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A survey on artificial intelligence approaches for medical image classification

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Abstract

In this paper, a survey has been made on the applications of intelligent computing techniques for diagnostic sciences in biomedical image classification. Several state-of-the-art Artificial Intelligence (AI) techniques for automation of biomedical image classification are investigated. This study gathers representative works that exhibit how AI is applied to the solution of very different problems related to different diagnostic science analysis. It also detects the methods of artificial intelligence that are used frequently together to solve the special problems of medicine. SVM neural network is used in almost all imaging modalities of medical image classification. Similarly fuzzy C means and improvements to it are important tool in segmentation of brain images. Various diagnostic studies like mammogram analysis, MRI brain analysis, bone and retinal analysis etc., using neural network approach result in use of back propagation network, probabilistic neural network, and extreme learning machine recurrently. Hybrid approach of GA and PSO are also commonly used for feature extraction and feature selection.

Keywords: Medical Imaging, Artificial Intelligence (AI), Neural Networks (NN), Fuzzy Logic (FL), Genetic Algorithms (GA), Particle Swarm Optimization (PSO)

Introduction

Research in Computer Aided Diagnosis (CAD) is a rapidly growing dynamic field with modern computer techniques, new imaging modalities, and new interpretation tasks. Model-based intelligent analysis and decision-support tools are important in medical imaging for computer-assisted diagnosis and evaluation. CAD helps radiologist who uses the output from a computerized analysis of medical images as a second opinion in detecting lesions, assessing extent of disease, and improving the accuracy and consistency of radiological diagnosis to reduce the rate of false negative cases. The typical architecture of a CAD system includes selection of training samples, image pre-processing, definition of region(s) of interest, features extraction and selection, classification and segmentation.

The general approach for CAD is to find the location of a lesion and also to determine an estimate of the probability of a disease. The most important process involved in automatic CAD schemes are: (1) Image classification- a stage where features are extracted and categorization of objects into classes are done. i.e. normal or abnormal. (2)Image segmentation - a stage where the pixels are grouped into regions based on image features. The result of the segmentation is a set of objects that can be analyzed and quantified individually, representing determined ROC (Receiver Operating Characteristics) characteristic of the original image.

The efficiency of the system is based on the following parameters:

Sensitivity - Sensitivity (also called recall rate in some fields) measures the proportion of actual positives which are correctly identified as such (e.g. the percentage of sick people who are correctly identified as having the condition). Specificity - Specificity measures the proportion of negatives which are correctly identified (e.g. the percentage of healthy people who are correctly identified as not having the condition). Efficacy -the results of different treatments can be more properly evaluated and validated.

Artificial intelligence

According to Stuart Russell & Peter (2002), the central scientific goal of computational intelligence is to understand the principles that make intelligent behaviour possible, in natural or artificial systems. It is a field of “the study and design of intelligent agents", where an intelligent agent is a system that perceives its environment and takes actions that maximize its chances of success. Basic approaches and techniques in medical image analysis at various phases are highlighted in Fig. 1.

Artificial neural networks approach on diagnostic science

Artificial Neural Networks (ANN) are nonlinear information processing devices, built from interconnected elementary processing devices called neurons inspired by the way biological nervous systems. The development of the ANN started in 1943 by McCulloch and Pitts and is still growing extravagantly. The advantages of ANN include adaptive learning, self organization, parallelism, fault tolerance etc., Applications involve in knowledge extraction, pattern recognition, forecasting, clinical diagnosis, security systems and still wider. In this paper, survey is made on applications of Neural Networks to diagnostic science. The following subsections discuss on how ANN is utilized for image classification over generations.

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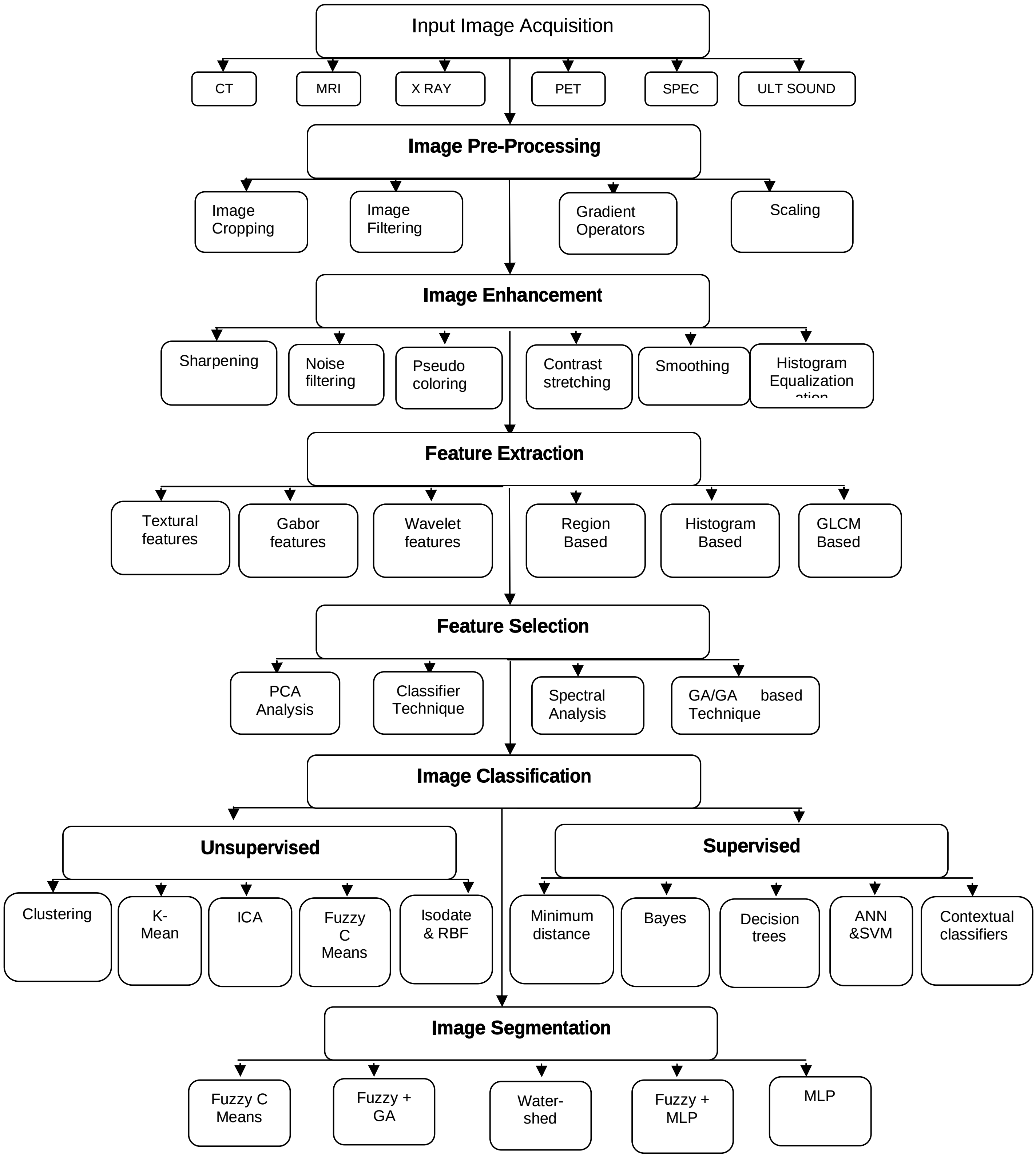
Fig. 1. Various approaches in Biomedical Image Processing



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Endoscopic images

Image classification is an important step in CAD approach. Recent research deals with artificial intelligence techniques than the conventional classifiers, which has very high classification accuracy, adaptive nature etc. Reports of the use of artificial intelligence network methods in endoscopic images classification based on texture features using SOM and BP was proposed with reasonable stability and classification accuracy from the texture method and interpreted on its own. More prominent texture properties such as ulcer or Melanosis coli should be considered for better classification accuracy instead of only blood vessels (Wang *et al.,* 2001). In classification of endoscopic images a hybrid implementation by advanced fuzzy inference neural network which combines fuzzy systems and Radial Basis Function (RBF) was proposed. The concept of fusion of multiple classifiers dedicated to specific feature parameters with an accuracy of 94.28%, but RBF was characterized by a very fast training rate than fuzzy. It extracted both texture and statistical features (Vassilis & John, 2008).

