Expert Systems with Applications 41 (2014) 5526–5545

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Computer-aided diagnosis of human brain tumor through MRI: A survey and a new algorithm

El-Sayed A. El-Dahshan [a,b,*], Heba M. Mohsen [c], Kenneth Revett [d,e], Abdel-Badeeh M. Salem [f]

[a] Faculty of Science, Ain Shams University, Postal code 11566 Cairo, Egypt
[b] Egyptian E-Learning University, 33 El-mesah St., El-Dokki, Postal code 12611 Giza, Egypt
[c] Faculty of Computers and Information Technology, Future University, Cairo, Egypt
[d] The School of Computer Science, University of Westminster, London HA1 3TP, UK
[e] Faculty of Informatics and Computer Science, British University of Egypt, Cairo, Egypt
[f] Faculty of Computer and Information Science, Ain Shams University, Cairo, Egypt

ARTICLE INFO

Keywords:
Human brain tumors
Medical imaging
Medical informatics
Magnetic resonance images
Segmentation
Feature extractions
Classification
Intelligent computer-aided diagnosis systems

ABSTRACT

Computer-aided detection/diagnosis (CAD) systems can enhance the diagnostic capabilities of physicians and reduce the time required for accurate diagnosis. The objective of this paper is to review the recent published segmentation and classification techniques and their state-of-the-art for the human brain magnetic resonance images (MRI). The review reveals the CAD systems of human brain MRI images are still an open problem. In the light of this review we proposed a hybrid intelligent machine learning technique for computer-aided detection system for automatic detection of brain tumor through magnetic resonance images. The proposed technique is based on the following computational methods; the feedback pulse-coupled neural network for image segmentation, the discrete wavelet transform for features extraction, the principal component analysis for reducing the dimensionality of the wavelet coefficients, and the feed forward back-propagation neural network to classify inputs into normal or abnormal. The experiments were carried out on 101 images consisting of 14 normal and 87 abnormal (malignant and benign tumors) from a real human brain MRI dataset. The classification accuracy on both training and test images is 99% which was significantly good. Moreover, the proposed technique demonstrates its effectiveness compared with the other machine learning recently published techniques. The results revealed that the proposed hybrid approach is accurate and fast and robust. Finally, possible future directions are suggested.

1. Introduction

Brain tumor is one of the most common major causes for the increase in Mortality among children and adults in the world. Brain tumor is a group of abnormal cells that grows inside of the brain or around the brain (Selvanayaki & Karnan, 2010). Many different types of brain tumors exist. Some brain tumors are noncancerous (benign), and some brain tumors are cancerous (malignant). The National Brain Tumor Foundation (NBTF) for research in United States estimates that, in children, brain tumors are the cause of one quarter of all cancer deaths. Also, NBTF reported most research in developed countries show that the number of people who develop brain tumors and die from them has increased perhaps as much as 300% over past three decades (Logeswari & Karnan, 2010). Early detection of the brain tumor is very important and the motivation for further studies. In the brain magnetic resonance imaging (MRI), the tumor may appear clearly but for further treatment, the physician also needs the quantification of the tumor area. The computer and image processing techniques can provide great help in analyzing the tumor area (Marshkole, Singh, & Thoke, 2011).

On the other side, computer-aided detection (CAD) has been developing fast in the last two decades. The main idea of CAD is to assist radiologists in interpreting medical images by using dedicated computer systems to provide ‘second opinions’. Studies on CAD systems and technology show that CAD can help to improve diagnostic accuracy of radiologists, lighten the burden of increasing workload, reduce cancer missed due to fatigue, overlooked or data overloaded and improve inter- and intra-reader variability (Fujita et al., 2008; Marshkole et al., 2011). The final medical

* Corresponding author at: Faculty of Science, Ain Shams University, Postal code 11566 Cairo, Egypt. Tel.: +20 201064259498.

E-mail addresses: esldahshan@eelu.edu.eg (E-S.A. El-Dahshan), hmohsen@fue.edu.eg (H.M. Mohsen), revettk@westminster.ac.uk (K. Revett), abmsalem@yahoo.com (A-B.M. Salem).

http://dx.doi.org/10.1016/j.eswa.2014.01.021
0957-4174/

decision is made by the radiologists. Consequently, radiologists expect that CAD systems (Arimura, Magome, Yamashita, & Yamamoto, 2009; Arimura, Tokunaga, Yamashita, & Kuwazuru, 2012; Cherkassky & Mulier, 2007) can improve their diagnostic abilities based on synergistic effects between the radiologist and the computer with medical image analysis and machine learning techniques (Arimura et al., 2012; Duda, Hart, & Stork, 2001). Therefore, the CAD systems should have abilities similar to the radiologists in terms of learning and recognition of brain diseases. For this reason, pattern recognition techniques including machine learning play important roles in the development of CAD systems (Graña et al., 2011; Mohsen, El-Dahshan, & Salem, 2012; Yamamoto et al., 2010). Pattern recognition is the act of extracting features from objects (e.g. lesions) in raw data and making a decision based on a classifier output, such as classifying each object into one of the possible categories of various patterns. In general, there are two types of CAD systems for brain evaluation i.e. systems that detect lesions (normal or pathological brain) and those that differentiate diseases (benign or malignant lesions).

Many different techniques are used for developing a CAD scheme, various techniques have been summarized in several review purpose. Generally; CAD systems are executable on all imaging modalities and all kinds of examination. To create a CAD system, the integration of various image processing operations (techniques) such as image segmentation, feature extraction and selection, and classification are essential. Recently, various types of brain computer-aided detection methods (Arimura et al., 2009; Cherkassky & Mulier, 2007; Fujita et al., 2008; Graña et al., 2011; Mohsen et al., 2012; Yamamoto et al., 2010) have been developed by a number of researchers, including our group (El-Dahshan, Hosny, & Salem, 2010; Mohsen et al., 2012), using brain MR images based on several types of machine learning classifiers. The challenge remains to provide CAD systems that work in all cases regardless of the quality and the size of the database. CAD systems of human brain MR images are primarily motivated by the necessity of achieving maximum possible accuracy. Our motivation of this study is to improve the performance of a CAD system for human brain tumor detection. CAD system remains an open problem. Motivated by the above needs, we make the following contributions in the development of automatic and accurate CAD system for characterizing of brain tumors as benign and malignant.

The main contribution of this study is twofold. On one side, to review the most recent segmentation and classification algorithms and their state-of-the-art. We summarized the advantages and disadvantages of the reviewed algorithms in tables to provide a structured vision aspects involved in these algorithms. On the other side, in the light of this review, we developed a robust classification technique capable to perform an efficient and automated MRI normal/abnormal brain images classification.

The organization of the paper is as follows. Section 2 presents the brain imaging techniques, Section 3 reviewing on the existing MRI CAD systems with comparative study on the recent segmentation and classification techniques for Brain tumors, Section 4 presents the proposed technique methodology with a short description for its four phases: defining the region of interest (ROI), feature extraction and reduction, and classification, Section 5 presents the experiment results and discussion and Section 6 presents the conclusion and future work.

2. Brain imaging techniques

Brain imaging techniques allow doctors and researchers to view activity or problems within the human brain, without invasive neurosurgery. There are a number of accepted, safe imaging techniques in use today in research facilities and hospitals throughout the world. The cells which supplies the brain in the arteries are tightly bound together thereby routine laboratory test are inadequate to analyze the chemistry of brain. There are many imaging modalities that allow the doctors and researchers to study the brain by looking at the brain non-invasively (Latif, Kazmi, Jaffar, & Mirza, 2010). Computed tomography (CT), positron emission tomography (PET) and MRI can provide information about brain tissues, from a variety of excitation sequences. Compared to all other imaging modalities, MRI provides superior contrast for different brain tissues. MRI is efficient in the application of brain tumor detection and identification, due to the high contrast of soft tissues, high spatial resolution and since it does not produce any harmful radiation, and is a non-invasive technique (Georgiadis et al., 2008).

Additionally, MR images encapsulate valuable information regarding numerous tissue parameters (proton density (PD), spin–lattice (T1) and spin–spin (T2) relaxation times, flow velocity and chemical shift), which lead to more accurate brain tissue characterization. These unique advantages have characterized MRI as the method of choice in brain tumor studies.

MRI is often the medical imaging method of choice when soft tissue delineation is necessary. This is especially true for any attempt to classify brain tissues. Radiologist used it for the visualization of the internal structure of the body. MRI provides rich information about human soft tissues anatomy. MRI helps for diagnosis of the brain tumor. Images obtained by the MRI are used for analyzing and studying the behavior of the brain. The strength of the MRI signal depends primarily on three molecules. Other two parameters are T1 and T2 relaxation, which reflect different features of the local environment of individual protons (Latif et al., 2010). The 'pathological' T2 scan is useful for locating the lesioned region in the brain. The 'anatomical' T1 scans usually have the best scan resolution, and are useful for localizing anatomical structures. The PD scan shows overall hydrogen density per cubic mm. Fig. 1 shows the sample brain MRI.

An attractive feature of MRI is that different contrasts between tissue types (multispectral image data of the same subject) can be easily obtained. For that in the recent years, MRI has evolved into a popular technique to study the human brain. This non-invasive technique can provide high resolution spatial images and its rich information content can be suitably utilized to develop automated diagnostic tools, which can aid the medical fraternity to draw quicker and easier inferences about the condition of the brain under study.

3. Generic methodology of MRI (CAD) scheme

The development of automated tools can be of immense importance to help in diagnosis, prognosis and pre-surgical and post-surgical procedures, depending on whether the subject is a healthy one or is a pathological subject, suffering from some brain disorder, e.g. Alzheimer's disease, Parkinson's disease, etc. The extraordinary level of detail that can be obtained with brain MR images can be efficiently utilized by performing some powerful signal or image processing techniques, especially suitable for automated analysis. This is because, with the huge information repository associated with MRIs, it becomes almost impossible to manually interpret each image, necessitating the development of automated tools (Jafari & Kasaei, 2011).

Fig. 2 shows the details of the system. First MR image for diagnosis is provided to the system as an input. Second step of the proposed system is to extract features from this input image. After feature extraction, these features independently are used for classification as malignant and benign MR image. It classifies the brain image on the bases of multiple classifiers. No more processing is

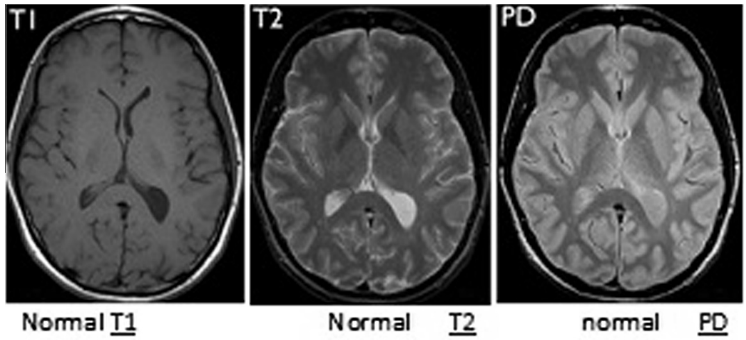

Fig. 1. Sample of MRI images for a normal brain: (a) T1-weighted, (b) T2-weighted, and (c) PD- proton density (Parizel et al., 2010).

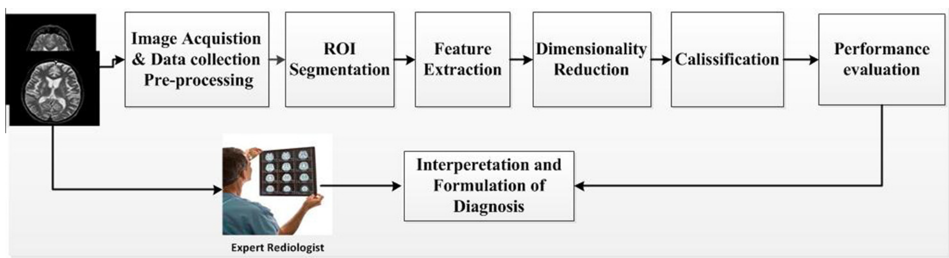

Fig. 2. Typical methodology of a CAD scheme.

required once the MR image is determined as benign. But when the MR image is determined as malignant by the classifier it is further processed for extracting tumor portion from it (Selvanayaki & Karnan, 2010).

In the following two subsections various segmentation, feature extraction, and classification methods and their performances of CAD brain tumor through MRI have been reviewed and compared for the last 10 years and most of them are in the last 3 years. We identified the strengths and the weaknesses of the reviewed algorithms from the literature.

3.1. Image acquisition and preprocessing

To obtain a real brain images (e.g. MRI) and to make up a research is a very complex because of a privacy issue. Most of the data are obtained from the web ((https://ida.loni, 2014; Brainweb, 2014; Department of Radiology, 2014; Harvard Medical School, 2014; http://buscahospital, 2014; Indian Devaki Cancer Institute, 2014). The state-of-the-art of now-a-days technologies of digital medical image acquisition are improving tremendously, which gives images of high quality and resolution but the noise on the images is still an issue. Image preprocessing and enhancement stage is the simplest stage of medical image analysis. This stage is used to reduce the noise and improve resolution contrast the image. Several de-noising approaches can be used (Gonzalez & Woods, 2008). The median filter is most de-noising method used to reduce noise and improve the quality in an image. The median filter preserves the edges of the images.

3.2. Segmentation techniques for MR medical images

Through this study, we have made a survey on the segmentation techniques used for medical images specifically brain images. In this section we have made a comparison that includes our approach along with a number of the published segmentation techniques where some hybrid techniques are used and others are the modified version of its basic. Table 1 shows a comparison between more than 30 segmentation techniques for different brain imaging techniques.

