Automatic Brain MRI Slices Classification Using Hybrid Technique

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Abstract

This paper presents an intelligent classification technique to identify normal and abnormal slices of the magnetic resonance human brain images(MRI). The prtoposed hybrid technique consists of four subsequent stages; namely, dimensionality reduction, preprocessing, feature extraction, and classification. In the initial stages, the enhancement and removed unwanted information are applied to provide a more appropriate image for the subsequent automated stages. In feature extraction stage, the most efficient features like statistical, and Haar wavelet features are extracted from each slice of brain MR images. In the classification stage, initially performs classification process by utilizing Fuzzy Inference System (FIS) and secondly Feed Forward Neural Network (FFNN) is used to classify the brain tissue to normal or abnormal.

The proposed automated system is tested on a data set of 572 MRI images using T1 horizontal transverse (axial) section of the brain. Hybrid method yields high sensitivity of 100%, specificity of 100% and overall accuracy of 95.66% over FIS and FFNN. The classification result shows that the proposed hybrid techniques are robust and effective compared with other recently work.

Keywords: Brain Tumor Classification; Fuzzy Inference System; Feed Forward Neural Network; MRI .

التصنيف التلقائي للدماغ لصور الرنين المغناطيسي باستخدام تقنية هجينة

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الملخص

تستعرض هذه الورقة تقنية ذكية لتصنيف شرائح صور الدماغ بالرنين المغناطيسي إلى طبيعية أو مرضية .التقنية الهجينة المقترحة تشمل أربعة مراحل : تقليل أبعاد صور الرنين ، تجهيزها، واستخراج الميزات ، والتصنيف. في المراحل الأولى، يتم استخدام تقنيات لإزالة المعلومات الغير مفيدة لتوفير صورة أكثر ملائمة لمراحل لاحقة. في مرحلة استخراج الميزات، يتم استخراج الميزات الأكثر كفاءة وهي إحصائية، وميزات المويجات لكل شريحة من صور الرنين المغناطيسي. في مرحلة التصنيف، يتم أولا استخدام نظام الاستدلال الضبابي ثم الشبكة العصبية الاصطناعية لتصنيف إلى حالات طبيعية وأخرى مرضية.

تم اختبار النظام الأوتوماتيكي المقترح باستخدام البيانات ل572 صورة رنين مغناطيسي لمقطع أفقي محوري لصور الدماغ. الطريقة الهجينة أعطت حساسية عالية مقدارها 100% وكذلك لعامل الخصوصية وبدقة مقدارها 95.66% بدمج المنطق المضبب والشبكة العصبية. نتائج التصنيف أثبتت كفاءة الطريقة المقترحة مقارنة مع أعمال حديثة.

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1. Introduction

Tumor is one of the most common brain diseases, according to the data from World Health Organization (WHO), it accounts for the top-ten mortality over the world today. Accurate and earlier diagnosis and appropriate treatment can be a great help for reducing the mortality[1].

Recently the development in medical imaging techniques provides us with more and more facilities for better diagnosis and treatment, such as ultrasonic (US), computed tomography (CT), magnetic resonance imaging (MRI) and other modalities. MRI is the most frequently used imaging technique in neuroscience and neurosurgery for these applications, especially in the diagnosis of tumor. MRI creates a 3D image which perfectly visualizes anatomic structures of the brain such as brain tissues and brain tumors if existing. The advantages of MRI over other diagnostic imaging modalities are its higher spatial resolution and its better discrimination of soft tissue, for example, tumor in brain. Fully automatic normal and diseased human brain classification from magnetic resonance images (MRI) is of great importance for research and clinical studies.

In order to distinguish different tissues, RF pulses are applied by the imaging system to the human body in the main magnetic field. When the resonator detects a signal under controlled condition, different images can be acquired and information related to tissue contrast may be obtained, revealing details that can be missed in other conditions. The amount of signal produced by specific tissue types is determined by their number of mobile hydrogen protons, the speed at which they are moving, and the time needed for the protons within the tissue to return to their original state of magnetization (T1) and the time required for the protons perturbed into coherent oscillation by the radiofrequency pulse to loose their coherence (T2) relaxation times. As T1 (spin-lattice) and T2 (spin-spin) relaxation times are time dependent, the timing of the radio frequency pulse and the reading of the radiated RF energy change the appearance of the image[2,3].

MRI imaging sequences are composed of multiple slices, of which the positions and thickness can be chosen randomly, and each image indicates a different essential parameter of inner anatomical structures in the same body section with multiple differences, based on the local variations of spin–spin relaxation time (T2), spin–lattice relaxation time (T1) as shown in Figure 1 [4].

The rest of the paper is organized as follows: Section 2 reviews the related works with respect to the proposed method. Section 3 describes the proposed methodology for MRI brain image tissues classification. Section 4 discusses about the implementation of the proposed algorithm, and Section 5 demonstrate the experiment result. Finally, conclusions are drawn in Section 6.

