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iajpb.editor@gmail.com
editor@iajpb.com



Brain Tumor Classification Using CNN

S.RAHULRAJA1,DrD.GOWRISANKARREDDY2

ABSTRACT- Classification of brain tumors is commonly accomplished using a variety of imaging modalities. MRI, on the other hand, is frequently employed due to its greater image quality and lower radiation exposure. Deep learning (DL), a branch of machine learning, has recently shown greater results, particularly in classification and segmentation. There is a primary goal of obtaining and classifying the brain tumor. It is possible to do this by using Alexnet's Convolution and Fully-Connected layers. These Layers extract aspects of the tumor and identify the grade, and they locate the tumor in the brain with high accuracy.

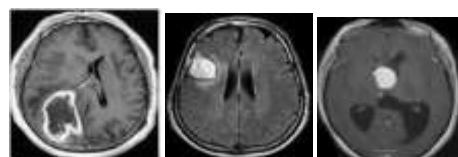
Keywords:CNN,Alexnet,DeepLearning,ConvolutionandFullyConnectedlayers.

I.INTRODUCTION

Brain Tumors are the result of aberrant cell



development in the brain. It is critical to locate a tumor as soon as possible. We can discover aberrant cell growth in any part of our bodies using ultrasound pictures. Magnetic Resonance Imaging (MRI) is commonly used to categorize aberrant cells in the brain based on their temporal length of life. To reduce the number of deaths from brain tumors, the use of high standards of specific imaging is critical. The location, size, and growth of a tumor in the brain can't be predicted, thus treatment is tailored to the



patient's specific needs. Rather than harming other areas of the brain, treatment is aimed at eradicating or eliminating the tumor. Classification and detection of tumor sites in patients' brains can be accomplished in a variety of ways, as illustrated in the following steps.

Figure-1normalimages

Figure-2Abnormalimages

MRI pictures can now be used to classify brain cancers, according to a novel approach. In the preprocessing stage, a variety of photos are provided. In the second stage, features and parameters are extracted and calculated. To turn a grayscale image into a three-channel RGB image, a single channel is replicated. The first layer of AlexNet was fed by 227x227 random croppings from the 256x256 photos..

1M.Tech,DepartmentofElectronicsandCommunicationEngineering,S.V.University,Tirupati
2AssistantProfessor,DepartmentofElectronicsandCommunicationEngineering,S.V.University,Tirupati
1rahulrajasamini@gmail.com

II. LITERATURE REVIEW

1. Tian, Jie Jian Xue, Yakang Dai, Jian Chen, Jian Zheng, used a Novel Package platform to integrate the thought algorithms for medical image processing and analyzed intervals of standardized framework, as well as

reconstruction, segmentation, registration, visual image, etc., and provides a robust tool for each scientist and engineers.

2. El-Sayed A. El-

Dahshan, Heba M. Mohsen, Kenneth Revett, Abdel-

Badeeh M. Salem, had executed the experiments on a single zero-one snapshot of a real human brain MRI dataset, with 14 normal and 87 atypical (malignant and benign tumors) findings. The 99 percent accuracy rate for each training and test photograph was a notable fact..

3. M. Soltaninejad, et al, MRI images are identified and categorized using an automated process. The classification of each Super Pixel and the Super Pixel Technique are the foundations of this approach. There are two different methods used to classify each super pixel: Extremely randomized trees (ERT) and SVM. MRI FLAIR images and BRATS datasets are used in this method (2012).

4. S. Pereira, et al, Tumors were detected by utilizing a CNN with three tiny kernels and an automatic classification approach. At the BRATS Challenge 2013, the technique achieved first place in the whole, core, and enhancing areas of the dice similarity, coefficient metric (0.88, 0.83, 0.77).

