Brain Tumor Detection Using Deep Learning

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ABSTRACT

A brain tumor is a disease caused due to the growth of abnormal cells in the brain. Brain tumor is categorized into two categories, cancerous brain tumor (malignant) and non-cancerous brain tumor (benign). Due to the rareness and various different types of tumors, the rate of survival of a tumor prone patient is hard to predict. According to a cancer research by the UK, fifteen out of a hundred people with brain cancer have a chance of survival of ten years or more after diagnosis. Treating a patient with brain tumor is dependent on numerous factors such as: the type of tumor, abnormality of the cells and location of the tumor in the brain, etc. With development in the field of Artificial Intelligence, diagnosis of brain tumors is done by using deep learning models using magnetic resonance imaging (MRI) scans. Magnetic Resonances Imaging (MRI) is a type of scanning method that uses strong magnetic fields and radio waves to produce detailed images of the inner body. The project uses VGG-16 architecture which is a deep learning model for detection of the tumors in the scanned brain images.

Keywords: AI, Deep Learning, Machine Learning, CNN

1. INTRODUCTION

The brain consists of a very large number of cells and with a multitude of complex functions occurring every second. Brain damage affect a number of bodily processes. Unusual development of tissue in the human brain that frustrates the best possible working of the brain is known as the brain tumor. Because of the fact that it will boost the outcome of the study in a field where the margin for error is very low, computer assistance is strongly advanced in therapeutic organizations. The cost of two-dimensional MRI readings is exorbitant, but excellent programming to assist people in clinical settings is of great interest these days. Human onlookers describe the tumor's highlights of traditional techniques. A mechanized symptomatic structure with certain anatomical highlights has been implemented to increase the accuracy of the present framework. To improve accuracy, a symptomatic system has been developed. Manual segmentation is time consuming and has reduced precision. Programmed segmentation is used to avoid this problem. Programmed segmentation provides information of the tissues encompassing tumor. This is due to variation of intensity between similar groupings. With development in picture guided surgical methodologies, segmentation in MRI is being used more and more in treatment. An important advancement is the laying out of tumor contours. This method relies on the support of CNN and acquires knowledge of the highlights that are specific to gliomas detection and segmentation.

2. LITERATURE SURVEY

Sobhaninia, Zahra, et al. have considered various angles of brain magnetic resonance images and used various networks for segmentation. Comparison of the evaluation of a single network is used as an evaluation of the outcome by using different networks for segmentation of MRI. 0.73 is the dice score achieved for a single network whereas 0.79 is achieved for various networks after experimental evaluation. [1]

Deepa P L, Aditya Raj, Abhishek Anil, Naveen Chandran R and H Aravind Sarma have proposed a method that consists of a classification network. This classification network is used to classify the MR image which is used as input, into two classes: 1. Tumorous and 2. Non-Tumorous. Here, transfer learning is the technique used to perform classification through the re-training of the classifier, to detect brain tumor. The results obtained are proven to outdo the other existing techniques currently in use.[2]

Ms. Vengurlekar Samidha Girish and Mrs. Shinde Apurva Swapnil have primarily focused on the preparation of a comparative study based on the following:

- Methodology
- Feature Extraction
- Classification Methods
- Future Scope

They have also considered the pros and cons of the work done different researchers on the subject and compiled it into a single study. This paper provides insight into the directions that can be followed for future research. [3]

Mihaela Lascu, Dan Lascu and Mircea Gurbin have done differentiation of a normal brain from tumorous brain in this study. Magnetic resonance imaging (MRI) of the brain is used to review certain types brain tumors like sarcoma, metastatic bronchogenic carcinoma tumor and glioblastoma. Support vector machines (SVM) and wavelet transforms are used to detect and classify brain tumors. [4]

In this study Daisuke Hirahara has used Xception, a novel architecture that allows both increased performance and reduced size as well as computational cost function of CNN using depth wise separable convolution to develop increased computing power of computer aided diagnosis system for detection of brain tumor using MRI. Initial valuation for the Xception model utilizing transfer learning established respectable performance with high prediction and accuracy probability. [5]