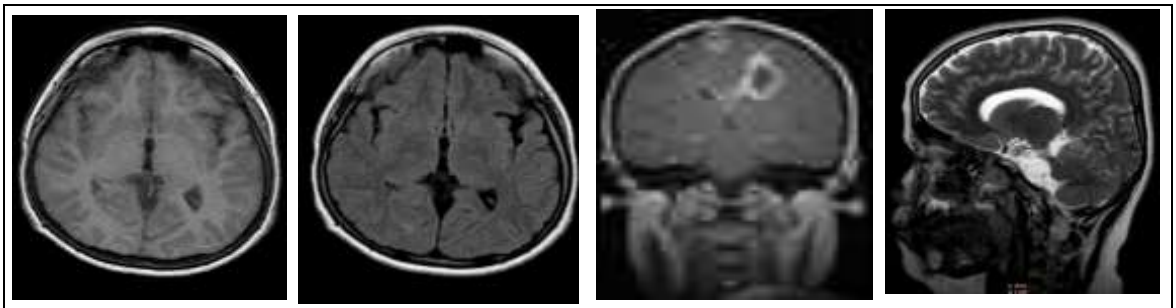


Figure1: Examples of MRI weighted images

2. Related Works:-

Detection of the tumors from brain is very difficult at the regions where a tumor is overlapped with dense brain tissues. Visually detection of these abnormal tissues may result in misdiagnosis of volume and location of unwanted tissues due to human errors caused by visual fatigue. Nowadays, automatic brain tumor detection in MRI images is very important in many diagnostic and therapeutic applications. In the early research of medical tumor detection, the algorithms have directly used the classic methods of image processing (such as edge detection and region growing) based on gray intensities of images. In recent years, those techniques have been combined with artificial neural networks (ANNs)[5], genetic algorithm (GA)[6], fuzzy logic[7], and Texture features are used for classification and segmentation in Ref.[8,9,10,11]. Recent works Zhang Nan 2011, have shown that classification of human brain in MRI images is possible via multi-kernel support vector machine (SVM) and adaptive training is designed to follow-up the changes of tumors during several MRI examinations. In Ref. [3], the author perform unsupervised brain tumor segmentation, and region detection using hybrid intelligent fuzzy Hopfield neural network.

The authors in Ref. [2] develop a segmentation technique initially performs classification process by utilizing Fuzzy Inference System (FIS) and FFBNN. In several of previous works [8, 9, 10, 11] demonstrated the effectiveness of texture features in characterizing brain tumor tissue and analyzed the irregular texture variations of tumors in MRI. M. Jafari and S. Kasaei suggest a novel neural network-based classifier to distinguish normal and abnormal (benign or malignant) brain MRIs[12]. V. Sheejakumari and B. S. Gomathi presents optimal features for classifying tissues from the testing image dataset using Hybrid Genetic Algorithm-Neural Network (HGANN).

The contribution of this paper is the integration of an efficient feature extraction tool and a robust classifier to perform a more robust and accurate automated MRI normal/abnormal brain images classification. The proposed hybrid technique initially performs classification process by utilizing Fuzzy Inference System (FIS) and FFNN. Both classifiers are utilizing the extracted image features as an input for the classification process.

3. Proposed Automatic Tumor Classification Method:

This paper describes a hybrid method to classify the normal and pathological tissues in the MRI brain images using FIS and FFNN. Four major stages are involved in the proposed methodology:

- preprocessing
- Feature Extraction
- Classification by FIS
- Brain tissue classification by FFNN

3.1 preprocessing

Segmentation of brain tissue in MRI is a crucial preprocessing step in several medical research and clinical applications:

1. Label Removal: first of all, remove all labels and markings(patient name, age, gender,,etc) from the image by applying a background color to there places.
2. Image Cropped: Then the images are cropped from all sides until reach the boundaries of the skull to get rid of unnecessary information which represent the background, and by removing labels from the image in the first step we actually converted that portions of the image to the background which is cropped now.

3. Size Standardization: The variations in the brain size and shape of persons need to be taken into account before any general technique is applied. To handle this issue, each MRI image is first cropped by detecting the brain boundary and then resized to 256*256.

3.2 Feature Extraction

To perform the tissue classification process, efficient and appropriate features are selected from the MRI images. The feature selection process plays an important role in the tissues classification and extraction of useful features is a challenging task. Many statistical and other histogram based features are used in the existing methods, which are discussed in the literature. In the proposed system, five features are extracted from the MRI images: they are two dynamic statistical features and three 2D wavelet decomposition features. Namely, statistical features such as mean and variance, and multilevel 2D wavelet decomposition features such as horizontal, vertical, diagonal bands of wavelet transform. The feature vector :

$F_s=\{M_s, E_s, H_s, V_s, D_s\}$ …… (1)

Mean and Variance features are extracted directly from the section slices, as below:

$$M_s = \frac{1}{N*M} \sum_{m=1}^{M} \sum_{n=1}^{N} S(n,m) \quad \text{…… (2)}$$

$$E_s = \frac{1}{N*M} \sum_{m=1}^{M} \sum_{n=1}^{N} (S(n,m) - Ms)^2 \quad \text{……(3)}$$

Where S is the MR image slices, N and M are number of pixels available in rows and columns of images respectively.

To obtain the wavelet features, here haar wavelet is applied to the slice and performed two levels of wavelet transform. After preformed the second level of wavelet transform, three features are extracted (HL, LH and HH) from the result image. The computation of these three features are described in the following equations:

$$H_s=\frac{1}{I*J} \sum_{j=1}^{J} \sum_{i=1}^{I} h(i,j) \quad \text{……(4)}$$

$$v_s=\frac{1}{I*J} \sum_{j=1}^{J} \sum_{i=1}^{I} v(i,j) \quad \text{……(5)}$$

$$D_s=\frac{1}{I*J} \sum_{j=1}^{J} \sum_{i=1}^{I} d(i,j) \quad \text{……(6)}$$

In equations (4), (5), (6) the parameters h,v and d are the coefficients of the horizontal, vertical, and diagonal bands of MRI image slice. I and J are number of pixels available in rows and columns of each bands.

