Research Journal of Recent Sciences ____ ISSN 2277-2502
Vol. **2(6),** 1-10, June **(2013)** *Res.J.Recent Sci.*

Framework for the Comparison of Classifiers for Medical Image Segmentation with Transform and Moment based features

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Available online at: www.isca.in
Received 10th October 2012, revised 14th November 2012, accepted 7th February 2013

Abstract

The paper depicts and elaborates a new framework for the comparison of classifiers for medical image segmentation with transform and moment based features. Medical images modalities such as Ultrasound (US) bladder, Ultrasound (US) phantom, Computerized Tomography (CT) and Magnetic Resonance (MR) images are segmented using different algorithms namely, k-Nearest Neighbor (kNN), Grow and learn (GAL) and Incremental Supervised Neural Networks (ISNN). Segmentation is performed by applying feature extraction methods such as 2D Continuous Wavelet Transform (2D-CWT), Moments of gray level histogram (MGH) and a combined version of both 2D-CWT and MGH, called Hybrid features. With different iterations, the analysis results indicate that kNN performs better than GAL, and the performance of GAL is better than that of the ISNN for image segmentation. During analysis a comparison has been drawn between the performance of kNN, GAL and ISNN on the above three feature extraction schemes and also provides the qualitative and quantitative analysis of three classifiers. Results indicate that the performance of 2D-CWT and that of Hybrid features is consistently better than MGH features for all image modalities. The demonstrated frame work or the system is capable to meet the demand for selecting best approach in order to meet the given time constraints and accuracy standards in medical image segmentation.

Keywords: kNN, GAL, ISNN, 2D-CWT, MGH

Introduction

Automatic tissue segmentation of images is helpful for radiologists, as it is used to facilitate doctors during diagnosis. Segmentation of medical images means to classify and identify the structure of interest in medical images. The overall objective is the computer-aided identification of the area of interest to help the doctors and radiologist during diagnosis and treatment of specific disease. Feature extraction is used for extracting sufficient and desired information from the image resulting by different variations from its features. Peculiar features having relevant information are chosen failing which culminates the segmentation process not to be executed correctly/properly[1-5]. For extracting right features, there is need of efficient feature extraction methods. In this paper three transform and moment based segmentation techniques namely, 2D-CWT, MGH and hybrid are analyzed with three different classifiers.

In the literature, there are several approaches for image segmentation to be used for different applications, such as edge detection based segmentation[6], region growing based segmentation method[7], threshold based segmentation[8], level set method based segmentation[9], neural network based segmentation techniques[10], Watershed algorithm based segmentation[3,5], graph theory based segmentation[1,11], clustering based segmentation[12], active counter model based segmentation[10,13], Marcove random field model based segmentation[14], deformable model based segmentation[15] and improved mean shift based segmentation[16]. In the literature there are different transform and texture features extraction based segmentation approaches are found[17-19]. Similarly 2D continuous, discrete wavelet transforms and 2D discrete cosine transform based feature extraction methods for segmentation are represented by Wang et al. and Ghazali et al.[20-21]. The main problem with some of the above methods is that they need too much computational resources and time for segmentation process. Some of them require too many parameters for proper performance yet these fail to meet the desired performance level.

The main work in this paper is to find out the best combination of classifiers with feature extraction schemes to achieve efficient segmentation for medical images. Recently, grow and learn (GAL) and incremental supervised neural network (ISNN) are compared under two feature extraction methods (moment of grey level histogram (MGH) and two dimension continuous wavelet transform (2D-CWT)). Neural network and SVM based classifiers[22] are compared to check which classifier has better performance. Similarly, different classifiers[23-24] are compared for checking performance results. In this paper KNN, GAL and ISNN under MGH, 2D-CWT and hybrid are comparatively analyzed to find out best combination of classifier and feature extraction scheme.

Methodology

In the proposed work kNN, GAL and ISNN are compared with each other as classifiers under MGH, 2D-CWT and hybrid feature extraction method. According to recent work ISNN performs better than GAL but according to the proposed work GAL results are better than ISNN by comparing their no of nodes, computational time and performance. It can also be seen from results that kNN is better classifier than GAL and GAL is better than ISNN by comparing their computational load and performance. The performance evaluation is given on the basis of four modalities which are: US bladder image, US phantom image, CT image and MRI. For accurate performance, the results are taken on the basis of 11 images of MRI modality. The proposed work is expressed diagrammatically in figure 1. The step wise explanation of proposed work is as follows:

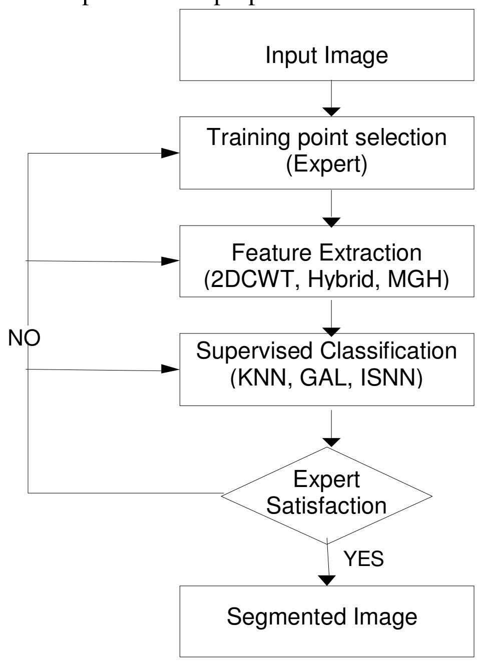


Figure-1
Specific Processing Blocks

Training Point Selection: In the segmentation phase first step is the selection of training points from the original image. Here 100 training points are selected then Select the points from each class in such a way e.g. if image has two classes (1 and 2) then select half points from class 1 and remaining half from class 2. Selection is the most important step in segmentation process. If points will not select correctly then segmentation cannot be performed accurately.

Feature Extraction: After selecting points, the second step is extraction of features by using three feature extraction methods which are 2D-CWT, MGH, and hybrid (the combine version of both 2D-CWT and MGH) as competitors [20-21]. Extract 9 feature vectors from the test data (original image) and also from the training data.

Here statistical moments are use for feature extraction. The equation for the *n*th order moments is as follows:

$$\mu_n = \sum_{i=0}^{L-1} (Z_i - m)^n . p(z_i) \tag{1}$$

Where, m = Mean intensity. zi = Random variable intensity. P (zi) = Histogram of the intensity levels in a region. L = Possible intensity levels.

Here, 9 statistical moments are used for feature extraction which are:

$$Mean = F_{m1} \sum_{i=0}^{L-1} Z_i . p(z_i) \tag{2}$$

Standard Deviation $= F_{m2} = \sqrt{\mu_2}$ (3)

Smoothness = $$F_{m3} = 1 - \frac{1}{1+\sigma^2} \tag{4}$$

Third Moment= $$F_{m4} = \sum_{i=0}^{L-1} (Z_i - m)^3 . p(z_i) \tag{5}$$

Uniformity= $$F_{m4} = \sum_{i=0}^{L-1} p^2(z_i) \tag{6}$$

Entropy= $$F_{m4} = \sum_{i=0}^{L-1} P(Z_i).Log_2(p(z_i)) \tag{7}$$

$$F_{m7} = \sum_{i=0}^{L-1} P^3(Z_i) \tag{8}$$

$$F_{m8} = \sum_{i=0}^{L-1} P^4(Z_i) \tag{9}$$

$$F_{m9} = \sum_{i=0}^{L-1} P^4(Z_i) \tag{10}$$

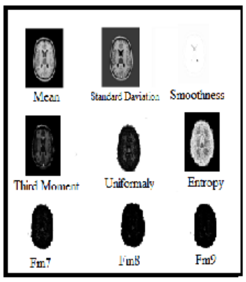
Feature vector in MGH is given below: $X_T = [F_{m1}, F_{m2}, F_{m3}, F_{m4}, F_{m5}, F_{m6}, F_{m7}, F_{m8}, F_{m9}]$, F_{m1}=>measures average intensity, F_{m2}=>measures average contrast, F_{m3}=>measures smoothness, F_{m4}=>measures skewness of histogram, F_{m5}=>measures uniformity in histogram, F_{m6}=>measures randomness, F_{m7}, F_{m8}, F_{m9}=>having least information and for completeness of feature vector dimension.

2D-continuous wavelet transform CWT splits a continuous time function in to wavelets. It has the ability to create a time-frequency representation of an image for getting more information. CWT evaluation is macro based (not pixel based). Here scale parameter is used for transformation. Scaling function is responsible for improving the coverage of the wavelet spectrum. At high scale value, image components having low frequency are fitted with rich and opposite is the case at low scale value. 2D-CWT is applied (by Gaussian wavelet) for eight different scale values to the original image such as 1.0, 1.6, 2.6, 3.9, 4.0, 5.0, 5.4 and 7. Time and frequency domain equations for 2D-CWT 20 are given in equation 11 and 12 below respectively.