Shaikh Anowarul Fattah, Shahriar Rifat and Tamjid Imtiaz, in this work, have put forward a fully automated brain tumor segmentation method in which the basic processing unit used for classification is the local region of pixels rather than the pixel-based classification scheme which is used conventionally. K means clustering algorithm is used to cluster the local regions which are extracted, into 2 groups for various feature points. The clustering performance is effectively amplified due to this. Various statistical measures obtained from the Gaussian filter bank like textural features and intensity are used here as features. The combination of all of the local tumor regions is used to build segmented tumor volume. The dice comparability measure of the method is comparable with the state of art methods and also has increased efficiency compared the other complex approaches within the perspective of duplicability, small computational cost, and simplicity. [6]
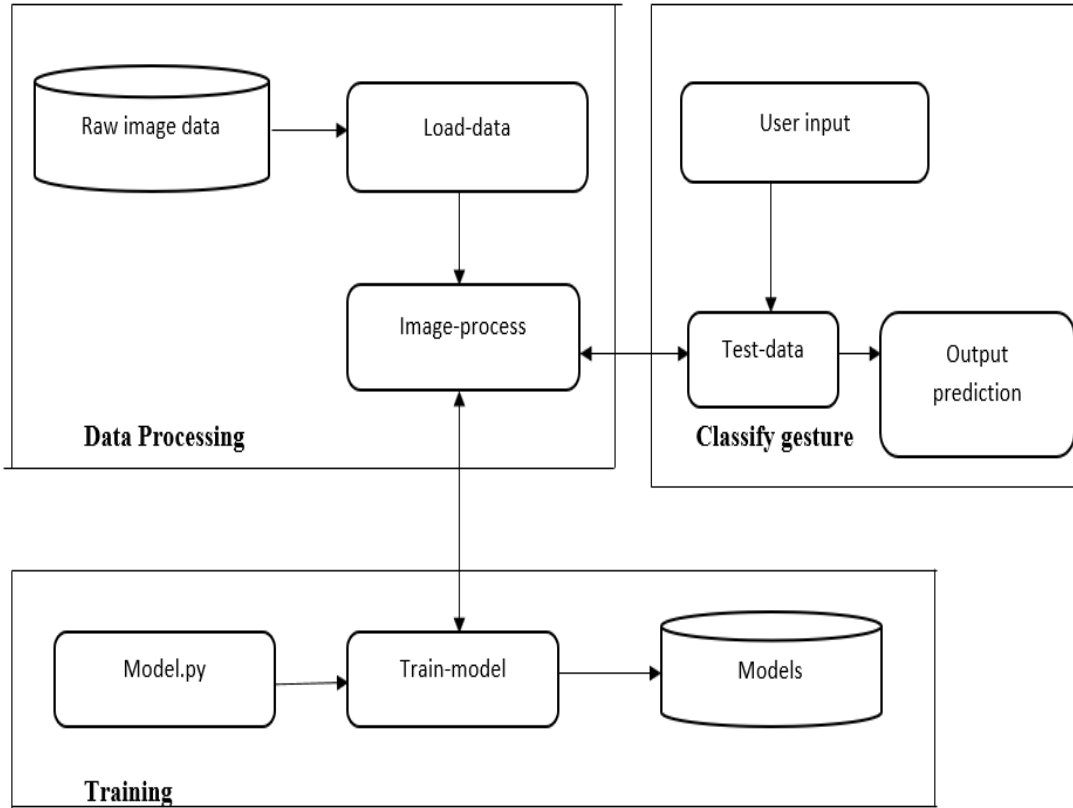
3. METHODOLOGY

Figure 1: Methodology

3.1 Data Collection

The initial step of developing a deep learning network is to collect the dataset. The images as well as the labels associated with each image are required. These labels should come from a finite set of groups, such as: groups = glioma tumors, meningioma tumors, no tumors and pituitary tumors. Additionally, the amount of images for every group should be relatively unvarying (i.e., identical amount of samples in each group) then the classifier will become naturally biased to over-fitting into these highly-represented groups. There are various ways to overcome class imbalance, which is a common problem in machine learning. Avoiding class imbalance is the best way to reduce learning because of class imbalance. As the major focus of the system is detection of brain tumors, the data is gathered as MRI images. The dataset obtained consists of several images with the presence of tumor and in several images with the absence of tumor.