From the table, it can be found that several algorithms and techniques that have been developed for segment brain tumor regions from MR images. Fig. 3 summarizes the segmentation techniques. It have been noticed that the most common used techniques were the C-means and fuzzy sets combined with other techniques to achieve better performance with the MR images uncertainties and regions. Also, in order to compare different segmentation methods (Gonzalez & Woods, 2008; Selvaraj & Dhanasekaran, 2013) clearly, advantages and disadvantages of the most commonly used methods in brain tumor detection are summarized briefly in Table 2. In fact, hybrid techniques (combination of two or more techniques) and Soft computing (SC) techniques (i.e. fuzzy logic, neural network and genetic algorithms) have found wide applications in image segmentation. The guiding principle of soft computing is that it exploit the tolerance for imprecision, uncertainty, partial truth, and approximation to achieve tractability, robustness and low solution cost. As soft computing techniques resemble human brain, the results are fast and accurate. Also, PCNN and its modification forms are widely applied to image segmentation.

3.3. Feature extraction and classification techniques for Brain MRI

One of the most common problems of pattern recognition in medical image analysis is the classification of a set of features into the proper class. Feature extraction and selection are important steps in brain tumor detection and classification. An optimum feature set should have effective and discriminating features, while mostly reduce the redundancy of feature space to avoid "curse of dimensionality" problem. A key stage of classification by CAD schemes is feature analysis and extraction (Cheng, Shan, Ju, Guo, & Zhang, 2010; Cherkassky & Mulier, 2007).

Feature extraction: the transformation of an image into its set of features is known as feature extraction. Useful features of the image are extracted from the image for classification purpose. It

Table 1
An overview of Segmentation techniques for medical images.

Author	Segmentation technique	Purpose	Additional features
Mohsen et al. (2012)	Feedback pulse-coupled neural network (FPCNN)	Segmentation of tumor in brain MRI	Use the feedback feature where the input experience feedback shunting that is not uniform for the entire input
Jafari and Kasaei (2011)	Seeded region growing segmentation (SRGS) + connected component labeling (CCL)	Starts by brain detection from skin–neck–bone and ventricles and then distinguish brain regions from scalp and pathological tumor tissues from normal tissues in Brain MRI	A hybrid technique been used to select and improve of a rugged segmentation results
Masulli and Schenone (1999)	Possibilistic neuro fuzzy C-means algorithm (PNFCM)	Segmentation of tumor, edema, white matter, grey matter and skull based on brain MRI (T1-weighted, T2-weighted, proton density)	Combine the possibilistic approach to clustering by assuming that the membership function of a point in a fuzzy set is absolute
Demirhan and Güler (2011)	Self-organizing map (SOM) + learning vector quantization (LVQ)	T1-weighted Brain MRI are segmented into grey matter, white matter and background regions	The hybrid technique used to segment the images then define class regions for the data space
Zarandi et al. (2011)	Prossibilistic C-mean (PCM) + type II fuzzy concepts	Segment different tissue classes in brain MRI: tumor, cerebrospinal fluid, white matter and gray matter	For better performance for handling the uncertainties in images as Type II fuzzy sets membership functions are fuzzy themselves
Zhang, Ruan, Lebonvallet, Liao, and Zhu (2011)	Support Vector Machine (SVM) + region growing	SVM learn the brain tumor and select the features from MRI to automatically segment the tumor then refine the tumor contour by a region growing technique	Hybrid to automatically segment the tumor region then refine the tumor contour
Dubey, Hanmandlu, and Gupta (2009)	Stable 3D level-set	Semi-automated segmentation for brain tumor volume measurements based on brain MRI	Replacing the constant propagation term in level sets by a statistical force for a stable solution
Yang, Hu, Lin, and Lin (2002)	Alternative fuzzy C-means (AFCM)	MRI segmentation in Ophthalmology provides more information that can reduce noise effects and better detect abnormal tissues	Replace the Euclidean norm with the new metric in C-means clustering
Juang and Wu (2010)	Color-converted based segmentation + K-means	Brain tumor object tracking in MRI by converting gray-level image into a color space image and operating the image labeled by cluster index to detect exactly tumor size and region	Convert the gray-level image into color space and operate the image labeled by cluster index
Ratan, Sharma, and Sharma (2009)	Watershed	Successfully segment tumors in brain 2D and 3D MRI where the difference in intensity level between tumor and non tumor regions is high	Used the basic watershed technique
Weili et al. (2009)	Improved PCNN (based on Tsallis entropy)	Automatic segmentation for human head MRI and medical images	Combine the techniques so that segmentation done automatically without selecting the PCNN parameters
Kang (2005)	G-wire (Livewire based on generalized mutli-dimensional graph formulation)	Accurate and smooth segmentation of tumors even in noisy images	The new technique incorporate the internal energy of the boundary curve while preserving the principle of the optimality
Marx and Brown (2000)	Progressive livewire (combine between livewire and active contour)	Track structures such as brain, skin, or vessels in sequences of MRI and CT scans	Combines the two techniques by training the livewire to segment single image in a sequence of images that would be further used to initialize a special type of snake to be used with the remaining images
Maitra and Chatterjee (2008)	Improved orthogonal discrete wavelet transform (DWT), known as the Slantlet transform (ST), and FCM	Automated segregation of brain MR images	The proposed technique has been applied to several benchmark brain MR images and the results reveal excellent accuracy in characterizing human brain MR imaging
Kuwazuru et al. (2012)	Using an artificial neural network (ANN) and controlled level-set method	Automated segmentation scheme for multiple sclerosis (MS) lesions in magnetic resonance images	Scheme improved the sensitivity and the number of FPs in the detection of MS lesions.
Fu et al. (2010)	Automatic hybrid image segmentation model that integrates the statistical expectation maximization (EM) model and the spatial PCNN for brain MRI segmentation	Brain MRI segmentation	The performance of the adaptive EM–PCNN is compared with that of the non-adaptive EM–PCNN, EM, and bias corrected fuzzy C-means (BCFCM) algorithms
Ramasamy and Anandhakumar (2011)	FFT based EM-GMM algorithm	MR image segmentation	FFT based EM–GMM algorithm improves the classification accuracy as it takes into account of spatial correlation of neighboring pixels and as the segmentation done in Fourier domain instead of spatial domain
Chao, Chen, Lin, Shih, and Tsang (2009)	Boosted decision tree	Brain tissue classification in magnetic resonance (MR) imaging using a boosted decision tree segmentation algorithm	Improved the accuracy rate of MR brain tissue segmentation
Chao et al. (2008)	Automatic segmentation method based on a decision tree to classify the brain tissues in magnetic resonance (MR) images	Automatic segmentation method based on a decision tree to classify the brain tissues in magnetic resonance (MR) images	Perform automatic segmentation for both phantom and tissue regions in brain MR images

(*continued on next page*)

Table 1 (*continued*)

Author	Segmentation technique	Purpose	Additional features
Tanga et al. (2000)	Combining both spatial and intensity information in image	Combining both spatial and intensity information in image,	Approach based on multi-resolution edge detection, region selection, and intensity threshold methods
Siyal and Yu (2005)	Modified FCM algorithm for bias (also called intensity in-homogeneities) estimation and segmentation of MRI	Modified FCM algorithm for bias (also called intensity in-homogeneities) estimation and segmentation of MRI	The proposed algorithm accurately segments the different tissue classes under serious intensity variations and noise environment.
Ortiza et al. (2013)	Segmentation method based on the growing hierarchical self-organizing map (GHSOM) and multi-objective-based feature selection to optimize the performance of the segmentation process	Brain image segmentation	Provide new and additional ways to diagnose some brain disorders such as schizophrenia or the Alzheimer disease
Gasmi, Kharrat, Messaoud, and Abid (2012)	A new general automatic method for segmenting brain tumors in magnetic resonance (MR) images. Our approach addresses all types of brain tumors	Feature extraction via wavelet transform (WT), dimensionality reduction using genetic algorithm (GA) and classification of the extracted features using SVM	The resulting method is aimed at early tumor diagnostics support by distinguishing between the brain tissue benign tumor and malignant tumor tissue
Ayachi and Ben Amor (2009)	Use SVM	Segmentation of human brain MRI	The aim is to distinguish between normal and abnormal pixels on the basis of several features, normal intensity and texture
Somasundaram and Kalaiselvi (2010)	We propose two brain extraction algorithms (BEA) for T2-weighted magnetic resonance imaging (MRI) scans	only 2D information of slices and is named as 2D-BEA	Experimental results on 20 MRI data sets show that the proposed 3D-BEA gave excellent results. The performance of this 3D-BEA is better than 2D-BEA and other popular methods, brain extraction tool (BET) and brain surface extractor (BSE)
Sachdeva et al. (2012)	Intensity-based active contour models such as gradient vector flow (GVF), magneto static active contour (MAC) and fluid vector flow (FVF) have been proposed to segment homogeneous objects/tumors in medical images	The proposed method content-based active contour (CBAC) uses both intensity and texture information present within the active contour to overcome above-stated problems capturing large range in an image	Tumor volume is efficiently extracted from 2-dimensional slices and is named as 2.5-dimensional segmentation
Tanoori et al. (2011)	Active contour models and SVM.	The method is based on the idea of active contour models and SVM classifiers. The main contributions of the presented method are effective modifications on brain images for active contour model and extracting simple and beneficial features for the SVM classifier	A novel automatic approach to identify brain structures in magnetic resonance imaging (MRI) is presented for volumetric measurements. This method validation is done using the gold standard brain MRI data set
Rajendran and Dhanasekaran (2012)	Fuzzy clustering and deformable model	Tumor Segmentation on MRI Brain image	The method is more accurate and robust for brain tumor segmentation
Zexuan et al. (2012)	Generalized rough fuzzy C-means algorithm	Brain MR image segmentation	The proposed algorithm is more robust to the initialization, noise, and bias field, and can produce more accurate and reliable segmentations
Donoso, Veloz, and Allende (2010)	Modified Expectation Maximization	MRI Segmentation	Approaches proposed in the image segmentation literature using the size and shape test, obtaining accurate and robust results in the presence of noise
Merisaari et al. (2009)	Gaussian mixture model-based	A fully automatic brain segmentation method for T1-weighted images	The proposed method is found to produce more uniform results in comparison to Three accustomary segmentation methods originally developed for adults
Noreen, Hayat, and Madani (2011)	Wavelets and Fuzzy C-means	MRI Segmentation	Robust against noise
Balafar, Ramli, Saripan1, Mahmud, and Mashohor (2008)	Combination of Learning Vector Quantization (LVQ), segmentation more	MRI Brain Image Segmentation	Robust against inequality of content with semantic, low contrast, in homogeneity and noise.
Shanthi, Sasikumar, and Kesavadas (2010)	Hybrid method combining the classical Fuzzy C Means algorithm with neural network for segmentation	Segmentation of brain magnetic resonance images (MRI)	The study of volume changes helps in analyzing many neural disorders such as epilepsy and Alzheimer disease
Vrooman et al. (2007)	K-Nearest-Neighbor	Fully automated brain tissue classification	Our new fully automated, non-rigid registration-based method gives accurate and robust segmentation results
Ortiz, Gorriz, Ramırez, and Salas-Gonzalez (2013)	Two unsupervised approaches for brain image segmentation. The first one is based on the use of relevant information extracted from the whole volume histogram which is processed by using SOM. The second method proposed consists of four stages including MRI brain image acquisition,	Brain image segmentation	The proposed algorithms have been successfully evaluated providing a good segmentation results

Table 1 (*continued*)

Author	Segmentation technique	Purpose	Additional features
	first and second order feature extraction using overlapping windows, evolutionary computing-based feature selection and finally, map units are grouped by means of a novel SOM clustering algorithm		
Mehmood, Ejaz, Sajjad, and Baik (2013)	Using prioritization methods	Segmentation of lesions and image prioritization	Obtain a rapid, approximate idea of the significance of images under analysis

is a challenging task to extract good feature set for classification. There are many techniques for feature extraction e.g. texture features, Gabor features, feature based on wavelet transform, principal component analysis, minimum noise fraction transform, discriminant analysis, decision boundary feature extraction, non-parametric weighted feature extraction and spectral mixture analysis (Zarandi, Zarinbal, & Izadi, 2011).

The most recent and more efficient human brain CAD systems perform discreet wavelet transform (DWT) decomposition of the MR human brain images to obtain the wavelet coefficients at different levels. Principal components analysis (PCA), independent components analysis (ICA) and linear discriminant analysis (LDA) are used to reduce the dimension of data. A small set of highly significant features from the MR brain images have been extracted and uses them in simple classifiers to accurately classify them into normal, abnormal classes. The integration between the feature extraction (DWT) and the feature reduction (PCA, ICA or LDA) algorithms led to developing a CAD technique which is capable of classifying human brain with clinically acceptable accuracy using less number of features that can be extracted with less computational cost. The developed CAD system can be used as an automated, simple, objective, fast, and cost-effective efficient secondary diagnostic tool that provides additional confidence to the clinician's initial diagnosis of the human brain tumors.

Classification: classification is the technique for classifying the input patterns into analogous classes. Selection of a suitable classifier requires consideration of many factors: (a) classification accuracy, (b) algorithm performance, (c) computational resources.

In this study we present most recent published classification techniques. Table 3 shows a survey on the classification techniques for brain MRI that published during 2002–2012. There are many classification algorithms for classifying the brain MRI and these algorithms have different strengths and weaknesses. Table 4 gives the advantages and disadvantages of the most commonly used classifiers (Duda et al., 2001). It illustrates that classification of human brain in MRI is possible via supervised techniques such as artificial neural networks and support vector machine, and unsupervised classification techniques such as SOM and fuzzy C-means. Other supervised classification techniques, such as k-NN can be used to classify the normal/pathological T2-weighted MRI images (El-Dahshan et al., 2010).

Also, hybrid intelligent systems using soft computing techniques are used for classifier design. Soft computing consists of several intelligent computing paradigms, including fuzzy logic, neural networks, and bio-inspired optimization algorithms (genetic algorithm and genetic programming), which can be used to produce powerful hybrid intelligent classification systems.

The studies on feature extraction and classification of brain MRI are given in Table 3 for a comparative study.

