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Performance Analysis upon Classification and SVM Based Segmentation

S.Venkata Lakshmi[1] and Dr.J. Janet[2]

[1]Research Scholar, Computer Science and Engineering, Manonmaniam Sundaranar University, Tirunelveli, Tamilnadu, India.
[2]Professor, Computer Science and Engineering, Velammal Engineering College, Chennai, Tamilnadu, India.

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ABSTRACT

Breast cancer is the oldest known type of cancer in humans. In the modern medical science there are plenty of newly devised methodologies and techniques for the timely detection of breast cancer. Most of these techniques make use of highly advanced technologies such as medical image processing. This research study is an attempt to highlight the available breast cancer detection techniques based on image processing and provides an overview about the affordability, reliability and outcomes of each technique. Breast cancer has become a common factor now-a-days. Despite the fact, not all general hospitals have the facilities to diagnose breast cancer through mammograms. Waiting for diagnosing a breast cancer for a long time may increase the possibility of the cancer spreading. Therefore a computerized breast cancer diagnosis has been developed to reduce the time taken to diagnose the breast cancer and reduce the death rate. This paper summarizes the survey on breast cancer diagnosis using various machine learning algorithms and methods, which are used to improve the accuracy of predicting cancer. This survey can also help us to know about several papers that are implemented to diagnose the breast cancer.

1. INTRODUCTION

"Breast Cancer affects one in eight women in their lifetime", a general saying about a malignant tumor that begins in cells of the breast and gets into the surrounding tissues as well. This disease is usually evident in women but men can also get affected from it. Medical research targeting breast cancer is not something new and its roots go back into 16th century. Recent advancement in medical field and more precisely the involvement of information technology in the medical field introduces a new diagnosis mechanism called Medical Image Processing. Medical Image Processing is not only limited to cancer disease, instead it has helped greatly in the diagnosis of different kinds of diseases and it is evident through statistics. With the help of image processing techniques it has become easier to detect tumor from an infected breast and diagnose breast cancer. Early detection can help in proper diagnosis and treatment resulting in minimizing the risk of most unwanted outcome of this disease (death). Medical images are different in nature and need special processing before diagnosis is made. Also there are many different sources (machines) which produce the images of human body parts. A special technique to deal with special kind of images is required thus leading to different categories and mechanisms for diagnosis process. In this research study we have attempted to provide an insight of the available different breast cancer detection techniques and their numerous impacting factors.

2. NEURAL NETWORK TECHNIQUES FOR DIAGONOSIS OF BREAST CANCER

Machine Learning Algorithms

Machine learning, a branch of artificial intelligence, is a scientific discipline concerned with the design and development of algorithms that allow computers to evolve behaviors based on empirical data, such as from sensor data or databases

- Supervised learning.
- Unsupervised learning.
- Semi-supervised learning.
- Reinforcement learning.
- Transduction.
- Learning to learn

Various artificial intelligence techniques have been used to improve the diagnose procedures and to aid the physician's efforts [1], [2]. A neural network is a model that is designed by the way human nervous systems such as brain that process the information. Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. Many neural network models, even biological neural networks assume many simplifications over actual biological neural networks. Such simplifications are necessary to understand the intended properties and to attempt any mathematical analysis. Even if all the properties of the neurons are known, simplification is still needed for analytical purpose. Neural networks are adaptive statistical devices. This means that they can change (synaptic weights) as a function of their performance. In ANNs, all the neurons are operating at the same time, which makes ANN to perform tasks at faster rate.

A. Multilayer Perception (MLP)

MLP is a class of feed forward neural networks which is trained in a supervised manner with the capability to outcome prediction for new data [3]. The structure of MLP is shown in figure 1. An MLP consists of a set of interconnected artificial neurons connected only in a forward manner to form layers. One input, one or more hidden and one output layer are the layers forming an MLP [4]. Artificial neuron is basic processing element of a neural network. It receives signal from other neurons, multiplies each signal by the corresponding connection strength that is weight, sums up the weighted signals and passes them through activation.

