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Computerized Cancer Detection and Classification Using Ultrasound Images: A Survey

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Abstract:- Cancer is the leading cause of death for human being in worldwide, because the cause of the disease is unknown and the early detection of cancer is also tedious. To save the people around world many diagnosis and treatment techniques was developed. In medical image processing ultrasound images is the most popular development area. The key point ultrasound image is referred as the detailed study of imaging function and structure of the image in the real world entity. Ultrasound imaging techniques is one of the tools to diagnose the cancer and to detect and identify the malignant and benign tissue in the human body. To improve the treatment of cancer computerized ultrasound screening techniques are used.

Keywords:- Ultrasound, Prostate Cancer, Breast Cancer, Cervical Cancer, Ovarian Cancer.

I. INTRODUCTION

Cancer is the public health problem for men and women in this century. According to the survey more than 8% of women will affect breast cancer [1][2][150]-[153], 29% of men will affect prostate cancer [3][4][5][6][7], 31% of women will affect cervical cancer [8] and 70% of women will affect ovarian cancer [9]. Since the causes of cancer still remain un-known, better treatment can be provided to detect from the early stage [10][11][12][13][14]. The most modality for detecting the diagnosing is mammography [10] [15] [16]. To the low specificity mammography many biopsy operations are used [17][18][19]. Currently one of the best alternative method is called ultrasound imaging technique, and it will show cancer detection[20][21][22][23][24].According to the survey showed that more than one out of every four researches using ultrasound images. It provided accuracy results [25]. Ultrasound techniques are more convenient and safer than mammography [26].It is also cheaper than mammography. Different countries and continents used for ultrasound [27][28].ultrasound are more sensitive [29][30] and faster method. Hence it is valuable for people than 35 years of age [31].Elastography is an automatic method for measuring the elasticity of tissue based on analysis of ultrasound tissue compression [32][33][34].Recently developed some of the computerized approaches [35] used for ultrasound imaging.

This survey focuses different approaches for breast [36], prostate [37], cervix [8], and ovarian [9] cancer detection and classification method for Ultrasound images. Usually this involves four stages. From these stages we can evaluate the result, which is shown in figure 1.

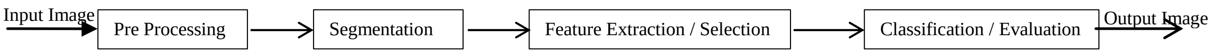

Fig.1. Computerized system for cancer detection and classification

1) **Image preprocessing:** Ultrasound images are affected by noise such as speckle noise [38][39],impulse noise[40],multiplicative noise[40].To suppress the noise some filtering techniques [40][41][42] , wavelet domain techniques[43]-[45][46][47][48] and de-speckling methods[49] are used.
2) **Image Segmentation:** This method sub categories the image into number of small portions and differentiate the object from the background [50].
3) **Feature extraction and selection:** This stage we extract some features from normal tissue and abnormal cancer tissue. So extracting and selecting some essential features is very needful for classification. The survey features are listed in table 11.
4) **Classification**: After the feature extraction we classify the tissue we decide and make a conclusion of normal and abnormal.

In computer processing system only the texture features are used as inputs [26][51].

II. PRE-PROCESSING

The pre-processing of breast, prostate, cervix and ovarian ultrasound images consists of noise reduction and image enhancement. Speckle in the form of noise generated by a number of scatterers [52] with random phase within the resolution cell of ultrasound beam [40]. Many speckle reduction techniques are listed in table 1 and the noise reduction techniques advantages and disadvantages are listed in table 2.

