-based surgery, treatment of radiation therapy, and developing tumor growth models.

## **LITERATURE SURVEY:**

### **Literature Survey 1**

**Title:** Brain Tumor analysis Based on Shape Features of MRI using Machine Learning

**Year:** 2018

**Author:** Bhagyashri H. Asodekar, Sonal A. Gore and A. D. Thakare

Brain tumor are segmented by using image processing techniques. For feature extraction shape-based features are used. Extracted shape-based features are fed to machine learning algorithms such as support vector machine and random forest algorithm to classify benign and malignant brain tumors. SVM showed accuracy of 81.42% and with RF 86.66% accuracy is achieved.

### **Literature Survey 2**

**Title:** Speckle and Rician Noise Removal from Medical Images and Ultrasound Images

**Year:** 2020

**Author:** Saurabh U. Saoji, M. V. Sarode

A filtering system to combine both the Median filter and Gaussian filter to remove the Speckle noise from Medical and Ultrasound images is proposed. The image quality is measured through statistical quantities: Peak signal to noise ratio (PSNR). Experimental results show that the proposed model removes more noise than existing median or gaussian filter. But there is no considerable improvement in efficiency.

### **Literature Survey 3**

**Title:** Brain tumor classification using deep CNN features via transfer learning

**Year:**2019

**Author:** S. Deepak, P.M. Ameer

The proposed classification system adopts the concept of deep transfer learning and uses a pre-trained GoogLeNet to extract features from brain MRI images. Proven classifier models are integrated to classify the extracted features. The experiment follows a patient-level five-fold cross-validation process, on MRI dataset from figshare. The proposed system records a mean classification accuracy of 98%, outperforming all state-of-the-art methods. Other performance measures used in the study are the area under the curve (AUC), precision, recall, F-score and specificity. In addition, the paper addresses a practical aspect by evaluating the system with fewer training samples. It achieves an accuracy of 98% on average.

#### **Literature Survey 4**

**Title:** Brain Tumor Segmentation Using Deep Learning by Type Specific Sorting of Images

**Year:**2019

**Author:** Zahra Sobhaninia, Safiyeh Rezaei, Alireza Noroozi, Mehdi Ahmadi, Hamidreza Zarrabi, Nader Karimi, Ali Emami, Shadrokh Samavi

Different angles of brain MR images are applied with different networks for segmentation. The effect of using separate networks for segmentation of MR images is evaluated by comparing the results with a single network. Experimental evaluations of the networks show that Dice score of 0.73 is achieved for a single network and 0.79 in obtained for multiple networks. But it is time-consuming.

#### **Literature Survey 5**

**Title:** Brain tumor classification using SVM and KNN models for SMOTE based MRI images

**Year:** 2020

**Author:** R S Latha, G R Sreekanth, P Akash, B Dinesh, S Deepak kumar

The brain tumor MR images are taken and the tumors are first segmented using Otsu's threshold technique using MATLAB processing tools. Segmented images further transmitted to discrete wavelet transform (DWT) to get the features of the images. Identified images features are further applied to principle component analysis (PCA) for dimensionality reduction. Further, synthetic minority over-sampling technique (SMOTE) is used to balance the samples in the dataset classes. The proposed work has been tested with K-nearest neighbor(KNN)and support vector machine(SVM) models for predicting the classification accuracy. The proposed model shows the accuracy to be 88.75% with respect to KNN and 93.32% with respect to SVM.

But the necessity of SMOTE quite seem only to increase the accuracy value subjectively and not for any true qualitative purposes.

## **Literature Survey 6**

**Title:** Brain and pancreatic tumor segmentation using SRM and BPNN classification

**Year:** 2019

**Author:** Jithendra Reddy Dandu, Arun Prasath Thiyagarajan, Pallikonda Rajasekaran Murugan & Vishnuvarthanan Govindaraj

The detection of the brain tumor and pancreatic tumor using DBCWMF (Decision Based Couple Window Median Filter) algorithm, Statistical region merging (SRM), Cat Swarm Optimization and Scale-invariant feature transform (CSO-SIFT) extraction and classification through Back Propagation Neural Network (BPNN) is presented. DBCWMF works effectively in the pre-processing compared to Median and PGPD filter, segmentation done with SRM algorithm. After that, the feature selection techniques CSO and SIFT are used for detecting the part in tumor images which is

affected and final classification through BPNN classification works effectively compared to ANN and AdaBoost classifier. It is one of the effective models.

### **Literature Survey 7**

**Title:** Detection of brain tumour in 2D MRI: implementation and critical review of clustering-based image segmentation methods

**Year:** 2020

**Author:** Lim Jia Qi, Norma Alias, Farhana Johar

The images are pre-processed and undergo an important process called skull stripping. Then, image segmentation techniques such as k-means clustering, Gaussian mixture model segmentation and fuzzy c-means are applied to the pre-processed MR images. The image segmentation results are evaluated using several performance measures, such as precision, recall, Tanimoto coefficient and Dice similarity index in reference to ground truth images. The highest average Dice coefficient is achieved by k-means (0.189) before post-processing and GMM (0.208) after postprocessing. Unsupervised clustering-based brain tumour segmentation based on just image pixel intensity in single-spectral brain MRI without adaptive post-processing algorithm cannot achieve efficient and robust segmentation results.

K-means is proved to be the best. FCM algorithm suffers from long computational time, has the lowest precision, Dice and Jaccard similarity indices and high recall.

### **Literature Survey 8**

**Title:** Design and implementing brain tumor detection using machine learning approach

**Year:** 2019

**Author:** G.Hemanth, M.Janardhan, and L.Sujihelen

It proposes an automatic segmentation method that relies upon CNN (Convolution Neural Networks), determining small  $3 \times 3$  kernels. By incorporating this single technique, segmentation and classification is accomplished. CNN (a ML technique) from NN (Neural Networks) wherein it has layer based for results classification. Various levels involved in the proposed mechanisms are: 1. Data collection, 2. Pre-processing, 3. Average filtering, 4. segmentation, 5. feature extraction, 6. CNN via classification and identification. By utilizing the DM (data mining) techniques, significant relations and patterns from the data can be extracted. The techniques of ML (machine learning) and Data mining are being effectively employed for brain tumor detection and prevention at an early stage.

The segmentation is founded on the CNN by determining small  $3 \times 3$  kernels (To contradict over-fitting). It also employs intensity normalization as a pre-processing process which being unusual in CNN based segmentation methods. It may reduce the memory space required but it may cause serious accuracy issues.

## **SYSTEM ANALYSIS:**

### **EXISTING SYSTEM:**

The brain tumor detection and classification can be done using three methods. They can be manual, semi-automatic and automatic. Manual segmentation is more accurate than their counterparts but it is time-consuming. And the classification can be done provided the expert has the knowledge about it.

Semi-automatic segmentation is the process where the advantage of manual and automatic segmentation is synergized. The automatic segmentation is the trending of all now. Numerous methodologies are in survival for such automatic brain tumour detection and classification applications. They provide fair results. But not all of the tumorous portion is brought within the window with respect to segmentation methods. And with respect to classification systems, the output lacks the accuracy and provides a platform to implement possible improvements to some extent.

## **PROPOSED SYSTEM:**

The automatic brain tumour classification is provided by three Deep Neural Networks – ResNet50, VGG16 and VGG19. And a performance analysis is done. Experimental results show that the VGG19 architecture achieves a rate of 93% accuracy with low complexity compared with the all-other state of arts method.

## **ADVANTAGES:**

- Data-augmentation is performed to improve the accuracy for smaller dataset
- Batch Normalization is done which reduces the memory requirements
- Drop-out is performed where nodes are temporarily 'dropped' in the convolutional neural network. It helps to reduce the training time required for epoch.
- Ensures to avoid over-fitting which is the common problem in this neural network-based classification.

## CHAPTER 3

### DEVELOPMENT ENVIRONMENT:

#### Software Requirements:

**Tools:** Anaconda (Jupyter Notebook)

**Packages:** Tensorflow, Keras

**Algorithms:** CNN (Convolutional Neural Network), ResNet 50, VGG-16, VGG-19

**Library:** OpenCV, MATPLOTT

**OS:** Windows

**Language:** Python

Python 3.7 version has been used for this project. Python is a statistical mathematical programming language like R.

Python is selected over MATLAB due to the following reasons:

- 1) Python code is more compact and readable than MATLAB
- 2) The python data structure is superior to MATLAB
- 3) It is an open source and also provides more graphic packages and data sets  
Keras (with TensorFlow backend 2.3.0 version)

- Keras is a neural network API consisting of TensorFlow, CNTk, Theano etc. Python packages like Numpy, Matplotlib, Pandas for mathematical computation and plotting graphs, SimpleITK for reading the images which were in .mha format and Mahotas for feature extraction of GLCM Kaggle can be used to obtain the online dataset. GitHub and Stackoverflow were used for reference in case of programming syntax errors. OpenCV (Open Source Computer Vision) is a library of programming functions aimed at real time computer vision i.e. used for image processing and any operations relating to image like reading and writing images, modifying image quality, removing noise by using Gaussian

Blur, performing binary thresholding on images, converting the original image consisting of pixel values into an array, changing the image from RGB to grayscale etc.

It is free to use, simple to learn and supports C++, Java, C, Python. Its popular application lies in CamScanner or Instagram, GitHub or a web-based control repository.

Google Colaboratory (open-source Jupyter Notebook interface with high GPU facility) - Google Colab /Colaboratory is a free Jupyter notebook environment that requires no setup and runs entirely on cloud. With Colab, the codes can be executed, the analysis can be done. It also provides a way to access powerful computing resources, all for free from browser.

Jupyter Notebook is a powerful way to iterate and write on your Python code for data analysis. Rather than writing and rewriting an entire code, one can write lines of code and run them at a time. It is built off of iPython which is an interactive way of running Python code. It allows Jupyter notebook to support multiple languages as well as storing the code and writing own markdown.

