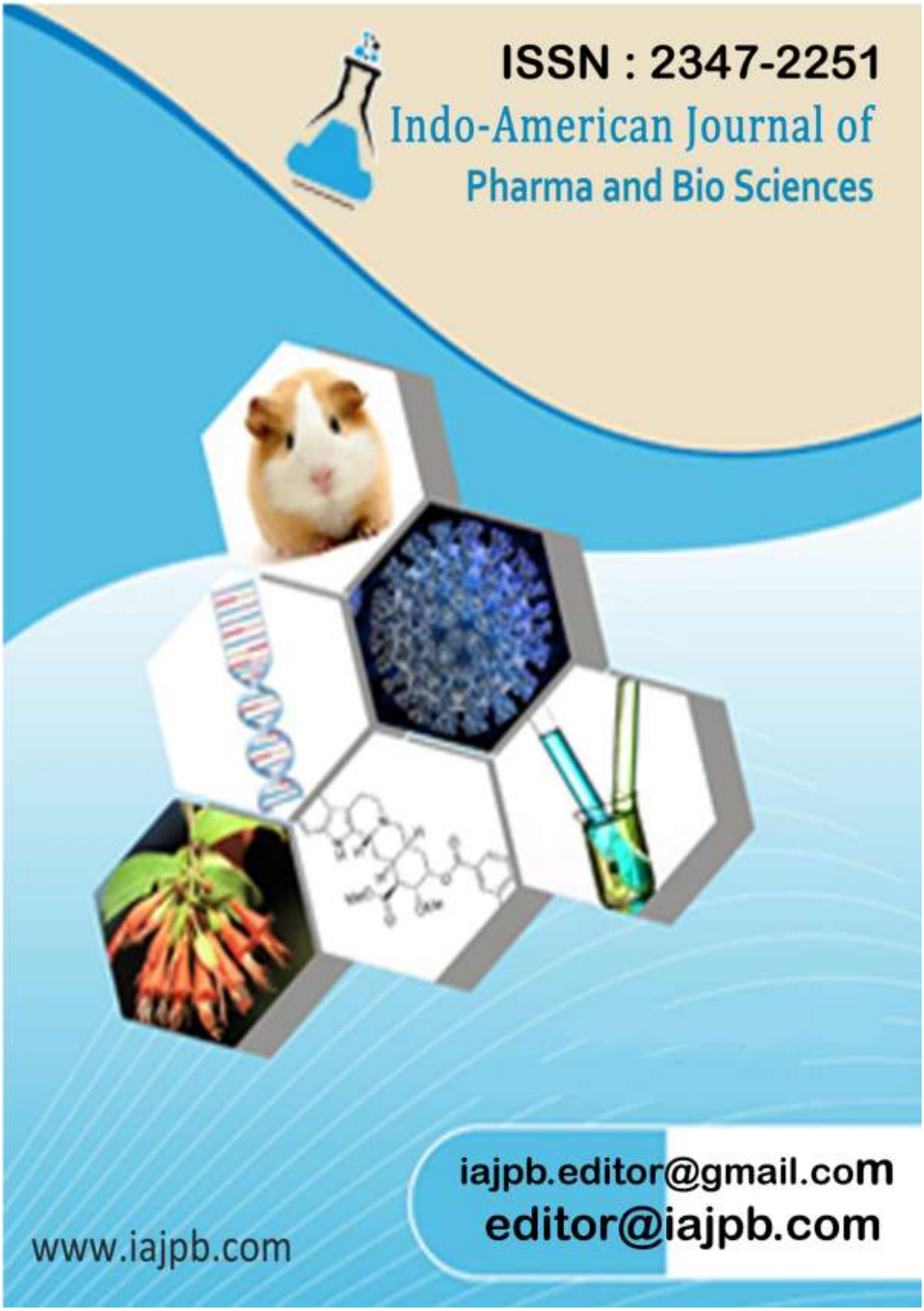
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Brain Tumor Classification Using CNN

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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

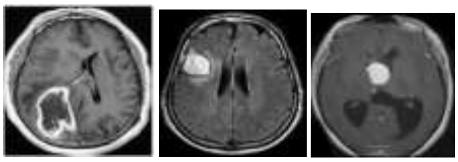

Figure-2Abnormalimages

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..