3.3 Fuzzy Inference System (FIS)

The fuzzy inference system normally contains three major operations: Fuzzification, Rules Evaluation and Defuzzification. Fuzzy inference is the process of creating a mapping from a given input to an output by means of a fuzzy logic. Then, the mapping provides a basis from which decisions can be made, or patterns discerned. The process of fuzzy inference

involves Membership Functions, Logical Operations, and If-Then Rules. The schematic diagram of the fuzzy inference system (FIS) is shown in Figure:2.

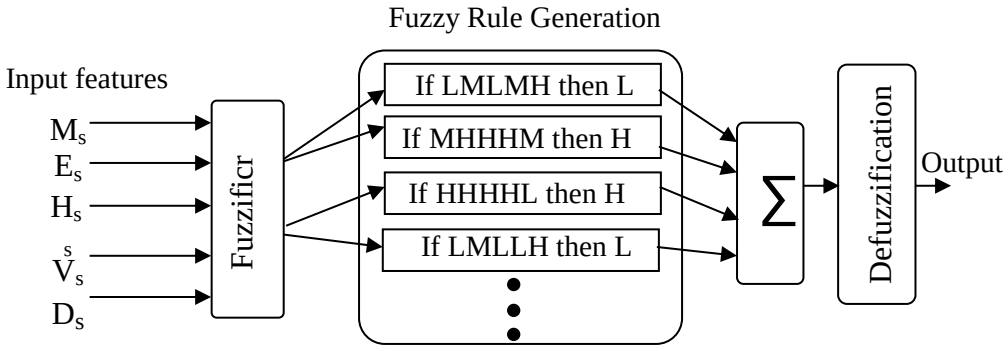


Figure 2: Fuzzy Inference System

Here in the FIS the rules are extracted from all features of each training slice. Values of these features are considered as inputs to the fuzzy system and these features are collected and divided into three levels: High denoted by (H), Medium denoted by (M) and Low denoted by (L), and the output is divided into two levels: high (H) which indicates that there is an abnormal tissue (tumor) in the slice and Low (L) which indicates that the slice is normal.

3.4 Neural Network:

A neuro-based classifier model is added for best discrimination of abnormal and normal patterns from brain regions based on the same extracted features. A three-layer Feed-Forward Neural Network (FFNN) has been constructed for excellent decision. Five neurons are used in the input layer, which equal to the number of features, three in the hidden layer and one in the output layer as shown in Figure: 3.

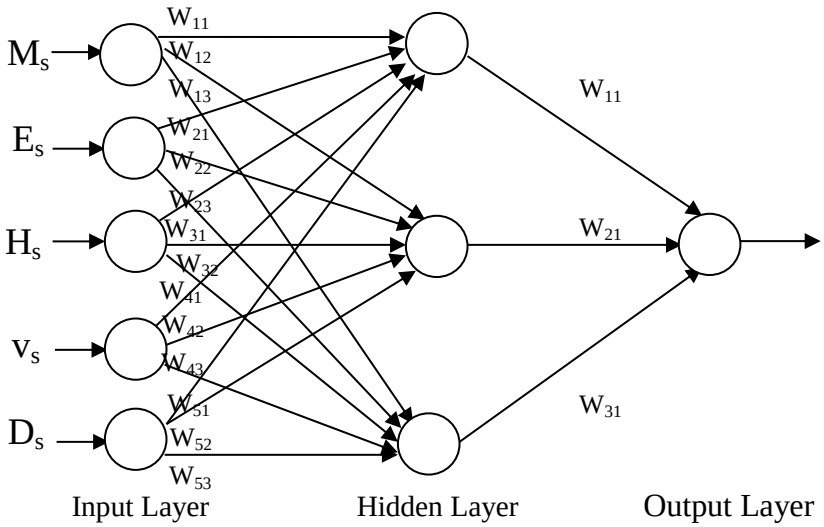


Figure 3: Feed Forward Neural Network

4. Implementation of Proposed Methodology

4.1 MR Image Data

All slices in this work were gathered on 1.5T magnetic field, by PHILIPS MR Scanner manufactured by Philips Medical System/Netherlands with a serial number of 20415 having the following features: a DCM coding scheme designator having a pixel bandwidth of 235.3 Hz and a pixel presentation of Monochrome and a 2D acquisition type. Thickness of the slice is 5mm with 2 mm gap between slices and total number of slices of 22 slice. The view sections are the sagital, coronal and axial with all the T1W-FFE, T2W-TSE, T2W-Fair and MR survey.

4.2 Training & Testing Data

The MRI image slices were grouped into two classes, namely normal and abnormal depending on the tumor present in the slice. The MRI data set contains 572 slices (69 abnormal slices and 503 normal slices) and from which two different sets are grouped to have FIS and FFNN training of classifier. After detecting the infected slices using the Fuzzy system, only 33 slice are remained to be used with the feed forward neural network. In the beginning set, an FIS system is applied to all features, containing rules about all the normal and abnormal slices for all patients. If the output is less than DV(40%-60%) the slice is considered as normal. If it's output is greater than DV it is considered as abnormal, but if it's output equals Dv then it needs the next step which is the neural network and as mentioned before, 33 slice remained to be applied to it, 22 of them were used as a training set and 12 of them as testing. Figure:4 represents the proposed feature in training phase and testing phase.