3.2 Splitting the dataset and pre-processing

The initial dataset is divided into 2 portions:
- A training set
- A testing set

The classifier uses a training set to learn about each category by making predictions on the input data and correcting itself on erroneous predictions. After the classifier has been trained, performance is evaluated on a testing set.

The independence of that the training set from testing set is very important. They should not overlap each other. If this is not ensured then, then the classifier has a biased gain as the model has already come across and learned from the testing samples before. Instead, the testing set must be kept entirely separate from the training process and used only to evaluate the network. Common split sizes for training and testing sets include 66:6%33:3%, 75%=25%, and 90%=10%, respectively. Neural networks have hyperparameters that have to be dialed and tuned to obtain ideal performance. In practice, bunches of the hyperparameters are tested to identify the set of parameters that works the best. A third data split called the validation set is created. This set of the data is taken from the training data and is utilized as pseudo test data so that hyperparameters can be tuned. Final accuracy results are

collected after the determination of hyperparameter values. 10-20% of the training data is allocated for validation.

3.3 Pre-processing

The main purpose of pre-processing is to advance image highlights required for further processing. Additional pre-processing requires the input image to be converted to grayscale. The image is then thresholded and further erosion and dilation is applied to the thresholded image. This image is utilized to extract the contours and extreme points.

3.4 Training

The goal here is for the network to learn how to identify every category in the labelled data. When the model makes an error, it learns from the error and corrects itself. In general, a form of gradient descent is applied for training the network.

3.5 Evaluation

The network is presented with all the images from the testing set to predict the label of the image. The model's prediction for the images from the testing set are then tabulated.

The predictions of the model are then compared to the ground-truth labels from the testing set. The depiction of the category the image belongs to is done by the ground truth label. Based on the number of predictions the classifier gets correct, collective information like f-measure, precision and recall, that measure the performance of the network all together, are computed.

4. IMPLEMENTATION
4.1 Libraries Imported

4.1.1 OpenCV
OpenCV is a huge open-source library for computer vision applications, machine learning applications, and image processing applications.

4.1.2 Imutils
Imutils are convenience functions to make basic image processing functions such as translation of images, rotation of images, resizing of images, as well as skeletonization, and displaying Matplotlib images easier with OpenCV

4.2.3 NumPy
Python library which deals with arrays, basically used for scientific computations. Used for performing linear algebra, matrix multiplication, Fourier transform.

4.2.4 Tensor Flow
TensorFlow is a library that can be used for a variety of tasks, this is completely free and is also open source. TensorFlow is used for model building, hence helping us to train and deploy models anywhere and it has a simple and very flexible architecture.

4.1.3 Keras
Keras is the deep learning API for Python that is used for our model, that runs alongside TensorFlow. It is simple, flexible and powerful.

4.1.4 Tkinter
This is the basic Python GUI toolkit shipped with Python, used for GUI based applications. It is the most commonly used platform due to its simplicity and ease of modification.

4.1.5 Pillow
Python pillow library is used to open, manipulate and save images. The image modules that belong to the pillow package have a few inbuilt functions such as load images or create new image.

4.2 Software Requirements
4.2.1 Python
Python is one of the commonly used high level languages. It was developed in late 1980s. It is object-Oriented programming Language. We have made use of the object feature to the maximum extent. It improves productivity, interpreted language, free and open sourced, vast libraries are supported.

4.2.2 Python Idle
The Integrated Development and Learning Environment for Python, this in turn helped us to write the code with more ease and also eliminated problems that we would have faced. We have utilized this since it provides several useful features that would help us implement the code in Tkinter, it also works in Windows, MacOS and also UNIX.