Bone analysis

In the analysis of bone structure in osteoporosis by (Agus *et al.,* 2005), a structure used Fourier transform to generate a “spectral fingerprint” of an image. Principal components analysis is then applied to identify key features from the Fourier transform and back propagation network is used for classification. Testing on a series of 100 histological sections of trabecular bone from patients with OP and OA and a normal group correctly classified over 90% of the OP group with an overall accuracy of 77%-84%. A CAD system was developed based on mathematical morphology for identifying post-menopausal women with low skeletal BMD or osteoporosis that automatically determines cortical erosion of the mandible on dental panoramic radiographs and to assess the validation of this CAD system The sensitivity and specificity for identifying women with osteoporosis were 94.4% and CAD applied to dental panoramic radiographs are likely to be useful only for identifying post-menopausal women with low skeletal BMD or osteoporosis (Agus *et al.,* 2007).Using a novel fuzzy thresholding, the fuzzy inference system incorporated with multi-layer perceptron(MLP) neural network. It identified post menopausal women with osteoporosis with mean sensitivity and specificity with 94.5 % accuracy (Nakamoto *et al.,* 2008). Advancement lead to Intelligent Medical Diagnostic System (IMDS) accessible through common web-based interface, to on-line perform initial screening for osteoporosis, using four layered fuzzy neural network. The model classifier generates 58 misclassifications (71% correct) on 200 training cases, and 15 misclassifications (66.7% correct) on 45 testing cases. This leads to a recognition rate of 70.2% (73 misclassifications) on the total data set, while the author claims for better interpretability in the proposed method (Chin *et al.,* 2008).

Breast cancer

In recent work of examinations, there are considerable interest in the use of computational techniques to aid in the detection and diagnosis of breast cancer focus on mammography. It is the primary tool for the detection of breast lesions and the subsequent decision to biopsy suspicious lesions. By far, back propagation neural network is most widely used in beast cancer diagnosis with improvement corresponded to increases in sensitivity from 73.5% to 87.4 % (Jiang *et al.,* 1999). Similarly the auto associative BP network was used to determine the constraints on constraint satisfaction neural network (CSNN) was modelled for breast cancer predictive and analysis tool. The predictive performance with ROC index 0 .84+-.02 was far better than BPN (Georgia *et al.,* 2001). A method to segment mammogram image using a self-organizing neural network based on spatial isomorphism was proposed. A modified algorithm is that it avoids the traditional problems of the Active Contour Models with distant border contour and objects with large concavity (Aida *et al.,* 2007).Early breast cancers are often characterized by masses and micro calcifications. Detection of masses by using growing neural gas algorithm for image segmentation along with Ripley’s K function and classification based on SVM was proposed with 89.3% accuracy (Leonardo *et al.,* 2009). A supervised diagnosis system for digital mammogram is developed, by transforming the data of the images into a feature vector using wavelets multilevel decomposition with MLP achieves good results in classification(Essam, 2006).Similarly breast cancer detection using multi wavelets and ANN was proposed (Sepehr *et al.,* 2005). Analysis using ranklet image representation, using polynomial SVM Kernel classification proposed high results for all types of radiographic images and handled very high dimensional feature spaces. Though it achieved accuracy of 90%, feature reduction was not much concentrated (Matteo, 2006).The neural network was trained on the wavelet based feature vectors extracted from the mammogram masses for both benign and malign data. Therefore, in this study, Multilayer ANN was trained with the Back propagation, Conjugate Gradient and Levenberg-Marquardt algorithms and ten-fold cross validation procedure was used. A satisfying sensitivity percentage of 89.2% was achieved with Levenberg - Marquardt algorithm (Niyazi *et al.,* 2010).

A novel approach was proposed to combine a neural network based auto-associator and a classifier for the classification of micro calcification patterns in breast cancer patterns. The results proved highly satisfactory which obtained 85 % classification accuracy with 14 image features (Rinku & Brijesh, 2004). An evolved hierarchical RBF network was employed to detect the breast cancer. For evolving a hierarchical RBF network

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model, Extended Compact Genetic Programming (ECGP), a tree-structure based evolutionary algorithm and the Differential Evolution (DE) are used to find an optimal detection model. The classification accuracy in benign cancer type was 96.83% and malignant was 96.83% (Yuehui *et al.,* 2006). The proposed system by (Ireaneus, 2009) to detect tumours as suspicious regions incorporates filtering, top hat operation, DWT as enhancement procedure. The segmentation method used is thresholding. Using the SVM classifier, tested on 75 mammographic images, the method achieved a sensitivity of 88.75%. The main aim of the method by (Mohammed, 2010) is to increase the effectiveness and efficiency of the classification process in an objective manner to reduce the numbers of false-positive of malignancies in mammograms. Three layer artificial neural network (ANN) MLP with seven features was proposed for classifying the marked regions into benign and malignant. It achieved 90.91% sensitivity and 83.87% specificity that is very much promising compared to the radiologist's sensitivity of 75%. A new approach for detecting Micro calcification in digital mammograms employing the combination of Non sub-sampled Contourlet transform (NSCT) and artificial neural networks (ANN) for building the classifiers was proposed by(Leena *et al.,* 2010),with 88% classification accuracy.

Skin lesion analysis

New intelligent method of classifying benign and malignant melanoma lesions implemented using wavelet approach for feature extraction and classification with BPN proved accuracy of 95% and SVM of 85% accuracy (Andy *et al.,* 2007). Similarly, both the discriminating power of the digital dermoscopy analyzer with single layer perceptron artificial neural network was compared with histologic diagnosis. A feature selection procedure indicated that as few as 13 of the variables were sufficient to discriminate the 2 groups of lesions, and this also ensured high generalization power. The artificial neural network designed with these variables enabled a diagnostic accuracy of about 94 % (Pietro *et al.,* 2002). A local thresholding algorithm proposed for skin lesion separation, border, texture and color based features, are then extracted from the digital images. Extracted features are used to construct a classification module based on Support Vector Machines (SVM) for the recognition of malignant melanoma versus dysplastic nevus with exponential radial basis function. The method provided 91.84% accuracy with sigma value 7 (Ilias *et at.,* 2006). This paper (Karol *et al.,* 2010) describes a decision-support system which is based on semantic analysis of melanoma images and further classification of characteristic objects commonly found in pigmented skin lesions. For classification support vector machines were used. Better success rate had been obtained for linear SVM - 97.44% for 70/30 train to test ratio.

