Brain Tumor Classification Using CNN

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ABSTRACT- Several imaging techniques are accustomed for brain tumors classification. However, MRI is commonly used because of its superior image quality and also the fact that it has less radiation. Deep learning (DL) which is a part of machine learning and recently showed a better performance, especially in classification and segmentation issues. The main objective is to obtain and classify the tumor which grows inside and around the brain. In order to obtain this we can use Convolution and Fully-connected layers which are part of Alexnet used in CNN. These Layers extract features of the tumor and classify the grade and locates the tumor in the brain accurately.

Key words: CNN, Alexnet, Deep Learning , Convolution and Fully Connected layers.

I. INTRODUCTION

The formation of abnormal growth of cells in brain is known as Brain Tumor. Identifying the tumor in earlier stages is very important. Ultrasound images are useful in identifying the abnormal growth of cells in any part of our body. Usually Magnetic Resonance Imaging is useful in categorizing the abnormal cells in the brain at temporal length of event's existence particularly. Using of high standards of specific images to decrease the deaths from brain tumor is very important. No one can predict the growth of tumor in the brain and treatment is done depending on the tumor location, size and its growth. Treatment is meant to eradicate or eliminate the tumor part without affecting the other parts or cells of the brain. The following steps shows the different kinds of methods to classify and to detect the tumor location in the brain of patients.

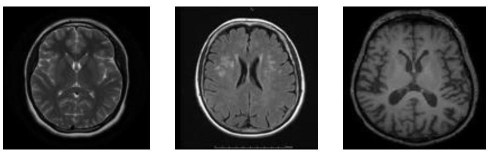


Figure -1 normal images

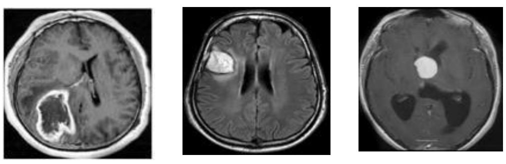


Figure -2 Abnormal images

Here a new technique has brought into light to classify brain tumors from the MRI images. In the preprocessing state various types of images are given as input. Feature extraction, parameters calculation is done in second stage.The input image is grayscale, it is converted to an RGB image by replicating the single channel to obtain a 3-channel RGB image. Random crops of size 227×227 were generated from inside the 256×256 images to feed the first layer of AlexNet.

II. LITERATURE REVIEW

1. Tian, JieJianXue, Yakang Dai, Jian Chen, JianZheng , used a Novel Package platform to integrate the thought algorithms for medical image process and analyzed intervals of standardized framework, as well as reconstruction, segmentation, registration, visual image, etc., and provides a robust tool for each scientists and engineers.

2. El-Sayed A. El-Dahshan, Heba M. Mohsen, Kenneth Revett, Abdel- Badeeh M. Salem, had executed **t**he experiments on one zero one snapshot consisting of 14 normal and 87 unusual (malignant and benign tumors) from an actual human mind MRII dataset. The category accuracy on each schooling and test photographs is 99% which was significantly true.

3. M. Soltaninejad, et al, used an automated method is used to identify and categorize MRI images. This method is based on the Super Pixel Technique and the classification of each Super Pixel. Extremely randomized trees (ERT) classifier is compared with SVM to classify each super pixel into tumor and normal. This method has two datasets, which are 19 MRI FLAIR images and BRATS 2012 dataset.

4. S. Pereira, et al, used an automatic classification method to identify a tumor using a CNN with 3 _ 3 small kernels. The method obtained simultaneously the first position for the complete, core, and enhancing regions in dice similarity, coefficient metric (0.88, 0.83, 0.77), at the BRATS Challenge 2013.

5. L. Szilagyi, et a, has proposed a multi-stage Fuzzy C-Means (FCM) framework to segment brain tumors from MRI images.The algorithm was tested on six selected volumes from the BRATS 2012 database. The achieved accuracy is generally characterized by a Dice score in the range of 0.7 to 0.9.