Table1 Speckle Reduction Techniques

cancer	Noise	Reduction Techniques	Methods
Breast cancer	Speckle noise[38] Multiplicative noise[40]	Filtering methods[40]-[42]	1. Linear filter[57] 2.Nonlinear filter(order statistic filter[40]

	Impulse noise[40]	Wavelet domain techniques[43]-[48]	1.Wavelet shrinkage[43][58] 2.Wavelet de-speckling under Bayesian framework[46][47][44][48][45][59] 3.Wavelet filtering and diffusion: Wiener filter[38]
		Compounding approaches[56]	Spatial compounding[56]
Prostate cancer	Speckle noise[39] White Gaussian noise[49]	Filtering methods[60][61]	Nonlinear filter: Median filter[62]
		De-speckling method[49][68]	1.Wavelet method[63][64] 2.Computation method[65] 3.Least square method[66] 4.Structural based approaches[67] 5. Novel Monte Carlo de-speckling algorithm[68]
Cervical cancer	Speckle noise[8]	Filtering method[69]	Linear filter: Low pass filter[70]
Ovarian cancer	Speckle noise[71]	Wavelet based Techniques[72]	Thresholding algorithm[71]

Table 2 Comparison of different noise reduction techniques

cancer	Method	Description	Advantages	disadvantages
Breast	Filtering methods[40]-[42]	Reduce speckles	Simple an speed	Single representation is difficult to differentiate signal from noise
	Wavelet domain techniques[43]-[48]	Remove noise by modifying the wavelet co-efficient	Statistic soft the signals are simplified	DWT and IDWT computations increase time complexity
	Compounding approaches[56]	Average images are obtained	Noise and signals are processed at different scales	Need hardware support. Increase time complexity and reconstruction
prostate	Filtering method[60][61]	Reduce speckles	Simple and faster	Single representation is difficult to differentiate signal from noise
	De-speckling method[49][68]	Remove multiple and additive noise	Better performance and faster	Difficult to identify abnormal tissue pattern
cervix	Filtering method[69]	Reduce speckle	Faster convergence rate	Difficult to identify abnormal tissue pattern
Ovarian	Wavelet based techniques [72]	Reduce speckle	Reduce image contrast, detailed resolution	Difficult to identify abnormal tissue pattern

2.1 Filtering techniques

All the filters are spatially in nature. It can be divided into linear and nonlinear filters.

a) Linear filters

Adaptive mean filter (AMF): To eliminate the blurring effect we used AMF. The Lee [53], Kuan [54] and frost [55] filters are well known examples of adaptive mean filters.

Low pass filter: It is used to reduce speckle noise and blurring the edges [70]. The stick techniques are used to reduce the noise and improve the edge information. They use the linear projection operation.

b) Non Linear Filters:

Order Statistic Filter: This filter reduces noise. The median filter is one of the order statistic filters. It preserves the edge sharpness and produce less blurring than median filters [40], specifically it is effective but most of the Ultrasound image is affected by impulse noise.

2.2 Wavelength Domain Techniques

The discrete Wavelength transform (DWT) [63][64] translate the image into sub band consisting of a set of details sub band orientation and resolution scale wavelet coefficient [73]. It is a best method for separating noise from an image.

Wavelet Shrinkage:

It is based on thresholding [71]. It suppresses the coefficient noise and enhances the image features. The drawback of thresholding methods is choice of threshold is usually done manual.

Wavelet de-speckling under Bayesian network

It contains Bayesian rules [44]-[48][59] here we apply the Wavelet coefficient statistics. This approach assumes that p is a random variable with PDF. The two sided generalized Nakagami Distribution (GND)[48][74]-[77] is used to model the speckle wavelet coefficient or modelled by generalized Gaussian distribution (GGD). The disadvantage of Wavelet de-speckling under Bayesian network is that is relies on prior distribution of the noise free image.

Wavelet filtering and diffusion

This method is used to reduce speckle noise [38]. Wiener filtering is applied in the wavelet domain [[63][64]. Different speckle images in the image domain and wavelet domain is presented [63][64].It compared wavelet coefficient shrinkage and several standard filters [Lee, Kuan, Frost, Geometric, Kalman, Gamma etc]. The disadvantage of wavelet based de-speckling method is the time complexity is increased during transform operations.

2.3 Compounding approaches

In this method we produced several images of the same region that are partially correlated or non- correlated and averages to form single image. 3D spatial compounding is adopted to reduce speckle noise in 3D ultrasound images [56].