MRI brain tumour analysis

A general regression neural network (GRNN) based automatic three-dimensional classification method for the MRI brain tumour images was proposed which proved good time consuming rate and classification accuracy (Jiawan & Jizhou, 2004). RBF kernel based SVM for brain tumour detection was used by (Sathish *et al.,* 2009). The results obtained are compared with another powerful efficient classifier AdaBoost. The comparative results showed that though the difference between the performance measures is marginal, SVM gives higher precision and low error rates. Various levels of MR glioma images were performed using classification of support vector machine in (Guo-Zheng *et al.,* 2006). This method claimed to be better than fuzzy rule based systems but the accuracy reported in the paper is low. The disadvantage is that it deals only with glioma images. A Least squares support vector machines (LS-SVMs) with radial basis function kernel for brain tumour recognition proposed by (Jan *et al.,* 2007) was compared with linear discriminant analysis (LDA). Pair wise class probability combination schemes for multiclass classification was illustrated. Four different methods that combine pair wise class probabilities into global class probabilities are compared. But no global performance of the classifier was achieved.

Another intelligent classification technique to identify normal and abnormal slices of brain MRI data based on Least Squares Support Vector Machines (LS-SVM) was proposed (Selvaraj *et al.,* 2007). LS-SVM had a higher accuracy of classification over other classifiers. The number of false negative in LS-SVM was very low compared to SVM and a high degree of sensitivity of the classifier to abnormal images. Due to automatic defects detection in MR images of brain, extensive research is being performed. A Novel automatic brain tumour detection method using Gabor wavelets was proposed (Amir *et al.,* 2010). The neural network had been trained using back propagation algorithm and training process was continued until the Mean Square Error (MSE) became constant with about accuracy of 98.15%. This work has some limitations because of using all 3 modalities T1, T2_weighted and PD MR Images. The designed brain cancer detection and classification system by Dipali *et al*., (2007) use conceptually simple classification method using the Neuro Fuzzy logic. Texture features are used in the Training of the Artificial Neural Network. Co- occurrence matrices at different directions are calculated and Grey Level Co-occurrence Matrix (GLCM) features are extracted from the matrices. This system provides precision detection and classification of astrocytoma type of cancer.

Lung images

For increasing the classification accuracy of chest images between normal and lesion images, medical image classification method adapting small samples was proposed (Shao *et al.,* 2010). In order to get the decision-making function, SVM classifier was applied to study on training set of chest DR images with classification accuracy of 93%. A CT liver image diagnostic classification system is presented which will automatically find, extract the CT liver boundary and further classify liver diseases .It implements a modified probabilistic neural network (PNN) in conjunction with feature descriptors which are generated by fractal feature information and the gray-level co-occurrence matrix. The proposed system was evaluated by 30 liver cases and shown to be efficient and very effective (Liang, 1998). A classifier based on the support vector machine for automatic classification in liver disease was formulated discriminating between cysts, hepatoma, cavernous hemangioma, and normal tissue as a supervised learning problem. SVM was applied to classify the diseases using gray level and co-occurrence matrix features and region-based shape descriptors, calculated from regions of interest (ROIs), as input (Chien, 2007).

A Computer Aided Diagnosis (CAD) system for the characterization of hepatic tissue from Computed Tomography (CT) images presented by (Mougiakakou *et al.,* 2003), includes five distinct sets of texture features extracted using the following methods: first order statistics, spatial gray level dependence matrix, gray level difference method, Laws' texture energy measures, and fractal dimension measurements. If the dimensionality of a feature set is greater than a predefined threshold, feature selection based on a Genetic Algorithm (GA) is applied. Classification of the ROI was then carried out by a system of five neural networks. The members of the NN system (primary classifiers) are 4-class NNs trained by the back propagation algorithm with adaptive learning rate and momentum. The same author proposed an improved optimization of a neural network classifier by means of GA gives better classification rate, but lower dimension feature vectors (Gletsos *et al.,* 2003). A novel feature extraction scheme is proposed (Kumar & Moni, 2010), based on multi-resolution fast discrete curvelet transform for computer-aided diagnosis of liver diseases. The liver is segmented from CT images using adaptive threshold detection and morphological processing. The suspected tumour region was extracted from the segmented liver using FCM clustering. The textural information obtained from the extracted tumour using Fast Discrete Curvelet Transform (FDCT) is used to train and classify the liver tumour into hemangioma and hepatoma employing artificial neural network classifier. A (CAD) system proposed (Gomathi & Thangaraj, 2010) for detection of lung cancer with Fuzzy Possibilistic C Mean (FPCM) algorithm was used for segmentation because of its accuracy. After segmentation, rule based technique was applied to classify the cancer nodules. Finally, a set of diagnosis rules are generated from the extracted features. From these rules, the occurrences of cancer nodules are identified clearly. The learning is performed with the help of Extreme Learning Machine (ELM) because of its better classification.

Other diagnostic science

In work related to content based image retrieval (CBIR), automatic x-ray image classification was proposed with multilevel feature extraction (global, local and pixel features) used SVM classifier. The result of accuracy with SVM was 89% when compared with K-Nearest neighbour with 82% (Mueen *et al.,* 2007). Other research work in diagnostics is a computer-assisted diagnosis tool based in a principal component analysis (PCA) dimensional reduction of the feature space approach and a support vector machine classification method for improving the Alzheimer's diagnosis accuracy by means of SPECT images (lvarez *et al.,* 2009).The classification and diagnosis of brain haemorrhages has worked out into a great importance in early detection of haemorrhages which reduce the death rates. Ramana and Raghu (2010) proposed a perception based feed forward neural network for early detection of haemorrhages. The CAD system introduces a Region Severance Algorithm (RSA) for detection and location of haemorrhages and an algorithm for finding threshold band.

Gene expression analysis

Gene expression profiles are becoming a powerful tool for clinical diagnosis, as they have the potential to discover gene expression patterns that are characteristic for a particular disease. A new method of gene selection utilizing Support Vector Machine methods based on Recursive Feature Elimination (RFE) by Isabelle *et al.* (2002) demonstrates experimentally that the genes selected by the techniques yield better classification performance and are biologically relevant to cancer. In patients with leukemia, the method discovered 2 genes that yield zero leave-one-out error, while 64 genes are necessary for the baseline method to get the best result (one leave-one-out error). In the colon cancer database, using only 4 genes, method is 98% accurate, while the baseline method is only 86% accurate. An ensemble network method combined with different feature selections to classify the cancer gene expression data is proposed (Xiaogang *et al.,* 2008). The result is superior to the unitary neural network and one feature selection method validated by most popularly used datasets .Higher recognition rate of samples was obtained. The advantage of using ensemble neural network is to reduce the variance and avoid the error surface of neural network training being trapped into local minima. Gene expression profiling by microarray technique has been effectively utilized for classification and diagnostic guessing of cancer nodules. The paper by (Revathy & Amalraj, 2011) proposes a technique called Enrichment Score for ranking purpose. The classifier used in the proposed technique was Support Vector Machine (SVM).

Implementation on lymphoma data set showed better accuracy of classification when compared to the conventional method.

Retinal and eye analysis

A computer aided diagnosis system was proposed to develop an automated system to analyze the retinal images for important features of diabetic retinopathy using image processing techniques and an image classifier based on artificial neural network which classify the images according to the disease conditions. The consistent identifying and quantifying of changes in blood vessels and different findings such as exudates in the retina over time can be used for the early detection of diabetic retinopathy. Vascular network, optic disc and lesions like exudates are identified. A neural network classifier is developed and a comparative study on the performance is also presented in (David *et al.,* 2005).

