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Hybrid intelligent techniques for MRI brain images classification

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ABSTRACT

This paper presents a hybrid technique for the classification of the magnetic resonance images (MRI). The proposed hybrid technique consists of three stages, namely, feature extraction, dimensionality reduction, and classification. In the first stage, we have obtained the features related to MRI images using discrete wavelet transformation (DWT). In the second stage, the features of magnetic resonance images have been reduced, using principal component analysis (PCA), to the more essential features. In the classification stage, two classifiers have been developed. The first classifier based on feed forward back-propagation artificial neural network (FP-ANN) and the second classifier is based on *k*-nearest neighbor (*k*-NN). The classifiers have been used to classify subjects as normal or abnormal MRI human images. A classification with a success of 97% and 98% has been obtained by FP-ANN and *k*-NN, respectively. This result shows that the proposed technique is robust and effective compared with other recent work.

1. Introduction

Magnetic resonance imaging (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 [1]. The most important advantage of MR imaging is that it is a non-invasive technique [2]. The use of computer technology in medical decision support is now widespread and pervasive across a wide range of medical area, such as cancer research, gastroenterology, heart diseases, brain tumors, etc. [3]. Fully automatic normal and diseased human brain classification can be obtained from magnetic resonance images; which is a great importance for research and clinical studies.

Recent work [2,5] has shown that classification of human brain in magnetic resonance (MR) images is possible via supervised techniques such as artificial neural networks and support vector machine (SVM) [2], and unsupervised classification techniques such as self-organization map (SOM) [2] and fuzzy *c*-means [5]. Other supervised classification techniques, such as *k*-nearest neighbors (*k*-NN) [1] can be used to classify the normal/pathological T2-weighted MRI images. In this study, we used supervised machine learning algorithms (ANN and *k*-NN) to obtain the classification of images under two categories, either normal or abnormal.

Wavelet transform is an effective tool for feature extraction, because they allow analysis of images at various levels of resolution. This technique requires large storage and is computationally more expensive [4]. Hence an alternative method for dimension reduction scheme is used. In order to reduce the feature vector dimension and increase the discriminative power, the principal component analysis (PCA) has been used. Principal component analysis is appealing since it effectively

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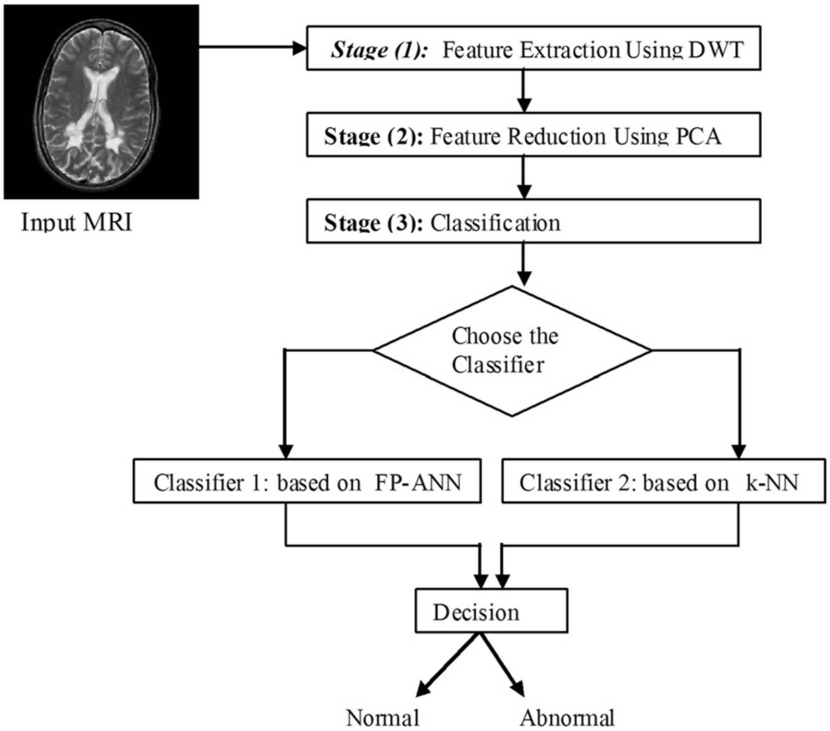

Fig. 1. The methodology of the proposed technique.

reduces the dimensionality of the data and therefore reduces the computational cost of analyzing new data. To perform the classification on the input data, the *k*-NN and ANN have been used.