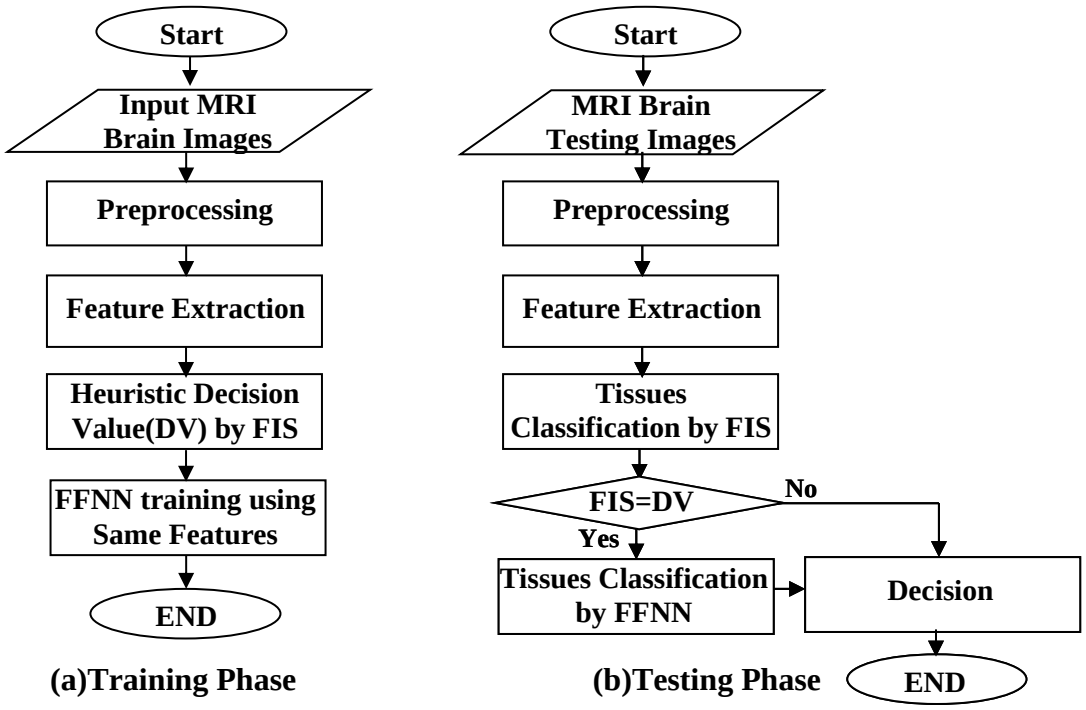


Figure 4: Proposed Classification Method (a)Training Phase (b)Testing Phase

The hybrid learning system use the statistical and wavelet features from the segmented MRI brain slice then these features are given as input to the Fuzzy membership and it is fuzzification using the gbell membership function to the inputs that have three levels L, M and H and to the output that has two levels L and H as shown in figure 5:

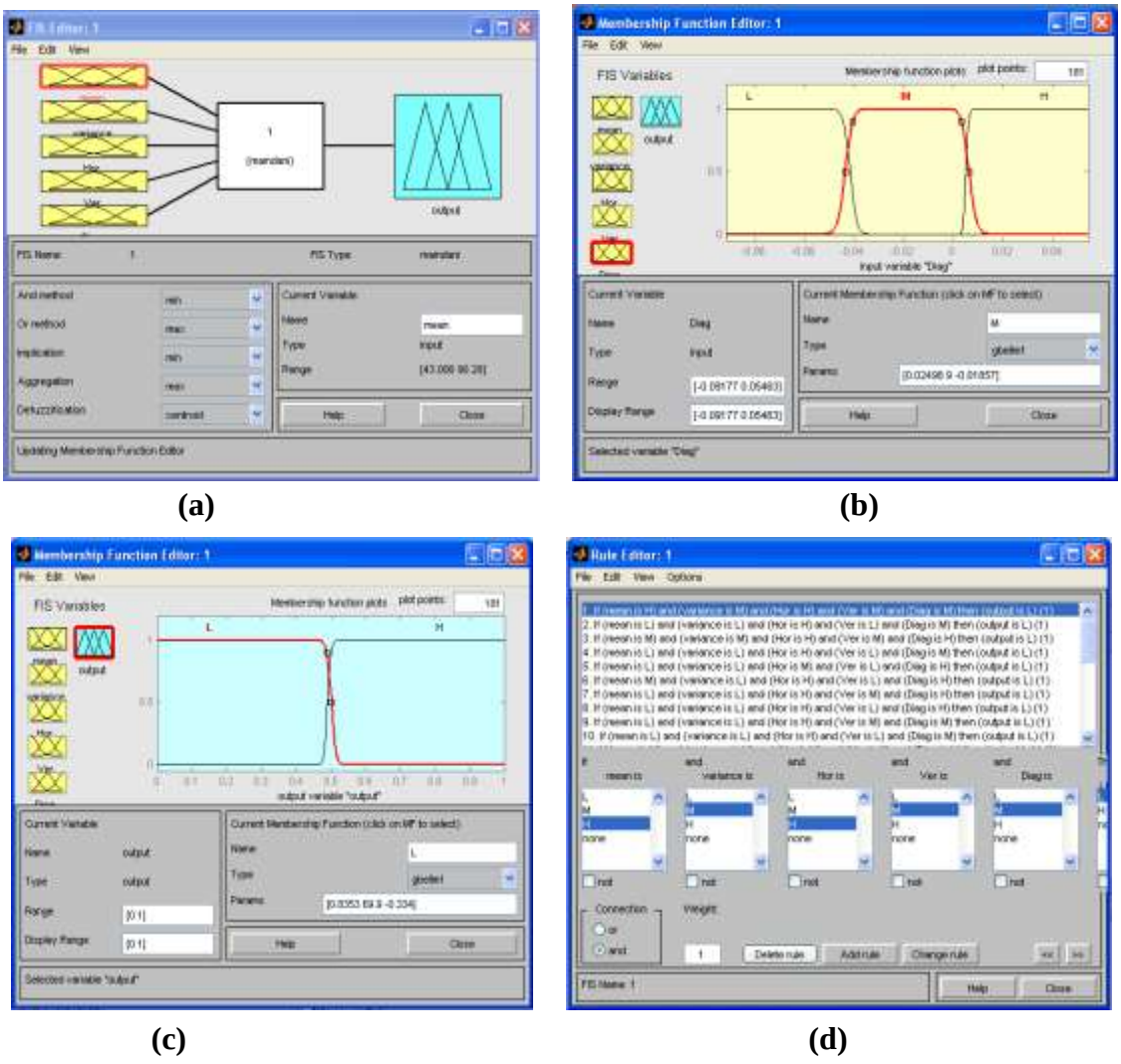


Figure 5: (a) Fuzzy Inference System (b) Membership function of the input (c) Membership function of the output (a) Fuzzy Rules

According to the classification results, the proposed fuzzy system is not enough for some cases when the output between (0.4-0.6) Decision Value. Therefore, neural classifier are added for these cases utilizing same features as input to the additional classified stage which perform by feed forward neural network as shown in figure 6.

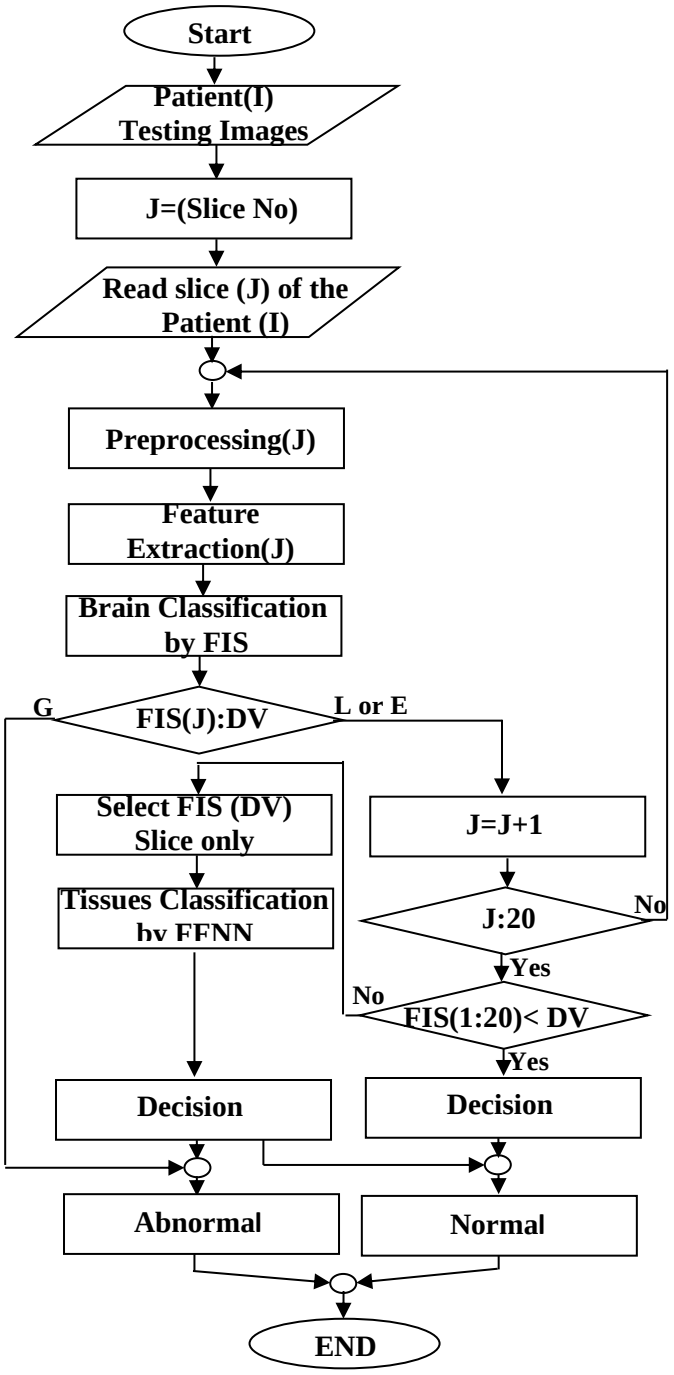
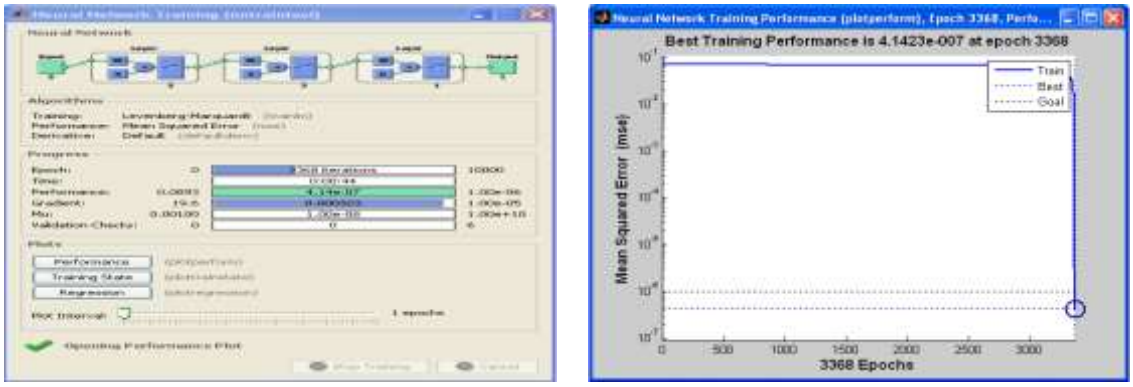