An automated system based on artificial neural network was proposed for eye disease classification (Anitha *et al.,* 2009). Abnormal retinal images from four different classes' namely non-proliferative diabetic retinopathy (NPDR), Central retinal vein occlusion (CRVO), Choroidal neovascularisation membrane (CNVM) and central serous retinopathy (CSR) are used in this work. A suitable feature set is extracted from the pre-processed images and fed to the classifier; Classification of the four eye diseases is performed using the supervised neural network namely back propagation neural network (BPN). Experimental results show promising results for the back propagation neural network as a disease classifier. A modified Counter Propagation Neural Network was proposed to eliminate the iterative training methodology which accounts for the high convergence time. To prove the efficiency, this technique was employed on abnormal retinal image classification system (Anitha *et al.,* 2010). Real time images from four abnormal classes are used in this work. An extensive feature vector is framed from these images which forms the input for the CPN and the modified CPN. The experimental results of both the networks are analyzed in terms of classification accuracy and convergence time period. The results suggest the superior nature of the proposed technique in terms of convergence time period and classification accuracy. A fast algorithm was proposed (Rahib & Koray, 2008) for the localization of the inner and outer boundaries of the iris region. Located iris is extracted from an eye image, and, after normalization and enhancement, it is represented by a data set. Using this data set a Neural Network (NN) is used for the classification of iris patterns. The recognition rate of NN system was 99.25%.

Fuzzy logic approach in diagnostic science

Fuzzy Logic (FL) was initiated in 1965 by Prof.Lotfi A. Zadeh. It is an organized method for dealing with imprecise data; Its multivalued logic allows intermediate values to be defined between conventional evaluations like true/false, yes/no, high/low, etc. Fuzzy Logic has emerged its applications in the controlling and steering of systems, complex industrial processes, as well as for household and entertainment electronics, segmentation of MRI Images etc. Fuzzy approach requires a sufficient expert knowledge for the formulation of the rule base, the combination of the sets and the defuzzification. In following sections the various fuzzy approaches in diagnostic applications is being surveyed.

Mammogram analysis

A research on mammography images using morphological operators and Fuzzy c means clustering for cancer tumour mass segmentation was proposed by Saheb and Prasad (2009). Using Morphological operators masses and micro calcifications from background tissue are segmented and finally fuzzy C means clustering method (FCM) was implemented for intensity - based segmentation. A hybrid segmentation method developed by Riyahi *et al.* (2010) for detection of masses in digitized mammograms uses three parallel approaches: adaptive thresholding method, Gabor filtering and fuzzy entropy feature as a computer-aided detection (CAD) scheme. The algorithm achieves a sensitivity of 90.73% and specificity of 89.17%. This approach showed that good behaviour of local adaptive thresholding. A new method FCM based parallel neural networks proposed by Sang *et al.* (2007) employs FCM for classifying breast cancer data. The other is designing the multiple neural networks using classified data by FCM. Correct diagnosis rate of over 99% is obtained and it was found useful for classification problems of high complexity and nonlinear system with huge data. The model proves impractical for real time implementations because of low storage. A similar method proposed an adaptive neuro fuzzy system for ROI classification in mammograms as malign or benign, dealing specifically with calcifications (Fernandes *et al.,* 2010). The neuro fuzzy ANFIS model utilized in the mammogram ROI's classification phase, reached a maximum accuracy rate of 99.75%.

A fuzzy technique in conjunction with three features was used by Brijesh and John (2001) to detect a micro calcification pattern and a neural network to classify it into benign/malignant. The three features- entropy, standard deviation, and number of pixels, is the best combination to distinguish a benign micro calcification pattern from one that is malignant. It uses mammographic database, a simple fuzzy detection feature extraction, selection of most significant features, and classification of features into benign or malignant using a back propagation network. A high classification rate of 88.9% was achieved. In this paper (Gerald *et al.,* 2007) breast cancer detection based on thermography, using a series of statistical features extracted from the thermograms coupled with a fuzzy rule-based classification system for diagnosis was proposed. The features stem from a comparison of left and right breast areas and quantify the bilateral differences encountered. Following this asymmetry analysis the features are fed to a fuzzy classification system. This classifier was used to extract fuzzy if-then rules based on a training set of known cases. Experimental results on a set of nearly 150 cases show the proposed system to work well accurately classifying about 80%.

A modified fuzzy c-means radial basis functions network was proposed (Essam, 2010). The model diagnoses cancer diseases by using fuzzy rules with relatively small number of linguistic labels reduce the similarity of the membership functions and preserve the meaning of the linguistic labels. The modified model is implemented and compared with adaptive neuro-fuzzy inference system (ANFIS). The Three rules are needed to obtain the classification rate 97% by using the modified model (3 out of 114 classified wrongly). On the contrary, more rules are needed to get the same accuracy by using ANFIS.

MRI brain analysis

Feature difference between neighboring pixels λ and relative location of the neighboring pixel ζ are the two influential factors in segmentation where address issues of neighborhood attraction occurs. A new computational method (Nosratallah *et al.,* 2007) based on PSO was introduced to compute optimum values of these two parameters. An improved FCM model was introduced to solve sensitivity of FCM to noise. Simulation results demonstrated effectiveness of new model to find optimal values of λ and ζ. Due to slowly varying shading artefact over the image that can produce errors with conventional intensity- based classification. The algorithm formulated by Ahamed (*et al.,* 2002) modified the objective function of the standard fuzzy c-means (FCM) algorithm to compensate such non-homogeneities and to allow the labelling of a pixel (voxel) to be influenced by the labels in its immediate neighbourhood. The neighbourhood effect acts as a regularizer and biases the solution toward piecewise-homogeneous labelling. The FCM, however, has the advantage of working for vectors of intensities while the BCFCM is limited to single-feature inputs. The BCFCM algorithm produced similar results as the EM algorithm with faster convergence. In noisy images, the BCFCM technique produced better results than the EM algorithm as it compensates for noise by including a regularization term.

Kang *et al.* (2011) proposed an intelligent generalized tissue classification system which combines both the Fuzzy C-means algorithm and the qualitative medical knowledge on geometric properties of different tissues. The FCM algorithm with 5 classes results in bad segmentation. So it is applied to 3 classes because only three grey levels can be observed (p = 3). Two principles are proposed to define the priorities for these rules in order to optimize their application. One issue to be considered is the geometric features used in the system may be sensitive to geometric transformations like rotation or flipping. Similarly, new two-dimensional FCM clustering algorithm for image segmentation was proposed by Zhou *et al.* (2008). By making use of the global searching ability of the predator-prey particle swarm optimization, the optimal cluster center could be obtained by iterative optimization, and the image segmentation could be accomplished. The simulation results showed the segmentation accuracy ratio of the proposed method as above 98%. The proposed algorithm has strong anti-noise capability, high clustering accuracy and good segment effect, indicating that it is an effective algorithm for image segmentation. A new fuzzy multi wavelet packet transformation based brain MR image classification method was investigated by Ramakrishnan *et al.* (2010). A fuzzy-set based theory for selection of the sub bands and the classification is carried out using WPNN proposed in (Ramakrishnan & Selvan, 2006). Experiments show that the fuzzy-based criterion achieves higher recognition rate with relatively smaller sub bands than signal energy-based criterions. Experimental results also show that the proposed approach achieves higher recognition under noisy environment with lesser number of sub bands compared to the existing approaches.

Membership function expression of FCM is introduced. As uncertainties in the data and missing values existed, a fuzzy rule extraction algorithm based on a fuzzy min-max neural network (FMMNN) was used (Ye *et al.,* 2002). The performance of a multi-layer perception network (MLP) trained with the error back-propagation algorithm (BP), the decision tree algorithm ID3, nearest neighbour and the original fuzzy min-max neural network were also evaluated. The results showed that two fuzzy decision rules on only six features achieved an accuracy of 84.6% (89.9% for low-grade and 76.6% for high-grade cases). Investigations with the proposed algorithm revealed that age, mass effect, oedema, post contrast enhancement, blood supply, calcification, haemorrhage and the signal intensity of the Tl-weighted image were important diagnostic factors.

