Deep Wavelet Autoencoder Based Brain Tumor Detection Analysis Using Deep Neural Network

T.Balamurugan[1], E.Gnanamanoharan[2], L.Martin[3]

[1]Assistant professor,Department of ECE,Government college of Engineering,Dharmapuri,Tamilnadu,India
[2]Assistant professor, Department of ECE,Annamalai university,Chidambaram,Tamilnadu,India
[3]Associate professor, Department of Mechanical ,Sri Manakula Vinayagar Engineering College, Puducherry

Article History: Received: 11 January 2021; Revised: 12 February 2021; Accepted: 27 March 2021; Published online: 10 May 2021

Abstract. In recent year, the brain imaging techniques has continually played an essential role in inspecting and concentrating on new visions of anatomy and brain functions. The image processing mechanism is extensively used in medicine to enhance early detection and treatment. Segmentation and classification is vital role for MRI brain image processing. The aim of this work is to develop a system that helps in tumour detection and brain MRI image recognition through the process of the proposed image classifier. In this work, we recommend a Deep Neural Network for classification and segmentation. This work proposes an image compression technique using a Deep Wavelet Auto encoder (DWA) that combines the ability to minimize the primary function of automatic encoders with the image degradation property of the wavelet transform. The combination of the two has an essential impact on reducing the size of the function set to withstand in addition classification tasks with DNN. A brain system has been eliminated and the proposed DNN- DWAE image classification is considered. The performance evaluation for the DNN- DWAE classifier has been improved compared with different existing method.

Keywords: Deep neural network, Denoising autoencoder, segmentation, tumour detection

1. Introduction

The initial detection of the malignant region always helps in the early detection of an affected person, which is one of the factors to reduce death. Magnetic resonance imaging is ideal for brain analysis exams and is widely recognized for the provision and transmission of anatomical information. It is quite non-invasive and has a high spatial resolution. Segmentation of the brain image is very difficult issues in image processing. Image segmentation is crucial role in various image processing applications. Brain image segmentation is a fairly demanding and complex segmentation task. However, if precision is maintained during the segmentation task, this would greatly facilitate the detection of tumors, neurotic tissue, etc. Identifying the structure of the brain by magnetic resonance imaging is of utmost importance in neuroscience and has many uses, such as examining brain development, analyzing neuroanatomy, examining the brain, etc.

Therefore, MRI images are primarily used to understand and conduct research analysis. used in the segmentation of medical images. Magnetic resonance segmentation using learning strategies and model recognition techniques was very successful for brain image analysis.The automatic classification and detection of different medical images of tumors is driven by the need for excessive accuracy in dealing with human life. In addition, computer assistance is required in medical institutions because it can improve people's performance in an area where cases of false negatives must be very low. Conventional diseases for the monitoring and diagnosis of diseases are based on the detection of the presence of special characteristics of a human observer. Due to the large number of patients in intensive care and the need for continuous observation of these conditions, various strategies for automated diagnostics have been developed in recent years to try to solve this problem. These techniques work by transforming the predominantly qualitative diagnostic criteria into a more objective quantitative classification problem of the traits

In this project, the automatic classification of brain images is proposed with the help of certain prior knowledge such as pixel intensity and certain anatomical functions. At present, there are no generally accepted techniques, consequently, automatic and reliable tumors detection techniques are of excellent need and interest. These included specific grouping and classification methods for large-scale RM image problems with data and times and energy that they consumed if done manually.

Therefore, a method of recognition, classification or grouping is fundamental in neural network systems, especially in medical problems. The segmentation of brain tissues into gray matter, white matter and tumor in medical images is not only of excessive interest in monitoring the serial treatment of "disease burden" in tumour imaging, but also gained a reputation with the improvement of image-guided surgical procedures. There are various attempts at brain tumor segmentation in the literature that use a single modality, mix multimodalities and use previously obtained from population.