B. Radial Basis Function Neural Network (RBFNN)

RBFNN is trained to perform a mapping from an m-dimensional input space to an n-dimensional output space. An RBFNN consists of the m-dimensional input x being passed directly to a hidden layer. Suppose there are c neurons in the hidden layer. Each of the c neurons in the hidden layer applies an activation function, which is a function of the Euclidean distance between the input and an m-dimensional prototype vector. Each hidden neuron contains its own prototype vector as a parameter. The output of each hidden neuron is then weighted and passed to the output layer. The outputs of the network consist of sums of the weighted hidden layer neurons [5]. The transformation from the input space to the hidden-unit space is nonlinear where as the transformation from the hidden-unit space to the output space is linear [6].

C. Probabilistic Neural Networks (PNN)

PNN is a kind of RBFNN suitable for classification problems. It has three layers. The network contains an input layer, which has as many elements as there are separable parameters needed to describe the objects to be classified. It has a pattern layer, which organizes the training set such that an individual processing element represents each input vector. And finally, the network contains an output layer, called the summation layer, which has as many processing elements as there are classes to be recognized [7]. For detection of breast cancer output layer should have 2 neurons (one for benign class, and another for malignant class). Each element in this layer combines via processing elements within the pattern layer which relate to the same class and prepares that category for output [8].

D. Fuzzy- Neuro System

Fuzzy-Neuro system uses a learning procedure to find a set of fuzzy membership functions which can be expressed in the form of if-then rules [9-13]. A fuzzy inference system uses fuzzy logic, rather than Boolean logic[14].Its basic structure includes four main components- a fuzzier, which translates crisp (real-valued) inputs into fuzzy values; an inference engine that applies a fuzzy reasoning mechanism to obtain a fuzzy output; a defuzzier, which translates this latter output into a crisp value; and a knowledge base, which contains both an ensemble of fuzzy rules, known as the rule base, and an ensemble of membership functions, known as the database. The decision-making process is performed by the inference engine using the rules contained in the rule base [15].

E. Generalized Regression Neural Networks (GRNN)

GRNN is the paradigm of RBFNN, often used for function approximations [8]. GRNN consists of four layers: The first layer is responsible for reception of information, the input neurons present the data to the second layer (pattern neurons), the output of the pattern neurons are forwarded to the third layer (summation neurons), summation neurons are sent to the fourth layer (output neuron)[9]. If f(x) is the probability density function of the vector random variable x and its scalar random variable z, then the GRNN calculates the conditional mean E(z\x) of the output vector. The joint probability density function f(x, z) is required to compute the above conditional mean. GRNN approximates the probability density function from the training vectors using Parzen windows estimation [16]. GRNNs do not require iterative training; the hidden- to-output weights are just the target values tk, so the output y(x), is simply a weighted average of the target values tk of training cases xk close to the given input case x. It can be viewed as a normalized RBF network in which there

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is a hidden unit centered at every training case. These RBF units are called kernels and are usually probability density functions such as the Gaussians. The only weights that need to be learned are the widths of the RBF units h. These widths (often a single width is used) are called smoothing parameters or bandwidths and are usually chosen by cross validation.

