

# CEREBRO: BRAIN TUMOR DETECTION AND GRADING

Anakha P Kumar<sup>1</sup>, Christy Zachariah<sup>2</sup>, Govind Mohandas<sup>3</sup>, Er. Ashwin P V<sup>4</sup>

<sup>1-3</sup>UG Scholar, Department of ECE, SAINTGITS College of Engineering, Kerala, India

<sup>4</sup>Assistant Professor, Department of ECE, SAINTGITS College of Engineering, Kerala, India

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**Abstract** - Glioblastoma Multiforme is a high grade, very aggressive brain tumor. But Gliomas is a low grade, which are less aggressive, but they can evolve into higher grade tumors over time. Tumor grading is important for sufficient treatment planning and monitoring. As we know the "perfect" method to grade a tumor is by the histopathological diagnosis of biopsy specimens. But, this procedure is invasive, time consuming, and prone to sampling error (rare) but for many cases surgery is not possible. Because of these disadvantages, automatic tumor grading from widely used MRI protocols would be clinically important, for the treatment planning and assessment of tumor. In this project, we propose to use transfer learning to predict tumor type and grade by Magnetic Resonance Spectroscopy. In this way, we will overcome the need for expert annotations for marking the important regions of interest and tumor those images that required a radiologist to classify and analyse will only require the nurse.

**Key Words:** Brain Tumor, MRI Image, Raspberry Pi, Touch Screen Display, Cluster

## 1. INTRODUCTION

Well as we know a tumor is an abnormal growth of tissue when the presence of this tissue is in the brain, it's called a brain tumor. A tumor can be life-threatening depending on its location, size and state of development. Brain tumors can be divided into high and low grade or suitable called malignant or benign respectively. Benign brain tumors usually grow slowly, have fixed volume and they rarely spread. Malignant brain tumors (cancerous) usually grow rapidly, are invasive, aggressive and can often be life-threatening. But benign brain tumor growth can cause depletion to blood supply to different regions of the brain hence compressing the neurons. Due to the limited space in the brain this compression can cause death of brain cells or clots. Astrocytoma is the most common type of glioma and begins in astrocytes of the cerebrum or cerebellum. Apart from glioma we have 3 main types of brain tumor namely glioma, pituitary brain tumor and meningioma brain tumor. Detecting the type of tumor can give a better understanding of the approach of treatment, the risks of the surgery and the efficiency of treatment. The amount of NAA CHO Cr levels in Spectroscopy can give is a fair idea on the grade of the tumor the ratio is

calculated and compared to the predetermined threshold depending on which its grade is classified.

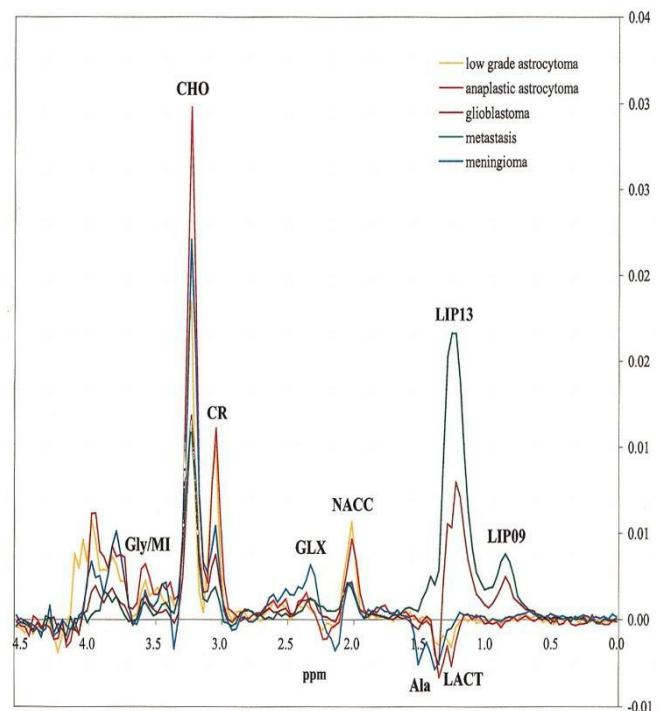


Chart -1: Mean spectra of five tumor types

## 2. OBJECTIVES

- ☑ Detect the tumor presence and reduce the risks that can happen during a biopsy and provide easier first examination of the presence to tumor.
- ☑ To Compute the result of the MRI and MR Spectroscopy almost instantly, depicting the position of tumor along with its name and grade.

## 3. HARDWARE DESCRIPTION

The hardware consists of Raspberry Pi and Touch Screen Display.