4.3 Image Fundamentals
4.3.1 Image Coordinate System
Every image is made of pixels that is considered in a graph. Taking a graph, the origin of the graph taken as (0, 0) shows the top left corner of the image. Moving below and across, the values of the coordinate x and coordinate y increase.
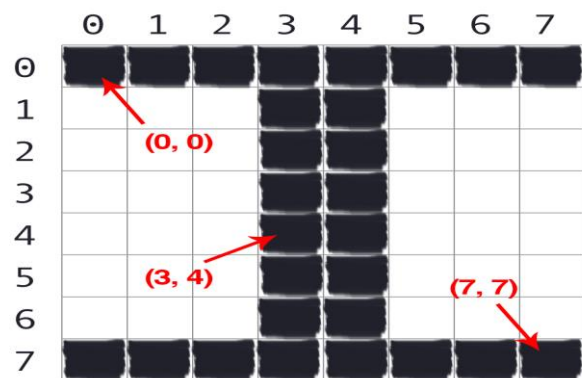

Figure 2: Visual representation of this "graph paper" representation

Figure 2 provides a visual representation of this "graph paper" representation. This is an 8x8 from (0 to 7) grid with a total of 8x8=64 pixels as shown in Figure 2. Python is zero indexed, that means that counting starts from 0 and not 1. Hence as shown above the letter 'I' in the graph, each pixel is represented by their X coordinate and their Y coordinate. Where X is horizontal and Y is vertical. This can be shown in the above image for the coordinate point (3, 4) that represents the pixel 4 to the right horizontally and 5 to the bottom vertically.

4.3.2 Images as NumPy Arrays

When images are taken from processing libraries for OpenCV the images have to be represented as multidimensional NumPy arrays with the factors of height width and depth. Matrix notation is used here, and height of the array is considered first before the width of the array. This is used to define the dimensions of the matrix, in the form of (Rows X Columns).

4.3.3 RGB and BGR Ordering

OpenCV stores the values of the pixels in the order of Blue-Green-Red and not Red-Green-Blue. This is purely due to a historical reason, since at the time of creation of OpenCV, most of the popular camera manufacturers and developers used a similar Blue-Green-Red format.

4.3.4 Scaling and Aspect Ratios Scaling
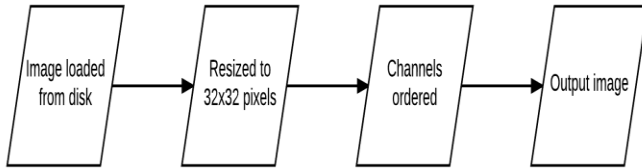
Figure 3: Image pre-processing pipeline

It can be defined as the process of making an image bigger or smaller, that is, the height and width of the image can be increased or decreased. Image pre-processing pipeline incurs in four steps:
1. Firstly, the image must be loaded from the storage.
2. The image is then resized to 32x32 pixels.
3. Then the channel dimensions are put in order.
4. Finally, an image that is required is formulated from the above steps.

The main goal of the above steps is to make sure that Artificial intelligence can make similar decisions that we humans make without hesitation by just our understanding, of course it is more difficult for a machine, yet with the current development in machines, the same can be achieved with prior training.

4.4 Convolutional Neural Networks (CNN)

VGG16 is a convolution neural net (CNN) architecture, it achieves high accuracy with having all the data provided to it and this has been verified by ImageNet. Given the dataset and the time training the model not only can the model further improve it can also learn to be more accurate throughout the process.
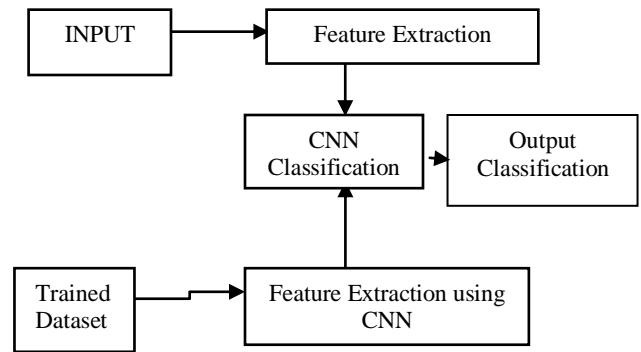
4.5 System Architecture

