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Brain Tumor Detection from MRI Image Using Deep Learning

Debjyoti Ghosh[1*], Utpal Roy[2]

[1,2]Dept. of Computer and System Sciences, Siksha Bhavan, Visva Bharati, Santiniketan-731235, India

[*]*Corresponding Author: debjyotighsh@gmail.com, roy.utpal@gmail.com*

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***Abstract*—** Nowadays it is believed that Brain tumor is one of the most harmful diseases that may lead to serious cancer. Major issue of the treatment of brain tumor is early detection of it before leading to malignant stage. More importantly early diagnosis of brain tumors plays an important role in improving further treatment possibilities and thus increases the survival rate of the patients. Here in this study, we have developed a system that can accurately detect tumor from brain Magnetic Resonance Imaging (MRI) images. To do this we have prepared a laboratory made moderate size database collecting various types of brain Magnetic Resonance Imaging images. In this experiment the brain MRI image has been preprocessed first, then the image has been separated into tumor or non-tumor portion of the image using deep neural net.

***Keywords*—**Brain Tumor, MRI, CNN, Anisotropic Diffusion

I. INTRODUCTION

With the advent of faster, more accurate and less invasive devices medical imaging has been undergoing a revolution in the past decade. MRI is a very powerful diagnostic method to detect any abnormalities.

MRI is a medical imaging technique, and radiologists use it for visualization of the internal structure of the body. Magnetic Resonance Imaging can provide various informations about human soft tissues anatomy as well as helps in diagnosis of brain tumor. A powerful, uniform, external magnetic field is employed to align the protons that are normally randomly oriented within the water nuclei of the tissue being examined. This alignment (or magnetization) is next perturbed or disrupted by introduction of an external Radio Frequency (RF) energy. The nuclei return to their resting alignment through various relaxation processes and in so doing emit RF energy. After a certain period following the initial RF, the emitted signals are measured. Fourier transformation is used to convert the frequency information contained in the signal from each location in the imaged plane to corresponding intensity levels, which are then displayed as shades of gray in a matrix arrangement of pixels. By varying the sequence of RF pulses applied & collected, different types of images are created. Repetition Time (TR) is the amount of time between successive pulse sequences applied to the same slice. Time to Echo (TE) is the time between the delivery of the RF pulse and the receipt of the echo signal.

The most common MRI sequences are T1-weighted and T2-weighted scans. T1-weighted images are produced by using short TE and TR times. The contrast and brightness of the image are predominately determined by T1 properties of tissue. Conversely, T2-weighted images are produced by using longer TE and TR times. In these images, the contrast and brightness are predominately determined by the T2 properties of tissue.

In general, T1- and T2-weighted images can be easily differentiated by looking the CSF. CSF is dark on T1-weighted imaging and bright on T2-weighted imaging.

A third commonly used sequence is the Fluid Attenuated Inversion Recovery (Flair). The Flair sequence is similar to a T2-weighted image except that the TE and TR times are very long. By doing so, abnormalities remain bright but normal CSF fluid is attenuated and made dark. This sequence is very sensitive to pathology and makes the differentiation between CSF and an abnormality much easier.

Human brain is the most complex organ present in the human body. The functioning of the brain is complex and various research works are being carried out to completely interpret the functioning of the brain. The brain contains complex anatomical features and different abnormalities can arise at different regions involving specific tissue structures and organs.

A brain tumor is an abnormal growth of cells within the brain, which can be cancerous or non-cancerous (benign). It is generally caused by abnormal and uncontrolled cell division, normally either in the brain itself (neurons, glial cells (astrocytes, oligodendrocytes, ependymal cells),