Lung cancer

Fatma and Rachid (2010) presented a modified Hopfield Neural Network (HNN). A FCM Clustering Algorithm, was used in segmenting sputum colour images. The segmentation results will be used as a base for a Computer Aided Diagnosis (CAD) system for early detection of lung cancer. Both methods are designed to classify the image of N pixels among M classes or regions. Due to intensity variations in the background of the raw images, a pre-segmentation process is developed to standardize the segmentation process. In this study, 1000 sputum colour images to test both methods, and HNN has shown a better classification result than FCM; however the latter was faster in converging.

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Genetic algorithm in diagnostic science

Evolutionary programming was developed with the concepts of evolution, selection and mutation. John Holland introduced the concept of Genetic Algorithm (GA) as a principle of Charles Darwinian theory of evolution to natural biology. GA learning methods are based on computational models of natural adaptation and evolution. These learning systems improve their performance through procedures which model population genetics and survival of the fittest. GA had widespread applications in solving problems requiring effective and efficient search, in business, scientific and engineering circles like synthesis of neural networks architectures, travelling salesman problem, scheduling, numerical optimization and pattern recognition and image processing. Analysis of GA approach with other AI techniques is reported in survey in subdivisions for diagnostic science.

Mammogram analysis

Mammogram image are classified into normal image, benign image and malignant image. A hybrid approach of feature selection proposed by Vasantha *et al.* (2010) reduces 75% of the features. Totally 26 features including histogram intensity features and GLCM features are extracted from mammogram image. A combined approach of Greedy stepwise method and Genetic Algorithm is proposed to select the optimal features. The selected optimal features are considered for classification decision tree algorithms are applied to mammography classification by using these reduced features .This method proves easier and less computing time than existing methods. This approach effectively addresses the feature redundancy problem.

A novel representation of Cartesian genetic programming (CGP) in which multiple networks is used in the classification of high resolution in mammograms seems to be very effective. The main limitation of the data available is the low number of usable images from a fairly old database (Katharina *et al.,* 2009). The novelty of this work (Nandi *et al.,* 2006) is the adaptation and application of the classification technique called genetic programming (GP), which possesses feature selection implicitly. To refine the pool of features available to the GP classifier, feature-selection methods, including the introduction of three statistical measures–Student's t test, Kolmogorov-Smirnov test, and Kullback-Leibler divergence is used. Both the training and test accuracies obtained were high: above 99.5% for training and typically above 98%. Rolando and Hugo (2010) reported a procedure for classification of micro calcification clusters in mammograms using sequential difference of Gaussian filters (DoG) and three evolutionary artificial neural networks (EANNs) compared against a feed forward artificial neural network (ANN) trained with back propagation .Genetic algorithms (GAs) was used for finding the optimal weight set for an ANN, Improvements in overall accuracy, sensitivity and specificity of an ANN, compared with other networks trained with simple back propagation is achieved. Arpita and Mahua (2009) proposed a computer assisted treatment planning system implementing Genetic algorithm based Neuro-fuzzy approach. The boundary based features of the tumour lesions appearing in breast have been extracted for classification. The shape features represented by Fourier Descriptors, introduce a large number of feature vectors with classification rate at 87%.

MRI brain analysis

A hybrid approach was made by Ahmed *et al.* (2010) for classification of brain tissues in magnetic resonance images (MRI) based on genetic algorithm (GA) and support vector machine (SVM). A wavelet based texture feature set is derived. The optimal texture features are extracted from normal and tumor regions by using spatial gray level dependence method (SGLDM). These features are given as input to the SVM classifier. The choice of features, which constitute a big problem in classification techniques, is solved by using GA. RBF Kernel was used with classification accuracy from 96.39 to 98.79 % in the mean standard deviation format (Mean±SD) of 97.59±1.2 %.

An enhanced method using GA for feature selection was employed by Hong and Cho(2006). This technique repeats the GA algorithm for several iterations till the specified classification accuracy is reached. This makes the system user dependent and it also depend on the target classification accuracy. An optimization technique based on hierarchical genetic algorithm with a fuzzy learning-vector quantization network (HGALVQ), to segment multi-spectral human-brain was proposed by Jinn (2008) using MRI. Evaluation of this approach is based on a real case with human-brain MRI of an individual suffering from meningioma. The HGALVQ was verified by the comparison with other popular clustering algorithms such as k-means, FCM, FALVQ, LVQ, and simulated annealing. Experimental results show that HGALVQ not only returns an appropriate number of clusters and also outperforms other methods in specificity. An automatic segmentation technique of multispectral magnetic resonance image of the brain using new fuzzy point symmetry based genetic clustering technique was proposed (Saha & Bandyopadhyay, 2007). The proposed real-coded variable string length genetic fuzzy clustering technique (fuzzy-VGAPS) is able to evolve the number of clusters present in the data set automatically. The algorithm is fixed number of generations. Moreover, the elitist model of Gas has been used. Present Fuzzy-VGAPS clustering algorithm will not work well for the data sets having clusters whose centres collide at a same point. The algorithm should improve for spatial information.

The applicability of Genetic Algorithm (GA) for multiclass problem of binary representations was explored (Kishore *et al.,* 2009). The samples belonging to the same class are accepted by this GA approach and the other samples are rejected based on the strength of association measure. A comparative analysis is also performed with the maximum likelihood classifier. A discriminate function is evolved through training examples for each class, and only samples belonging to the same class are credited by strengths of association degrees. In their work, a separate expression-tree is evolved per class, assessing whether unseen test instances belong to the class being tested

Diagnostics in heart

An automated medical diagnosis based on coactive neuro-fuzzy inference system (CANFIS) was presented for prediction of heart disease (Latha & Subramanian, 2007). The proposed CANFIS model combined the neural network adaptive capabilities and the fuzzy logic qualitative approach which is then integrated with genetic algorithm to diagnose the presence of the disease. In order to improve the learning of the CANFIS, quicker training and enhance its performance, use of genetic algorithms to search for the best number of membership function for each input, and optimization of control parameters such as learning rate, and momentum coefficient. The mean square error was only 0.000842. Khazaee & Ebrahimzadeh (2010) proposed a new power spectral-based hybrid genetic algorithm-support vector machines (SVMGA) technique to classify five types of electrocardiogram (ECG) beats, namely normal beats and four manifestations of heart arrhythmia. The GA is called a population-based technique because instead of operating on a single potential solution. The free parameters greatly affect the classification accuracy of SVM model. Therefore, GA is used to search for better combinations of the parameters in SVM. First the best optimal parameters obtained by SVMGA method were used to classify ECG beats in five classes, and then the classification was performed again only with spectral coefficients. The best accuracy that obtained for the test set by SVMGA is 96.00%

PSO approach in diagnostic science

Particle swarm optimization (PSO) is a population based stochastic optimization technique developed by Eberhart and Kennedy in 1995, inspired by social behaviour of bird flocking In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles. PSO can be easily implemented and is computationally inexpensive since its memory and CPU speed requirements are low. PSO has been successfully applied in many areas: function optimization, artificial neural network training, fuzzy system control, and other areas where GA can be applied (Geetha & Thanushkodi, 2008). PSO approaches for image analysis classifications are discussed in the literature in further divisions.