Figure 4: System Architecture

The proposed model contains:

4.5.1 Feature Extraction

The basic set of data used to help a program understand how to apply a neural network and produce results to implement it. It is then made better by validation and testing dataset. The very first step that we are taking is to ensure that the images that we are training is already pre-processed to make sure that the learnt process is sped up.

4.5.2 CNN Classification

By feature extraction we take into consideration all that the model has learnt in the higher layers of the network to help us and the model differentiate the given data and hence make it more manageable for further processing. In feature extraction stage any given redundancy from the data is removed.

4.5.3 Training Dataset

A perceptron is used to analyze the data for supervised learning. Mainly in the case of image classification and due to its high accuracy. This is a major breakthrough in image recognition that we are glad to be implementing in our model.

5. RESULTS

After considering the dataset and training our model, the following results were achieved:
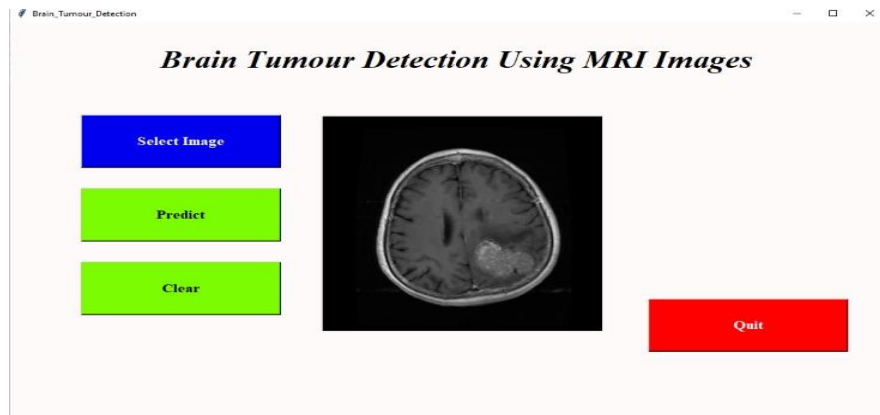

Figure 5: UI for the Brain Tumor Detection Model

The working of the GUI is as follows:
- Images are selected from the data stored on the system using the GUI
- The Predict option helps us detect:
- No Tumour
- Glioma Tumour
- Pituitary Tumour
- Meningioma Tumour