### **Hardware Requirements:**

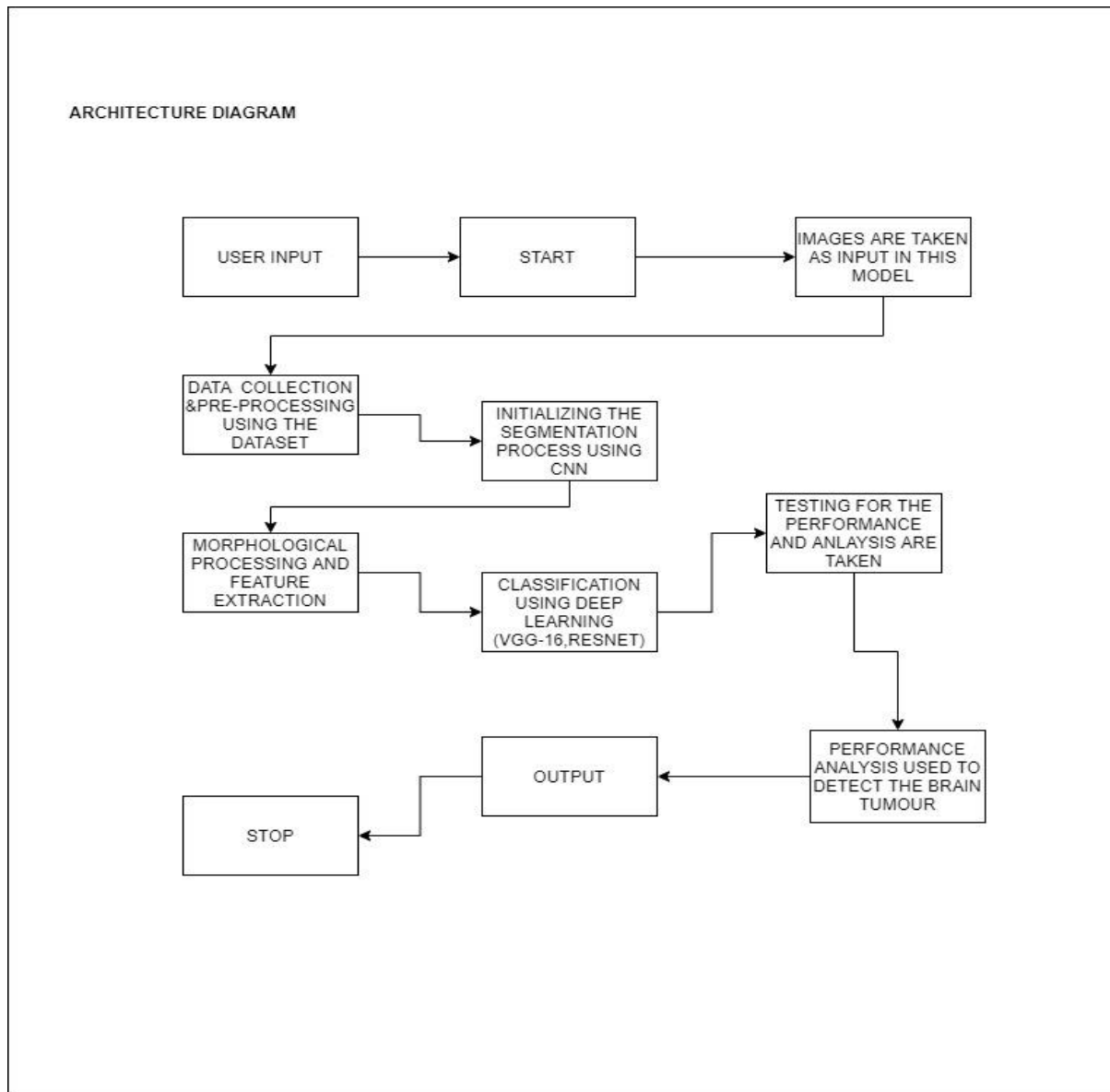
**PROCESSOR:** Intel Core i5 or above

**RAM:** 4 GB DD RAM

## ARCHITECTURAL DETAILS:

### ARCHITECTURE DIAGRAM:

**Data architecture** provides the standard models that govern how data is collected, stored, sorted, grouped, and put to practical use in the application systems.



**Figure. 3.2.1.1 Architecture Diagram**

Here the datasets are activated using the MRI images which are taken as input in this process when the data from datasets are implemented then the processing

using the data collected from dataset is starts to processing the next step called segmentation. Segmentation is used to verify the images by providing it into several images and collects the details then it is processed into morphological processing then the features are extracted from those morphological and segmentation process. Then the extracted feature is used to classify through performance analysis. The analysis from the performance analysis is used to show the accuracy and helps to predict the brain tumour.

## **MODELS - Explained:**

### **Image Acquisition:**

#### **Kaggle dataset:**

Images can be in the form of .csv (comma separated values), .dat (data) files in grayscale, RGB, or HSV or simply in .zip file as was in the case of our online Kaggle dataset. It contains 2 folders. One with 98 healthy MRI images and 155 tumor infected MRI images.

#### **Data Augmentation:**

Data augmentation consists of Grey Scaling, Reflection (flipping), Gaussian Blur, Histogram equalisation (contrast enhancement), Rotation (To some degrees), Translation (moving the image along an axis).

Data augmentation is done when only few training samples are available. It helps to increase the prediction accuracy.

#### **Image Pre-Processing:**

Our pre-processing includes rescaling, noise removal to enhance the image, applying morphological operations like erosion and dilation, contour forming (edge-based methodology). In the first step of pre-processing, the memory space of the image is reduced by scaling the gray-level of the pixels in the range 0-255. We used Median filter and also have given a performance analysis with PSNR value as to prove why median filter is chosen instead of Gaussian or mean filters.

#### **Segmentation and Feature Extraction:**

Brain tumor segmentation involves the process of separating the tumor tissues (Region of Interest – ROI) from normal brain tissues and solid brain tumor with the help of MRI images or other imaging modalities. Its mechanism is based on identifying similar type of subjects inside an image and forms a group of such by either finding

the similarity measure between the objects and group the objects having most similarity or finding the dissimilarity measure among the objects and separate the most dissimilar objects in the space.

Segmentation algorithms can be of two type which are bi-clusters (2 sub-parts) or multi-clustered (more than 2 sub-parts) algorithms.

Segmentation can be done by using

- a) Edge Detection
- b) Region Growing
- c) Watershed
- d) Clustering via FCM
- e) Spatial Clustering
- f) Split and Merge Segmentation and
- g) Neural Network.

The problems associated with primitive approaches are that it results in loss of texture and the threshold value comes out to be different for different images. Hence, we are looking for a more advanced segmentation algorithm, like CNN itself.

UNet is the subset of the traditional convolutional neural network. It was mainly used to process bio-medical images. Mostly all the convolutional neural network focuses only on image classification. But in cases of biomedical applications, it requires us not only to identify if there is a disease, but also to localise the area of abnormality. UNet is dedicated to solving this problem more efficiently.

## **Classification**

Deep Neural Networks are used for the classification purpose. VGG 16, VGG 19 and ResNet 50 are used. Each architecture and weights are taken as a base model. Eliminate the last fully connected layer i.e., Output layer, uses the pretrained model. It is used as a fixed feature extractor. From the output that we get, the features are obtained. It can be used to train a new classifier. Actually, VGG16 architecture is an image classification model and also Pretrained on the ImageNet Dataset. If we want to train all the layers, we need to train the whole layer, it consumes high time. It will

affect the model performance. So only the last layer is trained in the proposed CNN. We don't have to train all the layer.

The accuracy can be increased with the help of loss function estimation. If the loss function shows peak or high values, then the accuracy is low and vice-versa.

### **Algorithm for Neural Network based Classification**

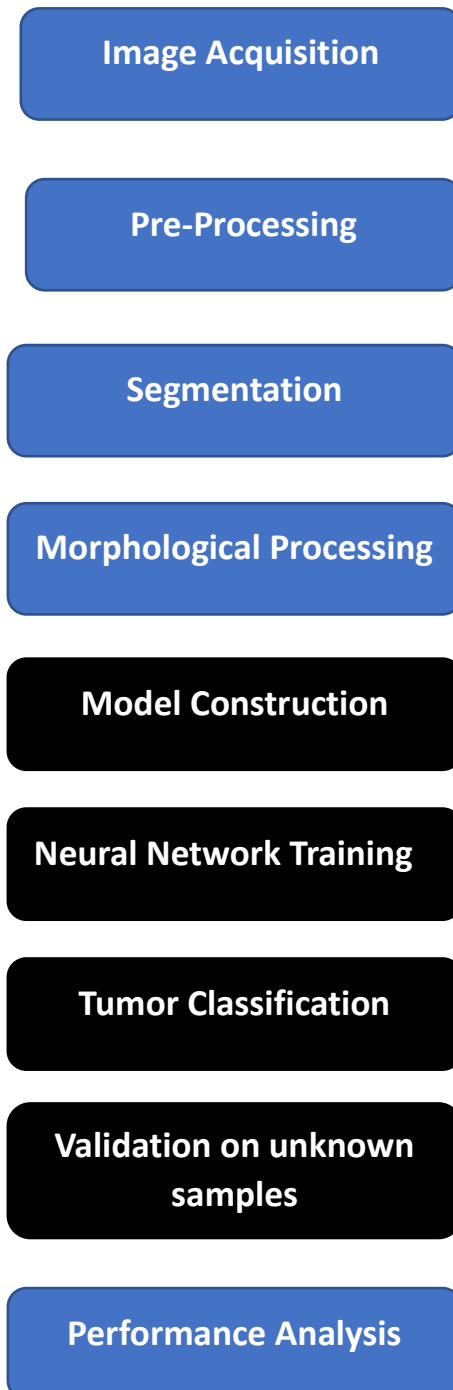
- Collecting Data
- Image pre-processing steps
- Import "ImageDataGenerator" for Data Segmentation
- `Train_datagen.flow_from_directory()` by using this generate the data
- Apply Transfer Learning and download the weights of VGG16 model.
- Add dense layers with Sigmoid Activation function
- The model is compiled (Accuracy and loss metrics as parameters)
- Run the model by using `model.fit_generator()`
- Repeat the steps for the remaining models

### **Performance analysis:**

In this work, efficient automatic brain tumour detection is performed by using convolution neural network. Simulation is performed by using python language. The accuracy is calculated with the other existing methods. The training accuracy, validation accuracy and validation loss are calculated to find the efficiency of proposed brain tumour classification scheme.

