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CLASSIFICATION OF MRI BRAIN IMAGES USING DISCRETE WAVELET TRANSFORM AND K-NN

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ABSTRACT
Presented work is a feature extraction and classification study for diagnosis of Brain cancer (abnormal) and normal brain images. The proposed method consists of two stages, namely feature extraction and classification. In the feature extraction stage features are extracted using discrete wavelet transformation (DWT) from MRI images. In the second stage, a non-parametric statistic technique based on k-nearest neighbor (k-NN) algorithm is used for classification. The classifier has been used to classify images as normal or abnormal MRI brain images. We applied this method on 80 images (50 training images divided into 25 normal, 25 abnormal) and (30 test images divided into 15 normal, 15 abnormal) and dimensions of the images 256*256 pixel. The classification accuracies on both training and test images are 98%, has been obtained by the proposed classifier k-NN.

KEYWORDS: Magnetic resonance imaging (MRI), discrete wavelet transformation (DWT), k-nearest neighbor (k-NN), Classification.

INTRODUCTION
Magnetic resonance imaging (MRI) is an imaging technique that produces high quality images of the anatomical structures of the human body, especially in the brain, and provides rich information for clinical diagnosis and biomedical research. The diagnostic values of MRI are greatly magnified by the automated and accurate classification of the MRI images [1].

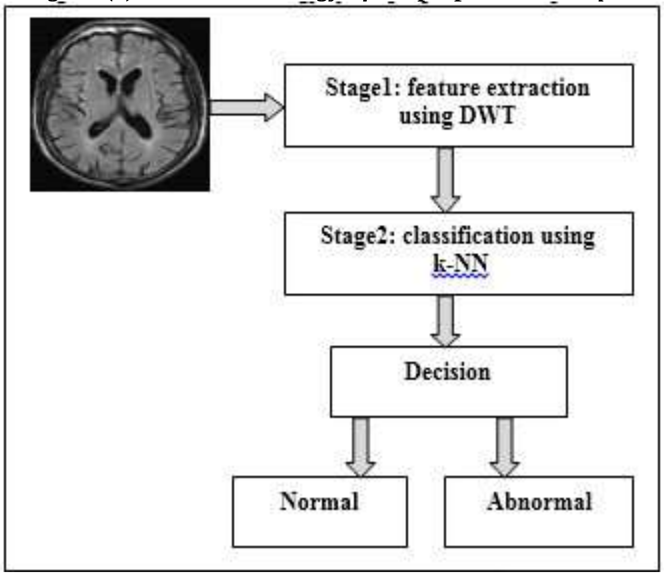
The most important advantage of MR imaging is that it is a non-invasive technique. The use of computer technology in medical decision support is now widespread and pervasive across a wide range of medical area, such as cancer research, gastroenterology, heart diseases, brain tumors, etc. Brain is a kernel part of a body. It regulates all the functions of the body. Any defect in it causes major problem in all systems of body. So the early detection of cancer is very essential [2].

Brain Cancer
The Brain tumor is caused by the tumor pressing on or encroaching on other parts of the brain and keeping them from functioning normally. Some symptoms are caused by swelling in the brain primarily caused by the tumor or its surrounding inflammation. The symptoms of primary and metastatic brain cancers are similar in men, women and children [3].

Magnetic resonance Imaging (MRI)
MRI is a medical imaging technique. It is superior to computer tomography X-RAY or other imaging techniques. Also it does not cause any harmful ionization effect to internal structure of brain. Clinical Magnetic Resonance Imaging uses the magnetic properties of hydrogen and its interaction with both a large external magnetic field and radio waves to produce highly detailed images of the human body [4].

METHODOLOGY
The proposed method consists of two stages: (1) feature extraction stage and (2) classification stage. These MRI images are given as input to the DWT. Haar wavelet is used for extract the features from MRI images. K-NN used to classify the images as a normal or abnormal. Then different 16 Features of the images are calculated for some set of data to give analysis result. Figure (1) show the proposed technique.

Figure (1): The methodology of the proposed technique.