lymphatic blood vessels), in the cranial nerves (myelin-producing Schwann cells), in the brain envelopes (meninges), skull, pituitary and pineal gland, or spread from cancers primarily located in other organs (metastatic tumors). Brain tumors are of two types: primary and secondary. Primary brain tumors include any tumor that starts in the brain. Primary brain tumors can start from brain cells, the membranes around the brain (meninges), nerves, or glands. Primary brain tumors are classified as: 1) benign; 2) malignant. Benign tumors can be removed, and they seldom grow back. Benign brain tumors usually have an obvious border or edge. They don't spread to other parts of the body. However, benign tumors can press on sensitive areas of the brain and cause serious health problems. Malignant brain tumors are generally more serious and often are a threat to life. They are likely to grow rapidly and crowd or invade the nearby healthy brain tissue. Cancer cells may break away from malignant brain tumors and spread to other parts of the brain or to the spinal cord. They rarely spread to other parts of the body. Its threat level depends on the combination of factors like the type of tumor, its location, its size and its state of development. The brain is encapsulated by the skull so tumors are not visible from outside. We can detect different types of tumors and cancerous growth within the brain and other associated areas within the brain by using computerized methods on MRI images of a patient. It is also possible to track the growth patterns of such tumors.

Rest of the paper is organized as follows, Section II contains the existing methods, Section III contains the architecture and essential steps and explaining, Section IV describes results and discussion, Section V concludes research work with future directions.

II. RELATED WORK

Many of the researchers proposed many methods, and algorithms for to find brain tumor, stroke and other Kinds of abnormalities in human brain using MR Images.

Manoj K Kowar and Sourabh Yadav et al, in their study [4], they presents the novel techniques for the detection of brain tumor using segmentation, histogram and thresholding.

Rajesh C. Patil et al [5] focused on Meyer's flooding Watershed algorithm for segmentation and also presents the morphological operation.

In 2014 Vinay Parameshwarappa and Nandish S. et al [6] proposed an algorithm for segmented morphological approach.

In 2013 M. Karuna and Ankita Joshi et al [7] presents the algorithm which incorporates segmentation through Neuro Fuzzy Classifier.

R. B. Dubey, M. Hanmandlu, Shantaram Vasikarla [8] in 2011, compare the image segmentation techniques, they applied preprocessing techniques like; de-noising, image smoothing, image contrast enhancement and comparison of the level set methods and morphological marker controlled watershed approach and modified gradient magnitude region growing technique for MRI brain tumor segmentation. They concluded the MGMRGT method gives better result.

Roy and Bandyopadhyay [9] proposed automatic brain tumor detection approach using symmetry analysis. They first detected the tumor, segmented it and then found out the area of tumor. One of the important aspects is that after performing the quantitative analysis, we can identify the status of an increase in the disease. They have suggested multi-step and modular approached to solve the complex MRI segmentation problem. Tumor detection is the first step of tumor segmentation. They have obtained good results in complex situations.

In 2014 Sentilkumaran N and Thimmiaraja et al [10], presented the study of image enhancement techniques and comparison of histogram equalization basic method like Brightness preserving adaptive histogram equalization (AHE), Local histogram equalization (LHE), global histogram equalization (GHE), Dynamic histogram equalization using different quality objective measures in MRI images. They also presented the better result on contrast using BPDHE method.

In 2011 R. Preetha and G. R. Suresh et al [11], used fuzzy C means clustering for segmentation. That method given the high computational complexity. FCM shows good performance result in segmented the tumor tissue and accuracy of tumor. Segmentation was identified by applied the SVM classifier.

Amer AlBadarneh, Hasan Najadat and Ali M. Alraziqi et al, 2012, [12] proposed a method for brain tumor classification of MRI images. The research work applied, based on Neural Network (NN) and k- Nearest Neighbor (k-NN) algorithms on tumor classification has been achieved 100% accuracy using k-NN and 98.92% using NN.

III. METHODOLOGY

The proposed methodology for detecting brain tumor from MRI image using deep neural net is as follows:

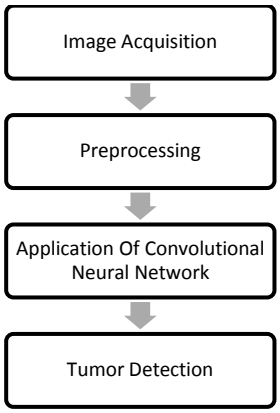

Figure 1 Proposed Methodology

1. Image Acquisition

Database

The sample image and tumor data set were collected from Institute of Neurology and Genetics, Nicosia, Cyprus [13][14][15][16] and The Cancer Imaging Archive[17][18].

