ISSN:0975-9646

A.Sivaramakrishnan et al, / (IJCSIT) International Journal of Computer Science and Information Technologies, Vol. 5 (1) , 2014, 236-246

Medical Image Analysis – A Review

A.Sivaramakrishnan [1], Dr.M.Karnan [2], Dr.R.Sivakumar [3]

[1]Assistant Professor, Department of Computer Application, Karunya University, India
[2]Professor and Head, Department of Computer Science and Engineering, Tamilnadu College of Engineering, India
[3]Professor, Department of Information Technology, Tamilnadu College of Engineering, India

Abstract— **In this survey work various automatic detection methods of microcalcifications and brain tumor through mammograms and MRI has been studied and compared for the period of more than two decades. This is used to focus on the future of developments of medical image processing in medicine and healthcare. We have described several methods in medical image processing and to discussed requirements and properties of techniques in tumor detection. This work is used to give more information about tumor detection and segmentation. It is a milestone for analyzing all technologies relevant to tumor from mammogram and MRI in Medical image processing. In this work, various steps in detection of automatic detection :i) The Preprocessing and Enhancement Technique ii) Segmentation Algorithm iii) Feature Extraction iv) Classification v)Performance Analysis using Receiver Operating Characteristics and their performance have been studied and compared.**

Keywords— **MRI, mammogram, Enhancement, Feature Extraction, Receiver Operating Characteristics.**

I. INTRODUCTION

In this chapter, methods of automatic detection of tumour in digitized MRI and mammograms used in various stages of intelligent systems for detection of masses and brain tumour are summarized and compared. In particular, the preprocessing and enhancement, segmentation algorithms, feature extraction, selection and classification, classifiers, receiver operating characteristics curve analysis and their performance are studied and compared.

II. ENHANCEMENT AND PREPROCESSING

Several authors have suggested various techniques for preprocessing and enhancement in the last two decades. The task of medical image enhancement is to sharpen the edges to increase the contrast between suspicious regions and the background. Image enhancement includes intensity and contrast manipulation, noise reduction, background removal, edges sharpening, filtering, etc. Table 2.1 and 2.1a shows the overview of enhancement techniques for mammogram and MRI

Table 2.1 An overview of enhancement techniques for mammogram

Method	Description
median filter(Lai et al 1989)	This filter can remove the noise without significantly distorting the signal.
Central Weighted Median Filter (Qian et al 1994)	A CWMF with a large central weight preserves more image detail but suppresses less noise than a filter with a smaller central weight.
Model-based, scatter function (Highnam et al 1994)	A weighting mask has been calculated which represents the percentage of the total scatter reaching the central pixel and coming from the column of Lucite above each pixel in a neighborhood.
First derivative and the local statistics (Kim et al1997)	The adaptive image enhancement method exploits the first derivative operations using the Sobel operators or the compass operators and the local statistics of a mammographic image are used for an adaptive realization.
Fractal modeling (Li et al 1997)	The key point of fractal modeling is to explore the self-similarity property of images.
Median filter[Thangavel and karnan 2005]	Computer aided detection of microcalcification in digitized mammogram using median filter and genetic algorithm.
Fuzzy logic (Kovalerchuk et al 1997)	Fuzzy logic has the potential of opening a new and promising direction for effective and early breast cancer diagnosis.
Wavelet transform, multiscale features (Chang and Laine 1999)	Wavelet transform, multiscale features, Coherence measure and dominant orientation clearly improved discrimination of features from complex surrounding tissue and structure in dense mammograms.
Filtering tech (Kobatake et al 1999)	This filter output for the tumor is very high and its region is well isolated from its background.
Region based Enhancement (Ferrari et al 1999)	Region based contrast enhancement uses each pixel as a seed to grow a region. Applying an empirical transformation based on each region's seed pixel value, its contrast and its background enhances contrast.
Wavelet, Morphological operation (Cordella et al 1999)	Fractal approach compared with the partial wavelet reconstruction and the morphological operation approaches.
Unsharp Masking, Sobel Operators (Bhangale et al 2000; Enderwich and Tzanakou 1997]	The Unsharp masking method reduces the low frequency information while amplified the high frequency detail.
Adaptive noise equalization (Veldkamp and Karssemeijer 2000)	It gives much better results than does a fixed noise equalization, probably because noise characteristics are mammogram dependent, caused by variation of film type and film development characteristics.
Gaussian smoothing	This method cumulatively modulate the

Method	Description
and sub-sampling (Mudigonda et al 2001)	intensity patterns of mass regions to form smooth hills with respect to their surroundings in the low resolution image and help in estimating the approximate extent of isolated regions present in the image.
Quantum noise assumption (Rogova et al 1999)	If quantum noise is assumed the dominant noise source present, a square root model will provide an accurate estimate of the noise with respect to gray level.
Matched filtering (Bocchi et al 2004)	In particular, Fractional Brownian Motion (FBM) can model non-stationary random fields with stationary increments. In addition, a stationary power spectrum can be attached to FBMs leading to an approximate implementation of the enhancement filter via conventional matched filtering.

Table 2.1.a An overview of enhancement techniques for MRI

Methods	Description
Oliver et al (2005) Standard Imaging Protocol	MRIs have been acquired in the standard follow-up.after surgical resection.
Dana et al (2007) Statistical Parametric Mapping, Pipe line Approach	It provides the solution of noise reduction, Inter-slice intensity variation correction, Intra-volume bias field correction
Jayaram et al (2002) Content Based model,Shape based,Texture based technique, Histogram and Profilling Method	It showed detections of tumor with decrease in pixel count in binary images, increase in image intensity, High numbers of high intensity pixel.
Tracking algorithm [Jaya et al 2009]	De-noising of MR brain images using the tracking algorithm .
Elizabeth et al (2005) Pixel Histograms, Morphological Process	It was more robust to noise and it can improve the integrity performance.
Leung et al (2003) Boundary Detection Algorithm, Generalized Fuzzy operator(GFO),	To obtain the fine result in the tumor consideration.
Zu et al (2004) Histogram based(HB),Sub-second imaging technique	Separate brain image, from head image removal of residual fragments such as sinus, cerebrospinal/fluid, dura, marrow.
Gray (1997) Neural Networks, Genetic Programming	Large volume of data processed successfully.
Mark et al (2005) Statistical Parametric Mapping Method	It is used to align the image properly and it uses left-to-right symmetry to confer robustness to areas of abnormality.
Toshiharu et al (2003) Independent Component Analysis(ICA)	Separate the components in MR images
Farahat et al (2006) Head Model, Finite Difference Time-Domain(FDTD)	It is used to analyse different Tissue types.
Kyeong et al (2004) Discrete Wavelet Transform(DWT)	DWT provides higher intensity images than other.
Lim et al (1989) Stripping algorithm	To remove the skull and scalp portions from each axial section.
Thangavel et al (2005) Gradient-Based Method, Median Filter, Normalization Method	Shows the validity of detection of Memmographic lesions.
Chunyan et al (2004) Triple Quantum Filtered Sodium MRI (TQF) Technique	Detects neoplastic changes in the brain before angiogenesis and blood brain barrier (BBB) breakdown develop.
Tsai et al (1995) Low pass Filter	Takes care of local noisy fluctuations from MR images.
Boada et al (2004) Triple Quantum Filtered (TQF) Sodium NMR	Minimizes the effects of extra cellular fluids and Found Non-Contrast Enhancing tissue
Aria et al (2002) Gadolinium-Diethylenetriaminepentaacetic acid (Gd DTPA)Enhancement	Provides additional independent information and improve the accuracy.
Boada (2004) Novel image Approach	Earlier detection of non-contrast enhancing tissue.
Amini (2003) Prewitt edge-finding filter	This filter enhances the tumor tissue greatly.
Zhe chen (2003) Morphological Filter	It is used to remove background.
Corina et al (2005) Gaussian Filter	Enhances image Boundaries.
Dimitris et al (2006) Gabor Filter Bank technique	It is used to remove the tagging lines and enhance the tag-patterned region.
Hideki et al (1990) V-filter	Enhances the image by smoothing the noise gray level distribution while retaining the edge.
Gordon et al (2006) Anisotropic sample	Enhances the utility of glyph-based tensor visualization.
Shishir et al (2006) Non linear Filter	Non – Contrast enhancing Brain Volumes are linearly aligned.
Salman et al (2005) Region Growing Filter	It is usually convenient to preprocess the image by using a noise reduction filter.
Sean et al (2001) K-nearest neighbour Algorithm	It generates enhancement data volumes. These are highly correlated with manually defined standard.
Michael et al (1988) Non linear Filter	Filter noise from source image.
Sonali et al (2012) Median Filter	To Remove noise on the MRI.