- Clear option clears the result displayed
- Quit option closes the application

From this model we were able to achieve the following results:
- To identify the presence of the tumour using MRI image
- To classify the type of the tumour affected to the individual
- To avoid rate of irregularity in detection of tumour.
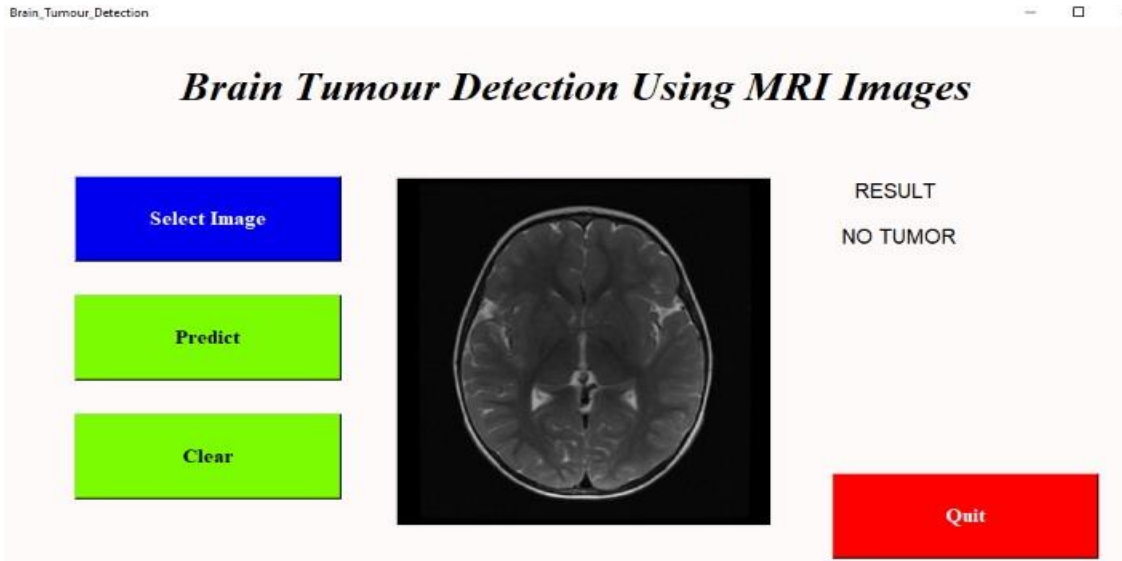- To get better accuracy from the existing system.
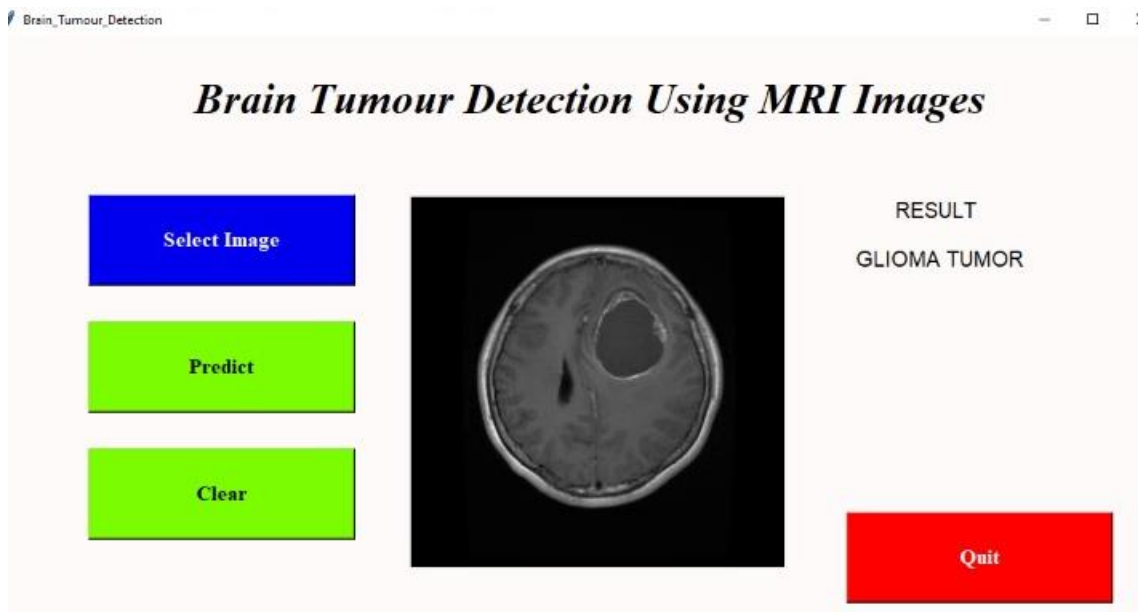

Figure 6: Model detects "No Tumor"