FEATURE EXTRACTION USING DWT

The proposed method uses the discrete wavelet transform (DWT) coefficients as feature vector. The wavelet is a powerful mathematical tool for feature extraction used for extracting the wavelet coefficient from MR images. The main advantage of wavelets is that they provide localized frequency information about the function of a signal, which is particularly beneficial for classification [5]. 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 separates data into different frequency components, and then studies each component with resolution matched to its scale. DWT can be expressed as [6].

$$\mathrm{DWT}\ x(n) = \begin{cases} d\ j,k = \sum \left(x\ (n) h \ast j(n - 2\ jk) \right) \\ \\ d\ j,k = \sum \ (x\ (n)\ g \ast j(n - 2\ jk)) \end{cases} \qquad (1)$$

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, given function can be analyzed at various levels of resolution [7]. Figure (2) illustrates DWT schematically. The original image is process along the x and y direction by h(n) and g(n) filters which, is the row representation of the original image. Because of this transform, there are four subband (LL, LH, HH, and HL) images at each scale. (Figure 2). Subband image LL is used only for DWT calculation at the next scale. To compute the wavelet features in the first level, the wavelet coefficients are calculated for the LL subband using Haar wavelet function.

Haar Transform

The Haar transform is one of the basic transformation from the space/time domain to a local frequency domain, which reveals the space/time-variant spectrum. The feature extraction of the Haar transform, including fast for implementation and able to analyze the local feature of the image. The family of *N* Haar functions $h_k(t)$are defined on the interval $0 \le t \le 1$Error! Reference source not found. [8]**.**. The shape of the Haar function, of an index *k*, is determined by two parameters: *p* and *q*, where

$$k = 2^p + q - 1 \ldots\ldots\ldots (2)$$

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Moreover, k is in a range of $k = 0, 1, 2, \cdots, N-1$.
When $k = 0$, the Haar function is defined as a constant $h_0(t) = 1/\sqrt{N}$; when $k > 0$, the Haar function is defined as

$$h_k(t) = \frac{1}{\sqrt{N}} \begin{cases} 2^{p/2} & (q-1)/2^p \le t < (q-0.5)/2^p \\ -2^{p/2} & (q-0.5)/2^p \le t < \frac{q}{2^p} \\ 0 & \text{otherwise} \end{cases} \qquad (3)$$

From the above equation, one can see that p determines the amplitude and width of the non-zero part of the function, while q determines the position of the non-zero part of the Haar function [7,8]. Figure (2) shows the DWT schematically.

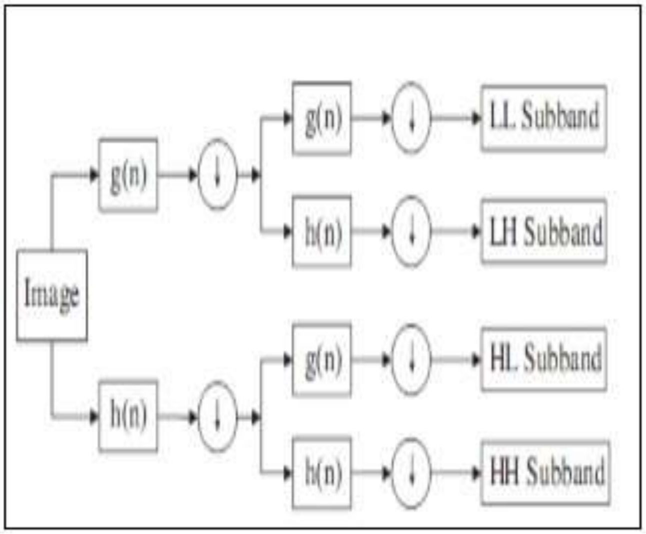

Figure (2): DWT Schematically

Features

Features gives the characteristics of the objects of interest, are representative of the maximum related information that the image has to offer for a complete depiction of a tumor. Features are used as inputs to classifiers, which assign them to the class that they represent. Some features used in this research are as given below, these features like energy, mean, entropy, standard deviation these features provide best results better than other features [9]. These features are extracted from image by Haar wavelet manipulated with image as 4 bands each band 4 features the result 16 features each image. In this research, four features are selected as below:

Energy:

This is a measure of local homogeneity in the image. Its value is high when the image has very good homogeneity. In a non-homogenous image, where there are many gray level transitions, the energy gets lower values [10].

$$\text{Energy} = \sum_i \sum_j P(i,j)^2 \quad \ldots\ldots \quad (4)$$

Mean:

The mean defines the average level of intensity of the image [11].

$$\mu = \sum_{i=0}^{Ng-1} ip(i) \ldots\ldots\ldots . (5)$$

Entropy:

It measures the randomness of the elements in the matrix. When all elements of the matrix are maximally random, entropy has its highest value. Therefore, a homogeneous image has lower entropy than an inhomogeneous image [12].