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II.**LITERATUREREVIEW**

1.Tian,JieJianXue,YakangDai,JianChen,JianZheng,usedaNovelPackageplatformtointegratethe thoughtalgorithmsformedicalimageprocessandanalyzedintervalsofstandardizedframework,aswellas reconstruction, segmentation, registration, visual image, etc., and provides a robust tool for each scientists andengineers.

2.El-SayedA.El-Dahshan,HebaM.Mohsen,KennethRevett,Abdel-BadeehM.Salem,hadexecutedtheexperiments onA single zero-one snapshot of a real human brain MRII 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).

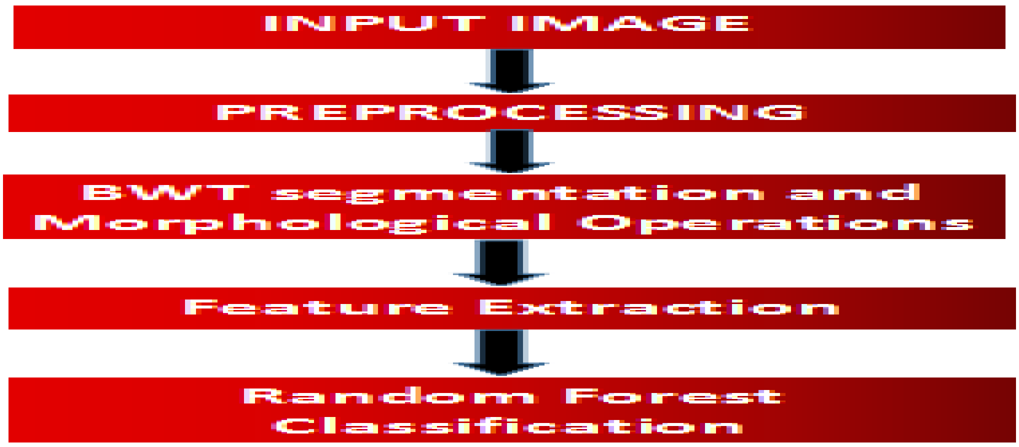
5.L. Szilagyi, etafor segmenting MRI images of brain tumors using a multi-stage fuzzy C-Means architecture. Tested on six volumes from the BRATS2012 database, using the algorithm. A Dice score between 0.7 to 0.9 indicates a usually high level of calculated accuracy.

6.Y. Pan, et al,has studied multiphase MRI images in tumor grading and a comparison has been made between theresultsofdeeplearningstructuresandbaseneuralnetworks.Theresultsshowthatthenetwork performancebased on the sensitivityand specificityof CNNimproved by18% compared to theneural networks.

III.**EXISTINGMETHOD**

Theblock diagram fortheexistingmethod is shownin below figure:

Figure-3:BlockdiagramofExisting 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 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. **ContrastEnhancementandSkullStripping**

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. **SegmentationandMorphologicalOperations**

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,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 ordertoextract thetumor part in theMRIimage.

A. **FeatureExtraction**

$$\frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

Feature extraction can be carried out by calculating ABCD parameters.A=perimeter/Area B=Perimeter/Majoraxislength C=Majoraxislength* ((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.RandomForest 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.Thetreesgetinformation inaresolutionforestwhichcamethroughhaphazardfragment.
- BootStrappingshows allreplaced ornew fragments.Few fragmentsareusedmanytimes inonefragment.
- Inthiscombinationoftotalguidanceinformationandtheintegratedforestwillhavelowtendency rateandlowdifference.
- Ifbootstrapgoeswrongwecangowithhaphazardbyhavingequalinformationwithindividualtrees.
- UsingthismethodanddatainRandomForestClassifier,sixclassesofdataisclassifiedusingABCDparameterswith an accuracyof 95%.

C. PerformanceMeasure

- Performancemeasuretoclassifywhetheritisatumorornontumorisobtainedbasedonfourevents,twoclassificationsand two misclassifications.
- Accuracy=TP+TN/(TP+FN+TN+FP)
- Structural similarity index measure (SSIM) =Where,
- TP :TruePositive,TN:TrueNegative,FP: FalsePositiveandFN:False Negative
- Accuracy:Itis the ratioof correctlyclassifiedpixels tothe total numberofpixels inthe image.
- SSIM : SSIM is defined as how much amount of similarity is between the ground truth and input image.Range: 0 <=SSIM<=1

LIMITATIONS

Complexityrises with thenumberof decision trees.