2. Illustrations

Preliminary detection of the malignant region always helps to detect an affected person early, which is one of the factors in reducing death. The image processing approach has made an unexpected collection from all parts of the section and the application of the image processing mechanism has increased in recent years [1]. The storage and acquisition of medical images is largely preserved in a digital environment, and understanding the internal information needed if it has always been a tedious and time-consuming operation [2-3]. Brain Magnetic Resonance (MRI) is a very well-known medical activity used for the evaluation and diagnosis of many neurological diseases [4]. A system that is completely managed by machines or computers normally helps to automate this process to get accurate and fast results [5].

Magnetic resonance imaging is extremely suitable for brain analysis research and is widely accepted for providing and transmitting anatomical information. It is quite non-invasive and depicts excessive spatial resolution. Segmentation of the brain image is the most difficult problems. On the other hand, image segmentation is an essential task in various computer views and image processing applications. The segmentation process is to split the input image into more than one region based on some measures for further processing [6].

It has been very successful in analyzing brain images. The approach technically defines a parametric model that takes into account the selected properties based on the density function [7]. Deep neural networks (DNNs) [8] have attracted rapid attention in recent years. Auto encoder is basically a type of artificial neural network (ANN) [9-11] to learn efficient coding of data in an unattended way. The basic automatic encoder is generally robust and has the ability to learn functions without supervision, while the wavelet function has a wonderful location feature with time frequency and face functions. a deep wavelet auto encoder was constructed for enhance the quality of learned functions The goal of deep wavelet coding is to establish high-level training and an automatic fault diagnosis technology.

Hiralal et al [15] present the overview of the distinctive brain image segmentation techniques for brain MRI images. It give the very clear discussion for selecting the suitable segmentation approach for MRI scans for evaluation and prognosis. Pashna M and Hematian A et al. [16] introduced an overview of methodologies for segmenting brain imaging segments, taking into account the intensity of in homogeneity, noise and partial volume, etc.

Varatharaj M et al. [23] proposed an approach in which weighted fuzzy was used to segment the brain tumor from the provided images and the core metrics were used to expand segmentation performance. Zhang L [25] proposed a excessive efficiency and precision compared to any different method prevailing in this field. A Wavelet-like (WAE) automatic encoder using the neural network has broken down the original image into low-resolution images for classification purposes. These channels or low-resolution images are further used as input for the convolution neural network (CNN) to minimize computational complexity without changing the precision factor.

2.1 Problem statement

In existing non deep learning method ,the main problem of tumor detection of images are,Poor discriminatory power, High computational load, Loss of edge details due to shift variant property and Less accuracy in classification Medical Resonance images contain a noise caused by operator performance which can lead to serious inaccuracies classification.

2.2 Motivation of the work

The objective of this work is to build a system that would help determine tumour and in the detection of the brain's MRI image through the proposed image classification technique. The theme is further utilized to use a deep automatic wavelet coding to extract high level functionality for MRI images of the standard brain structure. The suggested DNN-DWAE image classification has been tested and has been observed to outperform in terms of accuracy.
Bengio Y et al. [26] set up an automatic stack denoising encoder that uses a denoising criterion to research the essential representation of a deep learning network. The deep neural network method was regarded using diffusion wavelet transform technology to extract audio functionality for musical data sets.

3. Proposed model

The proposed approach describes the category of MRI images deep learning based wavelet autocoder for detection of disease. Figure 1 illustrates the design of the proposed deep wavelet autocoder, that uses a deep neural network to diagnose brain disease, MR imaging. The data set images were acquired in DICOM format.This file needs to be processed to extract the images from it. After preprocessing, all images are displayed in 2D format and the 2D array is reconstructed in 2D data record format. Because the number of images is very large, it has been divided into a different number of small secondary arrays for optimal performance. These image subfields are then processed via DWAE to obtain the encoded images. In the first step, the coded approximation images are further taken into account in order to train and test a predefined deep neural network.