From Table 3, it can be seen that:

1. The most common methods for feature extraction are discrete wavelet transform and texture analysis.
2. Most common methods for classification are hybrid systems that give best accuracy combined with a pre-feature extraction and different machine learning techniques.
3. Hybrid intelligent systems (especially soft computing systems) have an impact on the efficiency and accuracy of classification systems. It gives very high accuracy (in the range 97–100%).

The advantages and disadvantages of the most used classifiers for human brain MR images are summarized in Table 4 (Duda et al., 2001). Hybrid approaches appear to offer higher detection success rates. We believe that the machine learning approaches can be integrated with other approaches to offer a higher detection success rate.

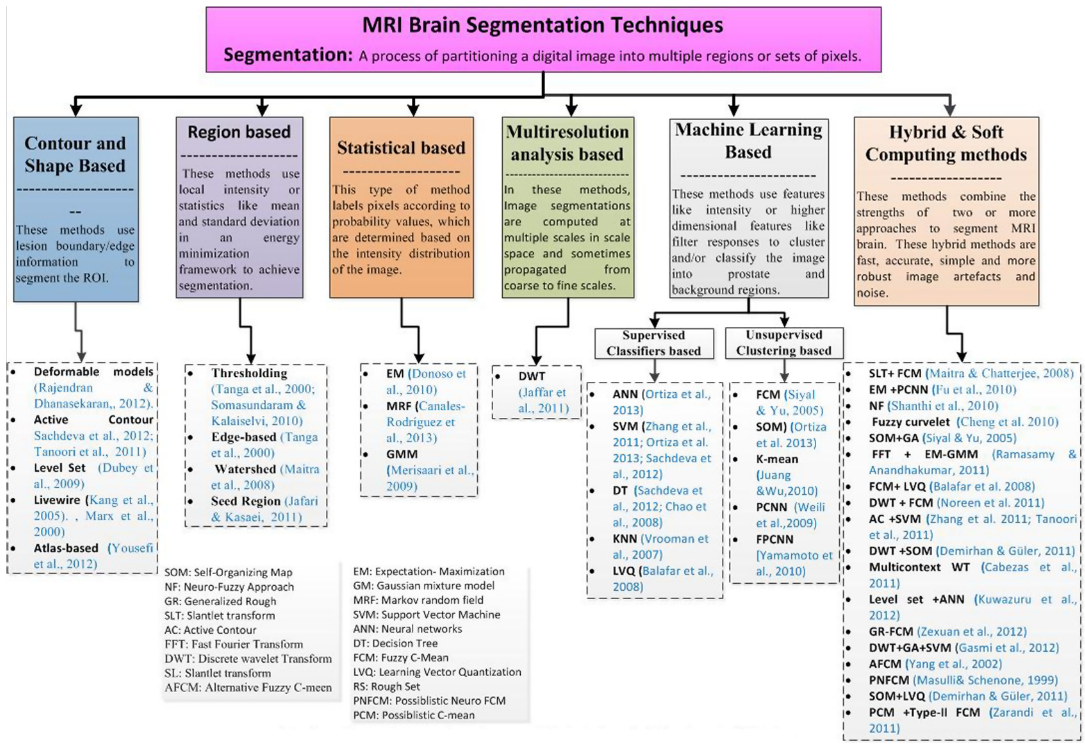

Fig. 3. Overview of the most commonly used segmentation techniques in CAD systems for MRI brain.

Table 2
The advantages and disadvantages of the most used segmentation methods for human brain tumors through MR images.

Approach	Advantages	Disadvantages
Threshold based	These threshold techniques are very much useful for image linearization which is very essential task for any type of segmentation	This algorithms does not work properly for all type MRI of brain image, This is because of large intensity variation of the foreground and background image intensity
Deformable model	able to expand or contract over time, within an image and confirm to specific image features	deformable models, when applied to noisy images with ill-defined boundary, may produce shapes that have inconsistent topology with respect to the actual object
Region growing	Region growing methods can correctly separate the regions that have the same properties we define. It performs well with respect to noise	It requires a seed point that is manually selected by the user and removes all pixels connected to the Preliminary seed based on some predefined condition. very much sensitive to noise
Watershed	the best methods to group pixels of an image on the basis of their intensities	The main problem of watershed transform is its sensitivity to intensity variations, resulting in over segmentation, which occurs when the image is segmented into an unnecessarily large number of Regions. The over segmentation problem still exists in this method
Atlas based	Atlas-guided approaches are that labels are transferred as well as the segmentation. They also provide a standard system for studying morphometric properties.	The disadvantage of an atlas-based can be in the time necessary for atlas construction wherever iterative procedure is incorporated in it, or a complex non-rigid registration. Since the atlas based segmentation is usually used when the information from the gray level intensities are not sufficient, it is difficult to produce objective validation
	The atlas-based segmentation has an ability to segment the image with no well defined relation between regions and pixels' intensities. Another important advantage of atlases is in their use in clinical practice, for computer aided diagnosis whereas they are often used to measure the shape of an object or detect morphological differences between patient groups	
Level set	Level set methods present a commanding approach for the medical image segmentation because it can handle any of the cavities, concavities, convolution, splitting, or merging	However, this method needs identifying initial curves and can only provide superior results if these curves are placed near symmetrically with respect to the object boundary
K-nn	Some advantages of k-NN are it is easy to implement and debug, in situations where an explanation of the output of the classifier is useful, k-NN can be very effective if an analysis of the neighbors is useful as explanation and there are Some noise reduction techniques that work only for k-NN that can be effective in improving the accuracy of the classifier. k-NN is very simple to understand and easy to implement	Disadvantages are k-NN can have poor run-time performance if the training set is large because all the work is done at run-time, k-NN is very sensitive to irrelevant or redundant features because all features contribute to the similarity and thus to the classification and this can be ameliorated by careful feature selection or feature weighting

Table 2 (*continued*)

Approach	Advantages	Disadvantages
MRF	Markov random field models (MRFs) are not deterministic, are best characterized by their statistical properties	This is only applicable to tumors that are homogeneous enough to be segmented into a single normal tissue class, therefore is not generally applicable to heterogeneous tumors and it allows the identification of tumor structures that have normal intensities but are too thick to be normal
SVM	The SVM approach is considered as a good candidate due to high generalization performance, especially when the dimension of the feature space is very high. The SVM method has the advantage of generalization and working in high dimensional feature space, it assumes that data are independently and identically distributed which is not appropriate for tasks such as segmenting medical images with in-homogeneity and noise	Although the training time is very high. In addition the problem of patient specific learning and storage must be added to the disadvantage of SVM-based methods
ANN	Neural networks execute very well on complicated, difficult, multivariate non linear domains, such as tumor segmentation where it becomes more difficult to use decision trees, or rule-based systems. They also perform a little better on noisy fields and there is no need to assume a fundamental data allocation such as usually done in statistical modeling. But there are several disadvantages in using neural networks for tumor segmentation. Usually they need a patient-specific learning which a very time consuming process is. Another disadvantage is that neural networks do not give explicit knowledge representation in the form of rules, or some other easily interpretable form. The model is implicit, hidden in the network structure and optimized weights, between the nodes	The conventional neural network approach is in high time consuming of learning process mainly by using the gradient type learning methods
FCM	Unfortunately MR images always contain a significant amount of noise caused by operator, equipment, and the environment, which lead to serious inaccuracies in the segmentation. It should be mentioned that the membership functions to classes have a counter intuitive shape, which limits their use, fuzzy C means is a popular method for medical image segmentation but it only considers image intensity thereby producing unsatisfactory results in noisy images	The major drawback of the FCM algorithm is the huge computational time. The results show that it does not produce a standard segmentation result always due to the random nature of initial membership values. This is the main drawback in conventional FCM
k-mean	The algorithm also runs quickly enough that real time image segmentation could be done with the K-means algorithm	K-means fairly simple to implement and image segmentation are impressive. As can be seen by the results, the number of partitions used in the segmentation has a very large effect on the output
PCNN	Significant advantage of PCNN is the invariance of generated time signal to rotation, dilatation or translation of images. Therefore PCNN is advisable for the feature generation and pattern recognition in the classification tasks using conventional neural networks or the other methods	Some algorithms require multiple PCNN parameters and a satisfactory result strongly depends on the parameters and there is so far no mathematical theory to explain the relations of segmentation results and parameters selections. There is no automatic procedure to stop the PCNN; another disadvantage is a large number of parameters that should be determined appropriately the lack of a stopping mechanism, which leaves users to design ad hoc stopping rules or arbitrarily assign the number of iterations
	The advantage of PCNNs is that the segmentation mechanism conforms to the clustering property of organs or tissues in medical imaging. The major drawback is	
SOM	Self-organizing network had as main advantage its training algorithm that was easier and faster. SOMs is that they provide effective software tool for the visualization of high-dimensional data, automatically discover The advantage of using statistically salient features of pattern vectors in data set, and can find clusters in training data pattern space which can be used to classify new patterns	One obstacle of SOM application, especially to new users, would be the choice of many tunable parameters, which may prevent potential users from pursuing further SOM applications The main shortcoming of the SOM is that the number of neural units in the competitive layer needs to be approximately equal to the number of regions desired in the segmented image
HMM	The advantage of this type of model is that arbitrary features (i.e. functions) of the observations can be modeled, allowing domain-specific knowledge of the problem at hand to be injected into the model To produce ever finer resolution in spectral, spatial and temporal data, Non-brain structures removed and it estimates the tissue intensity variation	The types of prior distributions that can be placed on hidden states are severely limited; It is not possible to predict the probability of seeing an arbitrary observation. This second limitation is often not an issue in practice, since many common usages of HMM's do not require such predictive probabilities
GA	Genetic algorithms are population based process to find exact or approximate solution to optimization the search problem is inspired by the generic process of biological organism used in computing	One of the disadvantages of the genetic algorithms is that it truly depends upon the fitness function
GMM	The main advantage of the standard GMM is that it is easy to implement and requires a small number of parameters. The log likelihood function that is used to estimate the parameters is inherently simple. However, one of the main drawbacks of this model is that the prior distribution j has no dependence on the pixel index i. One of the other problems is that the spatial relationships between the neighboring pixels are not taken into its account An advantage of the standard GMM is that it requires a small amount of parameters. Another advantage is that these parameters can be efficiently estimated by adopting the EM algorithm to maximize the log likelihood function	However, the major disadvantage of GMM is that the model assumes that each pixel is independent of its neighbors

(*continued on next page*)

Table 2 (*continued*)

Approach	Advantages	Disadvantages
DWT	Preservation of edge sharpness, no dependency on image segmentation. It provides localized frequency information about a function of a signal, which is particularly beneficial for classification	Shift sensitivity: a transform is shift sensitive, if the shifting in time, for input-signal causes an unpredictable change in transform coefficients. (b) Poor directionality: An m-dimensional transform ($m > 1$) suffers poor directionality when the transform coefficients reveal only a few feature orientations in the spatial domain. (c) Absence of phase information: For a complex-valued signal or vector, its phase can be computed by its real and imaginary projections

Although significant progress has been made over the last decade much works is still needs to develop more effective CAD systems. Most of existing CAD system suffer from drawbacks high dimensionality of feature vector, high computational complexity and generalization capability. The motivation of this work is to develop an CAD system that overcome these drawbacks. So, in the next sections, we propose a CAD to detect the brain tumor from MRI. In our approach, we employ a hybrid intelligent system based on a committee of different algorithms. In this way, we are able to exploit the strengths and the weaknesses thus leading to more robust and typically better CAD system performance.

4. The proposed methodology

In order to develop a CAD system with a low computational cost and…, we have proposed a hybrid intelligent system. The architecture for the proposed CAD brain MRI system is shown in Fig. 4. It comprises four main processes for (i) image acquisition and preprocessing, (ii) segmentation of ROI, (iii) feature extraction and selection, and (iv) classification of the selected ROI and performance evaluation.

4.1. Image acquisition and preprocessing

Image acquisition techniques like MRI, X-Ray, ultrasound, mammography, CT-scan are highly dependent on computer technology to generate digital images. After obtaining digital images, image pre-processing techniques can be further used for analysis of region of interest. A pre-processing is performed in order to remove noise and clean-up the image background. In this stage, preprocessing based on median filter and high pass filter are presented. The preprocessing stage used to improve the quality of the images and make the rest stages more reliable. The median filtering techniques is applied to remove the high frequency components in MR images. The advantage of using the median filter is that it removes the noise without disturbing the edges.

4.2. Segmentation of region of Interest based on FPCNN

Image segmentation and defining the region of interest is an important approach and the most time-consuming part of image analysis and processing, which can divide the images into different parts with certain distinctions. The PCNN is considered a very powerful front-end processor for an image recognition system. The pulse coupled neural network, is a biological model inspired of mammalian visual cortex, proposed by Eckhorn, Reitboeck, Arndt, and Dicke (1990). PCNN is considered as the third generation of neural network models, which increase the level of realism in a neural simulation. The PCNN is advisable to solve tasks as the feature generation for image, pattern recognition, edge extraction and image segmentation (Kinser & Johnson, 1996; Mohsen et al., 2012). Here in this study we used it as image segmentation.

The PCNN based image segmentation process for defining the ROI can be viewed as a region growing method where seed pixels are identified by the neurons that fire during primary firing and the region growing is accomplished by capturing spatially connected neighboring neurons through secondary firing. Every neuron is made up of three sections: receptive section, modulation and pulse generator section, which can be described by discrete equations. The PCNN produces a dynamic output that contains edge, texture and segmentation information at different times (Chang & Chung, 2012). This is performed by continual iterations of the input and output signals using the Eqs. (1)–(4).

$$L_{ij}[n] = e^{-\alpha_L} L_{ij}[n-1] + V_L \sum_{kl} W_{ijkl} Y_{kl}[n-1] \tag{1}$$

$$U_{ij}[n] = S_{ij}[n]\left(1 + \beta L_{ij}[n]\right) \tag{2}$$

$$Y_{ij}[n] = \begin{cases} 1, & (U_{ij}[n] > \theta_{ij}[n]) \\ 0, & (U_{ij}[n] \leqslant \theta_{ij}[n]) \end{cases} \tag{3}$$

$$\theta_{ij}[n] = e^{-\alpha_\theta} \theta_{ij}[n-1] + V_\theta Y_{ij}[n] \tag{4}$$

Eqs. (1)–(4) describe the PCNN neurons. i, j are the neuron markings, n is the iterations, S is neurons external stimulation, L is connecting input, U is internal activity items, θ is dynamic threshold;

W are connection weight matrixes V_L, V_θ are amplitude constants for L, θ respectively; V_L, V_θ, $\propto_L$, α_θ are corresponding attenuation coefficients respectively; β is the weak connection (linking) coefficient; Y is PCNN binary output.

