

## Detection Of Brain Tumour Using Convolutional Neuralnetwork

Manikanta Y<sup>1</sup>, Yashwanth B S<sup>2</sup>, DeepthiMurthy T S<sup>3</sup>, Hemanth Gowda<sup>4</sup>Santosh Borganve<sup>5</sup>

<sup>1</sup>Student, Electronics and communication, Reva University, (India)

<sup>2</sup>Student, Electronics and communication, Reva University, (India)

<sup>3</sup>Proffesor, Electronics and communication, Reva University, (India)

<sup>4</sup>Student, Electronics and communication, Reva University, (India)

<sup>5</sup>Student, Electronics and communication, Reva University, (India)

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**Abstract:** The human brain is the center of the nervous system. Healthy functioning of this intensifies the activity of the human body. Various causes affect the disciplined working of the human brain. One such case is the brain tumor, which is the abnormal growth of cells in the brain. Observation of the brain can be done in many ways. MRI is one such method to recognize the brain. It is very much important to detect the brain tumor and treat it at an early stage. As the patient per doctor ratio has increased, the detection may be prone to human errors. The solution for the detection of brain tumor can be done using Convolutional neural network. MRI image is given as input and the model decides the presence or absence of the tumor in the given MRI image.

**Keywords:** Benign, Convolutional Neural Network, Malignant, MRI, Tumor

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### Introduction

The abnormal and rapid development of cells in the brain causes brain tumor, which can occur to the people of any ages. The size, area and the location of this cell region decides whether the tumor cells are cancerous or non-cancerous. Benign and Malignant are the larger classifications of the brain tumor. The initial stages of the tumor are Benign and are easily curable and can be controlled by taking proper medications, compared to the malignant. This tumor region is also known as the Primary tumor region and usually a non-cancerous tumor. Pituitary tumors, Gliomas and Meningiomas are three types of tumors in the primary region. Malignant are the most dangerous and critical stage of cancerous cells. These are also called as secondary tumor regions. Malignant tumors are only curable if radiation therapy treatment or surgery is given to the affected patients. This deadly disease can only be controlled if detected at an early stage. Scanning is the only possible way to detect the tumor at the early stage. The different scanning techniques are CT scan, MRI scan, Ultrasound image. In this paper MRI scanning is preferred other than any scanning techniques MRI scanning provides more clear information like contrast in enhanced regions and its clear visibility than any other scanning techniques. Brain tumor classification and segmentation can be done in many ways. The brain tumor classification can be done using many models such as Support vector machine (SVM), K-Nearest Neighbors (KNN), Logistic Regression Convolution Neural (CNN). We are using Convolutional neural network model to classify the MRI images. The old machine learning methods have been using kernels like Gaussian for getting the occurrence detail, but CNNs pick up the kernel set based on the training data as provided. CNNs are accurate in extracting the features and representing the complex relationships of an image, that makes it effective in image processing tasks. A web page is where we can deploy the CNN model. Usage of Webpage makes the model available for the common people where the MRI image could be uploaded by the user and the model gives the output as either tumor or non-tumor MRI image.

### Literature survey

K. Pathak et al [1] in the year 2019 proposed a model to detect tumor and also did the segmentation for the same CCN is an efficient approach for tumor detection and segmentation. CCN gives the best performance. Manjunath et al [2] has discussed in their paper about the comparison between CNN and ANN. Paper also shows the importance of Convolutional Neural Networks over other classification techniques. Totakura Varun [3] exhibits how to create the web interface for faster brain tumor detection. Web interfaces makes it easier to the common people to use and it makes faster for the doctor to check the tumor. Hossain et al in the year 2019 [4] again compares the different types of traditional algorithms and concludes that CNN classifies accurately compared to others Neethu Ouseph et al in 2017[5] has mentioned in their paper about the Specificity and sensitivity in Convolutional Neural Networks which are used to evaluate model capability in classification. Heba Mohsen et al[6] best describes the combination of Discrete wavelet transform and Dense neural networks and tumor detection which is classified into 3 different tumors: glioblastoma, sarcoma and metastatic

bronchogenic carcinoma. Abiwinand et al[7] proposed a model using Convolutional Neural Networks where it classifies three types of tumors that is Glioma, Meningioma, and Pituitary. Anil Singh Parihar in the year 2017 [8] does the Tumor segmentation using CNN's and also Normalizing the pixel intensities to improve segmentation results. J. Seetha et al[9] mentions Fuzzy C Means based segmentation and DNN based classification Two path CNN for tumor segmentation and also different architectures of CNN. Jiachi Zhang et al[11] describes the Convolutional Neural Networks. Here they use hierarchical dice loss function to calculate error. Sergio Pereira in the year 2016[12] mentions CNN based segmentation, Data Augmentation and Xavier Initialization.