Figure 6: Flow Chart of the Proposed Hybrid Technique

A three layer neural network was created with five nodes in the first (input) layer, one to five nodes in the hidden layer, and one node as the output layer. The training required 3368 epochs to decide truly about the existence of tumors having a mean square error about 4.14e-7 and total time about 44 sec using Levenberg-Marquardt algorithm of training as shown in figure 7. The number of nodes in the hidden layer are varied from (1to 5) in a simulation in order to determine the optimal number of hidden nodes. Due to hardware limitations, three nodes in the hidden layer were selected to run the final simulation.



(a) **(b)**

Figure 7: (a) Feed Forward Neural Network System FFNN (b) FFNN Performance Platform

The output node resulted in either a 0 or 1, for control or patient data respectively. Since the nodes in the input layer could take in values from a large range, a transfer function was used to transform data first, before sending it to the hidden layer, and then was transformed with another transfer function before sending it to the output layer. In this case, a sigmoid transfer function was used between the input and hidden layer, and a sigmoid function was used between the hidden layer and the output layer.

5. Experimental Results

Two datasets have been constructed, one for the training and the other for testing both datasets contain normal cases and abnormal cases at different types of brain tumor.

The Proposed algorithm successfully trained in Matlab version 7.12.0.635, the results of dual classifiers for all patients are tabulated in Table 1. The hybrid proposed algorithms are evaluated in terms of sensitivity (Se), specificity (Sp) and accuracy (Acc). Taking Table 2 into account the metrics are defined as:

$$S_e = \frac{Tp}{Tp+FN} * 100\%) \quad \text{.....(7)}$$

$$S_P = \frac{Tp}{TN+FP} * 100\%) \quad \text{.....(8)}$$

$$A_{cc} = \frac{Tp+TN}{Tp+FN+TN+FP} * 100\%) \quad \text{.....(9)}$$

Where::

True Positive (TP): the classification result is positive in the presence of the clinical abnormality.

True Negative (TN): the classification result is negative in the absence of the clinical abnormality.

False Positive (FP): the classification result is positive in the absence of the clinical abnormality.

False Negative (FN): the classification result is negative in the presence of the clinical abnormality.