III. SEGMENTATION

Segmentation is the initial step in any image analysis. There are two different tasks for segmentation of medical images. The main task is to obtain the locations of suspicious regions to assist radiologists in diagnosis. Image segmentation has been approached from a wide variety of perspectives: region-based approach, morphological operation, multi-scale analysis, fuzzy approaches and stochastic approaches have been used for mammogram image segmentation but with some limitations. Table 3.1 and 3.1.a shows the overview of segmentation techniques for mammogram and MRI.

Table 3.1 An overview of segmentation techniques for mammogram

Methods	Description
Gaussian filter, morphological filter, conditional thickening (Dengler et al 1993)	The weighted difference of Gaussian makes use of the knowledge of the approximate size of the spots. It also requires an idea of the inter-spot distance.
Adaptive thresholding, MRF model-based method, fuzzy binary decision tree (Li et al 1995)	An MRF model-based segmentation belongs to partitional clustering, but it also has the ability to model image joint distributions in terms of local spatial interaction.
Fractal [Li et al 1997; Li et al 1996) model	Mammograms possess structures with high local self-similarity that is the basic property of fractal object. However, the computation time is high.
Metaheuristic algorithm [Thangavel et al 2005, 2006]	Mammogram image analysis using metaheuristic algorithm. Ant Colony algorithm and genetic algorithm is used to detect the microcalcification in digitized mammogram.
Region growing approach, Surrounding region dependency (Kim et al 1998)	Works best when the region homogeneity criterion is easy to define. It depends on the selection of seed region and the termination conditions.
Top-hat, Morphological filters with multi-scale and Multi elements [Mossi and Albiol 1999].	When using the multi-scale and multi-structuring elements, the results are not affected by the complex background and the extracted images are not distorted much.
Histogram thresholding, MRF (Peters and Skowron2004)	It does not need a prior information for the histogram thresholding of the image and can be used widely work very well with low computation complexity.
Fuzzy logic (Cheng et al 1998; Cheng et al 1998 ; Cheng et al 2004)	Due to variable shapes of masses, it is best to use fuzzy rules to perform approximate inference. However, the determination of fuzzy membership is not easy.
ACO [Subash Chandra Bose et al 2012]	Microcalcification identification in Mammograms using Soft Computing Techniques
Meta Heuristic Algorithm [Rajiv Gandhi et al 2012]	A Hybrid Meta Heuristic Algorithm for Discovering Classification Rule in medical Data Mining
Enhanced Artificial Bee Colony Optimization [Sivakumar and Karnan 2012]	Early Breast cancer detection through Mammogram Image using Enhanced Artificial Bee Colony Optimization Algorithm
FCM [Joseph Peter and Karnan 2013]	Medical Image Analysis Using Unsupervised and Supervised Classification Techniques
Multi-channel wavelet transform, Multi-scale analysis, Decimated wavelet transform (Bocchi et al 2004; Pandey et al 2000 ; Song et al 1996)	Due to its ability of discriminating different frequencies, the method can preserve the resolution of the portion of ROI. Moreover, it does not require the use of heuristics or a prior knowledge of the size and the resolution of the mammogram.
Edge detection, thresholding, Deformable model (Valverde et al 2004)	A partial thresholding is performed for noise reduction. A Setting threshold value is also obtained from the edge detector evaluation. This image is introduced as input to the local approach stage, where the contour snake is initialized with a circumference.
Particle Swarm Optimization [Karnan et al 2008]	Automatically Detect the Breast Border and Nipple position to Identify the Suspicious Regions on Digital Mammograms Based on Asymmetries using hybrid Particle Swarm Optimization

Table 3.1a. An overview of segmentation techniques for MRI

Methods	Description
Genetic Algorithm (karnan and logeswari)	It segment tumor region from background MRI.
Fuzzy Cmeans (FCM) unsupervised clustering(Philips et al.1995)	It extracts the image edges robustly and moves the vertices towards the boundaries of the desired structure.
Supervised k-nearest neighbor(kNN)rule, semi-supervised fuzzy c-means(SFCM) (vaidyanathan et.al.1997)	A sample set of pixel vectors (ROI) is selected by an expert observer, and the vectors are assigned to different tissue classes.
Level set Surface Model (james et.al 2000)	To produce qualitative results from several different datasets for brain tumor segmentation.
Fuzzy C Means Clustering Algorithm (SR Kannan2005)	To segment tumor regions from background MRI well.
Seed Growing Method(1997) (vaidyanathan et.al.1997)	Seed propagation was independently performed.
Genetic Algorithm (Thangavel and karnan 2007)	To segment and identify nipple position from mammogram image.
Pipe line approach, Expectation Maximization (EM) Algorithm(Jeffrey and soloman 2004)	To estimate and processed tumor volume successfully.
Hybrid Deformable model,Meta Morphs model, Novels Shape, Texture Integration, Graphical Model, Learning Methods (dimitris et al.2006)	It Integrates both shape and interior texture, its dynamics are derived coherency from both boundary and region information in a common variational framework.
Fuzzy C-means Clustering Algorithm(FCM),Neural Network Model (shan shen et al.2005)	It processes seeking the optimal labeling of the image pixels.
Atlas Matching Technique, Finite Element	To Simulate the invasion of the GBM in the brain paren chyma.

Method(FEM) (oliver et.al 2005)	
Artificial Bee Colony [Neeraja et al 2013]	Brain Tumor Segmentation In MRI Image Using Unsupervised Artificial Bee Colony And FCM Clustering
Soft Computing [Sivaramakrishnan and Karnan 2013]	A Novel Based Approach for Extraction of Brain Tumor in MRI Images Using Soft Computing Techniques
Expectation Maximization scheme(EM) (benedicte et.al.2005)	Its performance is below than Seni-Automated.
Automatic Two – dimensional Segmentation.(zhen chen et.al 2003)	Each PET plane is segmented.
Ground Truth Algorithm (marcel et.al 2003,2003,2004, 2007,2009)	It can provide the means for objective assessment of segmentation performance.
Texture Features, Self-Organizing Map(SOM) (logeswari and karnan 2010)	The tumor area is segmented from brain MRI.
Morphological Operations, Fuzzy model of Regions of Interest(ROI) (jing et.al.2001)	It is use to represent more appropriately the knowledge about distance, shape and interactions of structures.
Fuzzy C-means(Philips et al.1995: siyal et.al.2005)	To generate segmentation images that display clinically important neuroanatomic tissue and neuropathologic tissue contrast information from raw MR image data.
Amanpreet (2012)	To segment and deduct suspicious region from background using PSO algorithm based on colony aptitude and provide better result than other parallel algorithm.
Region-based method, Region growing method, Region-of-interest(ROI), Multi resolution edge detection method, modified region segmentation method(angel et.al 2012)	To segment brain tissue structure from the multi-resolution images are utilized.
Graph-Based Method,Generative Model, Weighted Aggregation Algorithm(jasoncary 2006)	It Indicates the benefit of incorporating model-aware affinities into the segmentation process for the difficult case of brain tumor
Iterative Self-Organizing Data Analysis Techniques(ISO DATA),Unsupervised Computer Segmentation Algorithm,Novel Model (Michel Jacob 2001)	Multiparametric ISODATA volume was significantly Identifies.
Spatio-Temporal Model(Jeffery soloman et al.2006)	The sensitivity and specificity of tumor segmentation using this spatio-temporal model is improved over commonly used spatial or temporal models alone.