### 3.1 Raspberry Pi

As everyone is familiar with its a series of small single-board computers developed by Raspberry Pi Foundation in collaboration with Broadcom. It is widely used for weather monitoring, because of its low cost, modularity, and open design. It basically can do the entire work of a computer with ease.



Fig -1: Raspberry Pi Model 4

### 3.2 Touch Screen Display

A touchscreen or touch screen is the assembly of both an input ('touch panel') and output ('display') device. The touch panel is layered on the top of a visual display of an information processing system. This is an LCD display while the system is usually a laptop, tablet, or smartphone. A user input is given by touching the touchscreen with a special stylus or their fingers. Many of the touchscreens use the specially coated gloves to work while others may only work using a special stylus or pen. The user can use the touchscreen to interact with the GUI and it used it following the instructions which we provide in our interface.



Fig -2: Touch Screen Display

### 4. METHODOLOGY

- a) The user will be providing us with the MRI image data. The brain MRI scan result image is taken as the input. It can be a .jpg / .jpeg / .png image.
- b) After confirmation, this image is passed on to our neural network model.
- c) The result and accuracy of the classification is stored in the variables.

- d) There is an image segmentation process also running along side to segment the MRI image which we receive segregate region of interest of the MRI scan result.
- e) The output and the accuracy is shown along with a detailed description of the tumor type is provided.
- f) Grading option is also provided based on the data provided by the MR Spectroscopy result and we know if the tumor is high or low grade tumor.

### 5. WORKING

#### 5.1 Neural Network (Mobilenet V2)

This neural network uses the principles of transfer learning to achieve higher accuracy results. Transfer learning is used to provide a strong framework of weights. There is Mobilenet v2 weights usage for transfer learning and its layers. The loss and accuracy graph shown below along with accuracy per classes and confusion matrix with the help of Google framework to create a separate weighted model.

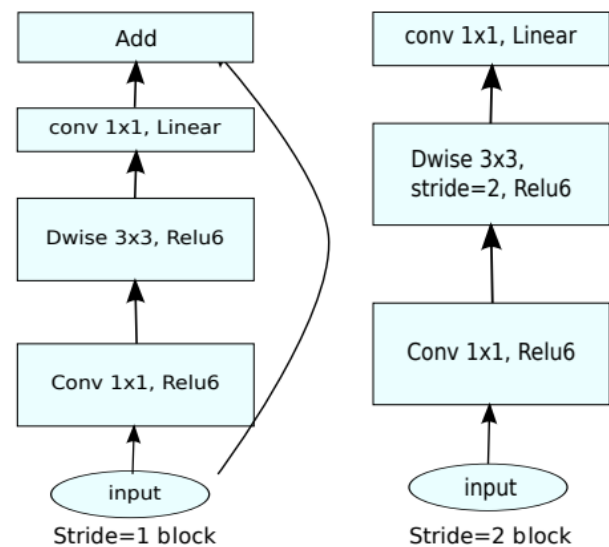


Fig -3: Architecture of Mobilenet v2

Epochs: 50  
 Batch size: 32  
 Loss per epoch: 0.201 or 20%  
 Accuracy per epoch: 0.97 or 97%