Table1: Experiment Result of the Proposed Hybrid Technique

Patients	Slice1	Slice2	Slice3	Slice4	Slice5	Slice6	Slice7	Slice8	Slice9	Slice10	Slice11	Slice12	Slice13	Slice14	Slice15	Slice16	Slice17	Slice18	Slice19	Slice20
Patient1	FIS	0,307	0,248	0,248	0,248	0,248	0,254	0,252	0,248	0,248	0,248	0,708	0,500	0,747	0,747	0,500	0,248	0,248	0,248	0,248
	FFNN	x	x	x	X	x	X	x	x	x	x	x	x	x	x	x	x	x	x	x
	result	N	N	N	N	N	N	N	N	N	N	A	A	A	A	A	N	N	N	N
Patient2	FIS	0,274	0,248	0,257	0,248	0,248	0,252	0,248	0,250	0,248	0,248	0,248	0,250	0,248	0,248	0,500	0,248	0,248	0,706	0,500
	FFNN	x	x	x	x	x	X	x	x	x	x	x	x	x	x	x	x	x	x	x
	result	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	A	A
Patient3	FIS	0,308	0,248	0,248	0,248	0,500	0,693	0,519	0,747	0,248	0,248	0,248	0,400	0,248	0,248	0,447	0,248	0,248	0,248	0,500
	FFNN	x	x	x	x	x	X	x	x	x	x	x	x	x	x	x	x	x	x	x
	result	N	N	N	N	A	A	A	A	N	N	N	N	N	N	N	N	N	N	N
Patient4	FIS	0,302	0,248	0,248	0,747	0,500	0,500	0,5	0,744	0,500	0,316	0,248	0,250	0,248	0,248	0,250	0,252	0,248	0,248	0,248
	FFNN	x	x	x	x	x	X	x	x	x	x	x	x	x	x	x	x	x	x	x
	result	N	N	N	A	A	A	A	A	A	N	N	N	N	N	N	N	N	N	N
Patien5	FIS	0,303	0,248	0,250	0,252	0,248	0,500	0,249	0,251	0,500	0,500	0,5	0,249	0,500	0,248	0,500	0,248	0,248	0,500	0,265
	FFNN	x	x	x	x	x	Need	x		need	need	need	x	need	x	need	x	x	need	x
	result	N	N	N	N	N	N	N	N	N	A	A	N	N	N	N	N	N	N	N
Patien6	FIS	0,248	0,248	0,248	0,248	0,250	0,248	0,248	0,248	0,248	0,248	0,250	0,747	0,747	0,248	0,252	0,250	0,5	0,258	0,248	0,248
	FFNN	x	x	x	x	x	X	x	x	x	x	x	x	x	x	x	x	x	x	x	x
	result	N	N	N	N	N	N	N	N	N	N	A	A	A	N	N	N	N	N	N	N
Patient7	FIS	0,255	0,249	0,248	0,253	0,248	0,248	0,248	0,250	0,248	0,747	0,5	0,747	0,500	0,747	0,500	0,500	0,248	0,500	0,249
	FFNN	x	x	x	x	x	X	x	x	x	x	x	x	x	x	x	x	x	x	x
	result	N	N	N	N	N	N	N	N	N	A	A	A	A	A	A(N)	A(N)	N	N	N
Patient8	FIS	0,253	0,248	0,249	0,248	0,248	0,500	0,500	0,500	0,500	0,500	0,500	0,747	0,747	0,7454	0,5	0,747	0,747	0,254	0,248
	FFNN	x	x	x	x	x	X	x	x	x	x	x	x	x	x	x	x	x	x	x
	result	N	N	N	N	N	A	A	A	A	A	A	A	A	A	A	A	A	N	N
Patient9	FIS	0,264	0,248	0,248	0,248	0,261	0,248	0,256	0,248	0,248	0,248	0,500	0,747	0,747	0,744	0,747	0,500	0,747	0,747	0,5	0,747
	FFNN	x	x	x	x	x	X	x	x	x	x	x	x	x	x	x	x	x	x	x	x
	result	N	N	N	N	N	N	N	N	N	A(N)	A	A	A	A	A	A	A	A	A	A
Patie.10	FIS	0,279	0,248	0,248	0,253	0,248	0,254	0,261	0,249	0,747	0,500	0,500	0,746	0,500	0,745	0,500	0,500	0,248	0,248	0,248	0,248
	FFNN	x	x	x	x	x	X	x	x	x	x	x	x	x	x	x	x	x	x	x	x
	result	N	N	N	N	N	N	N	N	A	A	A	A	A	A	A	A	N	N	N	N
Patients	Slice1	Slice2	Slice3	Slice4	Slice5	Slice6	Slice7	Slice8	Slice9	Slice10	Slice11	Slice12	Slice13	Slice14	Slice15	Slice16	Slice17	Slice18	Slice19	Slice20
t1	3	0,348	0,248	0,249	0,267	0,248	0,248	0,251	0,250	0,248	0,635	0,747	0,500	0,744	0,747	0,5	0,5	0,500	0,746	0,500	0,500

	FFNN	x	x	x	X	x	X	x	x	x	x	x	x	x	x	x	x	x	x	x	x
	result	N	N	N	N	N	N	N	N	N	N	N	N	A	A	A	A	A	A	A	A
Pat.12	FIS	0,273	0,248	0,248	0,248	0,253	0,248	0,249	0,248	0,248	0,248	0,248	0,248	0,248	0,2481	0,500	0,248	0,248	0,41687	0,248	0,248
	FFNN	x	x	x	X	x	X	need	x	x	x	x	x	x	need	need	x	x	x	x	x
	result	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N
Pat.t3	FIS	0,304	0,249	0,248	0,2481	0,248	0,248	0,248	0,248	0,248	0,500	0,248	0,248	0,248	0,308	0,248	0,248	0,248	0,248	0,248	0,248
	FFNN	x	x	x	X	x	X	x	x	x	need	x	x	x	x	x	x	x	x	x	x
	result	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N
Pat.14	FIS	0,256	0,248	0,248	0,248	0,281	0,500	0,253	0,249	0,248	0,248	0,248	0,500	0,248	0,248	0,248	0,248	0,248	0,248	0,248	0,248
	FFNN	x	x	x	X	x	need	x	x	x	x	x	need	x	x	x	x	x	x	x	x
	result	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N
Pat.15	FIS	0,388	0,253	0,252	0,248	0,250	0,248	0,248	0,248	0,248	0,248	0,248	0,248	0,248	0,248	0,248	0,248	0,248	0,248	0,248	0,248
	FFNN	x	x	x	X	x	X	x	x	x	x	x	x	x	x	x	x	x	x	x	x
	result	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N
Pat.16	FIS	0,294	0,249	0,249	0,248	0,5	0,249	0,500	0,248	0,248	0,248	0,248	0,500	0,248	0,248	0,447	0,248	0,248	0,248	0,248	0,248
	FFNN	x	x	x	X	need	X	need	x	x	x	x	need	x	x	x	x	x	x	x	x
	result	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N
Pat.17	FIS	0,306	0,252	0,248	0,248	0,248	0,248	0,249	0,248	0,392	0,265	0,248	0,254	0,248	0,251	0,248	0,248	0,341	0,248	0,500	
	FFNN	x	x	x	X	x	x	x	x	x	x	x	x	x	x	x	x	x	x	need	
	result	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	
Pat.18	FIS	0,281	0,248	0,248	0,248	0,248	0,248	0,500	0,256	0,248	0,252	0,500	0,248	0,500	0,500	0,248	0,2482	0,394	0,255	0,252	0,249
	FFNN	x	x	x	X	x	x	need	x	x	x	need	need	need	need	need	x	x	x	x	x
	result	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N
Pat.19	FIS	0,281	0,248	0,248	0,248	0,248	0,248	0,248	0,250	0,249	0,5	0,248	0,248	0,248	0,248	0,248	0,500	0,248	0,248	0,5	0,248
	FFNN	x	x	x	X	x	x	x	x	x	need	x	x	x	x	x	need	x	x	need	x
	result	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N
Pat.20	FIS	0,257	0,248	0,249	0,248	0,248	0,248	0,248	0,248	0,248	0,248	0,255	0,500	0,249	0,248	0,248	0,248	0,248	0,253	0,425	
	FFNN	x	x	x	X	x	x	x	x	x	x	x	need	x	x	x	x	x	x	x	
	result	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	

