ADVANCEMENT IN AUTOMATIC DIAGNOSIS OF BRAIN TUMOR USING CONVNETS

D.Bharathi Shree[1], Dr. J. Augustin Jacob[2], K.Ramya[3], M. Poornalakshmi [4]

PG Scholar[1,3,], Department of ECE, Sri Vidya College of Engineering and Technology, Virudhunagar, India.

Associate Professor[2], Department of ECE, Sri Vidya College of Engineering and Technology, Virudhunagar, India.

Assistant Professor[4], Department of ECE, Sri Vidya College of Engineering and Technology, Virudhunagar, India.

ABSTRACT

In the present days, Brain tumor is an epidemic disease that threatens the human life. Because, brain tumor is considered as leading cancer which increases the mortality among children and adults. The main reason behind this tragic end is not doing the early screening. Magnetic resonance imaging (MRI) technique is widely used for early detection of any abnormal change in Brain. The manual diagnosis of spatial and structural variability of brain tumor is a challenging task in the field of medical science because of not sufficient domain experts and also a time-consuming process. In recent years, many computer aided diagnosis for automatic classification of brain tumor has been developed. Among them, advancement in automatic diagnosis of brain tumor using ConvNets presents a novel method for brain tumor diagnosis using Convolutional Neural Networks (CNN, or ConvNets) to provide deeper architecture and positive results against over fitting. The proposed system obtained's DSC, accuracy of 100% and provided the better diagnosis of tumor. The method obtains accurate results in all three views of MRI images, which will help neurosurgeon in fast analysis.

Keyword: brain tumor classification, Convolutional Neural Network, Deep Learning, SVM, MRI images.

INTRODUCTION

Now a day, Brain tumors are life - threatening because it has significant impact on quality of life. Most research on developed countries show that the number of people who develop brain tumors and die from them has increased as much as 300 over past years. An estimation of 7,00,000 people in the United States are victim of primary brain tumor, and over 79,000 more people were diagnosed with brain tumor in 2018. Among them, 55,150 people are suffering from benign and 23,830 people are suffered from malignant.

Diagnosis of a brain tumor is done by a CT scan (computer tomography scan), magnetic resonance imaging (MRI), angiogram and biopsy. Magnetic Resonance Imaging (MRI) is employed as a precious tool of diagnosing in neurology and neurosurgery. The most common MRI sequences used are T1-weighted and T2-weighted scans. In general, T1- and T2- weighted images are often simply differentiated by examining the CSF. CSF will be dark on T1- weighted imaging and bright on T2-weighted imaging. MRI is examined by radiologists based on visual interpretation of the films to identify the presence of tumor tissues.

Manual detection may become tough once radiologists need to analyze more MRI images. So, computerized detection methods are developed over years. The traditional computerized diagnosis consists of several phases like preprocessing, segmentation, features extraction, feature reduction and classification. Several segmentation strategies have been used previously. Computerized Tumor Boundary Detection using a Hopfield Neural Network is initially used to detect the boundary of the brain tumor in each image slice [1]. Various methods such as adaptive thresholding technique and canny edge detection, to detect the change of luminance intensity around the tumor in the segment of the tumor region, are presented [2 - 5]. In the earlier reports, it is reported that the histogram based segmentation and Ostu binarization provide the better results [6, 7]. Sometimes, the tumor is identified as wrong class because previous method detects the region that includes other matter of tissues as edge. To overcome these, relays on segmentation based on conditional random field [8], region growing, fuzzy C-mean [9], k-mean clustering [10, 11] and wavelet transform [12] was adapted. Especially the post extraction was performed using SVM, DWT, PCA and biologically inspired BWT [13, 14**].**

Another learning approach that has successfully applied in brain tumor segmentation and classification is Support Vector Machine. SVM is well suited for binary classification of images as mentioned by many researchers [15-20]. Later to obtain better accuracy several kernels SVM is preferred [21]. The problem in classifying many objects, Neural Network is emerged as a classification algorithm to provide the better diagnosis as of human brain neurons predict [22]. But among Neural Network architectures, Deep Learning is preferred [23].