The contribution of this paper is the integration of an efficient feature extraction tool and a robust classifier to perform a more robust and accurate automated MRI normal/abnormal brain images classification. Also, this paper focuses on a comparison of our results with a similar study using supervised and unsupervised methods that were carried out by other authors [2,5].

This paper is organized as follows. A short description of the input dataset of images presented in Section 2 and methods for feature extraction and reduction as well as for classification presented in Section 3. Section 4 contains results and discussion; while the conclusion and future work are presented in Section 5.

2. Methodology

The proposed hybrid techniques are based on the following techniques: discrete wavelet transforms DWT, PCA, FP-ANN, and *k*-NN. It consists of three stages: (1) feature extraction stage, (2) feature reduction stage, and (3) classification stage. The proposed hybrid technique for MRI image classification is illustrated in Fig. 1. In the following sections, a review of basic fundamental of *k*-NN, principal component analysis, and wavelet decomposition are introduced.

2.1. Feature extraction scheme using DWT

The proposed system uses the discrete wavelet transform (DWT) coefficients as feature vector. The wavelet is a powerful mathematical tool for feature extraction, and has been used to extract the wavelet coefficient from MR images. Wavelets are localized basis functions, which are scaled and shifted versions of some fixed mother wavelets. The main advantage of wavelets is that they provide localized frequency information about the function of a signal, which is particularly beneficial for classification [6]. A review of basic fundamental of wavelet decomposition is introduced as follows.

The continuous wavelet transform of a signal $x(t)$, square-integrable function, relative to a real-valued wavelet, $\Psi(t)$ is defined as [7]:

$$W_{\psi}(a,b) = \int_{-\infty}^{\infty} x(t) * \Psi_{a,b}(t)\,dx \tag{1}$$

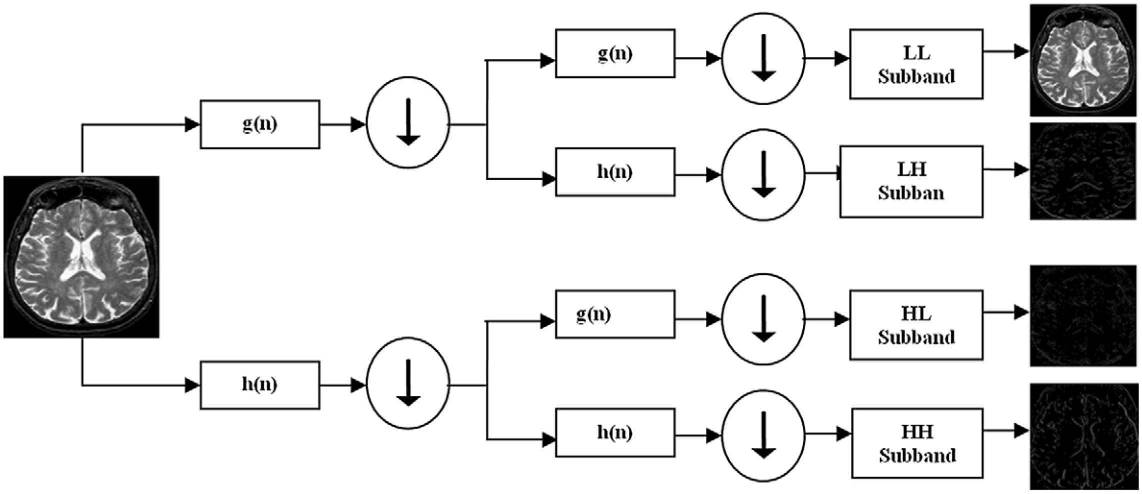

Fig. 2. DWT schematically.

