



## BRAIN TUMOR CLASSIFICATION USING PRE-TRAINED MODELS

**Mr. GOTTIPATI SRINIVAS BABU** Associate Professor, Department of ECE, NRI Institute of Technology AP, Email ID:gsrinivasbabu@yahoo.co.in

**SK. AYESHA FIRDOSS, S. PRAVACHANA, SK. SHARFUDDHIN, SK. ABDUL KAREEM**  
B. Tech, Student, Department of ECE, NRI Institute of Technology

### ABSTRACT

The human brain is the major controller of the humanoid system. The abnormal growth and division of cells in the brain lead to a brain tumor, and the further growth of brain tumors leads to brain cancer. In the area of human health, Computer Vision plays a significant role, which reduces the human judgment that gives accurate results. CT scans, X-Ray, and MRI scans are the common imaging methods among Magnetic Resonance Imaging (MRI) that are the most reliable and secure. MRI detects every minute objects. In this project we are observing different factors such as Accuracy value and identification of type of tumor, here we are observing the loss curves confusion matrix by using pre- Trained models like VGG16 and RESNET-50. Our project eliminates the manual process from the process of diagnosis and use machine learning instead. Training, testing, and validation datasets are used. Based on our project, we will predict whether the subject has a brain tumor or not. The resultant outcomes will be examined through various performance examined metrics that include accuracy, loss curves, confusion matrix. It is desired that the proposed work would exhibit a more exceptional performance over its counterparts. RESNET-50 has shown promising results due to its scalable nature. VGG-16 showed the best results with training and validation accuracy of 87.67% and 89.55% respectively.

**Key Words:** Brain Tumor, VGG -16, ResNet-50, Accuracy, Loss Curves, Confusion matrix.

### I. INTRODUCTION

The brain is the most important organ of the body which controls the other organs. A tumor is the abnormal growth of the cells due to the uncontrolled division of cells. Tumors are divided into two grades, low and high. Low-grade tumors are benign and are not cancerous, while high-grade tumors are malignant and can spread to other parts of the body and can cause death. Unlike benign tumors in other organs, brain benign tumors can sometimes cause life threatening conditions. Some (for example, meningiomas) may rarely turn into malignant tumors.

World Health Organization (WHO) has graded brain tumors according to brain health behaviour, into grade 1 and 2 tumors that are low-grade tumors also known as benign tumors, or grade 3 and 4 tumors which are high-grade tumors also known as malignant tumors. This use of pre-trained models helps in faster convergence and the model can be trained on fewer resources and fewer datasets.

Our project deals with automated brain tumor classification by using pre trained models such as VGG16 and RESNET50. Normally the anatomy of the brain is analysed by MRI scans. The aim of the project is tumor identification in brain MR images. The main reason for detection of brain tumors is to provide aid to clinical diagnosis. The proper combination and parameterization of the phases enables the development of adjunct tools that can help on the early diagnosis or the monitoring of the tumor identification and locations.

### II. LITERATURE SURVEY

In Medical diagnosis, robustness and accuracy of the prediction algorithms are very important, because the result is crucial for treatment of patients. There are many popular classification and



clustering algorithms used for prediction. The goal of clustering a medical image is to simplify the representation of an image into a meaningful image and make it easier to analyses.

### **Brain Tumor Diagnosis and Classification via Pre-Trained CNN**

This paper presents an application of machine learning in the domain of medical imaging for brain tumor detection and classification. Image augmentation and transfer learning was used to mitigate the effects of small dataset and computational power.

#### **A Performance Comparison of Pre-Trained Learning Models to classify Brain Tumor**

In this study, performance comparison of various deep learning-based classification approaches for the classification of brain MRI images is presented. It has been observed that the application of pre-trained based on deep learning architectures to classify Brain MRI images as normal and tumor has yielded effective results.

#### **Brain tumor classification in MRI image using CNN**

In this paper, a new approach was presented to classify brain tumors. First, using the image edge detection technique, we find the region of interest in MRI images and cropped them then, we used the data augmentation technique for increasing the size of our training data. Second, we provide an efficient methodology for brain tumor classification by proposing a simple CNN network.

#### **MRI Brain Image Classification Using CNN**

This Method Permits the Tumorous and Normal Brain Images By using CNN. MRI has shown more promising results than the other two kinds of radiology methods. In MRI the brain tumor can be spotted as the brightest part. MRI generated an image on basis of the number of hydrogen atoms in the body.