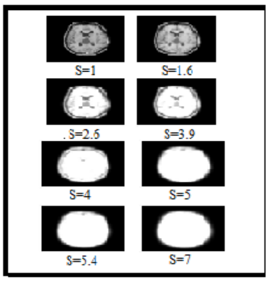
$$cwt(s,a,b) = \frac{1}{\sqrt{s}} \iint f(x,y) \psi(\frac{x-a}{s}, \frac{y-b}{s}) dxdy \tag{11}$$

$$cwt(s, w1, w2) = \sqrt{s}F(w1, w2)\Phi(sw1, sw2) \qquad (12)$$

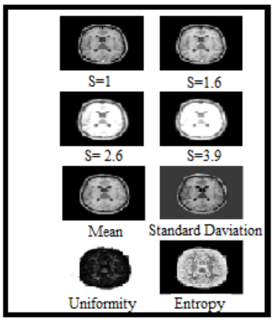
In above equations 11 and 12, ‘a’ and ‘b’ are translation parameters and ‘s’ is a scale parameter for wavelet Ψ. Whereas, ‘x’ and ‘y’ are spatial domain coordinates and w1, w2 are frequency domain coordinates. Hybrid features are formed by combining both 2D-CWT and MGH features. Nine dimensional hybrid features vector is formed by combining first five features from 2D-CWT and remaining four features from MGH features. First five features of 2D-CWT correspond to original image plus features generated using four different scale parameters as first features carry much information. The scale parameter values are 1, 1.6, 2.6 and 3.9 which generate four filtered transformed images. The remaining four features are taken from MGH. These features are selected based on their high information content. The important features that carry much information compared to others in MGH are mean, standard deviation, uniformity and entropy. In figure 2, MGH, 2D-CWT and hybrid features are shown:



(a) MGH Features



(b) 2D-CWT Features for eight different scale values



(c) Hybrid Features

Figure-2

Features extracted by three feature extraction methods (a) MGH , (b) 2D-CWT and (c) Hybrid features

Classification: After feature extraction, the classification process takes place. GAL, ISNN and kNN are used as classifiers. Classification process has two phases namely the training phase and testing phase. The data is trained and weights are assigned to that data in the training process, then labels are assigned to the whole original image in the testing process. Hence, this is the reason to use supervised classifiers in which expert chooses training points from each class of input image which is to be segmented. Here kNN, GAL and ISNN are competitor classifiers to be used for classification. The performance of kNN is much superior to that of the other two classifiers used in this work. It is a non-parametric classifier which is defined in equation 13 as:

$$p(\mathbf{x}) = k/LV \qquad (13)$$

Where L are available training samples, **x** is the test object (input feature vector) and p(**x**) is the probability around **x.** Construct the region around **x** and then count the number of samples in this region. k is the no of samples (or no of neighbors) and V is the volume in that region. In kNN, fix the count k and determine V. An object is classified by a more votes of its neighbors. K is always a positive integer and usually small. Here we use k=1.

ISNN is a two layer neural network which is proposed by Enhui et al. [22]. In ISNN, classification takes place by assigning weights to the training data during training and then labels are assigned to the test data (original image) by finding minimum distance between the weights of the test data and training data.

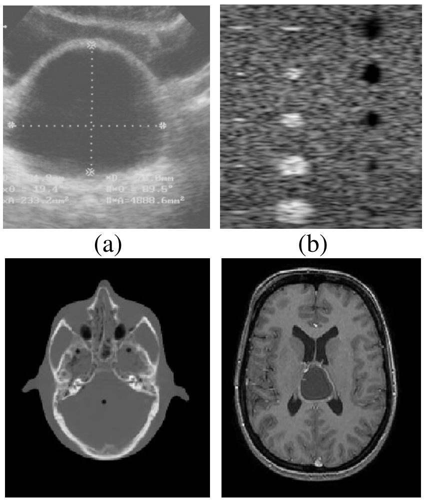
Grow and learn GAL is same as ISNN. The only difference is that when class of winner node is equal to the class of the input vector there is no increment in weights. Enhui et al. [22] claimed that ISNN is better than GAL by comparing the segmentation time. But when we calculated the results of classification which is shown in the next section, GAL perform better than ISNN. GAL performance percentage is better than ISNN as less no of nodes generate during training and use less training and segmentation time as compared to ISNN.

Results and Discussion

In this section, segmentation of four modalities takes place. The modalities are segmented using supervised classifiers as kNN, ISNN and GAL under the transform and moment based feature extraction namely MGH, 2D-CWT and hybrid feature extraction method. The simulation is performed on IBM Compatible, Intel Pentium IV PC by using Matlab 7.10 on windows 2007.

As there is supervised classification usage therefore 100 training points are selected from the original data of each modality by an expert. Select the points equaly from each class of all modalities (except phantom image where 50 points are selected from liquid medium to reduce noise). There are nine dimensional feature vectors therefore the size of training data is 100*9 and size of training labels is 100*1. The size of test data is (no. of rows of image) *(no. of columns of image) *9.