Deep Learning deals with automatic learning of features directly from dataset provided. The main motto for the author in the field of deep learning is to design the architectures. CNN operates over images using kernel filters. Thus, it has been used to win several challenges. Recently, the authors have investigated various architectures. Basic CNN architecture contains subsequent layers of convolution, pooling, activation, and fully connected. To perform a prediction of an input data, the output scores of the final CNN layer are connected to loss function [24-27]. Hence, we have been inspired by the groundbreaking work of Alex Krizhevesky on deep CNNs. In this paper, various pretrained imagenet is investigated to find whether the pretrained nets which are capable in classify new data categories and to train with biomedical dataset. It provides the deeper CNNs and use of non linearity ReLU after every convolutional layer makes the architecture less prone to over-fitting.

The remaining paper is organized as follows. Section II presents the Proposed Architecture. Section III describes the dataset and evaluation metrics. Section IV provides detail explanation on results and discussion. Finally, Section V represents the conclusion of the work.

PROPOSED ARCHITECTURE:

A CNN is composed of an input layer, an output layer, and many hidden layers in between them. The hidden layers includes multiple convolutional layers, RELU layer i.e. activation function, pooling layers and fully connected layer. Alexnet architecture consists of five convolutional layers, three sub sampling layers and three fully connected layers.

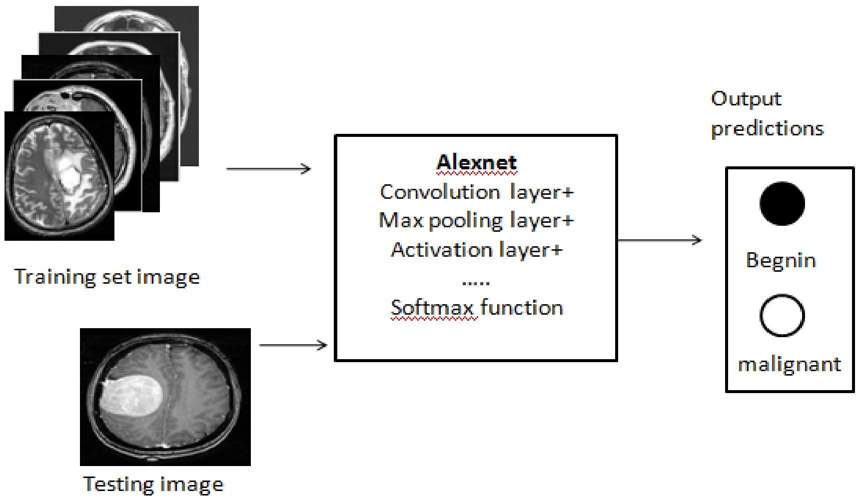


Fig1: Block Diagram of proposed method

The input of the net is zero normalized and is in size of 227 x 227 x 3. The Alexnet input layer is set to process RGB image. Preprocessing of an image is performed to the dataset images. After input layer, Convolutional layer processes with multiple kernels of same size are used to extract the feature map directly from the image by sliding the kernel over the image and computing the dot product. The first convolutional layer uses 96 kernels of size 11x11x3. The width and height of the kernel are same as of the number of channels. Alexnet uses a different activation function called Rectified Linear Unit (ReLU) after every convolutional layers. ReLU transforms the convolutional layer linear output as non linearity data. Using ReLU nonlinearity, deep CNNs can provide faster training compare to activation function such as tanh and sigmoid. ReLU function is given by

$$F(x) = \max(0,x)$$

Max pooling layer such as 3x3 max pooling with 2 cells are used after convolutional layers of 1, 2 and 5. Max pooling layer will downsample the width and height of the images, keeping the depth same. The arrangement of convolutional and pooling layers reduces the number of input features from 154587 to 4096 before processing fully connected layers. The output of third pooling layer is inputted to fully connected layers. Processing called Dropout is carried out to reduce overfitting after fully connected layers. Finally the 4096 neurons are carried to softmax function having class labels.