2.4 De-speckling methods:

Contrast ultrasound diffusion:
The accuracy of parameter distribution[155][156] is determined by temporal characteristics of IDC noise [157][158].

Computation method

Geometric based diffusion techniques are used to reduce speckle and improve the Transrectal ultrasound image [65]. Order statistics filtering approach is used for computation technique.

Least square method:

It is an effective method to suppress the speckle and we get the anatomical characteristics of an image [66].

Structural based approaches:

It is based on boundary enhancement and reduced speckle noise for the Ultrasound images. From this we extract the structural features such as contour, line and boundary detection [66].

Monte Carlo de-speckling algorithm:

The novel Monte Carlo de-speckling algorithm [86] provides image acquisition particularities specifically noise statistics of TRUS images, it allowing better speckle noise suppression.

To measure the performance of the TRUS image applied signal to noise ratio (SNR), contrast to noise ratio (CNR) and edge preservation(α)

$SNR\ (f_0)=10\ \log10(var(f_{ref})/var(f_0-f_{ref}))$

f_{ref} → variance of the reference speckle free log envelope image, f_0-f_{ref} → noise variance

$CNR=1/R\{\sum_{k=0}^{n}(Ub - Un)/\sqrt{rn^2+rb^2}\}$

Ub, rb^2 → Mean and variance of prostate region, Un, rn^2 → mean, variance of the nth region

$\alpha=\{\sum(£^2fref-£^{2'}fref)(£^2fo-£^{2'}fo)\}/\{\sqrt{\sum(£^2fref-£^{2'}fref)^{2.}\sum(£^2fo-£^{2'}fo)^{2.}}\}$

$£^2fref$, $£^2fo$ → laplacian operator on reference speckle free log envelope image and reconstruction speckle free log envelope image, $£^{2'}fref$, $£^{2'}fo$ → mean value

Performance measures for different filters SNR, CNR and α are shown in table 3

Table 3 Performance measures for different filters SNR, CNR and α

Method	S-SNR (dB)	CNR (dB)	α
Original	13.75	3.69	N/A
Adaptive median filter	16.92	5.39	1.40
Enhanced Frost	19.64	7.01	1.56
Wavelet	17.94	6.06	1.61
Despeckling method	22.84	9.68	1.98

2.2 Image Enhancement

As stated in the beginning of the pre-processing section, many methods enhance the image and remove speckle at the same time. A contrast enhancement algorithm based on Fuzzy logic and characteristics of ultrasound images [84] were proposed. Experimental results show that methods could effectively enhance the image details without over or under enhancement.

III. SEGMENTATION

In segmentation methods [85][86][149] divide the image into number of small segments. The goal of segmentation is to identify the correct areas and to analyse the diagnosis. This method provides neural network segmentation [87]. The different segmentation methods are listed in table 4.

Table 4 Different segmentation methods

cancer	Segmentation	Techniques
Breast	Active contour model[88]-[91]	Level set method[88]
	Markov random field[92][93]	Iterative segmentation technique[92][93] Gibbs random field method[92]
Prostate	Information tracking method[94][95]	Level set method[94][96][97]
	Classical approach[87]	Supervised machine learning approach[87][98]
Cervix	Histogram thresholding[8]	Threshold value: optimal threshold, gray level threshold variation[8]
	Region based segmentation[8]	Range selection[8]
Ovarian	Unsupervised segmentation[99]	Biomarkers[99]

Active Contour Model

It is an edge based segmentation method .This approach minimizes energy associated with current contour as the sum of the internal and external energies. Level set method [88] is employed to improve the active contour segmentation for ultrasound images.

Markov Random Field (MRF)

Markov random field model has been used for US image segmentation [92][93].The algorithms based on Markov random filed and Gibbs Random field [92] was adapted to segment the US images.

Information tracking method

The ultrasound image u(x) to be scalar function in the subset of R^2.M to be the map which transforms u(x) into its corresponding feature image I(x)=M[u(x)], it can be viewed using a vector valued image[85].