Multiscale Method, Multiscale linking Model, Supervised Segmentation Method (naaaathan moon et al.2002)	It was shown that the errors are in the order of or smaller than reported in literature.
Semi-Supervised Fuzzy C-Means Clustering Method,K nearest neighbor(Knn),Gray level thresholding & Seed Growing(ISG-SG),Manual Pixel Labelling(GT) (vaithyanathan et.al.1995)	This method was achieved good performance and reduction operation time.
Hybrid level set (HLS)(xie et.al,2005)	It provides objective, reproducible segmentations that are close to the manual results.
Fuzzy Model(webei et.al.2007)	Average Probability of correct detection was found.
Deformable Model,Med-Volumeter(chunvan et.al.2004)	The target area is segmented under level set frame.
3D Variational Segmentation Method(dana cobzas et.al.2007)	The tumor area was segmented accurately.
Fuzzy k-means, GA (maoyang et,al2005)	A thresholding is performed for noise reduction.
Supervised technique-Mountain Method,Maximum Likelihood,K-nearest neighbour,Artificial neural network.(Robert et.al.1997)	Producing excellent partitions of large data sets.
Fuzzy Connectedness & Fuzzy sets(jayaram udupa and punam saha 2003)	It allows the spatio-topological concept of hanging-togetherness of image elements in the presence of a gradation of intensities stemming from natural material heterogeneities, blurringand other phenomenonrelated artifacts.
Expectation-Maximization (EM)(Nathan mano et.al.2002)	It separates WM,GM and CSF from ti and t2 weighted image.
Classic snaks,Deformable Contour model (amini et.al.2003)	To segment T1 weighted images of the brain with low –contrast structures and discontinuous edges
Markov random field model (kabir et .al.2007)	Segmentations obtained with single sequences to that obtained with multiple sequences.
Generalized fuzzy operator(GFO),Contour Deformable model(leung et.al.2003)	The tumor regions are segmented
Atlas-based segmentation (pierreyes et.al 2005)	Propagation of the labeled structures on to the MRI
Expectation-Maximization Technique,Robest Estimation,VALMET Segmentation validation tool (marcel et.al.2003)	To segment tumor, edema and ventricles.
Multilayer segmentation, Automatic region	The original image is segmented into various spatial

segmentation (xinbai et.al.2003)	regions.
Content-based retrieval technique (zhechen et.al.2003)	Image segmented successfully.
Atlas-driven segmentation (guido 2003)	Automatically tumor region is segmented successfully.
Fuzzy methods(zushan et.al.2004)	Results show relatively high accuracy.
Active Contour Model(corina draphca et.al 2005)	The tumor regions are segmented from MRI.
Evaluating Image Segmentation Algorithm (jayaram udupa 2002)	High Accuracy appeared in segmentation.
Fuzzy mean Algorithm(FCM),Silhovette Method(SM)(SR kannan2005)	Its provide Easiest way to find appropriate structure in the data of MRI
Contour Tracing Algorithm, Region Segmentation(hideki et. Al 1990)	To establish boundaries in order to partition the image space into meaningful regions.
Soft-Margin Support Vector Machine(SVM)(mark Schmidt et.al. 2005)	It can involve millions of training and testing instances with a relatively small feature set.
k-means Clustering Algorithm(2004)	It separates background from brain pixels accurately.
k-means clustering(ming et.al 2007)	It is used to convert a given gray-level MR image into a color space image and it separates the position of tumor objects from MRI
Statistical Model ,Markov Random Field, Level Set Method, Non-Uniformity Correction Method(ranos et.al 2004)	Non-brain structures removed and it estimates the tissue intensity variation.
Multi-Scale Watershed Segmentation(erck dam et.al 2004)	It is used to select the subsets of the expected regions automatically.
Deformable Region Model, Shrinking Method and Snake Method (chan et.al.1996)	It is used to locate the boundary of an object quickly.
Hidden Markov Chain Model(HMC) (briq et.al.2008)	To produce ever finer resolution in spectral, spatial and temporal data.
Seeded Region Growing, Active Contour Snakes Model (salman et.al 2005)	It is based on extraction of a connected set of pixels whose pixel intensities are consistent with pixel statistics of a seed point.
Hybrid level Set (HLS) Model(kai xie et.al 2005)	It is used to segment edema and tumor.
Expectation Maximization(EM) Algorithm, MRF(david gerind et.al.2002)	It is used to select the subsets of the expected regions efficiently.
Population-Based Tissue Maps, K Nearest Neighbor Model. (sean haney et.al 2001)	It is used to differentiate tissue types with high accuracy.
Level-Set Surface Model (aaron et.al 2003)	It is used to segment target regions from background tissue.
Support Vector machine(zhou et.al. 2005)	It is used to locate the boundary of an object quickly.
GPU based Segmentation(aaron et.al 20032003)	This system found interactivity users to produce good, reliable segmentation on MRI and it produced qualitative and quantitative for brain tumor detection
Genetic Algorithm (karnan and thangavel 2007)	Segment objective region from MRI.
Self organizing Map(SOM) (logeswari and karnan 2010)	Segment the suspicious region.
Standard Deterministic Annealing(DA) and Fuzzy C Means (xi-lei yang et.al 2008)	To apply robust segmentation on brain MRI images for segmenting tumor pixels on MRI.
Bacteria Foraging Optimization Algorithm [Ben George and Karnan 2012]	MRI Brain Image Enhancement , Feature Extraction and Classification of Brain Tumor using BFOA

IV. Feature Extraction And Selection

The textural features can be extracted from the co-occurrence matrix. They are related to specific textural characteristics such as the homogeneity, contrast, entropy, energy and regularity of the structure. In this paper, the texture analysis methods such as, Surrounding Region Dependency Matrix, Spatial Gray Level Dependency Matrix, Gray Level Difference Matrix, Gray Level Run Length Matrix are used to extract the features from the segmented image.Feature extraction is a general term for methods of constructing combinations of the variables to get around these problems while still describing the data with sufficient result. It is defined as the operation to quantify the image quality through various parameters or functions, which are applied to the original image. Feature extraction involves simplifying the amount of resources required to describe a large set of data accurately.

Today, one of the main problems in machine learning and statistics is keeping track of the most relevant information. For this purpose, feature selection techniques are addressed. The major aims of feature selection for classification are finding a subset of variables those results in more accurate classifiers and constructing more compact models. Therefore, feature selection will filter out those variables that are irrelevant for the specific model. The selection should only capture the relevant features while not over fitting the data. Also there is a reduction in the sample size needed for good generalization.

Table 4.1 an overview for Feature Extraction and Selection

Methods	Description
Back Propagation Network(BPN), Ant Colony Optimization technique(ACO) (thangavel and karnan 2005)	Masses were extracted completely.
Multi-scale Gabor-type Feature set(dana cobaz et.al.2007)	Accurate results to be obtained with a relatively small number of training images.
Deformable region	The model provides fast

Methods	Description
model,Active contour model,Kolmogorov-Smirnov(KS),Point Sampling technique.(albert law 2002)	result.
Wavelet Transform,Wavelet Packets(azadeh et.al 2004)	Related features are extracted from the background issue.
Fuzzy C-means(FCM) Unsupervised clustering, Morphological Operators.(amini et.al.2003)	To extract the image edges robustly.
Optimal Residual Extraction (xin bai et.al.2003)	Masses were extracted completely
Morphologic Operation(zuchen et.al 2004)	To extract the sulcal images from the brain images.
Rough Set Particle Swarm Optimization(xiang vang et.al 2006)	It can generate more general decision rules and better classification quality of new samples.
Kruskal-Wallistest, Fisher Discriminant Criterion ,Relief-F Algorithm and Least Squares – Support Vector Machine(LS-SVM) (jan luts et.al.2007)	It is used to reduce the dimension of the input space and can extract feature set.
Quick Reduct algorithm [Jaganathan et al 2007]	Classification rule discovery with ant colony optimization and improved Quick Reduct algorithm for the medical images.
Relative Reduct Algorithm [Kalyani and Karnan 2010]	Medical data Attribute Reduction using Forward Selection and Relative Reduct Algorithm
Artifcial Bee colony [Mary Jeyanthi Prem and Karnan 2013]	Business Intelligence using Optimization techniques for Decision Making

V. CLASSIFIERS

Classifiers play an important role in the implementation of intelligent system to identify the tumour from mammogram and MRI image. The features are given as input to the classifiers to classify the medical image into normal and abnormal