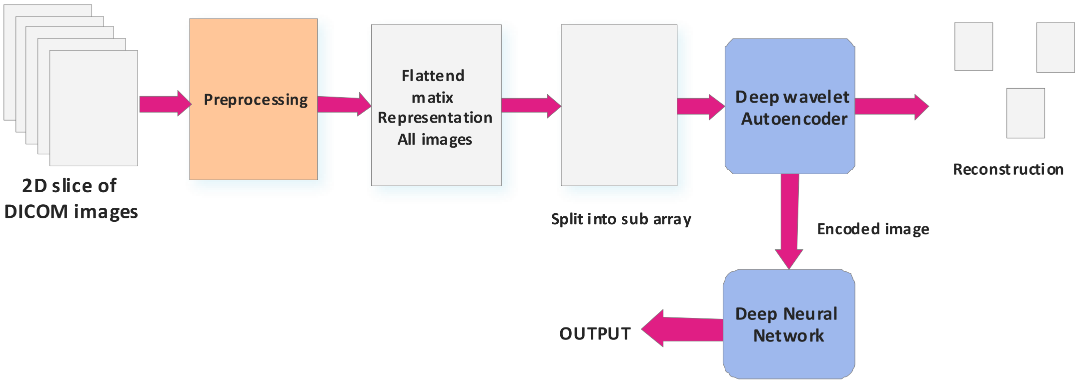


Figure 1. Proposed architecture of DNN-DWAE model

3.1 Autoencoder

The autoencoder [29-30] is as an optimization technique with which the main components of the distribution of high amounts of data can be extracted and learned. It is mainly considered a deep learning technique because it has the ability to create a deeper network that the network structure can handle itself to adapt to the desired environment. It is commonly used to extract, compress, remove noise, etc. In this research study, we used this technique as an image compression technique. The autoencoder can be considered the best pre-processing technique for classifying images with a deep neural network is shown in figure 2.

Since the input size is very large, we considered an additional hidden intermediate layer for coding and also for decoding (Figure 3). The intermediate layer that actually contains the 64 x 64 encoded image. Mathematically let Xi be the input, Hi the hidden layer and Y the activation functions used