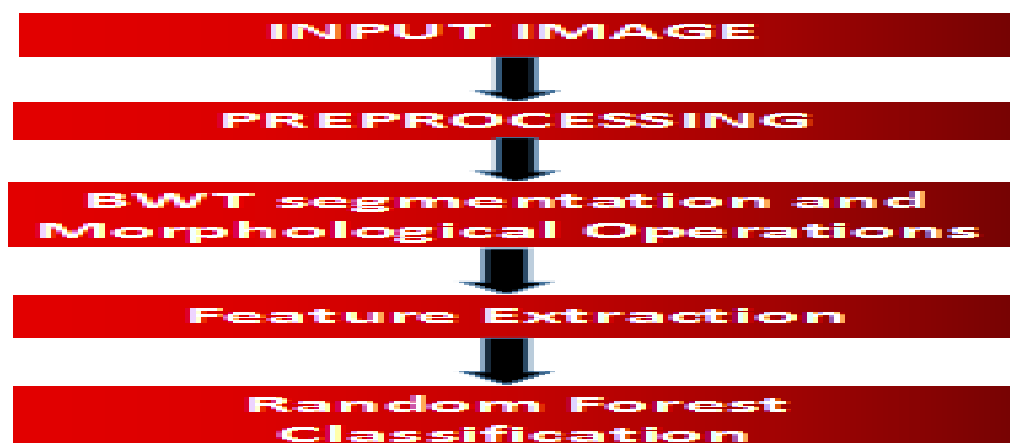
5. L. Szilagyi, et al for segmenting MRI images of brain tumors using a multi-stage fuzzy C-Means architecture. Tested on six volumes from the BRATS2012 database, using the algorithm. A Dice score between 0.7 to 0.9 indicates a usually high level of calculated accuracy.

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 basic 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 existing method is shown in below figure:

Figure-3: Block diagram of Existing method



To improve the MRI image quality, preprocessing is used. People and systems

benefit from this process, which helps them perceive the world in a more accurate way.

This article can be downloaded from <http://www.iajpb.com/currentissue.php>

This preprocessing method is used to improve the MRI images and frameworks, as well as to raise the signal to noise ratio, information storage capacity, and overall quality of the images. This pre-processing is also utilized to remove any unneeded or distracting elements from the circumferences. The boundaries of the image are stored in this preprocessing approach. MRI signal-to-noise ratio needs to be improved, as well as the MRI itself cleaned up. We used a modified sigmoid function to apply adaptive contrast enhancement.

B.

Contrast Enhancement and Skull Stripping

Contrast Enhancement is used to improve the appearance of low-resolution MRI images so that they may be processed by either a human or a machine vision system. Non-brain tissues such as fat, skin and skull are removed from pictures via Skull Stripping. In brain MRI pictures, the histogram analysis technique is utilized to exclude objects that aren't related to the brain.

C.

Segmentation and Morphological Operations

7. 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, in order 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.

A.

Feature Extraction

Feature extraction can be carried out by calculating

parameters. A = perimeter / Area

B = Perimeter / Major axis length

C = Major axis length *

((1/major) - (1/minor)) D = Major - Minor

The lesion's area (A) is the number of pixels. The number of pixels in a contour's perimeter is denoted by the letter P.

The major axis length (Ma L) is the distance between the two farthest boundary points of

the lesion and the line going through its centroid. The minor axis length (Mi L) is the distance between the two neighboring boundary points that passes through the centroid of the lesion blob.

B. Random Forest Classifier

Regression and classification tasks can be performed using numerous decision trees in Random Forest, a machine learning technique. A Random Forest classifier is used to identify the class from the extracted features. Instead of collecting average or mean values, we are employing certain specific keys to generate random numbers. Hapless forest analysis is another name for it. A higher specific rate and a consistency indication are obtained by combining multiple resolutions rather than by using individual indicator trees. The trees get information in a resolution forest which came through haphazard fragment.

Bootstrap 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%.

C. 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) = Where,

TP : True Positive, TN: True Negative, FP: False Positive and FN: 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: $0 \leq SSIM \leq 1$

LIMITATIONS

Complexity rises with the number of decision trees.