Methods	Description
Woods et al. 1993 Binary decision tree	Area under ROC curve is 0.9 for 24 images.
Woods et al. 1993 Quadratic Classifier	Area under ROC curve is 0.918 for 24 images.
Caldwell et al 1990., Nishikawa et al 1990. Woods et al 1995. Nishikawa et al 1992. Nishikawa et al 1993. Linear classifier	Maximum area 0.70 under ROC for 70 images.
Cordella et al. 2000 Multiple expert system	The area under the ROC curve is 0.786 for 40 images.
Caldwell et al. 1990	Maximum area 0.86 under ROC.
Woods et al. 1993	Area under ROC curve 0.935 for 24 images.
Dhawan et al. 1996	Maximum area 0.76 under ROC for 191 images.
Kim and Park 1999 Neural Networks	The area under ROC curve is 0.88 for 120 images.
Woods et al. 1993 K-Nearest Neighbor Classifier	Area under ROC curve 0.929 for 24 images.
Recursive feature elimination based on Support Vector Machine(SVM RFE), Genetic Algorithm (GA) (mao yang 2005)	To determine these optimal hyper-planes, It Solves a convex quadratic programming problem. It is use to get optimal values. It Achieves high classification accuracies with genes. Performance is very Satisfied.
Support Vector Machines(SVM)(dana cobzas et.al. 2004)	To predict sub cellular localization.
Multi-Layer Feed Forward Neural Network, Support Vector Machine(SVM)(corina drapaca 2005)	Used to classify the tumor regions from non-tumor regions.
Bayesian Model(Jason carso 2006)	Each region is assigned a most likely model class according to a set of learned model classes
3D-Expectation Maximization Method, Hidden Markov Model (Jeffrey soloman 2006)	To classify the tumor Region
Voxel Classification, Geometric Model(guido 2003)	To classify the tumor regions from non-tumor regions.
Multilayer preceptron neural network.(azadeh 2004)	To classify the tumor features extracted from the spectra.
Supervised voxal Classification. (guido2003)	The tumors classified successfully.
Support Vector Machines(SVMs),Decision Tree(DT) (gotsos 2003)	90.8%low from high grade tumors and 85.6% less from highly aggressive tumors are classified clearly. The ability of SVM to ensure good performance even with limited training samples was verified.
Quadratic Discriminant Analysis(QDA),Support Vector Machine(SVM) (hongmin 2007)	SVM classification is combined with QDA based classification to obtain a better tumor profile.
Linear Discriminant Analysis, Least Squares Support Vector Machines(LS-SVM),Linear Kernel Techniques (or) Radial Basis Function(devos 2005),(jain luts 2007)	Classifiers were evaluated over 100 stratified random splitting of the dataset into training and test sets.
Multi-Scale Jet -Based Classification(erick dam et.al.2004)	It is used to automatically select a subset of the regions generated by the watershed segmentation method.
Statistical Classification method(war field 2000)	Classify the tumor is benign , malignant or normal

VI. ROC ANALYSIS

The Receiver Operating Characteristics Curve (ROC) is a popular tool in Medical and Image processing research to analyze the rate of classification. ROC Analysis is based on statistical decision theory developed in the context of electronic signal detection and has been applied extensively to diagnostic systems in Clinical medicine. The ROC curve is a plot of the classifier's true positive detection rate and its false positive rate. True positive (TP) detection rate is the probability of correctly classifying a target object and false positive (FP) detection rate is the probability of incorrectly classifying a target object. The following figures show that the sample ROC curves. The Researchers suggested various techniques of ROC and they are available in the survey. Each classifier is constructed using the training set and is evaluated by ROC Analysis.

Table 6.1 An overview of ROC Analysis

Methods	Description
Devos (2005) MRI with Peak Integration	Performance of ROC is 0.99 for 76 patients with 142 data's. It's performed higher than other classifier.
Devos (2005) 29 Principal Component Analysis(PCA) –LS SVM	Area Under Curve (AUC) higher than 0.94 for low versus high grade gliomas fro 70 data sets. Higher result than PCA/LDA
Devos(2006) 29 Linear Discriminant Analysis(LDA)	Area Under Curve (AUC) higher than 0.91 for low versus high grade tumors. Performs better than PCA
Devos(2006) Least Square-Support Vector Machine	Area Under Curve (AUC) higher than 0.91for low versus high grade gliomas.Gives accurate result.
Devos(2006) Least Square-Support Vector Machine and Radial Basis Function Kernal(RBF)	Area Under Curve (AUC) higher than 0.99 for gliomas versus meningiomas. LS-SVM and RBF Combination gives better improvement than other classifier.

VII. CONCLUSIONS

In this survey work various automatic detection methods of microcalcifications and brain tumor through mammograms and MRI has been studied and compared for the period of more than two decades .This is used to focus on the future of developments of medical image processing in medicine and healthcare. We have described several methods in medical image processing and to discussed requirements and properties of techniques in tumor detection .This work is used to give more information about tumor detection and segmentation. It is a milestone for analyzing all technologies relevant to tumor from mammogram and MRI in Medical image processing. In this work, various steps in detection of automatic detection :i) The Preprocessing and Enhancement Technique ii) Segmentation Algorithm iii) Feature Extraction iv) Classification v)Performance Analysis using Receiver Operating Characteristics and their performance have been studied and compared.

REFERENCES

[1] Lai, S., Li, X. and Bischof, W.F. "On Techniques for Detecting Circumscribed Masses in Mammograms," IEEE Transactions on Medical Imaging, Vol. 8, No. 4, pp. 377–386, 1989.

[2] Qian, W., Clarke, L.P., Kallergi, M. and Clark, R.A. "Tree-Structured Nonlinear Filters in Digital Mammography," IEEE Transactions on Medical Imaging, Vol. 12, No. 1, pp. 25–36, 1994.

[3] Highnam, R.P., Brady, J.M. and Shepstone, B.J. "Computing the Scatter Component of Mammographic Images," IEEE Transactions on Medical Imaging, Vol. 13, No. 2, pp. 301–313, 1994.

[4] Kim, J.K., Park, J.M., Song, K.S. and Park. W. "Adaptive Mammographic Image Enhancement Using First Derivative and Local Statistics," IEEE Transactions on Medical Imaging, Vol. 16, No. 5, pp. 495-502, 1997.

[5] Li, H., Liu, K.J.R. and Lo, S.C.B. "Fractal modeling and segmentation for the enhancement of microcalcifications in digital mammograms," IEEE Transactions on Medical Imaging, Vol.16, No. 6, pp. 785–798, 1997.

[6] Kovalerchuk, B., Traintaphyllou E.J.F. Ruiz and J. Clayton, J. "Fuzzy Logic in Computer-Aided Breast Cancer Diagnosis: Analysis of Lobulation," Artificial Intelligence in Medicine, Vol. 11, pp. 75–85, 1997.

[7] Chang, R.F., Wu, W.J., Tseng, C.C., Chen, D.R. and Moon, W.K. "3-D Snake for US in Margin Evaluation for Malignant Breast Tumor Excision Using Mammotome," IEEE Transactions on Information Technology in Biomedicine, Vol. 7, no. 3, pp. 197–201, 2003.

[8] Kobatake, H., Murakarni, M., Takeo, H. and Nawano, S. "Computerized Detection of Malignant Tumors on Digital Mammograms," IEEE Transactions on Information Technology in Biomedicine, Vol. 18, No. 5, pp. 369–378, 1999.

[9] Ferrari, R.J., De Carvalho, F., Marques, P.M.A. and Frere. A.F. "Computerized classification of breast lesions: shape and texture analysis using an artificial neural network," 7th international conference on Image Processing and its applications, pp. 517–521, 1999.

[10] Cordella, L.P., Tortorella, F. and Vento, M. "Combing experts with different features for classifying clustered microcalcifications in mammograms," Proceedings of 15th International Conference on Patten Recognition, pp. 324–327, 2000.

[11] Bhangale, T., Desai, U.B. and Sharma, U. "An unsupervised scheme for detection of microcalcifications on mammograms," IEEE International Conference on Image Processing, pp. 184–187, 2000.

[12] Enderwich, C.Y. and Tzanakou, E.M. "Classification of mammographic tissue using shape and texture features," Proceedings of the 19th International Conference-IEEE/EMBS, pp. 810–813, 1997.

[13] Veldkamp, W.J.H. and Karssemeijer, N. "Normalization of local contrast in mammograms," IEEE Trans. Med. Imag., Vol. 19, No. 7, pp. 731–738, 2000.

[14] Mudigonda, N.R., Rangayyan, R.M. and Desautels, L."Detection of Breast Masses in Mammograms by Density Slicing and Texture Flow Field Analysis," IEEE Tran. On Medical Imaging, Vol. 20, No. 12, pp. 1215–1227, 2001.

[15] Rogova, G.L., Stomper, P.C. and Ke, C. "Microcalcification texture analysis in a hybrid system for computer aided mammography," SPIE, Vol. 3661, pp. 1426–1433, 1999.

