Detection of Brain Tumor Using FFBP Neural Networks

Ms.S. Suruthi[1], Mrs.G.Jayanthi[2], Mrs.Dr.G.Gandhimathi[3]
[1]*B.E, M.E Communication systems, Dept. of ECE, Parisutham Institute of Technology & Science, Thanjavur*
[2]*M.E, Assistant Professor, Department of ECE, Parisutham Institute of Technology & Science, Thanjavur*
[3]*M.E, P.hd, Professor, Department of ECE, Parisutham Institute of Technology & Science, Thanjavur*

Abstract- **Brain is an organ that controls activities of all the parts of the body. Recognition of automated brain tumor in Magnetic resonance imaging (MRI) is a difficult task due to complexity of size and location variability. This automatic method detects all the type of cancer present in the body. Previous methods for tumor are time consuming and less accurate. In the present work, statistical analysis morphological and thresholding techniques are used to process the images obtained by MRI. Feed-forward back-prop neural network is used to classify the performance of tumors part of the image. This method results high accuracy and less iterations detection which further reduces the consumption time.**

Index Terms- **Tumor, MRI.**

I. INTRODUCTION

Early detection and classification of brain tumors is very vital in clinical observe. Many researchers have proposed totally different techniques for the classification of brain tumors based on totally different sources of information. In this paper we propose a method for brain tumor classification, focusing on the analysis of Magnetic Resonance (MR) images and Magnetic Resonance Spectroscopy (MRS) knowledge collected for patients with benign and malignant tumors. Our aim is to achieve a high accuracy in discriminating the 2 types of tumors through a mix of many techniques for image segmentation, feature extraction and classification. The proposed technique has the potential of assisting clinical identification. Necessary preprocessing steps prior to characterization and analysis of regions of interest (ROIs) are segmentation and registration. Image registration is used to see whether 2 subjects have ROIs in the same location. However, in this work we do not take into consideration the placement of the growth in the classification model so we tend to do not use registration. Image segmentation is required to delineate the boundaries of the ROIs ensuring, in our case, that tumors are printed and labeled systematically across subjects. Segmentation can be performed manually, automatically, or semi-automatically. The manual method is time intense and its accuracy extremely depends on the domain knowledge of the operator. Specifically, various approaches have been projected to deal with the task of segmenting brain tumors in MR images. The performance of these approaches usually depends on the accuracy of the spatial probabilistic information collected by domain specialists. In previous work, we projected associate degree automatic segmentation rule that is supported the fuzzy connectedness concept.

II. BRAIN TUMOR

A primary brain tumor is an abnormal growth that starts in the brain and usually does not spread to other parts of the body. Primary brain tumors may be benign or malignant. A benign brain tumor grows slowly, has distinct boundaries and rarely spreads .Although its cells are not malignant, this tumor composed of benign cells and located in vital areas.

Brain tumor occurred when the cells were dividing and growing abnormally. It is appear to be a solid mass when it diagnosed with diagnostic medical imaging techniques. There are two types of brain tumor which is primary brain tumor and metastatic brain tumor. Primary brain tumor is the condition when the tumor is formed in the brain and tended to stay there while the metastatic brain tumor is the tumor that is formed elsewhere in the body and spread through the brain.

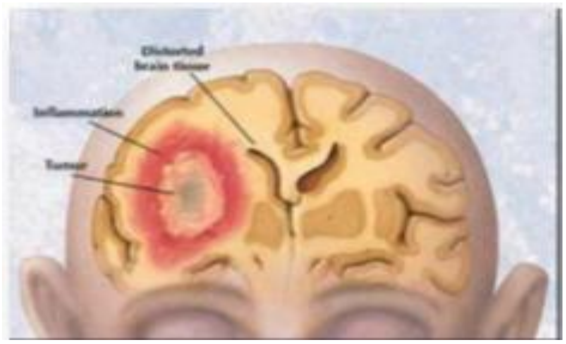


Fig.1.1. BRAIN TUMOR

III. TYPES OF BRAIN TUMOR

There are over 120 different types of brain tumors. Common brain tumors include:

- Astrocytoma
- Pilocytic Astrocytoma (grade I)
- Diffuse Astrocytoma (grade II)
- Anaplastic Astrocytoma (grade III)
- Glioblastoma Multiforme (grade IV)
- Oligodendroglioma (grade II)
- Anaplastic Oligodendroglioma (grade III)
- Ependymoma (grade II)
- Anaplastic Ependymoma (grade III)

a. SYMPTOMS

Tumors can affect the brain by destroying normal tissue, compressing normal tissue, or increasing intracranial pressure. Symptoms vary depending on the tumor's type, size, and location in the brain. General symptoms include.

- headaches that tend to worsen in the morning
- seizures
- stumbling, dizziness, difficulty walking
- speech problems (e.g., difficulty finding the right word)
- vision problems, abnormal eye movements
- weakness on one side of the body
- increased intracranial pressure, which causes drowsiness, headaches, nausea and vomiting, sluggish responses.

III.METHODLOGY

The system it deals with the feed forward back propagation neural networks. It also involves several techniques image smoothing, adaptive thresholding and noise removal. The problem is to find the accurate location, pre-state analysis and the stages of the tumor cells. The proposed method takes the input MRI images that will undergo grey image conversion, template creation, computation of correlation undergoes tumor location detection. Brain tumor segmentation and training. The proposed method takes the input MRI images that will undergo grey image conversion, template creation, computation of correlation undergoes tumor location detection. Brain tumor segmentation and training.

The detection of boundaries and its layers are not accurately possible by the biopsy method through the microscope. The sample of image of cell and its tissue are identified by the process of image segmentation and the region segmentation. After detection of cancerous cells of different shape and size, it is necessary to analyze whether it is a harmful cancer or a harmless cancer. It can be done by the comparisons of resulted images with the past observations and medical view of analysis. The image reconstruction shows the difference between the original image and a processed image which a segmented cancerous image cells or tissue. Each cell lineage differs in the nature specifically with respect to the genes in the nuclei of the cell.

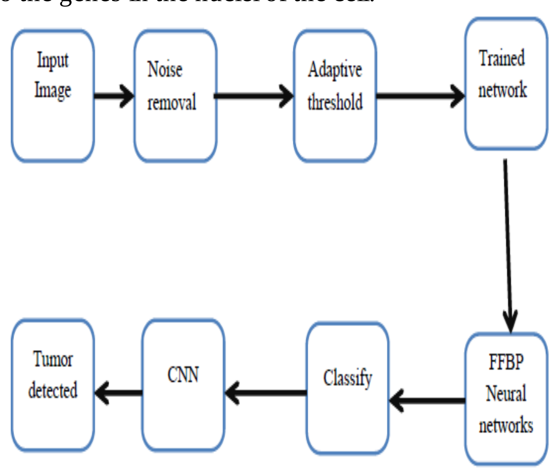


FIG.2. BLOCK DIAGRAM OF PROPOSED SYSTEM

a) MRI Scan Input Image

It is an imaging test uses special dye has radioactive tracers which is inserted into the human body in order to locate the disease or an abnormal areas. This dye can be inserted through the air inflow by which the tissues can absorb the tracer. It shows the problems at the cellular level and it detects how the cancer metabolizes, spread or metasized to the new areas. It is less exposure to harmful radiation and it gives the accurate clear imaging analysis than the MRI scan image. It does not use the x-ray beams inside the body.

FIG .3. MRI SCANNER

b) Feed Forward Back Propagation (BPNN)

BPNN was designed and trained using ntool in Matlab. First, one hidden layer between input and output layers with 250 nodes was chosen. The type of activation function chosen in the first was Log sigmoid. Then for the same network, activation function was replaced first by Tan sigmoid function, and then by pure linear functions. Using the network with Log sigmoid function, a number of nodes in hidden layer were first increased to 270 and then decreased to 230 to find out if this application needs more or less nodes.

c) Neural Network Design:

For image recognition application; Feed Forward Back Propagation neural network is good choice. The number of layers, nodes and activation functions are determined according to the application needed and there is no specific rule for choice. This study suggests a new approach using trial and error but with specific strategy.