Patients		Slice1	Slice2	Slice3	Slice4	Slice5	Slice6	Slice7	Slice8	Slice9	Slice10	Slice11	Slice12	Slice13	Slice14	Slice15	Slice16	Slice17	Slice18	Slice19	Slice20
Pat21	**FIS**	**0,252**	**0,249**	**0,248**	**0,250**	**0,248**	**0,248**	**0,248**	**0,248**	**0,248**	**0,248**	**0,248**	**0,248**	**0,248**	**0,2481**	**0,248**	**0,251**	**0,248**	**0,248**	**0,248**	**0,252**
	FFNN	x	x	x	x	x	X	x	x	x	x	x	x	x	x	x	x	x	x	x	x
	result	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N
Pat. 22	FIS	0,313	0,248	0,248	0,248	0,248	0,500	0,500	0,252	0,263	0,248	0,248	0,490	0,278	0,257	0,270	0,271	0,248	0,248	0,248	0,248
	FFNN	x	x	x	X	x	Need	need	x	x	x	x	x	x	x	x	x	x	x	x	x
	result	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N
Pat. 23	FIS	0,248	0,248	0,248	0,248	0,248	0,248	0,299	0,248	0,251	0,249	0,248	0,249	0,249	0,500	0,248	0,500	0,255	0,257	0,248	0,500
	FFNN	x	x	x	X	x	X	x	x	x	x	x	x	x	need	x	need	x	x	x	need
	result	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N
Pat. 24	FIS	0,302	0,248	0,248	0,248	0,277	0,248	0,253	0,248	0,500	0,248	0,248	0,248	0,249	0,248	0,248	0,248	0,248	0,248	0,248	0,251
	FFNN	x	x	x	X	x	X	x	x	need	x	x	x	x	x	x	x	x	x	x	x
	result	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N
Pat. 25	FIS	0,274	0,248	0,249	0,248	0,248	0,248	0,248	0,251	0,248	0,2483	0,248	0,500	0,248	0,248	0,248	0,252	0,248	0,248	0,248	0,248
	FFNN	x	x	x	X	x	X	x	x	x	x	x	need	x	x	x	x	x	x	x	x
	result	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N
Pat. 26	FIS	0,280	0,252	0,248	0,249	0,248	0,3836	0,2491	0,5	0,249	0,248	0,248	0,2489	0,248	0,248	0,248	0,248	0,250	0,248	0,248	0,248
	FFNN	x	x	x	x	x	X	x	need	x	x	x	x	x	x	x	x	x	x	x	x
	result	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N

X: no need N: Normal A:Abnormal

Table:2 Classification Results of Various Classifiers

Classifier Type	Algorithm	Reference	Sensitivity %	Specificity %	Accuracy %
Support Vector Machine	LSSVM- RBF	13	99.64	95.50	98.64
	LSSVM-linear	13	97.48	92.13	96.17
	SVM- RBF	13	96.40	91.10	95.09
	SVM-linear	13	93.53	89.89	92.64
Neural	MLP	13	94.24	83.15	91.55
	RBF	13	94.60	85.39	92.37
Statistical	KNN	13	93.53	77.53	89.65
Fuzzy	FCM	14	55	62	60
Geostatistical Possibilistic	GPC	14	76	78	74
Geostatistical Fuzzy	GFCM	14	90	94	95
Hybrid Technique	DWT+PCA+ANN	15	98.3	81.8	95.7
	DWT+PCA+k-NN	15	98.4	100	98.6
	SGLDM+GA+SVM	16	91.87	100	94.44
	DWT+SGLDM+GA+SVM	16	94.6	100	96.29
Proposed Technique	FIS+FFNN(Slices)		100	100	95.66
Proposed Technique	FIS+FFNN(Patients)		100	100	100

6. Conclusion

In this paper, the computer based technique for automatic classification of MRI slices as normal or abnormal with various MR image features using dual classifiers was proposed. The performances of the classifiers in terms of statistical measures such as sensitivity, specificity and classification accuracy are analyzed. The results indicated that the FIS-FFNN approach yielded the better performance when compared to other classifiers.

According to the experimental results, total number of processed image slices were 572 slice for 26 person, 11 of them have tumors and 15 are tumor free. 10 persons are detected from total 11 using the designed FIS system which makes the success rate in persons equals to 90.909%.The affected image slices are 69 slice and all of them are detected but with addition of normal slices which makes the success rate of MRI image slices about 95.66%.

This FIS system was able to find two persons from a total of 15 persons who are not affected thus the system worked on normal tissues too but with a simple rate that is about 13.33% and it was completed to 100% by applying the FFNN to the remaining slices which couldn't be detected using the FIS system so the success rate of the Neuro-Fuzzy system was assured by 100% for all slices of normal and abnormal images.

The FIS system completed 46.15% from the overall work and the Neural Network completed the remaining which is 53.85% to become 100%.

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