**Proposed methodology**

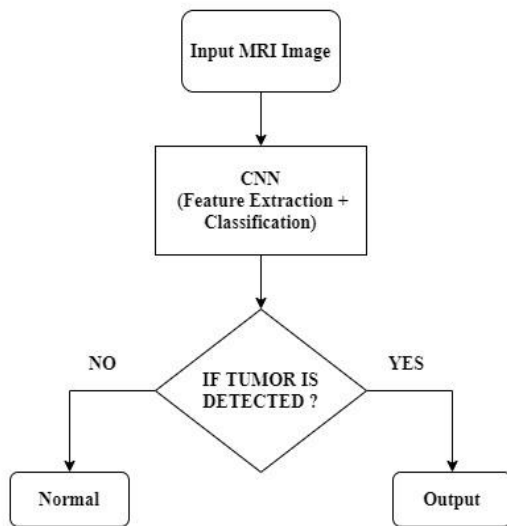


Figure.3.1Block diagram of proposed methodology

The Brain MRI images are collected from Kaggle website. Total number of images are 1866. Brain MRI Image as shown in the Fig 3.2 is preprocessed (resizing, normalizing). The preprocessed image is as shown in the Fig 3.3 and it is given as an input to convolutional neural network and internally the CNN performs feature extraction by performing convolution and pooling operations. After the training, CNN has an ability to classify the tumorous and non-tumorous image. Basically, this is a binary classification problem. The output can be of two classes tumor or non-tumor. The block diagram of this model is as shown in the Fig 3.1

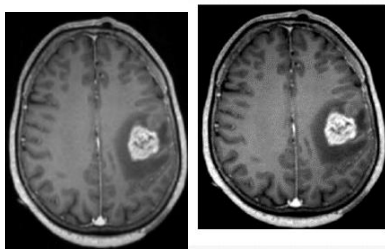


Fig.3.2 Input Image using pillow library

Fig.3.3 Contrast enhancement

**Convolutional Neural Network (CNN)**

A Convolutional Neural Network (ConvNet / CNN) is a Deep Learning algorithm which can take in an input image and learn the patterns of various objects in the image and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in Traditional methods filters are hand-engineered, with enough training, ConvNets can learn these filters/characteristics on their own. A ConvNet can successfully capture the Spatial and Temporal dependencies in an image through the application of relevant filters. Convolutional neural networks are composed of multiple

layers of artificial neurons. Mathematical functions that calculate the weighted sum of multiple inputs and outputs an activation value.

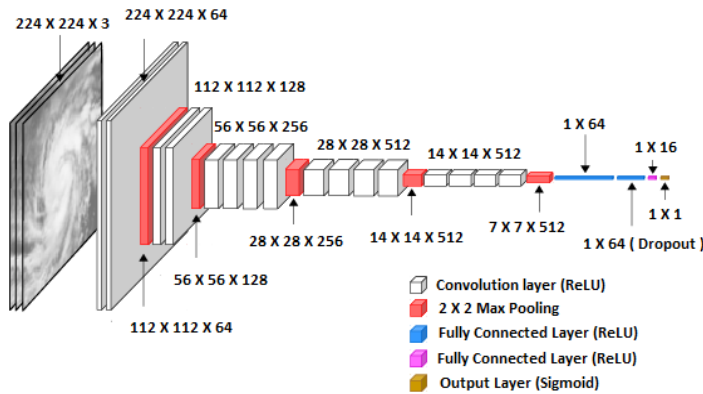


Fig.4.1 Architecture of CNN

#### 4.1. Convolution Layers

This layer is responsible for configuring the filters that extracts features of input image. Internally, the convolution operation is performed on input image. A convolution is a linear operation that involves the dot product of a filter (set of weights) with the input image. The output of convolution is referred as feature map.