#### **Brain Tumor Classification Using CNN**

This concept can detect the images using Keras, by building an artificial convolutional neural network and used the data augmentation technique for increasing the size of our training data.

MRI images generated from MRI scanners using strong magnetic fields and radio waves to form images of the body which helps for medical diagnosis. This paper gives an overview of the various techniques used to detect the tumor in the human brain using MRI images.

### **III. PROPOSED SYSTEM**

We proposed the use of pre-trained convolutional neural networks (CNN) for the diagnosis and classification of brain tumors. Here by using MRI Images and CT Images for classification of Tumor. Networks that have been used are VGG16, Resnet50. Here we are considering many numbers of MRI pictures are included in the original dataset we are identifying the cancerous samples as well as the non-Cancerous samples. Magnetic resonance imaging (MRI) images are gathered from a variety of sources. In the convolution layer, the given input image is separated into various small regions. For Identification of Tumor, we are using two pre-Trained models like VGG16 and Resnet50 models.

This provides the architecture of the system that would be developed by our hands. It consists of six steps where the execution starts from taking an input image from the data set followed by the image pre-processing, image enhancement, Image segmentation using binary thresholding and the brain tumor classification using Convolutional Neural Network. Finally, the output is observed after all the above steps are completed.

Each module is unique. Every step has its importance. This architecture also includes a testing and training data set. The data set used is has been downloaded which consists of nearly 2000 images that are used to test and train the system. Image segmentation is a commonly used technique in digital image processing and analysis to partition an image into multiple parts or regions, often based on the characteristics of the pixels in the image.

Since images are defined over two dimensions (perhaps more) digital image processing may be modelled in the form of multidimensional systems.

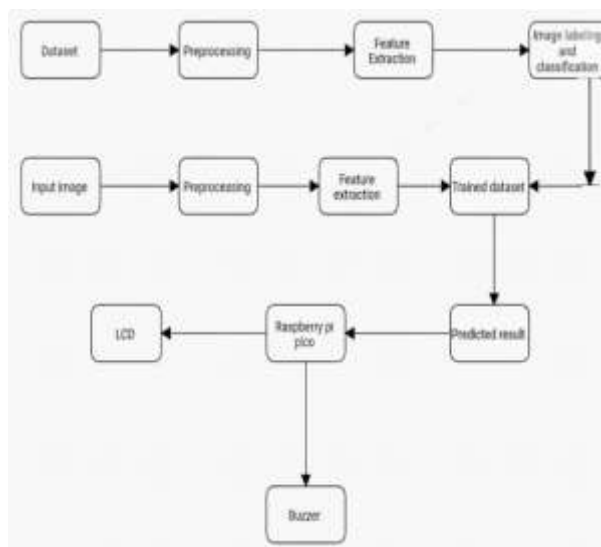


Fig1. Block diagram

### Image Pre-processing

The Brain MRI image dataset has been downloaded from the Kaggle. The removal of unwanted noise is done using the adaptive bilateral filtering technique to remove the distorted noises that are present in the brain picture. This improves the diagnosis and increase the classification accuracy rate.

### Convert the Image from One Color Space to Another

There are more than 150 colour-space conversion methods available in OpenCV. For color conversion, we use the function `cv2.cvtColor(input image, flag)` where flag determines the type of conversion. In our work, we convert the input image into the gray-scale image.

### Median filter

It is a non-linear filtering technique used to remove noise from the images. This filter removes the speckle noise and salt and pepper noise through 'ON' and 'OFF' of pixels by white and dark spots.

### Bilateral filter

It is also a non-linear, noise-reducing smoothing filter for images. Bilateral filtering smooth images while conserving edges utilizing a nonlinear grouping of neighboring image pixels.

### Image Enhancement

Image enhancement is a technique used to improve the image quality and perceptibility by using computer-aided software.

### Image Segmentation Using Binary Threshold

Image segmentation is a technique of segregating the image into many parts. The basic aim of this segregation is to make the images easy to analyses and interpret with preserving the quality.

### Thresholding

Thresholding is the simplest method of image segmentation. It is a non-linear operation that converts a grey-scale image into a binary image where the two levels are assigned to pixels that are below or above the specified threshold value.

### Morphological Operations

Morphological operations apply a structuring element to an input image, creating an output image of the same size. Erosion and Dilation are two methods of morphological operations which used in this proposed work. We perform both Erosion and dilation operations used together.