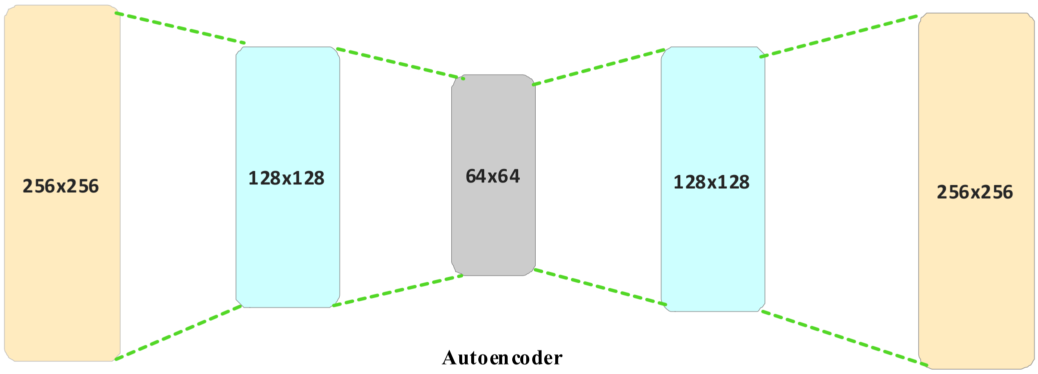


Fig.2 Autoencoder model with 3-hidden layers for encoding and decoding of images

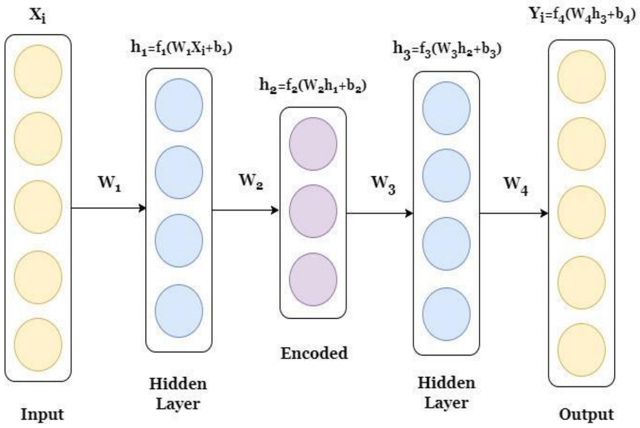


Fig.3 Auto encoder model with different layers, functions and parameters

3.2 Denoising Autoencoder

The deep neural networks are non-linear and therefore not worthy of great challenges. Pre-training with the noisy data was therefore required. This resulted in a process of artificially adding noise to each layer for higher performance and fast training as proven in figure 5 below. Denoising auto-encoder was introduced for Deep Network [17].The denoising auto-encoders is quite simple and straightforward. This auto-encoder for noise removal is said to be standard auto-encoder, in which two things are implemented: it encodes the input; and it loosens the effect of the corruption process applied to the input. The training process for the denoising auto encoder is a pretty simple task. One way to exercise this is to randomly destroy the data sets and then feed them to the neural network. Based on this, the auto-encoder can be trained in addition to the original data set. Another option is to destroy data by simply deleting parts of the data. This would result in an autoencoder predicting the missing input. To build a balance between outputs and inputs, denoising auto-encoders can even be stacked on top of one another the adaptive process of learning..

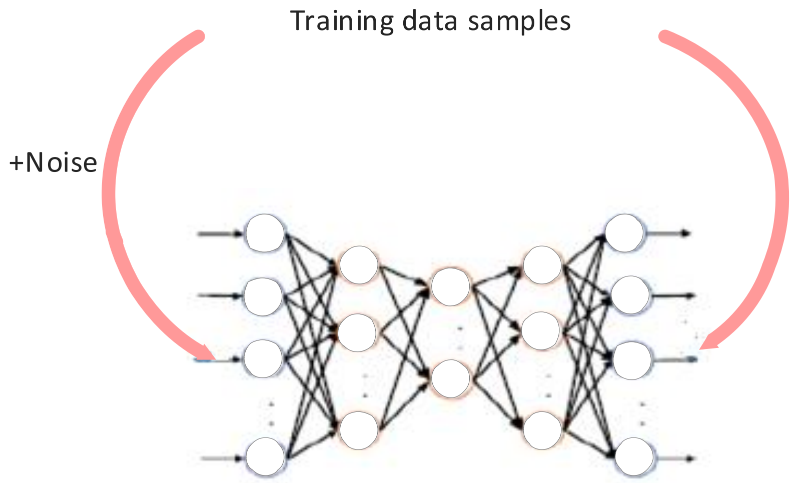


Figure 4. Schematic overview of denoising autoencoder

Table.1 Parameter setup

Technique	Parameters	Values
Autoencoder	**Number of layer**	**5**
	Encoded units	**64x64**
	Unit type	**Logistics**
	Lambda(Weight decay)	**0.002**
	Beta(weight of sparsity penalty	**6**
	Optimization Method	**BFGS**
	Maximum iteration	**2000**
Deep neural network	**Activation function**	**Sigmoid**
	Learning rate	**0.8**
	Momentum	**0.5**
	Number of epochs	**2000**

Algorithm

Step1: Pre-processing of DICOM images to extract the specific image matrix only.
Step2: Flattening of image matrices to construct image dataset.
Step3: Splitting of dataset to sub arrays
Step4: for each sub array continue the steps 5 to 9
Step5: Input the image sub array to Deep Wavelet Autoencoder for encoding
Step6: Pass the encoded image through low pass and high pass filter using discrete wavelet transform for decomposition.
Step7: Apply inverse wavelet transform to combine and decode the images to get original image
Step8: Run the Autoencoder for number of epochs to get optimized weight and bias values
Step9: Extract approximation coefficients from the hidden layer, combine them and provide as input to a deep neural network for classification.

Step10: Train the DNN with the inputs provided by step9 and tests the network for different metrics measurement.

4. Results and discussion

Table 2, shows the performance comparison between proposed DWA-DNN model and other traditional classification techniques.