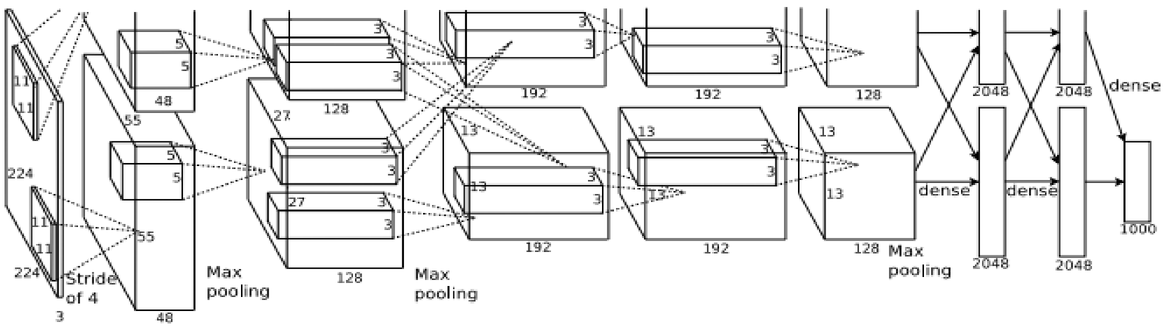


Fig2: Alexnet architecture

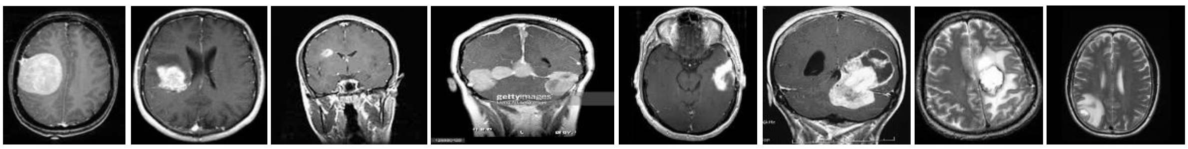
Table1: Architecture of the CNN. Where CL refers to Convolutional Layer and ML to Max Pooling Layer and FC to Fully Connected Layer.

Layer	Type	Input	Filter size	FC units	Stride	No of filter
1	CL	227x227x3	11x11x3	0	4x4	96
2	MPL	55x55x96	3x3	0	2x2	-
3	CL	27x27x96	5x5x48	0	1x1	256
4	MPL	27x27x256	3x3	0	2x2	-
5	CL	13x13x256	3x3x256	0	1x1	384
6	CL	13x13x384	3x3x192	0	1x1	384
7	CL	13x13x384	3x3x192	0	1x1	256
8	MPL	13x13x256	3x3	0	2x2	0
9	FC	6x6x256	0	4096	0	0
10	FC	4096	0	4096	0	0
11	FC	4096	0	2	0	0

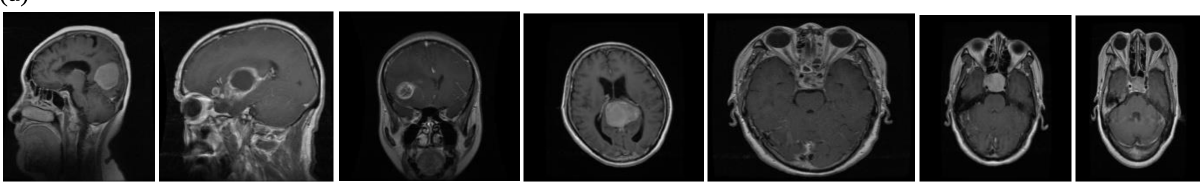
EXPERIMENTAL SETUP:

DATABASE:

The proposed method was validated on both the T1 and T2 weighted MRI images dataset. The first set of dataset based on T2 weight MRI images are used to compare proposed method with traditional method for classification of tumor as begnin and malignant. The dataset comprises of 18 MRI images whereas 9 are begnin tumor and remaining 9 images are malignant. Training set contains 6 begnin and 6 malignant tumor MRI images. Second set of dataset contains T1-weighted contrast-enhanced images from various patients with three kinds of brain tumor: meningioma, glioma and pituitary tumor. The dataset are from figshare. From that dataset, 100 meningioma, 100 glioma and 100 pituitary tumor MRI images used for evaluating the proposed architecture's efficiency. Training dataset consists of 70 meningioma, 70 glioma and 70 pituitary tumor MRI images.



(a)



(b)

Figure3: Sample images in dataset (a) Private data (b) Figshare dataset.

EVALUATION:

The evaluation of the segmentation is based on four metrics: Dice Similarity Coefficient (DSC), Accuracy, Sensitivity and Positive Predictive Value (PPV).

Table2: Evaluation Metrics with their respective mathematical formula. Where TP,FP,TN and FN are the numbers of true positive, numbers of false positive, numbers of true negative and numbers of false negative prediction.