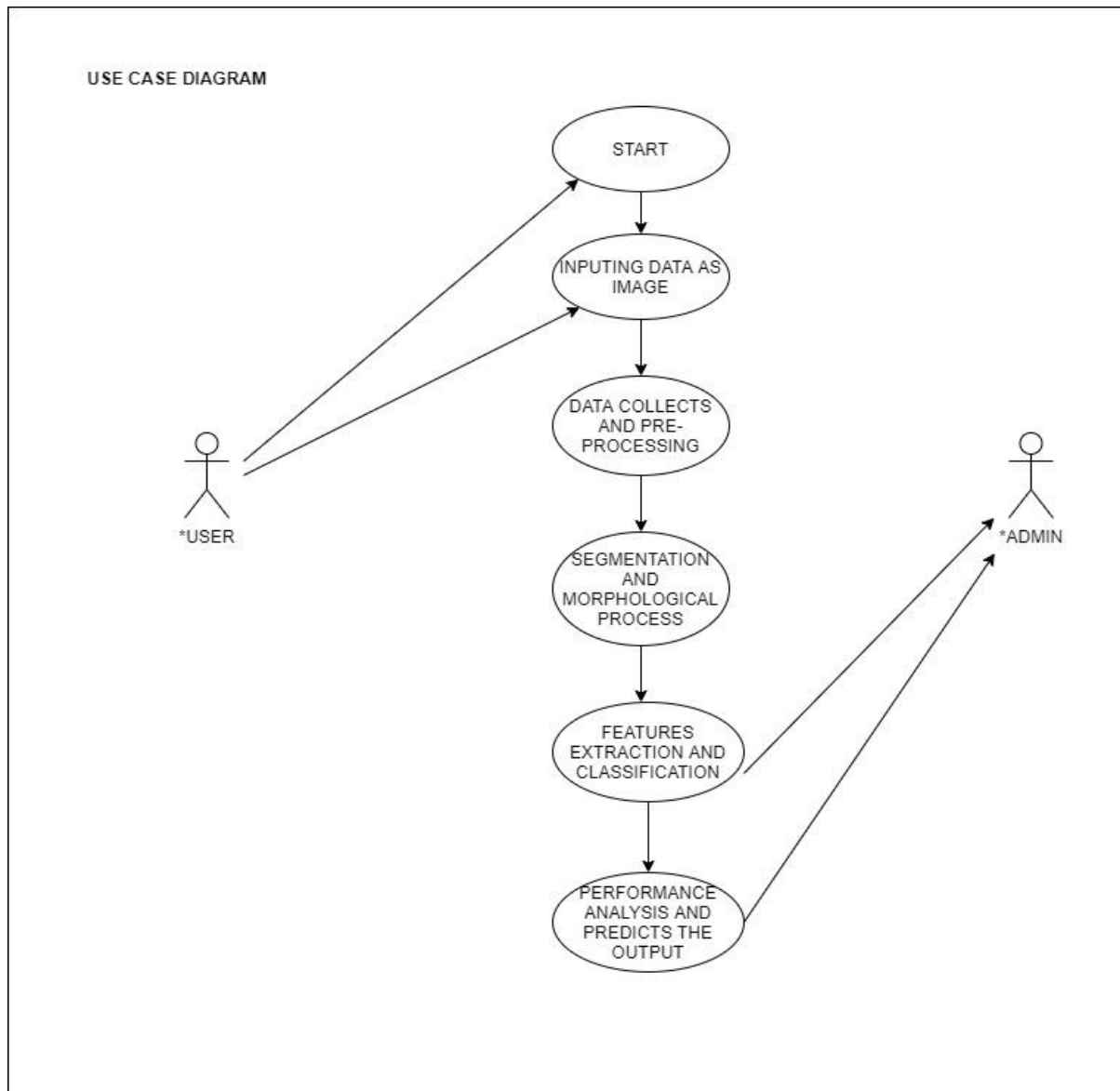
## SYSTEM DESIGN:

### FLOWCHART FOR DESIGN AND DEVELOPMENT OF PROPOSED PROJECT:



## USE CASE DIAGRAM:

A use case diagram defines how user interacts the system. It can be used to identify, modify, and organize the models according to system requirements.

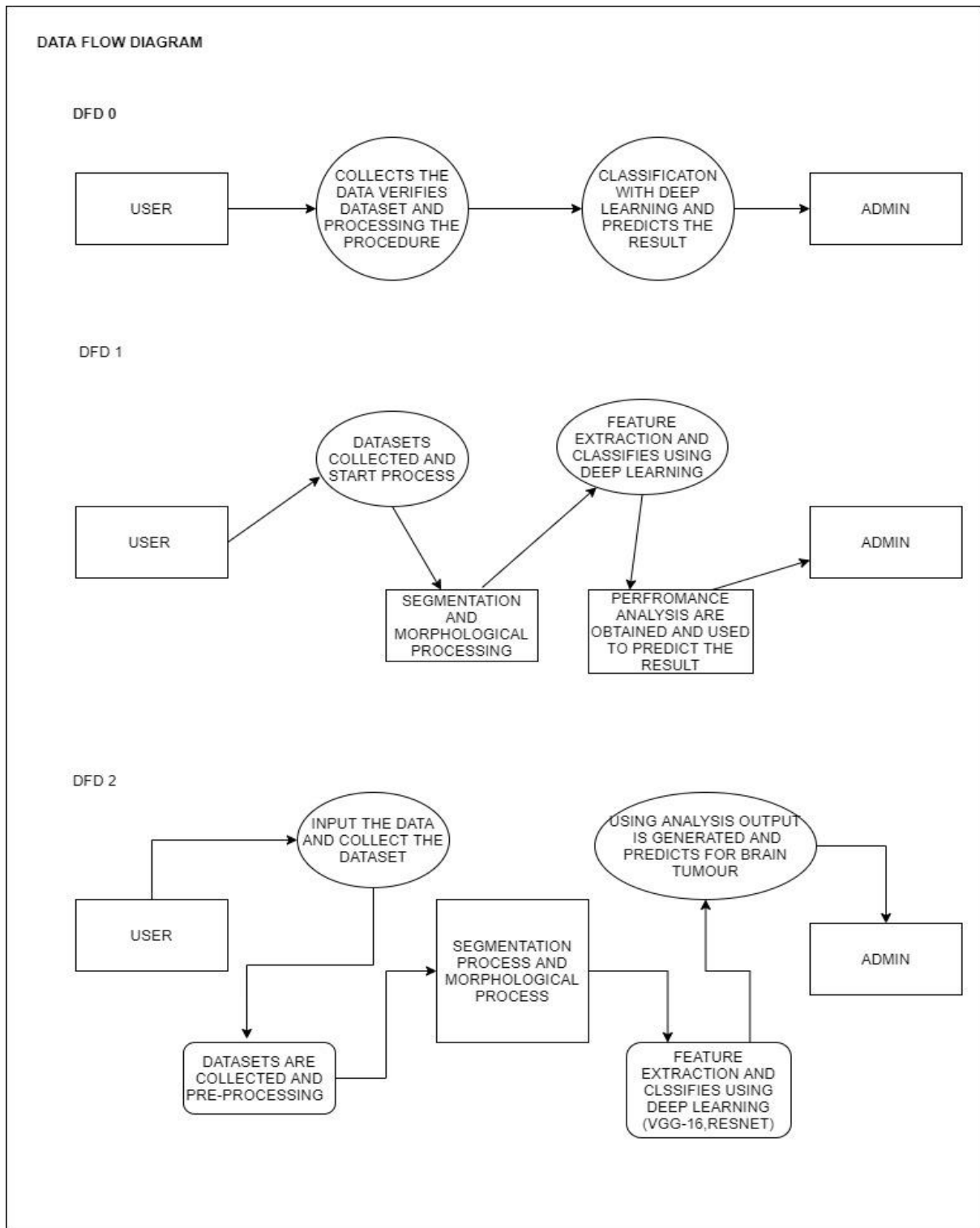


### 3.3.2.1 Use Case Diagram

**DF DIAGRAM:**

Data flow diagram gives the graphically represents the flow of data in the face mask detection system DFD describes the processes involved in a system to transfer data from the input to the file storage and generates reports.

DFD 0, DFD 1, DFD 2 are the data flow diagram that represents the flow of data process and generates the report.