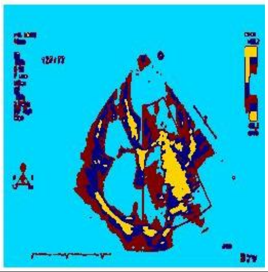
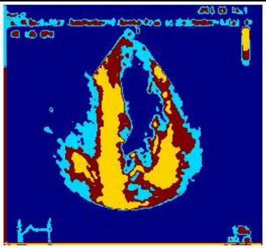
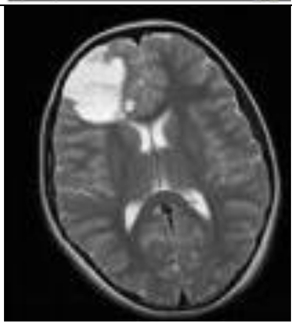
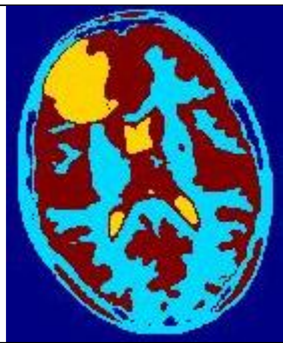
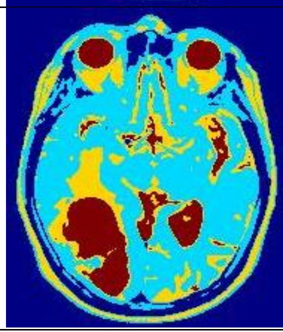
S.NO	Input images	Segment images
1		
2		
3		
4		

Table.3 Performance analysis result

Parameter	Image 1	Image 2	Image 3	Image 4
Contrast	0.9754	0.3251	0.4853	0.3360
Correlation	0.5409	0.8135	0.8778	0.888
Dissimilarity	0.2921	0.1449	0.1885	0.1785
Energy	0.5905	0.4331	0.4771	0.3735
Entropy	1.0443	1.2640	1.2773	1.4310
Homogeneity	0.9305	0.9501	0.9404	0.9348
Max.probability	0.7624	0.6217	0.6773	0.5659
Variance	29.02	26.09	24.672	24.45
Autocorrelation	28.77	26.31	24.775	24.152
Accuracy	93.63	92.25	95.31	96.18
Types of tumuor	Beginal	Malignant	Beginal	Malignant

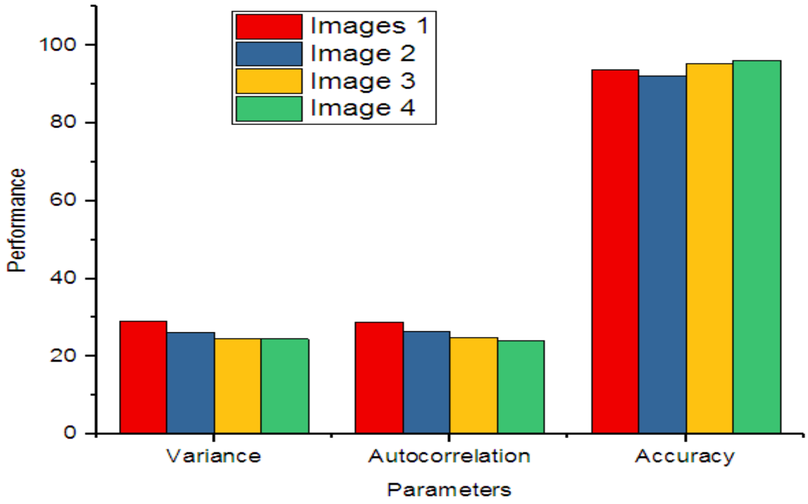


Fig.5 Performance analysis by different images

Measuring the overall accuracies (OAs), Specificity, Sensitivity and average accuracies (AAs) of ten runs of trainings and tests of DNN and DWA-DNN is presented below in table 4 and Figure.5. It can be clearly seen that the DWA-DNN technique have an overtly good accuracy when compared to DNN algorithm and also the specificity and sensitivity measure is quite good as compared to the existing algorithm. Further a comparison has been made between DNN and proposed DWA-DNN technique.