6. Y. Pan, et al ,has studied multiphase MRI images in tumor grading and a comparison has been made between the results of deep learning structures and base neural networks. The results show that the network performance based on the sensitivity and specificity of CNN improved by 18% compared to the neural networks.

III.EXISTING METHOD

The block diagram for the existingmethod is shown in below figure :

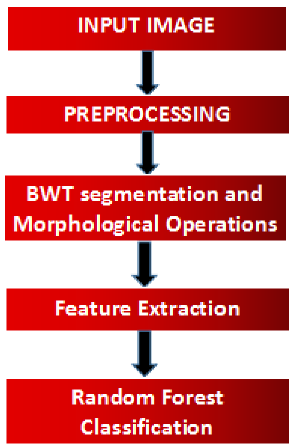


Figure-3: Block diagram of Existing method

A.Image Pre-processing

The preprocessing is done to improve the MRI image quality. This process makes appropriate perception for people and systems. In order to increase the signal to noise ratio, information storage capacity and also to improve the MRI images and frameworks we are use this preprocessing method.This preprocessing is also used to clear the disturbances and unnecessary things in the circumferences.This preprocessing method stores the boundaries of the image. In order To improve the signal-to-noise ratio, and to clear the MRI.We appliedthe adaptive contrast enhancement based on modified sigmoid function.

B. Contrast Enhancement and Skull Stripping

The visual appearance of low resolution MRI image is done by Contrast Enhancement and make it in a form suited for processing by human or machine vision system.Skull Stripping, which eleminates the non brain tissues and also cerebral tissues such as fat, skin and skull in the brain images.Histogram analysis techniqueis used to remove non brain tisssues in the brain MRI images.

C. Segmentationand Morphological Operations

For effective segmentation of brain MRI image, Berkely Wavelet Transform (BWT) is employed. Pre-processed MRI image is converted into binary, with a threshold range of 128. In Morphological operations, inorder to eliminate white pixel, an erosion operation is performed. By doing reverse operation to eroded image, white matter is converted to black, viceversa. Finally, original image gets subtracted from eroded image in order to extract the tumor part in the MRI image.

D.Feature Extraction

Feature extraction can be carried out by calculating ABCD parameters.

A=perimeter/Area

B=Perimeter/Major axis length

C=Major axis length*

((1/major)-(1/minor))

D=Major - Minor

Where Area(A) is number of pixels of the lesion
Perimeter(P) is number of contour pixels
Major axis length(Ma L) is the length of the line passing through lesion centroid and joining the two farthest boundary points. Minor axis length(Mi L) is the length of the line passing through lesion blob centroid and joining the two adjacent boundary points.

E. Random Forest Classifier

Random Forest is an accumulation of machine learning technique capable of performing both regression and classification tasks using multiple decision trees. Extracted features are given as input to Random Forest classifier in order to identify the class. The random means, we are using some special keys instead of taking mean or average values. It is also known as haphazard forest analysis. Here we consider number of resolutions and their combination gives a high specific rate and an constancy indicator than separate indicator trees.

- The trees get information in a resolution forest which came through haphazard fragment.
- Boot Strapping shows all replaced or new fragments. Few fragments are used many times in one fragment.
- In this combination of total guidance information and the integrated forest will have low tendency rate and low difference.
- If bootstrap goes wrong we can go with haphazard by having equal information with individual trees.
- Using this method and data in Random Forest Classifier , six classes of data is classified using ABCD parameters with an accuracy of 95%.

F. Performance Measure

- Performance measure to classify whether it is a tumor or non tumor is obtained based on four events, two classifications and two misclassifications.

- Accuracy=TP+TN/(TP+FN+TN+FP)
- Structural similarity index measure (SSIM) = $\dfrac{(2\mu_x\mu_y + c_1)\,(2\,\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)\,(\sigma_x^2 + \sigma_y^2 + c_2)}$

Where,

- TP is True Positive, TN is True Negative, FP is False Positive and FN is False Negative
- Accuracy : It is the ratio of correctly classified pixels to the total number of pixels in the image.
- SSIM : SSIM is defined as how much amount of similarity is between the ground truth and input image.