**3.3.3.1 Data Flow Diagram**

## CHAPTER 4

### SIMULATION RESULTS:

#### Module I – Pre-Processing Stage Cropped Image

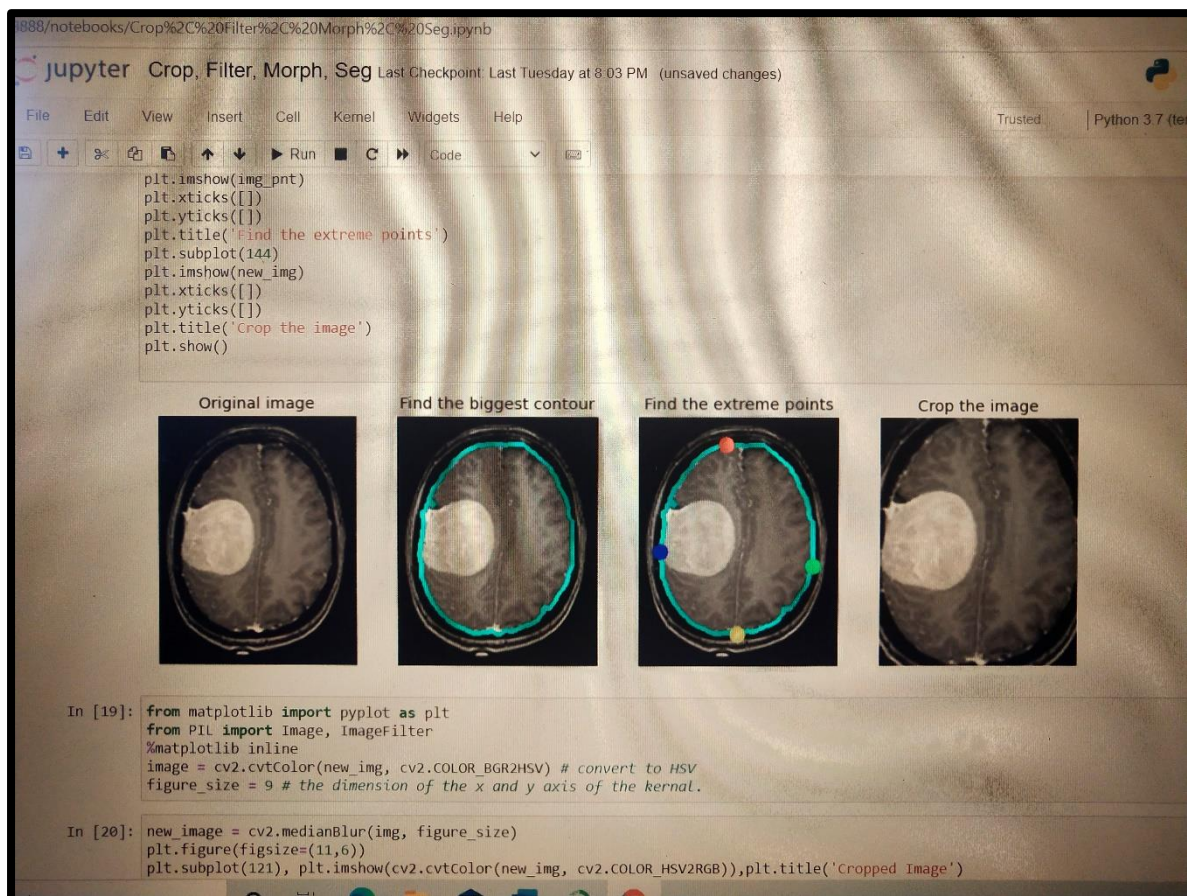


Figure 4.1.1 Cropped Image

## Module I – Pre-processing Stage

### Median Filtered Image

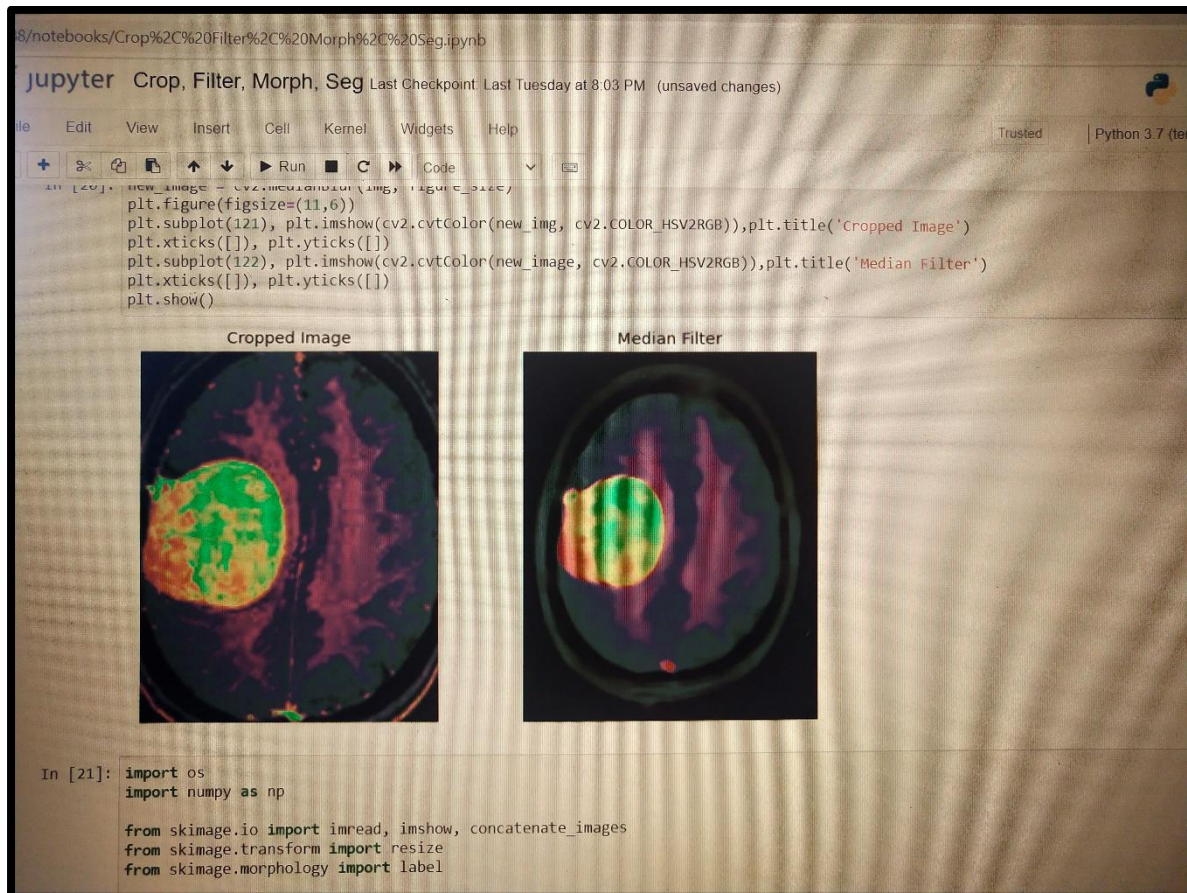


Figure 4.1.2 Median filtered Image

## Module II – Segmentation Stage

### U-Net Segmented Image

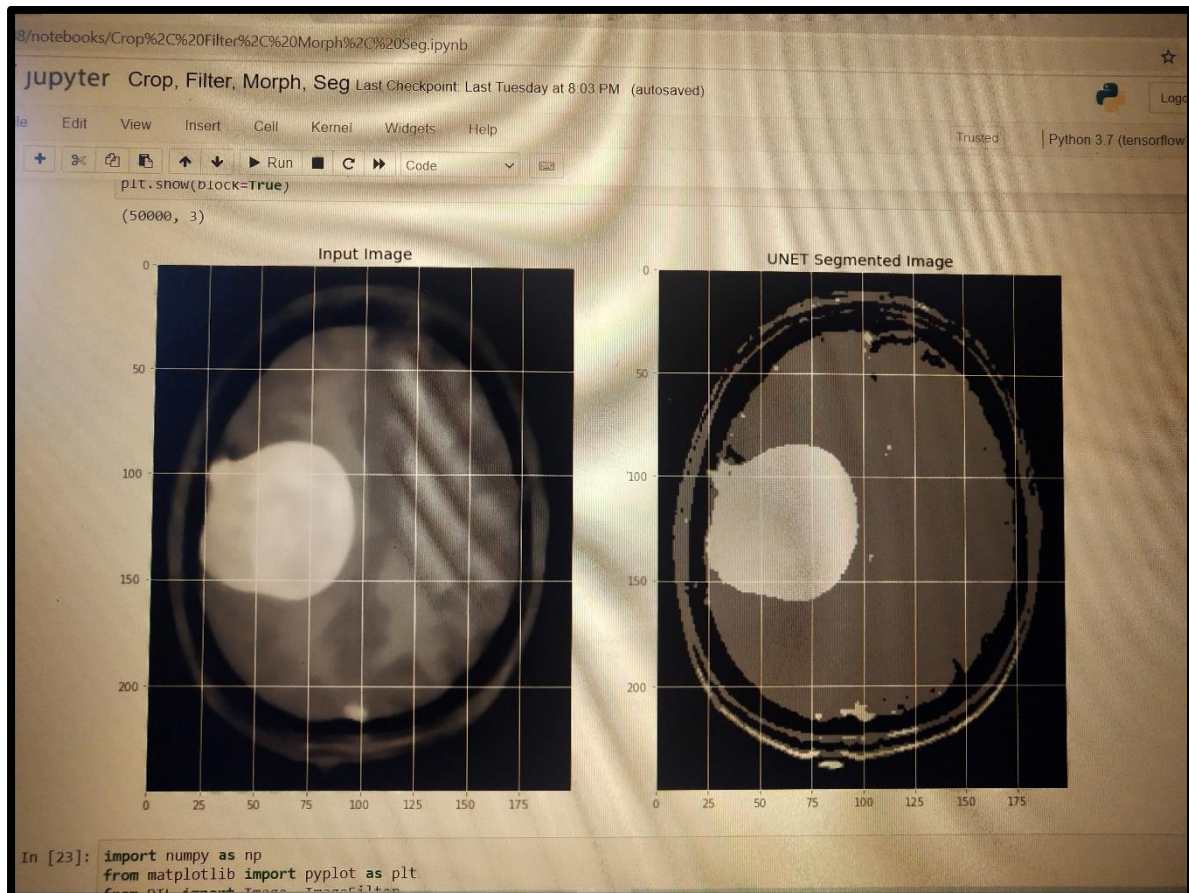


Figure 4.1.3 U-Net Segmented Image

## Module III – Morphological Processing Stage

### Opening and Closing Images

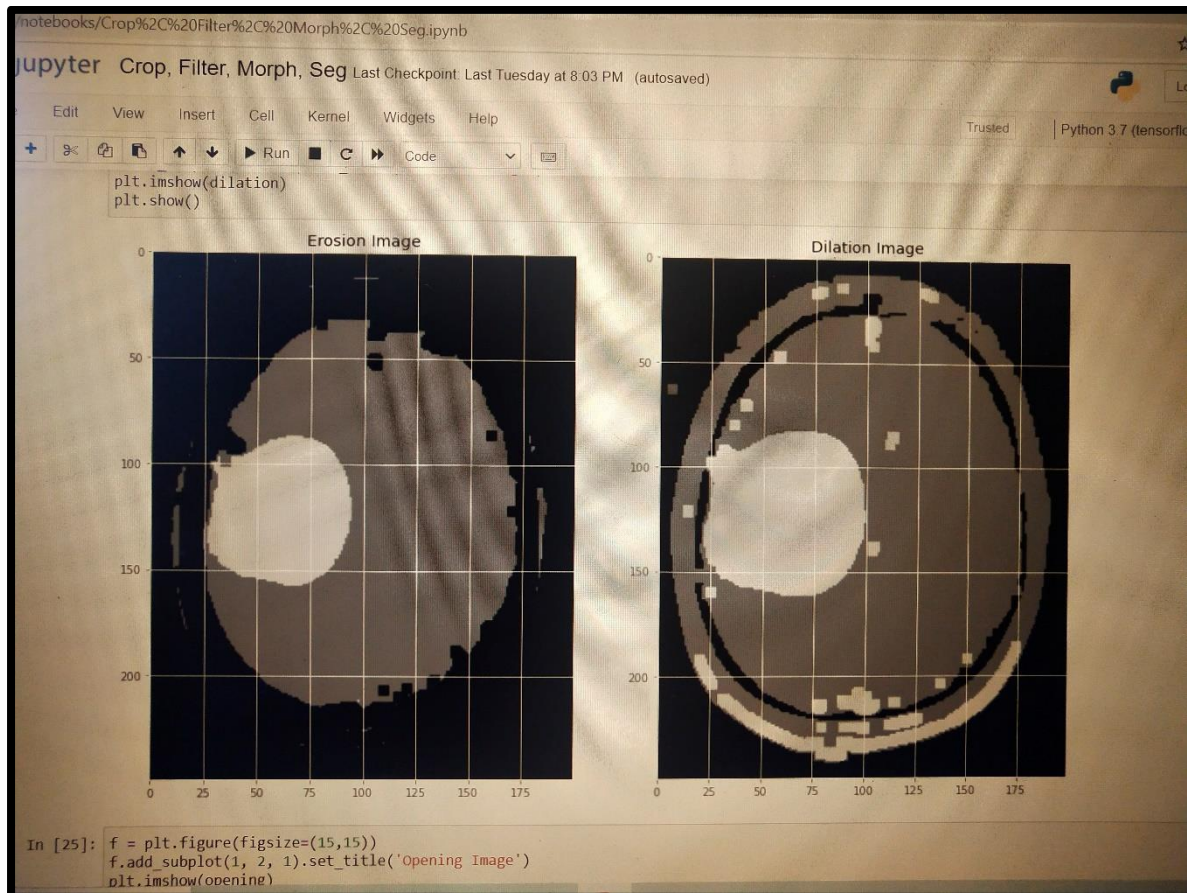


Figure 4.1.4 Opening and Closing

## Module III – Morphological Processing Stage

### Erosion and Dilation Images

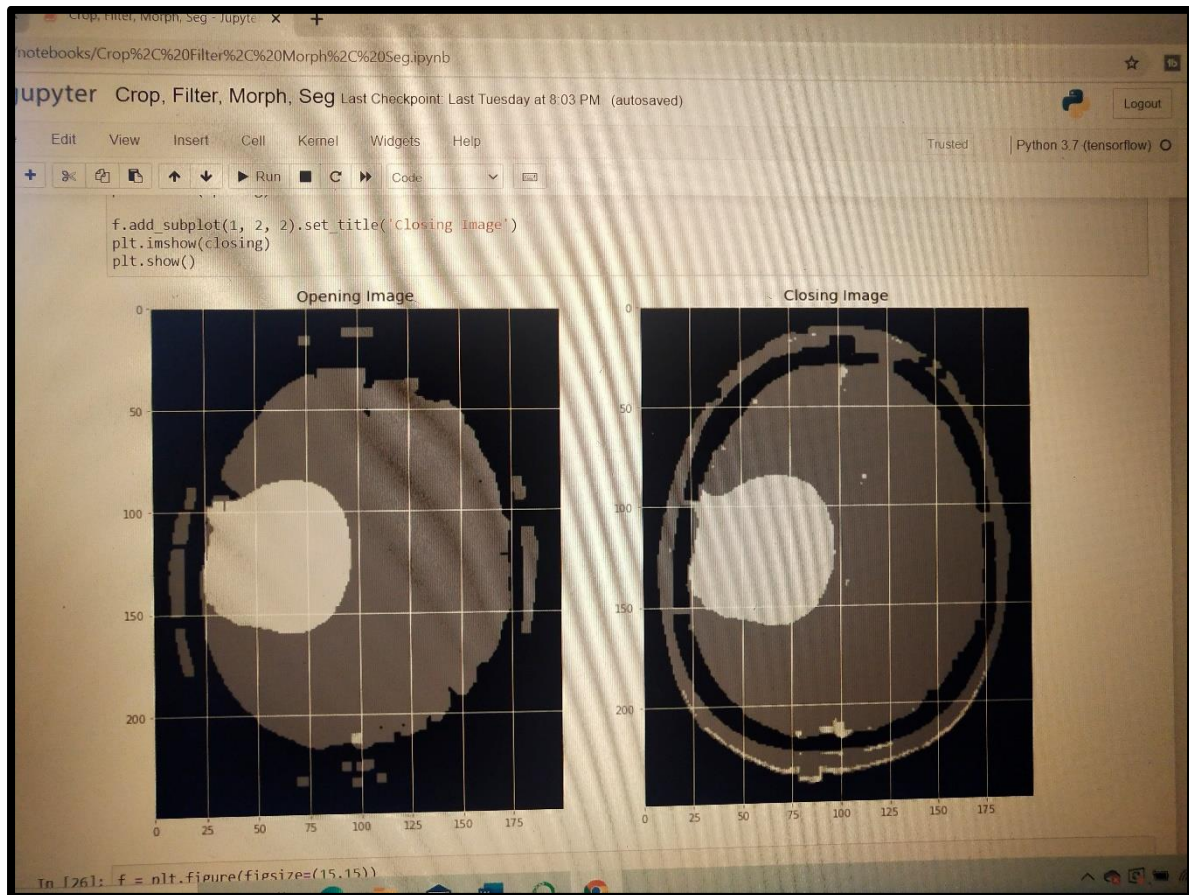


Figure 4.1.5 Opening and Closing

## Module III – Morphological Processing Stage

### Gradient Images

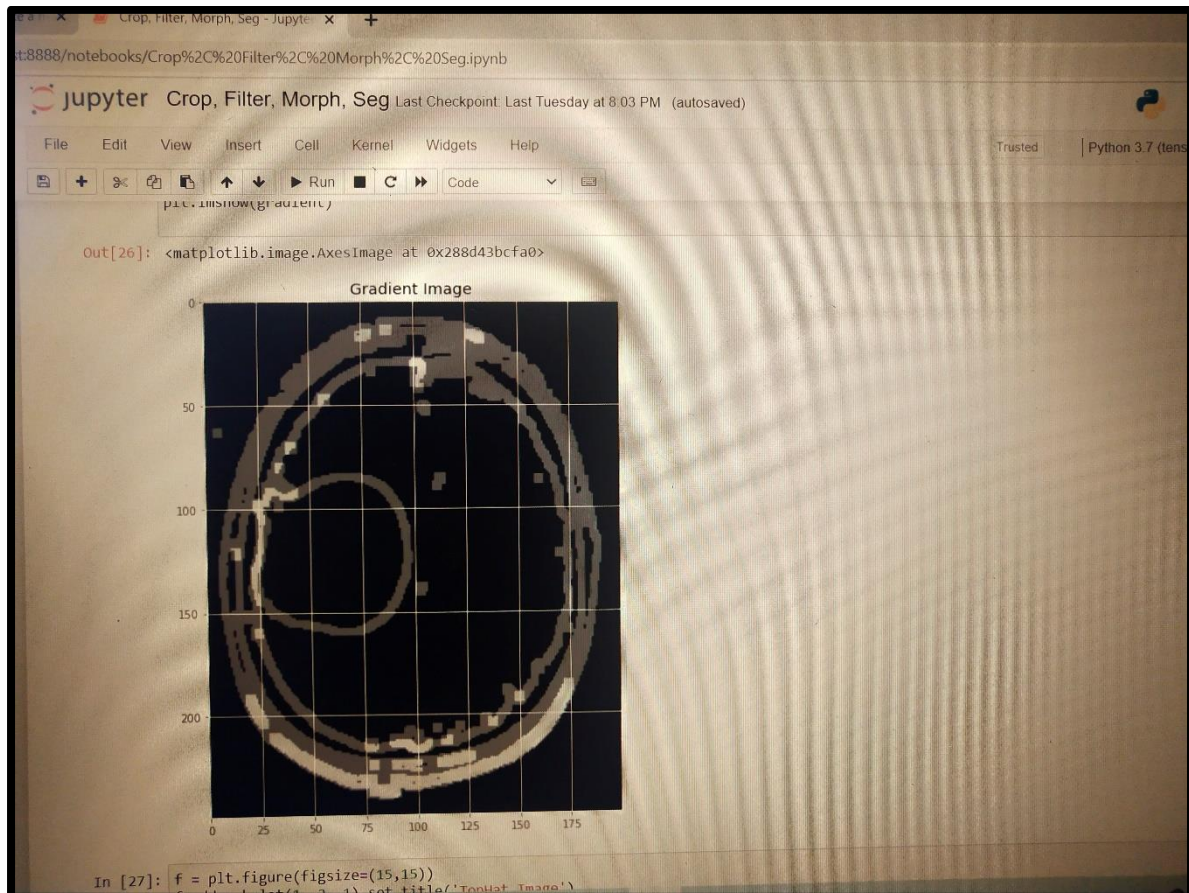


Figure 4.1.6 Gradient

## Module III – Morphological Processing Stage

### Top Hat and Black Hat Images

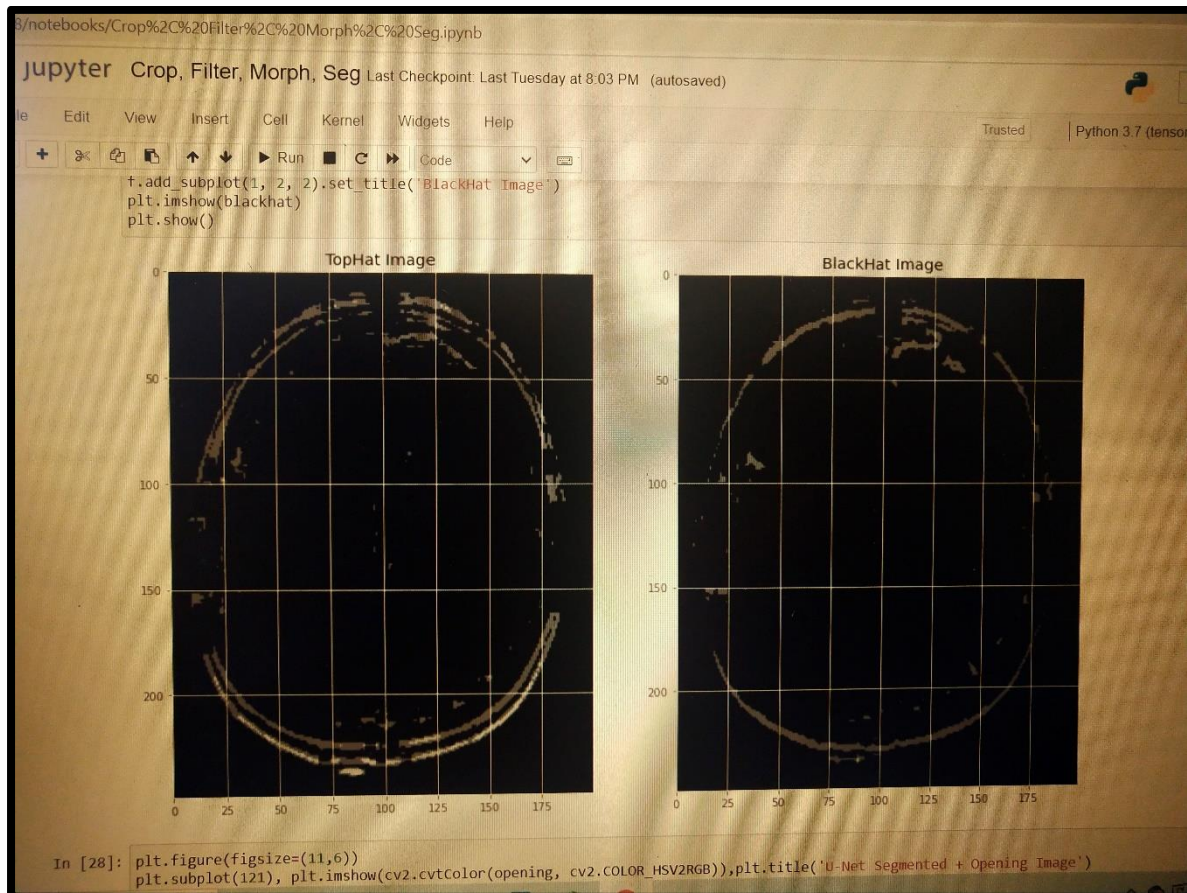


Figure 4.1.7 Top Hat and Black Hat

## Module IV– Classification Stage

### VGG 16

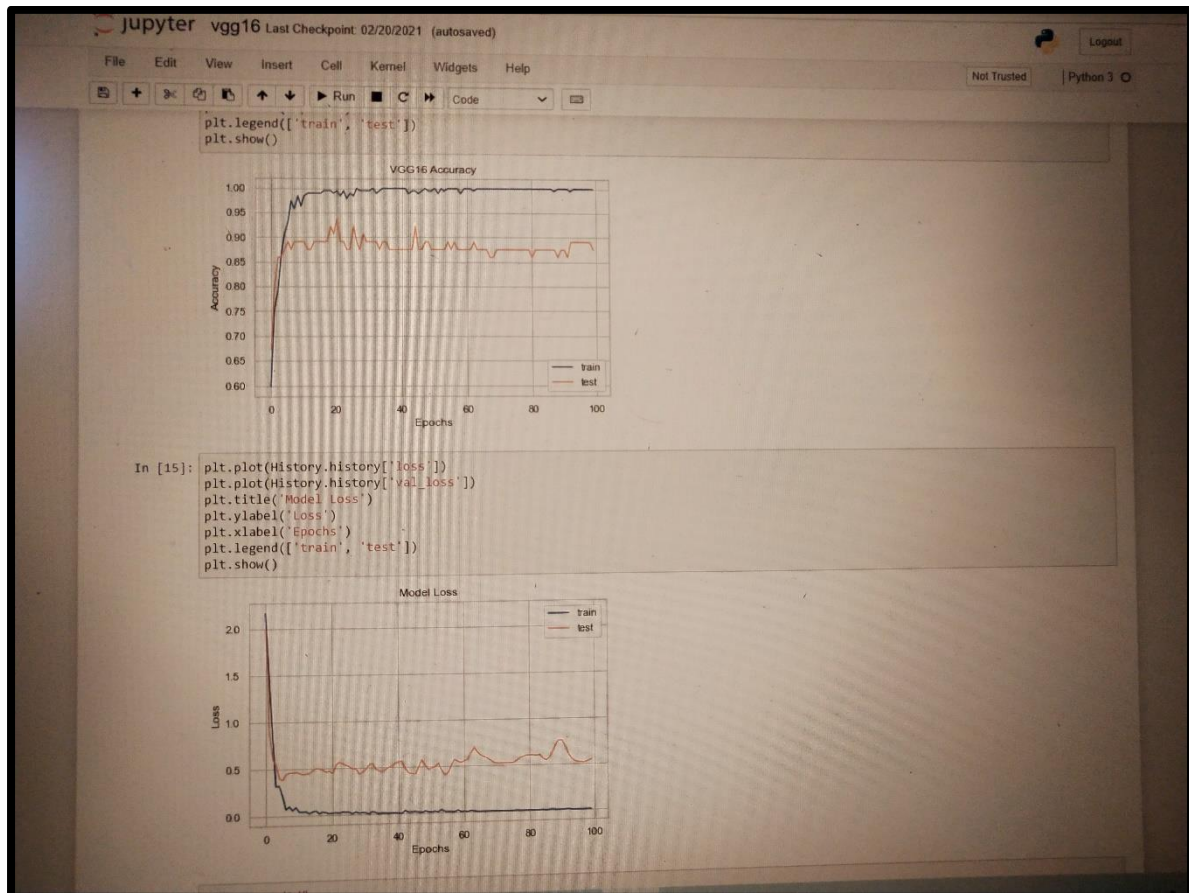


Figure 4.1.8 VGG 16 Model – Accuracy and Loss

## Module IV– Classification Stage

### VGG 19

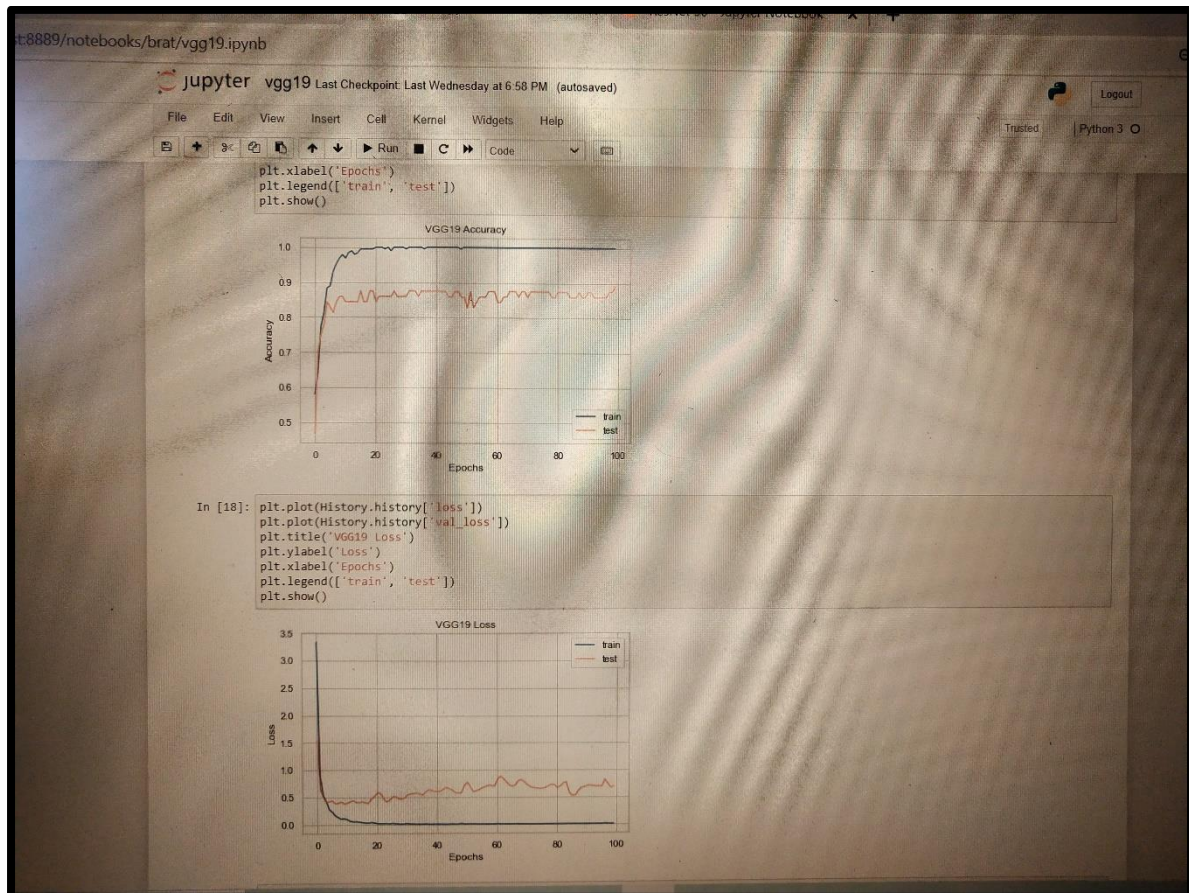


Figure 4.1.9 VGG 19 Model – Accuracy and Loss

## Module IV– Classification Stage

### ResNet 50

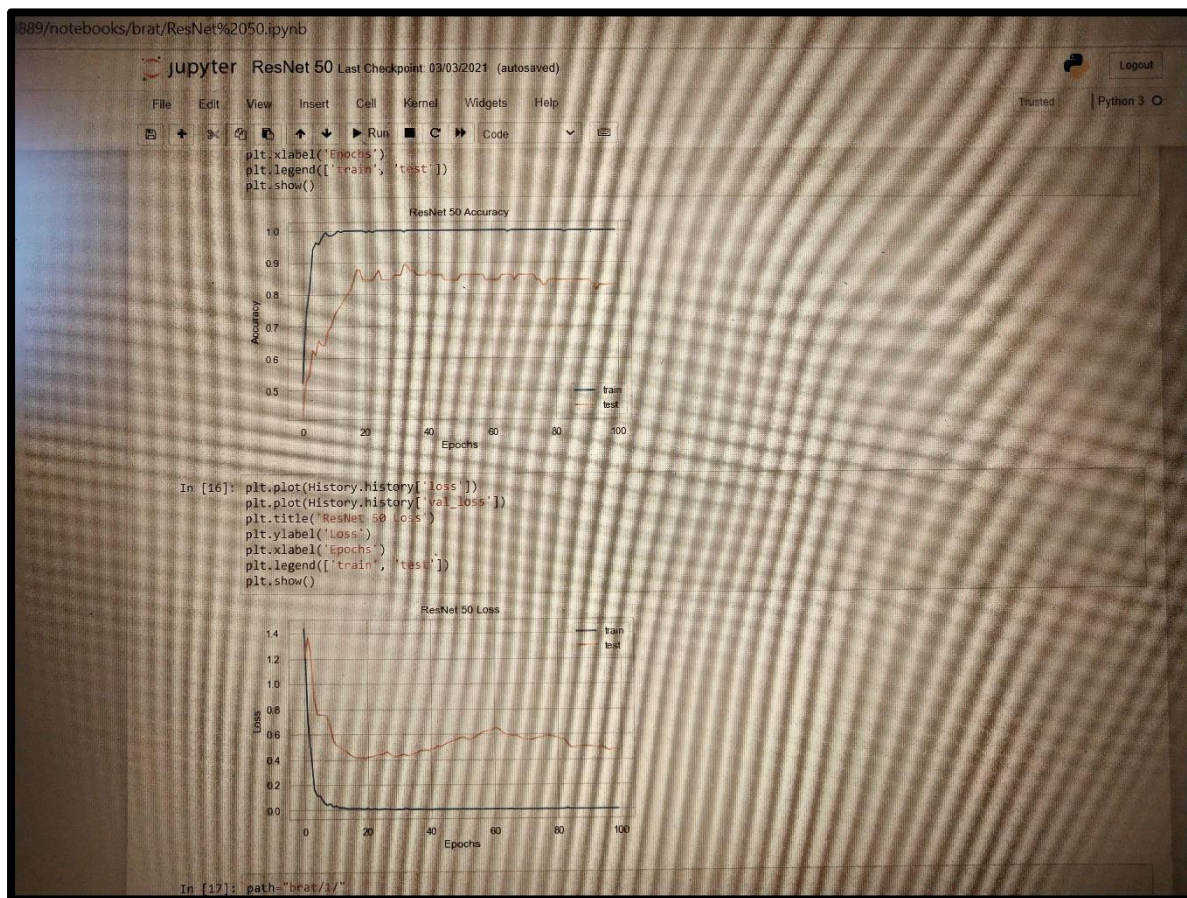


Figure 4.1.10 ResNet 50 Model – Accuracy and Loss