HighComputationalcoststotrainhugedata.

Itdidn'tclassifyBrainTumorGrades.

RandomForestclassifiercanonlyworkwith TabularData.

IV. PROPOSEDMETHOD

TheProposedprocessinvolvesinclassifyingfour typesoftumor gradesandsixclassestodetectitslocation

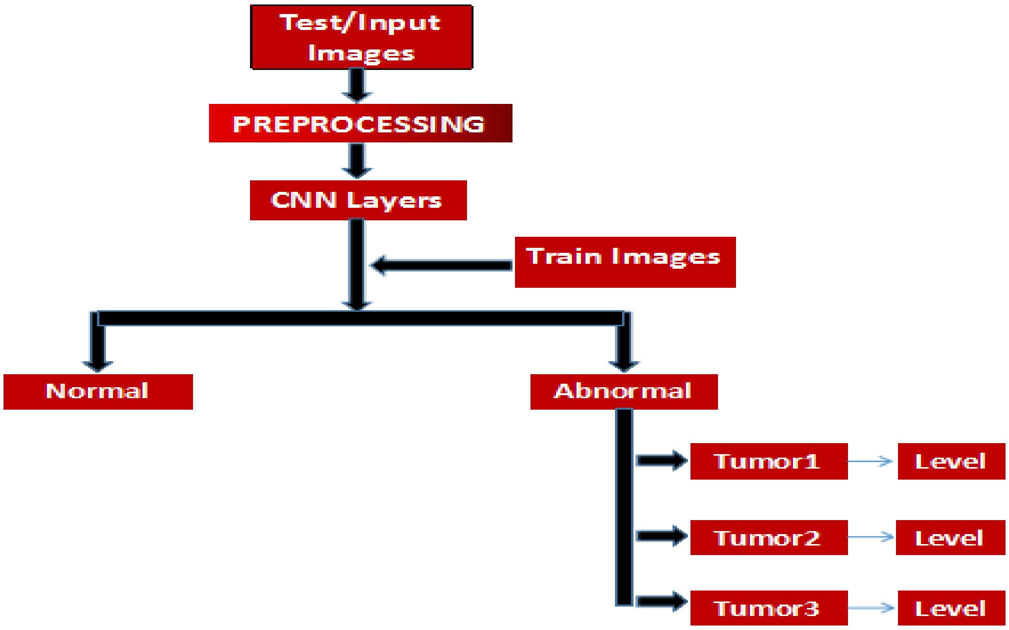


Figure4:Blockdiagramofproposed method

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.CNNLayers

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

Convolution layerWC=K2*C*NBC=N

PC=WC+BC

Fully connected layerWfc=O2*F*N

Bfc= F

Pfc=WC+BC

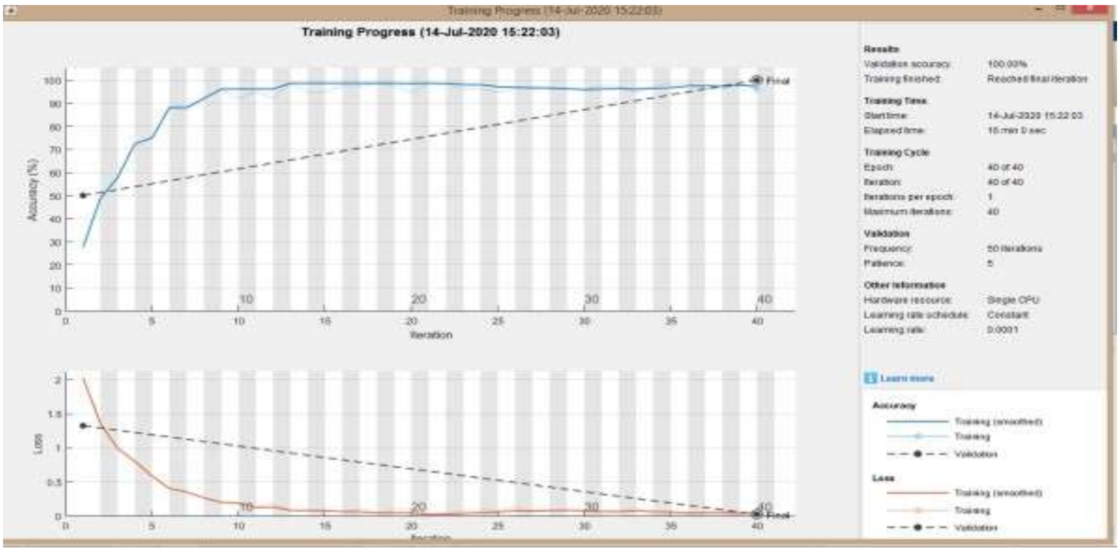
WC=Number of weights of the Convolution Layer.BC=Numberofbiasesof theConvolutionLayer.
PC=Number of parameters of the Convolution Layer.Wfc= Number of weights of the Fully Connected Layer.Bfc=NumberofbiasesoftheFullyConnected Layer.
Pfc = Number of parameters of the Fully Connected Layer.K = Size (width) 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*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