After completing the opening operations next step is the closing operation. Dilation and Erosion are the basic morphological operations. Dilation adds pixels to the boundaries of objects in an image, while erosion removes pixels on object boundaries.

### Watershed Method



Considers the gradient magnitude of an image as a topographic surface where high gradient denotes peaks, while low gradient denotes valleys. To avoid that, barriers are built in the locations where water merges. Continue the work of filling water and building barriers until all the peaks are under water. Then the created barriers give the segmentation result

### **Brain Tumor Classification Using CNN**

Classification is the best approaches for identification of images like any kind of medical imaging. All classification algorithms are based on the prediction of image, where one or more features and that each of these features belongs to one of several classes.

The Pre-processing required in a CNN is much lower as compared to other classification algorithms. The architecture performs a better fitting to the image dataset due to the reduction in the number of parameters involved and reusability of weights. Sequential is used to initialize the neural network. Convolution2D is used to make the convolutional network that deals with the images. MaxPooling2D layer is used to add the pooling layers. Flatten is the function that converts the pooled feature map to a single column that is passed to the fully connected layer. Dense adds the fully connected layer to the neural network.

#### **Sequential**

To initialize the neural network, we create an object of the Sequential class.

#### **Convolution**

To add the convolution layer, we call the add function with the classifier object and pass in Convolution2D with parameters. The first argument feature detectors which is the number of feature detectors that we want to create. The second and third parameters are dimensions of the feature detector matrix.

We used 256 feature detectors for CNNs. The next parameter is input shape which is the shape of the input image. The images will be converted into this shape during pre-processing. If the image is black and white it will be converted into a 2D array and if the image is colored, it will be converted into a 3D array.

The final parameter is the activation function. Classifying images is a nonlinear problem. So, we use the rectifier function to ensure that we don't have negative pixel values during computation. That's how we achieve non-linearity.

#### **Pooling**

The Pooling layer is responsible for reducing the spatial size of the convolved feature. Furthermore, it is useful for extracting dominant features which are rotational and positional invariant, thus maintaining the process of effectively training of the model.

. On the other hand, Average Pooling returns the average of all the values from the portion of the image covered by the Kernel. Generally, we use max pooling.

#### **Fully Connection**

The next step is to use the vector we obtained above as the input for the neural network by using the Dense function in Keras. The first parameter is output which is the number of nodes in the hidden layer. You can determine the most appropriate number through experimentation.

➤ classifier.add (Dense (output = 64))

The next layer we have to add is the output layer. In this case, we'll use the sigmoid activation function since we expect a binary outcome. If we expected more than two outcomes, we would use the SoftMax function. The output here is 1 since we just expect the predicted probabilities of the classes.

#### **Feature Extraction**

CNN's output layer typically uses the neural network for multiclass classification. CNN uses the feature extractor in the training process instead of manually implementing it. CNN's feature extractor consists of special types of neural networks that decide the weights through the training process.

Feature extraction techniques are helpful in various image processing applications e.g. character recognition. As features define the behavior of an image, they show its place in terms of storage taken, efficiency in classification and obviously in time consumption also.

### Raspberry Pi Pico

Raspberry Pi Pico is a microcontroller board built on silicon designed by Raspberry Pi. Microcontrollers are computers stripped back to their essentials. You don't use monitors or keyboards, but program them to take their input from, and send their output to the input/output pins. Using these programmable connections, you can light lights, make noises, send text to screens, and much more.

### Python

Its language constructs and object-oriented approach aim to help programmers write clear, logical code for small and large-scale projects. Python is dynamically typed, and garbage collected. It supports multiple programming paradigms, including procedural, object-oriented, and functional programming.

### Raspberry Pi Pico

If you are into IoT, robotics, or automation, then there are good chances that you must have heard about the latest revelation from the Raspberry Pi foundation, i.e., the Pi Pico. It works at frequencies up to 133MHz and albeit looking powerless when compared to the other members of the Pi family it has a lot to offer. Unlike the other Pi boards which are basically a Linux based single board computer, Pico is a budget friendly microcontroller with 264kB multi-bank high-performance SRAM, 16 kb of on-chip cache, and 2MB of flash storage.

Raspberry Pi Pico is a microcontroller board built on silicon designed by Raspberry Pi. Microcontrollers are computers stripped back to their essentials. You don't use monitors or keyboards, but program them to take their input from, and send their output to the input/output pins. Using these programmable connections, you can light lights, make noises, send text to screens, and much more.