In this paper we used feedback pulse-coupled neural network (FPCNN) which is a modification of PCNN (Fu, Chen, Chai, Wong, & Li, 2010).

A FPCNN neuron shown in Fig. 5. As the original PCNN, FPCNN contains three main parts: the receptive fields, the modulation product and the pulse generation. The major difference of this model from the original PCNN model is that the feeding input is replace the input stimulus and the output feedback to modify the input.

The feedback PCNN (FPCNN) sends the output information in an inhibitory fashion back to the input in a similar manner to the rat's olfactory system (Kharrat, Gasmi, Messaoud, Benamrane, & Abid, 2010). For the case of the FPCNN the input experience feedback shunting that is not uniform for the entire input. This is the point where the PCNN and the FPCNN differ.

For the FPCNN, the outputs are collected as a weighted time average, A, in a fashion similar to the computation of θ except for a the constant V,

$$A_{ij}[n] = \exp(-\alpha_A) A_{ij}[n-1] + V_A Y_{ij}[n] \tag{5}$$

where the two new parameters α_A, and V_A (α_A the decay constant effecting on the memory of previous state of A_{ij}, V_A is the adjusting constant) are introduced.

The input is then modified by,

$$S_{ij}[n] = \frac{S_{ij}[n-1]}{A_{ij}[n-1]} \tag{6}$$

The FPCNN iterates the PCNN Eqs. (1)–(4) with (5) and (6) inserted at the end of each iteration (Lindblad & Kinser, 2005; Xue et al., 2005).

Table 3
Feature extraction and Classification techniques for Brain MRI.

Authors	Feature extraction	Classification technique	Performance measures			Data
			Sensitivity (%)	Specificity (%)	Accuracy (%)	
Herlidou-Meme et al. (2003)	Texture analysis	Hierarchical ascending classification	–	–	–	Images were obtained from the hospital's database
Maitra and Chatterjee (2008)	Improved orthogonal DWT	Fuzzy C-means (FCM) clustering	–	–	100	Harvard
Maitra and Chatterjee (2006)	Wavelet transform based methods are a well-known tool for extracting frequency space information from non-stationary signals DWT for feature extraction, called Slantlet transform, employing wavelet transform,	Neural networks and support vector machines	–	–	100	Harvard
Zacharaki et al. (2009)	Manual feature extraction + t-test/Constrained Linear Discriminant Analysis (CLDA)	• Based on SVM	87	79	85	Collected data from 98 patients.
Georgiadis et al. (2008)	Texture feature extraction + non-parametric Wilcoxon rank sum test method.	Non linear least squares features transformation with probabilistic neural networks (LSFT–PNN)	–	–	95	General Hellenic Airforce Hospital, MRI Unit, Katehaki, Athens, Greece.
Wang et al. (2008)	–	Multiscale fuzzy C-means (MsFCM)	–	–	88	McGill brain MR database
El-Dahshan et al. (2010)	(DWT) + PCA	• Feed forward back propagation artificial neural network (FP-ANN) • k-NN	–	–	97 98.6	Harvard
QURAT-UL-AIN et al. (2010)	Texture feature extraction	Ensemble base classifier, SVM and ANN	–	–	99	Harvard
Kharrat et al. (2010), Zhang, Wang, and Wu (2010)	Spatial gray level dependence method (SGLDM) + WT	• GA + SVM • GA + SVM	92 95	100 100	95 97	Harvard
Zhang et al. (2010), Selvaraj, ThamaraiSelvi, Selvathi, & Gewali, 2007	DWT + PCA	adaptive chaotic particle swarm optimization forward neural network (ACPSO–FNN)	–	–	98.75	Harvard
Selvaraj et al. (2007), Chaplot, Patnaik, and Jagannathan (2006)	Texture feature extraction	• Least squares-SVM (LS-SVM) • SVM • Multi layer perceptron (MLP) • Radial basis function (RBF) • k-NN	98.9 98.2 97.7 93.3 93.7 84.2 90.7	98.9 96.7 96.7 91 91 94.4 83.2	98.9 97.9 97.6 93 93.41 94.2 89.8	Indian Devaki Cancer Institute, Devaki Cancer Hospital Madurai http://devakicancerinstitute.com/
Chaplot et al. (2006), Zhang, Dong, Wu, and Wang (2011)	Wavelet transform (daubechies-4 wavelet)	• SOM • SVM • SVM with radial basis function based kernel	–	–	94 96 98	Harvard
Zhang et al. (2011), Zöllner et al. (2012)	WT + PCA	Back propagation neural network (BPNN)	–	–	100	Harvard
Zöllner et al. (2012), (Jafarpour, Sedghi, and Amirani (2012)	(i) Pearson's correlation coefficients (PCC), (ii) PCA and (iii) independent component analysis (ICA)	• SVM + PCA • SVM + PCC • SVM + ICA	–	–	• 85 • 82 • 79	DSC–MRI data (patient data included 101 pre-operative patients (aged 8–79 years, mean age 51; 51 males, 50 females))
Yamamoto et al. (2010)	Multiple-gray levels Effective diameter Area circularity Slenderness The difference in the mean pixel value within the inner and outer region of candidate regions	A consisted of a rule-based method, a level set method, and a support vector machine	81.5	–	84.3	Brain MR FLAIR images; doi:http://dx.doi.org/10.1016/j.compmedimag.2010.02.001
Graña et al. (2011)	Authors contribute a feature selection process based on the correlation of fractional anisotropy (FA) and mean diffusivity (MD) voxels with the subject class indicative variable	SVM classifier	100	100	100	from Hospital de SantiagoApostol (Vitoria-Gasteiz), http://buscahospital.com/hospital/hospital-santiago-apostol-vitoria-gasteiz
Jafarpour et al. (2012), Khayati, Vafadust, Towhidkhah, and Nabavi (2008)	Authors use gray level co-occurrence matrix (GLCM) to extract features from brain MRI and for selecting the best features, PCA + LDA is implemented	The classifiers based on ANN and k-NN	–	–	100	Harvard & LONI (https://ida.loni.usc edu/login.jsp) Laboratory of Neuro imaging: L NI

Table 4
The advantages and disadvantages of the most used classification methods for human brain tumors through MR images.

Approach	Advantages	Disadvantages
k-nn	It provides accurate about distance, weighted average about pixels and it can be used for large number of training sets The high degree of local sensitivity makes nearest neighbor classifiers highly susceptible to noise in the training data. (3) It is a simple and powerful, algorithm	The disadvantage of this algorithm is the choice of k affects the performance of the k-NN algorithm It is memory intensive, its classification/estimation is slow. The accuracy of the k-NN algorithm can be severely degraded by the presence of noisy or irrelevant features, or if the feature scales are not consistent with their importance
ANN	A neural network can perform tasks that a linear program cannot. A neural network learns and does not need to be reprogrammed. Neural networks are data driven self-adaptive methods in that they can adjust themselves to the data without any explicit specification of functional or distributional form for the underlying model. Neural networks are nonlinear models, which makes them flexible in modeling real world complex relationships	The neural network needs training to operate. Requires high processing time for large neural networks. Minimizing over fitting requires a great deal of computational effort
SVM	It minimizes the number of misclassifications in any possible set of samples The important advantage of SVM is that it offers a possibility to train generalizable, nonlinear classifiers in high dimensional spaces using a small training set	Most implementations of SVM algorithm require computing and storing in memory the complete kernel matrix of all the input samples The optimality of the solution found can depend on the kernel that has been used, and there is no method to know a priori which will be the best kernel for a concrete task. The best value for the parameter C is unknown a priori
FCM	This technique has two main advantages: it determines a membership degree of data to each class, thus allowing soft clustering, and it is an unsupervised algorithm	The main disadvantage is that one has to know in advance the clusters number. The requirement for initialization of several initial parameters including the seed pixel is one of the disadvantages of this system
SOM	The advantages of SOM are simple and easy to understand and good for visualization	The disadvantage of SOM is distance accuracy among input vectors. It is easy to see the distribution of input vectors on the map, but it is difficult to evaluate correctly distances and similarities between them. Moreover, if the output dimension and learning algorithms are chosen improperly, similar input vectors may not always close to each other and the trained network may converge to some local optima is that it requires necessary and sufficient data in order to develop meaningful clusters. The weight vectors must be based on data that can successfully group and distinguish inputs. Lack of data or extraneous data in the weight vectors will add randomness to the groupings. Another problem with SOMs is that it is often difficult to obtain a perfect mapping where groupings are unique within the map
	The reduction of dimensionality and grid clustering makes it easy to observe similarities in the data. SOMs are capable of handling several types of classification problems while providing a useful, interactive, and intelligible summary of the data	
EM	The main advantages of this algorithm are its simplicity and speed which allows it to run on large datasets	A common disadvantage of EM algorithm is that the intensity distribution of brain images is modeled as a normal distribution. The drawback of EM is, it does not directly incorporate spatial modeling and can therefore be sensitive to noise and intensity in-homogeneities
GMM	Less time consuming when applied to a large set of data	Ability to track time-evolving patterns is slow. (2) It cannot exclude exponential functions
	It is text independent. It is easy to implement It follows the Probabilistic frame work (robust) It is computationally efficient	
Hybrid techniques	Hybrid methods aim at combining the advantages of different paradigms within a single system. Hybrid methods which combined the relative strengths from the different classifiers and applied them in a sequence in such a way that the overall accuracy was the maximized	Sophisticated and high computational costs

4.3. Feature extraction based on wavelet transform

In this study, the feature extraction of MRI images is obtained using the discrete wavelet transform. The wavelet is a powerful mathematical tool for feature extraction (Daube, 1991; Hiremath, Shivashankar, & Pujari, 2006).

The use of wavelet transform is particularly appropriate since it gives information about the signal both in frequency and time domains.

DWT is a frequently used image processing technique which performs the function of transforming images from the spatial domain into the frequency domain. By applying DWT, we are able to decompose an image into the corresponding sub-bands with their relative DWT coefficients.

The DWT is implemented using cascaded filter banks in which the low pass and high pass filters satisfy certain specific constraints. The basic scheme of DWT decomposition and its application to MR images is shown in Fig. 6. Where the functions $h(n)$ and $g(n)$ represent the coefficients of the high-pass and low-pass filters, respectively.

As a result, there are four sub-band (LL, LH, HH, HL) images at each scale. The LL sub-band can be regarded as the approximation component of the image, while the LH, HL, HH sub-bands can be regarded as the detailed components of the image. For feature extraction, only the sub-band LL is used for DWT decomposition at next scale. Also, the LL sub-band at last level is used as output feature vector. In our algorithm, a two and three level decomposition via Haar wavelet was utilized to extract features. Fig. 6 shows a schematic diagram of 3rd level wavelet transform decomposition Haar Wavelet transform along with its conceptual expression diagram. A layout of DWT sub-bands with three-scale dyadic decomposition of Lena image is shown in Fig. 6.

4.4. Feature reduction based on PCA

Excessive features increase the computation time and memory storage which sometimes causes some complications in the classification process (the curse of dimensionality), and so it is required to reduce the number of features. The principal component analysis is the most well-known used subspace projection technique as it provides suboptimal solution with a low computational cost and computational complexity. PCA is an efficient strategy for transforming the existing input features of a data set consisting of a large number of interrelated variables into a new lower-dimension feature space while retaining most of the variations. The input feature space is transformed into a lower-dimensional feature space using the largest eigenvectors of the correlation matrix and forms a new set of ordered variables

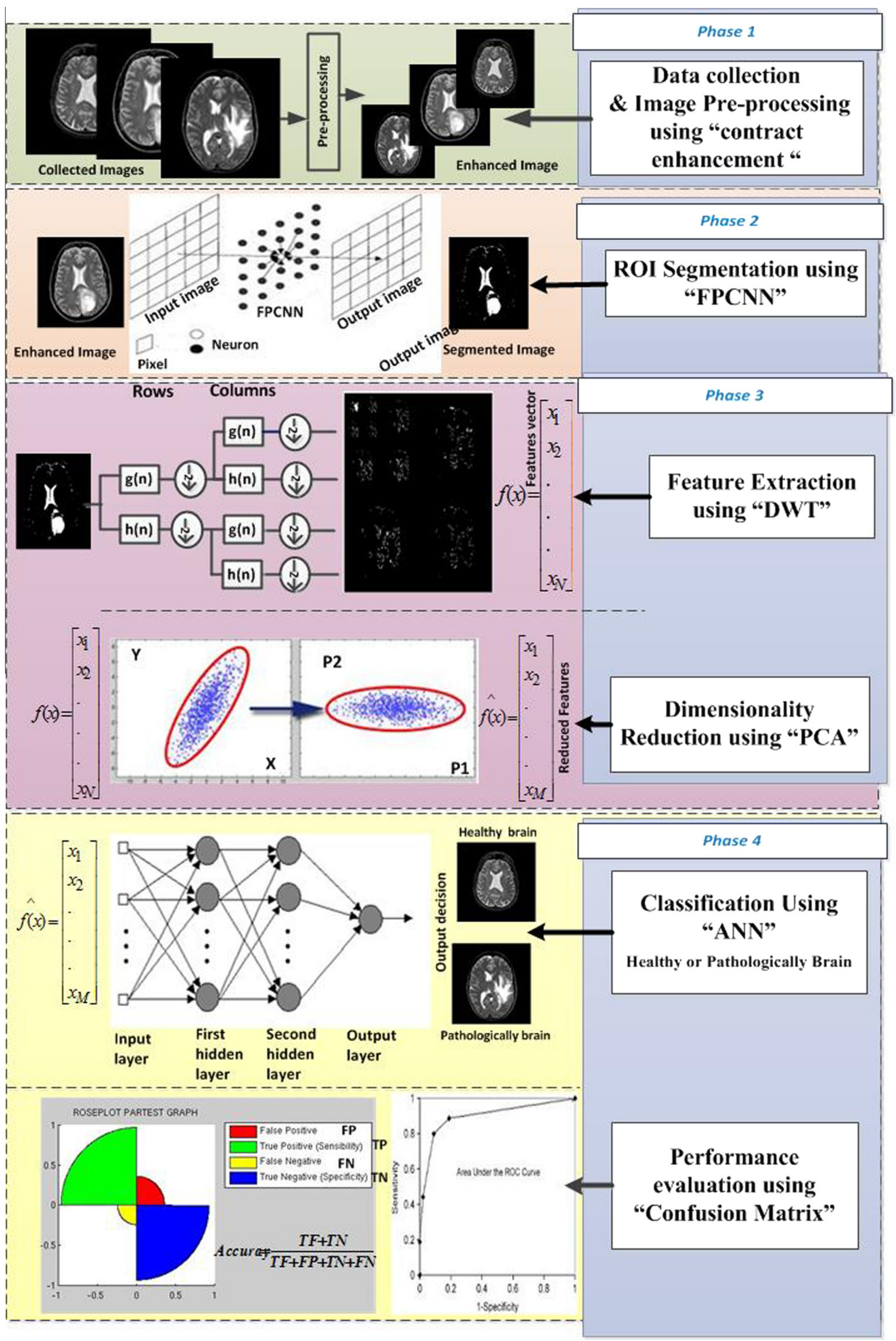

Fig. 4. The proposed methodology of CAD brain MRI system.