Table.4 Measures of classification technique

Classification technique	Overall accuracy	Average accuracy	Sensitivity	Specificity
DNN	89.27	90.85	0.92±0.23.	0.87±0.46
DNN-DWAE	95.32	93.15	0.96±0.43	0.94±0.38.

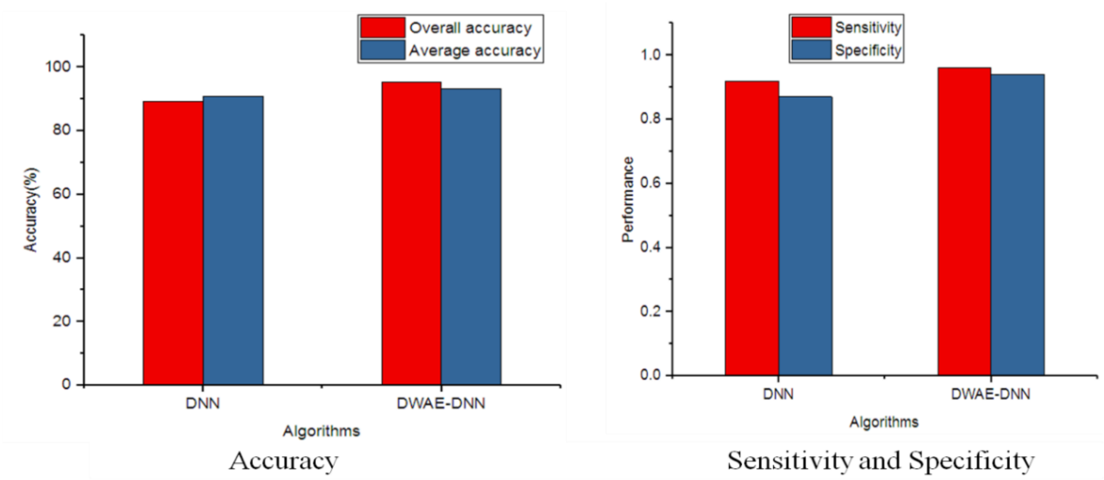


Fig.6 Performance of Accuracy, Sensitivity and Specificity

The proposed DWAE with DNN algorithm overall accuracy, average accuracy, sensitivity and specificity are, 95.32, 93.15, 0.96±0.43 and 0.94±0.38. The performance of proposed technique is improved compared with existing DNN technique. It was shown in figure.6

5. Conculsion

Interpreting the medical imaging data set has always been a slow process and handling it in itself is challenging. In this work, denoising wavelet autoencoder was proposed to detect the brain tumour determination and performance of evaluation can be improved. The proposed DNN-DWAE classifier achieved better results in the factor precision, specificity, sensitivity, and other performance measurements. The results of the proposed DNN-DWAE technology show that its precision and statistical measurements are much more competitive than other technique.

References

[1]Alhadidi B, Zu'bi MH, Mammogram Breast Tumour Image Detection Using Image Processing Functions. Information Technology Journal 6(2): 217–221 (2007).

[2]Pham DL, Xu C and Princo JL A Survey On Current Methods In Medical Image Segmentation, Annual Review of Biomedical Engineering, (2000)

[3] Langote VB, Chaudhuri DS (2012) Segmentation Techniques for Image Analysis. International Journal of Advanced Engineering Research and Studies 2(1): 252-255.

[4] Sathya A, Senthil S, Samuel A. (2012) Segmentation of breast MRI using effective Fuzzy C-Means method based on Support Vector Machine. Information and Communication Technologies (WICT) 67-72.

[5]Singh M, Verma A, Sharma N (2018) An Optimized cascaded stochastic resonance for the enhancement of Brian MRI. Innovation and Research in BioMedical Engineering (IRBM) 39(5): 334-342.

[6] Pham TX, Siarry P, Oulhadj H (2018) Integrating fuzzy entropy clustering with an improved PSO for MRI brain image Segmentation. Applied Soft Computing 65: 230-242.