where

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\Psi\big((t-a)/b\big)$$

and the wavelet $\Psi_{a,b}$ is computed from the mother wavelet Ψ by translation and dilation; a is the dilation factor and b is the translation parameter (both being real positive numbers). Under some mild assumptions, the mother wavelet Ψ satisfies the constraint of having zero mean [8,9]. Eq. (1) can be discretized by restraining a and b to a discrete lattice ($a = 2^b$, $a \in \mathbb{R}_+$, $b \in \mathbb{R}$) to give the discrete wavelet transform. There are several different kinds of wavelets which have gained popularity throughout the development of wavelet analysis. One important discrete wavelet is the Haar wavelet. The Haar wavelet is one of the simplest wavelets. Basically, it is one period of a square wave. Because of its simplicity, it is often the wavelet to be chosen [10].

The discrete wavelet transform is a linear transformation that operates on a data vector whose length is an integer power of two, transforming it into a numerically different vector of the same length. It is a tool that separates data into different frequency components, and then studies each component with resolution matched to its scale. DWT can be expressed as [11]:

$$\mathrm{DWT}_{x(n)} = \begin{cases} d_{j,k} = \sum x(n)h_j^*(n-2jk), \\ a_{j,k} = \sum x(n)g_j^*(n-2jk). \end{cases} \tag{2}$$

The coefficients $d_{j,k}$ refer to the detail components in signal $x(n)$ and correspond to the wavelet function, whereas $a_{j,k}$ refer to the approximation components in the signal. The functions $h(n)$ and $g(n)$ in the equation represent the coefficients of the high-pass and low-pass filters, respectively, whilst parameters j and k refer to wavelet scale and translation factors. The main feature of DWT is multiscale representation of function. By using the wavelets, the given function can be analyzed at various levels of resolution [12]. Fig. 2 illustrates DWT schematically. The original image is a process along the x and y direction by $h(n)$ and $g(n)$ filters which, is the row representation of the original image. As a result of this transform there are 4 sub-band (LL, LH, HH, HL) images at each scale. Sub-band image LL is used only for DWT calculation at the next scale. To compute the wavelet features in the first stage, the wavelet coefficients are calculated for the LL sub-band using Haar wavelet function.

2.2. Feature reduction scheme using PCA

The principal component analysis and independent component analysis (ICA) are two well-known tools for transforming the existing input features into a new lower-dimension feature space. In PCA, the input feature space is transformed into a lower-dimensional feature space using the largest eigenvectors of the correlation matrix. In the ICA, the original input space is transformed into an independent feature space with a dimension that is independent of the other dimensions. PCA is the most widely used subspace projection technique. These methods provide suboptimal solution with a low computational cost and computational complexity [13].

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 [9,14]. 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

Let X be an input data set (X: matrix of dimensions $M \times N$).
Perform the following steps:

Step 1. *Calculate the empirical mean*: $u[m] = \frac{1}{N} \sum_{n=1}^{N} X[m, n]$.

Step 2. *Calculate the deviations from the mean and store the data in the matrix* $B[M \times N]$: $B = X - u \cdot h$, where h is a $1 \times N$ row vector of all 1's: $h[n] = 1$ for $n = 1, \dots, N$.

Step 3. *Find the covariance matrix* C: $C = \frac{1}{N} B \cdot B^*$.

Step 4. *Find the eigenvectors and eigenvalues of the covariance matrix* $V^{-1}CV = D$: V – the eigenvectors matrix; D – the diagonal matrix of eigenvalues of C, $D[p, q] = \lambda_m$ for $p = q = m$ is the mth eigenvalue of the covariance matrix C.

Step 5. *Rearrange the eigenvectors and eigenvalues*: $\lambda_1 \geqslant \lambda_2 \geqslant \lambda_3 \geqslant \cdots \geqslant \lambda_N$.