The initial number of layers, nodes and activation function determined; and the value of performance error recorded. Then, for the same architecture; activation function type changed and the performance error recorded. This procedure repeated, and the activation function that provides the least performance error selected.

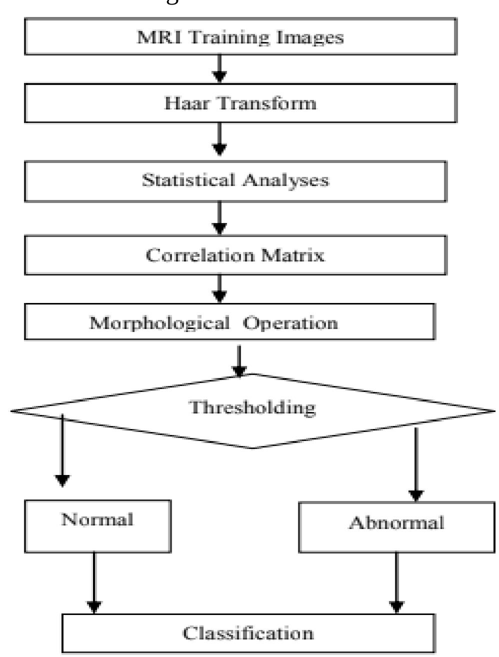
The number of hidden nodes should be increased and then decreased. The performance error was recorded. This was mainly done to study whether the application needs to optimize the number of nodes. If the performance error value is still high, a new layer must be added. Finally the ANN that gives the least performance error will be selected.

d) Training

Training is a process in which preparation and coaching of the network are performed. Once the training phase of the network is completed the network is automatically modified in accordance with its error.

The input MRI images that will undergo grey image conversion, template creation, computation of correlation undergoes tumor location detection. Brain tumor segmentation and training. The proposed method takes the input MRI images that will undergo grey image conversion, template creation, computation of correlation undergoes tumor location detection. Brain tumor segmentation and training. The proposed method framework.

Filtering is done to remove non-brain tissue. Haar wavelet transform is used for the pre-processing of image. Wavelet coding is suitable for the applications where tolerable degradation and scalability are important. Haar wavelet transform decomposes the input signals into a set of the basis function are called wavelets. A prototype wavelet is called mother wavelet other wavelets are obtain this by shifting or dilations called daughter wavelet.



VII. RESULTS AND DISCUSSION

We evaluate completed to analysis the classification; with the help of analysis of the classification accuracies the training sets were determined.
Here data set was separated exclusively into data sets, is training data set. Now in our project training data set was used to prepare, instruct and train (coaching) the network, on the other hand the testing data set were employed to network (trained) for the brain tumor classification. check especially for accuracy and efficiency of the