Classical approach

It is an essential tool for segmentation. It is used to classify the pixel inside and outside of the prostate gland [87].

Histogram Thresholding

Histogram thresholding [100] is one of the widely used techniques for monochrome image segmentation [101]. Histogram thresholding was proposed for segmenting US images [102].

Region based segmentation:

In cervical cancer we use a region based method to segment the left part of the cervical ultrasound image where the internal os is located. A gray level value is selected from the histogram of the image.

The advantages and disadvantages of various segmentation methods are represented in table 5.

Table5 Advantages and disadvantages of various segmentation methods

cancer	Methods	Descriptions	Advantages	Disadvantages
Breast	Active contour model[88]-[91]	Deformation mode is utilized	Extract lesion with different shape	Slow and repetition process
	Markov random field[92][93]	Based on intensity statistics	Accurate	Complex and time consuming
Prostate	Information tracking method[94][95]	Tracking the features	Maximum accuracy and efficiency	complexity
	Classical approach[87]	Classify the image pixel	Extract the cluster the features	over segmentation done by this method
Cervix	Histogram thresholding[8]	Segment the image based on threshold value	Simple and speed	Not get the better result
	Region based segmentation[8]	Segment the image based on the range value	Common findings of variable size collection and a proximal region	Segmentation results many disconnected areas
Ovarian	Unsupervised segmentation[99]	Predict the prognosis and segment vascular stained region	Effectively and accurately segment the region	To represent hierarchical data it takes more time.

IV. FEATURE EXTRACTION AND SELECTION

Feature extraction and selection [154] are important steps in cancer detection and classification. Textures extracted from the RF series [103] and neural network classifiers used for detection of prostate cancer [103].In the cervical cancer most of the edge detection algorithms use a linear projection operation. To extract some features such as geometric, statistical, texture and histogram features [104][105].In ovarian cancer feature selection algorithms are applied for the two data sets and increase the classification accuracy. To evaluate the reduction and feature selection [96] techniques used simple classifier. The survey features are listed in table 6.

Table 6 Feature extraction and selection methods

Cancer	Feature	Description
Breast	Texture features(TF)	TF1: Auto Covariance coefficient[26][51][55]
		TF2: Block difference of inverse probabilities(BPID)[51]
		TF3: Block variance of local correlation coefficient(BVLC)[51]
		TF4: Mean and variance of order statistics after wavelet decomposition[106]
		TF5: Auto correlation in depth of R(COR)[107][108][109]
		TF6: Posterior acoustic behavior, minimum side difference (MSD) or Posterior Acoustic Shadow[25][107][109]-[111]
		TF7: SGLD matrix based features: Correlation, energy, entropy, sum entropy, difference entropy, inertia and local homogeneity[[26][112]
		TF8: GLD matrix based feature: Contrast, mean ,entropy, inverse difference moment and angular second moment[26]
		TF9: Fractal and dimensional related features[112]-[115]
		TF10:entropy(ENT), Contrast(CON), Sum average(SA), Sum entropy(SENT)[116]
	Morphologic features(MF)	MF1: Spiculation[109][117]
		MF2: Depth to width ratio and width to depth ratio[25][107][109] [111] [118][119][120]
		MF3: Number of lobulations [109][110][121][122]
		MF4: Margin sharpness[123]
		MF5: Margin echogenicity[123]
		MF6: Angular variance in margin[123]
		MF7: Area of lesion[110][120]
		MF8: Normalized radial gradient along the margin[107][109][111]
		MF9: Margin circularity[110]
		MF10: Degree of abrupt interface[121]
		MF11: Angular Characteristics[121]
		MF12: Tumor contour: shape, orientation, margin(tumor circularity, standard deviation, area ratio, roughness index)[124]
	Descriptor Features(DF)	DF1: Non circumscribed or spiculated image[25][31][118]-[120][125][126]
		DF2: Shape(round, oval or irregular)[25][31][118][119][125][126]
		DF3: Presence or calcifications[25][118][125][126]
		DF4: Posterior shadow[118][119][126]
		DF5: Decreased sound transmission or acoustic transmission[31]

