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 ii) 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

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>median filter(Lai et al 1989)</td>
<td>This filter can remove the noise without significantly distorting the signal.</td>
</tr>
<tr>
<td>Central Weighted Median Filter (Qian et al 1994)</td>
<td>A CWMF with a large central weight preserves more image detail but suppresses less noise than a filter with a smaller central weight.</td>
</tr>
<tr>
<td>Model-based, scatter function (Highnam et al 1994)</td>
<td>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.</td>
</tr>
<tr>
<td>First derivative and the local statistics (Kim et al 1997)</td>
<td>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.</td>
</tr>
<tr>
<td>Fractal modeling (Li et al 1997)</td>
<td>The key point of fractal modeling is to explore the self-similarity property of images.</td>
</tr>
<tr>
<td>Fuzzy logic (Kovalerchuk et al 1997)</td>
<td>Fuzzy logic has the potential of opening a new and promising direction for effective and early breast cancer diagnosis.</td>
</tr>
<tr>
<td>Wavelet transform, multiscale features (Chang and Laine 1999)</td>
<td>Wavelet transform, multiscale features, Coherence measure and dominant orientation clearly improved discrimination of features from complex surrounding tissue and structure in dense mammograms.</td>
</tr>
<tr>
<td>Filtering tech (Kobatake et al 1999)</td>
<td>This filter output for the tumor is very high and its region is well isolated from its background.</td>
</tr>
<tr>
<td>Region based Enhancement (Ferrari et al 1999)</td>
<td>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.</td>
</tr>
<tr>
<td>Wavelet, Morphological operation (Cordella et al 1999)</td>
<td>Fractal approach compared with the partial wavelet reconstruction and the morphological operation approaches.</td>
</tr>
<tr>
<td>Unsharp Masking, Sobel Operators (Bhangale et al 2000; Enderwich and Tzanakou 1997)</td>
<td>The Unsharp masking method reduces the low frequency information while amplified the high frequency detail.</td>
</tr>
<tr>
<td>Adaptive noise equalization (Veldkamp and Karssmeijer 2000)</td>
<td>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.</td>
</tr>
<tr>
<td>Gaussian smoothing</td>
<td>This method cumulatively modulate the</td>
</tr>
</tbody>
</table>
Table 2.1.a An overview of enhancement techniques for MRI