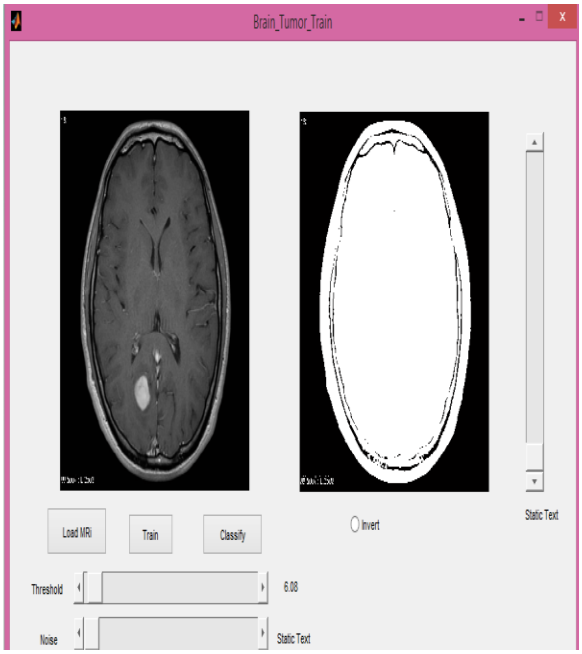


FIG 4 Threshold image

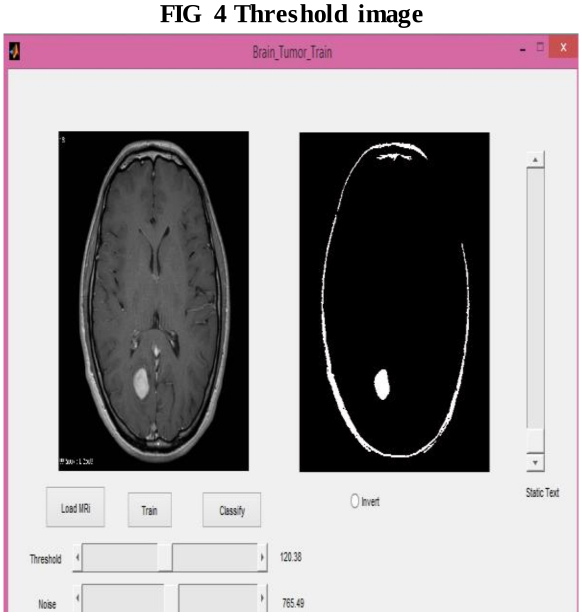


FIG.5. NOISE REMOVAL

FIG.6. MANUAL SEGMENTED FOR TRAINING

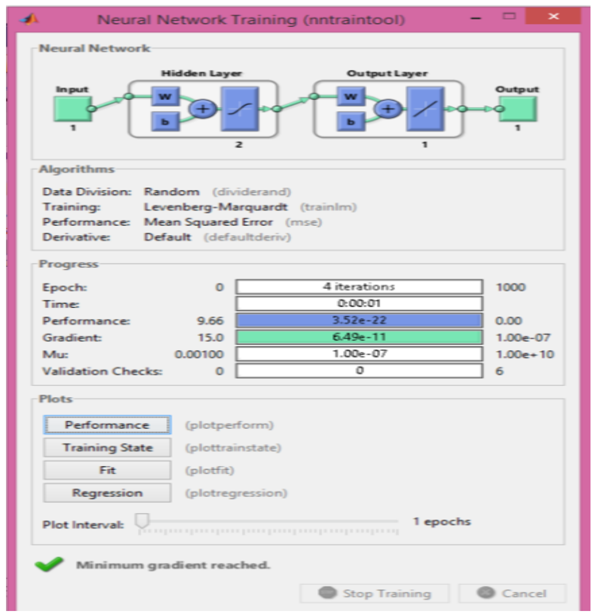


FIG.6. NEURAL NETWORK TRAINING

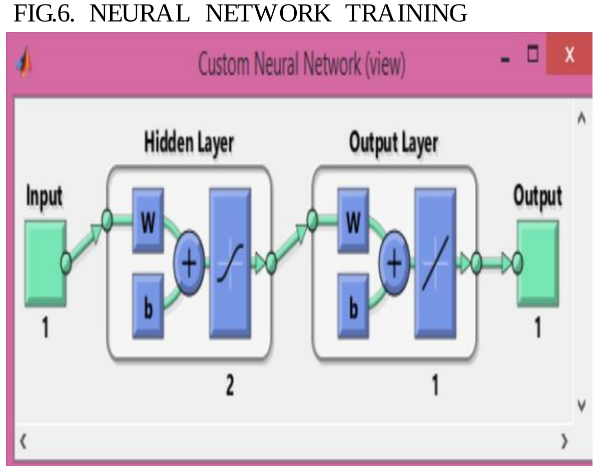
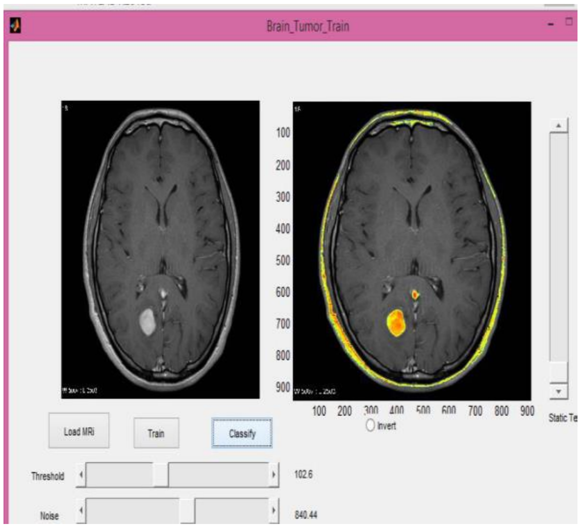