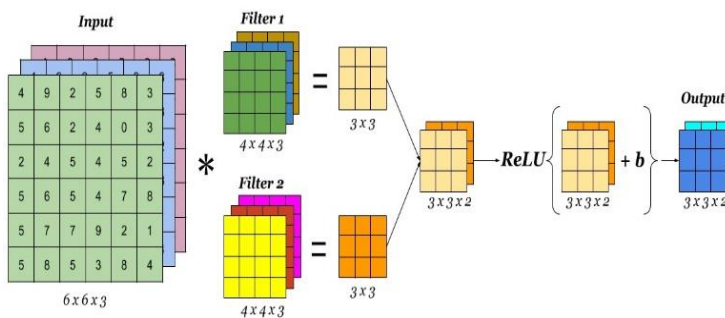


Fig.4.2 Convolution Layer

#### 4.2 Padding

Padding operation appends the zero pixels over input image. This operation is used to avoid information loss while performing convolution. The dimension of output will be same as input image after padding + convolution.

$$n_{out} = \left\lfloor \frac{n_{in} + 2p - k}{s} \right\rfloor + 1 \dots (4.1)$$

$n_{in}$  : number of input features

$n_{out}$  : number of output features

$k$  : kernel (filter) size

$p$  : Padding size

$s$  : stride size

#### 4.3 Rectifier Activation Function (ReLU)

After performing convolution on i/p image, applying RELU on convolved image(feature map) helps in extracting the nonlinear patterns and relationships. There are different activations like sigmoid, tan h, etc. In this work, ReLU function is used due to its better performance than other functions and its non vanishing gradient behaviour.

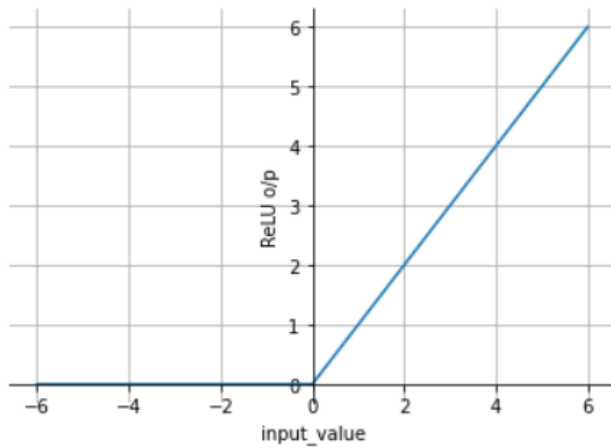


Fig.4.3ReLU Activation Function

#### 4.4 Pooling Layers

Pooling layer is responsible to decrease the dimension of the convolved image without information loss. There are two types of pooling, max pooling, average pooling. In this work, we used Max pooling that takes maximum value from a set of pixels in image.

#### 4.5 Fully Connected Layers

Fully Connected Layers are Traditional neural networks used to produce the classification output. These are also called as Dense networks. In CNN convolutional layers are used to extract features from images and fully connected layers are used to perform classification.

#### 4.6 Sigmoid

Sigmoid activation function is used to rescale the any kind of real value in the range of (0,1). The o/p of sigmoid function will be referred as probabilistic values. Sigmoid function is used in the o/p layer to perform binary classification.

$$f(x) = \frac{1}{1+e^{-x}} \dots (4.2)$$

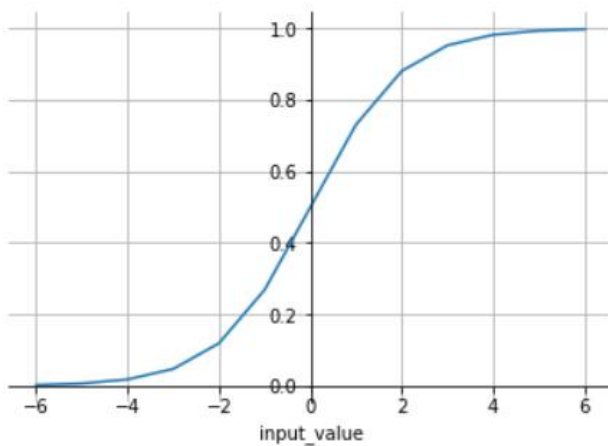


Fig.4.4 Sigmoid Activation Function

#### 4.7 Adaptive Movement Estimation

Adam is an optimization algorithm used to train deep learning models. Adam combines the operations of the AdaGrad and RMSProp algorithms that can handle sparse gradients on noisy problems. It is used for its nature of computationally efficient and less memory requirement. The initial learning rate used is 0.001. The learning rate might vary based on type of data, problem etc.