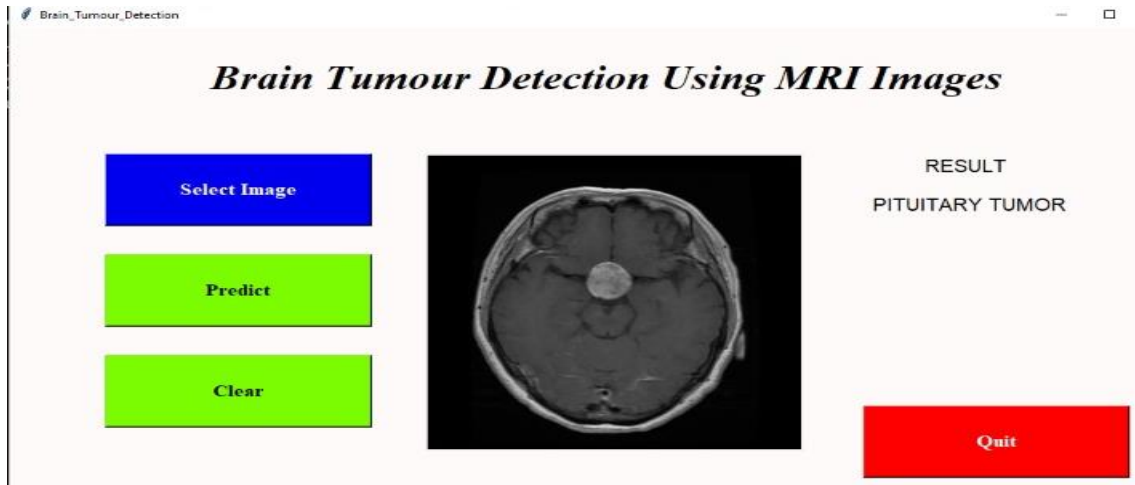**Figure 7: Model Detects "Glioma Tumor"**

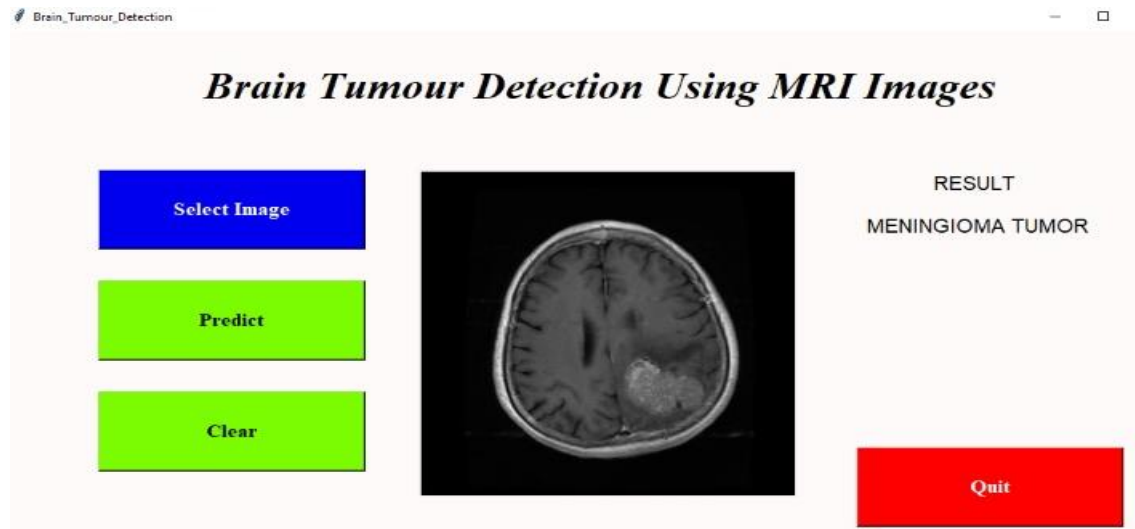**Figure 8: Model Detects "Pituitary Tumor"**

Figure 9: Model detects "Meningioma Tumor"

6. CONCLUSION

With all the aforementioned we were able to find that:

- In the current scenario, Brain tumour detection using MRI image helps doctors to diagnose very easily.
- Brain tumor could be detected using a CNN.
- Our project was to make a program that is simple yet effective, with high accuracy without compromising on simplicity.
- It helps for the detection of presence of tumour in the brain with utmost accuracy
- Helps to reduce the faultiness in the detection from manual prediction or human error

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