Step 6. *Choosing components and forming a feature vector*: save the first L columns of V as the $M \times L$ matrix W,

$$W[p, q] = V[p, q], \quad \text{for } p = 1, \dots, M,\ q = 1, \dots, L \quad \text{where } 1 \leqslant L \leqslant M.$$

Step 7. *Deriving the new data set*: The eigenvectors with the highest eigenvalues are projected into space, this projection results in a vector represented by fewer dimension ($L < M$) containing the essential coefficients.

Fig. 3. PCA algorithm.

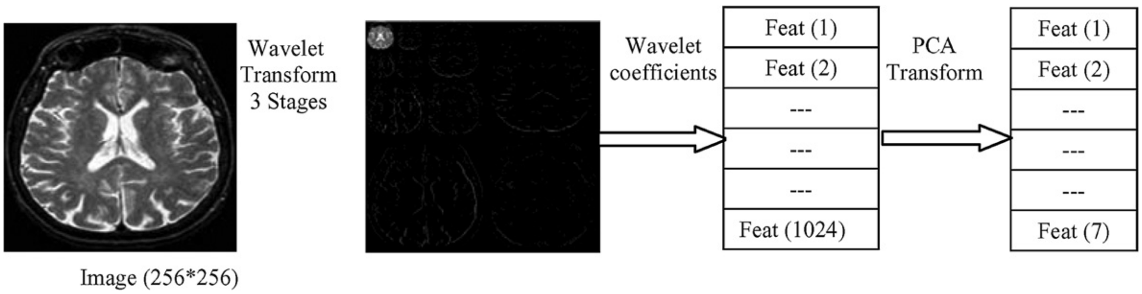

Fig. 4. Schematic diagram for the used feature extraction and reduction scheme.

in our approach is to reduce the dimensionality of the wavelet coefficients which results in a more efficient and accurate classifier.

The following algorithm is used to find out the principal components of the input matrix to the neural network. Now the input matrix consists of only these principal components. The size of the input matrix is reduced from (1024) to (7). Fig. 3 shows the steps involved for extracting the principal components of the input vector. Therefore, the feature extraction process was carried out through two steps: firstly the wavelet coefficients were extracted by the DWT and then the essential coefficients have been selected by the PCA (see Fig. 4).

3. Developing the supervised learning classifiers

3.1. k-Nearest neighbors based classifier

One of the simplest classification techniques is the *k-nearest neighbor* classifier. Classification of an input feature vector X is done by determining the k closest training vectors according to a suitable distance metric. Vector X is then assigned to that class to which the majority of those k nearest neighbors belong [9,15].

The k-NN algorithm is based on a distance function and a voting function in k nearest neighbors, the metric employed is the Euclidean distance. The k-nearest neighbor classifier is a conventional nonparametric supervised classifier that is said to yield good performance for optimal values of k [14]. Like most guided learning algorithms, k-NN algorithm consists of a training phase and a testing phase. In the training phase, data points are given in a n-dimensional space. These training data points have labels associated with them that designate their class. In the testing phase, unlabeled data are given and the algorithm generates the list of the k nearest (already classified) data points to the unlabeled point. The algorithm then returns the class of the majority of that list [14,16]. Fig. 5 describes the k-NN algorithm.

1. Determine a suitable distance metric.
2. *In the training phase*: Store all the training data set P in pairs (according to the selected features) $P = \{(y_i, c_i),\ i = 1, \ldots, n\}$, where y_i is a training pattern in the training data set, c_i is its corresponding class and n is the amount of training patterns.
3. *During the test phase*: Compute the distances between the new feature vector and all the stored features (training data).
4. The k nearest neighbors are chosen and asked to vote for the class of the new example.

The correct classification given in the test phase is used to assess the correctness of the algorithm. If this is not satisfactory, the k value can be tuned until a reasonable level of correctness is achieved.

Fig. 5. k-NN algorithm.