		DF6: Echogenecity[31][118][120][126] DF7: Heterogeneous echo texture[118][120][125][126] DF8: Thickened cooper ligaments[120] DF9: Distortion echogenic halo or rim of surrounding tissue[31][118] DF10: Micro lobulation[118]
Prostate	Spectral Features RF(RF)	RF-RF4->average value normalized spectrum Low, mid low, mid high, high RF5->intercept RF6->lope of line
	Fractal Features(FF)	Higuchi's algorithm: Mean Length(max=16)[127][128]
	LF Features (Lizzi, Feleppa)(LF)	LF1,LF2,LF3[53] Zero frequency, average lobe, mid band value LF and RF features: Spectral analysis, sliding hamming window[129]
	Textual Feature(TF)	TF1: Statistical Feature: Mean, Standard deviation, skewness, Kurtosis[103] TF2: Coherence Matrix: Correlation, energy, contrast, homogenity[103] TF3: ROI: Color Map[129]
	Morphologic features(MF)	Shape priors, principal component analysis(PCA)[130]
Cervical cancer	Geometric features(GF)	Primitive features: corners, edges[8]
	Texture features(TF)	Parameter control function: computer vision, range, average distance, stick size[8]
	Statistical features(SF)	Mean, Standard mean error or percentage[131]
	Histogram features(HF)	Bonferroni approach: pair-wise comparison, Correlation co-efficient Contrast, tumor range, tumor volume, vascularization index(VI),flow index(FI), Vascularization flow index(VFI)[131]
Ovarian Cancer	Statistical Features(SF)	Mean, standard deviation[132]
	Morphologic tumor indexing features(MTI)	Find observer variation, Morphological scoring system[133]-[136]
	Morphologic features(MF)	Wall structure ,cyst wall thickness, septation, echogenecity[137]
	Structural Features(STF)	Ovarian volume, cyst wall septae[138]
	Multiple Regression features (MRF)	Weighted scoring[138]

Texture Features

Texture is the basic and traditional techniques [139]. In breast and prostate cancer the texture is used for tissue analysis [94][103].In cervical cancer a parameter control function is used to measure the adjacent pixels and adjust the length of the stick. It also used to estimate the average distance between the adjacent pixels and also adjust the stick size [8].

Morphologic frames

In prostate cancer a maximum posteriori estimation framework is used to find the contour.i.e, a boundary of the prostate that are closely matches the prior shape model [130].In ovarian cancer we concentrated four different morphologic characteristics such as wall structure, cyst wall thickness, septation and echogenicity[137].

Descriptor features

Descriptor features are easier to understand because they are actually the empirical classification of the radiologists.

Spectral Features RF (RF)

The RF time series (RF1-RF6) corresponding to each spatial sample of RF data is a discrete signal of length M, where M is the number of frames acquired in the time series. We deducted the mean of the time series from all samples. The first four RF time series features (RF1,RF2,RF3,RF4) were the average value.

Fractal Features (FF)

To extract FF Features the computed the mean length of the time series scales. The computed the FF of all the RF time series within an ROI and averaged them to acquire one feature per ROI [128].

LF Features (Lizzi, Feleppa)(LF)

Lizzi, Feleppa and their colleagues have shown that the intercept extrapolated to zero structural (LF1),average slope(LF2) and mid point value(LF3) of a line fitted to the mid band portion of the structure.

RF Time series features (TS)

LF features and RF time series features are both computed based on spectral analysis of echo signals [141], they are fundamentally different. The LF features are computed based on spectral analysis, all originating from the same spatial location in the tissue. LF features are also called spectral features.

Geometric features:

In Geometric features due to the relative fixed position and high contrast between the internal cervical os and adjacent tissues, the location of the internal cervical os is desirable. Hence the geometric features of the cervix such as corner, edges are applicable in stepwise fashion [104].

Statistical features:

In SF he statistical features are analyzed using the package for the social sciences. Features are represented as mean, standard error mean or percentage [143].