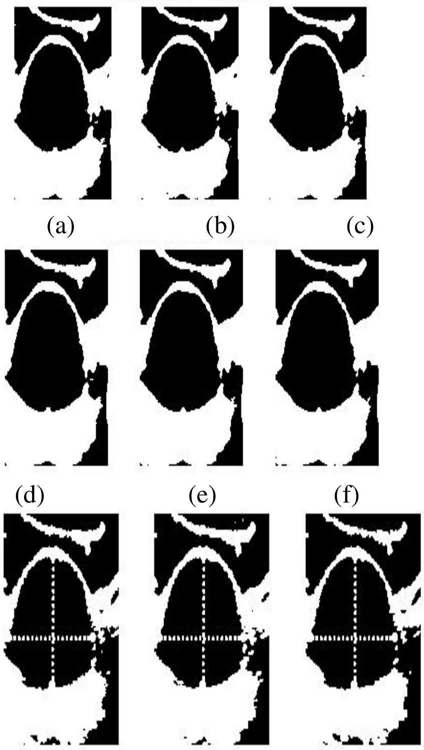
US bladder is segmented in to two classes (inner (1) and outer side (2) of bladder). Therefore 50 training points are selected from class 1 and 50 from 2. US phantom is segmented in to three classes. In phantom image, 25 points are selected from class 1 and 2 whereas 50 points are selected from class 3. In both modalities training points are select equally from each class.



(a) (b) (c) (d)

Figure-3
(a) US bladder image, (b) US phantom image, (c) CT head image, (d) MR head image

Segmented results are shown in figure 4, 5, 6 and figure 7. Note that three classifiers are analyzed with three different feature extraction schemes.



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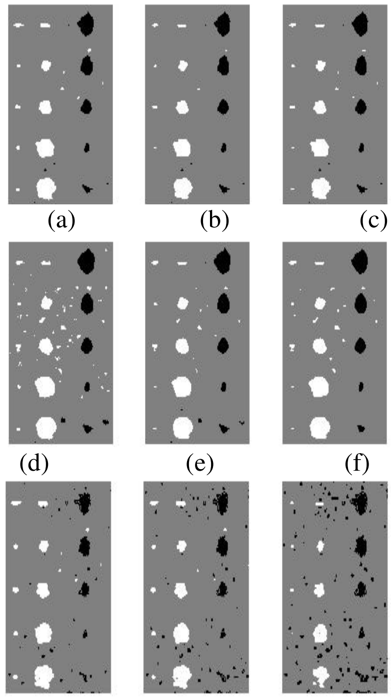
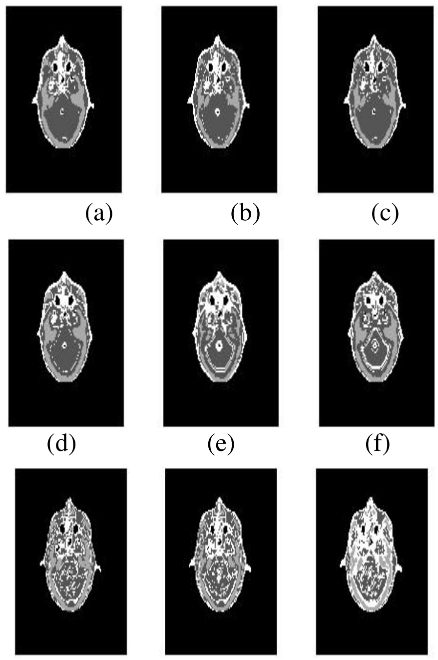
(a) (b) (c) (d) (e) (f) (g) (h) (i)

Figure-4
Segmented US bladder image by (a) KNN, (b) GAL, (c) ISNN using hybrid; (d) KNN, (e) GAL, (f) ISNN using 2D-CWT; (g) KNN, (h) GAL, (1) ISNN using MGH



(a) (b) (c) (d) (e) (f) (g) (h) (i)

Figure-5
Detected US phantom image by (a) KNN, (b) GAL, (c) ISNN using hybrid; (d) KNN, (e) GAL, (f) ISNN using 2D-CWT; (g) KNN, (h) GAL, (1) ISNN using MGH



(a) (b) (c) (d) (e) (f) (g) (h) (i)

Figure-6
Segmented CT head image by (a) KNN, (b) GAL, (c) ISNN using hybrid; (d) KNN, (e) GAL, (f) ISNN using 2D-CWT; (g) KNN, (h) GAL, (1) ISNN using MGH

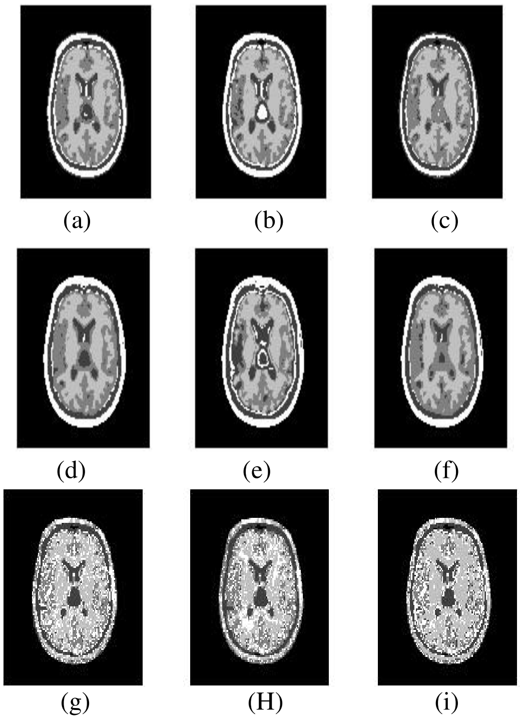


Figure-7
Segmented MR head image by (a) KNN, (b) GAL, (c) ISNN using hybrid; (d) KNN, (e) GAL, (f) ISNN using 2D-CWT; (g) KNN, (h) GAL, (1) ISNN using MGH