Mammogram analysis

Dheeba and Tamil Selvi (2010) presented a new classification approach for detection of micro calcification in digital mammogram using particle swarm optimization (PSO) algorithm based on clustering technique. FCM clustering technique, well defined for clustering data sets are used in combination with the PSO. The PSO was used to search the cluster centre in the arbitrary data set automatically. PSO can search the best solution from the probability option of the Social-only model and Cognition-only model. This simple and valid method, avoids the minimum local value. The investigation by Geetah *et al.* (2010) resulted in enhancing the mammogram images using median filter and normalize it. The GA is applied to enhance the detected border and the nipple position is found using PSO. True positive and false positive are used to measure algorithms' performance. The images in Corel image database are used to testify the classification performance of the proposed method (YuZhang *et al.,* 2001). The testing results show that the classification accuracy of PSO-SVM.

MRI brain analysis

The proposed PSO technique (Shafaf & Elaiza, 2010) found to produce potential solutions to the current difficulties in detecting abnormalities in human brain tissue area. The proposed PSO consist of four main steps that is the initial generation swarm of particles, the fitness function, the position and velocity update and finally the termination criterion. The PSO are found to be promising for segmentation of light abnormalities. Nevertheless, the PSO produced poor performance in dark abnormalities segmentation as it produces low correlation values in all conditions. Madhubanti and Amitava (2008) proposed a novel optimal multilevel thresholding algorithm for brain magnetic resonance image segmentation. This optimization algorithm, employed for image histogram-based thresholding, based on a relatively recently proposed evolutionary approach, namely, bacterial foraging (BACTFOR). The results obtained for the benchmark images were quite encouraging as BACTFOR could comprehensively outperform PSO inertia weight. Due to the requirement for a neural classifier which is computationally efficient and highly accurate, a modified Counter Propagation Neural Network (CPN) was proposed for brain classification (Jude *et al.,* 2010). For further enhancement of the performance of the classifier, PSO technique is used in conjunction with the modified CPN. There is no significant change in the accuracy with conventional CPN and proposed CPN, but the advantage of the modified CPN is the superior convergence rate since the network is free from iterations.

A new version of PSO, called Geometric PSO, is empirically evaluated for the first time in this work (Alba *et al.,* 2007) using a binary representation in Hamming space. This method compares the use of PSO and GA (both augmented with support vector machines SVM) for the classification of high dimensional microarray data. Both algorithms are used for finding small samples of informative genes amongst thousands of them. A SVM classifier with 10- fold cross-validation is applied in order to validate and evaluate the provided solutions. A first contribution is to prove that PSOsvm is able to find interesting genes and to provide classification competitive performance. ICGA is used with PSO-ELM (Saras *et al.,* 2011) to select an optimal set of genes, which is then used to build a classifier to develop an algorithm (ICGA-PSO-ELM) that can handle sparse data and sample imbalance. Performance of the proposed method is compared with conventional.

Conclusions

In this paper, a survey has been made on the applications of intelligent computing techniques for diagnostic sciences in biomedical image classification. The various features using the computing techniques have been brought out in this paper with their advantages and limitations. The future work is to develop certain new algorithms based on these computing techniques for diagnostic science applications and hence provide a better framework for development of emerging medical systems, enabling the better delivery of healthcare.

References

1. Agus Zainal Arifin, Akira Asano, Akira Taguchi, Takashi Nakamoto, Masahiko Ohtsuka and dan Keiji Tanimoto (2005) Computer-aided system for measuring the mandibular cortical width on panoramic radiographs in osteoporosis diagnosis. *Proc. SPIE Medical Imaging 2005 - Image Processing Conf. San Diego, California*. pp:813-819.
2. Agus Zainal Arifin, Asano A, Taguchi A, Nakamoto T, Ohtsuka M, Tsuda M, Kudo Y and Tanimoto K (2007) Developing computer-aided osteoporosis diagnosis system using fuzzy neural network. *J. Advanced Comput. Intelligence & Intelligent Informatics*, 11(8), 1049-1058.
3. Aida A Ferreira, Francisco Nascimento Jr, Ing Ren Tsang, George DC Cavalcanti, Teresa B Ludermir and Ronaldo RB de Aquino (2007) Analysis of mammogram using self-organizing neural networks based on spatial isomorphism. *Proc. IEEE Intl. Joint Conf. Neural Networks, Florida, USA*. pp:1796-1801.
4. Andy Chiem, Adel Al-Jumaily and Rami N Khushaba (2007) A novel hybrid system for skin lesion detection. *Intl. Conf. Intelligent Sensors, Sensor Networks & Information Processing*. pp: 567-572.
5. AmirEhsan Lashkari (2010) A neural network based method for brain abnormality detection in MR images using gabor wavelets*. Intl. J. Comput. Appl.* 4(7), 9-15.
6. Anitha J, Selvathi D and Hemanth DJ (2009) Neural computing based abnormality detection in retinal optical images. *IEEE Advance Comput. Conf.* pp: 630-635.
7. Anitha J, Kezi Selva Vijila C and Jude Hemanth D (2009) An enhanced counter propagation neural network for abnormal retinal image classification. *J. Nature & Biologically Inspired Comput.* pp: 1-6.
8. Arpita Das and Mahua Bhattacharya (2008) GA based neuro fuzzy techniques for breast cancer identification. *Intl. Machine Vision & Image Processing Conf.* pp:136-141.
9. Ahmed Kharrat, Karim Gasmi, Mohamed Ben Messaoud, Nacéra Benamrane and Mohamed Abid (2010) A hybrid approach for automatic classification of brain MRI using genetic algorithm and support vector machine. *Leonardo J. Sci.* 17, 71-82.
10. Alba E, Garcia-Nieto J, Jourdan L and Talbi EG (2007) Gene selection in cancer classification using PSO/SVM and GA/SVM hybrid algorithms. *IEEE Congress on Evolutionary Comput.* pp: 284-290.
11. Ahmed MN, Yamany SM, Mohamed N, Aly A Farag and T Moriarty (2002) Modified fuzzy C-means algorithm for bias field estimation and segmentation of MRI Data. *IEEE Transact. on Medical Imaging*. 21(3),193-199.
12. Brijesh Verma and John Zakos (2001) Computer-Aided diagnosis system for digital mammograms based on fuzzy-neural and feature extraction techniques*. IEEE Transactions on Information Technol. in Biomedicine*, 5(1), 46-54.
13. Chin-Ming Hong, Chin-Teng Lin, Chao-Yen Huang and Yi-Ming Lin (2008) An intelligent fuzzy-neural diagnostic system for osteoporosis risk assessment. *J. World Acad. Sci. Engg & Technol.* 42, 597-602.
14. Chien-Cheng Lee, Sz-Han Chen and Yu-Chun Chiang (2007) Classification of liver disease from CT images using a support vector machine. *J. Adv. Computational Intelligence & Intelligent Informatics*. 11(4), 396-402.
15. Dheeba J and Tamil Selvi (2010) Bio inspired swarm algorithm for tumor detection in digital mammogram*. Intl. Conf. Swarm, Evolutionary & Memetic computing.* pp: 404-415.
16. Dipali M Joshi, Rana NK and Misra VM (2010) Classification of brain cancer using artificial neural network. *Intl. Conf. Electronic Comput. Technol.* pp: 112-116.
17. David J Krishnan, Rekha A and Sukesh Kumar (2008) Neural network based retinal image analysis. *Congress on Image & Signal Processing.* pp:49-53.
18. Essam Al-Daoud (2010) Cancer diagnosis using modified fuzzy network. *Universal J. Comput. Sci. & Engg. Technol.* 1(2), 73-78.
19. Essam A Rashed and Mohammed G Awad (2006) Neural network approach for mammography diagnosis using wavelet features. In Proc. *First Can. Student Conf. Biomedical Computing.* paper no.105.
20. Fatma Taher and Rachid Sammouda (2010) Artificial neural network and fuzzy clustering methods in