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>and sub-sampling (Mudigonda et al 2001)</td>
<td>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.</td>
</tr>
<tr>
<td>Quantum noise assumption (Rogova et al 1999)</td>
<td>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.</td>
</tr>
<tr>
<td>Matched filtering (Bocchi et al 2004)</td>
<td>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.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Methods</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oliver et al (2005) Standard Imaging Protocol</td>
<td>MRIs have been acquired in the standard follow-up after surgical resection.</td>
</tr>
<tr>
<td>Jayaram et al (2002) Content Based model, Shape based, Texture based technique, Histogram and Profiling Method</td>
<td>It showed detections of tumor with decrease in pixel count in binary images, increase in image intensity, High numbers of high intensity pixel.</td>
</tr>
<tr>
<td>Elizabeth et al (2005) Pixel Histograms, Morphological Process</td>
<td>It was more robust to noise and it can improve the integrity performance.</td>
</tr>
<tr>
<td>Zu et al (2004) Histogram based(HB), Sub-second imaging technique</td>
<td>Separate brain image, from head image removal of residual fragments such as sinus, cerebrospinal fluid, dura, marrow.</td>
</tr>
<tr>
<td>Gray (1997) Neural Networks, Genetic Programming</td>
<td>Large volume of data processed successfully.</td>
</tr>
<tr>
<td>Mark et al (2005) Statistical Parametric Mapping Method</td>
<td>It is used to align the image properly and it uses left-to-right symmetry to confer robustness to areas of abnormality.</td>
</tr>
<tr>
<td>Farahat et al (2006) Head Model, Finite Difference Time-</td>
<td>It is used to analyse different Tissue types.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Methods</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lim et al (1989) Stripping algorithm</td>
<td>To remove the skull and scalp portions from each axial section.</td>
</tr>
<tr>
<td>Aria et al (2002) Gadolinium-Diethylenetriaminepentaacetic acid (Gd DTPA)Enhancement</td>
<td>Provides additional independent information and improve the accuracy.</td>
</tr>
<tr>
<td>Amini (2003) Prewitt edge-finding filter</td>
<td>This filter enhances the tumor tissue greatly.</td>
</tr>
<tr>
<td>Zhe chen (2003) Morphological Filter</td>
<td>It is used to remove background.</td>
</tr>
<tr>
<td>Dimitris et al (2006) Gabor Filter Bank technique</td>
<td>It is used to remove the tagging lines and enhance the tag-patterned region.</td>
</tr>
<tr>
<td>Hideki et al (1990) V-filter</td>
<td>Enhances the image by smoothing the noise gray level distribution while retaining the edge.</td>
</tr>
<tr>
<td>Salman et al (2005) Region Growing Filter</td>
<td>It is usually convenient to preprocess the image by using a noise reduction filter.</td>
</tr>
<tr>
<td>Sean et al (2001) K-nearest neighbour Algorithm</td>
<td>It generates enhancement data volumes. These are highly correlated with manually defined standard.</td>
</tr>
<tr>
<td>Sonali et al (2012) Median Filter</td>
<td>To Remove noise on the MRI.</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Methods</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gaussian filter, morphological filter,</td>
<td>The weighted difference of Gaussian makes use of the knowledge of the</td>
</tr>
<tr>
<td>conditional thickening (Dengler et al 1993)</td>
<td>approximate size of the spots. It also requires an idea of the inter-spot</td>
</tr>
<tr>
<td>Adaptive thresholding, MRF model-based</td>
<td>An MRF model-based segmentation belongs to partitional clustering, but it</td>
</tr>
<tr>
<td>method, fuzzy binary decision tree (Li et al</td>
<td>also has the ability to model image joint distributions in terms of local</td>
</tr>
<tr>
<td>1995)</td>
<td>spatial interaction.</td>
</tr>
<tr>
<td>Fractal (Li et al 1997; Li et al 1996)</td>
<td>Mammograms possess structures with high local self-similarity that is the</td>
</tr>
<tr>
<td></td>
<td>basic property of fractal object. However, the computation time is high.</td>
</tr>
<tr>
<td>Metaheuristic algorithm [Thangavel et al</td>
<td>Mammogram image analysis using metaheuristic algorithm. Ant Colony</td>
</tr>
<tr>
<td>2005, 2006]</td>
<td>algorithm and genetic algorithm is used to detect the microcalcification</td>
</tr>
<tr>
<td></td>
<td>in digitized mammogram.</td>
</tr>
<tr>
<td>Region growing approach, Surrounding region</td>
<td>Works best when the region homogeneity criterion is easy to define. It</td>
</tr>
<tr>
<td>dependency (Kim et al 1998)</td>
<td>depends on the selection of seed region and the termination conditions.</td>
</tr>
<tr>
<td>Top-hat, Morphological filters with multi-</td>
<td>When using the multi-scale and multi-structuring elements, the results</td>
</tr>
<tr>
<td>scale and Multi elements [Mossi and Albiol</td>
<td>are not affected by the complex background and the extracted images are not</td>
</tr>
<tr>
<td>1999]</td>
<td>distorted much.</td>
</tr>
<tr>
<td>Histogram thresholding, MRF (Peters and</td>
<td>It does not need a prior information for the histogram thresholding of the</td>
</tr>
<tr>
<td>Skowron 2004)</td>
<td>image and can be used widely work very well with low computation</td>
</tr>
<tr>
<td></td>
<td>complexity.</td>
</tr>
<tr>
<td>Fuzzy logic (Cheng et al 1998; Cheng et al</td>
<td>Due to variable shapes of masses, it is best to use fuzzy rules to perform</td>
</tr>
<tr>
<td>1998; Cheng et al 2004)</td>
<td>approximate inference. However, the determination of fuzzy membership is</td>
</tr>
<tr>
<td>ACO [Subash Chandra Bose et al 2012]</td>
<td>not easy.</td>
</tr>
<tr>
<td>Meta Heuristic Algorithm [Rajiv Gandhi et al</td>
<td>A Hybrid Meta Heuristic Algorithm for Discovering Classification Rule in</td>
</tr>
<tr>
<td>2012]</td>
<td>medical Data Mining.</td>
</tr>
<tr>
<td>Enhanced Artificial Bee Colony Optimization</td>
<td>Early Breast cancer detection through Mammogram Image using Enhanced</td>
</tr>
<tr>
<td>FCM [Joseph Peter and Karnan 2013]</td>
<td>Medical Image Analysis Using Unsupervised and Supervised Classification</td>
</tr>
</tbody>
</table>