Evaluation Metrics	Mathematical formula
Dice Similarity Coefficient(DSC)	DSC=2TP/(FP+2TP+FN)
Accuracy(ACC)	ACC = (TP+TN)/ (TP+TN+FP+FN)
Sensitivity(SN)	SN = TP/ (TP+FN) = TP/P
Positive Predictive Value(PPV)	PREC=TP/(TP+FP)

EXPERIMENTAL RESULTS AND DISCUSSION:

In this section, examination of the diagnosis result of brain tumor of type begnin and malignant using Alexnet architecture is undergone. Consequently, the results of deep learning are compared with the traditional system using SVM. Finally proposed system's result of second dataset containing three types of brain tumor is reported. The entire processes are carried out on software MATLAB version 2018 a.

Segmentation and Classification of Brain MRI Image initiates when the specialist needs to diagnosis the brain MRI image of the patient having tumor. The entire process starts by loading the testing MRI image using the MatLAB command uigetfile. The Alexnet is trained with some of the brain tumor MRI images. The test image and training images are sized to be in 227x227x3 dimensions. The training options used for training the dataset to imagenet are shown in the table. After training, the test results are reported as shown in the table3.

Table3: Proposed method Training Hyper parameters and efficiency of training process. First three columns shows the hyper parameters and remaining three columns shows the efficiency of training.

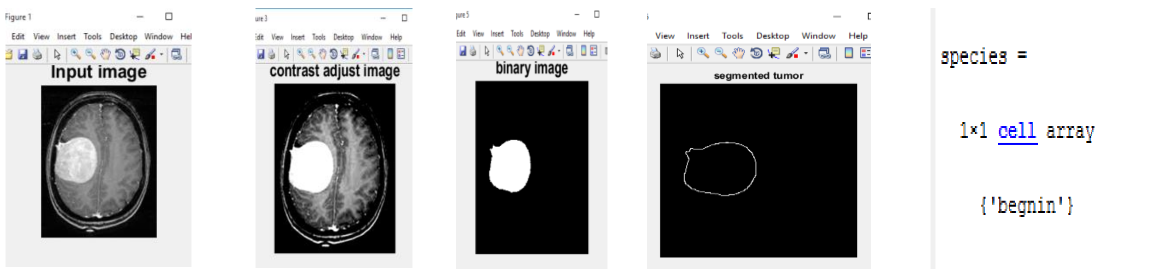
Epoch	Iteration	Base Learning Rate	Time Elapsed(seconds)	Mini –batch Loss	Mini- batch Accuracy
1	1	1.00e-04	122.86	0.8868	50%
15	15	1.00e-04	987.15	0.0082	100%

The system performance of CNN such as DSC, PPV, Accuracy and Sensitivity are evaluated after running system for all the images in the dataset and 100% result is obtained. Hence, the results are compared with the traditional method. The method involves the segmentation by thresholding, features are extracted by the using Discrete Wavelet Transform and Principal Analysis Component and finally classified using Support Vector Machine (SVM). The 13 feature values extracted from the image are Contrast, Correlation, Energy, Homogeneity, Mean, Standard Deviation, Entropy, RMS, Variance, Smoothness, Kurtosis, Skewness and IDM with help of GLCM(gray level co variance matrix). The some of the features values extracted for training images are listed in the table4.

Table 4: Features obtained for training tumor images. Where B1, B2, B3 are begnin tumor images and M1, M2 and M3 are malignant tumor images.

Feature/image	B1	B2	B3	M1	M2	M3
Contrast	0.3383	0.2326	0.1923	0.3558	0.3072	0.2261
Correlation	0.1451	0.1376	0.1158	0.1276	0.1026	0.0799
Energy	0.8842	0.8339	0.7857	0.8808	0.8557	0.8261
Homogeneity	0.9658	0.9523	0.9416	0.9641	0.9583	0.9512
Mean	0.0042	0.0019	0.0035	0.0051	0.0031	0.0023
Standard Deviation	0.0810	0.0811	0.0810	0.0810	0.0811	0.0811
Entropy	1.7492	2.8679	3.0937	1.9036	2.1424	2.7752
RMS	0.0811	0.0811	0.0811	0.0811	0.0811	0.0811
Variance	0.0066	0.0066	0.0066	0.0066	0.0066	0.0066
Smoothness	0.9594	0.9153	0.9523	0.9660	0.9460	0.9278
Kurtosis	45.5213	16.7751	7.9450	46.3076	28.4879	12.8849
Skewness	3.7531	1.2335	0.06354	3.9199	2.4350	1.1327
IDM	8.9147	0.6901	-0.8152	4.6068	0.5780	-0.2692