## Module IV– Classification Stage

### Tumor Classification using VGG 19

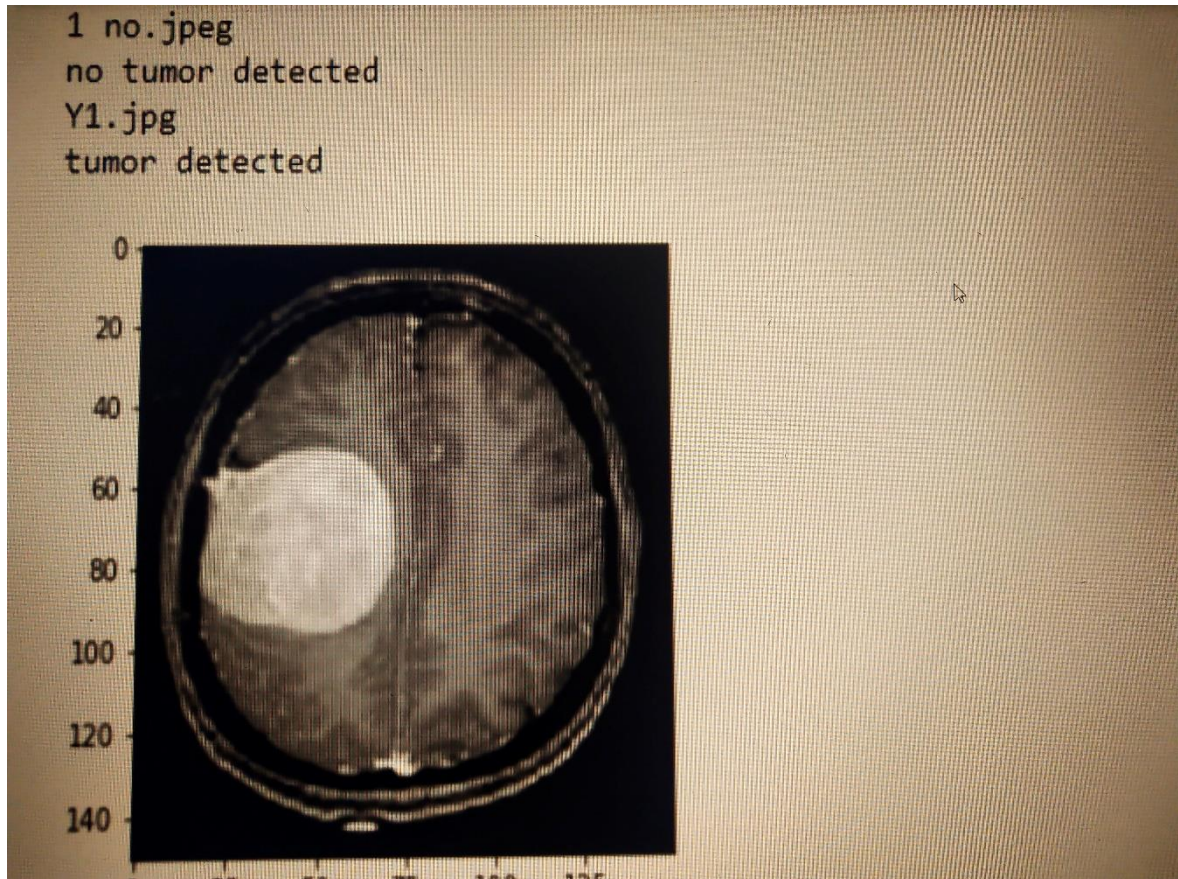


Figure 4.1.11 Tumour Classification Using VGG 19

## Module V– GUI for predicting Psychological effects

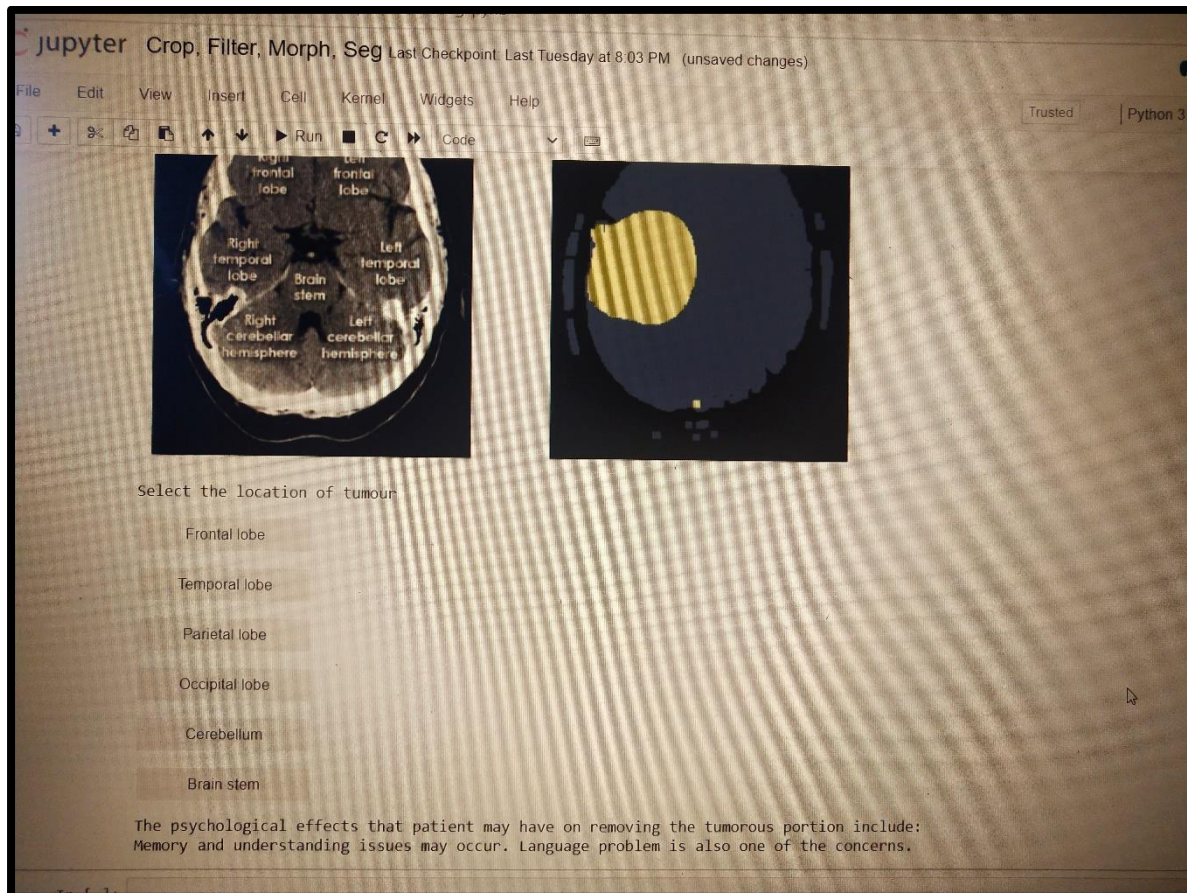


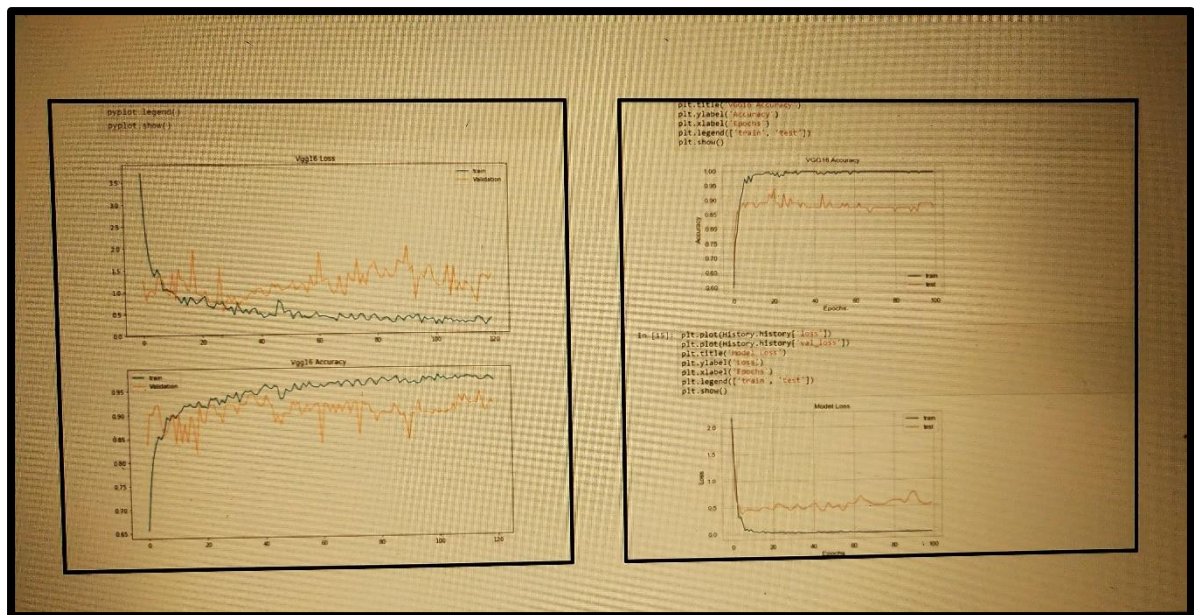
Figure 4.1.12 GUI for predicting the psychological effects

## PERFORMANCE ANALYSIS:

### Existing Vs Proposed

| Existing Architecture | Proposed Architecture |
|-----------------------|-----------------------|
| VGG (Original)        | VGG (Original)        |
| Dropout               | Dropout               |
| Flatten               | Dense                 |
| Dropout               | Dense                 |
| Dense                 | Dense                 |
|                       | Dense                 |

**Table 4.2.1. Existing versus Proposed Architecture Comparison**



**Figure 4.2.1. Existing versus Proposed Architecture – Graphical Comparison**

|                 | Existing Architecture | Proposed Architecture |
|-----------------|-----------------------|-----------------------|
| <b>Accuracy</b> | <b>87%</b>            | <b>90%</b>            |
| <b>Loss</b>     | <b>2</b>              | <b>0.4</b>            |

**Table 4.2.2. Existing versus Proposed Architecture – Accuracy and Loss**

## A) FILTERS

| <b>FILTER</b>          | <b>PSNR</b> |
|------------------------|-------------|
| <b>Mean Filter</b>     | 24.3609     |