[7]Tong J, Zhao Y, Zheng P, Chen L, Jiang L (2018) MRI brain tumor segmentation based on texture features and kernel sparse coding. Biomedical Signal Processing and Control 47: 387-392.

[8]Bengio Y, LeCun Y, Hinton G (2015) Deep Learning. Nature 521(7553): 436-444.

[9] Satapathy SK, Jagadev AK, & Dehuri S (2015) An empirical analysis of training algorithms of neural networks: a case study of EEG signal classification using java framework. In Intelligent Computing, Communication and Devices 151-160.

[10] Mishra S, Mishra D (2015) SVM-BT-RFE: An improved gene selection framework using Bayesian T-test embedded in support vector machine (recursive feature elimination) algorithm. Karbala International Journal of Modern Science 1(2):86-96.

[11] Jyoti A, Mohanty MN, Mallick PK (2014) Morphological based segmentation of brain image for tumor detection. Proc. of International Conference on In Electronics and Communication Systems (ICECS) 1-5.

[12] Abraham B, Nair SMComputer aided diagnosis of clinically significant prostate tumour from MRI images using sparse autoencoder and random forest classifier. Biocybernetics and Biomedical Engineering 38(3): 733-744 (2018).

[13] Despotovic I, Goosens B, Philips W (2015) MRI Segmentation of the Human Brain: Challenges, Methods, and Applications. Computational and Mathematical Methods in Medicine 1-24.

[14] Allaoui AEL and Mohammed M Evolutionary Region Growing for Image Segmentation. International Journal of Applied Engineering Research 13(5): 2084-2090 (2018).

[15] Hiralal H and Menon HP A Survey of Brain MRI Image Segmentation Methods and the Issues Involved. Proc. of International Symposium on Intelligent Systems Technologies and Applications 245- 259(2016).

[16] Yazdani S, Yusof R, Karimian A, Pashna M and Hematian A Segmentation Methods and Applications in MRI Brain Images. IETE Technical Review 32(6): 413-427 (2015) Image.

[17] Xiao J and Tong Y Research of Brain MRI Image Segmentation Algorithm based on FCM and SVM. Proc. of 26th Chinese Control and Decision Conference 1-6(2014).

[18] Nayak SK, Karali Y, Panda SC A Study on Brain MRI Image Segmentation Techniques. International Journal of Research Studies in Computer Science and Engineering 2(9): 4-13 (2015).

[19] Chen M, Yan Q and Qin M. A Segmentation of Brain MRI images utilizing intensity and contextual information by Markov random field. Computer Assisted Surgery 22(S1): 200-211(2017).

[20] Jose A, Ravi S, Sambath M Brain Tumor Segmentation Using K-Means Clustering and Fuzzy C-Means Algorithms And Its Area Calculation. International Journal of Innovative Research in Computer and Communication Engineering, 2(3): 3496-3501(2014).

[21]Ganesh M, Palanisamy V A Multiple Kernel Fuzzy C-Means Clustering Algorithm for Brain MR Image Segmentation. International Journal of Advances in Engineering & Technology 5(1): 406-415(2012).

[22] Shen S, Sandham W, Granat M, and Sterr A MRI Fuzzy Segmentation of Brain Tissue UsingNeighbourhood Attraction With Neural Network Optimization. IEEE Transactions on Information Technology in Biomedicine 9(3): 459-467(2005).

[23] Shalini R, Muralidharan V and Varatharaj M MRI Brain Tumor Segmentation using Kernel Weighted Fuzzy Clustering. International Journal of Engineering Research & Technology (IJERT) 3(4): 121-125(2014).

[24] Damodharan S, Raghavan D Combining Tissue Segmentation and Neural Network for Brain Tumor Detection. The International Arab Journal of Information Technology 12(1): 42-52(2015).

[25] Chen L, Lin L, Zuo W, Luo X, Zhang L Learning a Wavelet –like Autoencoder to accelerate Deep Neural Networks. Proc. on 32nd AAAI Conf. on Artificial Intelligence 1-8(2018).