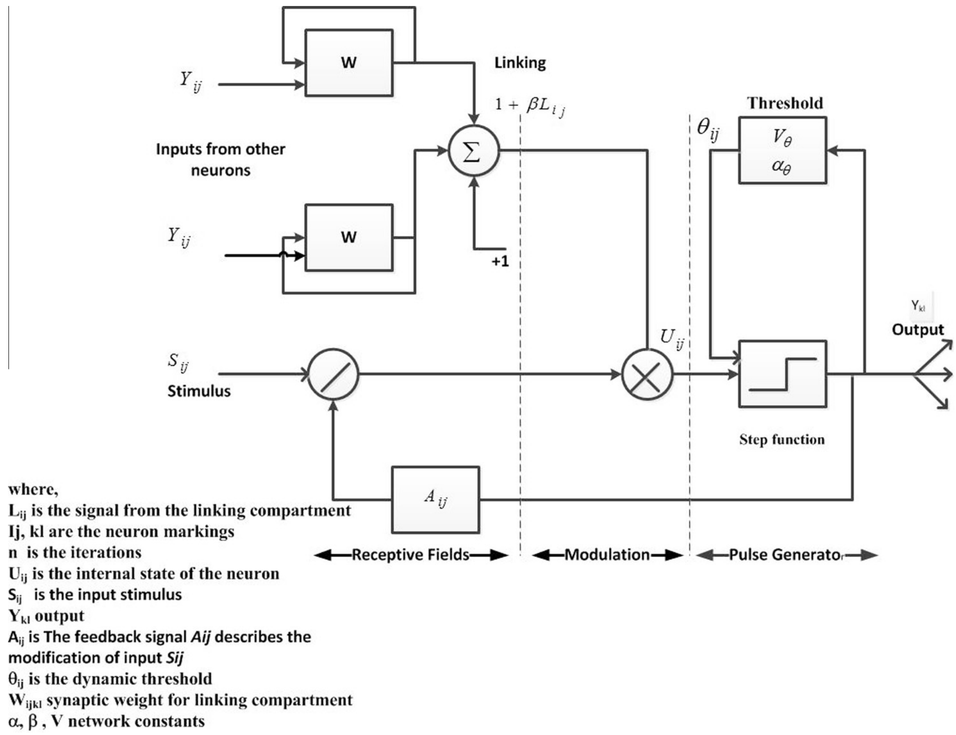

Fig. 5. The architecture of the FPCNN.

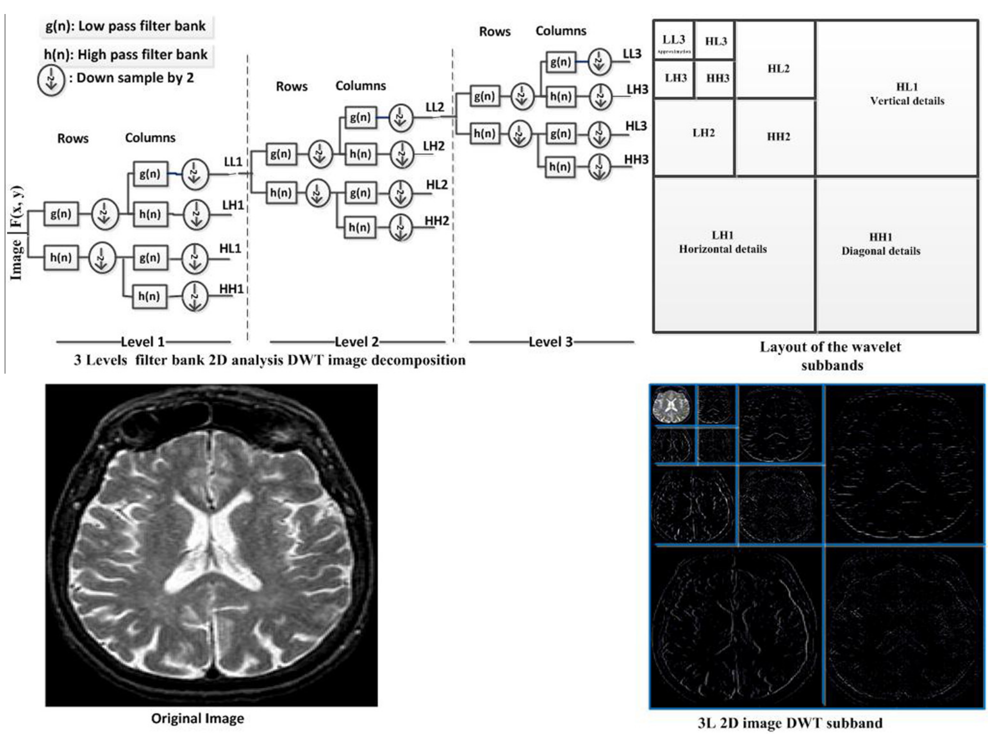

Fig. 6. A schematic diagram of 3rd level wavelet transform decomposition.

according to their variances or their importance (Jain, Duin, & Mao, 2000).

The implementation of PCA is shown in Fig. 7. Additional information and implemented studies about PCA can be reached from (Jolliffe, 1986; Polat & Gunes, 2008; Smith, 2002; Wang & Paliwal, 2003).

PCA is a statistical method used to decrease the data dimensions while retaining as much as possible of the variation present in the data set to process the data faster and effective (Jolliffe, 2002).

This technique has three effects: it orthogonalizes the components of the input vectors so that uncorrelated with each other,

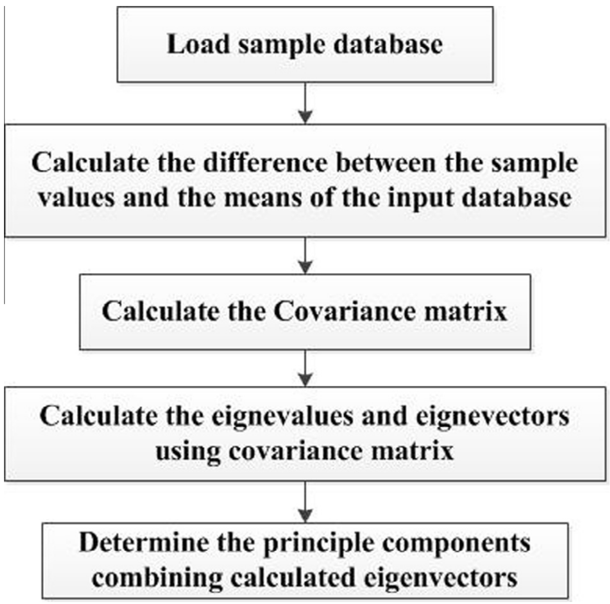

Fig. 7. The implementation of PCA.

it orders the resulting orthogonal components so that those with the largest variation come first, and eliminates those components contributing the least to the variation in the data set. Using a system of feature reduction based on PCA limits the feature vectors to the component selected by the PCA which leads to an efficient classification algorithm. So, the main idea behind using PCA in our approach is to reduce the dimensionality of the wavelet coefficients which results in a more efficient and accurate classifier (Zöllner, Emblem, & Schad, 2012).

4.5. MRI image classification based on ANN

Neural networks are widely used in pattern classification since they do not need any information about the probability distribution and the a priori probabilities of different classes. A NN classification system mimics the human reasoning and in some cases, it gives the decision for more than one class to show the possibilities of other diseases. For brain MR image classification, as normal or abnormal, we used a Back-propagation neural network (BPNN) to classify inputs into the set of target categories (normal or abnormal) based on feature selection parameters. BPNN is a supervised learning method which is a non-linear generalization of the squared error gradient descent learning rule for updating the weights of the artificial neurons in a single-layer perceptron, generalized to feed-forward networks (Haykin, 2008).

ANN is a branch of artificial intelligence (AI). It can imitate the way in which a human brain works in processes such as studying, memorizing, reasoning and capable of performing massively parallel computations for data processing and knowledge representation. One advantage of the neural network approach is that most of the intense computation takes place during the training process. Once the ANN is trained for a particular task, operation is relatively fast and unknown samples can be identified.

Generally, an ANN can be defined as a system or mathematical model that consists of many nonlinear artificial neurons running in parallel and may be generated as one-layered or multilayered. Most ANNs have three layers: input, output, and hidden. The function of the hidden layer is to intervene between the external input and the network output in some useful manner. Detailed theoretical information about ANNs can be found in Hayki (2008). An ANN structure is shown in Fig. 8.

Feed forward multilayer neural network (FFNN) are dominantly used. The back propagation algorithm has been used in the training of the FFNN.

Two kinds of signals are identified in this network: The function signals (also called input signals) that come in at the input of the network, propagate forward (neuron by neuron) through the network and reach the output end of the network as output signals; The error signals that originate at the output neuron of the network and propagate backward (layer by layer) through the network.

The output of the neural network is described by the following equation:

$$y = F_o\left(\sum_{j=0}^{M} w_{0j}\left(F_h\left(\sum_{i=0}^{N} w_{ji}x_i\right)\right)\right) \quad (7)$$

where w_{oj} represents the synaptic weights from neurony in the hidden layer to the single output neuron, X_j represents the ith element of the input vector, F_h and F_o are the activation function of the neurons from the hidden layer and output layer, respectively, w_{ji} are the connection weights between the neurons of the hidden layer and the inputs.

The learning phase of the network proceeds by adaptively adjusting the free parameters of the system based on the mean square error E, described by Eq. (8), between predicted and mea-

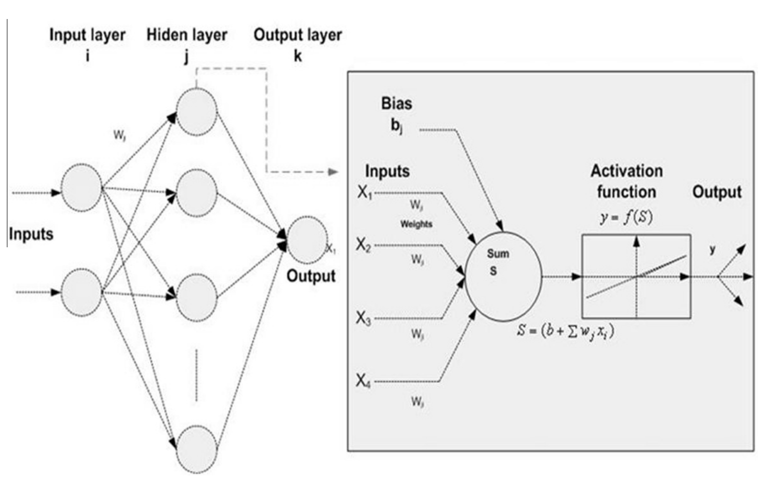

Fig. 8. Artificial neural network (ANN) architecture.

sured path loss for a set of appropriately selected training examples:

$$E = \frac{1}{2}\sum_{i=1}^{m}(y_i - d_i)^2 \tag{8}$$

where y_i is the output value calculated by the network and d_i represents the expected output. When the error between network output and the desired output is minimized, the learning process is terminated and the network can be used in a testing phase with test vectors. At this stage, the neural network is described by the optimal weight configuration, which means that theoretically ensures the output error minimization.

4.6. Performance evaluation

Quantitative evaluation of the proposed system and it is performance comparison with other state-of-the-art techniques were analyzing using different statistical measures.

Confusion matrix was used to calculate the performance of the CAD system. Confusion matrix contains information about actual and predicted classifications. For evaluating the proposed algorithm based on the confusion matrix, we used the metrics of sensitivity (measures the proportion of actual positives which are correctly identified), specificity (measures the proportion of negatives which are correctly identified), and accuracy (as given in Eqs. (9)–(11) and respectively).

$$\text{Sensitivity (true positive rate)} = \text{TP}/(\text{TP}+\text{FN}) \tag{9}$$

$$\text{Specificity (false positive rate)} = \text{TN}/(\text{TN}+\text{FP}) \tag{10}$$

$$\begin{aligned}&\text{Accuracy (percent of all samples correctly classified)}\\&\quad = (\text{TP}+\text{TN})/(\text{TP}+\text{TN}+\text{FP}+\text{FN})\end{aligned} \tag{11}$$

where: TP: (true positives) is the correctly classified positive cases, TN: (true negative) is the correctly classified negative cases, FP: (false positives) is the incorrectly classified negative cases and FN: (false negative) is the incorrectly classified positive cases.