$$\text{Entropy} = \sum_i \sum_j P(i,j) \log P(i,j) \quad \ldots\ldots \quad (6)$$

Standard deviation:
It is a measure that is used to quantify the amount of variation or dispersion of a set of data values in image [13].

$$STD = \sqrt{\frac{\sum_{r=0}^{R-1} \sum_{s=0}^{S-1} (f(r,s) - Mean)^2}{R * S}} .7$$

Algorithm (1) illustrates the Feature extraction using Haar wavelet

Input: 50 MRI images
Output: Features
Begin
Repeat for all images.
Read image.
[ca,ch,cv,cd] = Compute Haar wavelet to image
Compute features of four [ca,ch,cv,cd] as follows:
Features= (Energy, Mean, Entropy and Standard deviation)
Save Features.
End.

K-NEAREST NEIGHBORS BASED CLASSIFIER

The k-nearest neighbor classifier is one of the important classification techniques. 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 that k nearest neighbors belong [14, 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 [16]. The k-nearest neighbor classifier is a conventional nonparametric that is said to yield good performance for optimal values of k. k-NN algorithm consists of a training phase and a testing phase. In the training phase, data points are given in 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, 17].

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Algorithm (2) k-Nearest neighbors

1. Determine a suitable distance metric.
2. In the training phase: Stores all the training data set P in pairs (according to the selected Features) P = (yi, ci), i=1. Where yi is a training pattern in the training data set, ci is Its corresponding class and n is the amount of training patterns.
3. During the test phase: Computes 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.

DATABASE
The database consist of 80 images divided into two stages the first stage is training images and the second stage is test images. The training stage consist of (50 training images divided into 25 normal images, 25 abnormal images). The test stage consist of (30 test images divided into 15 normal, 15 abnormal) and dimensions of the images in both stages are 256*256 pixel.

RESULTS AND DISCUSSIONS
In this section, we will show the experimental results of the proposed method for the MRI images. The experiments were carried out on the laptop computer of 3 GHz main frequency and 2G memory, running under Windows 7 operating system. Figures (3,4 and 5) shows the classification results obtained using Haar wavelet and k-NN of query image (normal and abnormal brain images). Table (1) illustrates the results of Features are extracted using Haar wavelet.

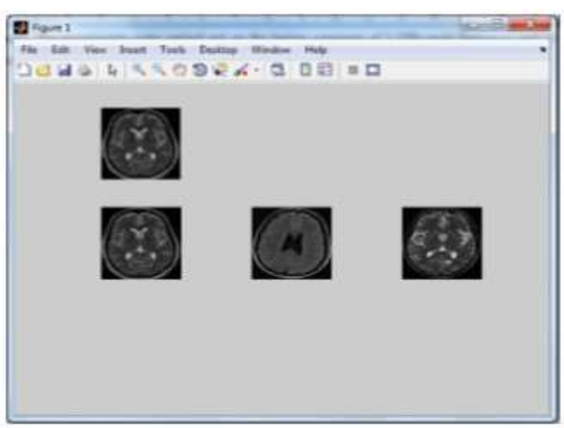

Figure (3):Shows the classification results obtained using Haar wavelet and k-NN of query image (normal brain image).

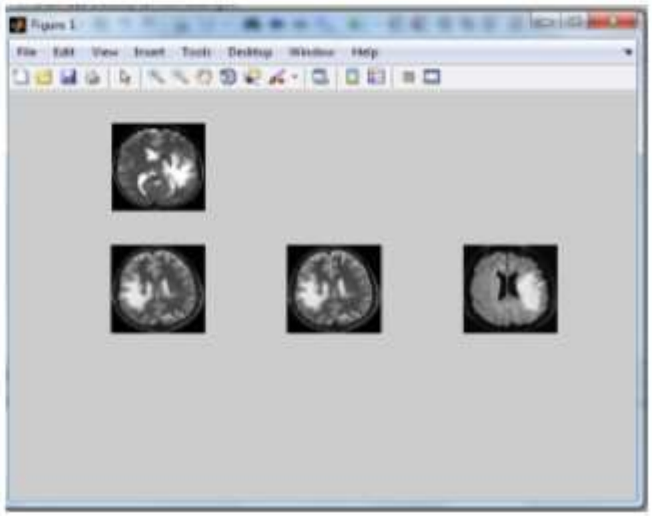

Figure (4):Shows the classification results obtained using Haar wavelet and k-NN of query image (abnormal brain image).