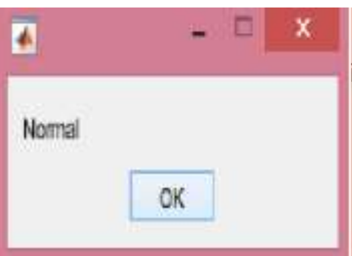
Advantages:

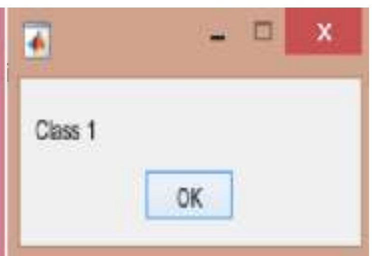
- Veryaccurate classification
- Lesscomplexity.
- Itcanworkwithdifferentdatatypes(tabulardata, images,audiovideoetc.,)

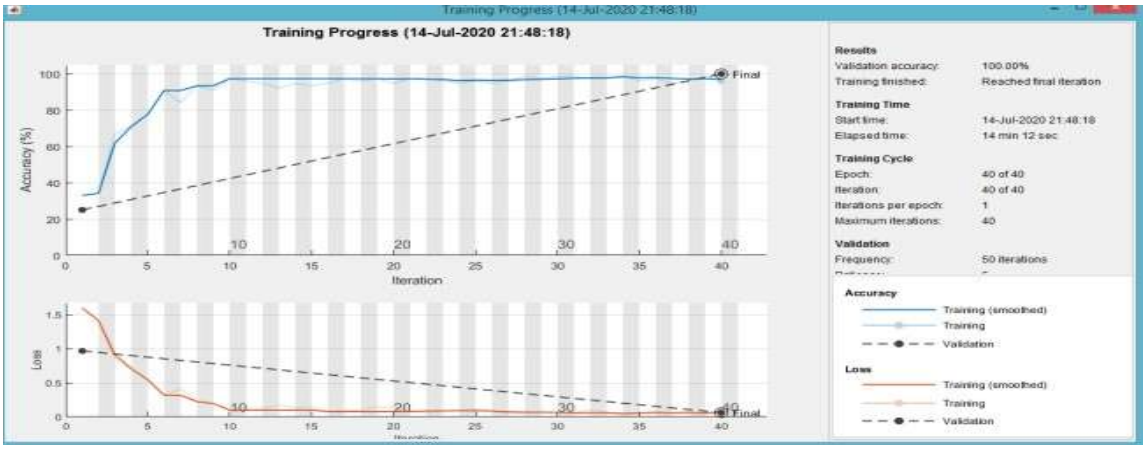


Accuracy(tumor)