In ovarian cancer all continuous data expressed as mean and standard deviation. Statistical features in ovarian cancer screening used four terms such as true positive, false positive, true negative, false negative[133].

Histogram features:

These features are used to distribute the data into different places and we can calculate the amplitude of the echo signals.

Morphologic tumor indexing features

Most ovarian masses deducted by ultra sound screening are benign. It is an effective method that decreases observer variation and false positive results. Here used morphologic scoring system which standardizing and quantifying the interpretation of ultra sound images.

Structural Features

Morphologic index system provided three structural characteristic including ovarian volume, cyst wall and septae. It provides high sensitivity at specificity [134].

Multiple Regression features

It is a most accurate method to simplify the index and apply weighted scoring to the structural component. The sensitivity of the index was 97% and specificity was 77%. Here using weighted scoring system for testing ovarian tumors [136].

V. CLASSIFIERS

After the extraction of feature and selection process we have to classify the images into lesion /non lesion or benign/ malignant or normal/ abnormal classes. Lesion detection [144] is necessary before the classification. We summarize the different ultrasound cancer detection and classification techniques are listed in table 7.

Linear Classifiers:

Frequently used linear classifiers for breast cancer detection and classification are linear discriminant analysis [174] and logistic regression (LOGREG) [145]. The main idea of LDA is to find the linear combination of the features which best separate two or more classes of the data.

Artificial Neural Networks:

Artificial neural networks are the collection of mathematical models that imitate the properties of biological nervous system and the functions of adaptive biological learning [10]. In the field of breast cancer detection and classification, three types of artificial neural networks are frequently used: Back-Propagation neural network, self-organizing map (SOM) and hierarchical ANN [123][146].

Bayesian Neural Network:

The idea behind BNN is to cast the task of training a network as a problem of inference, which is solved using Bayes' theorem [146]. A Bayesian neural network is more optimal and robust than conventional neural networks, especially when the training data set is small.

SVM Classifier

SVM training problem[104] allow for misclassification of noisy. In [51][55][112], SVM [103] was applied to classify the malignant and benign lesions. This method is 70% faster than ANN method.[112] proposed fuzzy support vector machine(FSVM) based on a regression model. The drawback of SVM is generated training errors.

Table 7 Classification Methods

cancer	Classifier	features
Breast	Linear Classifier: Construct decision boundaries by optimizing certain criteria: LDA and LOGREG[25][106][120][121]	Text Features(TF6-TF8,TF10,TF12) morphologic features (MF2,MF5-MF7)and descriptor features (DF1-DF4,DF6-DF7,DF9,DF12)
	ANN: Construct non linear mapping function: Back Propagation, SOM and hierarchical ANN[26][113][123]	Texture features(TF1,TF4,TF5], morphological features[MF1-MF4,MF8-MF13]
	BNN: A probabilistic approach to estimate the conditional probability density function[109]	Texture features(TF11,TF12,TF14], morphological features[MF2,MF5,MF14]
	SVM: Map the input data into a higher dimension space and seek an optimal hyper-plane to separate samples[51][55][110][112]	Texture features(TF1,TF7,TF19]
	Template matching: Uses retrieval technique to find database and assign query images[26]	Texture features(TF1-TF3,TF12,TF13],morphological features[MF4,MF13,MF15]
	Human Classifiers: Radiologists or Physicians use certain criteria to classify ultrasound images[31][118][119][125][126]	Texture features(TF1,TF7,TF9,TF15,TF16] Descriptive features[FD1-FD14) Morphological features(MF2)
Prostate	SVM Classifier[103]	Texture features(TF1,TF2,TF3), morphological features(MF), RF time series features
	Bayesian classifier[103]	ROC curve: generate the color map[52] Decision threshold[52]
Cervix	MAP(maximum posteriori techniques algorithm)[147]	Smoothness/Irregularity of lesion margins [147] Fourier descriptors of curvature smooth (black) and irregular (red) curvature segments[147]
Ovarian	Histologic classifier[133] Statistical classifier[148]	Screen results (positive, Negative) [133] Mass Spectrometry[148]

Template matching:

To differentiate the malignant and benign lesions image retrieval techniques are used. Here used feature vector to represent the query image and the images in the database. The advantage of the image retrieval technique is to classify breast lesions there is no training is needed. The disadvantages are the running time of the algorithm increases, it requires similar platform to run the images.