[16] Bocchi, L., Coppini, G., Nori, J. and Valli, G. "Detection of Single and Clustered Microcalcifications in Mammograms Using Fractals Models and Neural Networks," Medical Engineering and Physics, Vol.26, pp. 303 – 312, 2004

[17] Olivier Clatz, Maxime Sermesant, Pierre-Yves Bondiau, Herve Delingette, Simon Warfield, K, Gregoire Malandain & Nicholas Ayache, 'Realistic Simulation of the 3-D Growth of Brain Tumors in MR Images Coupling Diffusion With Biomechanical Deformation', IEEE on Trans Medical Imaging,vol.24,no.10, pp.1334-1346. 2005

[18] Dana Cobzas, Neil Birkbeck, Mark Schmidt & Martin Jagersand '3DVariational Brain Tumour Segmentation Using a High Dimensional Feature Set', IEEE 11th International Conference on Computer Vision, ICCV-2007, pp.1-8.2007

[19] Jayaram Udupa, K, Vicki Lablane, R, Hilary Schmidt, Celina Lmielinska, Punam Saha, K, George, J, Grevera, Ying Zhuge, Pat Molholt, Yinpengjin & Leanne Currie, M, 'A Methodology for Evaluating Image Algorithm', IEEE on Medical Image Processing, pp.1-14. 2002

[20] Elizabeth Bullitt, Donglin Zeng, Guido Gerig, Stephen Aylward, Sarang Joshi Keithsmith, J. Weili Lin, Matthew Ewend, G, 'Vessel Tortuosity and Brain Tumor Malingnancy:A Blinded Study', Academic Radiology, vol.12, pp.1232-1240.2005

[21] Leung, CC, Chen, WF, Kwok, PCK & Chan, FHY 2003, 'Brain Tumor Boundary Detection in MR Image with Generalized Fuzzy Operator', International Conference on Image Processing Proceedings, Barcelona, vol.2, pp.1057-1060.2003

[22] Zu Shan, Y, Jing Liu, Z & Guang Yue, H 2004, 'Automated Human Frontal lobe Identification in MR images based on Fuzzy-Logic Encoded Expert Anatomic Knowledge', Elsevier, Magnetic Resonce Imaging, Magnetic Resonance Imaging, vol.22, no.5, pp. 607-617.2004

[23] Gray, HF 2010, 'Genetic Programming for the Analysis of Nuclear Magnetic Resonance Spectroscopy Data', The Institution of Electrical Engineers, Centre For Development of Advanced Computing, IEEE Xplore, March 10.2010

[24] Mark Schmidt, Ilya Levner, Ressell Greiner, Albert Murtha & Aalo Bistritz 2005, 'Segmentation Brain Tumors using Alignment-Based Features', IEEE on Proceesings of the fourth International Conference on Machine Learning an Applications(ICMLA'05)", pp.215-220.2005

[25] Toshiharu Nakai, Shigeru Muraki, Epifanio Bagarinao, Yukio Miki, Yasuo Takehara, Kayako Matsuo, Chikako kato, Harumi Sakahara & Haruo Isoda 2003, 'Application of independent component analysis to magnetic resonance Imaging for enhancing the contrast of gray and white matter', Elsevier on Neuroimage,vol.2, no.1, pp. 251-260.2003

[26] Farahat, AS, El-Dewany, EM, El-Hefnawi, FM, Kadah, YM & Youssef, AA 2006, 'Calculations of Heating Patterns of Interstitial Antenna for Brain Tumors Hyperthermia Treatment Planning', The 23thNational Radio Science Conference, Faculty of Electronic Engineering, Menoufiya University.2006

[27] Kyeong-Jun Mun, Hyeon Tae Kang, Hwa-Seok Lee, Yoo-Sool Yoon, Chang-Moon Lee & June Ho Park 2004, 'Active Contour Model Based Object Contour Detection using Genetic Algorithm with Wavelet Based Image Preprocessing', International Journal of Control, Automation, and Systems vol. 2, no. 1.2004

[28] Lim, LO & Pfefferbaum, A 1989, 'Segmentation of MR brain images into cerebrospinal fluid spaces, white and gray matter', Journal of Comput. Assisted Tomog, vol .13, no. 4, pp. 588-593.1989

[29] Chunyan Jiang, Xinhua Zhang, Wanjun Huang & Christoph Meinel 2004, 'Segmentation and Quantification of Brain Tumor', IEEE International conference on Virtual Environment, Human-Computer interfaces and Measurement Systems, pp.12-14.2004

[30] Tsai, C, Manjunath, BS & Jagadeesan, R 1995, 'Automated Segmentation of brain MR Images', Pergamon, Pattern Recognition, vol.28, no.12.1995

[31] Boada, FE, Davis, D, Walter, K, Torres-Trejo, A, Kondziolka, D, Bartynski, W & Lieberman, F 2004, 'Triple Quantum Filtered Sodium MRI of Primary Brain Tumors', IEEE, Proc. Intl. Soc. Mag. Reson. Med.USA.2004

[32] Aria Tzika, A, Maria Zarifi, K, Liliana Goumnerova, Loukas Astrakas, G David Zurakowski, Tina Young- Poussaint, Douglas Anthony, Michael Scott, R & Peter McL. Black 2002, 'Neuroimaging in Pediatric BrainTumors:Gd-DTPA-Enhanced, emodynamic, and Diffusion MR Imaging Compared with MRSpectroscopic Imaging', AJNR Am J Neuroradiol ,vol.23, no 2, pp .322-333.2002

[33] Amini, L, Soltanian-Zadeh, H & Lucas, C 2003, 'Automated Segmentation of Brain Structure from MRI', Proc. Intl.Soc. Mag. Reson.Med.11.2003

[34] Zhe chen, David Dagan Feng & Weidong Cai 2003, 'Automatic Detection of PET Lesions', Pang-Sydney Area Workshop on Visual Information Processing, Conference in Research and Practice in IT, vol.22, pp.21-26.2003

[35] Corina Drapaca, S, Valerie Cardenas & Colin Studholme 2005, 'Segmentation of tissue boundary evolution from brain MR Image sequences usingmulti-phaselevel sets', Elsevier, Computer vision and image understanding,vol.100, no. 3, pp.312-329.2005

[36] Dimitris Metaxas, N, Zhen Qian, Xiaolei Huang, Rui Huang, Ting Chen & Leon Axal, 'Hybrid Deformable Models for Medical Segmentation and Registration', International conference on Control, Automation, Robotics and Vision(ICARCV'06),pp.1-6. 2006

[37] Hideki yamamoto, Katsuhiko Sugita, Noriki Kanzaki, Ikuo Johja, Yoshio Hiraki & Michiyoshi Kuwahara 1990, 'Magnetic Resonance Image Enhancement Using V- Filter', IEEE AES Magazine, vol.5, no.6, pp. 31 - 35.1990

[38] Gordon Kindlmann & Carl-Fredrik Westin 2006, 'Diffusion Tensor Visualization with Glyph Packing', IEEE Transactions on Visualization and Computer Graphics (Proceedings Visualization/ Information Visualization 2006) vol.12, no.5, pp.1329-1335.2006

[39] Shishir Dube, Suzie El-saden, Timothy Cloughesy, F & Usha Sinha 2006, 'Content Based Image Retrieval for MR image Studies of Brain Tumors', Proceedings of the 28th IEEE EMBS Annual International Conference, NewYork,vol.1,no.1,pp.3337-3340.2006

[40] Salman, YM, Assal, MA, Badawi, AM & El-Bavome, M 2005, 'Validation Techniques for Quantitative Brain Tumors Measurements', Proceedings of the 2005 IEEE Engineering in Medicine and Biology 27th annual Conference shanghai, China, vol.7, pp. 7048-7051.2005

[41] Sean Haney, M, Paul Thompson, M, Timothy Cloughesy, F, Jeffry Alger, R & Arthur Toga, W 2001, 'Tracking tumor Growth Rates in Patients with Malignant Gliomas', A Test of two Algorithms', American Society of Neuroradiology, AJNR Am J euroradiol,vol.22, no.1, pp. 73-82.2001

[42] Michael Wood, L & Val Runge, M 1988, 'Application of image Enhancement techinique to Magnetic Resonance Imaging', Radiographics,vol.8, no. 4,pp. 771-784.1988

[43] Sonali Patil & Udupi, VR 2012, 'Preprocessing to be considered for MR and CT images containing Tumors', IOSR journal of Electrical and Electronics Engineering, vol. 1, no. 4, pp. 54-57.2012

[44] Dengler, J., Behrens, S., and Desaga, J.F. "Segmentation of microcalcifications in mammograms," IEEE Transactions on Med. Imag., Vol. 12, no. 4, pp. 634–642, 1993.

[45] Li, H.D., Kallergi, M., Clarke, L.P., Jain, V.K., and Clark, R.A. "Markov Random Field for Tumor Detection in Digital Mammography," IEEE Transactions on Medical Imaging, Vol. 14, No. 3, pp. 565 – 576, 1995.

[46] Li, H., Liu, K.J.R. and Lo, S.C.B. "Fractal modeling of mammogram and enhancement of microcalcifications," IEEE Nuclear Science Symposium & Medical Imaging Conference, Vol. 3, pp. 1850–1854, 1996.