3.2. Artificial neural network based classifier

An ANN is a mathematical model consisting of a number of highly interconnected processing elements organized into layers, geometry and functionality of which have been resembled to that of the human brain. The ANN may be regarded as a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use [17].

The feed forward neural network which was employed as the classifier required in this study had three layers (after several trails for different hidden layers with different number of neurons). The first layer consisted of 7 input elements in accordance with the 7 feature vectors selected from the wavelet coefficients by the PCA. The number of neurons in the hidden layer was four. The single neuron in the output layer was used to represent normal and abnormal human brain.

The most frequently used training algorithm in classification problems is the back-propagation algorithm with the Levenberg–Marquardt learning rule which is used in this work also. The details of back-propagation (BP) algorithm are well documented in the literature [17].

The neural network has been trained to adjust the connection weights and biases in order to produce the desired mapping. At the training stage, the feature vectors are applied as an input to the network and the network adjusts its variable parameters, the weights and biases, to capture the relationship between the input patterns and outputs [17]. The performance is measured by mean squared error (*MSE*):

$$MSE = \frac{1}{n}\sum^{n}(y_{\mathrm{ex}} - y_{\mathrm{mod}})^2 \tag{3}$$

where y_{ex} is the target value, y_{mod} is the actual output, and n is the number of training data. The training error was 1.0×10^{-5}.

4. Case study

In this section, the proposed hybrid techniques have been implemented on a real human brain MRI dataset. All the input dataset (total images is 70: 60 images are abnormal and 10 normal) used for classification 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) [18]. Fig. 6 shows some samples from the used data for normal and pathological brain: a – normal, b – Glioma, c – Metastatic bronchogenic carcinoma, d – Alzheimer's disease, visual agnosia.

The algorithm described in this paper is developed locally and is successfully trained in MATLAB version 7.1 using a combination of the Image Processing Toolbox and Wavelet Toolbox (The MathWorks) for MATLAB. We performed all the computations of DWT + PCA + FP-ANN and DWT + PCA + k-NN classification on a personal computer with 1.5 MHz Pentium IV processor and 384 MB of memory, running under Windows-2000TM operating system. The programs can be run/tested on many different computer platforms where MATLAB is available. Fig. 7 depicts the pseudo-code of the proposed two classifiers. Fig. 8 shows a snap-shot for the GUI of the proposed hybrid technique.

5. Results and discussions

In this section, we present the performance evaluation methods used to evaluate the proposed approaches. Finally, we will show the experimental results and examine the performance of the proposed classifiers for the MRI dataset mentioned above. We evaluate the performance of the proposed method in terms of confusion matrix, sensitivity, specificity and accuracy. The three terms are defined as follows [19]:

Sensitivity (true positive fraction) is the probability that a diagnostic test is positive, given that the person has the disease,

$$Sensitivity = \frac{TP}{TP + FN}; \tag{4}$$

Specificity (true negative fraction) is the probability that a diagnostic test is negative, given that the person does not have the disease,

$$Specificity = \frac{TN}{TN + FP}; \tag{5}$$

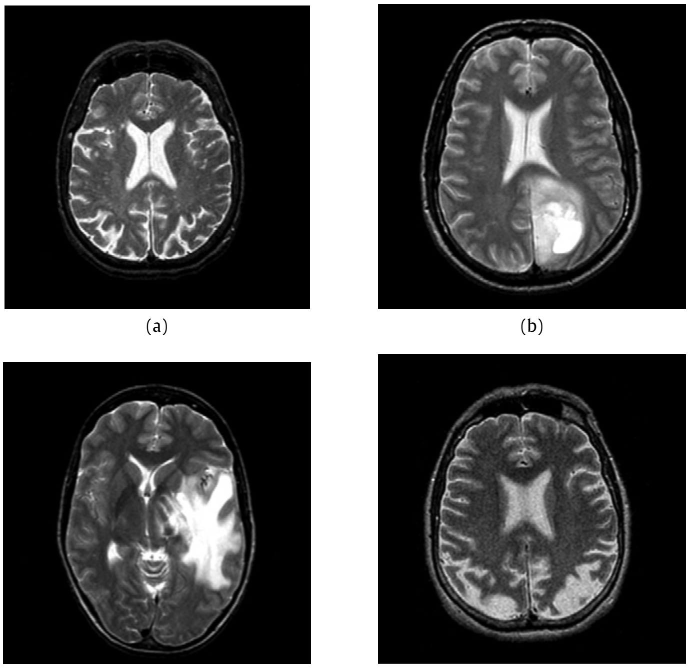

Fig. 6. Samples from the used data.