Images are obtained by MRI scan of brain and the output of MRI provides gray level images. A gray scale image is a data matrix whose value represents shades of gray. The elements of gray scale matrix have integer values or intensity values in range [0 255]. Different formats of digital images like jpg, png etc. have been used in the proposed method.

2. Preprocessing

This phase is implemented by applying a series of initial processing procedures on the image before any special purposes processing. It improves the image quality and removes the noise. Since, the brain images are more sensitive than other medical images; they should be of minimum noise and maximum quality.

Artefacts Removal

Now a day's artefacts are principally letter or metal related artefacts or Gibbs artefact. Letter artefact is present in most of the brain MRI images due to patient's information being embedded in them. High quality of MRI machine ensures metal related and susceptibility artefact are very few.

In the first stage, threshold value is calculated over an image to binarize an image. A statistical method i.e. standard deviation is used to calculate the threshold value. In this processing statistical descriptions separate foreground images and background images. A digitized image *I[m,n]* and h is the intensity of each pixel of the gray image. Thus the total intensity of the image is defined by:

$$T = \sum_I h[I]$$

The average intensity of the image is defined as the mean of the pixel intensity within that image and the average intensity is defined as I_{avg} by:

$$I_{avg} = \frac{1}{T}\sum_{(m,n)\epsilon I} I[m,n]$$

The standard deviation S_d of the intensity within an image is the threshold value of the total image is defined by:

$$S_d = \sqrt{\frac{1}{T-1}\sum_{m,n\epsilon I}(I[m,n] - I_{avg})^2}$$

Or

$$S_d = \sqrt{\frac{1}{T-1}\sum_{m,n\epsilon I} I^2[m,n] - T{I_{avg}}^2}$$

We have used the threshold intensity as global value i.e. the threshold intensity of the entire image is unique. The standard deviation of the image pixel of an image *I[m,n]* or matrix element for *I[m,n]* is given by :

$$I[m,n]=1 \quad \text{if } I[m,n] \geq S_d$$

$$I[m,n]=0 \quad \text{if } I[m,n] < S_d$$

In the above procedure maximum portion of MRI of brain part is extracted from the total image but due to presence of artefact, it also gets extracted from the original image and then second stage starts. In the second stage first, I label the different connected components and then calculate the area of different connected components of the label image and find the components with maximum area. This is done to remove the artefact. We keep the maximum component. Thus a binarized image without artefact is produced. To produce final output the convex hull of all one pixels in the binarized image is obtained. Then all pixels inside the convex hull of binarized image are set to one and the binarized image matrix is multiplied position wise to the original image to obtain MR image without artefacts. Convex hull is used for reducing metal related susceptibility and Gibbs artefact.

Noise Reduction

The noises in MRI images reduces the quality of image and also damage the segmentation task which can lead to faulty diagnosis. The most principal in image denoising is preserving the edges and fine details of an image through noise reduction.

Anisotropic Diffusion

In image processing and computer vision, anisotropic diffusion, also called Perona–Malik diffusion, is a technique aiming at reducing image noise without removing significant parts of the image content, typically edges, lines or other details that are important for the interpretation of the image. Anisotropic diffusion resembles the process that creates a scale space, where an image generates a parameterized family of successively more and more blurred images based on a diffusion process. Each of the resulting images in this family are given as a convolution between the image and a 2D isotropic Gaussian filter, where the width of the filter

increases with the parameter. This diffusion process is a *linear* and *space-invariant* transformation of the original image. Anisotropic diffusion is a generalization of this diffusion process: it produces a family of parameterized images, but each resulting image is a combination between the original image and a filter that depends on the local content of the original image. As a consequence, anisotropic diffusion is a *non-linear* and *space-variant* transformation of the original image.