The segmentation results are shown in the figure 4(a)-(d). After segmentation of tumor, classification process begins by calculating the feature values of testing image. The testing image is compared with the training image's feature value using linear SVM technique. The training images feature values are already trained to SVM using Fitcsvm function in MatLAB. If the training and testing images are matched, the tumor name will be displayed in as shown in figure 4(e). The proposed traditional method achieved a classification accuracy of 77.78%, Sensitivity of 77.78% and specificity of 77.78%. The area is estimated for all Brain MRI images in the dataset.



(a) *(b)* *(c)* *(d)* *(e)*

Fig4: Screenshot results for automatic diagnosis of traditional method in MATLAB: begnin tumor a) MRI brain image b) Preprocessed image c) Binary image using threshold d)Segmented tumor image using canny edge detection e) Classification result image.

Note if the loaded test image is of type begnin tumor output in the screenshot will be begnin or else output display will be malignant tumor.

Table5: Comparison result of both traditional (SVM) and proposed (CNN) method.

Measure	Notation	Calculated Value	
		SVM	**CNN**
Total testing images	Test	18	18
Number of Training images	Train	12	12
True Positive	TP	7	9
False Positive	FP	2	0
True Negative	TN	7	9
False Negative	FN	2	0
Accuracy	ACC	0.7778	100
Sensitivity, True positive rate and Recall	SN	0.7778	100
Precision, Positive predictive value	PREC	0.7778	100
Dice Similarity Coefficient	DSC	07.778	100

The table5 shows the comparison of traditional and proposed method. From this table, it proves that the CNN provides the better results on image classification. Then the proposed system is also validated on second dataset provided. In this, classifying three types of tumor such as meningioma, glioma and pituitary tumor is carried with dataset containing 100 images each. The training process is completed within 5 minutes for dataset results are shown in table 6.

Table6: Proposed method Training Hyper parameters and efficiency of training process on second dataset. First three columns shows the hyper parameters and remaining three columns shows the efficiency of training.

Epoch	Iteration	Base Learning Rate	Time Elapsed(h.m.s)	Mini –batch Loss	Mini- batch Accuracy
1	1	1.00e-04	00.00.20	1.4692	27.34
15	15	1.00e-04	00.05.01	0.2944	89.84

(a)

Epoch	Iteration	Base Learning Rate	Time Elapsed(h.m.s)	Mini –batch Loss	Mini- batch Accuracy
1	1	1.00e-04	00.00.19	1.1515	45.44%
15	15	1.00e-04	00.05.01	0.2011	92.19%

(b)

CONCLUSION

The proposed system provides a novel idea called Advancement in Automatic Diagnosis of Brain Tumor using ConvNet to distinguish type of tumor using MRI. To avoid manual errors, automatic classification using ConvNet and Support Vector Machine (SVM) has been used in this work. Among them, ConvNet provides the better result compared to the traditional method. The performance of the system is evaluated and obtained the Accuracy, Dice, Sensitivity and Specificity of 100%. The proposed system shows accurate classification of tumor type from various patients acquired in all views of MRI images.