InputImage **TumorGrade** **ClassType**

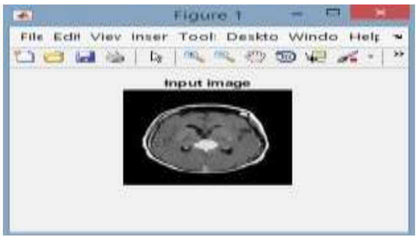


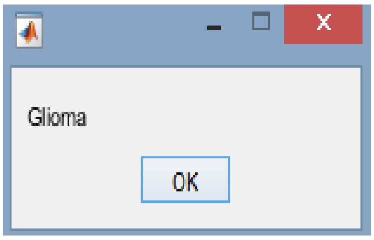


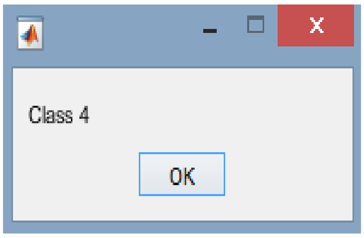


Accuracy(tumor)

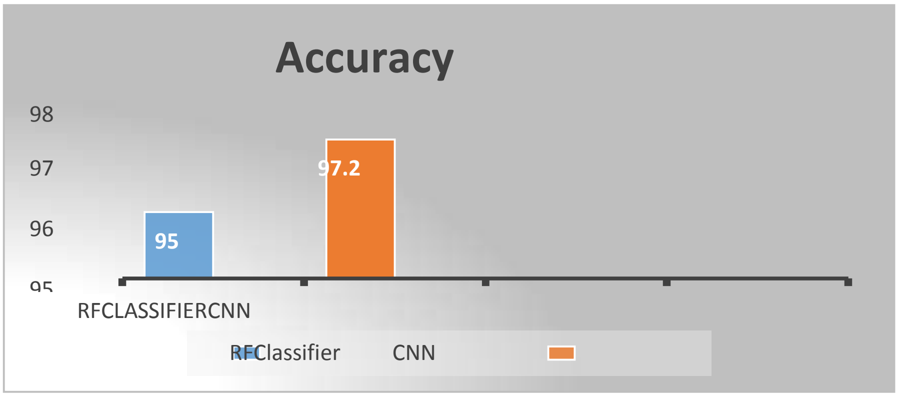
InputImage **TumorGrade** **ClassType**







VI. **COMPARISION**



VII. **CONCLUSION**

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

VII.REFERENCES

[1]Tian, JieJianXue, Yakang Dai, Jian Chen, JianZheng,A Novel package Platform for Medical Image process and Analyzing,IEEETrans.Inf. Technol.Biomed., vol. 12, no.6,pp.800–812, Nov. 2008.

[2]There are many different ways to identify cancer, but the most common one is to use a computer program to identify it. In this study, researchers used MRII to identify cancerous tumors in humans, and they found a novel formula that can help identify them.

[3]M. Soltaninejad et al, Automated detection and segmentation of FLAIR MRI brain tumors using superpixel-based very randomized trees, International journal of computer assisted radiology and surgery, pp. 183-203, 2017.

[4]The use of convolutional neural networks in MRI images for the segmentation of brain tumors was published in IEEE Transactions on Medical Imaging, 35(5) (2016) 1240-1251.

[5]This work was presented at the IEEE 12th International Conference on Fuzzy Systems

and Knowledge Discovery (FSKD), 2015, by L. Szilagyi and colleagues, who used a fuzzy c-means cascade technique to automatically segment brain tumors in multispectral MRI volumes (pp. 285-291).
[6]Sixth Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) (pp. 699–702) is an annual conference of the IEEE Engineering in Medicine and Biology Society (EMBC).
[7]Deep convolutional activation features for large-scale classification and segmentation of brain tumor histopathology images, in the 2015 IEEE international conference on acoustics, speech and signal processing (ICASSP), 2015 IEEE international conference on acoustics, speech and signal processing

[8] * Joint tumor segmentation and dense deformable registration of adult male brain images in Proc. MICCAI 2012, pp. 651–658. * S. Parisot, H. Duffau, S. Chemouny, and N. Paragios,

[9] For example, see S. Lahmiri and M. Boukadoum, "Feature extraction from mammograms using SVM using DWT and RT," in Proceedings of IEEE BioCAS 2011, pp. 412-415.

[10] ZümriayDokur and ZaferIscan are animal trainers, respectively. Victimization as a method of tumor identification On brain images, Zernike = moments on metameric resonance, professional Systems with,Applications, vol. 37, no. 3, pp. 2540–2549, March