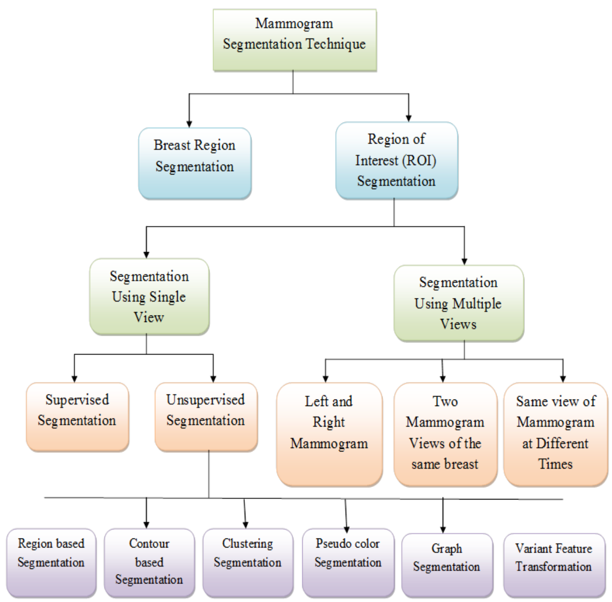

Figure 1: Categorization of mammogram image segmentation techniques

Table1: Performance of neural networks algorithms for detecting breast cancer

S.No	Year	Author	Algorithms/ Techniques used	Result
5	2012	JR Marsilin	SVM	78%
3	2011	F.Paulin, Dr.A.Santhak umaran	Back propagation, Quasi newton, levennberg Marquardt algorithm	99.28%
4	2011	Yao ying huang,wang sen li, Xiaojiao ye	Genetic algorithm, feature selection	99.1%
6	2011	Li Rong,Sunyuan	SVM-KNN classifier	98.06%
15	2011	G. Arulampalam, A. Bouzerdoum,	Shunting Inhibitory Artificial Neural Networks (SIANN)	100%
1	2010	F.Paulin, Dr.A.Santhak umaran	Back propagation algorithm used for training Multilayer Perceptron (MLP)	99.28%
2	2010	Dr.K .Usha rani	Feed forward, Back propagation	92%
10	2010	R. R. Janghel, A. Shukla, R. Tiwari, and R. Kala,	Symbiotic Adaptive Neuro-Evolution (SANE) [30]	98.7%
11	2010	M. Ashraf, L. Kim H. Xu	Information Gain and Adaptive Neuro-Fuzzy Inference System (IGANIFS)	98.24%
14	2010	P. Meesad G. Yen.,	Fuzzy	96.71%
7	2009	S Ozer, MA Haider, DL Langer	RVM	97%
12	2005	V. Bevilacqua, G. Mastronardi F. Menolascina	Xcyct system using leave one out method	90 to 91%
9	2004	T. Kiyan, T Yildirim	Generalized Regression Neural Network (GRNN)	98.8%
13	2003	W. Land, E. Veheggen	Adaptive Neuro-Fuzzy Inference System (ANFIS)	59.90%
8	1999	Yuan-Hsiang Chang BinZheng, Xiao-Hui Wang	Multilayer Perceptorn (MLP)	95.74%

3. SEGMENTATION BASED ON SUPPORT VECTOR MACHINE

A support vector machine (SVM) is a supervised learning method that analyzes data and recognizes patterns, used for classification and regression analysis. The standard SVM takes a set of input data which is of two possible classes' forms the input and predicts, for each given input, making the SVM a non-probabilistic binary linear classifier.

4. RELEVANCE VECTOR MACHINE

Relevance vector machine (RVM) is a machine learning technique that uses Bayesian inference to obtain parsimonious solutions for regression and classification. The RVM has an identical functional form to the support vector machine, but provides probabilistic classification. It is actually equivalent to a Gaussian process model with covariance function. The Bayesian formulation of the RVM avoids the set of free parameters of the SVM (that usually require cross-validation-based post-optimizations). However RVMs use expectation maximization (EM)-like learning method and are therefore at risk of local minima. This is unlike the standard Sequential Minimal Optimization (SMO)-based algorithms employed by SVMs, which are guaranteed to find a global optimum.RVM is used by many authors for

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detecting cancer in human beings. For detecting cancer such as ovarian cancers, optical cancers etc., relevance vector machine is used, which has been proved to give more accurate results than support vector machine.

Crisp K-Nearest Neighbor and Fuzzy C-Means: The intensity discriminations are utilized as a tool for detecting micro calcifications that further develop into a breast tumor 10, 11. Addition of standard deviation and window means to the visual figure helps to improve the segmentation results produced by the knn means 12. The technique mentioned in this paper used two methods and they are supervised (crisp k-nn) and unsupervised (fuzzy c-Means) 13. Both these methods use the physical labeling and clustering of input image by the operator or human14. The unsupervised method segments the breast tissues appearing in digital image in disconnected regions. In K-nn means, breast area is segmented by finding out the Euclidean norm and standard deviation. The unsupervised pixel is set to zero or 255 depending upon the result of K-nn i.e., the result show whether the pixel is a tumor tissue or not.

Vector Quantization:

The method of clustering and texture analysis is also known as vector quantization. This is the method used for segmentation of mammographic images that implement the generation of codebook or training vector by dividing the whole image into small boxes of equal size. The use of Linde Buzo and Grey Algorithm (LBG) for vector quantization is to classify the complete image into training vectors15. After that a centroid is computed and the Euclidean distance is computed between training vectors on the basis of which 8 clusters and a codebook of size 128 are formed. But image constructed using first code vector displayed the result correctly. There were certain other algorithms like Grey level co-occurrence Matrix algorithm (GLCM) 16 and watershed segmentation algorithm that segment the mammograms with 90% accuracy.