Perona & Malik introduce the flux function as a means to constrain the diffusion process to contiguous homogeneous regions, but not cross region boundaries. The heat equation (after appropriate expansion of terms) is thus modified to:

$$\frac{\partial I}{\partial t} = c(x,y,t)\Delta I + \nabla c \cdot \nabla I \quad \ldots\ldots(1)$$

where c is the proposed flux function which controls the rate of diffusion at any point in the image, Δ denotes the gradient, ∇ denotes the Laplacian.

A choice of c such that it follows the gradient magnitude at the point enables us to restrain the diffusion process as we approach region boundaries. As we approach edges in the image, the flux function may trigger inverse diffusion and actually enhance the edges.

Perona & Malik suggest the following two flux functions:

$$c\left(||\nabla I||\right) = e^{-(||\nabla I||/K)^2}$$

$$c\left(||\nabla I||\right) = \frac{1}{1 + \left(\frac{||\nabla I||}{K}\right)^2}$$

The flux functions offer a trade-off between edge-preservation and blurring (smoothing) homogeneous regions. Both the functions are governed by the free parameter κ which determines the edge-strength to consider as a valid region boundary. Intuitively, a large value of κ will lead back into an isotropic-like solution.

Equation (1) can be discretized on a square lattice, with brightness values associated to the vertices, and conduction coefficients to the arcs. An 8-nearest neighbours discretization of the Laplacian operator can be used:

$$\begin{aligned} I_{i,j}^{t+1} = I_{i,j}^{t} + \lambda[&c_N.\nabla_N I + c_S.\nabla_S I + c_E.\nabla_E I \\ &+ c_W.\nabla_W I + c_{NE}.\nabla_{NE} I \\ &+ c_{SE}.\nabla_{SE} I + c_{NW}.\nabla_{NW} I \\ &+ c_{SW}.\nabla_{SW} I] \end{aligned}$$

Where $0 \leqslant \lambda \leqslant ¼$, N, S, E, W, NE, SE, NW, SW are the mnemonic subscripts for North, South, East, West, North-East, South-East, North-West, North-West, South-West, ∇ indicates nearest-neighbour differences:

$$\nabla_N I_{i,j} \equiv I_{i-1,j} - I_{i,j}$$
$$\nabla_S I_{i,j} \equiv I_{i+1,j} - I_{i,j}$$
$$\nabla_E I_{i,j} \equiv I_{i,j+1} - I_{i,j}$$
$$\nabla_W I_{i,j} \equiv I_{i,j-1} - I_{i,j}$$
$$\nabla_{NE} I_{i,j} \equiv I_{i-1,j+1} - I_{i,j}$$
$$\nabla_{SE} I_{i,j} \equiv I_{i+1,j+1} - I_{i,j}$$
$$\nabla_{NW} I_{i,j} \equiv I_{i-1,j-1} - I_{i,j}$$
$$\nabla_{SW} I_{i,j} \equiv I_{i+1,j+1} - I_{i,j}$$

Image Enhancement

Poor contrast is one of the defects found in acquired image. The effect of that defect has great impact on the contrast of image. When contrast is poor the contrast enhancement method plays an important role.

Contrast Stretching

Contrast stretching (often called normalization) is a simple image enhancement technique that attempts to improve the contrast in an image by `stretching' the range of intensity values it contains to span a desired range of values, e.g. the full range of pixel values that the image type concerned allows. It differs from the more sophisticated histogram equalization in that it can only apply a linear scaling function to the image pixel values. As a result the `enhancement' is less harsh. (Most implementations accept a graylevel image as input and produce another graylevel image as output.)

Before the stretching can be performed it is necessary to specify the upper and lower pixel value limits over which the image is to be normalized. Often these limits will just be the minimum and maximum pixel values that the image type concerned allows. For example for 8-bit graylevel images the lower and upper limits might be 0 and 255. Call the lower and the upper limits a and b respectively.