The receiver operating characteristic (ROC) curve is the plot that displays the full picture of trade-off between the sensitivity and (1-specificity) across a series of cut-off points. Area under the ROC

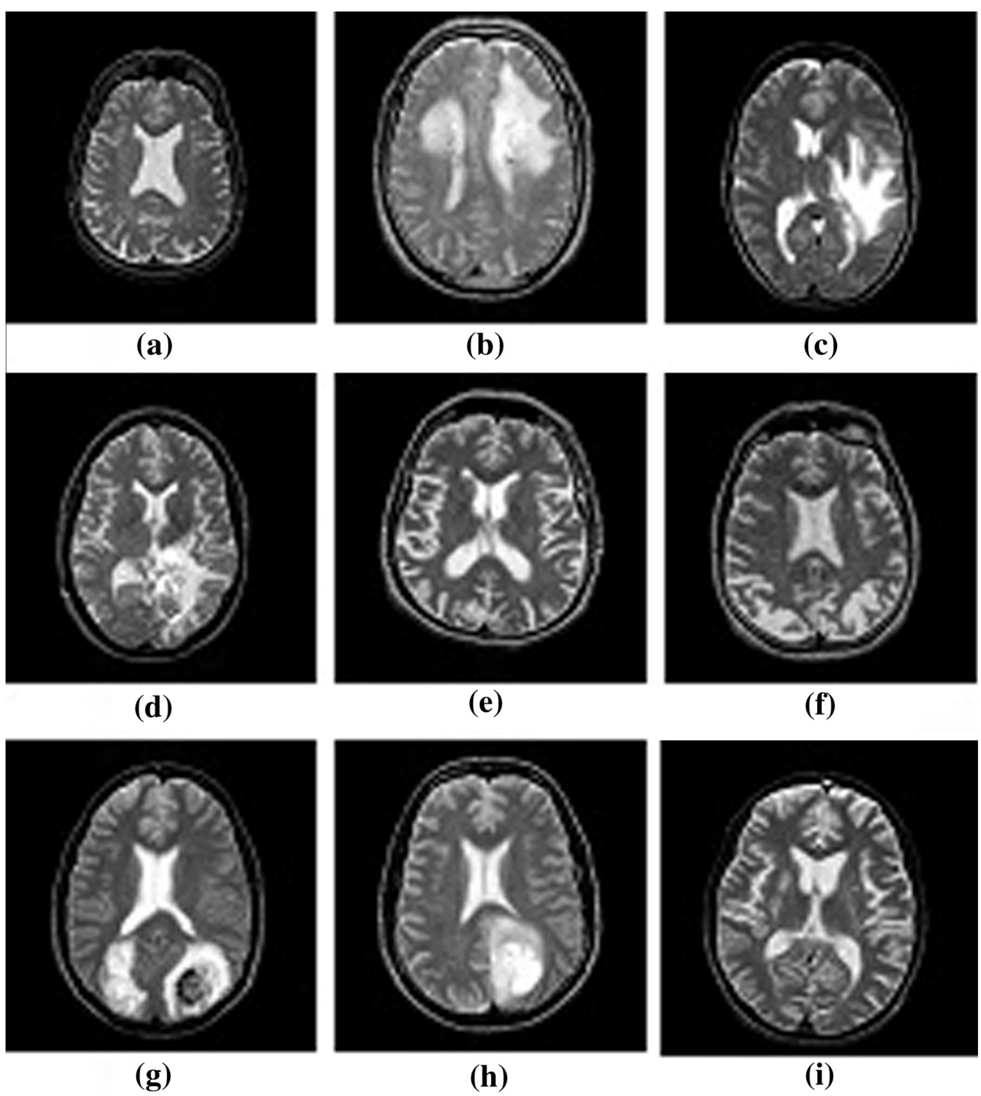

Fig. 9. T2-weighted samples of brain MRI from the database (Weili, Yu, Zhanfang, & Hongbiao, 2009) showing different types of brain tissue used for normal and abnormal brain images: (a) Normal, (b) Meningioma, (c) Metastatic bronchogenic carcinoma, (d) Glioblastoma, (e) Alzheimer's disease, (f) Alzheimer's disease with visual agnosia, (g) Sarcoma, (h) Glioma, (i) Pick's disease.

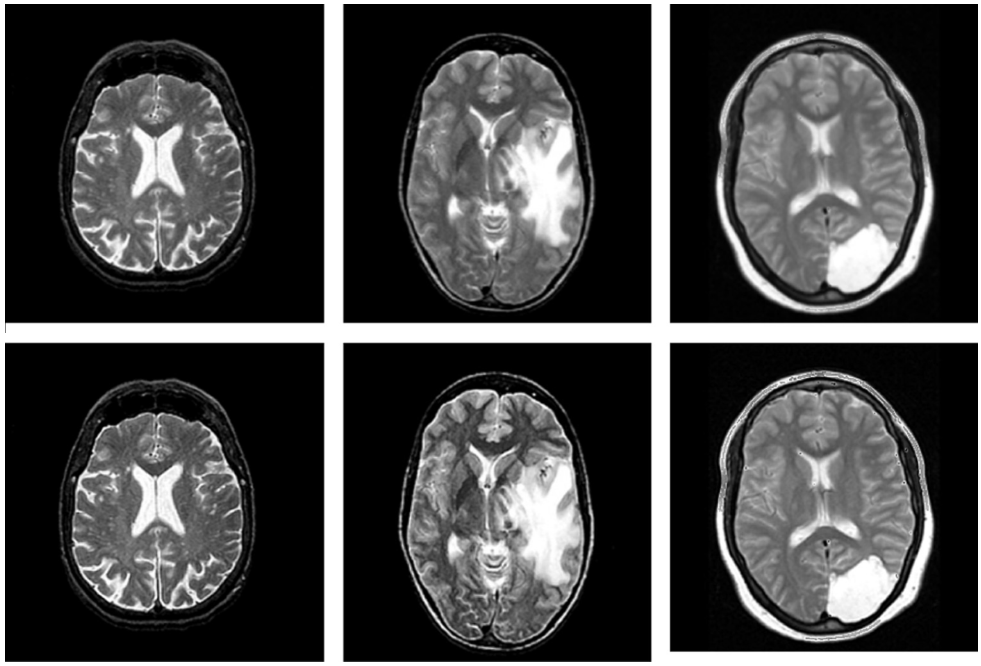

Fig. 10. Sample of human brain MRI from before and after preprocessing stage.

Table 5
FPCNN parameters values.

Constant	PCNN coefficient	Context
β	0.02	Linking coefficient
V_F	0.01	Feeding coupling
V_L	2	Linking coupling
V_θ	3	Magnitude scaling term for threshold
V_A	1	Weighted time average coupling
$\propto_F$	30	Feeding decay
$\propto_L$	0.15	Linking decay
$\propto_\theta$	0.06	Threshold decay
$\propto_A$	0.06	Weighted time average decay

curve (AUC) is considered as an effective measure of inherent validity of a diagnostic test. Partest plot and Roseplot test method is one of the methods in ROC curve method. Partest plot and Roseplot is an effective technique for displaying the data in confusion matrix and it indicates the proportion of the system results (Danciu et al., 2013).

5. Experiment implementation and discussion

The proposed technique was developed locally and successfully trained in MATLAB version 10.0 using combination of the PCNN, wavelet and neural network toolboxes running under windows-7 operating system with CPU 2.2 GHz, Core-Duo processor and 3 GB of memory (RAM). The programs can be run/tested on many different computer platforms where MATLAB is available.

5.1. Database

The algorithm were implemented based on 101 brain MRI images consisting of 14 normal and 87 abnormal (malignant and benign tumors) from a real human brain MRI dataset. The dataset

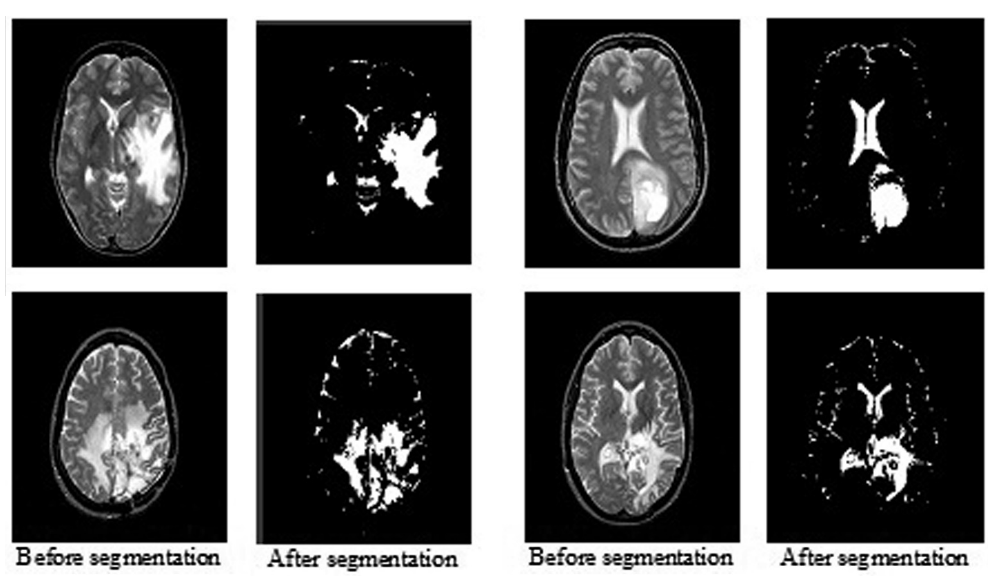

Fig. 11. Sample of brain MRI from the database before and after segmentation using PCNN.

used to performance evaluation. The dataset used consists of axial, T2-weighted, 256–256 pixel MR brain images. These images were collected from the Harvard Medical School website (http://www.med.harvard.edu/aanlib/home.html) (Harvard Medical School, 2014). Fig. 9 shows some sample images from the data set used for normal and abnormal brain images: (a) Normal, (b) Meningioma, (c) Metastatic bronchogenic carcinoma, (d) Glioblastoma, (e) Alzheimer's disease, (f) Alzheimer's disease with visual agnosia, (g) Sarcoma, (h) Glioma, (i) Pick's disease.

5.2. Preprocessing

A preprocessing stage should be considered to enhance the quality of the MRI brain before segmentation, feature extraction and classification. Image processing and enhancement stage is the simplest categories of medical image processing. This stage is used for reducing image noise, highlighting edges, or displaying digital images. Some more techniques can employ medical image processing of coherent echo signals prior to image generation. The enhancement stage includes resolution enhancement; contrast enhancement. These are used to suppress noise and imaging of spectral parameters.

For achieving best possible diagnosis it is necessary that the medical image should be sharp and noise free. In this work noise is removed by using median filter. Since it reduces the variance of the intensities in the image and also it is used to preserve edge shapes and the location of the edges. A 4×4 square window was used throughout this work. Fig. 10 shows the image enhancement with the median filter. After this stage the medical image is converted into standard image without noise, film artifacts and labels. This is followed by applying a PCNN-based segmentation algorithm to detect the boundary of the prostate image.

5.3. Segmentation

We apply PCNN to segment the ROI in the MRI images. The success of the application of PCNNs to image segmentation depends on the proper setting of the various parameters of the network, such as the linking parameter β, thresholds θ, decay time constants α_θ, and the interconnection matrices M and W. Table 5 shows the PCNN parameters values used in this application. Fig. 11 shows segmented boundary by PCNN.

The output of the segmentation processes was promising for a more accurate and efficient classification. Fig. 11 shows some the segmentation results after using the FPCNN.

5.4. Feature extraction and reduction

Based on adjusted and segmented images produced in stages 1 and 2, a set of features are extracted from each image. We then apply our reduction algorithm on these features.

Before the classification model can be built, meaningful features of the ROIs delineated during the process of segmentation, need to be extracted and used as input in the classification process. The DWT was used in our developed technique (mentioned in Section 4.3) for feature extraction. The wavelet is a powerful mathematical tool for feature extraction that was been successfully applied to medical images. DWT has been used to extract the wavelet coefficient from the segmented images produced by the FPCNN. The DWT is implemented so that it could be chosen through one to three levels of wavelet decomposition with Haaror Daubechies-1 and Daubechies-2 filter banks. The produced feature vector consisting of k attributes is formed to represent the ROI.

PCA is an efficient strategy for transforming the existing input features of a data set consisting of a large number of interrelated variables into a new lower-dimension feature space while retaining most of the variations. The input feature space is transformed into a lower-dimensional feature space using the largest eigenvectors of the correlation matrix and forms a new set of ordered variables according to their variances or their importance.

One of the most common forms of dimensionality reduction is principal components analysis. Given a set of data, PCA finds the linear lower-dimensional representation of the data such that the variance of the reconstructed data is preserved.

So, the main idea behind using PCA in our approach is to reduce the dimensionality of the wavelet coefficients. This leads to more efficient and accurate classifier.

5.5. Classification and performance evaluation

The images were randomly selected as there are one type of normal brain and 11 different types of abnormal brain in the data-

Table 6
Setting of training and test images.

Total No. of images	No. of images in training set (65)		No. of images in testing set (36)	
	Normal	Abnormal	Normal	Abnormal
101	10	55	4	32

Table 7
the network parameters used for training.

Parameters	ANN
Number of input layer units	7
Number of hidden layer	2
Number of first hidden layer unit	10
Number of first hidden layer unit	8
Number of output layer units	1
Momentum rate	0.88
Learning rate	0.70
Error after learning	0.000050

Table 8
Classification rates.