FIG4.5 CUSTOM NEURAL NETWORK



CONCLUSION AND FUTURE WORK

A.CONCLUSION

The above implementation was an effort to understand how an environment can be viewed in Virtual Reality. The application has been created it is used in a virtual realityenvironment for traditional real life tours for various campus.As the concept hold three steps of processes, the photographic images has beencreated using image acquisition followed by area selection which can be operated usingBluetooth with joystick and then quality of virtual reality has been analyzed using fuzzylogic. The virtual reality of a campus is viewed by the user with the help of a VR Headsetand smartphone. This virtual reality for campuses is used for both indoor and outdoornavigation.

The outcome of virtual reality has been interfaced with the computer to check the response of the field experiments.

REFERENCES

[1] P. Dvorák and B. Menze, "Structured prediction with convolutional neural networks for multimodal brain tumor segmentation," MICCAI Multimodal Brain Tumor Segmentation Challenge (BRATS), pp. 13–24, 2015.

[2] N. Subbanna, D. Precup, L. Collins, and T. Arbel, 2013 "Hierarchical probabilistic Gabor and MRF segmentation of brain tumours in MRI volumes,"Proc. MICCAI, vol. 8149, pp. 751–758.

[3] M. Havaei etal., Brain tumor segmentation with deep neural networks 2015 [Online]. Available: http://arxiv.org/abs/1505.03540,ArXiv:1505.03540v1.

[4] B. Girod, April, 2014 ,"Image segmentation", (Lecture notes).

[5] B. Girod, April, 2014, "Morphological Image processing", (Lecture notes).

[6] B. Girod, April, 2014 ,"Edge detection", (Lecture notes).

[7] Anil k. Jain, 2012,"Fundamentals of Digital Image processing", Pearson, Education, Inc.,

[8] Y. Chen, L. Shi, 2014, "Artifact suppressed dictionary learning for low-dose CT image processing," IEEE Trans. Med. Imaging, vol.33, pp. 2271-2292.

[9] S. Bauer etal., "A survey of MRI-based medical image analysis for brain tumor studies," Phys. Med. Biol., vol. 58, no. 13, pp. 97–129, 2013.

[10] H. Demuth and M. Beale. Neural Network Toolbox for Use with Mat lab, 1998.

[11] Lopar and Slobodan Ribaric Proceedings of the Croatian Computer Vision Workshop, Year 1 September 19, 2013,Zagreb, Croatia. reality for indoor navigation," IEEE Trans. Consum. Electron., vol. 54,no. 3, pp. 954–962, Aug. 2008.

[12] J. B. Kim, "A personal identity annotation overlay system using a wearable computer for augmented reality," IEEE Trans. Consum. Electron., vol. 49, no. 4, pp. 1457–1467, Nov. 2003.

[13] S. Kasprzak, A. Komninos, and P. Barrie, "Feature-based indoor navigation using augmented reality," in Proc. 9th Int. Conf., ACM Intell. Environ., 2013, pp. 100–107.

[14] A. Mulloni, H. Seichter, and D. Schmalstieg, "Handheld augmented reality indoor navigation with activity-based instructions," in Proc. 13th Int. Conf. Human Comput. Interact. Mobile Devices Serv., 2011, pp. 211–220.

[15] L. C. Huey, P. Sebastian, and M. Drieberg, "Augmented reality based indoor positioning navigation tool," in Proc. IEEE Conf. Open Syst., 2011,pp. 256–260.