  Range : 0 <= SSIM <= 1

LIMITATIONS

- Complexity rises with the number of decision trees.
- High Computational costs to train huge data.
- It didn't classify Brain Tumor Grades.
- Random Forest classifier can only work with Tabular Data.

IV.PROPOSED METHOD

The Proposed process involves in classifying four types of tumor grades and six classes to detect its location.

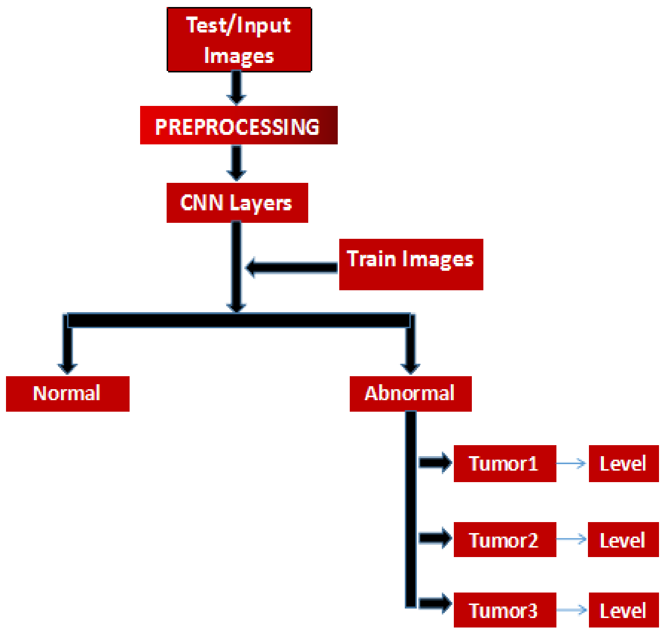


Figure 4: Block diagram of proposed method

G.Pre-processing

The pre-processing technique is used to improve the micro resonance image characteristics. This process makes appropriate perception of for people and systems. In order to increase the signal to noise ratio, information storage capacity and also to improve the MRI images and frameworks we are use this preprocessing method. This pre-processing is also used to clear the disturbances and unnecessary things in the circumferences. This pre-processing method clear the image and stores it boundaries. In order To improve the signal-to-noise ratio, and to clear the MRI.

H.CNN Layers

Convolution neural networks are part of deep learning usually used to analyze visual images. Convolution neural networks uses a mathematical operation which is known as Convolution. CNN uses convolution in place of traditional matrix multiplication in their layers. It consists of input, hidden and output layers. Input image layer is the first layer which takes input images of size 227x227x3, where 3 is the input channel size. Followed by Convolution, Max pooling layers and Fully connected layers are of hidden layers which are used to extract features to analyze, learn and finally to classify the images. Convolution layers uses different filters to extract features like edges, blobs and shapes. Filter size is depended on kernel size. In a CNN, each layer has two parameters : weights and biases. The total number of parameters is just the sum of all weights and biases. Let's define,