The simplest sort of normalization then scans the image to find the lowest and highest pixel values currently present in the image. Call these c and d. Then each pixel P is scaled using the following function:

$$P_{out} = (P_{in} - c)\left(\frac{b-a}{d-c}\right) + a$$

3. Convolutional Neural Network

Convolutional Neural Network (CNN) is one of the most popular algorithms in Deep Learning. CNNs are very useful for finding patterns in images to recognize objects, faces, and scenes. They learn directly from image data, using patterns to classify images and eliminating the need for manual feature

extraction. The application of Convolutional layers consists in convolving a signal or an image with kernels to obtain feature maps. So, a unit in a feature map is connected to the previous layer through the weights of the kernels. The weights of the kernels are adapted during the training phase by back propagation, to enhance certain characteristics of the input.

Generally, brain tumors are having large variability in their intra structures, which makes the tumor region segmentation process more complex. The internal architecture of CNN classifier is designed and tuned in order to reduce such complexity for differentiating the abnormal tumor image from the normal brain image. The architecture of CNN classifier is depicted in Figure 2.

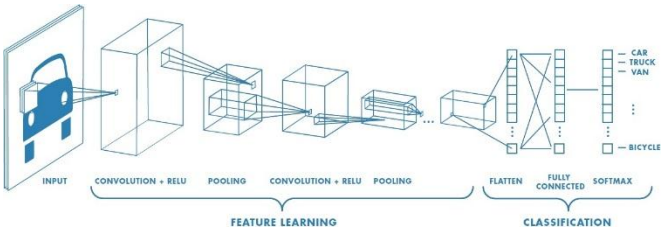

Figure 2 CNN Architecture

Like other neural networks, a CNN is composed of an input layer, an output layer, and many hidden layers in between. These layers perform operations that alter the data with the intent of learning features specific to the data.
Three of the most common layers are: convolution, activation or ReLU, and pooling.
Convolution puts the input images through a set of convolutional filters, each of which activates certain features from the images.
Rectified linear unit (ReLU) allows for faster and more effective training by mapping negative values to zero and maintaining positive values. This is sometimes referred to as activation, because only the activated features are carried forward into the next layer.
Pooling simplifies the output by performing nonlinear downsampling, reducing the number of parameters that the network needs to learn.
These operations are repeated over tens or hundreds of layers, with each layer learning to identify different features.
After learning features in many layers, the architecture of a CNN shifts to classification. The next-to-last layer is a fully connected layer that outputs a vector of K dimensions where K is the number of classes that the network will be able to predict. This vector contains the probabilities for each class of any image being classified.
The final layer of the CNN architecture uses a classification layer such as softmax to provide the classification output.

IV. RESULTS AND DISCUSSION

We have used Matlab R2015a for preprocessing steps and Python 3.7 for applying CNN. After applying the proposed method results are shown in Figure 4.

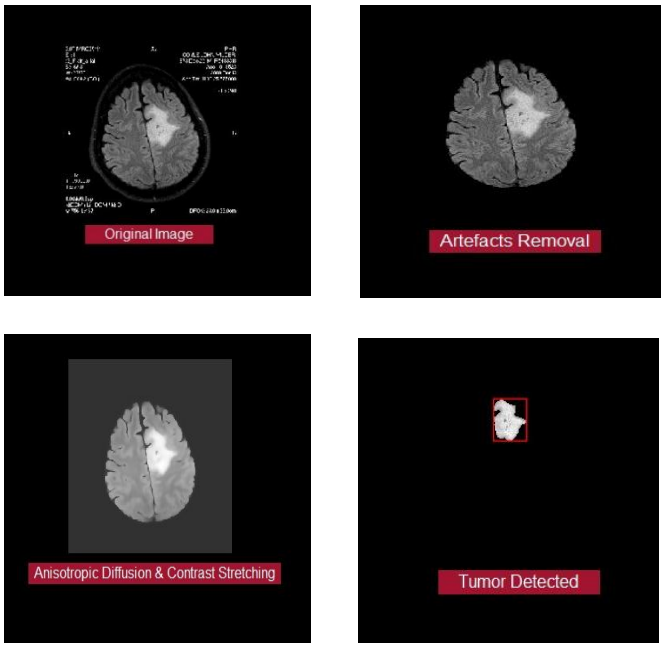

Figure 4. Input & Output Image

The Proposed method has been evaluated using following evaluation parameters.