Comparison of GAL and ISNN under MGH, 2D-CWT and Hybrid at different iterations: The test images are segmented using GAL and ISNN at different iterations. In the existing work, iteration no of GAL and ISNN were selected as 2000, and 10,000 respectively [22]. Therefore GAL and ISNN were not performing efficiently as too much computational time were consuming. Therefore after testing the results at different iterations, the suggested and tested iteration would be 20, 50 and 100 for both GAL and ISNN because at these iterations, GAL and ISNN are efficiently perform and use less training and segmentation time. Table 1 , 2 and 3 shows the comparison of GAL and ISNN at 20 , 50 and 100 iterations.

From the above tables it can be observed that the iteration no. 20, 50 and 100, results are more accurate. It is also observed that, the GAL is better than ISNN using all selected iterations as GAL generates less number of nodes than ISNN. Therefore GAL has good performance and low computational time than ISNN under different feature extraction schemes.

Performance analysis of KNN, GAL, ISNN under MGH, 2D-CWT, hybrid: The Performance results of segmentation for all four modalities are evaluated on the basis of one image. In the next section for identify more real performance of MR image we evaluate performance on the base of 11 MR images. Performance is the percentage comes by comparing training labels with testing labels. Here we also compare each classifier and feature extraction methods by comparing performance, computational time (both training time and segmentation time).

Table-1
Comparison of GAL and ISNN at 20

Image	ANN	Features	TT(sec)	ST(sec)	Total time(s) (ST+TT)	NON		Performance (%)
usbladder	GAL	Mgh	0.061746	2.495491	2.557237	6		100
	ISNN	Mgh	0.073545	2.502339	2.575884	5		100
	GAL	2d-cwt	0.061578	2.448884	2.510462	3		100
	ISNN	2d-cwt	0.073083	2.467418	2.540501	3		100
	GAL	Hybrid	0.061922	2.585885	2.647807	4		100
	ISNN	Hybrid	0.073207	2.629772	2.702979	5		100
usphantom	GAL	Mgh	0.062149	2.210711	2.272860	**eq** 5	**Uneq** 8	98
	ISNN	Mgh	0.072470	2.136215	2.208685	6	8	96
	GAL	2d-cwt	0.062934	2.238110	2.301044	5	6	99
	ISNN	2d-cwt	0.073083	2.293207	2.366290	6	12	99
	GAL	Hybrid	0.062992	2.184066	2.247058	5	9	99
	ISNN	Hybrid	0.073174	2.177684	2.257058	6	11	99
CT head	GAL	Mgh	0.068176	2.132186	2.200362	19		93
	ISNN	Mgh	0.092177	2.177600	2.269777	21		93
	GAL	2d-cwt	0.064881	2.041324	2.106205	18		99
	ISNN	2d-cwt	0.078795	2.062013	2.140808	19		96
	GAL	Hybrid	0.064251	2.028647	2.092898	15		97
	ISNN	Hybrid	0.076433	2.086171	2.162604	20		97
M head	GAL	Mgh	0.065476	2.086582	2.152058	23		93
	ISNN	Mgh	0.079302	2.122091	2.201393	29		91
	GAL	2d-cwt	0.063322	2.006598	2.069920	15		99
	ISNN	2d-cwt	0.073378	1.993947	2.067325	15		97
	GAL	Hybrid	0.063661	2.024473	2.088134	9		98
	ISNN	Hybrid	0.075210	2.042749	2.117959	10		96