REFERENCES

1. Yan Zhu and Hong Yan, Senior Member, IEEE(1997) "Computerized Tumor Boundary Detection Using a Hopfield Neural Network" IEEE Transactions On Medical Imaging, Vol. 16, No. 1, February 1997 .
2. Asra Aslama, Ekram Khanb, M.M. Sufyan Bega (2015) "Improved Edge Detection Algorithm for Brain Tumor Segmentation" Second International Symposium on Computer Vision and the Internet (VisionNet'15) Published by Elsevier.
3. Debnath Bhattacharyya and Tai-hoon Kim(2011) "Brain Tumor Detection Using MRI Image Analysis" UCMA 2011, Part II, CCIS 151, pp. 307–314, 2011.© Springer .
4. S. Taheri , S.H. Ong , V.F.H. Chong (2009) "Level-set segmentation of brain tumors using a threshold-based speed function" Image and Vision Computing 28 (2010) 26–37. Elsevier.
5. Xie Mei, Zhen Zheng, Wu Bingrong, Li Guo(2009) "The Edge Detection of Brain Tumor" progress in IEEE. 978-1-4244-4888-3/09/$25.00 ©2009 IEEE.
6. A. R. Abdulraqeb, W. A. Al_Haidri, L. T. Sushkova, M. M. Abounassif , P. J. Parameaswari, and M. A. Muteb, (2017) "An Automated Method for Segmenting Brain Tumors on MRI Images" Biomedical Engineering, Vol. 51, No. 2.
7. Umit Ilhana, Ahmet Ilhana,(2017) " Brain tumor segmentation based on a new threshold approach" 9th International Conference on Theory and Application of Soft Computing, Computing with Words and Perception, ICSCCW Elsevier.
8. Stefan Bauer_, Lutz-P. Nolte, and Mauricio Reyes G. Fichtinger,A.Martel, and T. Peters (2011) "Fully Automatic Segmentation of Brain Tumor Images Using Support Vector Machine Classification in Combination with Hierarchical Conditional Random Field Regularization"MICCAI 2011, Part III, LNCS 6893, pp. 354–361, 2011. Springer.
9. Parveen, Amritpal singh,(2015) "Detection of Brain Tumor in MRI Images, using Combination of Fuzzy C-Means and SVM" 2nd International Conference on Signal Processing and Integrated Networks (SPIN) IEEE.
10. Akshita Chanchlani, Makrand R. Chaudhari, Bhushan Y. Shewale & Ayush Jha(2017) "Tumor Detection in Brain MRI using Clustering and Segmentation Algorithm" Imperial Journal of Interdisciplinary Research (IJIR)Vol-3, Issue-5, 2017.
11. Nameirakpam Dhanachandra, Khumanthem Manglem and Yambem Jina Chanu(2015) "Image Segmentation using *K*-means Clustering Algorithm and Subtractive Clustering Algorithm" Eleventh International Multi-Conference on Information Processing-2015 (IMCIP-2015) Elesvier.
12. Demirhan A, Toru M, Guler I (2015) Segmentation of tumor and edema along with healthy tissues of brain using wavelets and neural networks. IEEE J Biomed Health Inform 19(4):1451–1458.
13. N. Varuna Shree, T. N. R. Kumar,(2017) "Identification and classification of brain tumor MRI images with feature extraction using DWT and probabilistic neural network"

BrainInformatics.doi.org/10.1007/s40708-017-0075-5 (springer).

14. Nilesh Bhaskarrao Bahadure, Arun Kumar Ray, and Har Pal Thethi, (2017) “Image Analysis for MRI Based Brain Tumor Detection and Feature Extraction Using Biologically Inspired BWT and SVM”, International Journal of Biomedical Imaging, Article ID 9749108, 12 pages.
15. M. Alfonse and A.-B. M. Salem,(2016) “An automatic classification of brain tumors through MRI using support vector machine,” Egyptian Computer Science Journal, vol. 40, pp. 11–21.
16. Chinnu A (2015), “MRI Brain Tumor Classification Using SVM and Histogram Based Image Segmentation”, International Journal of Computer Science and Information Technologies, Vol. 6 (2).
17. Hable, R.,(2012), “Asymptotic normality of support vector machine variants and other regularized kernel methods”, Journal of Multivariate Analysis, Vol. 106, 92{117}.
18. Hari Babu Nandpuru, Dr. S. S. Salankar, Prof. V. R. Bora, (2014) “MRI Brain Cancer Classification Using Support Vector Machine” IEEE Students' Conference on Electrical, Electronics and Computer Science.
19. Mohd Fauzi Bin Othman, Noramalina Bt Abdullah, Nurul Fazrena Bt Kamal#3,(2011) “MRI Brain Classification using Support Vector Machine” IEEE978-1-4577-0005-7/11.
20. Monika, Rajneesh Rani and Aman Kamboj(2018) “Brain Tumor Classification for MRImaging Using Support Vector Machine” Progress in Advanced Computing and Intelligent Engineering, Advances in Intelligent Systems and Computing 714© Springer .
21. Y. Zhang and L. Wu (2012), “An MR Brain Images Classifier via Principal Component Analysis And Kernel Support Vector Machine”, Progress In Electromagnetics Research, Vol. 130, 369-388.
22. S.k.Shil, F.P.Polly, M.A.Ifthekhar, M.N.Uddin, and Y.M.Jang , (2017) “An Improved Brain Tumor Detection and Classification Mechanism”, ICTC .,vol2.IEEE.
23. Ali Gooya, Member, IEEE, Kilian M. Pohl, Member, IEEE, Michel Bilello, Luigi Cirillo, George Biros, Member, IEEE, Elias R. Melhem, and Christos Davatzikos, Senior Member, IEEE(2012) “GLISTR: Glioma Image Segmentation and Registration” IEEE Transactions On Medical Imaging, Vol. 31, No. 10, October 2012 .
24. Pim Moeskops, Max A. Viergever, Adri¨enne M. Mendrik, Linda S. de Vries, Manon J.N.L. Benders and Ivana Iˇsgum (2012)“Automatic segmentation of MR brain images with a convolutional neural network” IEEE Transactions On Medical Imaging.
25. Saddam Hussain, Syed Muhammad Anwar, Muhammad Majid(2017) “ Brain Tumor Segmentation using Cascaded Deep Convolutional Neural Network” progress in IEEE. 978-1-5090-2809-2/17/$31.00 ©2017 IEEE.
26. Sérgio Pereira, Adriano Pinto, Victor Alves, and Carlos A. Silva(2016) “Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images” IEEE