Convolution layer

$W_C = K^2 * C * N$

$B_C = N$

$P_C = W_C + B_C$

Fully connected layer

$W_{fc} = O^2 * F * N$

$B_{fc} = F$

$P_{fc} = W_C + B_C$

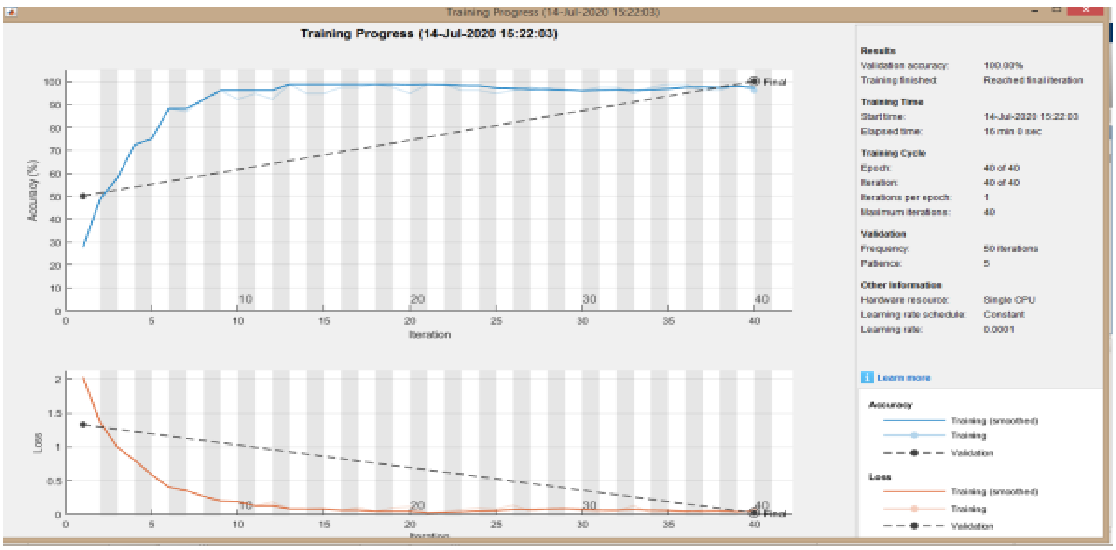
W_C=Number of weights of the Convolution Layer.
B_C=Number of biases of the Convolution Layer.
P_C=Number of parameters of the Convolution Layer.
Wfc= Number of weights of the Fully Connected Layer.
Bfc = Number of biases of the Fully Connected Layer.
Pfc = Number of parameters of the Fully Connected Layer.
K = Size (width) of kernels used in the Convolution Layer.
N = Number of kernels.
O= Size (width) of the output image of the previous Convolution Layer.
F = Number of neurons in the FC Layer
C = Number of channels of the input image.

In a Convolution Layer, the depth of every kernel is always equal to the number of channels in the input image. So every kernel has K2*C parameters, and N such kernels. The pool size, stride, and padding are hyper parameters. After extracting features and important information from the preprocessed images, this information is sent to FullyConnected layer. Here this FullyConnected layer learns about the features and compiles the whole data extracted from previous layers and computes the final output. FullyConnected layer predicts the best label for the input image. Before testing the test data we need to train the CNN layers with the given data sets. The given data sets are divided into training set and validation set. The training is useful to train the model and validation set is useful for validating the model's performance. Metrics of training set indicates the performance of its training whereas metrics of validation set indicates how well the model works for the data that hasn't experienced or trained before. Loss and accuracy are the measures calculated on training set, similarly val_loss and val_accuracy is calculated on validation set. Now the test data is given for testing. If it is a normal image the result shows as Normal grade type and Class 1 image. If the given test image is of any one of the tumor grade type, result displays the name of grade type and to detect its location the model has to train and validate with respective data sets again and displays as class 2/3/4/5/6. Which indicates the location of tumor in the brain

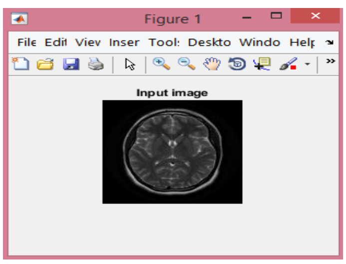
Advantages:

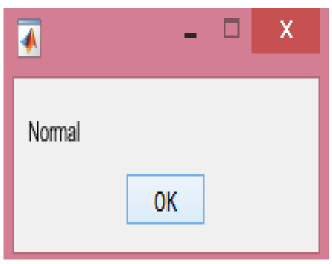
- Very accurate classification
- Less complexity.
- It can work with different data types (tabular data, images, audio video etc.,)