| <b>Median Filter</b>   | 29.9656     |
| <b>Gaussian Filter</b> | 28.4740     |

**Table 4.2.3. Filters – PSNR Comparison**

The PSNR is the peak signal-to-noise ratio between two images. The value is given in decibels. This ratio can be used as a quality measurement between the original and a compressed image. The higher the PSNR, superior is the quality of the compressed, or reconstructed image.

**Median filter** is proved to work better for the required application than the Mean and Gaussian filter.

## B) SEGMENTATION:

Neural Network based U-Net is quite appealing and more accurate than the conventional methods.

### C) MORPHOLOGICAL PROCESSING:

The choice of morphological processing is purely based on the qualitative analysis over which works fair to our general visible observance. Based on the output, it is concluded that **Opening** is more suitable for this work.

### D) CLASSIFICATION MODEL ACCURACY

| MODEL     | ACCURACY |
|-----------|----------|
| VGG 16    | 88%      |
| VGG 19    | 93%      |
| RESNET 50 | 86%      |

**Table 4.2.4 Classification Model Accuracy Comparison**

### E) CLASSIFICATION MODEL LOSS

| MODEL     | LOSS                |
|-----------|---------------------|
| VGG 16    | 0.5 Variation Error |
| VGG 19    | 0.4 Variation Error |
| RESNET 50 | 0.6 Variation Error |

**Table 4.2.5. Classification Model Loss Comparison**

Loss function can be used to give the estimation between the obtained values and the values predicted by the model. Greater the loss is, huger is the errors you made on the data.