Image processing techniques and optimization techniques:

A lot of research has been done for the early diagnosis of breast micro calcifications from the digitalized mammograms by the application of digital image processing techniques and different preprocessing algorithms proposed in different papers. All these papers follow almost the same steps with some difference in techniques. The common steps are preprocessing, segmentation of breast image, feature extraction, tumor segmentation and extracted feature classification. The tracking algorithm is applied to remove the noise that is in the form of X-ray marks from the digital mammographic image. This filtered image is then forwarded to median filter in order to further remove the noise and high frequency components without disturbing the edges. The infected region or a region with micro calcifications is segmented by Markov random field (MRF) hybrid with [17, 18] HPACO algorithm. Threshold or MAP value is computed through MRF. The segmented features are extracted for classification through Dependency Matrix (SRDM) and Grey Level Difference Matrix (GLDM). Receiver operating characteristics (ROC) is evaluated for classification performances. The results have shown that the detection rate of this algorithm is 94.8%.

Tumor Identification through Image Segmentation and 3d Structure Analysis:

There are many sources like mammography and electromagnetic imaging by which we can capture the image for cancer diagnosis. A high resolution mammography is the technique that uses high contrast X-ray system for breast examination. This imaging technique gives a bit inaccurate results in detection and determining the actual stage of tumor resulting in a need to add accuracy if this type of imaging technique is used38. The other technique used for early stage tumor detection is electromagnetic imaging which uses microwave technology and the concept of back scattering from the water content present in the tissues. This technique is further divided into three categories and they are microwave hybrid approach, microwave tomography and ultra wide band radar technique. The previous CAD system that identifies the early stage breast and lungs tumor with the help of image processing and artificial intelligence gives 85%-93.1% accurate results. The enhanced CAD system identifies the early stage tumor with 100% accuracy for both breast and lungs cancer. This proposed system provides the exact size of tumor with the help of image processing and 3D structure analysis. The detection technique needs to be dynamic because of its nature of image problems at the time of detection. For this all types of edge operators applied and the one which gives the ideal result for the particular nature of image is adopted. Next step feature extraction is applied to get the area of tumor and then to calculate this area 3D image reconstruction is used by taking multiple images of the same infected patient from different angles so that a complete tumor image can be reconstructed with the help of

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MATLAB 3D graph utility. Exact size of the tumor is calculated by the summation of 2D segmented pixels and the pixels of tumor thickness. Area calculation of tumor then proceeds towards the stage classification by the proposed CAD system.

Use of Hard Threshold and Multi Wavelet for De-Noising and Enhancement of Image:

Another technique known as multi wavelet with hard threshold is proposed which aims at making better contrast of the digital mammographic images and to remove the noise from these images as much as possible so that physician can do better interpretation on the digital mammograms42. In the preprocessing stage noise equalization process has been used. Previous researches used the technique of discrete wavelet transform (DWT) but it disturbs the image origin. So the multi wavelet approach was used which is flexible but it does not adjust any parameters for image de-noising. Recently the work has been done on this de-noising problem in multi wavelet based approach. Contrast enhancement takes place in preprocessing stage. Fluctuations are contained in all radiological images which make it difficult to detect small structures and abnormalities. Thus contrast of images can be increased by the equation provided in the paper that takes a form of high pass spatial filter. Different methods are proposed for calculating the threshold in image de-noising band in wavelet transform. All those data values are set to zero which are less than the threshold value whereas threshold value is assigned to data values that are greater than it. Area of multi wavelet transform having high frequency undergoes de-noising. At last original image is retrieved by inverse multi wavelet transform. Error is calculated between the original and transformed image for the evaluation of technique. So by experiments it has been proved that the proposed multi wavelet technique produced better results for physicians for diagnosis of breast tumor at the start. And the proposed method has also produced best peak signal to noise ratio (PSNR) value.