?

High Computational cost 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

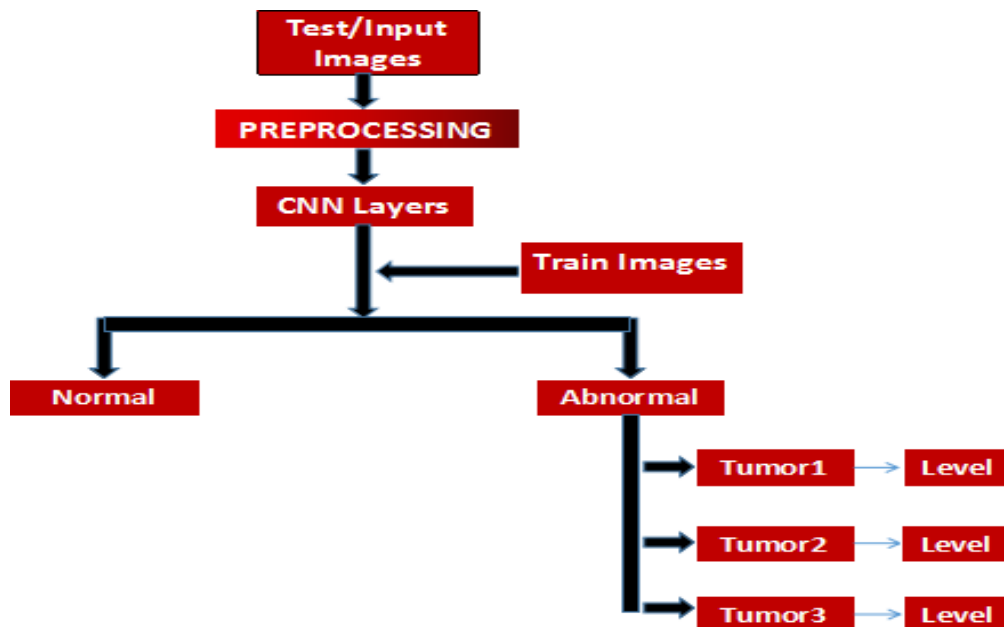


Figure4:Block diagram of proposed method

Using the pre-processing technique, the micro resonance picture can be improved. Using this method, individuals and systems can have an accurate understanding of each other. Adding more information will help improve the signal-to-noise ratio.

This preprocessing procedure is used to increase storage space and to improve the quality of MRI pictures and frameworks. In addition, this pre-processing is utilized to remove unwanted and distracting elements from the surrounding area. Prior to further processing, the image is cleaned up and its borders are saved. MRI signal-to-noise ratio needs to be improved, as well as the MRI itself cleaned up.

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 $227 \times 227 \times 3$, 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 $WC = K^2 * C * NBC = N$
 $PC = WC + BC$
Fully connected layer $W_{fc} = O^2 * F * N$
 $B_{fc} = F$
 $P_{fc} = WC + BC$

WC=Number of weights of the Convolution Layer.BC=Numberofbiasesof theConvolutionLayer.

PC=Number of parameters of the Convolution Layer.Wfc= Number of weights of the Fully Connected

Layer.Bfc=NumberofbiasesoftheFullyConnecte d 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 ofneurons in the FCLayer

C=Numberofchannelsoftheinputimage.

Every kernel's depth is equal to the number of channels in the input picture in a Convolution Layer. As a result, each kernel has $K2 \times C$ parameters, and there are N such kernels in total. Size of the pool, stride, and padding are all hyperparameters, as are other aspects of the ride. Using the preprocessed images, data is extracted and delivered to a layer called the FullyConnected layer. Here, the FullyConnected layer gathers all of the data gleaned from preceding layers, calculates the final result, and then learns about the characteristics. The input image's label is predicted by the FullyConnected layer.