$$v_t = \beta_1 * v_{t-1} - (1 - \beta_1) * g_t \dots (4.3)$$

$$s_t = \beta_2 * s_{t-1} - (1 - \beta_2) * g_t^2 \dots (4.4)$$

$$\Delta w_t = -\eta \frac{v_t}{\sqrt{s_t + \epsilon}} * g_t \dots (4.5)$$

$$w_{t+1} = w_t + \Delta w_t \dots (4.6)$$

$\eta$  : Learning rate

$g_t$  : Gradient along  $w^j$

$v_t$  : Exponential Average of gradients

$s_t$  : Exponential Average squares of gradients

$\beta_1, \beta_2$  : Hyperparameters

#### 4.8 Cross Entropy Loss

Cross entropy loss is used to measure the performance of a classification model. It is also called as log loss. The aim of the model during training is to minimize the loss the smaller the loss, the model is better. The output of the log loss ranges between 0 and 1.

$$Loss = -\frac{1}{N} \sum_{i=1}^N y_i * \log(y_i^{pred}) + (1 - y_i) * \log(1 - y_i^{pred}) \dots (4.7)$$

$y_i$  : Actual value (Ground Truth).

$y_i^{pred}$  : Predicted value.

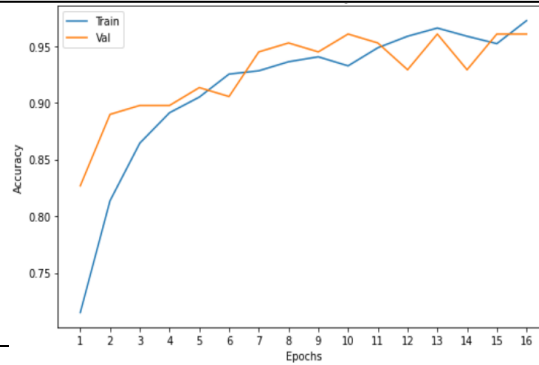
$N$  : Total number of Images.

#### 4.9 Model Architecture

Layer (type)	Output Shape	Param #
vgg19 (Functional)	(None, 7, 7, 512)	20024384
flatten_1 (Flatten)	(None, 25088)	0
dense_3 (Dense)	(None, 64)	1605696
dropout_1 (Dropout)	(None, 64)	0
dense_4 (Dense)	(None, 16)	1040
dense_5 (Dense)	(None, 1)	17
Total params: 21,631,137		
Trainable params: 1,606,753		
Non-trainable params: 20,024,384		

We used the Transfer learning approach for classifying the MRI images. Instead of building the CNN from scratch we can make use of pre-trained models. In this project we used VGG-19 model which is already trained on ImageNet data. So, the CNN will have an ability to identify the features of MRI efficiently. Additionally, VGG-19 is embedded with some Dense layers. ReLU function is used in the dense layers and Sigmoid is applied on the output layer for binary classification purpose. Threshold is set to 0.5, If the output value is < 0.5, it is treated as class 0 else class 1. Fig.4.5 Model's Architecture

More details regarding data, model training, performance is shown in Table 4.1.



Input size	227 x 227 x 3
Number of Training Images	1379
Number of Validation Images	127
Number of Testing Images	80
Optimizer	ADAM
Learning Rate	0.001
Batch size	64
Epochs	16

Table

4.1 Implementation details.

**Results and discussions**

In classification, there are different metrics to measure the performance of model, f1-score is the one of the important metrics used to measure the performance of model. It is the harmonic mean of both precision and recall. The following Table 5.1 summarizes the information of different metrics.

	Train	Validation	Test
Loss	0.07	0.08	0.09
Accuracy	99 %	97 %	96 %
Precision	0.99	0.97	0.97
Recall	0.98	0.98	0.98
F1-score	0.99	0.98	0.98

Table 5.1 Model Performance

The binary cross-entropy loss is calculated for every epoch for both training data and validation data. Precision tells us how much we can trust our model while making positive prediction and Recall gives you how many actual positive are correctly classified. F1-score is the harmonic mean of both Precision and Recall. It gives the balanced score of them.

Fig. 5.1 Epochs vs Accuracy

From the above Fig 5.1 we can see that model’s training, and validation accuracy is increasing after iterations. After 16 iterations the training accuracy is 99% and validation accuracy is 97 %.

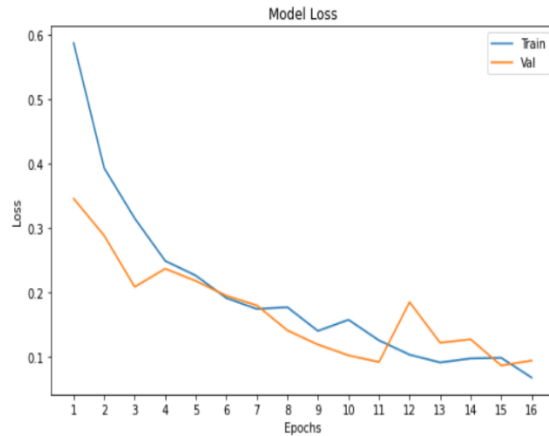


Fig. 5.2 Epochs vs Loss

From the above figure 5.2 we can see that model’s training, and validation loss is decreasing after iterations. After 16 iterations the training loss is 0.07 and validation loss is 0.08. It is pretty good, CNN is doing well.