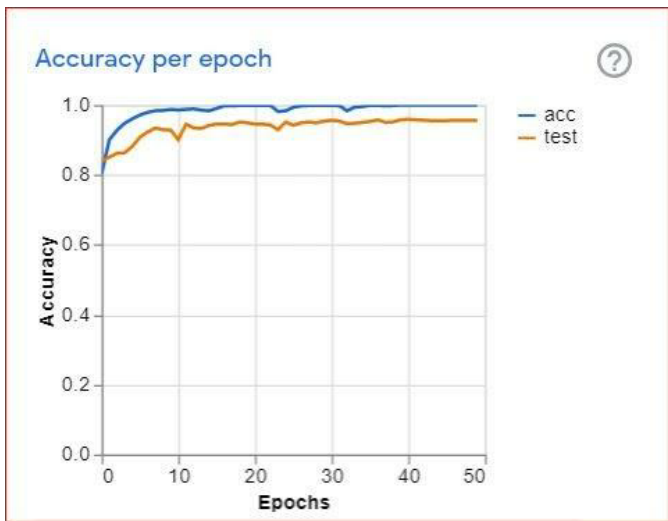


Fig -4: Accuracy per epoch

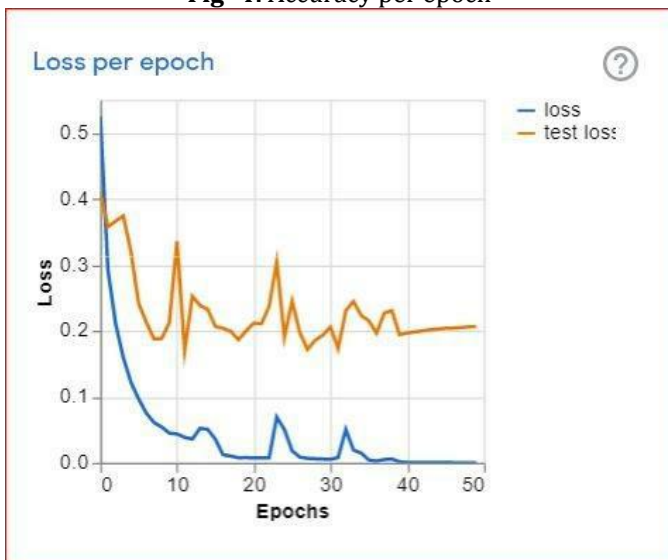


Fig -5: Loss per epoch

**Accuracy per class:**

No Tumor	97%
Glioma Tumor	87%
Pituitary Tumor	99%
Meningioma Tumor	96%

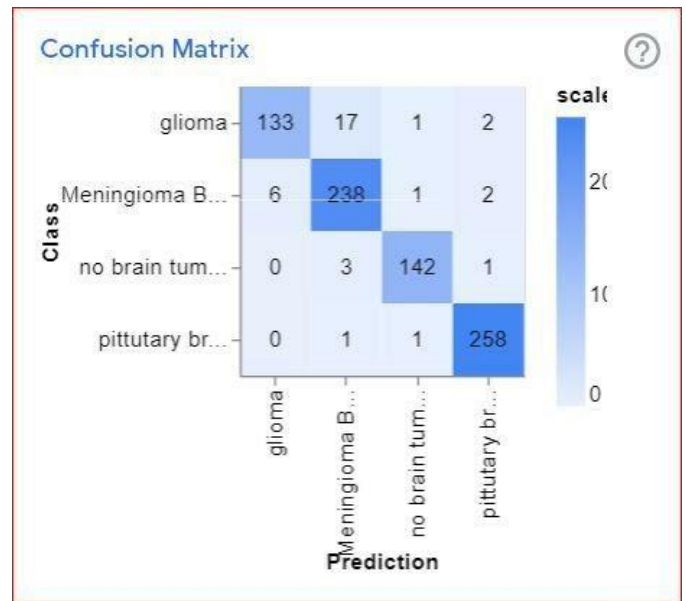


Fig -6: Confusion Matrix

**5.2 Tumor Isolation And Segmentation**

The segmentation is done with the help of Expectation Maximization (EM) model and the Gaussian Mixture Model (GMM) for parametric estimation and Kernel Density Estimation and K-Means Clustering for non-parametric estimation and compares the algorithms for performing image segmentation on a test image.

For a Gaussian mixture model (GMM) with K components, the GMM function is given by the equation:

$$N(\vec{x} | \vec{\mu}_i, \Sigma_i) = \frac{1}{\sqrt{(2\pi)^K |\Sigma_i|}} \exp\left(-\frac{1}{2} (\vec{x} - \vec{\mu}_i)^T \Sigma_i^{-1} (\vec{x} - \vec{\mu}_i)\right)$$

**5.2.1 EM for Gaussian Mixture Models**

Expectation maximization for mixture models consists of three step process:

- 1) To begin with we have the expectation step or E step, consists of calculating the expectation of the component assignments  $C_k$  for each data points.
- 2) Follow it we have as the maximization step or M step, which consists of maximizing the expectations calculated in the E step in relation to model parameters. Here we update the values  $\phi_k$ ,  $\mu_k$  and  $\sigma_k$ .
- 3) In conclusion we have a process repeats until the algorithm converges, giving a maximum likelihood estimate.

**5.2.2 K-Means Clustering**

In K-Means clustering the intension is to partition/ separate n objects into k clusters where each of the n object belongs to the cluster with the nearest mean or the centroid. This method can provide us with exactly k

different and variety clusters. The best number of clusters k leading to the greatest separation (distance) is not known as a priori and must be calculated from the provided data. The objective of K-Means clustering is to minimize total intra cluster variance, or, the squared error function.

- 1) We define a value k and divide the cluster into a group of k
- 2) We select as many as k random points as centers or centroid.
- 3) We use the Euclidean distance function to assign object to closest cluster centers.
- 4) We then have to calculate the mean of all the object within the cluster.
- 5) Repeat steps 2, 3 and 4 until the same points are assigned to each cluster in consecutive rounds
- 6) We have finalised the value of k as 3 based on our inferences to replicate the segments within the MRI scanned output of segmented image along with original MRI image.