Table-2
Comparison of GAL and ISNN at 50

Image	ANN	Features	TT(sec)	ST(sec)	Total time(s) (ST+TT)	NON		Performance (%)
usbladder	GAL	Mgh	0.152369	2.460263	2.612632	5		100
	ISNN	Mgh	0.169764	2.480009	2.649713	6		100
	GAL	2d-cwt	0.149049	2.462202	2.611251	4		100
	ISNN	2d-cwt	0.165828	2.464427	2.630255	6		100
	GAL	Hybrid	0.149489	2.460621	2.610110	4		100
	ISNN	Hybrid	0.167519	2.457495	2.625014	5		100
usphantom	GAL	Mgh	0.158182	2.165314	2.323496	**eq** 4	**Uneq** 7	98
	ISNN	Mgh	0.173404	2.160697	2.334101	6	9	96
	GAL	2d-cwt	0.150029	2.132721	2.282750	4	5	99
	ISNN	2d-cwt	0.166719	2.150088	2.316799	7	12	99
	GAL	Hybrid	0.156568	2.154378	2.310946	5	7	99
	ISNN	Hybrid	0.175836	2.029196	2.205032	6	12	99
CT head	GAL	Mgh	0.163830	2.064177	2.228007	13		93
	ISNN	Mgh	0.183346	2.085147	2.268493	22		91
	GAL	2d-cwt	0.158120	2.083779	2.241899	14		99
	ISNN	2d-cwt	0.172598	2.098529	2.271127	21		96
	GAL	Hybrid	0.161238	2.038472	2.19971	18		99
	ISNN	Hybrid	0.175836	2.029196	2.205032	20		96
MR head	GAL	Mgh	0.165803	2.025049	2.190852	24		90
	ISNN	Mgh	0.184973	2.098944	2.283917	34		90
	GAL	2d-cwt	0.151466	1.984369	2.135835	8		99
	ISNN	2d-cwt	0.170414	2.012171	2.182585	12		94
	GAL	Hybrid	0.152088	1.999095	2.151183	10		98
	ISNN	Hybrid	0.175413	2.077108	2.252521	10		96

Table-3
Comparison of GAL and ISNN at 100

Image	ANN	Features	TT(s)	ST(s)	Total time(s) (ST+TT)	NON		Performance (%)
Usbladder	GAL	Mgh	0.299269	2.504400	2.803669	5		100
	ISNN	Mgh	0.324763	2.511745	2.836508	6		100
	GAL	2d-cwt	0.298291	2.488165	2.786456	4		100
	ISNN	2d-cwt	0.329013	2.563743	2.892756	6		99
	GAL	Hybrid	0.300438	2.492378	2.792816	3		100
	ISNN	Hybrid	0.322719	2.450499	2.773218	3		99
Usphantom	GAL	Mgh	0.301321	2.183727	2.485048	**eq** 4	**uneq** 7	98
	ISNN	Mgh	0.320866	2.208548	2.529414	4	9	98
	GAL	2d-cwt	0.301311	2.167776	2.469087	5	8	99
	ISNN	2d-cwt	0.326056	2.161553	2.487609	10	8	98
	GAL	Hybrid	0.297357	2.157490	2.454847	5	8	99
	ISNN	Hybrid	0.321572	2.140950	2.462522	6	13	98
CT head	GAL	Mgh	0.315699	2.078036	2.393735	18		94
	ISNN	Mgh	0.349238	2.118836	2.468074	28		91
	GAL	2d-cwt	0.309857	2.078821	2.388678	14		98
	ISNN	2d-cwt	0.342323	2.072783	2.415106	21		92
	GAL	Hybrid	0.322229	2.114087	2.436316	18		97
	ISNN	Hybrid	0.361032	2.209156	2.570188	15		92
MR head	GAL	Mgh	0.320556	2.139310	2.459866	23		91
	ISNN	Mgh	0.345737	2.112361	2.570459	29		91
	GAL	2d-cwt	0.300305	1.986979	2.287284	9		99
	ISNN	2d-cwt	0.330680	2.024693	2.324998	14		96
	GAL	Hybrid	0.321592	2.130531	2.452123	15		99
	ISNN	Hybrid	0.350029	2.144014	2.494043	10		97

Table-4
Performance Comparison of KNN, GAL, ISNN under MGH, 2D-CWT, hybrid for four different images

Image	ANN	Features	Total time(sec)	Performance (%)
usbladder	kNN	Mgh	0.340182	100
	GAL	Mgh	2.612632	100
	ISNN	Mgh	2.649713	100
	kNN	2d-cwt	0.294831	100
	GAL	2d-cwt	2.611251	100
	ISNN	2d-cwt	2.630255	100
	kNN	Hybrid	0.287111	100
	GAL	Hybrid	2.610110	100
	ISNN	Hybrid	2.625014	100
usphantom	kNN	Mgh	0.266570	100
	GAL	Mgh	2.323496	98
	ISNN	Mgh	2.334101	96
	kNN	2d-cwt	0.251623	100
	GAL	2d-cwt	2.282750	99
	ISNN	2d-cwt	2.316799	99
	kNN	Hybrid	0.282517	100
	GAL	Hybrid	2.310946	99
	ISNN	Hybrid	2.205032	99
CT head	kNN	Mgh	0.465149	100
	GAL	Mgh	2.228007	93
	ISNN	Mgh	2.268493	91
	kNN	2d-cwt	0.401738	100
	GAL	2d-cwt	2.241899	99
	ISNN	2d-cwt	2.271127	96
	kNN	Hybrid	0.394566	100
	GAL	Hybrid	2.2.19971	99
	ISNN	Hybrid	2.205032	96
MR head	kNN	Mgh	0.421762	100
	GAL	Mgh	2.190852	90
	ISNN	Mgh	2.283917	90
	kNN	2d-cwt	0.387594	100
	GAL	2d-cwt	2.135835	99
	ISNN	2d-cwt	2.182585	96
	kNN	Hybrid	0.400457	100
	GAL	Hybrid	2.151183	99
	ISNN	Hybrid	2.252521	99

The results come by finding and comparing performance and computation time of KNN, GAL and ISNN under MGH, 2D-CWT and hybrid feature extraction method as shown in table 4, it is clearly observed that KNN has 100% performance in the segmentation of all 4 modalities and it has less computational time as compared to GAL and ISNN.