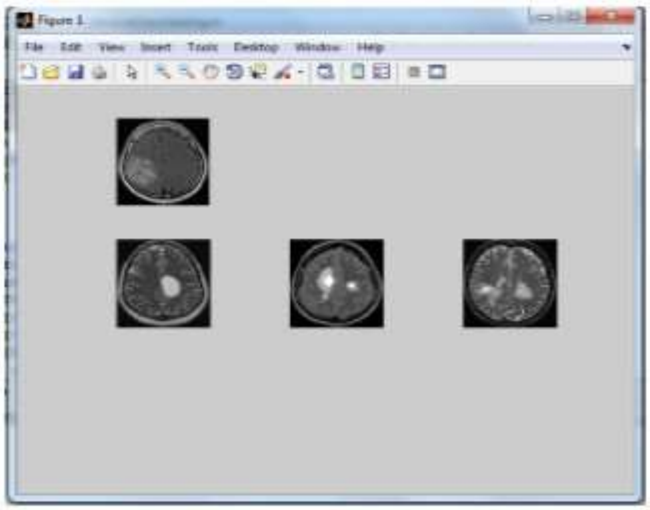

Figure (5):Shows the classification results obtained using Haar wavelet and k-NN of query image (abnormal brain image).

Table (1) illustrates the results of Features are extracted using Haar wavelet

Enegy (ca)	Enegy (ch)	Energy (cv)	Energy (cd)	Mean (ca)
15.817	18.296	90.560	1.198	1.152
10.575	10.168	67.943	1.4936	1.349
14.752	15.529	119.66	1.286	1.153
17.747	17.563	119.20	1.3444	1.1875
15.452	17.609	92.489	1.3762	1.294
21.439	20.644	137.38	1.3022	1.3058
9.395	11.738	67.771	1.495	1.352
20.807	20.745	101.77	1.3215	1.197
13.438	18.534	76.374	1.2493	1.184
10.321	10.864	72.518	1.428	1.330
7.7509	7.0335	121.39	1.492	1.323

12.316	12.485	92.305	1.476	1.311
20.777	23.236	118.13	1.3207	1.241
23.417	24.236	154.88	1.196	1.132
10.220	11.001	79.121	1.461	1.360
10.447	18.046	85.213	1.4655	1.3166
12.031	12.367	78.903	1.3762	1.2872
14.379	15.702	87.769	1.4467	1.3542
15.817	18.296	90.560	1.1980	1.1523
10.575	10.168	67.964	1.4933	1.349

Continued

Mean (ch)	Mean (cv)	Mean (cd)	Entropy (ca)	Entropy (ch)
1.120	0.129	-0.010	-0.005	0.003
1.308	0	-0.005	0.015	0.011
1.131	0.695	-0.002	-0.006	-0.024
1.177	0.030	0.0009	-0.039	0.004
1.227	0.733	-0.006	0.037	-0.999
1.2574	0.448	-0.011	-0.117	-0.063
1.279	0	-0.002	-0.021	0.023
1.166	0.655	0.026	0.038	-0.017
1.142	0.684	0.022	0.049	-0.143
1.298	0.044	-0.001	0.0092	-0.150
1.263	0.000	0.003	-0.008	-0.057
1.255	0.000	0.006	0.0127	-0.179
1.2182	0.174	-0.002	0.089	-0.042
1.132	0.778	0.007	0.065	0.085
1.318	0	0.005	0.0177	-0.001
1.2947	0	-0.002	-0.0247	-1.322
1.2333	0	-0.007	9.16E-	0.0058
1.2904	0.048	-0.001	0.0016	-0.086
1.1250	0.129	-0.010	-0.0059	0.0030
1.3087	0	-0.005	0.0155	0.01123

Continued

Entrpy (cv)	Entrpy (cd)	Standad deviatin (ca)	Standard eviation (ch)	Standard deviation (cv)
116.14	7.043	94.685	0.944	1.634
94.503	2.500	96.810	0.214	1.299
178.26	3.390	98.442	0.093	0.691
151.90	4.563	96.404	0.278	1.404
117.97	5.341	94.934	0.811	1.985
208.13	7.286	97.775	0.393	0.800
112.25	3.396	97.153	0.331	1.306
135.23	6.748	93.006	0.533	2.818
105.29	7.423	93.879	1.419	2.300
93.470	3.344	97.232	0.339	1.083
159.59	2.084	99.512	0.048	0.152
115.15	3.239	97.750	0.236	1.034