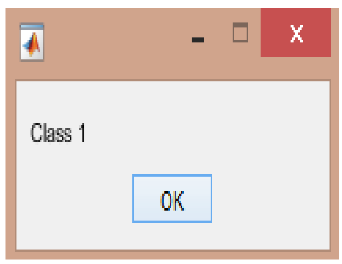
V.RESULTS



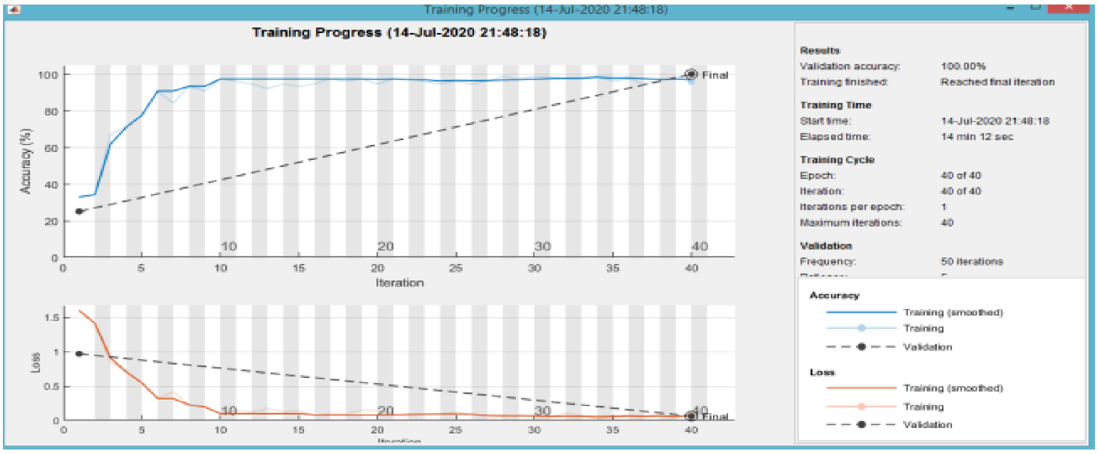
Accuracy(tumor)



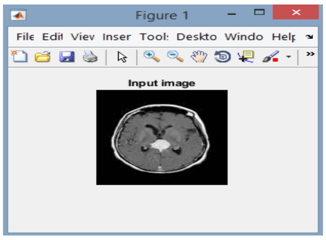


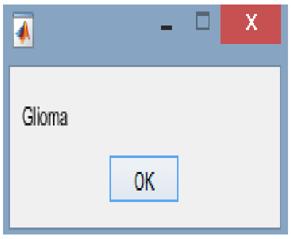


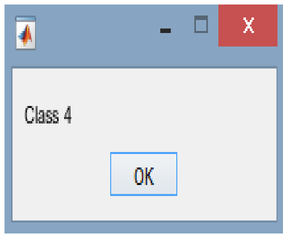
Input Image **Tumor Grade** **Class Type**



Accuracy(tumor)

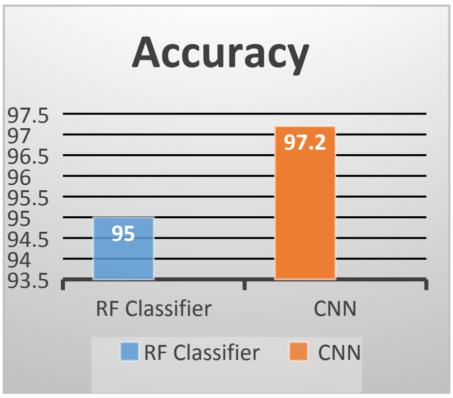






Input Image **Tumor Grade** **Class Type**

VI.COMPARISION



VII.CONCLUSION

This study shows that the classification of tumor using the CNN may yield better results when compared to previous methods. It also classify different types of Brain Tumor grades like Glioma, Meningioma and Pituatory and also detected its features and location.

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