Similarly GAL performance is better than ISNN and use less computational time than ISNN. In the above comparison we clearly observe that KNN is better than GAL and ISNN. GAL is better classifier than ISNN under all feature extraction methods as discuss above. Hybrid and 2D-CWT both perform equally and better than MGH. Hybrid has slightly better performance than 2D-CWT. 2D-CWT is good in performance and use less computational time than MGH.

Performance Evaluation: In the previous session we evaluate the performance of all images on the basis of 1 image but for more accurate results and to identify the original performance we evaluate the performance on the bases of 11 image comparison. Performance is evaluated using Leave-One-out Cross-Validation technique.

For more accurate performance results, the 11 MRI images are analyzed in order to come up with solid conclusion. There are total 11 patients MR real images of size 128×128 taken by Siemens MRI system in Abrar CT and MRI centre, Peshawar road, Rawalpindi. Leave-one out cross validation procedure is defined as in it one image is kept for testing and remaining 10 images for training i.e. classifiers are trained using training data of other 10 images and 11th image is tested. In simple words in first step 1st image will be a test data and 2 to 11 images will be a training data, then in second step 2nd image will be the test data and 1,3 to 11 images will be the training data and so on. In each step compare the resultant segmented image labels with its known training point's labels and performance percentage is calculated for each image. Then for each image we would have classifier's performance.

Quantitative and Qualitative performance analysis of classifiers for 11 MR images Using LOOCV: Table 5 shows the comparison of classifiers (kNN, GAL and ISNN) using Hybrid, 2DCWT and MGH features for 11 MR images. Performance percentages are calculated for each match with the visual results as it is mentioned before.

Table 6 is constructed by averaging performance percentages. Computational time is also shown for each classifier which is equal to training time plus segmentation time. It is clearly visible that for Hybrid and 2D-CWT features kNN performs best in time compared to GAL and ISNN and also its percentages are higher than GAL and ISNN. In table 6 the overall results which numerically match with the visual results. Priority wise classifiers in taking less computational time for Hybrid and 2D-CWT features are kNN, GAL and ISNN. I give these results at 50 iterations.

Since MGH features are not robust therefore kNN performance is not good. Some images shows less performance of kNN than as compared to GAL and ISNN but overall result i.e. kNN is better than GAL and GAL is better than ISNN. Overall results i.e. kNN is better than GAL and GAL is better than ISNN. Also it shows that percentages for hybrid and 2D-CWT features are higher than those for MGH features which show the effectiveness of Hybrid and 2D-CWT features.

Table 8 shows the overall results. Hybrid and 2D-CWT Features are equal in performance. The difference lies between them in their computational time. 2D-CWT features take less time than Hybrid features because Hybrid has to wait for execution of MGH function also. According to their computational time, 2D-CWT features are executed faster than Hybrid and MGH. Priority wise features better in computational time are 2D-CWT, MGH and Hybrid. Priority wise features better in performance are Hybrid, 2D-CWT and MGH round of performance is better than GAL and ISNN. Computational time of kNN is also much healthier than both neural networks classifiers.

Quantitative and Qualitative performance analysis of feature extraction methods for 11 MR images: Features are compared by fixing classifiers. Table 7 shows the comparison of features (Hybrid, 2D-CWT and MGH) under kNN, GAL and ISNN. Performance percentages are calculated for each image using Leave One out Cross Validation technique. Fig. 8 is constructed using tables 5 and 6. Percentages in figure 8 are calculated by taking mean of 11 percentages (11 images) in each table.

Table-5
Performance comparison of classifiers using hybrid, 2D-CWT and MGH features

Performance % using Hybrid				Performance % using 2D-CWT			Performance % using MGH		
Image	**kNN**	**GAL**	**ISNN**	**kNN**	**GAL**	**ISNN**	**kNN**	**GAL**	**ISNN**
1	95	90	88	95	81	79	82	84	83
2	92	88	84	96	90	90	84	82	82
3	97	90	88	95	86	88	86	90	86
4	97	96	90	100	92	89	90	89	86
5	96	88	91	96	92	84	89	90	81
6	96	96	90	99	91	89	84	88	90
7	97	88	87	95	95	88	80	83	80
8	96	92	92	95	91	91	89	90	84
9	99	93	94	100	95	93	95	86	81
10	96	94	90	97	93	90	88	81	81
11	92	91	90	95	92	87	89	82	81
Avg	**96**	**91**	**89**	**97**	**91**	**89**	**87**	**86**	**83**