[47] Kim, J.K., Park, J.M., Song, K.S. and Park. W. Detection of clustered microcalcifications on mammograms using surrounding region dependence method and artificial neural network," Journal on VLSI Signal Process, Vol. 18, pp. 251–262, 1998.

[48] Mossi, J.M., Albiol, A. "Improving detection of clustered microcalcifications using morphological connected operators," IEEE Image Proces. and its Applications, Vol. 5, No. 2, pp. 498–501, 1999.

[49] Peters, J.F. and Skowron, A. (Eds.). "Transactions on Rough Sets," Springer-Verlag, Berlin, 2004.

[50] Cheng, H.D., Cai, X., Chen, X.W., Hu, L. and Lou, X. "Computer Aided Detection and Classification of Microcalcifications in Mammograms: A Survey," Pattern Recognition, Vol. 36, pp. 2967–2991, 2003.

[51] Cheng, H.D., Chen, J.R., Freimanis, R.I. and Jiang, X.H."A novel fuzzy logic approach to microcalcification detection," Journal on Inform. Sci., Vol. 7, pp. 1-14, 1998.

[52] Cheng, H.D., Lui, Y.M. and Freimanis, R.I. "A novel approach to microcalcification detection using fuzzy logic technique," IEEE Trans. Med. Imag. Vol. 17, no. 3, pp. 442–450, 1998.

[53] Cheng, H.D., Wang, J. and Shi, X. "Microcalcification Detection Using Fuzzy Logic and Scale Space Approaches," Pattern Recognition, Vol. 37, pp. 363–375, 2004.

[54] Dippel, S., Stahl, M., Wiemker, R. and Blaffert, T. "Multiscale contrast enhancement for radiographies: Laplacian pyramid versus fast wavelet transform," IEEE Trans. Med. Imag., Vol. 21, No. 4, pp. 343–353, 2002.

[55] Pandey, N., Salcic, Z. and Sivaswamy, J. "Fuzzy logic based microcalcification detection, Neural Networks for Signal Processing," Proceedings of the IEEE Workshop, pp. 662–671, 2000.

[56] Valverde, F.L., Guil, N. and Munoz, J. "Segmentation of Vessels from Mammograms Using a Deformable Model," Computer Methods and Programs in Biomedicine, Vol.73, pp. 233–247, 2004.

[57] Phillips, WE, Velthuizen, RP, Phuphanich, S, Hall, LO, Clarke, LP & Silbiger ML 1995, 'Application of Fuzzy C-Means Segmentation Technique for tissue Differentlation in MR Images of a hemorrhagic Glioblastoma Multiforme', Pergamon on Megnetic Resonance Imaging,vol.13,pp. 277-290.1995

[58] Vaidyanathan, M, Clarke, LP, Hall, LO, Heidtman, C, Velthuizen, R, Gosch, K, Phuphanich, S, Wagner, H, Greenberg, H & Silbiger, ML 1997, 'Monitoring brain tumor Response to therapy using MRI segmentation', Elsevier on Magnetic Resonance Image, vol.15, no.3, pp.323-334.1997

[59] James Lin, C, Shinji hirai, Chin-Lin Chiang, Wen-Lin Hsu, Jenn-Lung Su, & Yu-Jin Wang 2000, 'Computer Simulation and Experimental Studies of SAR Distributions of Interstitial Arrays of Sleeved-Slot Microwave Antennas for Hyperthermia treatment of

Brain Tumors', IEEE Transactionson Microwavetheory and Techniques, vol.48, no.11, pp. 2191- 2198.2000

[60] Kannan, SR 2005, 'A New Clustering Algorithm for Segmentation of Magnetic Resonance Images Using Fuzzy C-Mean and Computer Programming', ICGST International Journal on Graphics, Vision and Image Processing, vol.2. 2005

[61] Kannan, SR 2005, 'Segmentation of MRI Using New Unsupervised Fuzzy C mean Algorithm', ICGST-GVIP Journal,vol.5, no.2.2005

[62] Jeffrey Solomon, John Butman, A & Arun Sood 2006, 'Segmentation of brain tumors in 4D MR images using the Hidden Markov model', Elsevier on Computer Methods and Programs in Biomedicine", USA, vol.84, no.2, pp. 76-85.2006

[63] Jeffrey Solomon, A, Butman & Arun Sood 2004, 'Data Driven Brain Tumor Segmentation in MRI Using Probabilistic Reasoning over Space and Time', Springer Link on Medical Image Computing, vol. 3216.2004

[64] Shan Shen, William Sandham, Malcolm Granet & Annette Sterr 2005, 'MRI Fuzzy Segmentation of Brain Tissue Using Neighbourhood Attraction with Neural- Network Optimization' IEEE Transactions on Information Technology in Biomedicine, vol.9, no.3, pp. 459-467.2005

[65] Benedicte Mortamet, Donglin Zeng, Guido Gerig, Marcel Prastawa & Elizabeth Bullitt 2005, 'Effects of Healthy Aging Measured By Intracranial Compartment Volumes using Designed MR Brain Database', Med Image Comput Comput Assist Interv Int Conf Med Image Comput Comput Assist Interv, vol.8, pp. 383-391. 2005

[66] Marcel Prastawa, Elizabeth Bullitt & Guido Gerig 2009, 'Simulation of Brain Tumors in MR Images for Evaluation of Segmentation Efficacy', Medical Image Analysis (MedIA), vol .13, no. 2, pp. 297-311.2009

[67] Marcel Prastawa, Elizabeth Bullitt, Nathan Moon, Koen van Leemput & Guido Gerig, 2003, 'Automatic Brain Tumor Segmentation by Subject Specific Modification of Atlas Priors', Academic Radiology. vol .10, no.12, pp. 1341-1348.2003

[68] Marcel Prastawa, Elizabeth Bullitt, Sean Ho & Guido Gerig 2003, 'Robust Estimation for Brain Tumor Segmentation', Medical Image Computing and Computer Assisted Intervention (MICCAI), Lecture Notes in Computer Science (LNCS), vol.2879, pp.530-537.2003

[69] Marcel Prastawa, Elizabeth Bullitt, Sean Ho & Guido Gerig 2004, 'A Brain Tumor Segmentation Framework Based on Outlier Detection' Medical Image Analysis, vol. 8, no.3, pp.275-283.2004

[70] Marcel Prastawa, W, John Gilmore, H, Weili Lin, Christopher Looney, BY, Sampath Vetsa, K, Rebecca Knickmeyer, C, Dianne Evans, D, Keith Smith, J, Robert Hamer, M, Jeffrey Lieberman, A & Guido Gerig 2007, 'Regional Gray Matter Growth, Sexual Dimorphism, and Cerebral Asymmetry in the Neonatal Brain', Journal of Neuroscience. vol.27, no. 6, pp.1255-1260.2007

[71] Jing-hao Xue, Su Ruan, Bruno Moretti, Marinette Revenu & Daniel Bloyet 2001, 'Knowledge-based Segmentation And Labeling of brain structure fromMRI images', Elsevier on Pattern Recognition Letters , vol.22, no. 3-4,pp. 395-405. 2001

[72] Siyal, MY & Lin, YU, 2005, An Intelligent modified fuzzy C-means based algorithm for bias estimation and Segmentation of brain MRI", Elsevier, Pattern Recognition Letters, vol.26,no.13,pp. 2052-2062.2005

[73] Amanpreet Kaur & Singh, MD 2012, 'An Overview of PSO- Based Approaches in Image Segmentation', International Journal of Engineering and Technology, vol.2, no. 8.2012

[74] Angel Viji, KS & Jayakumari, J 2012, 'Performance Evaluation of Standard Image Segmentation Methods and Clustering Algorithms for Segmentation of MRI Brain Tumor Images', European Journal of Scientific Research, vol. 79, no.2, pp. 166-179.2012

[75] Jason Carso 2006, Multilevel Image Segmentation and Integrated Bayesian Model Classification with an Application to Brain Tumor Imaging', Upcoming UCLA Statistics Seminar on Springer link, vol. 4191, pp. 790-798.2006

[76] Michael Jacobs, A, Panayiotis Mitsias, Hamid Soltanian-Zadeh, Sunitha Santhakumar, Amir Ghanei, Rabih Hammond, Donald Peck, J, Michael Chopp & Suresh Patel 2001, 'Multiparametric MRI Tissue Characterization in Clinical Stroke with Correlation to Clinical Outcome', American Heart Association, Stroke, pp.950-957.2001

[77] Nathan Moon, Elizabeth Bullitt, Koen Van Leemput & Guido Gerig 2002, 'Automatic Brain and Tumor Segmentation', Proceedings of the 5th International Conference on Medical Image Computing and Computer-Assisted Intervention-Part I, pp. 372-379. 2002