TP	TN	FP	FN	Sensitivity (%)	Specificity (%)	Accuracy (%)
87	13	1	0	100	92.8	99

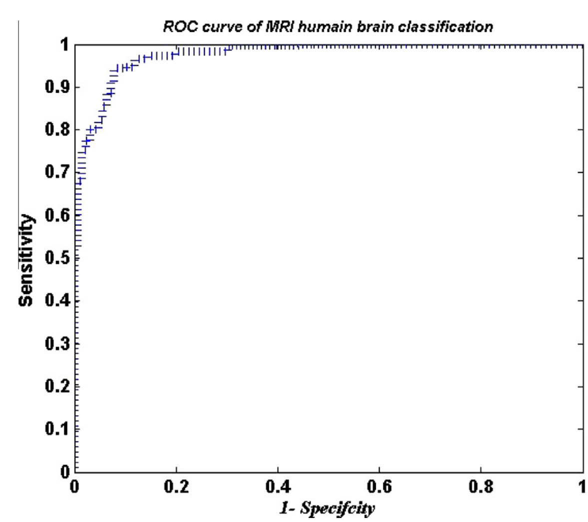

Fig. 12. ROC curve for classification human brain MR images using ANN classifier during validation phase.

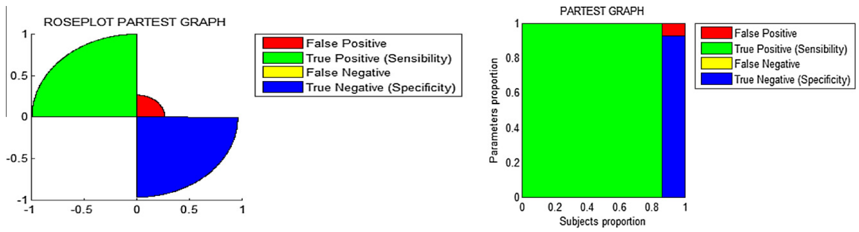

Fig. 13. Graphical representation of the results.

Table 9
The Classification accuracy comparison.

Approaches	Accuracy (%)	Sensitivity (%)	Specificity (%)
Our proposed method	99	100	92.8
DWT + PCA + BPNN (Yang et al., 2002; Zhang et al., 2011)	100	100**	100**
SRGS + CCL + DWT + PCA + BPNN (Yamamoto et al., 2010; Jafari et al., 2011)	99.8**	100	98
DWT + PCA + K-NN (Arimura et al., 2012; El-Dahshan et al., 2010)	98	96	97
DWT + PCA + ANN (Arimura et al., 2012; El-Dahshan et al., 2010)	97	95.9	96
DWT + SVM (Dubey et al., 2009; Chaplot et al., 2006)	96	*	*
DWT + SVM with radial basis function based kernel (Dubey et al., 2009; Chaplot et al., 2006)	98	*	*
DWT + SOM (Dubey et al., 2009; Chaplot et al., 2006)	94	*	*
PCA + SVM (Wang & Fei, 2009; Zöllner, 2012)	85	89	84
ICA + SVM (Wang & Fei, 2009; Zöllner, 2012)	79	87	75
PCC + SVM (Wang & Fei, 2009; Zöllner, 2012)	82	89	77

* Unknown values.
** Calculated with values of parameters published by the authors for each approach based on the Eqs. (8)–(10).

set 7 types of them where named previously, total 101 images consisting of 14 normal and 87 abnormal brain images (see Table 6).

The network configuration is $N_I * N_{H1} * 1$ (Fig. 8 shows the general architecture of the FFNN used for classification), N_I is the input layer and N_{H1} is the hidden layer.

The network configuration is $N_I * N_{H1} * 1$, such that a three-layer network with 7 input neurons for the feature vectors selected from the wavelet coefficients by the PCA, 8 and 10 neurons in the hidden layer and single neuron in the output layer was used to represent normal and abnormal human brain. Table 7 shows the network parameters used for training.

The experimental results for normal and abnormal classification are listed in Table 6. The effectiveness of our approach has been demonstrated in Table 6, with a small set of data. The classification accuracy of 99%, sensitivity of 92%, specificity of 100%. Also, the accuracy of a model in making predictions is evaluated regularly using an ROC analysis. An ROC curve is generated by combining the true positive fraction (sensitivity) and false positive fraction (1-specificity) by setting different thresholds. A quantitative measure of the accuracy of the classification technique is obtained by finding the area under the ROC curve (AUC) which varies between 0.0 indicating poor classification performance, and 1.0 indicating high classification performance. The area of the ROC curve results implied that our hybrid technique can provide a consistency high accuracy for classification of human brain MR images. In this methodology the AUC = 98.

Table 8 illustrates the results obtained using the proposed algorithm trained NN based classifier. The impact of sensitivity and specificity may lead to a more, objective and consistent diagnosis. (See Fig. 1 and 12).

The result obtained from the classification process is graphically represented as Partest and Roseplot plot, which gives the sensitivity, specificity and accuracy of the proposed method. The result is shown as graphical representation (Partest and Roseplot plot) in Fig. 13.

The results show that our method obtains quite perfect results on both training and test images. Moreover, for evaluating the effectiveness of the results our method we have made a comparison between the recently published techniques (10 state-of-the-art brain MR image classification schemes) for the brain MRI during the last seven years (2006–2012). Table 9 shows the classification accuracy comparison.

From the Table 9, it can be seen that: (a) Zhang et al. gives the highest accuracy results, (b) our proposed method, Zhang et al. and Jafari et al. give the highest sensitivity results and (c) Zhang et al. gives the highest specificity results. The highest results given by Zhang et al. is due to selecting a small number of brain MRIs from the dataset (66 images) which could not have a lot of varieties and then gave a better results.

The classification performances of this study show the advantages of this technique: it is rapid, easy to operate, non-invasive and inexpensive. The limitation of this work is that it requires fresh training each time whenever there is an increase in image in image database. Further investigation will be conducting with large set of data and trying integrate between other machine learning techniques to overcome the weakness of the generalization for any datasets to determining the generalization of these results.

6. Conclusion and future work

With the advance of computational intelligence and machine learning techniques, computer-aided detection attracts more attention for brain tumor detection. It has become one of the major research subjects in medical imaging and diagnostic radiology. In this study, we reviewed current studies of the different segmentation, feature extraction and classification algorithms. In particular, this paper reviews recent papers which are between 2006 and 2012. In light of this, we proposed a hybrid technique for processing of MRI brain images. The proposed technique first applies feedback pulse-coupled neural network as a front-end processor for image segmentation and detecting the region of interest, and then employs the discrete wavelet transform to extract features from MRI images. Moreover the principal component analysis is performed to reduce the dimensionality of the wavelet coefficients which results in a more efficient and accurate classifier. The reduced features are sent to back-propagation neural network to classify inputs into normal or abnormal based on feature selection parameters. A preliminary evaluation on MRI brain images shows encouraging results, which demonstrates the robustness of the proposed technique. We have realized a large number of algorithms that could also be applied to the developed system and compare the results with this one. According to the experimental results, the proposed method is efficient for automated diagnosis of brain diseases. Our proposed method produce classification accuracy of 99% with 100% sensitivity rate and 92% specificity rate. These experiment results show that the proposed classifier method can successfully differentiate between healthy and pathologically cases and can increase the diagnostic performance of human brain abnormality. We also compared the obtained results with other methods. The comparative analysis indicates that the proposed hybrid method effective and robust. The challenge remains to provide generalized CAD systems that works in all cases regardless of database size and quality. So, CAD system remains an open problem. There are several future directions which might further improve the CAD systems for human brain MR images: (1) the acquisition of large databases from different institutions with various image qualities for clinical evaluation and improvement in the CAD systems (2) improve the classification accuracy by extracting more efficient features and increasing the training data set. (3) There is still much room for additional researcher to utilize other machine learning techniques and integrate them into a hybrid one system. (4) Further experiments and evaluation are therefore desirable to establish whether the proposed approaches have generic applications.

References

Arimura, H., Magome, T., Yamashita, Y., & Yamamoto, D. (2009). Computer-aided diagnosis systems for brain diseases in magnetic resonance images. *Algorithms, 2*(3), 925–952.

Arimura, H., Tokunaga, C., Yamashita, Y., & Kuwazuru, J. (2012). Magnetic resonance image analysis for brain CAD systems with machine learning. In Kenji Suzuki (Ed.), *Machine learning. Computer-aided diagnosis: Medical imaging intelligence and analysis* (pp. 258–296). USA: The University of Chicago, IGI global. 2012.01.

Ayachi, R., & Ben Amor, N. (2009). Brain tumor segmentation using support vector machines; symbolic and quantitative approaches to reasoning with uncertainty. *Lecture Notes in Computer Science, 5590*, 736–747.

Balafar, M. A., Ramli, A. R., Saripan1, M. I., Mahmud, R., & Mashohor, S. (2008). Medical image segmentation using fuzzy c-mean (FCM), learning vector quantization (LVQ) and user interaction. In D. -S. Huang, et al. (Eds.), *Proceedings of international conference on intelligent computing, ICIC 2008, CCIS 15* (pp. 177–184). Berlin: Springer-Verlag.

Brainweb (2014). Brain web: Simulated brain database. <http://brainweb.bic.mni.mcgill.ca/cgi/brainweb2>.

Cabezas, M., Oliver, A., Lladó, X., Freixenet, J., & Cuadra, M. B. (2011). A review of atlas-based segmentation for magnetic resonance brain images. *Computer Methods and Programs in Biomedicine, 104*(3), 158–177.

Canales-Rodríguez, E. J., Radua, J., Pomarol-Clotet, E., Sarró, S., Alemán-Gómez, Y., Iturria-Medina, Y., et al. (2013). Statistical analysis of brain tissue images in the wavelet domain: Wavelet-based morphometry. *NeuroImage, 72*(15), 214–226.

Chang, F.-J., & Chung, C.-H. (2012). Estimation of riverbed grain-size distribution using image-processing techniques. *Journal of Hydrology, 440–441*, 102–112.

Chao, W. H., Chen, Y. Y., Cho, C. W., Lin, S. H., Shih, Y. Y. I., & Tsang, S. (2008). Improving segmentation accuracy for magnetic resonance imaging using a boosted decision tree. *Journal of Neuroscience Methods, 175*(2), 206–217.

Chao, W. H., Chen, Y. Y., Lin, S. H., Shih, Y. Y. I., & Tsang, S. (2009). Automatic segmentation of magnetic resonance images using a decision tree with spatial information. *Computerized Medical Imaging and Graphics, 33*(2), 111–121.

Chaplot, S., Patnaik, L. M., & Jagannathan, N. R. (2006). Classification of magnetic resonance brain images using wavelets as input to support vector machine and neural network. *Biomedical Signal Processing and Control, 1*(1), 86–92.

Cheng, H. D., Shan, J., Ju, W., Guo, Y., & Zhang, L. (2010). Automated breast cancer detection and classification using ultrasound images: A survey. *Pattern Recognition, 43*(1), 299–317.

Cherkassky, V., & Mulier, F. (2007). *Learning from data: Concepts, theory and methods* (2nd ed.). John Wiley and Sons.

Danciu, M., Gordan, M., Florea, C., Orghidan, R., Sorantin, E., & Vlaicu, A. (2013). A hybrid 3D learning-and-interaction-based segmentation approach applied on CT liver volumes. *Radio Engineering, 22*(1), 100–113.

Daubechies, I. (1991). Ten lectures on wavelets. *CBMS-NSF Series in Applied Mathematics (SIAM)*.

Demirhan, A., & Güler, I. (2011). Combining stationary wavelet transform and self-organizing maps for brain MR image segmentation. *Engineering Applications of Artificial Intelligence, 24*(2), 358–367.

Department of radiology (2014). Pakistan institute of medical sciences, Islamabad, Pakistan, Online: <http://www.pims.gov.pk/radiology.htm>.

Donoso, R., Veloz, A., & Allende, H. (2010). Modified expectation maximization algorithm for MRI segmentation; I. Bloch, & R. M. Cesar, Jr. (Eds.), CIARP 2010, LNCS 6419 (pp. 63–70).

Dubey, R. B., Hanmandlu, M., & Gupta, S. K. (2009). Semi-automatic segmentation of MRI brain tumor. *ICGSTGVIP Journal, 9*(4), 1–8.

Duda, R., Hart, P., & Stork, D. (2001). *Pattern classification*. New York: John Wiley & Sons Inc.

Eckhorn, R., Reitboeck, H. J., Arndt, M., & Dicke, P. (1990). Feature linking via synchronization among distributed assemblies: Simulation of results from cat cortex. *Neural Computation, 2*(3), 293–307.

El-Dahshan, E. A., Hosny, T., & Salem, A. B. M. (2010). Hybrid intelligent techniques for MRI brain images classification. *Digital Signal Processing, 20*(2), 433–441.

Fu, J. C., Chen, C. C., Chai, J. W., Wong, S. T. C., & Li, I. C. (2010). Image segmentation by EM-based adaptive pulse coupled neural networks in brain magnetic resonance imaging. *Computerized Medical Imaging and Graphics, 34*(4), 308–320.

Fujita, H., Uchiyama, Y., Nakagawa, T., Fukuoka, D., Hatanaka, Y., Hara, T., et al. (2008). Computer-aided diagnosis: The emerging of three CAD systems induced by Japanese health care needs. *Computer Methods and Programs in Biomedicine, 92*(3), 238–248.

Gasmi, K., Kharrat, A., Messaoud, M. B., & Abid, M. (2012). Automated segmentation of brain tumor using optimal texture features and support vector machine classifier; image analysis and recognition. *Lecture Notes in Computer Science, 7325*, 230–239.

Georgiadis, P., Cavouras, D., Kalatzis, I., Daskalakis, A., Kagadis, G. C., Sifaki, K., et al. (2008). Improving brain tumor characterization on MRI by probabilistic neural networks and non-linear transformation of textural features. *Computer Methods Programs Biomedicine, 89*(1), 24–32.

Gonzalez, R. C., & Woods, R. E. (2008). *Digital image processing* (3rd ed.). Pearson Prentice Hall (Prentice Hall, 2002).