Table 3.1a. An overview of segmentation techniques for MRI

<table>
<thead>
<tr>
<th>Methods</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Genetic Algorithm (karnan and logeswari)</td>
<td>It segment tumor region from background MRI.</td>
</tr>
<tr>
<td>Fuzzy C-means (FCM) unsupervised clustering</td>
<td>It extracts the image edges robustly and moves the vertices towards the</td>
</tr>
<tr>
<td>(Philips et al 1995)</td>
<td>boundaries of the desired structure.</td>
</tr>
<tr>
<td>Supervised k-nearest neighbor (KNN) rule,</td>
<td>A sample set of pixel vectors (ROI) is selected by an expert observer, and</td>
</tr>
<tr>
<td>semi-supervised fuzzy c-means (SFCM)</td>
<td>the vectors are assigned to different tissue classes.</td>
</tr>
<tr>
<td>(vaidyanathan et al 1997)</td>
<td></td>
</tr>
<tr>
<td>Level set Surface Model (james et al 2000)</td>
<td>To produce qualitative results from several different datasets for brain</td>
</tr>
<tr>
<td></td>
<td>tumor segmentation.</td>
</tr>
<tr>
<td>Fuzzy C Means Clustering Algorithm (SR</td>
<td>To segment tumor regions from background MRI well.</td>
</tr>
<tr>
<td>Karnan 2005)</td>
<td></td>
</tr>
<tr>
<td>Seed Growing Method (997)</td>
<td>Seed propagation was independently performed.</td>
</tr>
<tr>
<td>Genetic Algorithm (Thangavel and karnan</td>
<td>To segment and identify nipple position from mammogram image.</td>
</tr>
<tr>
<td>2007)</td>
<td></td>
</tr>
<tr>
<td>Pipe line approach, Expectation Maximization</td>
<td>To estimate and processed tumor volume successfully.</td>
</tr>
<tr>
<td>(EM) Algorithm (Jeffrey and soloman 2004)</td>
<td></td>
</tr>
<tr>
<td>Hybrid Deformable model, Meta Morphs model,</td>
<td>It integrates both shape and interior texture, its dynamics are derived</td>
</tr>
<tr>
<td>Novels Shape, Texture Integration, Graphical</td>
<td>coherency from both boundary and region information in a common variational</td>
</tr>
<tr>
<td>Fuzzy C-means Clustering Algorithm (FCM), Neural</td>
<td>It processes seeking the optimal labeling of the image pixels.</td>
</tr>
<tr>
<td>Network Model (shan shen et al 2005)</td>
<td></td>
</tr>
<tr>
<td>Atlas Matching Technique, Finite Element</td>
<td>To simulate the invasion of the GBM in the brain paren chyma.</td>
</tr>
<tr>
<td>Method (FEM)</td>
<td>Description</td>
</tr>
<tr>
<td>-------------</td>
<td>-----------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Artificial Bee Colony [Neeraja et al. 2013]</td>
<td>Brain Tumor Segmentation In MRI Image Using Unsupervised Artificial Bee Colony And FCM Clustering</td>
</tr>
<tr>
<td>Expectation Maximization scheme (EM) [benedicte et.al.2005]</td>
<td>Its performance is below than Semi-Automated.</td>
</tr>
<tr>
<td>Automatic Two - dimensional Segmentation. [Zhen Chen et al.2003]</td>
<td>Each PET plane is segmented.</td>
</tr>
<tr>
<td>Texture Features, Self-Organizing Map (SOM) [logeswari and karnan 2010]</td>
<td>The tumor area is segmented from brain MRI.</td>
</tr>
<tr>
<td>Morphological Operations, Fuzzy model of Regions of Interest (ROI) [jing et al.2001]</td>
<td>It is use to represent more appropriately the knowledge about distance, shape and interactions of structures.</td>
</tr>
<tr>
<td>Fuzzy C-means [Philips et al.1995: styal et.al.2005]</td>
<td>To generate segmentation images that display clinically important neuroanatomic tissue and neuropathologic tissue contrast information from raw MR image data.</td>
</tr>
<tr>
<td>Amanpreet (2012)</td>
<td>To segment and dedact suspicious region from background using PSO algorithm based on colony aptitude and provide better result than other parallel algorithm.</td>
</tr>
<tr>
<td>Region-based method, Region growing method, Region-of-interest(ROI), Multi resolution edge detection method, modified region segmentation method [angel et.al.2012]</td>
<td>To segment brain tissue structure from the multi-resolution images are utilized.</td>
</tr>
<tr>
<td>Graph-Based Method, Generative Model, Weighted Aggregation Algorithm [jasoncary 2006]</td>
<td>It Indicates the benefit of incorporating model-aware affinities into the segmentation process for the difficult case of brain tumor</td>
</tr>
<tr>
<td>Iterative Self-Organizing Data Analysis Techniques [ISO DATA], Unsupervised Computer Segmentation Algorithm, Novel Model [Michel Jacob 2001]</td>
<td>Multiparametric ISODATA volume was significantly Identifies.</td>
</tr>
<tr>
<td>Spatio-Temporal Model [Jeffery soloman et al.2006]</td>
<td>The sensitivity and specificity of tumor segmentation using this spatio-temporal model is improved over commonly used spatial or temporal models alone.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Multiscale Method, Multiscale linking Model, Supervised Segmentation Method [naaathan moon et al.2002]</td>
<td>It was shown that the errors are in the order of or smaller than reported in literature.</td>
</tr>
<tr>
<td>Semi-Supervised Fuzzy C-Means Clustering Method, K nearest neighbor (Knn), Gray level thresholding &amp; Seed Growing [SG-SG], Manual Pixel Labelling [GT] [vaithyanathan et al.1995]</td>
<td>This method was achieved good performance and reduction operation time.</td>
</tr>
<tr>
<td>Hybrid level set (HLS) [xie et al.2005]</td>
<td>It provides objective, reproducible segmentations that are close to the manual results.</td>
</tr>
<tr>
<td>Fuzzy Model [webei et.al.2007]</td>
<td>Average Probability of correct detection was found.</td>
</tr>
<tr>
<td>Deformable Model, Med-Volumeter [chunvan et.al.2004]</td>
<td>The target area is segmented under level set frame.</td>
</tr>
<tr>
<td>3D Variational Segmentation Method [dana cobzas et.al.2007]</td>
<td>The tumor area was segmented accurately.</td>
</tr>
<tr>
<td>Fuzzy k-means, GA [maoyang et al.2005]</td>
<td>A thresholding is performed for noise reduction.</td>
</tr>
<tr>
<td>Fuzzy Connectedness &amp; Fuzzy sets [jayaram udupa and punam saha 2003]</td>
<td>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, blurring and other phenomenon related artifacts.</td>
</tr>
<tr>
<td>Expectation-Maximization (EM) [Nathan mano et.al.2002]</td>
<td>It separates WM, GM and CSF from T1 and T2 weighted image.</td>
</tr>
<tr>
<td>Classic snakes, Deformable Contour model [amini et.al.2003]</td>
<td>To segment T1 weighted images of the brain with low contrast structures and discontinuous edges.</td>
</tr>
<tr>
<td>Markov random field model [kabir et al.2007]</td>
<td>Segments obtained with single sequences to that obtained with multiple sequences.</td>
</tr>
<tr>
<td>Generalized fuzzy operator [GFO], Contour Deformable model [leung et.al.2003]</td>
<td>The tumor regions are segmented</td>
</tr>
<tr>
<td>Atlas-based segmentation [pierreyes et al.2005]</td>
<td>Propagation of the labeled structures on to the MRI</td>
</tr>
<tr>
<td>Expectation-Maximization Technique, Robest Estimation, VALMET Segmentation validation tool [marcel et.al.2003]</td>
<td>To segment tumor, edema and ventricles.</td>
</tr>
<tr>
<td>Multi layer segmentation, Automatic region</td>
<td>The original image is segmented into various spatial</td>
</tr>
</tbody>
</table>
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