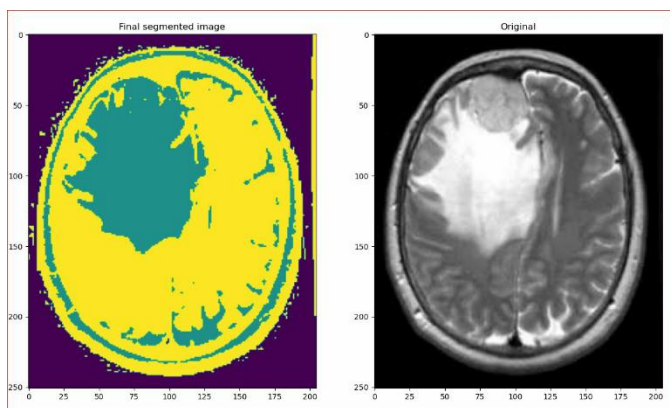


Fig -7: Segmented MRI Image

### 5.3 User Interface

The user interface is mainly done using Tkinter module in the same python frame work. We have created a Graphic User Interface (GUI) to input MRI image data from the user for correct analysing the input to confirm the input and a sophisticated way to display the result to the user such that the entire work is not displayed to the user but only the required part the output result is shown to the user. We have also kept the interface such that to add any other medical image analysing model directly rather than to rewrite the entire code from the beginning to the end.

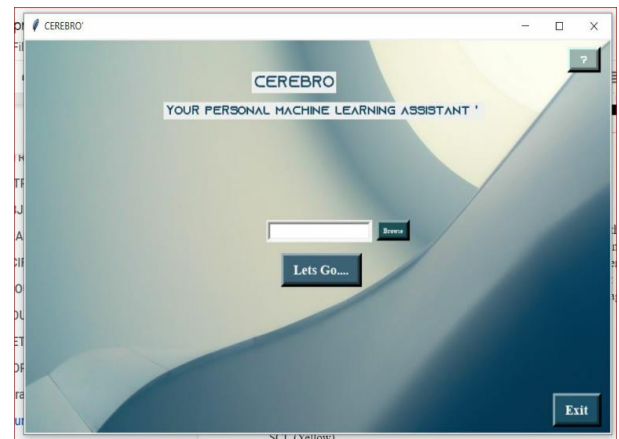


Fig -8: User Interface

### 5.4 Circuit Description

- Connect the touchscreen display to the Raspberry pi 4 by aligning them from the start to the end
- And now we can upload our software into our Raspberry desktop
- Start using the program as guided by the graphical interface

### 6. FUTURE SCOPE

In our device any models of individual training can be saved separately based on the need of classification and can be directly added to the model directory folder, since we use different model based on the classification of diseases classes we directly reduce the chances of error and increase its accuracy. We have lung cell image analyzer colon cell analyzer which is also added in the present model similarly a lot of other models can be added to this program basically it's a framework or like a database to save model data weights and use them to classify various other classes of medical images and implement them to classify it . Its storage can be extended to save more than 64 GB of data. Eventually it will be able to replicate the action that can be taken by an experienced doctor within the matter of seconds.

### 7. CONCLUSION

Upon the completion of this final year project we were able to diagnosis the brain tumor detection by the use of image processing. Apart from several existing brain tumor segmentation and detection methods are present for MRI of brain image. The current project model has a net overall accuracy of 97% based on it's data sets . All the steps for detecting brain tumors that have been discussed starting from MRI image acquisition, pre-processing steps to successfully classification of the tumor. Pre-processing involving operations like wavelet based methods has been discussed. Quality enhancement and filtering are important because edge sharpening, enhancement, noise removal and undesirable background removal improve

the image quality as well as the detection. Among the different filtering techniques, Gaussian filter suppressed the noise without blurring the edges and it is a better outlier without reducing sharpness of the image. Reduces the noise enhance the image quality and is computationally more efficient than other filtering methods. After the image quality improvement and noise reduction discussed here, segmentation methodology for a brain tumor from MRI of brain image is being used. Clustered based segmentation performs is straight forward, quick and manufactures sensible results for non-noise images except for noise pictures it leads to serious inaccuracy within the segmentation . Neural network based segmentation performs better on noise fields and there is no need for assumption of any fundamental data allocation but the learning process is one of the great disadvantages of it.

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## BIOGRAPHIES



Anakha P Kumar  
Department of ECE  
Saintgits College of Engineering



Christy Zachariah  
Department of ECE  
Saintgits College of Engineering



Govind Mohandas  
Department of ECE  
Saintgits College of Engineering



Er. Ashwin P V  
Assistant Professor  
Department of ECE  
Saintgits College of Engineering