V. RESULTS

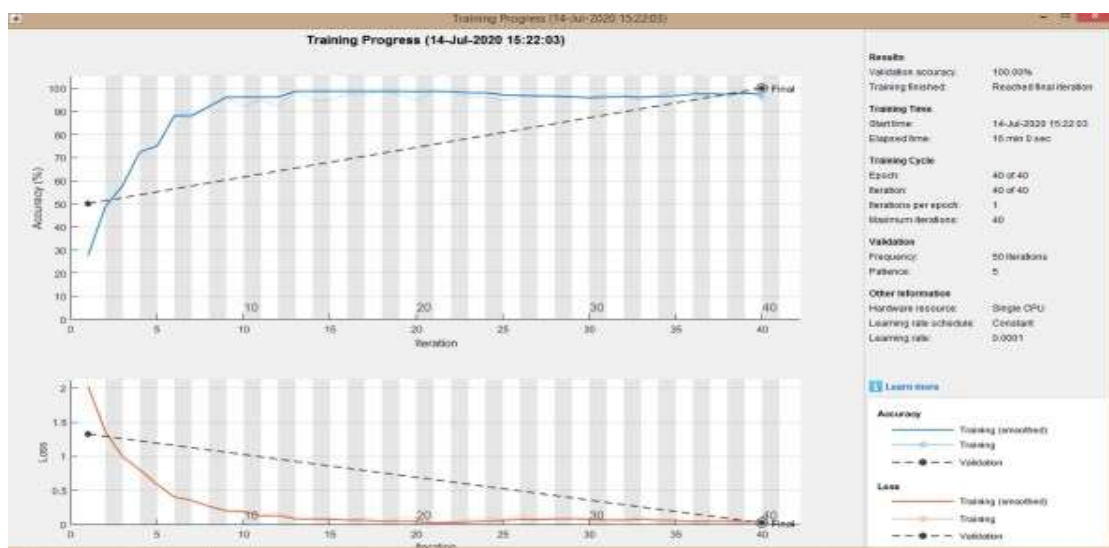
Training the CNN layers with the specified data sets is necessary prior to conducting a test. There are two sets of data provided: one for training and the other for validation. The training set is used to develop the model, whereas the validation set is used to verify the model's output. The training set's metrics show that

The measures of the validation set reveal how effectively the model works for data that has not previously been trained or experienced by the model itself. Training set loss and accuracy are measured, whereas validation set loss and accuracy are measured as well. Now that the test data has been provided, you can begin testing. In this case, the grade type is Normal, and the image is classified as Class 1. In order to correctly identify a given test image as belonging to a particular tumor grade, the model needs to be retrained and validated on a different set of data. In this way, the location of the tumor can be determined in the brain

Advantages:

- ☐ Veryaccurate classification
- ☐ Lesscomplexity.
- ☐

Itcanworkwithdifferentdatatypes(tabu lardata, images,audiovideoetc.,)