133.21	9.172	94.407	0.977	1.511
193.01	10.292	96.034	0.479	1.418
92.551	3.326	96.999	0.299	1.176
147.41	2.347	96.397	0.800	2.182
154.35	4.534	98.034	0.206	0.654
100.43	3.578	95.136	0.2650	2.230
116.14	7.043	94.685	0.944	1.634
94.503	2.500	96.810	0.214	1.299

Standard deviation (cd)
0.443
0.157
0.056
0.151
0.474
0.377
0.173
0.402
0.450
0.191
0.0314
0.084
0.792
0.405
0.196
0.055
0.117
0.198
0.443
0.157

CONCLUSION

In this study, manipulated with classification method to distinguish normal and abnormal brain MRIs. According to the experimental results, the proposed method is efficient for the classification of the human brain into normal and abnormal. The proposed method accuracies on both training and test images are 98%, has been obtained by the classifier k-NN.

The classification performances of this study show the advantages of this technique: it is rapid, easy to operate and non-invasive. The extension of the developed techniques for processing the pathological brain tissues (e.g. lesions and tumors types, e.g. sarcoma, glioma end Alzheimer etc.) is the topic of future research.

REFERENCES

[1] Yudong Z., Z. Dong, Lenan and Shuihua W., "A hybrid method brain image classification", in Elsevier journal, of selected topics in Expert Systems with Applications 38 (2011) .
[2] Chaplot, S., Patnaik, L. M., & Jagannathan, N. R., "Classification of magnetic resonance brain images using wavelets as input to support vector machine and neural network". Biomedical Signal Processing and Control, 1, 86–92, (2006).
[3] Raghaveerm R., S. Bopardikar,"wavelet transform, introduction to theory and applications". Pearson education Asia, (2002).
[4] Vrushali S., Takate and P. Vikhe"Classification of MRI Brain Images using FP_ANN ", in Elsevier journal, (2013).
[5] K. Karibasappa, S. Patnaik, "Face recognition by ANN using wavelet transform coefficients", IE (India) J. Computer Eng, (2004).
[6] D. Bouchara , J. Tan, "Structural hidden Markov models for biometrics: Fusion of face and Fingerprint"; Pattern Recognition ,(2008).
[7] T. Rosenbaum, VolkherEngelbrecht, Wilfried, Ferdinand A. van Dorstenc, Mathias Hoehn-Berlagec, Hans-Gerd Lenard; MRI abnormalities in neurobromatosistype 1 (NF1): a study of men and mice; Brain & Development 21 (1999).
[8] P. Ravirajand M.Y. Sanavullah," The Modified 2D-Haar Wavelet Transformation in Image Compression", Middle-East Journal of Scientific Research, 2007.
[9] M. Sasikalal and N. Kumaravel," Comparison of Feature Selection Techniques for Detection of Malignant Tumor in Brain Images," IEEE Indicon (2005) Conference, Chennai.
[10] Haralick, R. M., "Statistical and Structural Approaches to Texture", Proceeding of the IEEE, (1979).
[11] A. Matreka and M. Strzelecki, "Texture Analysis Methods - A Review", no. European Cooperation in Science and Technology, (1998).
[12] Hengl, T., "Visualisation of Uncertainty Using the HSI Colour Model: Computationswith Clours", International Institute for Geo-Information Science & Earth Observation, Enschede, Netherlands, 2004.
[13] Jianguo Z., and Tieniu T., " Brief of Invariant Texture Analysis Method" Pattern Recognition, (2002).
[14] A. Sengur, An expert system based on principal component analysis, artificial immune system and fuzzy NN for diagnosis of valvular heart diseases,Comp., (2007).
[15] F. Latifoglu, K. Polat, S. Kara, S. Gunes, Medical diagnosis of atherosclerosis from carotid artery Doppler signals using principal component analysis (PCA), k-NN basedweighting pre- processing and Artificial Immune Recognition System (AIRS),(2008).
[16] M. O'Farrell, E. Lewis, C. Flanagan, N. Jackman, Comparison of k-NN and neural network methods in the classification of spectral data from an optical fibre-based sensor system used for quality control in the food industry,(2005).
[17] S. Haykin, Neural Networks: A Comprehensive Foundation,Prentice Hall, (1999).