Table-6
Concluded Performance Comparison of Classifiers

Image	Feature	Classifier	Training+ Segmentation Time (seconds)	Performance (%)
MR head (128×128)	Hybrid	kNN	0.366181	96
	Hybrid	GAL	2.218106	91
	Hybrid	ISNN	2.259258	89
	2D-CWT	kNN	0.361703	97
	2D-CWT	GAL	2.171699	91
	2D-CWT	ISNN	2.166921	89
	MGH	kNN	0.373317	87
	MGH	GAL	2.249207	86
	MGH	ISNN	2.269919	83

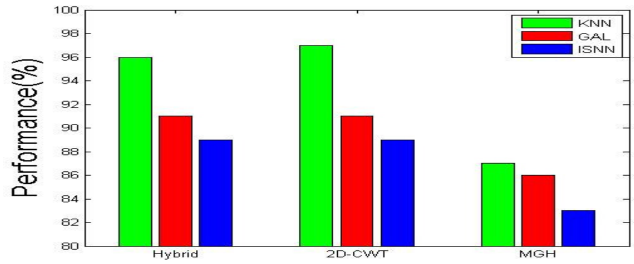


Figure-8
Comparison of classifiers

Table-7
Performance comparison of features under Knn, GAL and ISNN

Performance % under KNN				Performance % under GAL			Performance % under ISNN		
Image	Hybrid	2D-CWT	MGH	Hybrid	2D-CWT	MGH	Hybrid	2D-CWT	MGH
1	95	95	82	90	81	84	88	80	83
2	92	96	84	88	90	82	84	90	82
3	97	95	86	90	86	90	88	89	86
4	97	100	90	96	92	89	90	89	86
5	96	96	89	88	92	90	91	85	81
6	96	99	84	96	91	88	90	89	90
7	97	95	80	88	95	83	87	89	80
8	96	95	89	92	91	90	92	91	84
9	99	100	95	93	95	86	94	93	81
10	96	97	88	94	93	81	90	92	81
11	92	95	89	91	92	82	90	88	81
Avg	**96**	**97**	**87**	**91**	**91**	**86**	**89**	**89**	**83**

Table-8
Concluded performance Comparison of features under Knn, GAL and ISNN

Image	Feature	Classifier	Feature Extraction Time (seconds)	Performance (%)
MR head (128×128)	Hybrid	kNN	3.7420	96
	2D-CWT	kNN	0.741782	97
	MGH	kNN	3.000182	87
	Hybrid	GAL	3.7420	91
	2D-CWT	GAL	0.741782	91
	MGH	GAL	3.000182	86
	Hybrid	ISNN	3.7420	89
	2D-CWT	ISNN	0.741782	89
	MGH	ISNN	3.000182	83

Reason for superiority of 2D-CWT features is that it allows multi-resolution texture analysis due to which noise is reduced in segmentation. Reason for superiority of Hybrid features is that it is a combined version of both 2D-CWT and MGH important features. Figure 9 shows the overall result of feature extraction methods as MGH, 2D-CWT and Hybrid and classifiers as Knn,GAL ans ISNN performance comparison. Also figure 9 is the graphical explanation of table 8.

Conclusion

In this study medical image segmentation of four modalities as us bladder, us phantom, CT head and MR Head images are evaluated using kNN, GAL and ISNN as classifiers under MGH, 2D-CWT and hybrid feature extraction methods.

In the literature work it is claimed that ISNN is better than GAL but on the basis of this work we can conclude that GAL is better than ISNN because GAL uses less training time and segmentation time and generates less no of nodes during training than ISNN. The said observation is validated by testing GAL and ISNN at different iterations, so the preferable iterations would be 20, 50 and 100. The segmentation performance result of classifiers are evaluated on the bases of 11 MRI images and the conclusion can be drawn from the observed results that kNN is superior and outperformed both GAL and ISNN. For segmentation, GAL is better than ISNN under MGH, 2D-CWT and hybrid feature extraction methods. If there is comparison between features extraction methods, than hybrid and 2D-CWT gives much better performance than MGH.

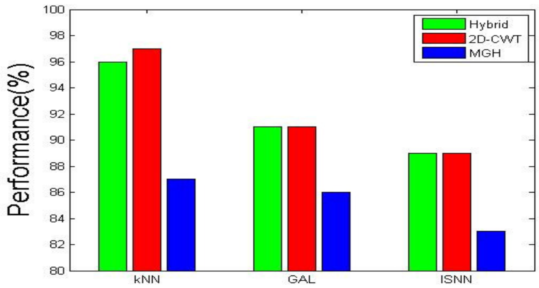


Figure-9
Comparison of features

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