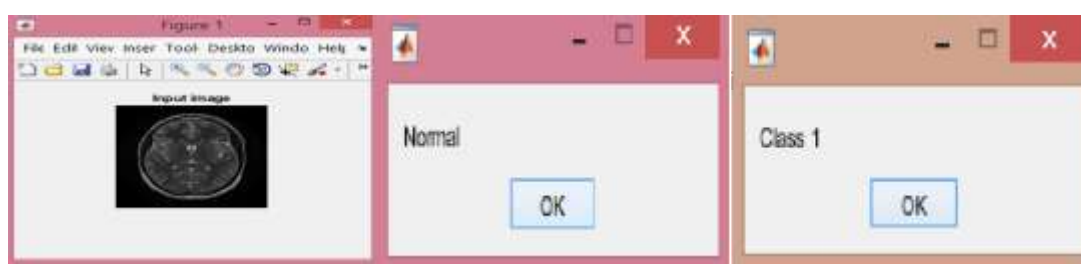


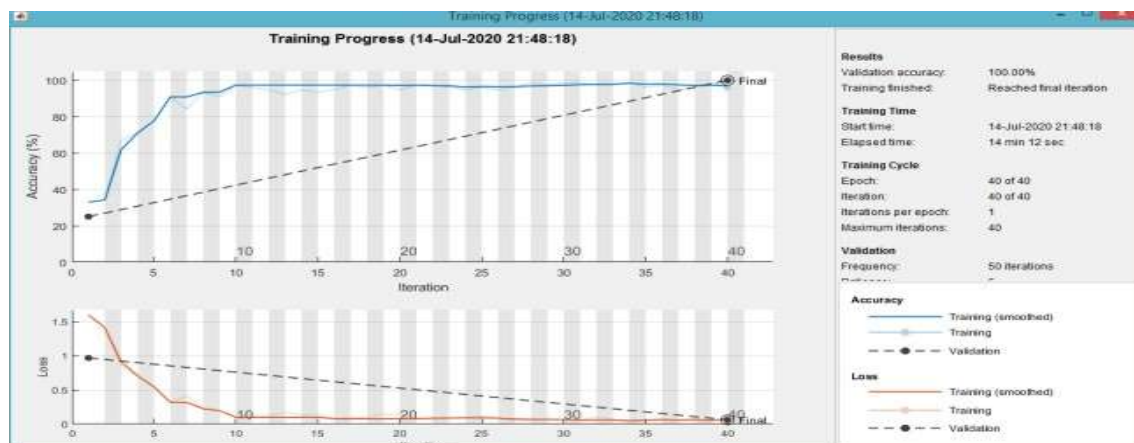
Accuracy(tumor)

InputImage

TumorGrade

ClassType



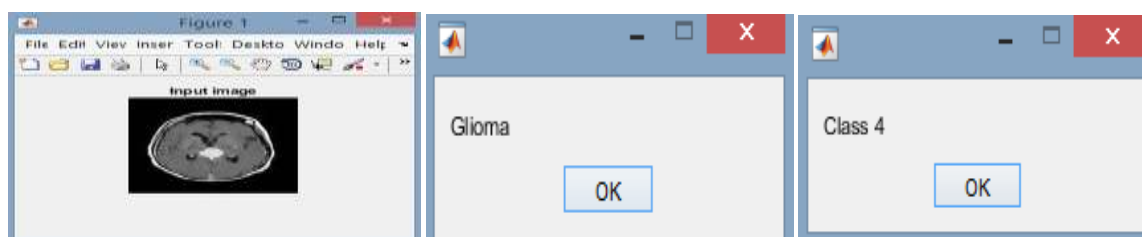


Accuracy(tumor)

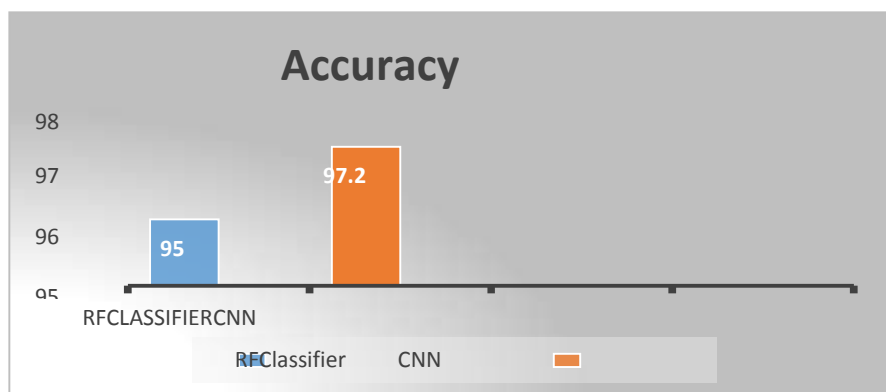
InputImage

TumorGrade

ClassType



VI. COMPARISON



VII. CONCLUSION

CNN-based tumor classification may be more accurate than prior methods, according to this study. Brain tumor grades like Gliomas, Meningiomas, and Pituitary were also categorized and recognized by the software.

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