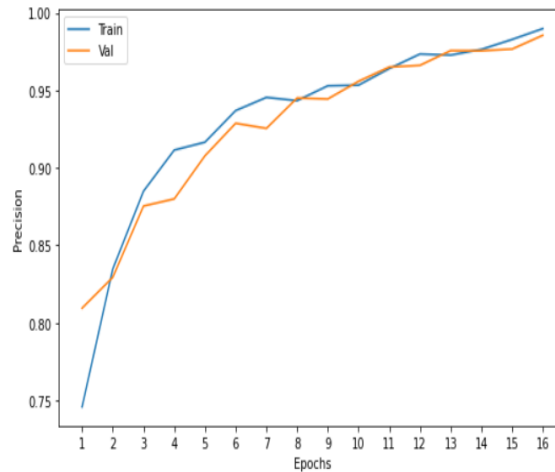


Fig. 5.3 Epochs vs Precision

The fig-5.3 shows the comparison and change in both training data, validation data precision for every epoch. The precision of train data and validation data are doing well

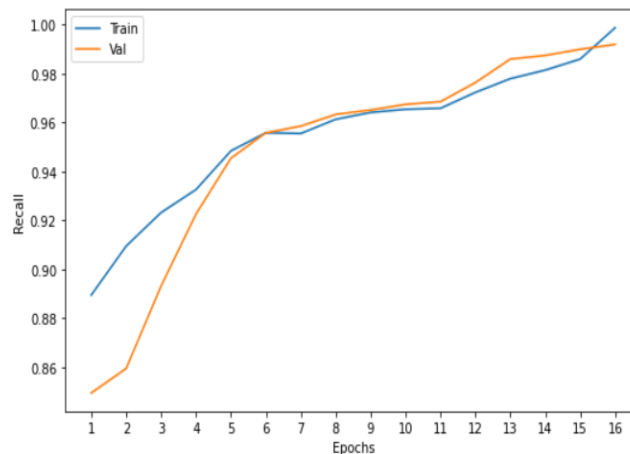


Fig. 5.4 Epochs vs Recall

The fig 5.4 shows the comparison and change in both training data, validation data recall for every epoch. The recall of train data and validation data are doing well

Fig. 5.5 Epochs vs F1\_score

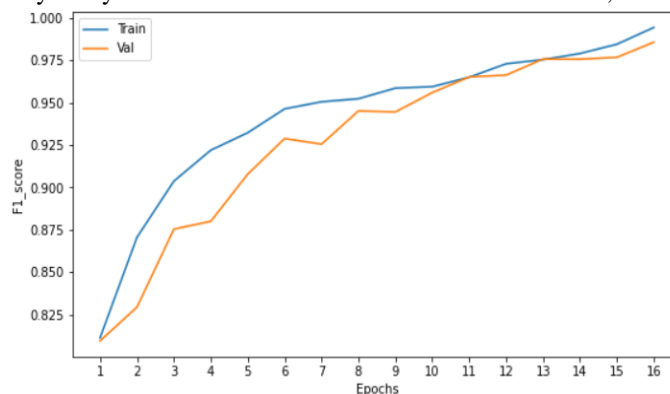
The fig 5.5 shows the comparison and change in both training data, validation data f1\_score for every epoch. The f1\_score of train data and validation data are doing well.

### Future scope

Further, this detection model can be improved by introducing segmentation (highlighting the tumor) concept. Training the model to classify different types of tumors in the brain like glioblastoma, Meningioma etc. This model can be deployed into a web-based application or as a mobile application. So, that user can access perform detection process anywhere at any time. We can also train the model on different types of images like MRI, CT and so on based on user flexibility. So that the model will not be limited to one image type.

### Conclusion

The Brain Tumor detection model is able to classify the MRI images of tumor and non-tumor with good accuracy. The Convolution neural network (CNN) and Fully connected networks are used in building the model. Resizing and contrast enhancement is done using python pillow library. Feature extraction is done by CNN and classification is done by Fully connected networks. From the result section, we can conclude that the model is



showing a good performance. There is only less accuracy difference between training and validation data. Therefore, model is not overfitting.

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