TRANSACTIONS ON MEDICAL IMAGING, VOL. 35, NO. 5, MAY 2016.

27. Leire Roa-Barco, Oscar Serradilla-Casado, Mikel de Velasco-V´azquez1, Asier L´opez-Zorrilla1, Manuel Gra˜na, Darya Chyzhyk, and Catherine Price (2018) "A 2D/3D Convolutional Neural Network for Brain White Matter Lesion Detection in Multimodal MRI" Springer International Publishing AG 2018.
28. Abdulraqeb, A. R., Sushkova, L. T., Abounassif, M. M., Parameaswari, P. J., and Muteb, M. M., (2016) "Significance of segmentation methods in assessing brain tumor magnetic resonance images," in: Russian_German Conference on Biomedical Engineering (2016), pp. 62_65.
29. M. B. Amien, A. Abd-elrefman, and W. Ibrahim,(2013) "An intelligent model for automatic brain –tumor diagnosis based-on MRI images" International Journal of Computer Applications vol. 72, no. 23, pp.21-24.
30. M. P. Arakeri and G. R. M. Reddy,(2015) "Computer-aided diagnosis system for tissue characterization of brain tumor on magnetic resonance images" Signal, Image and Video Processing, vol.9, no.2, pp.409-425.
31. E.Dandil, M. Cakiroglu, Z.Eksi,(2014) "Computer aided diagnosis of malign and begnin brain tumors on MR images" ICT Innovations .
32. Haralick RM, Shanmugam K, Dinstein I (1973) Textural features for image classification. IEEE Trans Syst Man Cybern 3(6):610–621.
33. Janki Naik , Prof Sagar Patel , Tumor Detection and Classification using Decision Tree in Brain MRI, IJEDR, ISSN: 2321-9939, 2013.
34. Sanjeev Kumar, Chetna Dabas, Sunila Godara, (2017) "Classification of Brain MRI Tumor Images: A Hybrid Approach"Information Technology and Quantitative Management (ITQM).
35. Shweta Jain, (2013) "Brain Cancer Classification Using GLCM Based Feature Extraction in Artificial Neural Network", IJCSET, ISSN: 2229-3345, VoL 4 No. 07 JuI.
36. K. Somasundaram, T. Kalaiselvi, (2011) "Automatic brain extraction methods for T1 magnetic resonance images using region labeling and morphological operations", ELSEVIER, Computers in Biology and Medicine 41 716-725.
37. Sujan, M., Alam, N., Abdullah, S., Jahirul, M., (2016) "A Segmentation based Automated System for Brain Tumor Detection" International Journal of Computer Applications, 153(10), 41-49.
38. K. Sudharani, Dr.T.C. Sarma, Dr. K. Satya Prasad,(2015) "Advanced morphological technique for automatic brain tumor detection and evaluation of statistical parameters", International Conference on Emerging Trends in Engineering, Science and Technology (ICETEST).
39. Vaishali et al. (2015) Wavelet based feature extraction for brain tumor diagnosis—a survey. Int J Res Appl Sci Eng Technol (IJRASET) 3(V), ISSN: 2321-9653.