Segmentation through Wavelet Transform:

Segmentation of solid nodule lesion of breast can also be done by acquiring the texture information and to accomplish this task 2D wavelet transform (DWT) is computed on the ultrasound image of breast. The phenomenon behind DWT is the decomposition of original image into sub bands i.e., in the higher and lower bands. Each pixel of the original image is searched for 4 features and they are: i. Texture extraction characteristics through 1-D and 2-D DWT algorithm, ii. Threshold value determination through the above texture information, iii. Texture classification, iv. Smoothening of classified region and segmentation in the end. Results have shown that segmentation results were correct most of the times but the proposed algorithm proved to be more successful in case of malignant tissues.

Segmentation of Breast Cancer Masses in Ultrasound Using Signal Derived Parameters of RF And Estimates of Strain:

Ultrasound images consist of speckle and attenuation noise. These images also have varying texture and shape. Due to invasion tumor area in these images lacks a proper boundary. To incorporate all these problems an algorithm for detection of breast cancer and its successful segmentation is proposed, that uses the concept of RF signal parameter with strain estimation in case of moving picture. This paper used the prior residue rp of AR model for power estimation without speckle and attenuation noise in the graph plotted images for the breast masses. The ultrasound moving image is acquired and recorded at some radio frequency and a sampling frequency is adjusted. To minimize shadowing effects from the ultrasound images a filter is applied so that horizontal features can be made prominent.

Automated Segmentation of Ultrasonic Breast Lesions through High and Low Level Empirical Facts:

The processing on ultrasound can detect images up to 100% accuracy and also eliminates the need for needle biopsy. CAD is used for the effectiveness of breast screening after acquiring the image. The technique proposed for breast cancer screening is fully automated that does not require human intervention. The lesion boundary and contours are extracted along with the texture, intensity and shape. Shadowing effects and false positive results in case of fat granular tissue are dealt. The proposed system proved to be robust as it can incorporate changes in the system parameters, training sequence and can also figure out seed point in the lesion. Low level model includes image enhancement by first removing the speckle noise and then enhancing the contrast or sharpening of edges of the lesions. The second major step is lesion intensity and texture classification. The third concern is the seed point determination followed by lesion feature extraction or region growing by estimating the threshold. Segmentation through region growing may separate all the pixels containing tumor. Boundary points are then found on the edges by calculating the directional gradient and drawing the radial lines. The boundary points sometimes consist of maxima that are removed and are known as outliers. Similarly segmentation is

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computed on high level areas and the results are proved to be highly accurate i.e., near to 99.089%. Table 4 compares the techniques applied on microscopic slide images.

Magnetic Resonance Images (MRI):

Mammography is the safest and cheap approach but suffers from the drawback of its low dose and high resolution as a result of which some 3D mass tissues get overlapped. So for this special case, the most suitable and appropriate techniques to diagnose the tumor masses and its classification are: Magnetic resonance (MR) & Computed Tomography (CT).

3D Hidden-Markov Model for Breast Tissue Segmentation and Density Estimation from MR Images:

For breast tissue detection and tumor segmentation 3D hidden Markov model (HMM) is taken in account. Previously in case of mammograms it is explained that 2D hidden Markov random field is applied to estimate density and other features from the mammographic images. According to the algorithm proposed first the background segmentation is performed through automatic edge detection. Due to this edge detection there remains some gaps on the edges for which 20 voxel average filters is applied to the edge detected image for making the edges thick Histograms are then drawn and threshold is estimated. HMM is then applied for tumor segmentation. Images are reconstructed by backscattered filtering. The results proved that HMM is highly robust with low training sequence. HMM segmentation proved to be reliable and accurate for breast tumor segmentation.

Segmentation of Breast Cancer Mass in Mammograms:

Detection of breast cancer at the earliest stage increases the percentage of life to 5years for the infected patient. It has four stages. In the first stage the size of mass varies between 0-2cm and diagnosis at this stage improves the life quality and the 5th year survival rate is 96%. At the last or fourth stage, there may be a need of partial or total removal of breast. At this stage 5 year survival rate drops to 20%. For diagnosis, a computer aided (CAD) system is developed for breast and tumor segmentation. Frequency and spatial domain filters are used for image enhancement. Because of this reason the MRI is much more expensive and having lower resolution as compared to mammography, it is not used for cancer diagnosis at starting stage. The following tables give the detailed comparison of various segmentation techniques and the images. Table2 represents the different diagnosis techniques on infrared images. Table 3 describes the Comparison between different diagnosis techniques on microscopic slide images. Table 4 represents the Comparison between different diagnosis techniques on mammographic images.