True positive (TP), Brain tumor images are correctly recognized. Which means the people who has brain tumor are correctly identified.The high is optimal.

True negative (TN), Non-Brain tumor images are correctly recognized as they do not have brain tumor. Easily Healthy people correctly identified as healthy.

False positive (FP), Non-Brain tumor images are incorrectly recognized. This indicates the people who do not have brain tumor are incorrectly identified as they have brain tumor. Simply Healthy people incorrectly identified as sick. The less is optimal.

False negative (FN), Brain tumor images are incorrectly recognized. Which represents the people who has brain tumor are incorrectly identified as they do not have brain tumor. Sick people incorrectly identified as healthy.

$$Sensitivity = \frac{TP}{TP + FN} \times 100\%$$

$$Specificity = \frac{TN}{TN + FP} \times 100\%$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100\%$$

$$Similarity\ Index = \frac{2(TP)}{2(TP) + FP + FN} \times 100\%$$

To calculate above mentioned parameters tumor images and no tumor images are needed.

Total tumor images tested = 100

Actual Abnormal Images= 72 Actual Normal Images=28

Table 1. Confusion Matrix

Total Images T=100	Predicted Normal Images	Predicted Abnormal Images
Actual Normal Images	(TN) = 18	(FP) = 10
Actual Abnormal Images	(FN) = 12	(TP) = 60

Table 2. Parameter Analysis

PARAMETER	VALUE (%)
Sensitivity	83.3
Specificity	64.3
Accuracy	78
Similiarity Index	84.5

V. CONCLUSION AND FUTURE SCOPE

Brain tumour diagnosis has become a vital one in medical field because they are caused by abnormal and uncontrolled growing of cells inside the brain. In this method we have tried to detect the tumor from brain MRI using Deep Learning. It has also provided a diagnosis decision whether the tumor is present or absent and can assist as a supportive aid which can be used at the doctor's discretion in finally declaring a decision. We are also trying to measure the tumor area to detect the tumor size so that we can monitor the change of tumor size over time.

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REFERENCES

[1] Nabanita Basu, Sanjay Nag, Indra Kanta Maitra and Samir K. Bandyopadhyay, "Artefact removal and edge detection from medical image", European Journal of Biomedical And Pharmaceutical Sciences, Ssn 2349-8870, Volume: 3, Issue: 4, 493-502, 2016

[2] Ian T. Young ,Jan J. Gerbrands , Lucas J. van Vliet, "Fundamentals of Image Processing", Version 2.3, pp-1-112.

[3] Rafel C. Gonzalez, Rechard E. Woods, "Digital Image Processing", Prentice-Hall, 3rd Edition, 2008

[4] Manoj K Kowear and Sourabh Yadev, "Brain tumor detection and segmentation using histogram thresholding", International Journal of engineering and Advanced Technology, April 2012.

[5] Rajesh C. patil, A.S. Bhalchandra, "Brain tumor extraction from MRI images Using MAT Lab", IJECSCSE, ISSN: 2277-9477, Volume 2, issue1.

[6] Vinay Parmeshwarappa, Nandish S, "A segmented morphological approach to detect tumor in brain images", IJARCSSE, ISSN: 2277 128X , volume 4, issue 1, January 2014

[7] M.Karuna, Ankita Joshi, "Automatic detection and severity analysis of brain tumors using gui in matlab" IJRET: International Journal of Research in Engineering and Technology, ISSN: 2319-1163, Volume: 02 Issue: 10, Oct-2013

[8] R. B. Dubey, M. Hanmandlu, Shantaram Vasikarla, "Evaluation of three methods for MRI brain tumor segmentation", IEEE computer society, ITNG.2011.92

[9] S. Roy and S.K. Bandyopadhyay, ―Detection and Quantification of Brain Tumor from MRI of Brain and it's Symmetric Analysis,‖ International Journal of Information and Communication Technology Research, KY, USA, June 2012.