Accuracy can be seen as the **number** of errors you made on the data.

That means:

- low accuracy and more loss mean huge errors
- low accuracy but low loss means less errors
- More accuracy with low loss means apparently less errors (best case)

In my case, **VGG 19** is proved to work with more accuracy and less loss. Hence, VGG 19 has been used for classification purposes.

## CHAPTER 5

### CONCLUSION:

The reduction of noises and quality enhancement of images were performed using spatial filters and histogram equalization respectively. The median filter was chosen for removing noises because it produces comparatively better PSNR than the Gaussian and Mean filters. The median filter was also able to retain the boundary and sharp edges. The separation of tumour has been successfully done by the novel U-Net based segmentation rather than the conventional methods. Since U-Net is based on the neural network, the system is more robust. The classification is performed using three different neural networks namely VGG 16, VGG 19 and ResNet 50. The performance analysis was done. The VGG 19 proves to be dominating with an accuracy of 93%. Besides the image has been normalized at the pre-processing stage and also batch normalization is done for the neural networks is done. Hence the storage requirement is significantly reduced. By the inclusion of drop-out, the over-fitting is also minimized.

## REFERENCES:

- [1] Bhagyashri H. Asodekar, Sonal A. Gore and A. D. Thakare , “Brain Tumor analysis Based on Shape Features of MRI using Machine Learning”, IEEE, 2018
- [2] Saurabh U. Saoji, M. V. Sarode, “Speckle and Rician Noise Removal from Medical Images and Ultrasound Images”, International Journal of Recent Technology and Engineering (IJRTE) ISSN: 2277-3878, Volume-8 Issue-5, January 2020
- [3] S. Deepak, P.M. Ameer, “Brain tumor classification using deep CNN features via transfer learning”, Elsevier, 2019.
- [4] Zahra Sobhaninia, Safiyeh Rezaei, Alireza Noroozi, Mehdi Ahmadi, Hamidreza Zarrabi, Nader Karimi, Ali Emami, Shadrokh Samavi, “Brain Tumor Segmentation Using Deep Learning by Type Specific Sorting of Images”, 2019.
- [5] R S Latha, G R Sreekanth, P Akash, B Dinesh, S Deepak kumar, “Brain tumor classification using SVM and KNN models for SMOTE based MRI images”, Journal of Critical Reviews, Vol 7, Issue 12, 2020
- [6] Jithendra Reddy Dandu, Arun Prasath Thiyagarajan, Pallikonda Rajasekaran Murugan & Vishnuvarthanan Govindaraj, “Brain and pancreatic tumor segmentation using SRM and BPNN classification”, Springer, 2019.
- [7] Lim Jia Qi, Norma Alias, Farhana Johar, “Detection of brain tumour in 2D MRI: implementation and critical review of clustering-based image segmentation methods”, Oncology and Radiotherapy – Research article, 2020.
- [8] G.Hemanth, M.Janardhan, and L.Sujihelen, “Design and implementing brain tumor detection using machine learning approach”, IEEE, 2019