Table 2: Comparison between different diagnosis techniques on infrared images

Algorithms/ Techniques	Advantages and characteristics	Limitations
Thermal infrared images	Tumor is diagnosed depending upon the radiation emitted by different body parts	May give false results in case of flat lower part of the breast
Automated image segmentation	Only lower breast part is taken into account and upper body parts are filtered out	-
Artificial Neural Network	BP neural network has been provided with fairly good results of classification and statistical parameters	Careful temperature inspection

Table3: Comparison between different diagnosis techniques on microscopic slide images

Algorithms/ Techniques	Advantages and characteristics	Limitations
Watershed64	Division of image on the basis of discontinuities	More accuracy and validation is needed in case of larger histological slides
Neural Network and morphology	Complete removal of spike noise through morphology	-
Marker controlled Watershed	Success rate is 81.2%	Low success rates as compared to other algorithms

Table4: Comparison between different diagnosis techniques on mammographic images

Algorithms/ Techniques	Advantages & characteristics	Limitations
Digital Mammography	Calcification, circumscribed, speculated and other ill defined masses can be diagnosed	Frequent intensity changes may not give 100% diagnostic results

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K-nn and fuzzy means algorithm10	Change of intensity is used as a discriminating feature	-
Vector quantization	Absence of over and under segmentation	Lot of segmentation areas and information
MRF and HPACO algorithm	Success rate of this algorithm is 94.8%	
Image segmentation with 3D structure analysis37	Exact size and thickness of tumor can be calculated	CAD system has to be combined with the segmentation algorithm to get highest success rate
Multi-wavelet and hard threshold42	Gives good results in case of dense mammograms by noise cancellation	
Screening Mammography	Diagnosis is based on the roughness (between normal and tumor tissues)	

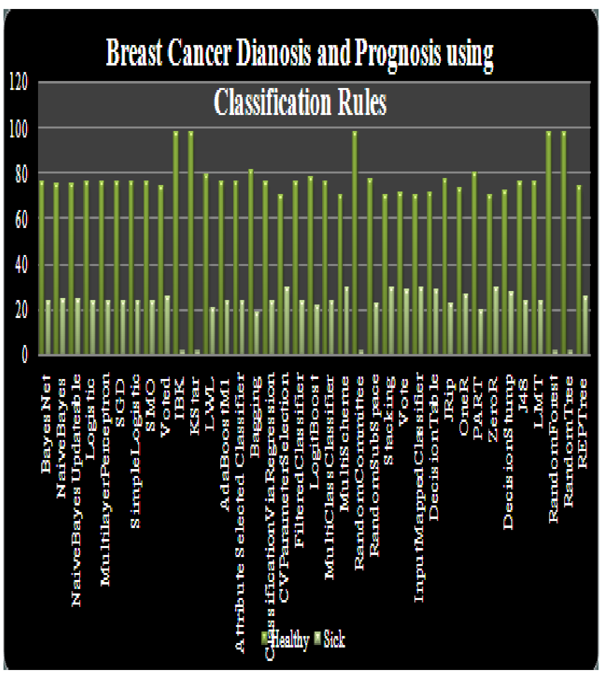

Figure 2: Breast cancer classifier performance Analysis

5. CONCLUSION

This survey paper overviewed the techniques and algorithms proposed for the detection and for interpreting its stage in some cases so that proper treatment can be given to the cancer patient for improving his life quality. Digital mammography technique is widely used in early stage breast cancer diagnosis but due to its negative effects on human body other safe techniques like infrared imaging, MRI, Biopsy are also proposed. The most accurate imaging techniques is Mammography. The figure 2 also represents the performance analysis cancer with various data mining rules. The last decade has witnessed major advancements in the methods of the diagnosis of breast cancer. It was found that the use of ANN increases the accuracy of most of the methods and reduces the need of the human expert. The neural networks based clinical support systems provide the medical experts with a second opinion thus removing the need for biopsy, excision and reduction of unnecessary expenditure.

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