Input: 256×256 brain images.
Parameters: N is number of images.

Stage (1). Features extraction using DWT.

Loop on $i = 1$ to N:
  Read the input images,
  Resize the images, and apply the DWT for the 3rd level using "Haar" family to extract the wavelet coefficients
  Put the wavelet coefficients in a matrix X $[M \times N]$
End Loop of i

Repeat the above loop for the test image to extract its wavelet coefficients.
Concatenate the feature coefficients of the training images and the test image in one matrix.

Stage (2). PCA Features reduction.

Loop on $j = 1$ to N:
  Apply PCA Transformation (according to algorithm 1) on the obtained wavelet coefficients.
  Put the new dataset in a matrix Y.
End Loop on j

Stage (3). Classification using two supervised techniques.

Classifier 1 (*based on ANN*)
Create the design of neural network with feed forward back-propagation algorithm. Create target vector. Train the net with the selected dataset and the desired target. Input the features of test image on trained the neural network.
Classify it
Output: Normal or abnormal brain.

Classifier 2 (*based on k-NN*)
Loop for $g = 1$ to 5
  For $j = 1$ to N
    Apply the k-NN algorithm.
  END Loop j
END Loop on g
Classify test image.
Output: Normal or abnormal brain.

Fig. 7. Pseudocode of the used hybrid techniques.

Accuracy is the probability that a diagnostic test is correctly performed,

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}, \tag{6}$$

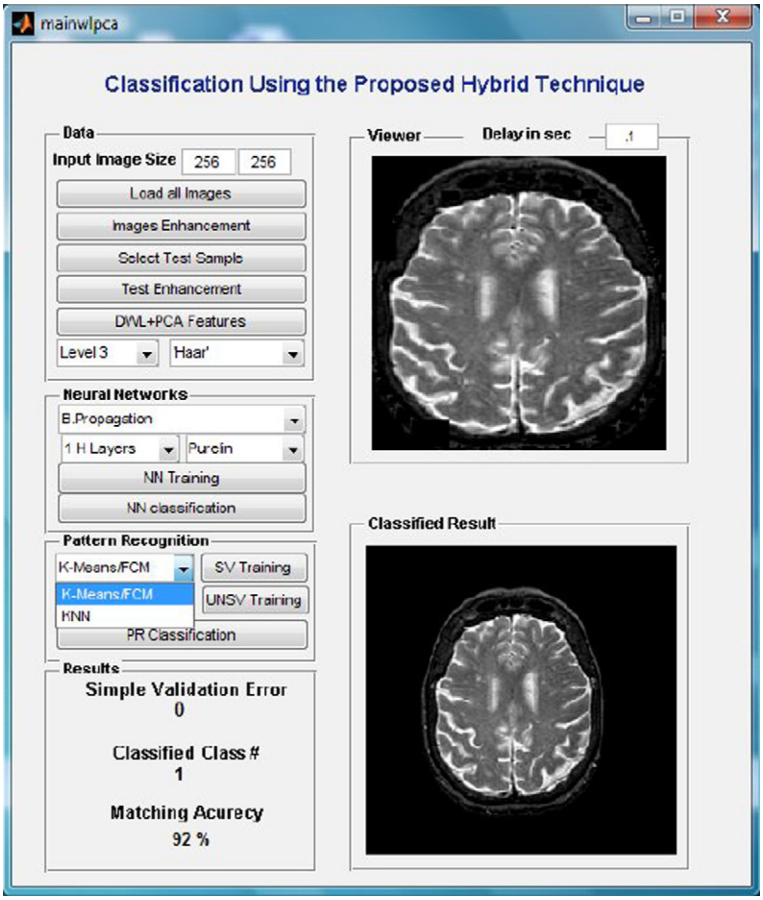

Fig. 8. The GUI of the proposed hybrid technique.