Fig 2. Raspberry Pi Pico Pinout

### LCD 16x2 Pin Configuration and Its Working

Nowadays, we always use the devices which are made up of LCDs such as CD players, DVD players, digital watches, computers, etc.



Fig 3. LCD Pin Configuration

### Buzzer

A buzzer or beeper is an audio signaling device, which may be mechanical, electromechanical, or piezoelectric (piezo for short).





Fig 4. Buzzer Pin

#### IV. RESULTS AND COMPARISONS

Here we are considering an Input Image we are Considering Input Image as MRI Image and we are performing different operations like Pre-Processing, Feature Extraction.

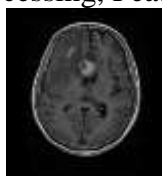


Fig 5. Input MRI Image

Here we are considering the MRI Brain Image along with skull as shown in the below fig 6.



Fig 6. Brain With Skull

Feature extraction refers to the process of transforming raw data into numerical features that can be processed while preserving the information in the original data set. It yields better results than applying machine learning directly to the raw data.

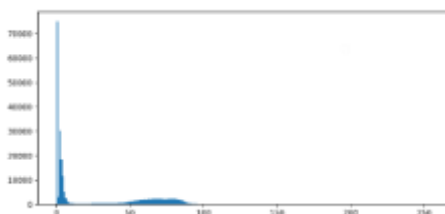


Fig 7. Graphical Representation

Otsu's method is a variance-based technique to find the threshold value where the weighted variance between the foreground and background pixels is the least. The key idea here is to iterate through all the possible values of threshold and measure the spread of background and foreground pixels.



Fig 8. Otsu's method

Any set of pixels which is not separated by a boundary is called connected. Each maximal region of connected pixels is called a connected component. The set of connected components partition an image into segments.

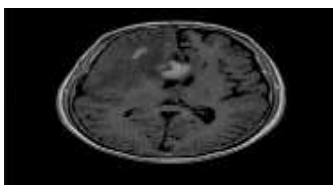


Fig 9. Tumor Identification

The Output of the Code Is given as input to Raspberry Pi Pico It displays whether the taken input image is having any type of tumor or no tumor. As shown in the below fig 10 and 11.



Fig 10. Meningioma tumor    Fig 11. No Tumor

### Comparisons

The most popular example of a learning curve is loss over time. Loss (or cost) measures our model error, or “how bad our model is doing”. So, for now, the lower our loss becomes, the better our model performance will be.

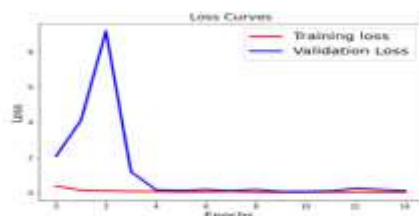


Fig 12. Loss Curves

Accuracy score in machine learning is an evaluation metric that measures the number of correct predictions made by a model in relation to the total number of predictions made. We calculate it by dividing the number of correct predictions by the total number of predictions.

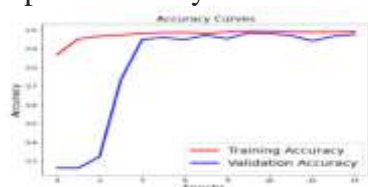


Fig 13. Accuracy Curves

It is a performance measurement for machine learning classification problem where output can be two or more classes. It is a table with 4 different combinations of predicted and actual values.

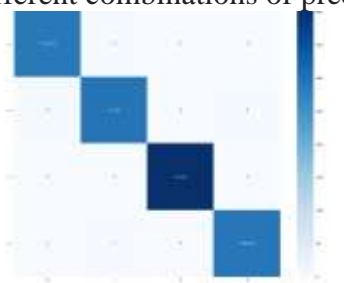


Fig 14. Confusion Matrix

	precision	recall	f1-score	support
0	0.98	0.99	0.98	294
1	0.98	0.97	0.98	303
2	1.00	1.00	1.00	403
3	0.99	0.99	0.99	294
accuracy			0.99	1294
macro avg	0.99	0.99	0.99	1294
weighted avg	0.99	0.99	0.99	1294

Fig 15. Comparison Table



### Performance Measures

The proposed algorithm has been assessed through various performance evaluation metrics that include True Positive, True Negative the former one that designates how many times does the proposed algorithm is able to correctly recognize the damaged region as damaged region and the later one designates how many times does the proposed algorithm correctly identified non-damaged region as non-damaged region. And the False Positive (FP) and False Negative (FN) the former one designates how many times does the proposed algorithm fails to recognize the damaged region correctly, and the later represents how many times does the proposed algorithm fails to identify the non-tumors region as non-tumors regions. Basing on values of TP, TN, FP, and FN, the values of Accuracy, Loss curves and confusion matrix, are calculated of the proposed algorithm.