[10] Senthilkumaran N, Thimmiaraja J,"Histogram equalization for image enhancement using MRI brain images", IEEE CPS,WCCCT.2014.45

[11] R. Preetha, G. R. Suresh, "Performance Analysis of Fuzzy C Means Algorithm in Automated Detection of Brain Tumor",IEEE CPS, WCCCT, 2014.

[12] Amer Al-Badarnech, Hassan Najadat, Ali M. Alraziqi, "A Classifier to Detect Tumor Disease in MRI Brain Images", IEEE Computer Society, ASONAM. 2012,142

[13] C.P. Loizou, V. Murray, M.S. Pattichis, I. Seimenis, M. Pantziaris, C.S. Pattichis, "Multi-scale amplitude modulation-frequency modulation (AM-FM) texture analysis of multiple sclerosis in brain MRI images," IEEE Trans. Inform. Tech. Biomed., vol. 15, no. 1, pp. 119-129, 2011.

[14] C.P. Loizou, E.C. Kyriacou, I. Seimenis, M. Pantziaris, S. Petroudi, M. Karaolis, C.S. Pattichis, "Brain white matter lesion classification in multiple sclerosis subjects for the prognosis of future disability," Intelligent Decision Technologies Journal (IDT), vol. 7, pp. 3-10, 2013.

[15] C.P. Loizou, M. Pantziaris, C.S. Pattichis, I. Seimenis, "Brain MRI Image normalization in texture analysis of multiple sclerosis", J. Biomed. Graph. & Comput., vol. 3, no.1, pp. 20-34, 2013.

[16] C.P. Loizou, S. Petroudi, I. Seimenis, M. Pantziaris, C.S. Pattichis, Quantitative texture analysis of brain white matter lesions derived from T2-weighted MR images in MS patients with clinically isolated syndrome", J. Neuroradiol., acepted.

[17] Scarpace, Lisa, Flanders, Adam E., Jain, Rajan, Mikkelsen, Tom, & Andrews, David W. (2015). Data From REMBRANDT. The Cancer Imaging Archive. http://doi.org/10.7937/K9/TCIA.2015.588OZUZB

[18] Clark K, Vendt B, Smith K, Freymann J, Kirby J, Koppel P, Moore S, Phillips S, Maffitt D, Pringle M, Tarbox L, Prior F. The Cancer Imaging Archive (TCIA): Maintaining and Operating a Public Information Repository, Journal of Digital Imaging, Volume 26, Number 6, December, 2013, pp 1045-1057

Authors Profile

Mr. Debjyoti Ghosh pursued Bachelor of Science in Computer Science in 2012 and Master of Computer Application in 2015 and M.Tech in Computer Science & Engineering in 2017 from University of Calcutta,Kolkata. He is currently pursuing Ph.D. in Department of Computer and Systen sciences Sciences, Shiksha Bhavan, Visva-Bharati, Santiniketan, India since 2018. His main research work focuses on Deep Learning, Image Processing, and Pattern recognintion, .

Dr. Utpal Roy completed his Ph.D. from Department of Mathematics, Visva-Bharati and went to LAVAL University, Quebec, Canada for Post Doctoral work in 1994. He worked at Indian Association for the Cultivation of Science, Jadavpur, Kolkata as CSIR Scientist Pool during 1996-1997. He Joined the Visva-Bharati at the end of 1997 as Asst. Prof in Computer Science to teach the MCA course. He worked as Visiting Scientist in Academia Sinica, Taipei, Taiwan during 2001-2002. He worked as Professor in IT in Assam University Silchar, Assam during 2008-2009. Presently he is a Professor and Former Head of the Department, Department of Computer & System Sciences, Visva-Bharati. He has been guiding Ph.D. students since long time and many students have been awarded Ph.D. under his supervision.