Human classifier:

The radiologist classifies the lesion using certain criteria. They are not a component and the human classifier to distinguish the malignant and benign lesions.

Bayesian classifier

It is a statistical classification method. The color maps are generated based on the ROC curve. We needed posterior probabilities of normal and cancer classes.

VI. EVALUATIONS

The images obtained with or without spatial compounding technique perform different operations in computer system [86]. The ROC curve is most frequently used because of its ability. The performance evaluation's shown in figure 2.

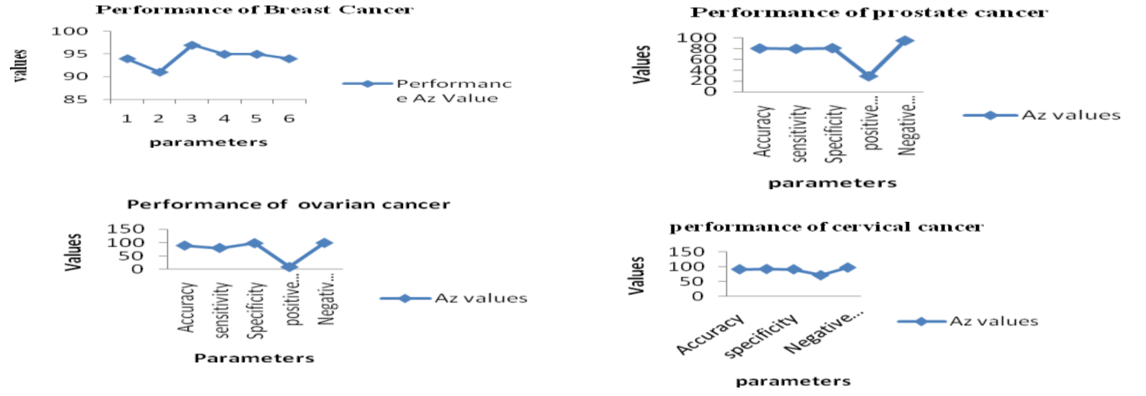

Fig.2. Performance Evaluation f different cancer

VII. SUMMARY

The survey summarizes the different ultrasound cancer evaluation and the performance results are listed in table 8.The various measurement techniques are shown in figure 4.

Table 8 Performance matrices

Measurement techniques	Breast	Prostate	Cervix	Ovarian
Accuracy (%)	94.25	80.5	92	90
Specificity (%)	91.67	79.8	93	81
Sensitivity (%)	96.08	81.1	92	98.9
Positive predictive value (%)	94.29	29	72	9.4
Negative predictive value (%)	94.23	95	98	99.97

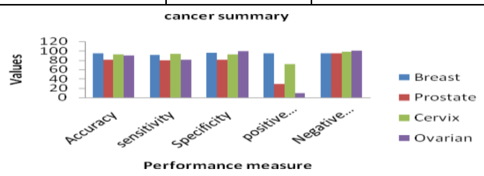

Fig.4.performance of ultrasound cancer

VIII. FUTURE DIRECTIONS

Currently the field of cancer computerized system using ultrasound images, most of the work concentrates on detection and classification. One of the future directions is high resolution ultrasound imaging devices can support detection of abnormal tissue. Three dimensional ultrasound imaging is another future direction which can provide more valuable information. We include more features is another future evaluation such as acoustic shadowing, punctate calcification, duct extension and Microlobulation etc.

IX. CONCLUSION

In this paper we reviewed computerized cancer detection and classification using ultrasound images in the literature. The techniques developed in the four stages (pre-processing, segmentation, feature extraction and classification) are summarized and the advantages and disadvantages are discussed. Different performance matrices are discussed. It is useful for the researches in image processing and radiology.

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