[78] Vaidyanathan, M, Clarke, LP, Velthuizen, RP, Phuphanich, S, Bensaid AM, Hall, LO, Bezdek, JC, Greenberg, H, Trotti A & Silbiger, M 1995, 'Comparison of Supervised MRI Segmentation methods for Tumor Volume Determination During Therapy', Pergamon,Magnetic Resonance Imaging, Magnetic Resonance Imaging, vol.13, no.5, pp.719-728.1995

[79] Xie, K, Yang, J, Zhang, ZG & Zhu, YM 2005, 'Semiautomated Brain tumor and edema segmentation using MRI', European Journal of Radiology, vol.56, no.1, pp.12-19.2005

[80] Weibei Dou, Su Ruan, Yanping Chen, Daniel Bloyet & Jean-Marc Constans 2007, 'A framework of fuzzy information fusion for the segmentation of brain tumor tissues on MR images', Image and Vision Computing, vol.25, no.2, pp. 164-171.2007

[81] MAO Yong, ZHOU Xiao-bo, PI Dao-ying, SUN Youxian & WONG Stephen TC 2005, 'Parameters selection in selection using Gaussian kernel support vector machines by genetic algorithm', Journal of Zhejiang University Science, vol. 6, no.10, pp.961–973.2005

[82] Robert Velthuizen, P, Lawrence Hall, Laurence Clarke, P & Martin Silbiger, L 1997, 'An Investigation of Mountain Method Clustering for Large Data Sets', Peron, Pattern Recognition, vol.30, no.7, pp. 1121- 1135.1997

[83] Jayaram Udupa, K & Punam Saha, K. 2003, 'Fuzzy Connectedness and Image Segmentation', Proceedings of the IEEE,vol.91,no.10, pp.1649-1669.2003

[84] Kabir, Y, Dojat, M, Scherrer, B, Forbes, F & Garbay, C 2007, 'Multimodal MRI Segmentation of ischemic stroke Lesions', 29th Annual International Conference of the IEEE in Engineering in Medicine and Biology Society, pp.1595-1598. 2007

[85] Pierre-Yves Bondiau,Gregoire Malandain, Stephane Chanalet & Pierre-Yves Marcy 2005, 'Atlas-Based Automatic Segmentation of MR Images:Validation Study on The Brainstem in Radiotherapy Context', Elsevier on radiation Oncology Biological Physis,vol. 6, no.1, pp.289-298.2005

[86] Xin Bai, Jesse Jin, S & Dagan Feng 2004, 'Segmentation Based Multilayer Diagnosis Lossless Medical Image Compression', Australian Computer Society, Pan Sydney Area Workshop on Visual Information Processing (VIP 2003), vol. 100,pp.9-14.2003

[87] Ming-Ni Wu, Chia-Chen Lin & Chin-Chen Chang 2007, 'Brain Tumor Detection Using Color-Based k- Means Clustering Segmentation', Third International Conference on Intelligent Information Hiding and Multimedia Signal Processing, vol. 2, pp.245-250. 2007

[88] Panos kotsas 2005, 'Non-rigid Registration of medical images using an Automated method', World academy of science, Engineering and Technology .2005

[89] Erik Dam, Marcoloog & Marloes Letteboer 2004, 'Integrating Automatic and Interactive Brain tumor Segmentation' Proceedings of the 17th International Conference on Pattern Recognition (ICPR'04),vol. 3,pp .790-793.2004

[90] Chan, FHY, Lam, FK, Poon, PWF, Zhu, H & Chan, KH 1996, 'Object boundary location by Region and Contour Deformation', IEEE, Proceedings on Vision, Image and Signal Processing,vol.143, no.6, pp.353-360.1996

[91] Bricq, S, Collet, Ch & Armspach, JP 2008, 'Unifying Framework for Multimodal brain MRI Segmentation based on Hidden Markov Chains', Elsevier on Medical Image Analysis, vol.12, no. 6, pp. 639-652.2008

[92] Kai Xie, Jie Yang, Zhang, ZG, & Zhu, YM 2005, 'Semiautomated brain tumor and edema Segmentation using MRI', Elsevier, European journal of Radiology, vol .56, no. 1, pp. 12-19.2005

[93] David Gering, Eric, W, Grimson, L & Kikinis, R 2002, 'Recognition Deviations from Normalcy for Braintumor Segmentation', Springer, vol.2488, pp.388-395.2002

[94] Aaron Lefohn, Joshua Cates & Ross Whitaker, 2003, 'Interactive GPU-Based level sets for 3D Brain Tumor Segmentation'.2003

[95] Zhou, J, Chan, KL, Chong, VFH & Krishnan, SM 2005, 'Extraction of Brain Tumor from MR Images Using One- Class Support Vector Machine', Proceedings of the 2005 IEEE Engineering in Machine and Biology ,27th Annual Conference, pp.6411-6414.2005

[96] Karnan, M & Selvanayaki, K 2010, 'Improved Implementation of Brain MR Image Segmentation using Meta Heuristic Algorithms', IEEE International Conference on Computational Intelligence and Computing Research,pp.28-29.

[97] Xu-Lei Yang, Qing Song, Yue Wang, Ai-Ze Cao & Yi-Lei Wu 2008, 'A Modified Deterministic Annealing Algorithm for Robust

Image Segmentation', Journal of Mathematical Imaging and Vision, vol.30, no. 3, pp.308 - 324.2008

[98] Albert Law, KW, Law, FK, Francis Chan, HY 2002, 'A Fast Deformable Region Model for Brain Tumor Boundary Extraction', Engineering in Medicine and Biology', Proceedings of the Second Joint 24th Annual Conference and the Annual Fall Meeting of the Biomedical Engineering Society (EMBS/BMES) Conference, vol.2, pp.1055-1056.2002

[99] Azadeh Yazdan - Shahmorad, Hamid Soltanianzadeh & Reza Zoroofi, A 2004, 'MRSI– Braintumor characterization using Wavelet and Wavelet packets Feature spaces and Artificial Neural Networks', Engineering in Medicine and Biology Society, 26th Annual International Conference of the IEEE, vol.1, no.1-5 pp.1810-1813.2004

[100] Xiangyang Wang, Jie Yang, Richard Jensen & Xiaojun Liu 2006, Rough set feature selection and rule induction for Prediction of malignancy degree in brain glioma', Elsevier on Computer Methods and Programs in Biomedicine ,vol.83,no.2,pp. 147-156.2006

[101] Jan Luts, Arend Heerschap, Johan Suykens, AK & Sabine Van Huffel 2007, 'A Combined MRI and MRSI based Multiclass System for brain tumor recognition using LS-SVMs with class probabilities and feature selection', Elsevier, Artificial Intelligence in Medicine, vol.40, no. 2, pp. 87-102.2007

[102] Woods, K., Doss, C., Bowyer, K., Clarke. L. and Clark, R. "A neural network approach to microcalcification detection," IEEE 1992 Nuclear Science Symposium and Medical Imaging Conference, Orlando, FL, pp. 1273–1275, 1992.

[103] Woods, K.S., Doss, C.C., Bowyer, K.W., Sulk, J.L., Probe, C.E., and Kegelmeyer, W.P. "Comparative evaluation of pattern recognition techniques for detection of microcalcifications in mammography," International journal on Pattern Recognition and Artificial Intelligence, Vol. 7, pp. 1417–1436, 1993.

[104] Caldwell, C.B., Stapleton S.J. Holsworth. and Jong, R.A. "Characterization of mammographic parenchymal pattern by fractal dimension," Phys. Med. Biol., Vol. 35, No. 2, pp. 235–247, 1990.

[105] Nishikawa, R.M., Giger, M.L., Dio, K., Vyborny, C.J. and Schmidt, R. A. "Computed-aided detection of clustered microcalcifications: An improved method for grouping detected signals," Med. Phys., Vol. 20, no. 6, pp. 1661–1666, 1993.

[106] Nishikawa, R.M., Giger, M.L., Dol, K., Vyborny, C.J. and Schmidt, R. A. "Computer-aided detection of clustered microcalcifications on digital mammograms," Med. Biol. Eng. Computer, Vol. 33, No. 2, pp. 174–178, 1995.

[107] Nishikawa, R.M., Jiang, Y., Giger, M.L., Doi, K., Vyborny, C.J., and Schmidt, R.A. "Computer-aided detection of clustered microcalcifications," Proceedings of the IEEE International Conference on Systems, Man and Cybernetics, pp. 1375–1378, 1992.