segmenting sputum color images for lung cancer diagnosis. *Intl. Conf. Signal Processing*. pp: 513-520.
21. Fernandes FC, Brasil LM, JM Lamas and R Guadagnin (2010) Breast cancer image assessment using an adaptative network based fuzzy inference system. *J. Pattern Recognition & Image Analysis.* 20(2), 192-200.
22. Gomathi M and P Thangaraj (2010) Computer aided diagnosis system for detection of lung cancer nodules using extreme learning machine. *Intl. J. Engg. Sci. & Technol.* 2(10), 5770-5779.
23. Gletsos M, Mougiakakou SG, Matsopoulos GK, Nikita KS, Nikita AS and Kelekis D (2003) A computer-aided diagnostic system to characterize CT focal liver lesions: design and optimization of a neural network classifier. *IEEE Transact. on Information Technol. Biomed.* 7(3). 153-162.
24. Geetha K and Thanushkodi K (2008) Particle Swarm Algorithm for automatic Detection in Breast cancer. *Intl. J. Soft Comput.* 3(2). 155-158.
25. Gerald Schaefer, Tomoharu Nakashima, Michal Zaivi-sek, Yasuyuki Yokota, Ale-s Drastich and Hisao Ishibuchi (2007) Breast cancer classification using statistical features and fuzzy classification of thermograms. *IEEE Conf. on Fuzzy Sys.* pp:1-5.
26. Guo-Zheng Li, Jie Yang, Chen-Zhou Ye and Dao-Ying Geng (2006) Degree prediction of malignancy in brain glioma using support vector machines. *J. Comput. Biol. & Med*. 36(3), 313-325.
27. Georgia D Tourassi, Mia K Markey, Joseph Y Lo and Carey E Floyd Jr (2001) A neural network approach to breast cancer - diagnosis as a constraint satisfaction problem. *J. American Associ. Phys. Medicine*. 28(5), 804-811.
28. Hong J and Cho S (2006) Efficient huge scale feature selection with speciated genetic algorithm. *J. Pattern Recognition Letters*. 27,143-150.
29. Ireaneus Anna Rejani Y and Thamarai Selvi S (2009) Early detection of breast cancer using SVM classifier technique. *Intl. J. Compu. Sci. & Engg.* 1(3), 127-130.
30. Ivarez A, Gorriz JM, Ramırez J, Salas-Gonzalez D, Lopez M, Puntonet CG and F Segovia(2009) Alzheimer's diagnosis using eigenbrains and support vector machines. *Electronics Letters* ,45(7), 342-343.
31. Isabelle Guyon, Jason Weston, Stephen Barnhill and Vladimir Vapnik (2002) Gene selection for cancer classification using support vector machines. *J. Machine Learning*. pp: 389-422.
32. Ilias Maglogiannis, Elias Zafiropoulos and Christos Kyranoudis (2006) Intelligent segmentation and classification of pigmented skin lesions in dermatological images. *Advances in Artificial Intelligence*. 3955. 214-223.
33. Jinn-Yi Yeh and J C Fu (2008) A hierarchical genetic algorithm for segmentation of multi-spectral human-brain MRI. *Expert sys. with Appli.* 34(2), 1285-1295.
34. Jan Luts , Arend Heerschap , Johan A K Suykens ,Sabine Van Huffel (2007) A combined MRI and MRSI based multiclass system for brain tumour recognition using LS-SVMs with class probabilities and feature selection. *J. Artificial Intelligence in Medicine*. 40(2), 87-102.
35. Jiawan Zhang and Jizhou Sun (2004) Automatic Classification of MRI Images for Three-dimensional Volume Reconstruction by Using General Regression Neural Networks. *IEEE Conf. on Nuclear Sci.* 5, 3188-3189.
36. Jiang Y, Nishiikawa RM, Schmidt RA, Metz CE, Giger ML and Doi K (1999) Improving breast cancer diagnosis with computer aided diagnosis. *J. Acad. Radiol.* 6(1), 22-33.
37. Jude Hemanth D, Kezi Selva Vijila C and Anitha J (2010) Performance improved PSO based modified counter propagation neural network for abnormal MR brain image classification. *Int. J. Advance. Soft Comput. Appl*. 2(1), 65-84.
38. Karol Przystalski, Leszek Nowak, Maciej Ogorzałek and Grzegorz Surówka (2010) Decision support system for skin cancer diagnosis. *Intl. Sym. Operations Res. & Appl.* pp: 406-413.
39. Katharina Völk, Julian F Miller and Stephen L Smith (2009) Multiple network CGP for the classification of mammograms. *Evolutionary Workshop '09,* Springer-Verlag. pp:405-413.
40. Kang H, Pinti A, Taleb-Ahmed A and X Zeng (2011) An intelligent generalized system for tissue classification on MR images by integrating qualitative medical knowledge. *J. Biomed. Signal Processing & Control*. 6, 21-26.
41. Kishore JK, Lalit M Patnaik, Mani V and Agrawal VK (2009) Application of genetic programming for multicategory pattern classification. *IEEE Trans. Evolutionary Computation*, 4, 242-258.
42. Khazaee and Ebrahimzadeh A (2010) Classification of electrocardiogram signals with support vector machines and genetic algorithms using power spectral features. *J. Biomedical Signal Processing & Control.* 5, 252-263.
43. Kumar SS and Moni RS (2010) Diagnosis of liver tumor from CT images using fast discrete curvelet transform. *Intl. J. Comput. Appl.* Special Issue on CASCT. 1, 1-6.
44. Latha Parthiban and Subramanian R (2007) Intelligent heart disease prediction system using CANFIS and genetic algorithm. *Intl. J. Biological & Life Sci.* 3,157-160.
45. Liang CE (1998) An automatic diagnostic system for CT liver image classification. *IEEE Trans. Biom. Engg*. 45(6), 783-794.