Table 1
Classification rates for the used classifiers.

Hybrid technique	*TP*	*TN*	*FP*	*FN*	Sensitivity (%)	Specificity (%)	Accuracy (%)
DWT + PCA + ANN	59	9	1	1	98.3	90	97
DWT + PCA + *k*-NN	60	9	1	0	100	90	98.6

where:

TP (True Positives) – correctly classified positive cases,

TN (True Negative) – correctly classified negative cases,

FP (False Positives) – incorrectly classified negative cases, and

FN (False Negative) – incorrectly classified positive cases.

Table 1 shows the classification rates for performing the proposed hybrid approach. In this experiment two classifiers based on supervised machine learning are presented for MRI normal/abnormal human brain classification. In the proposed methods using DWT, the first three levels coefficients of decomposition of MR images with Harr as mother wavelet are computed to extract the features. So, the 3rd approximation component and all detailed components are used as the wavelet coefficients. These coefficients are used for feature extraction. PCA is used for feature selection and NN and *k*-NN classifiers for MRI normal/abnormal human brain classification are used in methods 1 and 2, respectively.

For reducing the complexity of the system, PCA was used for feature reduction which was described in Section 3. The dimension of the feature vector was reduced from 1024 to 7 with the PCA algorithm. Limiting the feature vectors to the component selected by the PCA leads to an increase in accuracy rates. In this experimental, MRI dataset that have healthy and diseased brain are classified by the proposed classifiers. The experimental results of the proposed classifiers are compared in Table 1, which shows the percentage classification for the two different image classes. The analysis of the

Table 2
Classification performance (P) comparisons for the proposed technique and the recently works for the same MR images datasets.

Technique	P (%)
Our hybrid technique DWT + PCA + ANN	97
Our hybrid technique DWT + PCA + k-NN	98
DWT + SOM [2]	94
DWT + SVM with linear kernel [2]	96
DWT + SVM with radial basis function based kernel [2]	98

experimental results shows that classification accuracy 97% is achieved with the FP-ANN classifier and classification accuracy 98% with k-NN.

To evaluate the effectiveness of our methods we compare our results with recently results [2] for the same MRI datasets. Table 2 gives the classification accuracies of our method and recent results. This comparison shows that our system has high classification accuracy and less computation due to the feature reduction based on the PCA.

6. Conclusions and future works

In this study, we have developed a medical decision support system with normal and abnormal classes. The medical decision making system designed by the wavelet transform, the principal component analysis, and the supervised learning methods (FP-ANN and k-NN) that we have built gave very promising results in classifying the healthy and brain patient. The benefit of the system is to assist the physician to make the final decision without hesitation.

According to the experimental results, the proposed method is efficient for the classification of the human brain into normal and abnormal. Our proposal produced 98.3% sensitivity rate and 90% specificity rate for FP-ANN classifier and 100% sensitivity rate and 90% specificity rate for k-NN classifier. SOM and SVM [2,5] produced the similar results. ANN method gained the worst sensitivity and specificity rate.

Our results have been compared to the results reported very recently based on the same T2-weighted MRI database. Our method can be employed for all types of MR images T1-weighted, T2-weighted, and proton density (T1–T2-PD). This research developed two hybrid techniques, DWT + PCA + FP-ANN and DWT + PCA + k-NN to classify the human brain MR images. The stated results show that the proposed method can make an accurate and robust classifier. 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 database. The extension of the developed techniques for processing the pathological brain tissues (e.g. lesions, tumors) is the topic of future research.

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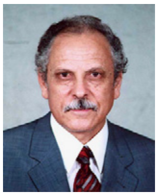

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