<table>
<thead>
<tr>
<th>Methods</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Back Propagation Network(BPN), Ant Colony Optimization technique(ACO)</td>
<td>Masses were extracted completely.</td>
</tr>
<tr>
<td>Multi-scale Gabor-type Feature set</td>
<td>Accurate results to be obtained with a relatively small number of training images.</td>
</tr>
<tr>
<td>Deformable region</td>
<td>The model provides fast</td>
</tr>
</tbody>
</table>
Woods et al. 1993 Area under ROC curve 0.929 for Neural Networks

Kim and Park 1999 Multiple expert system


Artificial Bee colony [Mary Jeyanthi Prem and Karnan 2013]

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

<table>
<thead>
<tr>
<th>Methods</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Woods et al. 1993 Binary decision tree</td>
<td>Area under ROC curve is 0.9 for 24 images.</td>
</tr>
<tr>
<td>Woods et al. 1993 Quadratic Classifier</td>
<td>Area under ROC curve is 0.918 for 24 images.</td>
</tr>
<tr>
<td>Cordella et al. 2000 Multiple expert system</td>
<td>The area under the ROC curve is 0.786 for 40 images.</td>
</tr>
<tr>
<td>Caldwell et al 1990</td>
<td>Maximum area 0.86 under ROC.</td>
</tr>
<tr>
<td>Woods et al. 1993</td>
<td>Area under ROC curve 0.935 for 24 images.</td>
</tr>
<tr>
<td>Dhawan et al. 1996</td>
<td>Maximum area 0.76 under ROC for 191 images.</td>
</tr>
<tr>
<td>Kim and Park 1999 Neural Networks</td>
<td>The area under ROC curve is 0.88 for 120 images.</td>
</tr>
<tr>
<td>Woods et al. 1993</td>
<td>Area under ROC curve 0.929 for 24 images.</td>
</tr>
</tbody>
</table>

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

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

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 Characteristic and their performance have been studied and compared.

REFERENCES


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