Graña, M., Termenon, M., Savio, A., Gonzalez-Pinto, A., Echeveste, J., Pérez, J. M., et al. (2011). Computer aided diagnosis system for Alzheimer disease using brain diffusion tensor imaging features selected by Pearson's correlation. *Neuroscience Letters, 502*(3), 225–229.

Harvard medical school (2014). Web: <http://www.med.harvard.edu/aanlib/home.html>.

Haykin, S. (2008). *Neural networks and learning machines* (3rd ed.). New Jersey: Pearson Prentice Hall.

Herlidou-Meme, S., Constans, J. M., Carsin, B., Olivie, D., Eliat, P. A., Nadal-Desbarats, L., et al. (2003). MRI texture analysis on texture test objects, normal brain and intracranial tumors. *Magnetic Resonance Imaging, 21*(9), 989–993.

Hiremath, P. S., Shivashankar, S., & Pujari, J. (2006). Wavelet based features for color texture classification with application to CBIR. *International Journal of Computer Science and Network Security, 6*(9A), 124–133.

<http://buscahospital.com/hospital/hospital-santiago-apostol-vitoria-gasteiz> (2014).

Indian Devaki Cancer Institute, 2014. Devaki Cancer Hospita Madurai, <http://devakicancerinstitute.com>.

Jafari, M., & Kasaei, S. (2011). Automatic brain tissue detection in MRI images using seeded region growing segmentation and neural network classification. *Australian Journal of Basic and Applied Sciences, 5*(8), 1066–1079.

Jafarpour, S., Sedghi, Z., & Amirani, M. C. (2012). A robust brain MRI classification with GLCM features. *International Journal of Computer Applications, 37*(12) (0975–8887).

Jaffar, M. A., MirzaA, A., & Mahmud, M. (2011). MR imaging enhancement and segmentation of tumor using fuzzy curvelet. *International Journal of the Physical Sciences, 6*(31), 7242–7246.

Jain, A. K., Duin, R. P. W., & Mao, J. (2000). Statistical pattern recognition: A review. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 22*, 4–37.

Jolliffe, I. T. (2002). *Principal component analysis* (2nd ed.). New York: Springer-Verlag.

Juang, L., & Wu, M. (2010). MRI brain lesion image detection based on color-converted K-means clustering segmentation. *Measurement, 43*(7), 941–949.

Kang, H. W. (2005). G-wire: A livewire segmentation algorithm based on a generalized graph formulation. *Pattern Recognition Letters, 26*(13), 2042–2051.

Kharrat, A., Gasmi, K., Messaoud, M. B., Benamrane, N., & Abid, M. (2010). A hybrid approach for automatic classification of brain MRI using genetic algorithm and support vector machine. *Leonardo Journal of Sciences, 9*(17), 71–82.

Kharrat, A., Gasmi, K., Messaoud, M. B., Benamrane, N., & Abid, M. (2011). Medical image classification using an optimal feature extraction algorithm and a supervised classifier technique. *International Journal of Software Science and Computational Intelligence, 3*(2), 19–33.

Kinser, J. M., & Johnson, J. L. (1996). Stabilized input with a feedback pulse-coupled neural network. *Optical Engineering, 35*(8), 2158–2161.

Kuwazuru, J., Arimura, H., Kakeda, S., Yamamoto, D., Magome, T., Yamashita, Y., et al. (2012). Automated detection of multiple sclerosis candidate regions in MR images: False-positive removal with use of an ANN-controlled level-set method. *Radiological Physics and Technology January, 5*(1), 105–113.

Latif, G., Kazmi, S. B., Jaffar, M. A., & Mirza, A. M. (2010). Classification and segmentation of brain tumor using texture analysis. In *Proceedings of the (9th)*

2010 WSEAS international conference on artificial intelligence knowledge engineering and data bases (pp. 147–155).

Lindblad, T., & Kinser, J. M. (2005). *Image processing using pulse-coupled neural networks*. Springer. Reading.

Logeswari, T., & Karnan, M. (2010). An improved implementation of brain tumor detection using segmentation based on hierarchical self organizing map. *International Journal of Computer Theory and Engineering, 2*(4), 1793–8201.

LONI (2014). (<https://www.ida.loni.usc edu/login.jsp>) Laboratory of neuro imaging: L NI.

Maitra, M., & Chatterjee, A. (2006). A Slantlet transform based intelligent system for magnetic resonance brain image classification. *Biomedical Signal Processing and Control, 1*(4), 299–306.

Maitra, M., & Chatterjee, A. (2008). Hybrid multiresolution Slantlet transform and fuzzy c-means clustering approach for normal–pathological brain MR image segregation. *Medical Engineering and Physics, 30*(5), 615–623.

Maitra, M., & Chatterjee, A. (2008). Hybrid multi-resolution Slantlet transform and fuzzy c-means clustering approach for normal–pathological brain MR image segregation. *Medical Engineering and Physics, 30*(5), 615–623.

Marshkole, N., Singh, B. K., & Thoke, A. S. (2011). Texture and shape based classification of brain tumors using linear vector quantization. *International Journal of Computer Applications, 30*(11), 21–23.

Marx, S. D., & Brown, C. M. (2000). Progressive livewire for automatic contour extraction. In *Proceedings, western NY image processing workshop*.

Masulli, F., & Schenone, A. (1999). A fuzzy clustering based segmentation system as support to diagnosis in medical imaging. *Artificial Intelligence in Medicine, 16*(2), 129–147.

Mehmood, I., Ejaz, N., Sajjad, M., & Baik, S. W. (2013). Prioritization of brain MRI volumes using medical image perception model and tumor region segmentation. *Computers in Biology and Medicine, 43*, 1471–1483.

Merisaari, H., Parkkola, R., Alhoniemi, E., Teräs, M., Lehtonen, L., Haataja, L., et al. (2009). Gaussian mixture model-based segmentation of MR images taken from premature infant brains. *Journal of Neuroscience Methods, 182*(1), 110–122.

Mohsen, H., El-Dahshan, E., & Salem, A. (2012). A machine learning technique for MRI brain images. In *Proceedings of the (8th) 2012 INFOS IEEE international conference on informatics and systems (INFOS2012)*. IEEE.

Noreen, N., Hayat, K., & Madani, S. A. (2011). MRI segmentation through wavelets and fuzzy c-means. *World Applied Sciences Journal, 13*, 34–39 (Special Issue of Applied Math).

Ortiz, A., Gorriz, J. M., Ramırez & Salas-Gonzalez, D. (2013). Improving MRI segmentation with probabilistic GHSOM and multi-objective optimization. *Neurocomputing, 114*, 118–131.

Ortiza, A., Górriz, J. M., Ramírez, J., Salas-González, D., & Llamas-Elvirac, J. M. (2013). Two fully-unsupervised methods for MR brain image segmentation using SOM-based strategies. *Applied Soft Computing, 13*(5), 2668–2682.

Parizel, P., van den Hauwe, L., De Belder, F., Van Goethem, J., Venstermans, C., Salgado, R., et al. (2010). *Magnetic resonance imaging of the brain*. Berlin: Springer.

Rajendran, A., & Dhanasekaran, R. (2012). Fuzzy clustering and deformable model for tumor segmentation on MRI brain image: A combined approach. *Procedia Engineering* (Vol. 30, pp. 327–333). (In *Proceedings of the international conference on communication technology and system design* 2012).

Ramasamy, R., & Anandhakumar, P. (2011). Brain tissue classification of MR images using fast Fourier transform based expectation–maximization Gaussian mixture model. *Advances in Computing and Information Technology Communications in Computer and Information Science, 198*, 387–398.

Ratan, R., Sharma, S., & Sharma, S. K. (2009). Brain tumor detection based on multi-parameter MRI image analysis. *ICGST International Journal on Graphics, Vision and Image Processing GVIP, 9*(3), 9–17.

Sachdeva, J., Kumar, V., Gupta, I., Khandelwal, N., & Ahuja, C. K. (2012). A novel content-based active contour model for brain tumor segmentation. *Magnetic Resonance Imaging, 30*(5), 694–715.

Selvanayaki, K., & Karnan, M. (2010). CAD system for automatic detection of brain tumor through magnetic resonance image-a review. *International Journal of Engineering Science and Technology, 2*(10), 5890–5901.

Selvaraj, D., & Dhanasekaran, R. (2013). A review on tissue segmentation and feature extraction of MRI brain images. *International Journal of Computer Science and Engineering Technology (IJCSET), 4*(10), 1313–1332.

Selvaraj, H., ThamaraiSelvi, S., Selvathi, D., & Gewali, L. (2007). Brain MRI slices classification using least squares support vector machine. *IC-MED, 1*(1), 21–33.

Shanthi, K. J., Sasikumar, M. N., & Kesavadas, C. (2010). Neuro-fuzzy approach toward segmentation of brain MRI based on intensity and spatial distribution. *Journal of Medical Imaging and Radiation Sciences, 41*(2), 66–71.

Siyal, M. Y., & Yu, L. (2005). An intelligent modified fuzzy c-means based algorithm for bias estimation and segmentation of brain MRI. *Pattern Recognition Letters, 26*(13), 2052–2062.

Somasundaram, K., & Kalaiselvi, T. (2010). Fully automatic brain extraction algorithm for axial T2-weighted magnetic resonance images. *Computers in Biology and Medicine, 40*(10), 811–822.

Tanga, H., Wua, E. X., Mab, Q. Y., Gallagherc, D., Pereraa, G. M., & Zhuang, T. (2000). MRI brain image segmentation by multi-resolution edge detection and region selection. *Computerized Medical Imaging and Graphics, 24*(6), 349–357.

Tanoori, B., Azimifar, Z., Shakibafar, A., & Katebi, S. (2011). Brain volumetry: An active contour model-based segmentation followed by SVM-based classification. *Computers in Biology and Medicine, 41*(8), 619–632.

Vrooman, H. A., Cocosco, C. A., Lijn, F. V. D., Stokking, R., Ikram, M. A., Vernooij, M. W., et al. (2007). Multi-spectral brain tissue segmentation using automatically trained k-nearest-neighbor classification. *NeuroImage, 37*(1), 71–81.

Wang, H., & Fei, B. (2009). A modified fuzzy c-means classification method using a multiscale diffusion filtering scheme. *Medical Image Analysis, 13*(2), 193–202.

Weili, S., Yu, M., Zhanfang, C., & Hongbiao, Z. (2009). Research of automatic medical image segmentation algorithm based on Tsallis entropy and improved PCNN. In *Proceedings of the IEEE international conference on mechatronics and automation* (pp. 1004–1008). IEEE.

XueY., Simon X., & Yang, S. X. (2005). Image segmentation using watershed transform and feed-back pulse coupled neural network. In W. Duch (Ed.), *International conference on artificial neural networks. ICANN 2005, LNCS* (Vol. 3696, pp. 531–536). Berlin: Springer-Verlag.

Yamamoto, D., Arimura, H., Kakeda, S., Magome, T., Yamashita, Y., Toyofuku, F., et al. (2010). Computer-aided detection of multiple sclerosis lesions in brain magnetic resonance images: False positive reduction scheme consisted of rule-based, level set method, and support vector machine. *Computerized Medical Imaging and Graphics, 34*(5), 404–413.

Yang, M. S., Hu, Y. J., Lin, K. C., & Lin, C. (2002). Segmentation techniques for tissue differentiation in MRI of ophthalmology using fuzzy clustering algorithms. *Magnetic Resonance Imaging, 20*(2), 173–179.

Yousefi, S., Azmi, R., & Zahedi, M. (2012). Brain tissue segmentation in MR images based on a hybrid of MRF and social algorithms. *Medical Image Analysis, 16*(4), 840–848.

Zacharaki, E. I., Wang, S., Chawla, S., SooYoo, D., Wolf, R., Melhem, E. R., et al. (2009). Classification of brain tumor type and grade using MRI texture and shape in a machine learning scheme. *Magnetic Resonance Medicine* (62), 1609–1618.

Zarandi, M. H., Zarinbal, M., & Izadi, M. (2011). Systematic image processing for diagnosing brain tumors: A type-II fuzzy expert system approach. *Applied Soft Computing, 11*(1), 285–294.

Zexuan, Ji., Sun, Q., Xia, Y., Chen, Q., Xia, D., & Feng, D. (2012). Generalized rough fuzzy c-means algorithm for brain MR image segmentation. *Computer Methods and Programs in Biomedicine, 108*(2), 644–655.

Zhang, Y., Wang, S., & Wu, L. (2010). A novel method for magnetic resonance brain image classification based on adaptive chaotic PSO. *Progress in Electromagnetics Research, 109*, 325–343.

Zhang, Y., Dong, Z., Wu, L., & Wang, S. (2011). A hybrid method for MRI brain image classification. *Expert Systems with Applications, 38*(8), 10049–10053.

Zhang, N., Ruan, S., Lebonvallet, S., Liao, Q., & Zhu, Y. (2011). Kernel feature selection to fuse multi-spectral MRI images for brain tumor segmentation. *Computer Vision and Image Understanding, 115*(2), 256–269.

Zöllner, F. G., Emblem, K. E., & Schad, L. R. (2012). SVM-based glioma grading: Optimization by feature reduction analysis. *Zeitschrift für Medizinische Physik, 22*(3), 205–214.

Further reading

Hassanien, A. E., Al-Qaheri, H., & El-Dahshan, E. A. (2011). Prostate boundary detection in ultrasound images using biologically-inspired spiking neural network. *Applied Soft Computing, 11*(2), 2035–2041.

Khayati, R., Vafadust, M., Towhidkhah, F., & Nabavi, S. M. (2008). A novel method for automatic determination of different stages of multiple sclerosis lesions in brain MR FLAIR images. *Computerized Medical Imaging and Graphics, 32*, 124–133.

Zhou, Z., & Ruan, Z. (2007). Multicontext wavelet-based thresholding segmentation of brain tissues in magnetic resonance images. *Magnetic Resonance Imaging, 25*(3), 381–385.