$$\text{ACCURACY} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

### V. CONCLUSION AND FUTURE SCOPE

We proposed a computerized method for the segmentation and identification of a brain tumor using the Convolution Neural Network. The input MR images are read from the local device using the file path and converted into grayscale images. These images are pre-processed using an adaptive bilateral filtering technique for the elimination of noises that are present inside the original image. The binary thresholding is applied to the denoised image, and Convolution Neural Network segmentation is applied, which helps in figuring out the tumor region in the MR images. The proposed model had obtained an accuracy of 98% and yields promising results without any errors and much less computational time.

It is observed on extermination that the proposed approach needs a vast training set for better accurate results; in the field of medical image processing, the gathering of medical data is a tedious job, and, in few cases, the datasets might not be available. In all such cases, the proposed algorithm must be robust enough for accurate recognition of tumor regions from MR Images. The proposed approach can be further improvised through in cooperating weakly trained algorithms that can identify the abnormalities with a minimum training data and self-learning algorithms would aid in enhancing the accuracy of the algorithm and reduce the computational time.

### REFERENCES

- [1] Brain Tumor Diagnosis and Classification via Pre-Trained Convolutional Neural Networks Dmytro Filatov
- [2] A Performance Comparison of Pre-trained Deep Learning Models to Classify Brain Tumor Aykut DIKER
- [3] Brain tumor classification in MRI image using convolutional neural network Hassan Ali Khan<sup>1</sup>, Wu Jue<sup>1,\*</sup>, Muhammad Mushtaq<sup>2</sup> and Muhammad Umer Mushtaq
- [4] MRI Brain Images Classification Using Convolutional Neural Networks Abdelhakim El Boustani, Mohamed Aatila(&), Essaid El Bachari, and Ahmed El Oirrak
- [5] Brain Tumor Classification Using Convolution Neural Network (J. Phys.: Conf. Ser. 1916 012206) Published 23 February 2022
- [6] A. Sivaramakrishnan And Dr.M.Karnan "A Novel Based Approach For Extraction Of Brain Tumor In MRI Images Using Soft Computing Techniques," International Journal Of Advanced Research In Computer And Communication Engineering, Vol. 2, Issue 4, April 2013.
- [7] Asra Aslam, Ekram Khan, M.M. Sufyan Beg, Improved Edge Detection Algorithm for Brain Tumor Segmentation, Procedia Computer Science, Volume 58,2015, Pp 430 437, ISSN 1877-0509.





- [8] B.Sathya and R.Manavalan, Image Segmentation by Clustering Methods: Performance Analysis, International Journal of Computer Applications (0975 – 8887) Volume 29– No.11, September 2011.
- [9] Devkota, B. & Alsadoon, Abeer & Prasad, P.W.C. & Singh, A.K. & Elchouemi, A.. (2018). Image Segmentation for Early Stage Brain Tumor Detection using Mathematical Morphological Reconstruction. Procedia Computer Science. 125. 115- 123. 10.1016/j.procs.2017.12.017.
- [10] K. Sudharani, T. C. Sarma and K. Satya Rasad, "Intelligent Brain Tumor lesion classification and identification from MRI images using k-NN technique," 2015 International Conference on Control Instrumentation Communication and Computational Technologies (ICCICCT), Kumaracoil, 2015, pp. 777-780. DOI: 10.1109/ICCICCT.2015.7475384
- [11] Kaur, Jaskirat & Agrawal, Sunil & Renu, Vig. (2012). A Comparative Analysis of Thresholding and Edge Detection Segmentation Techniques. International Journal of Computer Applications.vol. 39.pp 29-34. 10.5120
- [12] Li, Shutao, JT-Y. Kwok, IW-H. Tsang and Yaonan Wang. "Fusing images with different focuses using support vector machines." IEEE Transactions on neural networks 15, no. 6 (2004): 1555-1561.
- [13] M. Kumar and K. K. Mehta, "A Texture based Tumor detection and automatic Segmentation using Seeded Region Growing Method," International Journal of 49 Computer Technology and Applications, ISSN: 2229-6093, Vol. 2, Issue 4, PP. 855- 859 August 2011