[108] Nishikawa, R.M., Jiang, Y., Giger, M.L., Vyborny, C.J., Schmidt, R.A. and Bick, R. "Characterization of the mammographic appearance of microcalcifications: applications in computer-aided diagnosis," SPIE Image Process, Vol. 1898, pp. 422–429, 1993.

[109] Dhawan, A.P., Chitre, Y., Bonasso, C. and Moskowita, M. "Analysis of mammographic microcalcifications using grey-level image structure features," IEEE Trans. Med. Imag., Vol. 15, No. 3, pp. 246–259, 1996.

[110] Guido Gerig, Marcel Prastawa, Wili Lin & John Gilmore 2004, 'Assessing Early Brain Development in Neonates by Segmentation of High-Resolution 3T MRI', vol. 2879, pp. 979-980, MICCAI.2004

[111] Glotsos, D, Spyridonos, P, Petalas, P, Cavouras, D, Zolota, V, Dadioti, P, Lekka, I & Nikiforidis, G 2003, 'A Hierarchical Decision tree classification scheme for brain tumor astrocytoma grading using Support Vector Machines', Proceedings of the 3rd international Symposium on Image and Signal Processing and Analysis.

[112] Hongmin Cai, Ragini Verma, Yangming Ou, Seungkoolee, Elias Melhem, R , & Christos Davatzaikos 2007, Probabilistic Segmentation of brain tumors Based on Multi-Modality Magnetic Resonance Images', IEEE International Symposium on Biomedical Imaging (ISBI).2007

[113] Devos, A, Simonetti, AWV, Graaf, M, Lukas, L, Suykens, JAK, Vanhamme, L, Buydens, LMC, Heerschap, A & Van Huffel, S 2005, 'The use of multivariate MR imaging intensities versus metabolic data from MR classification', Elsevier Journal of Magnetic Resonance, vol.173, no. 2, pp.218-228.2005

[114] Warfield, SK, Michael Kaus, Ferenc Jolesz, A & Ron Kikinis 2000, 'Adaptive, template moderated, spatially varying statistical classification', Science Direct on Medical Image Analysis, vol. 2, no.1, pp. 43-55.2000

[115] Devos, A, Lukas, L, Simonetti, AW, Suykens, JAK, Vanhamme, L, van der Graaf, M, Buydens, LMC, Heerschap, A & Van Huffel, S 2004, 'Does the combination of Magnetic Resonance Imaging and Spectroscopic Imaging improves the classification of brain tumours', Proceedings of the 26th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, pp. 407-10.2004

[116] K Thangavel, M Karnan, R Sivakumar, AK Mohideen, "Automatic detection of microcalcification in mammograms-a review", International Journal on Graphics, Vision and Image Processing, 5 (5), 31-61 2005

[117] K Thangavel, M Karnan, A Pethalakshmi, "Performance analysis of rough reduct algorithms in mammogram", International Journal on Global Vision and Image Processing 5 (8), 13-21, 2005

[118] K Thangavel, M Karnan, R.SivaKumar, AK Mohideen, "Segmentation and classification of microcalcification in mammograms using the ant colony system", International Journal on Artificial Intelligence and Machine Learning, 5 (3), 29-40, 2005.

[119] K Thangavel, M Karnan, P Jeganathan, A Petha Lakshmi, R Sivakumar, G Geetharamani, "Ant colony algorithms in diverse combinational optimization problems-a survey", International Journal on Automatic Control and System Engineering 6 (1), 7-26, 2006

[120] K Thangavel, P Jaganathan, A Pethalakshmi, M Karnan, "Effective classification with improved quick reduct for medical database using rough system", BIME Journal 5 (1), 7-14, 2005

[121] M Karnan, K Thangavel , "Automatic detection of the breast border and nipple position on digital mammograms using genetic algorithm for asymmetry approach to detection of microcalcifications", Computer methods and programs in biomedicine 87 (1), 12-20, 2007

[122] K Thangavel, M Karnan , "CAD system for Preprocessing and Enhancement of Digital Mammograms", International Journal on Graphics Vision and Image Processing 5 (9), 69-74, 2005

[123] K Thangavel, M Karnan, "Computer aided diagnosis in digital mammograms: detection of microcalcifications by meta heuristic algorithms", GVIP Journal 5 (7), 41-55, 2005

[124] K Thangavel, M Karnan, "Automatic Detection of Asymmetries in Mammograms Using Genetic Algorithm International Journal on Artificial Intelligence and Machine Learning 5 (3), 55-62, 2005

[125] T Logeswari, M Karnan, "An Improved Implementation of Brain Tumor Detection Using Segmentation Based on Hierarchical Self Organizing Map", International Journal of Computer Theory and Engineering, 2 (4), 1793-8201, 2010

[126] T Logeswari, M Karnan, "An improved implementation of brain tumor detection using segmentation based on soft computing" , Journal of Cancer Research and Experimental Oncology 2 (1), 006-014, 2010

[127] J Jaya, K Thanushkodi, M Karnan, "Tracking algorithm for de-noising of MR brain images", International Journal of Computer Science and Network Security 9 (11), 262-267, 2009

[128] P Jaganathan, K Thangavel, A Pethalakshmi, M Karnan, "Classification rule discovery with ant colony optimization and improved Quick Reduct algorithm" IAENG International Journal of Computer Science 33 (1), 50-55, 2007

[129] M Karnan, R Sivakumar, M Almelumangai, K Selvanayagi, T Logeswari, "Hybrid Particle Swarm Optimization for Automatically Detect the Breast Border and Nipple position to Identify the Suspicious Regions on Digital Mammograms Based on Asymmetries", International Journal of Soft Computing 3 (3), 220-223, 2008

[130] E.Ben George, M Karnan, "MRI Brain Image Enhancement Using Filtering Techniques", International Journal of Computer Science & Engineering Technology, Vol. 3 No. 9, 399-403, 2012

[131] E.Ben George, M Karnan, "Feature Extraction and Classification of Brain Tumor using Bacteria Foraging Optimization Algorithm and Back Propagation Neural Networks", European Journal of Scientific Research, 88 (3), 327-333 2012

[132] EB George, M Karnan, "MR Brain Image Segmentation using Bacteria Foraging Optimization Algorithm", International Journal of Engineering and Technology 4 2012

[133] P Kalyani, M Karnan, “Attribute Reduction using Forward Selection and Relative Reduct Algorithm”, International Journal of Computer Applications 11 (3) 8–12, 2010
[134] Mary Jeyanthi Prem, M Karnan, “Business Intelligence: Optimization techniques for Decision Making”, International Journal of Engineering 2 (8) 1081-1092, 2013
[135] J.Subash Chandra Bose, KRS Kumar, M Karnan, “Detection of Microcalcification in Mammograms using Soft Computing Techniques”, European Journal of Scientific Research 86 (1), 103-122, 2012
[136] K.Rajiv Gandhi, SM Uma, M Karnan, “A Hybrid Meta Heuristic Algorithm for Discovering Classification Rule in Data Mining”, IJCSNS 12 (4), 116 2012
[137] R Sivakumar, M Karnan, “A Novel Evolutionary Approach to Detect Microcalcifications in Mammogram Image”, International Journal of Computer Applications 39 (17), 31-34, 2012.
[138] R Sivakumar, M Karnan, GG Deepa, “An Improved Modified Tracking Algorithm Hybrid with Fuzzy C Means Clustering In Digital Mammograms”, International Journal of Computer Technology and Applications 3 (2) 2012
[139] R Sivakumar, M Karnan , “Detection of Masses in Mammogram Image using Enhanced Artificial Bee Colony Optimization Algorithm”, European Journal of Scientific Research, 88 (1), 89-98, 2012.
[140] R Sivakumar, M Karnan, “Diagnose Breast Cancer through Mammograms Using EABCO Algorithm”, International Journal of Engineering and Technology 4 2012
[141] V.Joseph Peter, M Karnan, “Medical Image Analysis Using Unsupervised and Supervised Classification Techniques, “ International Journal of Innovative Technology and Exploring Engineering, Vol 3, Iss 5, Pp 40-45 (2013)
[142] Neeraja R Menon, M Karnan, R Sivakumar, Brain Tumor Segmentation In MRI Image Using Unsupervised Artificial Bee Colony And FCM Clustering International Journal of Computer Science and Management Research, Vol 2 Issue 5, 2450-2454, May 2013
[143] A Sivaramakrishnan, M Karnan, “A Novel Based Approach for Extraction of Brain Tumor in MRI Images Using Soft Computing Techniques”, Journal of Advanced Research in Computer and Communication Engineering, Vol. 2, Issue 4, 1845-1848, April 2013