46. Leonardo de Oliveira Martins, Aristofanes Correa Silva, Anselmo Cardoso de Paiva and Marcelo Gattass (2009) Detection of breast masses in mammogram images using growing neural gas algorithm and ripley's K function. *J. Signal Processing Sys.* 55, 77-90.
47. Leena Jasmine JS, Govardhan A and Baskaran S (2010) Classification of microcalcification in mammograms using non subsampled contourlet transform and neural network. *Eur. J. Scientific Res.* 46(4), 531-539.
48. Mueen A, Sapiyan Baba M and Zainuddin R (2007) Multilevel feature extraction and X-ray classification. *J. Applied Sci.* 7(8), 1224-1229.
49. Madhubanti Maitra and Amitava Chatterjee (2008) A novel technique for multilevel optimal magnetic resonance brain image thresholding using bacterial foraging. *J. Measurement*. 41(10), 1124-1134.
50. Mougiakakou, Valavanis SG, Nikita I, Nikita KS and Kelekis AD (2003) Characterization of CT liver lesions based on texture features and a multiple neural network classification scheme. *Proce. 25th Annual Intl. Conf. the IEEE in Med. & Biol. Soci.* pp:1287-1290.
51. Matteo Masotti (2006) A ranklet -based image representation for mass classification in digital mammograms. *J. Medical Phys.* 33(10), 3951-3961.
52. Mohammed J Islam, Majid Ahmadi and Maher A Sid-Ahmed (2010) An efficient automatic mass classification method in digitized mammograms using artificial neural network. *Intl. J. Artificial Intelligence & Appl.* 1(3),1-13.
53. Nakamoto T, Taguchi A, Ohtsuka M, Suei Y, FujitaM, Tsuda M, Sanada M, Kudo Y, Asano A and K Tanimot (2008) A computer-aided diagnosis system to screen for osteoporosis using dental panoramic radiographs. *J. Dentomaxillofacial Radiol.* 37(5), 274-281.
54. Nandi RJ, Nandi AK, Rangayyan RM and Scutt D (2006) Classification of breast masses in mammograms using genetic programming and feature selection. *J. Medical & Biological Engg. Computation*. 44, 683-694.
55. Niyazi Kilic, Pelin Gorgel, Osman N Ucan and Ahmet Sertbas (2010) Mammographic mass detection using wavelets as input to neural networks. *J. Med. Sys.* 34(6), 1083-1088.
56. Nosratallah Forghani, Mohamad Forouzanfar and Elham Fourouzanfar (2007) MRI fuzzy segmentation of brain tissue using IFCM Algorithm with particle swarm optimization. *IEEE Intl. Sym. Comput. & information sci.* pp:113-121.
57. Pietro Rubegni, Gabriele Cevenini, Marco Burroni, Roberto Perotti, Giordana Dell'Eva, Paolo Sbano, Clelia Miracco, Pietro Luzi, Piero Tosi, Paolo Barbini and Lucio Andreass (2002) Automated diagnosis of pigmented skin lesions. *Intl. J. Cancer*. 101(6), 576-580.
58. Rahib H Abiyev and Koray Altunkaya (2008) Personal iris recognition using neural network. *Intl. J. Security & its Appl.* 2(2), 41-50.
59. Ramakrishnan S and Selvan S (2006) Classification of brain tissues using multiwavelet transformation and probabilistic neural network. *Intl. J. Simulation: Sys. Sci. & Technol.* 7(9), 9-25.
60. Ramana KV and Raghu B Korrapati (2010) Neural network based classification and diagnosis of brain hemorrhages. *Intl. J. Artificial Intelligence & Expert Sys.* 1(2), 7-25.
61. Ramakrishnan S, Ibrahiem El and Emary MM (2010) Classification brain MR images through a fuzzy multiwavelets based GMM and probabilistic neural networks. *J. Telecom. Sys. Springer Sci.* 46(3), 245-252.
62. Revathy N and R Amalraj (2011) Accurate cancer classification using expressions of very few genes. *Intl. J. Comput. Appli.* 14(4),19-22.
63. Riyahi Alam N, Younesi F and Riyahi Alam MS (2009) Computer-Aided mass detection on digitized mammograms using a novel hybrid segmentation system*. Intl. J. Biol. & Biomedical Engg*. 3(4), 51-58.
64. Rinku Panchal and Brijesh Verma (2004) A Fusion of Neural Network Based Auto-associator and Classifier for the Classification of Microcalcification Patterns. *Intl. Conf. Neural Information Processing, Springer Berlin.* pp:794-799.
65. Rolando R Hernandez-Cisneros and Hugo Terashima-Marın (2010) Classification of individual and clustered microcalcifications in digital mammograms using evolutionary neural networks. *Mexican Intl. Conf. Artificial Intelligence.* pp: 1200-1210.
66. Saha S and Bandyopadhyay S (2007) MRI brain image segmentation by fuzzy symmetry based genetic clustering technique. *IEEE Congress on Evolutionary Computation.* pp: 4417 – 4424.
67. Saras Saraswathi, Suresh Sundaram, Narasimhan Sundararajan, Michael Zimmermann and Marit Nilsen Hamilton (2011) ICGA- PSO-ELM Approach for accurate multiclass cancer classification resulting in reduced gene sets in which genes encoding secreted proteins are highly represented. *IEEE/ACM Transactions on Computational Biol. & Bioinfo.* 8(2), 452-463.
68. Shafaf Ibrahim and Noor Elaiza Abdul (2010) Empirical study of brain segmentation using particle swarm optimization. *IEEE Intl. Conf. on Information Retrieval & Knowledge Managt*. pp:235-239.
69. Shao Hong, Ni Tian-yu, Kang Yan and Zhao Hong (2010) Chest DR image classification based on support vector machine. *IEEE Intl. Workshop on Education Technol. & Comput. Sci*. 170-173.

Indian Journal of Science and Technology Vol. 4 No. 11 (Nov 2011) ISSN: 0974- 6846

70. Saheb Basha S and Satya Prasad K (2009) Automatic detection of breast cancer mass in mammograms using morphological operators and Fuzzy C- means clustering. *J. Theoretical & Appl. Information Technol.* 5(6), 704-709.
71. Sang-Hyun Hwang, Dongwon Kim, Tae-Koo Kang and Gwi-Tae Park (2007) Medical diagnosis system of breast cancer using FCM based parallel neural networks. *Intl. Conf. Intelligent Comput.* Springer. pp:712-719.
72. Selvaraj H, Thamarai Selvi S, Selvathi D and Gewali L (2007) Brain MRI slices classification using least squares support vector machine. *Intl. J. Intelligent Comput. in Medical Sci. & Image Processing*. 1(1), 21- 33.
73. Sathish Chandra, Rajesh Bhat, Harinder Singh and Chauhan DS (2009) Detection of brain tumors from MRI using gaussian RBF kernel based support vector machine. *Intl. J. Digital Content Technol. & its Appli.* 1(9), 46-51.
74. Sepehr MH Jamarani, Behnam H and Rezai rad GA (2005) Multiwavelet based neural network for breast cancer diagnosis. *Intl. Conf. Graphics, Vision & Image Processing*, Egypt. pp:29-34.
75. Stuart Russell and Peter Norvig (2002) Artificial Intelligence: A modern approach (Second Edition), Prentice Hall.
76. Vassilis S Kodogiannis and John N Lygouras (2008) Neuro-fuzzy classification system for wireless-capsule endoscopic images. *J. World Acad. Sci. Engg. & Technol.*, 45, 620-628.
77. Vasantha M and Subbiah Bharathi V and Dhamodharan R (2010) Medical image feature, extraction, selection and classification. *Intl. J. Engg. Sci. & Technol.* 2(6), 2071-2076.
78. Wang P, Krishnan SM, Kugean C and Tjoa MP (2001) Classification of endoscopic images based on texture and neural network. *Proc. 23rd Annual EMBS Intl. Conf.* pp:3691-3695.
79. Xiaogang Ruan, Jinlian Wang, Hui Li and Xiaoming Li (2008) A method for cancer classification using ensemble neural networks with gene expression profile. *IEEE Conf. Bioinfor. & Biomed. Engg.* pp:342-346.
80. Ye CZ, Yang J, Geng DY, Zhou Y and Chen NY (2002) Fuzzy rules to predict degree of malignancy in brain glioma. *J. Med. Biol. Engg. Computation.* 40, 145-152.
81. YuZhang, YuZhang, Xiaopeng Xie and Taobo Cheng (2001) Application of PSO and SVM in Image Classification. *IEEE Intl. Conf. Compu. Sci. & Information Technol.* pp:629-631.
82. Yuehui Chen, Yan Wang and Bo Yang (2006) Evolving hierarchical RBF Neural networks for breast cancer detection. *Intl. Conf. Neural Information Processing*, Springer-Berlin. pp:137-144.
83. Zhou Xian-cheng, Shen Qun-tai and Liu Li-mei (2008) New two-dimensional fuzzy C-means clustering algorithm for image segmentation. *J. Central South Univ. Technol.* 15(6), 882-887.